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Forecasting Thai Agricultural Price: A Deep Learning Approach for Key Commodities

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***Abstract*—Accurate price forecasting is essential for informed decision-making by stakeholders in the agricultural sector, including farmers, traders, and policymakers. This study explored the use of deep learning models to predict market prices of four major agricultural commodities in Thailand, including rice, corn, cassava, and sugarcane. We evaluated and compared three network architectures across multiple forecasting horizons on a dataset from the Thai market. Overall, our findings suggested that the Long- and Short-term Time-series network or LSTNet was the most stable model, highlighting the advantage of capturing relationships among multiple variables. The results essentially pinpointed the strengths and limitations of each model, emphasizing the need for careful model selection based on characteristics of individual agricultural products.**

***Keywords*—agricultural price forecasting, time series prediction, deep learning, recurrent neural networks, long short-term memory**

I. Introduction

Food and agricultural products are fundamental to humans, supporting the health and well-being of populations worldwide. They also drive economies, especially in countries where agriculture is a major proportion of GDP and employment like Thailand. In Thailand, the agricultural sector accounts for nearly one-third of the country's workforce, yet its share of the national GDP remains relatively small. The prediction of agricultural prices has become an important research area due to the highly dynamic and influenced by diverse factors of agricultural markets. These factors include climate conditions, supply chain volatility, demand fluctuations of all related products, government policies, and global trade. Developing accurate and reliable models for agricultural price forecasting ensures economic stability and sustainable agricultural development. In essence, it enables all stakeholders related to the entire supply chain including farmers, policymakers, and market participants to make informed decisions regarding production, distribution, and investment.

Stakeholders can use prediction models to anticipate price peaks and drops well in advance. This insight allows farmers and traders to make strategic decisions about when to buy, sell or store agricultural products. By providing early warnings of desirable or unfavorable market conditions, the prediction models enable agribusiness to implement risk mitigation strategies. To support optimization of supply chains, predictive analytics help in aligning production schedules with market demand, minimizing storage costs, and improving distribution planning. In addition, policymakers and governments can implement timely measures to stabilize markets by understanding potential price shifts in advance. Agricultural policies and interventions can support both producers and consumers from price volatility. In conclusion, these stakeholders can benefit from the price prediction system to enhance market insights, support risk management associated with market volatility, optimize resource allocation of supply chains, and support policy formulations which further enhance overall agricultural sustainability.

The integration of technology in agriculture applications plays an important role in enhancing price prediction accuracy and improving risk management strategies. With rapid technological advancements, Artificial Intelligence (AI), especially Machine Learning (ML) and Deep Learning (DL) has revolutionized various applications in this era including the agricultural sector. By leveraging large amounts of relevant data, these data-driven models analyze patterns and extract valuable insights. For price prediction, these models help identify market trends, detect historical price patterns, and forecast future price fluctuations. Unlike traditional time series analysis, AI algorithms can process and analyze diverse datasets to uncover complicated relationships like temporal and inner-correlation patterns within the data. Motivated by the need for accurate agricultural price forecasting, this study proposed a deep learning-based framework to predict the prices of key agricultural commodities in Thailand, including rice, corn, cassava, and sugarcane. To build the predictive model, daily price data for these agricultural products were utilized as response variables. The study systematically evaluated and compared multiple deep learning models to determine their effectiveness in forecasting future price trends. The predictive capability of each model was assessed across different time horizons, ranging from short-term of 1-day ahead to long-term of 14-day ahead forecasts.

II. Literature Review

Agricultural prices naturally fluctuate due to various complicated factors [1–3]. Some price forecasting methods rely on qualitative analysis which aims to understand market price trends based on diverse relevant factors. Experience and expert judgement can be utilized to analyze the relationship of these factors and predict the direction of price movements. A majority of studies on agricultural price prediction have focused on quantitative analysis. Market price data was utilized with data-driven forecasting techniques to make numerical predictions of price changes. The quantitative analysis includes diverse methods such as regression analysis, traditional time series analysis, machine learning and deep learning models. Hybrid methods, which integrate multiple forecasting models, are also widely proposed in previous studies [4–9]. For example, Ge *et al.* [10] examined fluctuations in corn prices and associated factors. Two forecasting models, including a univariate nonlinear regression model using time as the independent variable, and a multiple linear regression model that incorporated production, consumption, import, and export volumes as independent variables, were employed and compared. The regression analysis benefited from its simplicity and interpretability but might suffer from capturing complicated relationships among factors. Several time series analysis methods have also been proposed in order to analyze historical price patterns over time. Particularly, exponential smoothing, moving averages, autoregressive models, and their combinations were utilized to mainly capture temporal relationships [11, 12].

In recent years, more advanced approaches such as ML and DL have gained significant attention from researchers due to their superior performance in various domains. They were designed to handle large and complicated patterns within the data that traditional methods might miss. Compared to ML, more advanced models like DL utilize relatively more complex networks to process large and diverse data structures, including time series data. Recurrent Neural Networks (RNNs) and their variations, such as the Gated Recurrent Unit (GRUs) and Long Short-Term Memory (LSTMs), are a subset of DL specifically designed to handle sequential data such as time series. Another class of deep learning models, Convolutional Neural Networks (CNNs), is designed to capture spatial relationships within the data. Several prior studies have compared LSTM to traditional methods for price prediction [13]. Silva *et al.* [14] compared LSTM with time series models and machine learning methods for corn and sugar prices. Other studies have evaluated LSTM against SARIMA and Holt-Winter's time series analysis for rice and arecanut price prediction [15, 16]. Further demonstrating this trend, several LSTM variants have been widely used for agricultural price forecasting. Murugesan *et al.* experimented with various LSTM architectures for predicting the prices of rice, wheat, gram, banana, and groundnut while Jaiswal *et al.* developed a deep LSTM model for maize and palm oil price prediction [17, 18].

A combination of advanced techniques has been integrated with DL architectures to improve their ability to handle complex and dynamic data patterns. For instance, Ouyang *et al.* utilized the Long- and Short-term Time-series network (LSTNet) developed by Lai *et al.* for 12 agricultural commodity futures price prediction [19, 20]. The results suggested that LSTNet offered a promising approach for multivariate time series forecasting within the challenging domain of agricultural commodity futures markets, characterized by price data integrating both long- and short-term information, as well as linear and non-linear structures. More recently, Feng *et al.* introduced a BiGRU-attention model optimized by the grey wolf optimizer while Yang *et al.* relied on a multi-module wavelet transform-based fusion forecasting model to predict corn prices [21, 22].

III. Materials and Methods

The objective of this study was to develop a predictive model for forecasting agricultural market prices in advance. As a case study, we collected daily price data for 4 important agricultural products having high economic impact in Thailand, including rice, corn, cassava, and sugarcane. This study followed a structured approach, starting with data collection and preprocessing. We then conducted exploratory data analysis to preliminary observe trends, seasonal patterns, and pronounced correlations within the historical price data. The core methodology focused on deep learning-based time series forecasting, where we treated the agricultural price as the target variable. Each model underwent hyperparameter tuning to optimize performance. To evaluate prediction performance, we experimented with different forecasting horizons, ranging from short-term of 1-day ahead to 14-day forecasts. All models were assessed using a widely accepted evaluation metric, ensuring their reliability and effectiveness in real-world applications.

A. Data Collection and Data Preparation

This study analyzed the historical prices of key Thai agricultural products: rice, corn, cassava, and sugarcane. Price data, recorded in Thai Baht, were obtained from the Ministry of Commerce's public data repository. This data, compiled from various statistical records and sample groups selected by the Department of Internal Trade, serves as reference points for economic analysis. The dataset spans from January 2009 to July 2023, comprising of 5,321 data points.

Due to the presence of missing values, data imputation was performed using a sequential approach to effectively utilize temporal relationships. Specifically, linear interpolation was first applied to estimate values between known data points, followed by backward fill to address initial missing entries, and finally forward fill to handle any remaining gaps at the end of the series. Fig. 1 visualizes the time series price data after preprocessing for each product. A clear upward trend is noticeable across all four products after 2020, suggesting the influence of potential external factors. Rice and cassava prices exhibit greater volatility while sugarcane prices show less fluctuations. In contrast, corn prices demonstrate a more structured upward trend with modest fluctuations.

Specifically, the price of rice declined from 2012 to 2016, remained relatively stable for a while, and began an upward trend around 2020 with a sharp rise in 2022–2023. Cassava prices are also highly volatile, with peaks observed around 2011, 2018, and 2023. Corn prices show a long-term upward trend, accelerating sharply after 2020 and peaking around 2023 before a slight decline. Sugarcane prices experienced fluctuations, with dips around 2015–2016 and 2019, followed by a steady increase after 2020, reaching peaks in 2023.

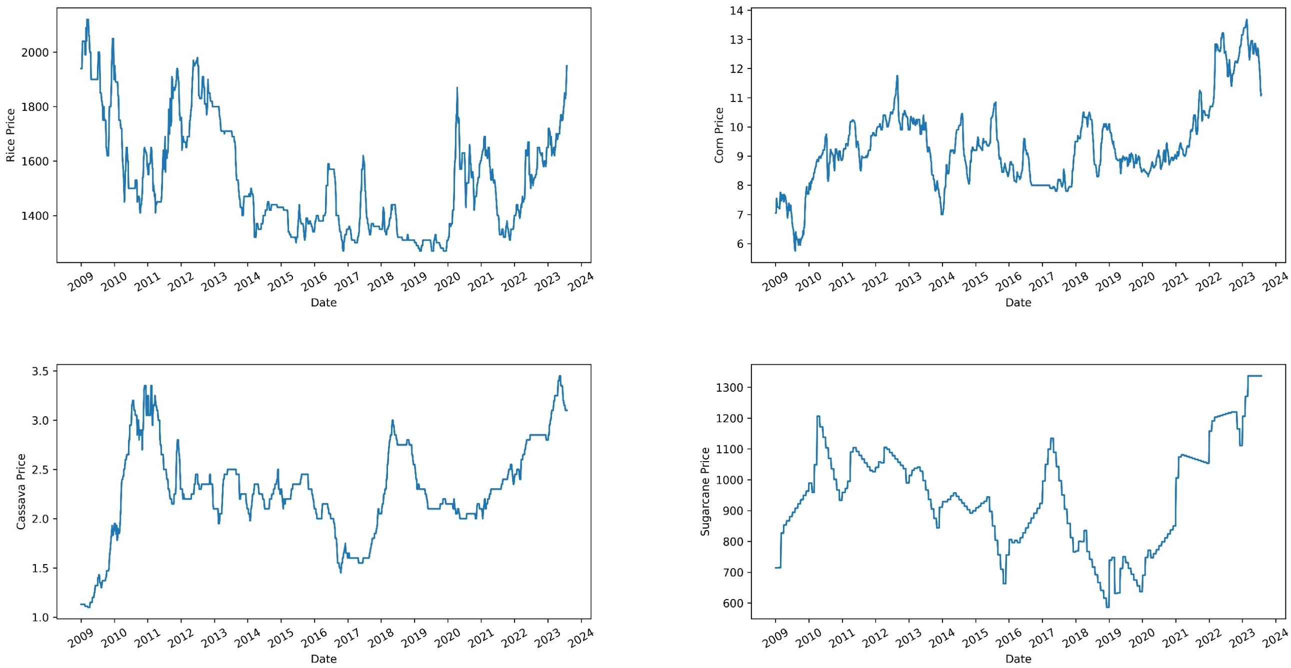

Fig. 1. Daily prices for rice, corn, cassava, and sugarcane.

B. Model Development

We implemented separate GRUs and LSTMs for each individual product. Both models were selected due to their ability to capture temporal dependencies and mitigate the vanishing gradient problem commonly encountered in traditional RNNs. In essence, GRUs and LSTMs employ gating mechanisms to control the information flow of the networks. GRUs with simpler structures of update and reset gates typically offer better computational efficiency. In contrast, LSTMs utilize input, forget, and output gates, which often enable them to capture long-term dependencies. Hence, LSTMs generally work well for long sequence data while GRUs are effective with less complicated data having moderate length. Each of these models was trained using only individual product price as input. In addition, we implemented LSTNet, a hybrid model designed to leverage both local short-term and long-term dependencies in multivariate time-series forecasting. LSTNet incorporates a Conv2D layer to detect short-term local patterns among multiple product prices, while its LSTM component captures long-term temporal relationships. Unlike GRUs and LSTMs which were trained on a single product price, LSTNet was trained using the prices of all four products simultaneously. It generated a multivariate output that predicted all prices at once.

For model development and evaluation, the dataset was divided into three subsets: training (60%), validation (20%), and testing (20%). The training data was used to fit the models, while the validation set was specifically included to fine-tune hyperparameters and prevent overfitting. The final models were evaluated on the held-out testing data to assess their generalization performance. Dividing data into three subsets reduces the amount of data, which can potentially lead to a loss of information. In contrast, a two-part split (train and test) preserves more data for training with a cost of not having a dedicated validation set for tuning hyperparameters. This can lead to suboptimal model's overfitting to the test set. This three-partition split was employed in our study to ensure the model's generalizability by enabling proper hyperparameter tuning without compromising the integrity of the final evaluation. To systematically evaluate short-term and long-term forecasting capabilities, we experimented with different forecasting horizons, ranging from 1-day ahead to 14-day ahead predictions using a rolling-horizon approach. In practice, longer forecasting horizons present greater challenges which often lead to increased prediction errors. However, longer forecasting horizons provide users with early insights, supporting proactive decision-making for relevant stakeholders.

To ensure a consistent and interpretable assessment, all experimented models were evaluated using mean absolute percentage error (MAPE) as the main performance metric. MAPE was specifically chosen due to its intuitive interpretation and ease of communication. It expresses the prediction error as a percentage of the actual values, making it easier for users to understand and compare across experimented models with different forecasting horizons. It is scale-independent and directly comparable across different agricultural products with varying price values. This characteristic makes MAPE particularly useful for our practical applications. To analyze how model accuracy progresses over different timeframes, MAPE was computed separately for each forecasting horizon. This approach enables us to observe error trends over time, providing insights into how forecasting accuracy decreases as the prediction window extends.

IV. Result and Discussion

A set of experiments was conducted using three different network architectures and a range of forecasting horizons. Individual GRUs and LSTMs were trained on each agricultural price product whereas LSTNet was trained on all four product prices. We carefully fine-tune models' hyperparameters to achieve desirable performance. Particularly, 2-layer stacked networks with 64 units were utilized for both GRUs and LSTMs. The LSTNet architecture follows the framework proposed in [20], comprising two main branches: a CNN-LSTM branch and an autoregressive branch. The CNN-LSTM branch consists of a Conv2D layer (100 filters with a kernel size of 6×16) followed by an LSTM layer (100 units) and a skip-LSTM layer (5 units). The outputs of the CNN-LSTM branch are combined with those of the autoregressive branch to produce the final prediction.

Table 1. An average mape of experimented models

Model	Rice	Corn	Cassava	Sugarcane
GRUs	1.64 (0.7, 2.3)	2.24 (1.1, 3.3)	1.89 (0.6, 4.0)	19.66 (7.0, 33.9)
LSTMs	1.90 (1.2, 2.5)	3.09 (1.1, 4.5)	2.48 (1.4, 4.3)	28.85 (18.1, 37.0)
LSTNet	2.09 (1.3, 2.7)	2.21 (1.3, 3.0)	1.41 (0.7, 2.0)	21.82 (11.3, 33.1)

* (minimum, maximum)

Table 1 illustrates a comparison of the model's forecasting performance in terms of MAPE, averaged across all forecasting horizons for all agricultural products. MAPE was selected as the primary measure of accuracy, with lower values indicating better predictive performance. We also reported the minimum and maximum values (shown in parentheses below the average value) to reflect the variability of model accuracy across forecasting horizons. In addition, Fig. 2 illustrates the trend of MAPE from 1-day to 14-day ahead predictions, providing deeper insights into how model performance evolves with longer forecasting horizons. This temporal trend highlights the changes of model performance as the prediction window extends. This offers a more comprehensive understanding of model robustness. While MAPE is particularly suitable for our comparative analysis, future work could incorporate additional evaluation metrics such as within-tolerance accuracy, direction-of-change accuracy to reflect the probability of correctly forecasting value. to support particular applications.

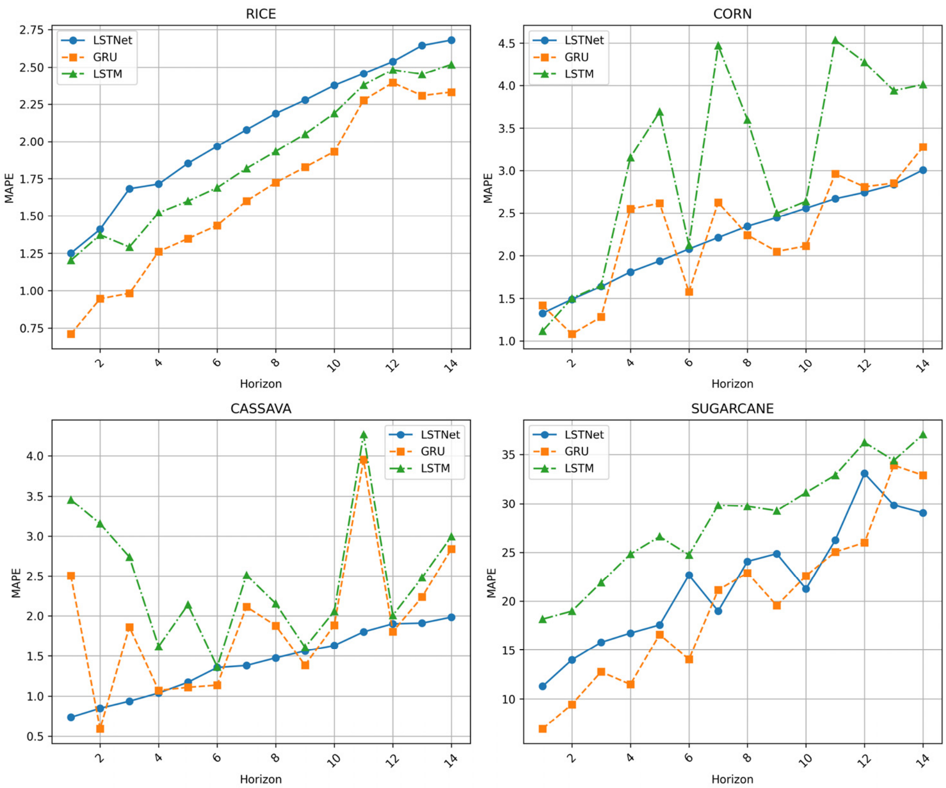

Fig. 2. MAPE across all forecasting horizons.

According to Table 1 showing the average MAPE for each model, LSTMs clearly underperformed across all agricultural products, exhibiting the highest MAPE values. In contrast, GRUs and LSTNet demonstrated comparable average MAPE values, with slight variations across crops. A more granular analysis, shown in Fig. 2, highlights MAPE trends across different forecasting horizons ranging from 1-day to 14-day ahead predictions. Considering all four agricultural products, LSTNet consistently delivered the most stable price forecasts, with slight exceptions in the case of sugarcane. This could be attributed to the relatively low-price fluctuations of sugarcane compared to the other crops. GRUs generally yielded lower MAPE values, aligning with the average MAPE reported in Table 1. However, they exhibited significant volatility across different forecasting horizons, particularly for corn and cassava. On the other hand, LSTMs tended to produce the least desirable results, suffering from both high MAPE values and obvious fluctuations over time.#In terms of computational time, the more complex LSTNet required a relatively longer training duration, taking 14.06 minutes per forecasting horizon, whereas GRUs and LSTMs required 8.38 and 8.75 min, respectively. #

Among all four crops, the models demonstrated the most reliable performance when forecasting rice prices. GRUs achieved the lowest MAPE across all forecasting horizons, making them the most effective model for rice price prediction. LSTMs and LSTNet followed in performance, with LSTNet exhibiting a stable but slightly higher error. In essence, the error increased in a steady manner for all three models as the forecasting horizon increased. For corn price forecasting, LSTNet was the most stable model, maintaining relatively low to medium MAPE values across all horizons. LSTMs, on the other hand, struggled considerably with stability. Noticeable error spikes could also be observed at specific horizons. While GRUs were more stable than LSTMs, they still exhibited greater error fluctuations than LSTNet, making them less reliable for corn price prediction. In essence, LSTNet consistently offered robust performance for corn price forecasting, with minimal variability across time.

In the case of cassava price forecasting, similar trends of MAPE were observed compared to those of corn prices. Both GRUs and LSTMs exhibited sharp fluctuations in MAPE, particularly in the mid-to-late forecasting horizons. This indicates challenges of both models in long-term predictions. The nature of cassava prices with sudden spikes, potentially contributes to the difficulty in achieving stable forecasts by considering individual prices alone. LSTNet proved to be the most reliable model, as it maintained a smoother and more stable error trend while achieving relatively lower MAPE values for longer forecasting horizons. For sugarcane prices, all three models exhibited an increasing error trend with some degree of fluctuation. They all struggled to provide high accuracy, as indicated by the highest MAPE among all crops. LSTNet initially maintained a steady error increase at shorter forecasting horizons but experienced more variability in later horizons. Both GRUs and LSTMs yielded slight variations in MAPE trends across different forecasting periods. Forecasting sugarcane prices is considerably challenging especially when the horizon extends.

According to contributions of our study, we utilized a unique dataset covering the historical prices of four major agricultural products in Thailand. To the best of our knowledge, this dataset has not been extensively explored in previous studies. Our study consequently provided insights into price trends and volatility in the Thai agricultural market. Second, we conducted a comparison of multiple deep learning models, including GRUs, LSTMs, and LSTNet, to evaluate their effectiveness in time series forecasting for agricultural commodities. This highlights model-specific strengths and limitations for real-world price prediction. We also explored the application of LSTNet in multi-step forecasting setting by employing a rolling horizon approach. However, there is room for further improvement. External economic and environmental factors, such as weather conditions, global market trends, and economic indicators, were excluded from the current analysis due to limitations in data consistency and temporal coverage. Future work could incorporate these external variables to further enhance model performance and capture broader market dynamics [23–25]. Experimenting advanced models with enhanced techniques may yield better performance such as decomposition techniques [26–29]. Further validation with rolling/expanding backtests or evaluation on an external dataset coupled with a significance testing would ensure reliability of the overall framework, encompassing both data preprocessing and model development. Lastly, enhancing model interpretability through explainable AI techniques such as permutation importance would help non-technical users gain deeper insights into the key factors influencing forecasting trends [30].

V. Conclusion

This study systematically evaluated the performance of deep learning mdoels – LSTMs, GRUs, and LSTNet – for multi-step agricultural price forecasting. The dataset for four Thai commodities including rice, corn, cassava, and sugarcane ranging from 2009 to 2023 was utilized. The results demonstrate that LSTNet consistently yields the most stable and reliable forecasts due to its capability to capture complex and interdependence among commodity prices. For LSTNet, Convolutional layers learn short-term local patterns while LSTM-based components capture long-term temporal relationships prior to further combining with autoregressive part to learn linear patterns. GRU models generally outperformed LSTMs, although both recurrent architectures exhibited increased volatility for certain horizons, highlighting the sensitivity of sequential models to specific temporal patterns. Among all crops, sugarcane was the most challenging commodity, suggesting that model performance relied on data volume and their volatility. These findings highlight the need to tailor forecasting models to the characteristics of each commodity. Future work should consider refining model architectures, adding advanced techniques, incorporating additional factors, further validating and including interpretability of the model. Overall, the study provides a methodological foundation for developing robust, data-driven price forecasting systems that can support informed decision-making for stakeholders in Thailand’s agricultural sector.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Issara Chaowuttisuk: Methodology, Formal analysis, Software, Data curation, Visualization; Papis Wongchaisuwat: Conceptualization, Methodology, Supervision, Validation, Writing – original draft, review & editing, Project administration, Funding acquisition. All authors had read and approved the final version.

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