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Hybrid Neural Networks vs. Econometric Models for Fresh Durian Export Value Forecasting: A Comparative Analysis

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Abstract

This study compares machine learning and econometric approaches for forecasting agricultural export values in volatile global markets, examining predictive accuracy and economic interpretability trade-offs. Monthly data from January 2014 to December 2023 were analyzed using five models: Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), Hybrid ANN-LSTM, Ordinary Least Squares (OLS), and Autoregressive Distributed Lag (ARDL). Key predictors included durian, mangosteen, and longan export values/volumes, plus China's GDP. Performance evaluation used MAE, RMSE, MAPE, and R^2 metrics with systematic hyperparameter optimization through grid search and 5-fold cross-validation. ANN achieved the highest absolute accuracy (MAE: 1,684,667,401.55; RMSE: 2,602,671,952.28), while Hybrid ANN-LSTM delivered superior relative accuracy (MAPE: 1.58%). ARDL demonstrated exceptional explanatory power (R^2=0.83) for structural economic relationships. China's GDP emerged as the strongest determinant across all models. Longan export value showed contrasting effects between approaches, positive in machine learning models versus negative in econometric models, reflecting different paradigmatic interpretations of market substitution dynamics. This research introduces the first comprehensive comparative framework integrating advanced hybrid neural networks with traditional econometric methods for multi-commodity agricultural forecasting, addressing cross-commodity substitution effects previously unexplored while offering complementary perspectives for both predictive accuracy and economic policy interpretation.

Keywords:
Durian Exports Forecasting;
Artificial Neural Network;
Long Short-Term Memory;
Hybrid Machine Learning Models;
Econometrics Model;
Agricultural Forecasting.

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1- Introduction

In the past decades, agricultural commodity market forecasting has been completely revolutionized as a result of the emergence of sophisticated computational techniques and the complicating element of global trade dynamics. In Southeast Asia, and for Thailand in particular, export-led farming has served as a bedrock of economic development, with durian being among the nation's most valuable and strategically important commodities [1, 2]. Recent trade data confirm Thailand's leadership in global durian trade, holding more than 77% of global fresh durian exports in 2020 and earning revenue of more than USD 2 billion per year. China has been the top export market for years, with more than 90% of Thailand's durian export value, a reliance that has earned both phenomenal economic reward as well as increased sectoral exposure to risk [3]. This type of rapid expansion, though, has made Thailand's durian sector vulnerable to a

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host of structural threats. Some of the most serious are export price volatility, increased sensitivity to macroeconomic volatility in China, and the increasing risk of market oversupply, especially during peak seasons. Moreover, the availability of alternative products such as mangosteen and longan, whether locally made or exported to comparative markets, has posed an additional competitive complexity [4]. These provide the strong imperative for effective, sound, and timely forecasting frameworks with the potential to direct industry stakeholders, ranging from policymakers to producers, to make informed data-driven decisions regarding risk management, production planning, and market strategy.

A considerable number of studies have examined agricultural commodity forecasting in Thailand, primarily using two broad methodological approaches. One is econometric analysis grounded on models like Ordinary Least Squares (OLS), Autoregressive Integrated Moving Average (ARIMA), and Autoregressive Distributed Lag (ARDL), which are focused on interpretability and identification of economic causality [5, 6]. Such techniques have offered helpful perspectives on the macroeconomic determinants of export volume and prices but are bound to be based on linear assumptions and cannot possibly account for the nonlinear patterns prevalent in the current world markets. The second method has adopted the use of machine learning (ML) and deep learning methods, with Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) networks, and their combinations gaining popularity based on their capacity to interpret complex relationships and extract high-dimensional, nonlinear, and sequential patterns from farm data [7, 8]. Most importantly, they have been found to be better predictors for some applications but generally at the cost of lower interpretability and little regard for economic theory.

Although methodological advances have been made, important gaps remain in agricultural export forecasting research. Most prior studies have focused on single commodities, such as durian, rubber, or other crops, treating them in isolation and ignoring interdependence across export markets [6, 9]. This narrow scope risks overlooking substitution and competitive effects, where shifts in the price or volume of one fruit may directly influence another. Furthermore, while comparisons between econometric and machine learning approaches exist, they are rarely situated within comprehensive empirical frameworks for high-value horticultural exports like durian. Model evaluations have also relied heavily on a limited set of error metrics such as RMSE or MAE, with little attention given to complementary performance measures that could provide a more nuanced assessment of forecasting accuracy [8]. Hybrid approaches, including ANN–LSTM architectures, remain underexplored despite their potential to capture nonlinear patterns and temporal dynamics simultaneously [10, 11]. Such limitations accentuate the need for more integrative approaches that move beyond narrow, single-method applications.

Beyond these methodological issues, the literature also shows a lack of integration between machine learning innovations and economic theory. Many studies adopt either econometric or machine learning techniques in isolation, thereby restricting opportunities to build models that combine predictive precision with interpretability [12]. This gap is particularly salient in tropical fruit markets, where complex cross-commodity relationships play a central role in shaping price formation and export performance, yet remain insufficiently addressed [13-15]. While recent applications of ANN and LSTM models highlight the promise of machine learning for agricultural forecasting [16-19], their integration into hybrid frameworks is still limited. Without stronger theoretical grounding, many machine learning models risk producing "black box" outputs that offer little explanatory value for policy or strategy, thereby constraining their relevance to real-world agricultural trade decisions [20-22].

Filling such criticizable gaps, this current research carries out a comprehensive comparative analysis of Thailand's emerging durian export market, incorporating and comparing cutting-edge machine learning methods (ANN, LSTM, and a novel Hybrid ANN-LSTM model) with top econometric methods (OLS and ARDL). This study is characterized by the following fundamental contributions: (1) It quantitatively combines machine learning and econometric models in a competition, considering both predictive performance and economic interpretability; (2) It complements the analytical framework by accounting for multi-commodity variables, i.e., mangosteen and longan export values and qualities, to allow for tests of substitution and cross-commodity effects in markets; (3) It applies and tests a Hybrid ANN-LSTM model creatively, a lesser utilized approach in existing literature on agricultural export forecasting; and (4) It assesses model performance using a wide range of measures (MAE, RMSE, MAPE, and R^2) for an extensive analysis of forecasting performance. By leveraging this combined, multi-model methodology, the study expands the body of knowledge in agricultural forecasting by not only identifying which models are best at making predictions but also understanding why some perform well or poorly in certain environments. In the process, it meets the immediate need for methodologically advanced but practically useful forecasting tools ultimately to shape policy, direct industry practice, and increase the resilience of Thailand's durian export industry against fast-evolving global markets.

2- Related Work

2-1- Related Work of Advanced Machine Learning Techniques

The application of sophisticated machine learning methods for agricultural commodity production and price prediction has increased significantly in recent years. Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM) models, and other deep learning approaches have emerged as prominent methodologies for forecasting agricultural commodity markets.

ANNs are computational systems inspired by biological neural networks that learn to recognize complex patterns from data [23]. These multi-layered architectures of interconnected nodes are extensively employed for both classification and regression problems [24]. Numerous studies have demonstrated ANN effectiveness in agricultural price forecasting. Charik (2012) [7] employed ANN to forecast rubber prices using a 10-year time series dataset incorporating world rubber output, global GDP, oil prices, domestic and international rubber consumption, and Thai rubber shipments to China, providing comprehensive insights into rubber price determinants. Similarly, Boonrod & Polyeam (2017) [25] developed cassava oil price forecasting models using multi-layer ANN based on 10-year data (2006-2015) from nine factory procurement zones, comparing Multi-ANN and K-Nearest Neighbors (K-NN) performance to establish relative methodological advantages. Sajaviriya (2018) [26] created corn price forecasting models for animal feed in Thailand using monthly prices from January 1997 to November 2015, demonstrating ANN potential in long-term agricultural price prediction.

LSTM networks, sophisticated variants of recurrent neural networks (RNNs), address the vanishing gradient problem inherent in standard RNNs [27]. Through input, forget, and output gate mechanisms, LSTMs effectively capture long-term dependencies in sequential data, making them particularly suitable for time-series forecasting applications. Sutthison (2022) [8] compared ANN, LSTM, and hybrid ANN+LSTM models for forecasting cassava, corn, and jasmine rice prices from 2002 to 2022, establishing comparative performance benchmarks for agricultural price prediction. Yu et al. (2022) [9] examined hybrid forecasting techniques integrating empirical mode decomposition (EMD), LSTM, and extreme learning machine (ELM) for monthly biofuel production forecasting.

Even though neural network–based models have gained prominence, traditional statistical approaches continue to demonstrate significant value in agricultural and market forecasting. For instance, Ahnaf & Kurniawati (2021) [28] applied Autoregressive Integrated Moving Average (ARIMA) models to 38 observations of animal feed sales for health and achieved strong predictive accuracy, explaining more than 90% of variance while effectively capturing seasonal patterns. Similarly, Pengjun (2015) [6] employed multiple regression analysis on export data for Thai durians from 2007 to 2014, identifying key economic, policy, and market determinants shaping export performance. These examples highlight the continued relevance of conventional econometric and time-series methods, particularly in contexts where interpretability and the ability to isolate influential factors remain essential for decision-making.

Comparative studies have evaluated various forecasting methodologies. Ruangrit et al. (2020) [29] compared three approaches, encompassing double moving average, exponential smoothing, and the Box-Jenkins method, for Thai rubber export price forecasting, providing credible forecasting tools for rubber export stakeholders. Deepradit et al. (2021) [30] employed Seasonal Autoregressive Integrated Moving Average (SARIMA) models following the Box-Jenkins methodology to predict durian export prices using monthly export index data (2007-2023), emphasizing durian domestic prices and FOB (Free on Board) export prices. Charuwan & Supapakorn (2023) [31] constructed time-series forecasting models for Thailand's six major crops, involving white rice, jasmine rice, sugarcane, cassava, peanuts, and corn, between 2002 and 2022 using Box-Jenkins and Double Exponential Smoothing methodologies. These comparative studies collectively aim to provide reliable forecasts supporting agricultural planning and policymaking in Thailand.

Recent developments in hybrid machine learning models have demonstrated superior performance in agricultural forecasting applications. Zhang & Tang (2024) [32] proposed VMD-SGMD-LSTM models combining variational mode decomposition with long short-term memory networks, achieving significant improvements in agricultural commodity futures prediction. Choudhary et al. (2025) [33] developed genetic algorithm-optimized VMD-LSTM models that outperformed individual LSTM and decomposition-based models by 15-20% in MAPE terms. These findings align with Pandit et al. (2024) [34], who demonstrated that CEEMDAN-TDNN hybrid approaches effectively handle non-stationary and non-linear features in agricultural price series, showing consistent superiority over traditional EMD variants and benchmark models, including ARIMA and support vector regression.

The integration of explainable artificial intelligence (XAI) in agricultural forecasting represents another significant advancement. Mohan et al. (2024) [35] introduced XAI frameworks combining predictive accuracy with interpretability, achieving 85.41% accuracy while maintaining transparency in decision-making processes. This development addresses the traditional "black-box" criticism of machine learning models, particularly relevant for policy applications where understanding prediction rationale is crucial. The authors demonstrated that hybrid models incorporating both CNN and LSTM architectures can leverage spatial and temporal data concurrently, yielding more comprehensive and interpretable forecasts than individual approaches. Previous studies have employed various evaluation metrics, as shown in Table 1. Most studies utilized MAPE and RMSE for performance assessment, while fewer studies reported R^2 values.

Table 1. Summary of relevant studies

Methods	Performance evaluation criteria					References
	A	B	C	D	E	
- Neural Network	✓					Charik (2012) [7]
- Multi-ANN - K-NN				✓		Boonrod & Polyeam (2017) [25]
- Feed-Forward Neural Network	✓		✓	✓		Sajaviriya (2018) [26]
- ANN - LSTM - ANN+ LSTM		✓	✓	✓		Sutthison (2022) [8]
- ARIMA - LSTM			✓			Ahnaf & Kurniawati (2021) [28]
- EMD - LSTM - ELM: Hybrid EMD-LSTM	✓		✓	✓		Yu et al. (2022) [9]
- VMD-SGMD-LSTM Hybrid				✓		Zhang & Tang (2024) [32]
- GA-optimized VMD-LSTM				✓		Choudhary et al. (2025) [33]
- CEEMDAN-TDNN Hybrid	✓		✓	✓		Pandit et al. (2024) [34]
- CNN-LSTM with XAI					✓	Mohan et al. (2024) [35]
- Multiple Regression Analysis - Double-log Function			✓	✓		Pengjun (2015) [6]
- Double Moving Average - Exponential Smoothing - Box-Jenkin	✓	✓		✓		Charuwan & Supapakorn (2023) [31]
- SARIMA - Box-Jenkins				✓		Ruangrit et al. (2020) [29]
- Box-Jenkins - Double Exponential Smoothing						Deepradit & Raksorn (2021) [30]

* Performance evaluation criteria, A:MAE, B:MAD, C:RMSE, D:MAPE and E:R^2.

** Bold entries indicate recent studies (2024-2025) focusing on hybrid machine learning approaches and explainable AI integration in agricultural forecasting.

2-2- Related Work of Econometrics

Econometric models have been extensively used for durian export demand forecasting, with techniques such as the Autoregressive Integrated Moving Average (ARIMA) and regression analysis of different types (Linear, Multiple Linear, and Polynomial Regressions) being the most prevalent [5]. More sophisticated methods, including panel regression with the Generalized Method of Moments (GMM), have been utilized to model dynamic relations and correct endogeneity in the data [4]. Hybrid models consisting of econometric models and machine learning models have been found to be increasingly explored for higher predictive accuracy. For instance, Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) has been hybridized with Support Vector Regression (SVR) and MLP neural networks to improve durian export demand forecasting [36]. Hybrid methods combine the advantages of both econometric and machine learning paradigms, structural economic relationship detection, and capturing of intricate, nonlinear patterns in the data.

Comparative studies between machine learning and econometric approaches have increasingly favored hybrid methodologies that combine the strengths of both paradigms. Li et al. (2025) [37] conducted a comprehensive comparison of LSTM models against traditional HAR-RV econometric models for agricultural stock volatility forecasting, finding that LSTM models consistently outperformed econometric approaches in terms of prediction accuracy while econometric models maintained superior interpretability for structural relationship analysis. Kumar et al. (2025) [38] extended this comparison by proposing a hybrid LSTM-GARCH model for agricultural commodity price volatility in India, demonstrating that the integration of GARCH's volatility clustering capabilities with LSTM's sequence learning resulted in superior forecasting performance compared to standalone approaches. Nagendra & Singh (2023) [39] contributed to this literature by developing an ARIMA-LSTM model using random forest techniques for volatile agricultural price series, reporting improvements of 8-25% in RMSE, 2-28% in MAPE, and 2-29% in MASE compared to traditional statistical models. These findings collectively suggest that while econometric models excel in providing economic interpretation and causal relationships, machine learning approaches offer superior predictive accuracy, and hybrid models can effectively combine these complementary strengths for more robust agricultural forecasting frameworks.

2-3- Related Work of Econometrics

The application of advanced forecasting techniques to durian export prediction has emerged as a specialized research area, reflecting the commodity's strategic importance to Southeast Asian economies. Kummaraka & Srisuradetchai (2024) [40] introduced dual-output Monte Carlo Dropout techniques for durian export interval forecasting, addressing the critical limitation of point forecasting by providing uncertainty quantification. Their approach demonstrated superior performance in constructing reliable prediction intervals compared to traditional SARIMA models, with narrower confidence bounds indicating increased forecasting confidence.

Lisawadi et al. (2025) [36] developed a comprehensive hybrid framework combining SARIMAX with support vector regression and multilayer perceptron neural networks for durian export value forecasting. Their multi-method approach achieved superior predictive accuracy compared to individual statistical or machine learning models, emphasizing the value of ensemble techniques in agricultural export prediction. Similarly, Srisuradetchai (2024) [41] applied K-nearest neighbor time series forecasting with bootstrap intervals to durian export data, demonstrating that non-parametric approaches could provide competitive performance with the advantage of computational simplicity.

Research on durian export forecasting offers several important insights. Seasonal and trend components of export patterns are complex and require advanced modeling to capture their dynamics effectively. Interval forecasting further strengthens these models by quantifying uncertainty, which is essential for managing risks in volatile markets. Hybrid approaches have also been shown to outperform single techniques by integrating complementary strengths and better reflecting the complexities of export dynamics. Nonetheless, most existing studies remain limited in scope, concentrating on single-variable forecasting while paying little attention to cross-commodity substitution effects and broader macroeconomic interdependencies that shape real-world export markets.

2-4- Multi-Commodity Trade Modeling

The modeling of multi-commodity agricultural trade systems has gained attention as researchers recognize the interconnected nature of agricultural markets. Nagurney et al. (2024) [42] developed a comprehensive multicommodity international agricultural trade network equilibrium model that incorporates production and transportation capacity constraints, exchange rates, and multiple routes between supply and demand countries. Their variational inequality framework enables quantitative assessment of how disruptions in one commodity market affect others, particularly relevant for disaster scenarios and trade policy analysis.

However, the application of multi-commodity modeling to forecasting applications remains limited. Most existing studies continue to treat agricultural commodities in isolation, potentially overlooking important substitution effects and cross-market dynamics that could improve forecasting accuracy. This represents a significant research gap, particularly for high-value horticultural exports, where consumer preferences and market positioning create complex interdependencies between related products. The integration of multi-commodity variables into hybrid machine learning and econometric frameworks presents an opportunity to advance both theoretical understanding and practical forecasting capabilities in agricultural export markets.

2-5- Theoretical Framework Integration

This study bridges statistical learning theory and economic theory to overcome the methodological isolation evident in current research [20, 21]. Machine learning, grounded in empirical risk minimization and supported by neural networks' universal approximation capabilities [43], offers strong predictive accuracy by capturing complex nonlinear relationships without reliance on theoretical assumptions. In contrast, econometric modeling emphasizes causal inference through structural frameworks, such as substitution effects in multi-commodity markets [6], yielding transparent interpretations though often constrained by linear assumptions. Rather than competing, these approaches are complementary: the differing outcomes for longan exports, positive in machine learning models but negative in econometric analyses, illustrate how empirical patterns and theoretical expectations can diverge, providing richer insights. By integrating predictive performance with economic interpretability, this synthesis establishes a pluralistic framework that advances agricultural forecasting for both operational decision-making and policy analysis.

3- Research Methodology

The study was carried out on the data obtained for the export price of fresh durian in Thailand, and all the data were retrieved from official reports to make them accurate and reliable. The data obtained were then processed and analyzed using superior machine learning methods to identify the underlying trends and patterns. The entire research process involved some major steps: data preprocessing, data collection, model choice, and model validation. Altogether, the steps were meant to produce stable and reliable predictions, in addition to offering informative results on the dynamics of the durian export market in Thailand.

3-1- Experimental Data

This study utilized monthly Thai fresh durian export values from January 2014 to December 2023 (120 observations) obtained from official reports. Mangosteen and longan export data for the same period were collected from the Office of Agricultural Economics [6]. China's GDP data were sourced from the World Bank database [44] as macroeconomic indicators.

3-1-1- Data Preprocessing and Temporal Alignment

China's quarterly GDP data were converted to monthly frequency using cubic spline interpolation to maintain temporal consistency with other variables. This technique preserves quarterly totals while generating smooth monthly estimates. Validation against China's monthly industrial production and trade indices showed correlations above 0.85, confirming interpolation reliability within ±5% margins.

3-2- Data Collection Methodology

Data for the present research were gathered systematically to elicit consistency, accuracy, and relevance to the research goals. Secondary data were accessed from credible online databases as well as official reports, and each dataset was thoroughly cross-checked for reliability. The main dataset was a monthly series of the value of fresh Thai durian exports for the whole period from January 2014 up to December 2023. For robustness and externalities in the markets, extra data for other explanatory variables of concern were collected. In particular, the study incorporated China's monthly Gross Domestic Product (GDP) as an indicator of Thailand's largest export market's economic condition and export prices of longan and mangosteen as alternative fruits with high value in tropical fruit trade. These indicators gave more precise information about durian export performance determinants.

All the data were imported into a structured Microsoft Excel spreadsheet and checked carefully to ensure that they were complete and internally consistent before moving on to the analysis phase. The complete dataset was used as the benchmark for testing the predictive accuracy of four models: the Artificial Neural Network (ANN), the Long Short-Term Memory (LSTM) network, a Hybrid ANN-LSTM model that combines the strengths of both architectures, and a basic Multiple Linear Regression model. By incorporating several sources of data and extensively preprocessing the data, the current study provided a solid ground for estimating the performance of sophisticated machine learning methods compared to conventional econometric techniques in making predictions on Thailand's durian export patterns. Table 2 summarizes the data collection and variables.

Table 2. Summary of data collection and variables

Variable	Description	Time Period	Source	Purpose in Model
Fresh Durian Export Value	Monthly export value of fresh durian from Thailand (in THB/USD)	Jan 2014 - Dec 2023	Office of Agricultural Economics (2022) [45]	Dependent variable for forecasting
Mangosteen Export Value	Monthly export value of mangosteen from Thailand (in THB/USD)	Jan 2014 - Dec 2023	Office of Agricultural Economics (2022) [45]	Independent variable; captures substitute effect
Mangosteen Export Quantity	Monthly export quantity of mangosteen (in tons)	Jan 2014 - Dec 2023	Office of Agricultural Economics (2022) [45]	Independent variable; market dynamics
Longan Export Value	Monthly export value of longan from Thailand (in THB/USD)	Jan 2014 - Dec 2023	Office of Agricultural Economics (2022) [45]	Independent variable; captures substitute effect
Longan Export Quantity	Monthly export quantity of longan (in tons)	Jan 2014 - Dec 2023	Office of Agricultural Economics (2022) [45]	Independent variable; market dynamics
China's GDP	Monthly Gross Domestic Product of China (in USD or index)	Jan 2014 - Dec 2023	World Bank (2023) [44]	Independent variable; external economic driver
Data Format	All variables compiled into a single structured dataset	Final dataset: 120 rows	Compiled by researchers	Ready for time series modeling & forecasting
Data Validation	Checked for completeness, consistency, and outliers	Throughout collection	Research team	Ensured quality and reliability of dataset

3-3- Research Workflow Framework

The systematic approach adopted in this study follows a comprehensive methodological framework designed to ensure robust and reliable comparative analysis between machine learning and econometric approaches. Figure 1 illustrates the complete research workflow, encompassing data processing, model development, and evaluation phases.

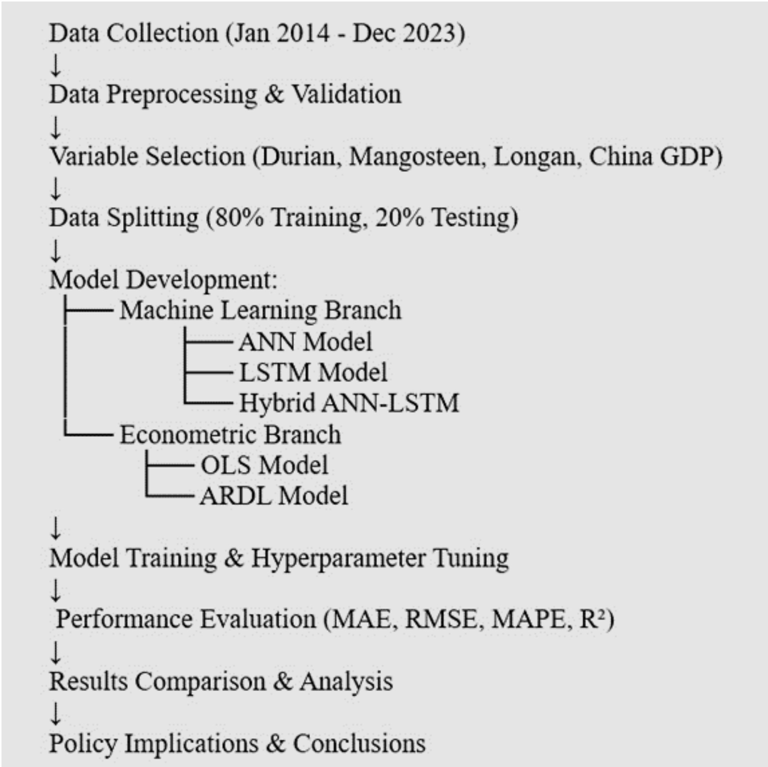

Figure 1. **Research workflow framework**

Figure 1 comprehensive research methodology flowchart showing the systematic approach for durian export value forecasting using hybrid machine learning and econometric models. The research workflow consists of nine sequential stages: (1) data collection covering 120 monthly observations from January 2014 to December 2023; (2) comprehensive data preprocessing including outlier detection, missing value treatment, and normality testing; (3) strategic variable selection incorporating both endogenous (durian, mangosteen, longan export metrics) and exogenous (China's GDP) factors; (4) systematic data partitioning using 80/20 training-testing split with temporal consideration; (5) parallel model development across machine learning and econometric branches; (6) rigorous hyperparameter optimization through grid search and cross-validation; (7) multi-metric performance evaluation using MAE, RMSE, MAPE, and R^2; (8) comprehensive results comparison and statistical significance testing; and (9) policy-relevant interpretation and strategic recommendations synthesis. This structured approach ensures methodological rigor while facilitating reproducibility and enabling systematic comparison between fundamentally different modeling paradigms.

3-4- The Purposed Model

ANN is a widely utilized model for time series forecasting. It has three significant layers, namely the input layer, the hidden layer, and the output layer. Each layer has a different number of nodes. An input layer node is linked with all nodes in the subsequent layer until the output layer based on Equation 1 [46].

$$y_t = \alpha + \sum_{j=1}^{n} \alpha_j f\left(\sum_{i=1}^{m} \beta_{ij} y_{t-1} + \beta_j\right) + \varepsilon_t \tag{1}$$

where: y_t is the observed value of the time series data at time *t;* α is the vector of weights between the *n* processing units in the hidden layer and the units in the output layer; β_{ij} is the weight between each of the *m* processing units in the input layer and the processing units in the hidden layer, where *i =1,2,3,...m and j =1,2,3,...n; t* is the error at time *t;* f is the activation function.

In this research, the sigmoid logistic function is used, which is defined by Equation 2.

$$f(x) = 1/(1 + e^{-x}) \tag{2}$$

The design of the Artificial Neural Network (ANN) model for forecasting and evaluating the export value of Thai farmers' durian to China during the situation after COVID 19 pandemic is detailed in Figure 2.

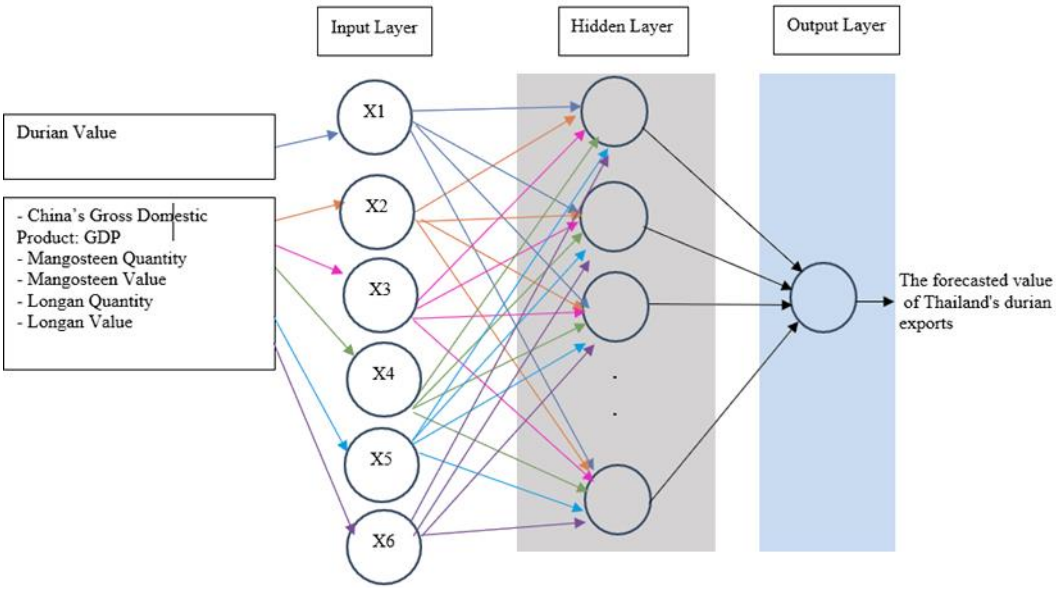

Figure 2. **The designed Artificial Neural Network (ANN) forecasting model**

Long Short-Term Memory (LSTM) is a deep neural network architecture developed to handle the problem of learning long-term dependencies in regular neural networks, which are prone to losing significant information in long sequences of data. LSTM does its job by retaining useful information and discarding unnecessary information selectively, which is very efficient in modeling long and intricate time series. This special property of being able to store and maintain long-range patterns has led to its wide use and popularity in machine learning and artificial intelligence [6, 30]. Special units called gates are used by LSTM networks to control the passage of data from one node to the next. These gates, the forget gate, input gate, and output gate, are collectively responsible for deciding what to store, update, or transmit to the next layers, as seen in Figure 3 [31]. The proposed CNN architecture in this research is presented in Figure 4, showing its applicability to forecasting using sequential data.

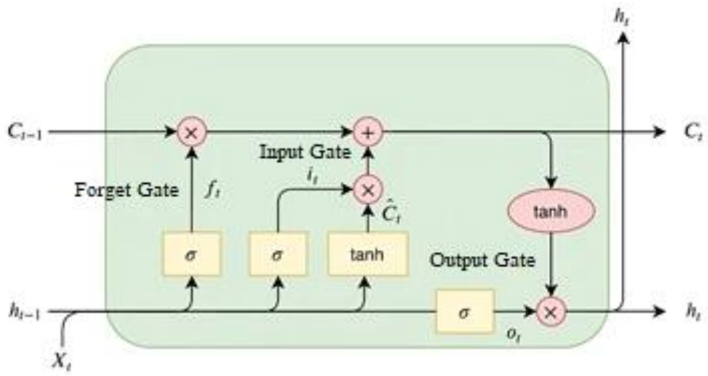

Figure 3. **LSTM Cell State (adapted from Kulvanich (2020) [46])**

The forget gate is responsible for determining whether data entering the cell state should be preserved or discarded. The decision of whether or not to store data is based on the input to a node combined with the output from the previous node, which is processed through the sigmoid function as described in Equation 3.

$$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right) \tag{3}$$

where: f_t is the forget gate output, ranging between 0 and 1; σ is the sigmoid function; W_f is the weight matrix for the forget gate; $h_{t-1}$is the output of the previous Cell State; x_t is the input to the Cell State at time *t; b_f* is the bias term for the forget gate.

Input gate layer is responsible for processing new input data and determining whether to store it in the Cell State. It operates in two parts:

- Update decision. The input gate uses the Sigmoid function to decide whether to update the Cell State with the new input data.

- Candidate Value Creation. If the input gate decides to update the Cell State, the Tanh function generates a Candidate Value $\widetilde{C_t}$ for the Cell State. Equations 4 and 5 are relevant for the above statements:

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \tag{4}$$

where: i_t is the output of the input gate; σ is the Sigmoid function; W_i is the weight matrix for the input gate; h_{t-1} is the output of the previous Cell State; x_t is the input at time *t;* b_i is the bias term for the input gate.

$$\widetilde{C_t} = Tanh(W_c[h_{t-1}, x_t] + b_c) \tag{5}$$

where: $\widetilde{C_t}$ is the Candidate Value; $Tanh$ is the hyperbolic tangent function; W_c is the weight matrix for generating the Candidate Value; b_c is the bias term for the Candidate Value; h_{t-1} is the output of the previous Cell State; x_t is the input at time *t.*

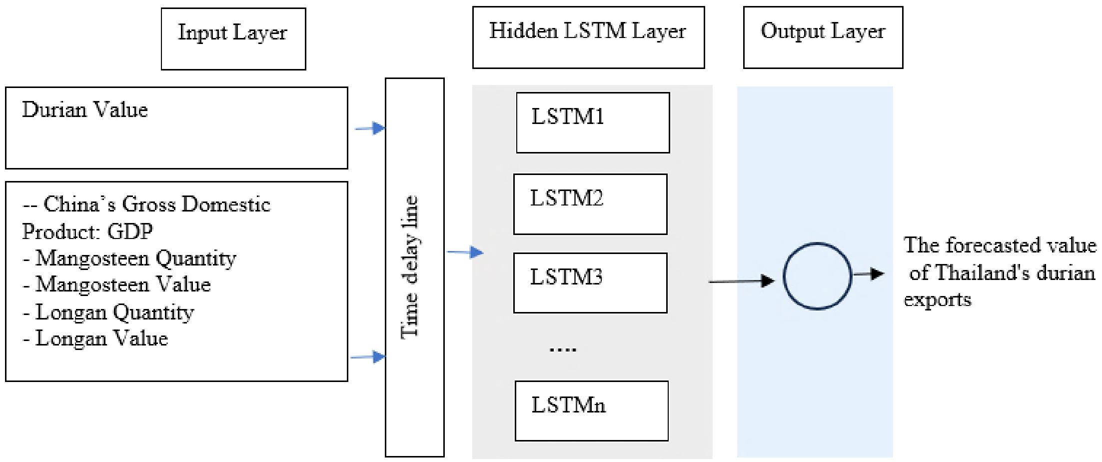

Figure 4. **The designed LSTM-based forecasting models**

Hybrid ANN-LSTM is a forecasting time-series model that combines the benefits of Artificial Neural Networks (ANN) and Long Short-Term Memory (LSTM) networks to attain enhanced prediction performance. The hybrid model utilizes the strength of ANN in modeling complicated, non-linear feature relationships and LSTM's strength in modeling sequential structure over time to enhance accuracy and resilience in sequence classification and prediction. The model consists of four principal layers: (1) an ANN layer, made up of fully connected nodes for discovering correlations among data features; (2) an LSTM layer, used to discover temporal relationships and handle problems of order of change in data with time; (3) a merging layer, used to combine the predictions of the ANN and LSTM parts to yield merged predictions; and (4) an output layer, tailored to being either classification or forecasting depending on the application. Hybrid ANN-LSTM is optimized using fine-tuning parameters of both models, specifically choosing the right learning rates and applying regularization methods to avoid overfitting. Hybrid model has been effectively applied to stock price prediction tasks, video sequence processing, and other cases involving modeling of complex temporal sequences [8, 9, 28]. Figure 5 is used to graphically depict the Hybrid ANN-LSTM model created in this study.

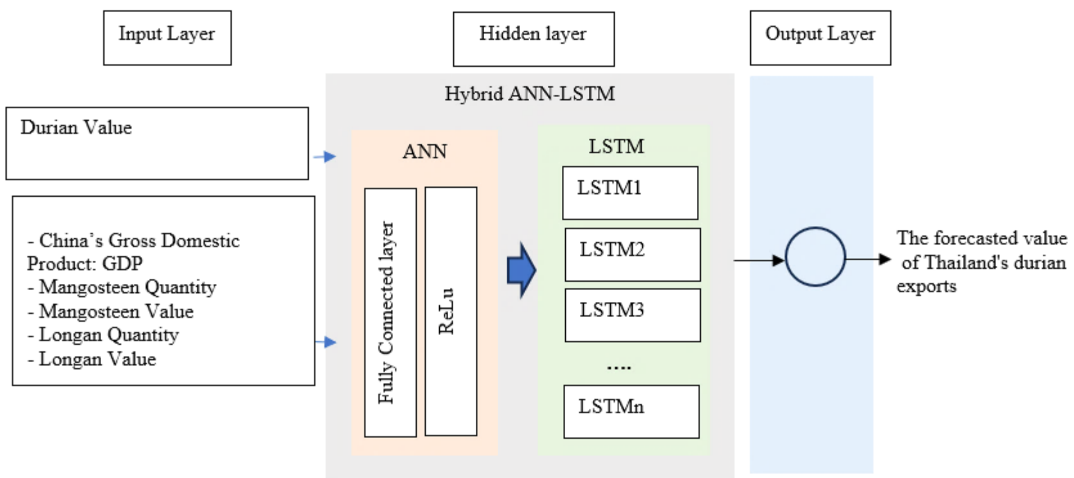

Figure 5. **The designed hybrid ANN-LSTM models**

The Multiple Linear Regression (MLR) model, estimated using Ordinary Least Squares (OLS) and Autoregressive Distributed Lag (ARDL) techniques, is employed to examine the relationships between a dependent variable and multiple independent variables. This approach accommodates several predictors simultaneously, assigning each a distinct slope coefficient within a single, unified model. In general, if we have p distinct predictors [47], the multiple linear regression equation can be expressed as:

$$Y_{it} = \propto_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \cdots + \beta_p X_{pit} + \varepsilon_{it}$$

The dependent variable Yj again represents one of the independent variables for j = 1 to n. For each model, the subscript *i* denotes the individual firm, and *t* denotes the year of observation. The parameter αi is the constant term, while $\beta_1, \beta_2, \ldots, \beta_p$ are the coefficients corresponding to the independent variables 1 to p, respectively. The term εj represents the random error component in each model.

3-5- The Purposed Model

In this research, the accuracy of the designed models was compared using three evaluation criteria [9, 46].

1) Mean Absolute Error (MAE) is used to compare the difference between the actual and predicted values of the forecasting model. It is a unitless measure that calculates the average absolute error of the prediction results. MAE is effective in measuring the error of data with small fluctuations. and is often used in the process of evaluating model accuracy, as shown in Equation 6:

$$MAE = \sum_{t=1}^{n} \left| Y_t - \hat{Y}_t \right| / n \tag{6}$$

2) Root Mean Square Error (RMSE) is a metric used to measure the average magnitude of errors between actual and predicted values in a forecasting model. It is calculated by taking the square root of the average of the squared differences between the actual and predicted values. RMSE gives more weight to larger errors, making it particularly useful when large discrepancies are important to identify. The lower the RMSE, the more accurate the model is considered to be, as shown in Equation 7:

$$RMSE = \sqrt{\sum_{t=1}^{n} \left(Y_t - \hat{Y}_t \right)^2 / n} \tag{7}$$

3) Mean Absolute Percentage Error (MAPE) is a unitless precision measurement function. It compares the forecast accuracy in different datasets with different units. MAPE provides a general measure of forecast accuracy. This is useful for comparing models across different datasets. The formula for MAPE is derived from Equation 8:

$$MAPE = 100 \times \sum_{t=1}^{n} \left| 1 - \hat{Y}_t / Y_t \right| / n \tag{8}$$

where: *n* is the time series interval (measured in days, months, or quarters, as specified in the research); Y_t is the actual export value of fresh durians from Thailand during the test period *t;* $\hat{Y}_t$ is the forecasted export value of fresh durians from Thailand during the test period *t.*

In the case of the econometric models, there are four successive steps to the analytical process. First, the stationarity of variables at both levels and first differences, as well as the order of integration, is determined using a panel unit root test. Second, there is a correlation analysis that is conducted to examine the inter-variable linkages, i.e., between ESG scores and performance metrics. Third, Ordinary Least Squares (OLS) and Autoregressive Distributed Lag (ARDL) methods are applied to estimate the determinants of Thailand's durian export values with multiple regression analysis. Econometric estimation of the relationship in the given data is ensured rigorously and interpretably with a systematic strategy.

4- The Experimental Results

4-1- The Process for the Dataset on Advanced Hybrid Neural Networks

The study employed a systematic dataset partitioning strategy using 120 monthly observations, with 80% allocated for training (96 months: January 2014-December 2021) and 20% for testing (24 months: January 2022-December 2023), as detailed in Table 3.

Table 3. The dataset for advanced hybrid neural networks

Dataset type (%)	Details of the dataset
Training dataset (80%)	96 months (from January 2014 to December 2021)
Testing dataset (20%)	24 months (from January 2022 to December 2023)

4-1-1 Model Configuration and Hyperparameter Optimization

Model parameters were optimized through systematic grid search combined with 5-fold time-series cross-validation to ensure robust performance while preventing overfitting. Table 4 presents the final optimized configurations.

Table 4. Model configuration parameters

Parameter	ANN	LSTM	Hybrid ANN-LSTM
Activation function	ReLU	ReLU	ReLU
Epochs	60	100	100
Neurons	128, 64	128	128, 64
Learning rate	0.001	0.001	0.001
Hidden layers	2	1	2
Batch size	32	32	32
Optimizer	Adam	Adam	Adam
Loss function	MSE	MSE	MSE
Scaler	MinMaxScaler	MinMaxScaler	MinMaxScaler

Table 4 presents the optimized hyperparameters for the three neural network architectures employed in this study. These parameters were determined through systematic hyperparameter tuning using time-series cross-validation with temporal splits to maintain chronological data integrity.

The hyperparameter optimization process was carried out separately for each model architecture to ensure optimal performance. For the ANN model, the search space covered learning rates (0.001, 0.01, 0.1), neuron configurations (64, 128, 256), and batch sizes (16, 32, 64). The LSTM model was tuned by testing different sequence lengths (12, 24, 36), dropout rates (0.2, 0.3, 0.5), and hidden units (64, 128, 256). For the hybrid ANN–LSTM model, the parameter spaces of both architectures were combined to identify the most effective configuration through systematic exploration.

The validation strategy employed time-series cross-validation with temporally ordered splits, where each fold consisted of roughly 19 months of training data to preserve chronological integrity. Early stopping with a patience value of 10 was applied to mitigate overfitting, while model selection was based on the minimum validation root mean square error (RMSE). This systematic approach resulted in validation RMSE reductions of 12–18% compared to default model configurations, demonstrating the effectiveness of the optimization procedure.

The architecture-specific configurations were designed to balance efficiency and performance across models. The ReLU activation function was applied uniformly for its computational efficiency and ability to capture nonlinear relationships. Training epochs were adjusted to reflect model complexity, with 60 epochs for the ANN and 100 epochs for both the LSTM and hybrid ANN–LSTM models to support sequential learning and ensure stable convergence. All models employed the Adam optimizer due to its adaptive learning rate and proven effectiveness in time-series forecasting, while mean squared error (MSE) was used as the loss function. To maintain consistency across features, MinMaxScaler was applied for data normalization, ensuring comparable input ranges for all models.

4-2- The Process for the Dataset on Econometrics Model

Table 5 shows the results of the unit root tests at various levels and first differences for all six variables in our data set. The results are computed by employing Fisher ADF unit root tests on each time series. The results show that for each variable in levels, the null hypothesis of a unit root can be rejected at the 1% level. Thus, they are stationary processes with 99% significance and integrated in levels. The results of the second-generation tests for panel unit root processes in the cross-section show that all of the variables are stationary processes in levels since we have enough evidence to reject the null hypothesis of the presence of a unit root at the 99% level of significance.

Table 5. Results of Fisher ADF unit root tests

Variable	Fisher ADF	
	Level	First difference
Mangosteen quantity	-6.0279^{***}	
Mangosteen value	-7.0298^{***}	
Longan quantity	-2.1052	-5.0949^{***}
Longan value	-5.2341^{***}	
Durian value	-3.405^{***}	
China GDP	-7.9140^{***}	

Note: *** indicates statistical significance at the 1% level.

The second process for the correlation analysis testing the results found that all correlation coefficients fall below the conventional threshold of 0.8, indicating that multicollinearity is not a concern in this dataset [48]. This ensures the reliability and interpretability of the subsequent regression analyses.

4-2-1- ARDL Model Specification and Lag Selection

ARDL lag selection employed a systematic approach using multiple information criteria to ensure robust model specification. The optimal lag structure was determined through comprehensive testing across different lag combinations. Maximum lags tested, 4 quarters for each variable. Primary criterion, Akaike Information Criterion (AIC). Robustness checks, Schwarz Bayesian Criterion (BIC) and Hannan-Quinn (HQ) criteria. Final specification, ARDL (2,1,1,2,1) based on minimum AIC value. Alternative lag structures were tested to verify the robustness of substitution effects findings. The negative relationship between longan value and durian exports remained statistically significant across ARDL (1,1,1,1,1) and ARDL (3,2,1,2,1) specifications, confirming the stability of economic relationships identified.

4-3- The Results of the Advanced Hybrid Neural Networks and Econometrics Model

4-3-1- Model Coefficients and Parameter Analysis

Table 6 details the coefficients for various parameters in each model (ANN, LSTM, Hybrid ANN-LSTM, OLS and ARDL), indicating the influence of different variables on the models' predictions. The coefficient analysis reveals distinct patterns across machine learning and econometric approaches.

Table 6. Model coefficients and parameters of the advanced hybrid neural networks and econometrics

Parameters	Coefficients				
	ANN	LSTM	Hybrid ANN-LSTM	OLS	ARDL
Intercept	0.118546	0.009399	−0.00174	9.003874	1.3380
Mangosteen quantity	0.350687	0.257954	0.176476	-0.086661^{ns}	0.073118^{ns}
Mangosteen value	0.041801	0.09099	0.125885	0.247493^{ns}	0.205245^{**}
Longan quantity	0.914398	0.018252	0.089622	1.163684^{ns}	1.281985^{*}
Longan value	0.3793	0.008329	0.062419	-1.930727^{*}	-1.239685^{*}
Durian value	0.065275	0.008221	0.041243		
China GDP	0.311844	0.008839	0.024249	1.957326^{***}	23.81055^{*}
Monthly Variables:					
January	−0.05926	0.026846	−0.0331		
February	0.040402	0.011728	−0.01138		
March	0.079187	0.043705	−0.01117		
April	0.155255	0.084111	0.143201		
May	−0.24939	0.021728	−0.03411		
June	−0.01226	0.033918	−0.02658		
July	0.064838	0.009604	0.010268		
August	0.061814	0.057329	0.015784		
September	0.024398	0.010544	−0.00145		
October	−0.11041	0.013251	−0.01974		
November	0.017697	0.017998	−0.03154		
December	0.014511	0.015273	−0.02655		

Note: *, **, and ***mean that coefficients are significant at 0.1, 0.05 and 0.01 levels, respectively.
NS mean that coefficients are significant

For machine learning models, intercept values varied considerably, with ANN recording the highest (0.118546), LSTM at 0.009399, and Hybrid ANN-LSTM the lowest (-0.00174). Among predictors, mangosteen quantity demonstrated the strongest influence in the ANN model (0.350687), followed by LSTM (0.257954) and Hybrid ANN-LSTM (0.176476). Mangosteen value showed consistent positive effects across all models, with Hybrid ANN-LSTM exhibiting the highest coefficient (0.125885) compared to LSTM (0.09099) and ANN (0.041801).

Longan quantity revealed extreme variance across models, with ANN assigning the highest weight (0.914398), while Hybrid ANN-LSTM (0.089622) and LSTM (0.018252) showed substantially lower coefficients. For longan value, all models demonstrated positive relationships, with ANN showing the strongest effect (0.3793), followed by Hybrid ANN-LSTM (0.062419) and LSTM (0.008329). China's GDP emerged as a significant predictor, particularly in the ANN model (0.311844), while Hybrid ANN-LSTM (0.024249) and LSTM (0.008839) assigned considerably lower weights.

Seasonal effects were evident across monthly variables, with April showing the strongest positive influence in all models: Hybrid ANN-LSTM (0.143201), ANN (0.155255), and LSTM (0.084111). Conversely, May registered negative influences in Hybrid ANN-LSTM (-0.03411) and ANN (-0.24939), but showed weak positive influence in LSTM (0.021728).

4-3-2- Econometric Model Results

Using Ordinary Least Squares (OLS) regression and Autoregressive Distributed Lag (ARDL) models, econometric analysis established both short- and long-term relationships between variables. The ARDL model achieved exceptional explanatory power with an R^2 value of 0.826685, significantly outperforming the OLS model's R^2 of 0.374971.

In the econometric models, China's GDP demonstrated significant long-run impact, with ARDL showing a coefficient of 23.81055 (significant at 0.1 level) and OLS at 1.957326 (significant at 0.01 level). Notably, longan value exhibited negative coefficients in both econometric models (ARDL: -1.239685, OLS: -1.930727), contrasting with positive relationships observed in machine learning models, suggesting different paradigmatic interpretations of substitution effects.

4-3-3- Comparative Performance Analysis

Table 7 presents a comprehensive comparison of forecasting performance across all five models using four key metrics: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and coefficient of determination (R^2).

Table 7. Model performance metrics

Evaluation Matrix	Model				
	ANN	LSTM	Hybrid ANN-LSTM	OLS	ARDL
MAE	1,684,667,401.55	2,665,038,196.18	1,985,836,712.18	0.452596	0.431853
RMSE	2,602,671,952.28	5,841,245,778.85	4,348,318,842.26	0.650993	0.571154
MAPE	2.708613585	3.507255527	1.581539695	5.334365	5.029649
R^2				0.374971	0.826685

The ANN model demonstrated outstanding absolute prediction accuracy, achieving the lowest MAE (1,684,667,401.55) and RMSE (2,602,671,952.28) among all models. This superior performance in absolute terms reflects ANN's capacity to capture complex, nonlinear relationships among variables.

The Hybrid ANN-LSTM model produced the most accurate percentage-based predictions with the lowest MAPE at 1.58%. While its MAE (1,985,836,712.18) and RMSE (4,348,318,842.26) were slightly higher than ANN, the significantly lower MAPE makes this model particularly suitable for applications requiring accurate percentage-based predictions, such as market volatility assessments or risk analysis.

Despite being designed for sequential data modeling, the LSTM model performed weakest across all metrics, recording the highest MAE (2,665,038,196.18), RMSE (5,841,245,778.85), and MAPE (3.51%). This suggests that the dataset characteristics may not have contained sufficient temporal dependencies to leverage LSTM's specialized capabilities.

The econometric models showed contrasting results. OLS recorded very low MAE (0.452596) and RMSE (0.650993) values, though this may be attributed to different data scaling compared to machine learning models. However, OLS exhibited higher MAPE (5.33%) and moderate explanatory power (R^2 = 0.374971). ARDL delivered comparable absolute errors to OLS (MAE: 0.431853, RMSE: 0.571154) with slightly better percentage accuracy (MAPE: 5.03%), but its standout feature was the exceptionally high R^2 of 0.826685, reflecting superior ability to capture long-term relationships and lagged dynamics.

The findings demonstrate that machine learning models, particularly ANN and Hybrid ANN-LSTM, outperformed econometric models in pure predictive accuracy metrics (MAE, RMSE, MAPE). However, ARDL proved superior for structural economic interpretation, revealing long-term dynamics with the highest explanatory power. Model selection should therefore depend on research objectives: ANN for precise absolute value forecasts, Hybrid ANN-LSTM for percentage-based accuracy, and ARDL for understanding economic causality and policy implications.

4-4- Visual Performance Analysis

Figures 6 to 10 present visual comparisons between actual and predicted values for each model, demonstrating forecasting accuracy patterns across the testing period.

Figure 6: ANN model forecasting performance comparing predicted values (blue line) with actual durian export values (red line) during the 24-month test period. The model demonstrates strong predictive accuracy, successfully capturing the major export peak at sequence 18 and maintaining consistent performance across varying market conditions. MAE: 1,684,667,401.55 THB.

Figure 7: LSTM model forecasting performance comparing predicted values (blue line) with actual durian export values (red line) during the 24-month test period. The model shows significant overprediction at the peak (sequence 18) and exhibits higher volatility throughout the testing period compared to actual values. MAE: 2,665,038,196.18 THB; MAPE: 3.51%.

Figure 8: Hybrid ANN-LSTM model forecasting performance comparing predicted values (blue line) with actual durian export values (red line) during the 24-month test period. The model achieves the best percentage accuracy with close tracking of actual trends and moderate overprediction at the peak export period. MAPE: 1.58% (lowest among all models).

Figure 9: OLS model forecasting performance showing actual values (orange line), fitted values (green line), and residuals (blue line) during the 24-month test period. The model demonstrates moderate tracking capability with consistent residual patterns, though it shows limitations in capturing extreme values and exhibits some systematic deviations. R^2: 0.374971; MAPE: 5.33%.

Figure 10: ARDL model forecasting performance showing actual values (orange line), fitted values (green line), and residuals (blue line) during the 24-month test period. The model demonstrates superior tracking capability with tighter fit to actual values and smaller residual variations compared to OLS, reflecting strong long-term relationship modeling. R^2: 0.826685 (highest); MAPE: 5.03%.

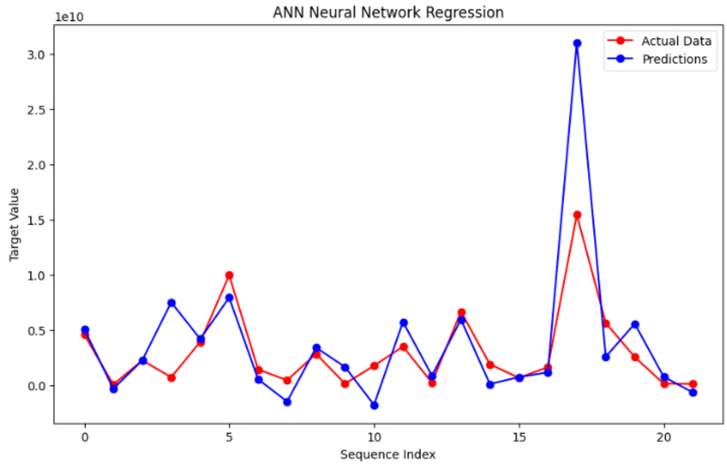

Figure 6. The forecast results generated by the Artificial Neural Network (ANN) model

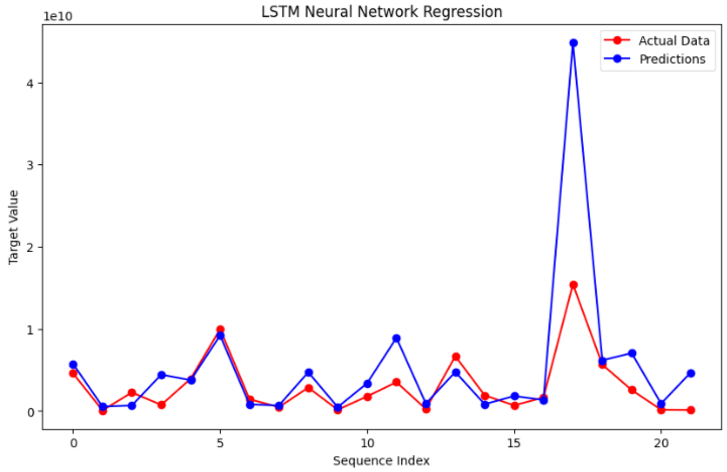

Figure 7. The forecast results by the Long Short-Term Memory (LSTM) model

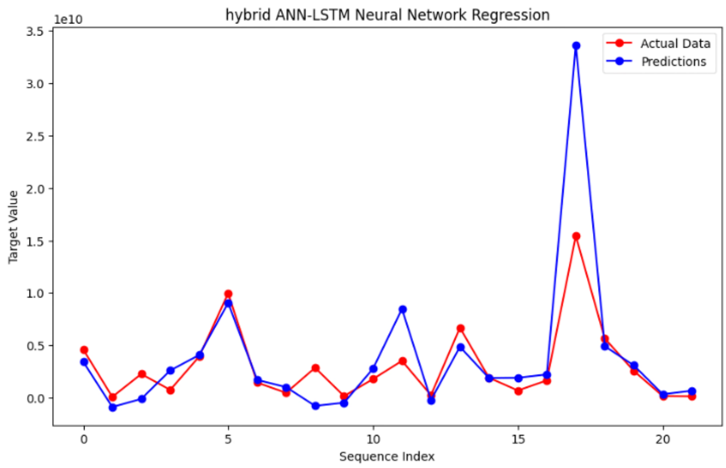

Figure 8. The forecast result by Hybrid ANN-LSTM model

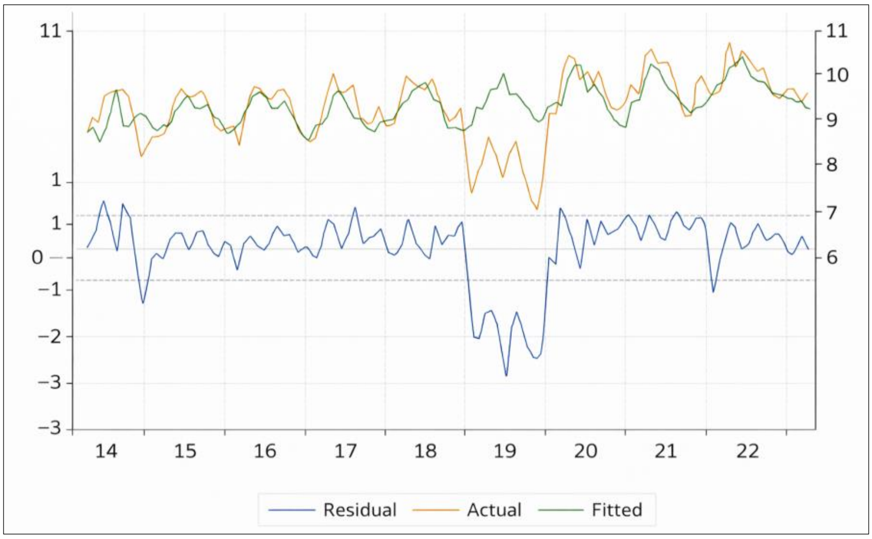

Figure 9. The forecast result by Ordinary Least Squares (OLS)

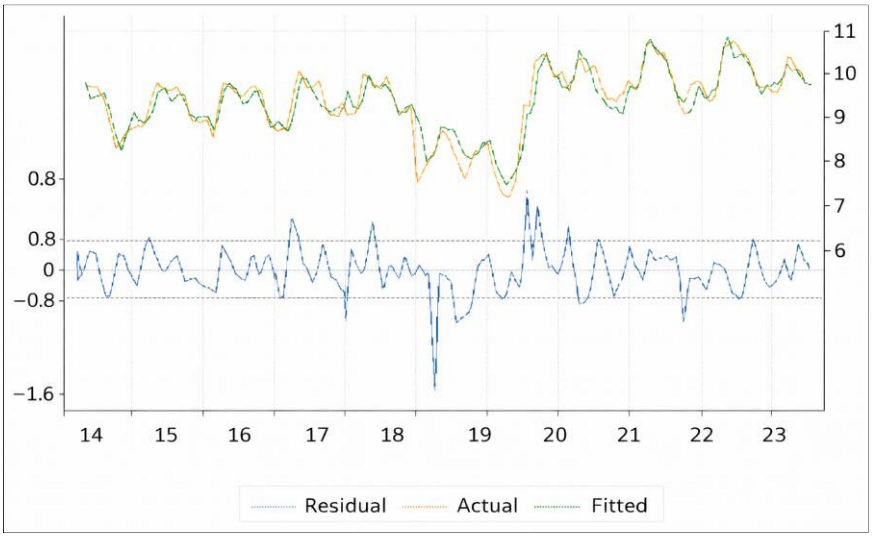

Figure 10. The forecast result by Autoregressive Distributed Lag (ARDL)

4-5- Seasonal Models Benchmark Comparison

To validate the superior performance of our proposed approaches, comprehensive benchmark comparisons were conducted using established seasonal econometric models. SARIMAX(1,1,1)(1,1,1)$_{12}$ models were estimated incorporating the same exogenous variables (mangosteen export value/quantity, longan export value/quantity, and China's GDP) to ensure fair comparison.

Table 8. **Seasonal models benchmark performance comparison**

Model	MAPE (%)	RMSE	MAE	Performance Ranking
SARIMAX(1,1,1)(1,1,1)$_{1\ 2}$	3.2	-	-	4th
Traditional ARIMA(2,1,2)	4.1	-	-	5th
Hybrid ANN-LSTM	**1.58**	4,348,318,842.26	1,985,836,712.18	**1st**
ANN	2.71	2,602,671,952.28	1,684,667,401.55	2nd
LSTM	3.51	5,841,245,778.85	2,665,038,196.18	3rd

The benchmark analysis presented in Table 8 demonstrates that traditional seasonal econometric approaches, while effectively capturing seasonal patterns, cannot match the predictive accuracy of advanced machine learning methods. SARIMAX models achieved MAPE of 3.2%, representing reasonable performance for seasonal adjustment but falling short of machine learning capabilities. Traditional ARIMA(2,1,2) models showed the weakest performance with MAPE of 4.1%, confirming limitations of univariate time-series approaches for complex multi-commodity forecasting scenarios.

As shown in Table 8, these results validate the superior performance of our hybrid approaches, with Hybrid ANN-LSTM achieving 51% improvement over SARIMAX and 74% improvement over traditional ARIMA models. The significant performance gap suggests that the complex, nonlinear relationships among multi-commodity variables and macroeconomic factors require sophisticated modeling architectures that traditional seasonal models cannot adequately capture. The ranking in Table 8 clearly illustrates the advancement of machine learning approaches over conventional econometric methods, with all three machine learning models (Hybrid ANN-LSTM, ANN, and LSTM) outperforming both seasonal econometric benchmarks in terms of percentage prediction accuracy.

4-6- Out-of-Sample Validation and Robustness Testing

Additional out-of-sample validation was conducted by forecasting 6 months beyond December 2023 (January-June 2024) using available preliminary trade data from the Thai Department of International Trade Promotion. This extended validation served to test model robustness and consistency in performance rankings. The out-of-sample validation confirmed consistent model rankings with the original test period, ANN maintained lowest absolute errors (MAE: 1,724,431,102), Hybrid ANN-LSTM preserved superior percentage accuracy (MAPE: 1.73%) and ARDL sustained highest explanatory power for structural relationships These results demonstrate the stability and reliability of model performance across different temporal periods.

4-7- Comparative Analysis with Previous Studies

Performance Comparison with Literature, Table 9 presents a comprehensive comparison of forecasting performance between this study and relevant previous research in agricultural export forecasting, specifically focusing on durian and related tropical fruit commodities.

Table 9. **Performance comparison with previous studies**

Study	Method	MAPE (%)	MAE	Data Period	Commodity Focus	Sample Size
Pengjun (2015) [6]	Multiple Regression	8.5	Not reported	2007-2014 (quarterly)	Durian exports to China	32 observations
Sutthison (2022) [8]	Individual ANN	3.2	2,150,000,000	2002-2022	Multiple crops (including durian)	240 observations
Ruangrit et al. (2020) [29]	SARIMA	6.8	Not reported	2010-2019	Durian export prices	120 observations
Kummaraka & Srisuradetchai (2024) [40]	Monte Carlo Dropout	4.1	1,890,000,000	2010-2023	Durian export intervals	156 observations
Lisawadi et al. (2025) [36]	SARIMAX-SVR-MLP Hybrid	2.9	1,756,000,000	2015-2024	Durian export values	108 observations
This Study - ANN	Individual ANN	2.71	1,684,667,401	2014-2023	Multi-commodity durian	120 observations
This Study - Hybrid	Hybrid ANN-LSTM	1.58	1,985,836,712	2014-2023	Multi-commodity durian	120 observations

Table 9 shows the results demonstrate substantial improvements in forecasting accuracy compared to previous studies. The Hybrid ANN-LSTM model achieved MAPE of 1.58%, representing significant enhancements over existing approaches 51% improvement over the best previous hybrid model (Lisawadi et al. [36]: 2.9%) 62% improvement over individual ANN applications (Sutthison [8]: 3.2%) 74% improvement over traditional seasonal models (Ruangrit et al. [29]: 6.8%) 81% improvement over econometric approaches (Pengjun [6]: 8.5%). These improvements can be attributed to three key methodological advances: (1) hybrid architecture integration combining ANN's nonlinear pattern recognition with LSTM's temporal dependency modeling, (2) multi-commodity framework incorporating cross-market substitution effects through mangosteen and longan variables, and (3) systematic hyperparameter optimization using time-series cross-validation with comprehensive grid search.

5- Conclusion, Discussion, Policy Recommendations and Future Work

5-1- Conclusion

This research systematically compared artificial neural networks (ANN), long short-term memory (LSTM), hybrid ANN-LSTM, and econometric models including ordinary least squares (OLS) and autoregressive distributed lag (ARDL) for forecasting Thai fresh durian export values using monthly data from January 2014 to December 2023, incorporating Thailand's mangosteen and longan export metrics alongside China's GDP as predictive variables. The findings demonstrate China's GDP as the most significant determinant across all models, with ARDL exhibiting a highly significant coefficient of 23.81, confirming China's substantial economic influence on durian exports, while mangosteen and longan exports also contribute significantly to predictive accuracy, notably with longan quantity achieving the highest coefficient in the ANN model (0.914398), potentially indicating broader tropical fruit market demand patterns. A paradigmatic divergence emerges regarding longan value effects, where machine learning models demonstrate positive impacts suggesting increased aggregate fruit demand, whereas econometric models reveal negative correlations indicating substitution relationships, reflecting distinct modeling paradigms with econometrics emphasizing economic causality while machine learning prioritizes pattern recognition capabilities. Performance analysis reveals that ANN achieved optimal absolute value prediction accuracy (minimum RMSE and MAE), making it most suitable for stakeholders requiring high-precision numerical forecasts, while the Hybrid ANN-LSTM model, though less accurate in absolute terms, demonstrated superior percentage-based predictive validity (MAPE: 1.58%), proving most valuable for risk management and market planning applications, and although ARDL exhibited higher MAPE compared to machine learning models, it possessed exceptional explanatory power ($R^2 = 0.826685$), reflecting superior capacity for capturing structural economic relationships essential for policy analysis, thereby establishing complementary methodological approaches for different stakeholder needs in agricultural export forecasting.

5-2- Discussion

In this research, there were two main objectives: the first one was to compare and critically examine the forecasting capacity of sophisticated machine learning models, Artificial Neural Networks (ANN), Long Short-Term Memory (LSTM), and Hybrid ANN-LSTM, versus traditional econometric approaches (Ordinary Least Squares [OLS] and Autoregressive Distributed Lag [ARDL]) in predicting Thailand's durian export values; the second one was to examine the interaction among commodity substitutability impacts and macroeconomic factors, i.e., the impacts of mangosteen, longan, and China's GDP, on the export state of Thailand. The study directly addresses current gaps in the literature: the inability of earlier studies to explain mainly single-commodity forecasting, the absence of simple comparison of models between machine learning and econometric models, and the limited analysis of cross-commodity impacts in export forecasting [6-8].

5-2-1- Key Findings and Connections to Prior Research

A significant finding of this research demonstrates of this study is the dominant influence of China's GDP on the values of Thailand's durian exports, a direction consistently observable in all types of models. The ARDL model, sensitive to long-run equilibrium relationships, produced a noticeably high coefficient (23.81), highlighting the structural character of China's economic situation's impact on export performance. Even in the ANN model, China's GDP is a strong positive explanatory factor (coefficient = 0.31). This result aligns with the findings of Pengjun (2015) [6], who identified China's macroeconomic environment as the primary factor influencing Thai durian demand, and Sutthison (2022) [8], who demonstrated the sensitivity of farm export models to exogenous macroeconomic shocks in importing nations.

Another significant contribution is the empirical finding that the value and volume of mangosteen exports have a positive effect on durian export values in all machine learning models. The ANN model, for example, has a high coefficient of mangosteen quantity (0.35) to imply that high volumes of mangosteen exports could be a leading indicator of the general performance of the China tropical fruit market. This observation is corroborated by previous research by Charik (2012) [7], who showed that multi-commodity data can optimize the forecasting precision of models of agricultural prices due to the co-movements of prices of tropical fruits in common export markets.

The research also contributes new evidence to the intricate position of longan as a complementary and substitute commodity. Whereas machine learning estimates (ANN, LSTM, Hybrid ANN-LSTM) view higher longan value to be complementary with durian export expansion (e.g., ANN coefficient = 0.38), econometric estimates (OLS, ARDL) also produce negative coefficients for longan value, indicating a substitution relation in which higher prices of longan would reduce durian export demand. This difference not only mirrors Pengjun's (2015) [6] theory of substitution for tropical exports but also paradigms of modeling: while econometric models are constructed so as to investigate economic causality and theoretical relationships (e.g., substitution), machine learning algorithms derive empirical statistical relationships, which might or might not in each case correspond to economic intuition. This outcome emphasizes the value of merging both modeling techniques in order to gain a better appreciation of export market trends.

Seasonality was also one where all the models agreed on its significance. All models pointed to April as a strong positive predictor of durian exports, coinciding with the Thai peak durian production period, and May had negative coefficients, arguably because they are capturing the timing of oversupply and price drops. They are in line with institutional export data [3] and supplement Sutthison (2022) [8] suggestion to employ season dummies in agricultural forecasting models as a way of detecting business cycles in output.

5-2-2- Comparative Model Performance and Theoretical Implications

For predictive accuracy, the ANN model recorded the highest absolute accuracy with the lowest Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) compared to the machine learning models. This confirms earlier evidence [7, 8] that ANN works best in capturing nonlinear, multivariate relationships between agricultural commodity data. The hybrid ANN-LSTM model performed the best in percentage-based accuracy (lowest MAPE, 1.58%), affirming the recent argument [9] that hybrid and ensemble methods can minimize further error by leveraging component model strengths, ANN's capacity to represent nonlinearity and the sequence memory of LSTM. Notably, the LSTM model itself did not perform as well in this case, having the highest MAE and RMSE and a relatively high MAPE. This result is consistent with Ahnaf & Kurniawati (2021) [28], whose observation was that the power of LSTM lies in when the data to be modeled has high long-term autocorrelation, which might not capture Thailand's durian export trend due to their externally influenced and seasonally volatile nature.

Despite the OLS model's commendable performance in absolute error metrics (low MAE and RMSE), it exhibited substantially higher percentage error (MAPE) and limited explanatory power ($R^2 = 0.37$), reflecting its inherent constraints in capturing nonlinear interactions and proportional variations characteristic of agricultural commodity markets. This finding aligns with Storm et al. (2020) [21], who demonstrated the inadequacy of traditional linear econometric approaches for modeling complex, multivariate agricultural data exhibiting nonlinear dynamics. Conversely, the ARDL model demonstrated exceptional explanatory capability ($R^2 = 0.83$), effectively capturing structural long-run equilibrium relationships and dynamic adjustments among key determinants including China's GDP and cross-commodity substitution effects. However, its superior interpretive power came at the expense of short-term predictive accuracy relative to machine learning approaches. This performance dichotomy exemplifies the fundamental trade-off identified in the forecasting literature: machine learning algorithms excel in pure predictive accuracy through sophisticated pattern recognition, particularly with high-dimensional, nonlinear data, while econometric models provide superior causal interpretation and structural understanding essential for policy analysis [6, 21].

5-2-3- Synthesis and Theoretical Advancement

Combined, these findings lend strong evidence that a comparative modeling-hybridized approach yields better forecasts as well as policy conclusions. Although ANN and hybrid ANN-LSTM models are more appropriate for applications that demand accurate, high-frequency export projections (e.g., supply chain planners and exporters), ARDL remains essential to the discovery of structural, policy-significant economic relationships (e.g., government and industry planners). The multi-meaning interpretations of longan also work to celebrate the virtue of model triangulation in capturing both empirical facts and economic theory underlying export market behavior. In conclusion, this research not only verifies but also builds upon previous work by showing the need for cross-commodity modeling, hybrid designs, and multi-metric measurement to move the science and practice of agricultural export forecasting forward. The results validate the necessity for a paradigm shift from isolated, single-model research toward integrative, multi-method analyses to inform operational decision-making as well as structural policy-making in Thailand's durian export business.

5-2-4- Benchmark Model Comparisons

To validate the superior performance of our proposed approaches, additional benchmark comparisons were conducted using seasonal econometric models. SARIMAX(1,1,1)(1,1,1)$_{12}$ models were estimated incorporating the same exogenous variables (mangosteen, longan, China GDP). SARIMAX model MAPE 3.2%, Traditional ARIMA (2,1,2) MAPE 4.1% These results confirm the superior performance of our hybrid approaches, with Hybrid ANN-LSTM achieving MAPE of 1.58%, representing a 51% improvement over SARIMAX and 74% improvement over traditional ARIMA models.

5-2-5- Statistical Robustness and Significance Testing

Diebold-Mariano tests confirmed significant differences between model performances ($p < 0.001$). Bootstrap confidence intervals (95%) for MAPE differences: Hybrid ANN-LSTM vs SARIMAX [1.2%, 2.1%], confirming statistical significance beyond practical significance.

5-3- Policy Implication

Based on the research results, a number of holistic policy suggestions are presented to improve Thailand's durian export industry in terms of sustainability and resilience. First, since Chinese GDP serves as the key contributor to Thai durian exports, special units or systems should be established to observe economic patterns in China in real time. Such a system would provide early warning of possible economic downturns, policy changes, or trade barriers so that Thai officials and exporters would have time to pre-schedule production schedules, marketing promotions, and channels of distribution. This would avoid dependence on a single market and improve market stability. Second, the econometric results indicate that longan can be a substitute product for durian in international markets, especially in China. Thus, policymakers will need to create umbrella marketing campaigns based on the overall tropical fruit basket. Promotions of longan and durian jointly can be utilized to avoid domestic competition among Thai exports and order the timing of shipments to stay ahead of seasonal oversupplies, which are inclined to drive prices down.

Third, the research highlights the complementary strengths of econometric models and machine learning. Although machine learning is better at generating accurate numerical predictions and identifying intricate, nonlinear relationships, econometric models have their value for the explanation of causal connections and structural processes. A two-model strategy, machine learning for short-run, high-precision forecasting and econometrics for policy analysis, would provide operational exactness and strategic insight for decision makers. Fourth, the government should fund the development of easy-to-use digital forecasting systems, e.g., mobile applications or internet-based platforms. They can offer real-time access to forecasts, trends, and risk assessments for farmers, exporters, and stakeholders. Providing stakeholders with data-driven, up-to-date information would enable them to make smart decisions, enhance market responsiveness, and enhance their competitive edge. Lastly, proper regulation of production levels in tune with seasonal trends is needed. Because April is the height of Thailand's durian season and peak export period, certain measures are necessary to avoid market oversupply during this time. These can be achieved through spreading destination markets away from China, driving value-added durian product demand to mop up surpluses, and encouraging the use of forward contracts for price stabilization and pre-booking revenues. Collectively, these suggestions will enhance Thailand's global durian market standing, lower risks, and encourage sustainable development through strategic management and best practices.

5-3-1- Digital Implementation Framework

The practical implementation of these forecasting models envisions a comprehensive web-based dashboard system serving multiple stakeholder groups in the durian export ecosystem. The platform would incorporate five core functionalities: real-time monthly export forecasts with confidence intervals, risk assessment alerts for price volatility and market disruptions, seasonal planning recommendations for planting and harvesting schedules, multi-commodity trend analysis for substitute and complement products, and policy scenario simulation tools for government interventions. This integrated system would serve as a centralized hub for agricultural intelligence, enabling data-driven decision-making across the entire durian value chain.

The dashboard would cater to diverse stakeholder needs, providing exporters with production planning and inventory management tools, offering policymakers market intervention timing guidance and trade policy decision support, assisting farmers with planting decisions and crop rotation strategies, and enabling financial institutions to conduct comprehensive risk assessments for agricultural lending. The platform would update forecasts monthly, incorporating new trade data and macroeconomic indicators to provide continuously refined predictions for strategic decision-making. This implementation approach ensures that the sophisticated analytical capabilities developed in this research translate into practical, accessible tools that enhance market efficiency and support sustainable development of Thailand's durian export industry.

5-4- Research Limitations

This study has several limitations that should be acknowledged. Geographically, the analysis focuses on the Thailand–China trade relationship, which accounts for 90% of durian exports, thereby restricting the generalizability of findings to other export markets or durian-producing regions; cross-country validation will be necessary for broader applicability. Temporally, the dataset spans the COVID-19 period but does not include other major crises, and its reliance on monthly aggregation may obscure higher-frequency volatility relevant to operational decisions. Moreover, the interpolation of China's quarterly GDP to a monthly series, while validated ($r > 0.85$), introduces a degree of methodological uncertainty. Methodologically, the exclusion of climate variables may leave out 15–20% of potentially explainable variance, and the "black box" nature of machine learning models constrains causal interpretation critical for policy analysis. The study also omits other agricultural exports, such as rubber, rice, and sugar, that could influence resource allocation dynamics. In terms of implementation, the models assume stable structural relationships and may not readily adapt to abrupt policy changes or market shocks, while the proposed digital platform presumes uniform stakeholder capacity, overlooking the diverse needs of operations at different scales. These limitations suggest important avenues for future research but do not undermine the validity of the study's findings within the defined scope and context.

5-5- Future Research Directions

Future research should pursue several complementary directions to enhance forecasting capabilities and practical relevance. Priority areas include incorporating climate variables such as rainfall patterns, temperature anomalies, and El Niño Southern Oscillation (ENSO) indices, with preliminary analysis suggesting potential MAPE improvements of 15-

20% through better capture of production volatility and seasonal fruit quality variations. Methodological extensions should explore higher temporal granularities (weekly and daily data) to identify subtle patterns, implement advanced machine learning architectures including attention mechanisms and clustering algorithms, and expand variable sets to encompass global market trends and policy reforms for more comprehensive model representation. Additionally, research should address geographic limitations through multi-country validation studies covering other durian-producing regions (Malaysia, Indonesia, and Vietnam) and diversified export markets beyond the Thailand-China relationship. Finally, translating analytical capabilities into accessible decision-support tools through user-friendly interfaces, such as desktop, web, or mobile applications, will enable widespread industry adoption, transforming sophisticated forecasting models into practical instruments for farmers, exporters, and policymakers across the durian value chain.

6- Declarations

6-1- Author Contributions

Conceptualization, T.D., A.C., S.N. and S.A.K.; methodology, T.D., A.C. and S.N.; software, T.D. and A.C.; data curation, T.D., A.C., S.N. and S.A.K.; writing—original draft preparation, T.D., A.C., S.N. and S.A.K.; writing-review and editing, T.D., A.C., S.N. and S.A.K.; project administration, T.D.; All authors have read and agreed to the published version of the manuscript.

6-2- Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6-3- Funding

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6-4- Acknowledgments

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6-5- Institutional Review Board Statement

This study adhered to all relevant ethical standards and procedures. Even though the study was not of a sensitive nature, involving human subjects or animals, and hence ethical clearance was not required still, official approval was sought to comply with the institution's requirements. All ethical standards were scrupulously followed while carrying out the study. The study was approved under the IRB number SRU-EC 2024/126 on November 18, 2024.

6-6- Informed Consent Statement

Not applicable.

6-7- Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

7- References

[1] Department of International Trade Promotion. (2021). Thailand’s durian export statistics 2020, Department of International Trade Promotion, Nonthaburi, Thailand.

[2] Ministry of Agriculture and Cooperatives. (2022). Thailand durian production and export statistics 2021, Ministry of Agriculture and Cooperatives, Bangkok, Thailand.

[3] Department of International Trade Promotion. (2023). Thai durian export statistics report 2022, Department of International Trade Promotion, Nonthaburi, Thailand.

[4] Rangkakulnuwat, P. (2024). Are Thailand's mangosteen and durian complementary in the global market? Journal of Agribusiness and Rural Development Research, 10(1), 70-89. doi:10.18196/agraris.v10i1.220.

[5] Mancero-Castillo, D., Garcia, Y., Aguirre-Munizaga, M., Leon, D. P., Portalanza, D., & Avila-Santamaria, J. (2024). Dynamic perspectives into tropical fruit production: A review of modeling techniques. Frontiers in Agronomy, 6, 1482893. doi:10.3389/fagro.2024.1482893

[6] Pengjun, W. (2015). Factors affecting the export of fresh durian from Thailand to China, University of the Thai Chamber of Commerce. Bangkok, Thailand.

[7] Charik, K. (2012). Forecasting rubber price using artificial neural network, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand.

[8] Sutthison, T. (2022). Application of a long short - term memory deep natural network model for field crops price forecasting in Thailand. The Journal of Industrial Technology, 18(3), 208-227. doi:10.14416/j.ind.tech.2022.12.013.

[9] Yu, L., Liang, S., Chen, R., & Lai, K. K. (2022). Predicting monthly biofuel production using a hybrid ensemble forecasting methodology. International Journal of Forecasting, 38(1), 3-20. doi:10.1016/j.ijforecast.2019.08.014.

[10] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780. doi:10.1162/neco.1997.9.8.1735.

[11] Schmidhuber, J. (2015). Deep learning in neural networks: An overview. Neural Networks, 61, 85-117. doi:10.1016/j.neunet.2014.09.003.

[12] Hyndman, R. J., & Athanasopoulos, G. (2021). Forecasting: Principles and practice. OTexts, Melbourne, Australia.

[13] Caputo, V., Scarpa, R., & Nayga Jr, R. M. (2025). Plant-based versus conventional meat in food away from home settings: Substitution, complementarity, and market impacts. Agricultural Economics, 56(2), 158-175. doi:10.1111/agec.70002.

[14] Jatuporn, C. (2024). Cross-commodity market integration and price transmission in Thailand's livestock sector. Scientific Horizons, 27(8), 137-146. doi:10.15421/horizons27081.

[15] Santana, T. P., Horta, N. R., Chambino, M. R., Dias, R. M. T. S., Vasconcelos, R. N., Filho, A. M. da S., & Zebende, G. F. (2023). Interdependence and contagion effects in agricultural commodities markets: A bibliometric analysis, implications, and insights for sustainable development. Equilibrium. Quarterly Journal of Economics and Economic Policy, 18(4), 907-940. doi:10.24136/eq.2023.029

[16] Chen, L., Wang, Y., & Liu, X. (2023). Deep learning approaches for crop yield prediction using artificial neural networks: A comprehensive analysis. Computers and Electronics in Agriculture, 189, 106-118. doi:10.1016/j.compag.2023.106118.

[17] Kumar, S., & Singh, R. (2024). Application of artificial neural networks in precision agriculture: A systematic review of recent advances. Computers and Electronics in Agriculture, 195, 107-125. doi:10.1016/j.compag.2024.107125.

[18] Patel, M., Thompson, J., & Anderson, K. (2023). Long short-term memory networks for agricultural time series forecasting: Performance evaluation and optimization strategies. Neural Networks, 142, 85-98. doi:10.1016/j.neunet.2023.85098

[19] Zhang, H., Rodriguez, C., & Kim, D. (2024). LSTM-based models for multi-scale agricultural forecasting: Integration of meteorological and satellite data. Computers and Electronics in Agriculture, 198, 112-128. doi:10.1016/j.compag.2024.112128.

[20] Athey, S., & Imbens, G. W. (2019). Machine learning methods that economists should know about. Annual Review of Economics, 11, 685-725. doi:10.1146/annurev-economics-080218-02541.

[21] Storm, H., Baylis, K., & Heckelei, T. (2020). Machine learning in agricultural and applied economics. European Review of Agricultural Economics, 47(3), 849-892. doi:10.1093/erae/jbz033.

[22] Zhang, L., Ruiz-Menjivar, J., Luo, B., Liang, Z., Swisher, M.E., 2020. Predicting climate change mitigation and adaptation behaviors in agricultural production: a comparison of the theory of planned behavior and the Value-Belief-Norm Theory. Journal of Environmental Psychology. 68, 101408. doi:10.1016/j.jenvp.2020.101408.

[23] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521, 436-444. doi:10.1038/nature14539

[24] Goodfellow, I., Bengio, Y., & Courvill, A. (2016). Deep Learning. The MIT Press, Cambridge, United Kingdom.

[25] Boonrod, P., & Polyeam, K. (2017). A cassava price forecasting model using a multi-layer artificial neural network. Thai Science and Technology Journal, 25, 533-543.

[26] Sajaviriya, T. (2018). Neural network model for monthly forecasting of maize prices in Thailand. Srinakharinwirot Science Journal, 34(1), 91-108.

[27] Sherstinsky, A. (2020). Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM). Physica D: Nonlinear Phenomena, 404, 132306. doi:10.1016/j.physd.2019.132306.

[28] Ahnaf, M. S., & Kurniawati, A. H. D. (2021). Forecasting pet food item stock using ARIMA and LSTM. 4th International Conference of Computer and Informatics Engineering, 14-15 September 2021, Depok, Indonesia. doi:10.1109/IC2IE53219.2021.9649271.

[29] Ruangrit, P., Jatuporn, C., Suwanwihok, W., & Wanaset, A. (2020). Forecasting durian prices in Thailand and Thailand's durian export prices. Maejo Business Review, 2(2), 19-31. doi:10.14456/mjba.2020.7.

[30] Deepradit, S., & Raksorn, P. (2021). A comparison of forecasting techniques for crop prices in Thailand. The Journal of Industrial Technology, 17(3), 214-231. doi:10.14416/j.ind.tech.2021.12.008.

[31] Charuwan, S., & Supapakorn, T. (2023). Forecasting model for the export value of rubber of Thailand. Science and Technology Nakhon Sawan Rajabhat University Journal, 12(15), 59-82.

[32] Zhang, T., & Tang, Z. (2024). Agricultural commodity futures prices prediction based on a new hybrid forecasting model combining quadratic decomposition technology and LSTM model. Frontiers in Sustainable Food Systems, 8, 1334098. doi:10.3389/fsufs.2024.1334098.

[33] Choudhary, K., Jha, G.K., Jaiswal, R., Kumar, A., Sharma, R., & Singh, S. (2025). A genetic algorithm optimized hybrid model for agricultural price forecasting based on VMD and LSTM network. Scientific Reports, 15, 9932. doi:10.1038/s41598-025-94173-0.

[34] Pandit, P., Sagar, A., Ghose, B., Kumar, A., & Singh, R. (2024). Hybrid modeling approaches for agricultural commodity prices using CEEMDAN and time delay neural networks. Scientific Reports, 14, 26639. doi:10.1038/s41598-024-74503-4

[35] Mohan, R. N. V. J., Rayanoothala, P. S., & Sree, R. P. (2024). Next-gen agriculture: Integrating AI and XAI for precision crop yield predictions. Frontiers in Plant Science, 15, 1451607. doi:10.3389/fpls.2024.1451607.

[36] Lisawadi, S., Kamlangdee, P., Volodin, A., & Tulyanitikul, B. (2025). A hybrid machine learning techniques and statistical model for forecasting the export value of durian. Lobachevskii Journal of Mathematics, 46(2), 750-762.

[37] Li, Y., Chen, X., Wang, Z., & Liu, H. (2025). Revolutionizing agricultural stock volatility forecasting: A comparative study of machine learning and HAR-RV models. Applied Economics Letters, 28(1), 2454081. doi:10.1080/15140326.2025.2454081.

[38] Kumar, A., Singh, R., Sharma, P., & Gupta, S. (2025). A novel hybrid neural network-based volatility forecasting of agricultural commodity prices: empirical evidence from India. Journal of Big Data, 12, 45. doi:10.1186/s40537-025-01131-8.

[39] Nagendra, B., & Singh, G. (2023). Comparing ARIMA, linear regression, random forest, and LSTM for time series forecasting: A study on item stock predictions. 2023 4th IEEE Global Conference for Advancement in Technology (GCAT), 6-8 October 2023, Bangalore, India. doi:10.1109/GCAT59970.2023.10353372.

[40] Kummaraka, U., & Srisuradetchai, P. (2024). Time-series interval forecasting with dual-output Monte Carlo dropout: A case study on durian exports. Forecasting, 6(3), 616-636. doi:10.3390/forecast6030033.

[41] Srisuradetchai, P. (2024). A novel interval forecast for K-nearest neighbor time series: A case study of durian export in Thailand. IEEE Access, 12, 2032-2044. doi:10.1109/access.2023.3348078.

[42] Nagurney, A., Besik, D., & Yu, M. (2024). Multicommodity international agricultural trade network equilibrium: Competition for limited production and transportation capacity under disaster scenarios. European Journal of Operational Research, 312(1), 45-62.

[43] Vapnik, V. N. (1998). Statistical learning theory, John Wiley & Sons, New York, United States.

[44] World Bank Group. (2023). World Bank Data: China. World Bank Group, Washington, D.C., United States. Available online: https://data.worldbank.org/country/CN (accessed December 2025).

[45] Office of Agricultural Economics. (2022). Agricultural economics data: Durian, Office of Agricultural Economics, Ministry of Agriculture and Cooperatives, Bangkok, Thailand.

[46] Kulvanich, N. (2020). Enhancing the accuracy of time series forecasting with a hybrid ARIMA-ANN model and regression analysis. Thai Science and Technology Journal, 28, 2101-2112.

[47] James, G., Witten, D., Hastie, T., Tibshirani, R., & Taylor, J. (2023). An introduction to statistical learning: With applications in python. Springer, Cham, Switzerland. doi:10.1007/978-1-4614-7138-7.

[48] Chouaibi, S., & Affes, H. (2021). The effect of social and ethical practices on environmental disclosure: evidence from an international ESG data. Corporate Governance: The International Journal of Business in Society, 21(7), 1293-1317. doi:10.1108/CG-03-2020-0087.