Food products pricing theory with application of machine learning and game theory approach

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Abstract

Demand for perishable food is sensitive to product prices and is affected by the prices of similar or alternative products. While brand loyalty influences the demand for products, determining a reasonable price for products requires a precise pricing strategy. In this paper, a pricing model for perishable food is presented in which the brand value of the product and the price of other manufacturers as competitors are considered. To this end, this study first predicts the price of competitors using a combination of optimized Neural Networks and presents an optimized model using a Genetic Algorithm. This algorithm combines a Convolutional Neural Network (CNN), Short-Term Memory (LSTM), and a Genetic Algorithm (GA). The proposed model is then used to merge with a game-theory model for the pricing of perishable foods in the second stage. In this game-theory model, pricing approaches are developed based on identified prices of competitors. In the coordination contract game-theory model, Multi Retailer- one Supplier and Price-sensitive demand of Perishable product are developed with and without quantity discount contract. Obtained results indicate that independent procurement provides retailers with higher profit, while lower profit will be presented when coordination is not considered. Also, with coordination, the ordering cycle increases, and the ordering frequency decrease.

Keywords: Forecasting, CNN-LSTM-GA, Game Theory, Perishable food pricing, CNN, LSTM, Genetic Algorithm

1. Introduction

Food consumers are becoming more aware of the quality and freshness of their food products to improve their standard of living and health. Consumers check the expiration date of products before buying (Tsiros & Heilman, 2005) and prefer to choose newer units (Chung & Li, 2013). The tendency to buy perishable items whose expiration date is near is less seen among consumers (Konuk, 2018). Research shows that the demand for perishable food products is influenced by price and expiration dates (Sebatjane & Adetunji, 2020) and linearly decreases until it reaches zero (S.-C. Chen, Min, Teng, & Li, 2016). In other words, the sale of perishable food will continue until the expiration date of the products has not expired. This decrease in demand could be due to a lack of confidence among consumers (Sarker, Mukherjee, & Balan, 1997) or because consumers can keep products with longer expiration dates (Avinadav, Herbon, & Spiegel, 2013). The expiration of food products, in addition to polluting the environment, imposes high costs on producers or sellers. That's why manufacturers are trying to maximize their profits with apropos pricing for their products.

Apart from the expiration date of food products, other factors such as the brand of the manufacturer affect the demand for food products. Consumers choose products that they trust the brands. After a while, loyalty will be created between the consumer and the brand. When a new food producer enters the field of competition, it must have a pricing policy to gain the most sales and the most profit by offering the price to maintain itself in the competition. By doing so, the producer can reduce the material and the environmental pollutants that result from the return and disposal of perishable goods. Also, fierce competition in this industry has caused consumers to always have a trade-off between price and the brand of products. This doubles the importance of pricing for these goods.

There are many products whose prices are influenced by the prices of other products or similar products (Rana & Oliveira, 2015). Also, increasing the price of a product can reduce the demand for that product or reduce our customers. This means that customers prefer to buy their desired products from another company at this price. Demand for perishable products is price sensitive (Azadi, Eksioglu, Eksioglu, & Palak, 2019), and their price is not elastic, and their demand elasticity is in the range of 0.3 to 0.8 (Andreyeva, Long, & Brownell, 2009). On the other hand, food prices are mainly set in factories and retailers are not able to change prices. At this time, the science of forecasting helps us. A reasonable pricing strategy can be provided by forecasting the other producer's pricing strategy, which may have a higher brand value. Proper pricing in today's volatile markets plays a vital role in the interaction between the manufacturer, the retailer, and the customer and has become a hot topic in recent research, for example (Karakotsios, Katrakilidis, & Kroupis, 2021).

Considering the various factors affecting the demand for perishable food products, the following questions arise:

- What is the best policy for pricing perishable food?
- Is there an interaction between the pricing strategies of producers on a particular product?

- How can a pricing model be considered in relation to the prices of other manufacturers and their brand value?
- How can the accuracy of the forecast be increased?

Applications of artificial intelligence and new technologies are gaining strong momentum in the management of production systems and logistics of today's food manufacturing (M. Mamoudan, D. Forouzanfar, Z. Mohammadnazari, A. Aghsami, & F. Jolai, 2021). For example, the use of blockchain technology can reduce the cost and time of transactions, increase transparency, security and efficiency of the process in food supply chains. While the blockchain technology flourishes and demonstrates its utility in numerous cryptocurrencies, numerous organizations and other entities aim to take advantage of its transparency and fault tolerance to address issues that arise when many unreliable actors participate in the distribution of a resource. Blockchain is viewed as a chance for the transparent distribution of foreign aid, for removing middlemen from the delivery process, for making assets and documents traceable and accessible, and, eventually, for responding more quickly and effectively to food supply chain disruptions.(K. Li, Lee, & Gharehgozli, 2021). Artificial intelligence algorithms can be used to forecasting the other producer's pricing strategy. Forecasting the pricing of various products is significant both at the micro and macro levels. By correctly forecasting food prices, policies can adopt to protect consumers and producers. Forecasting is very complex and arduous to model, even with expert systems. For this reason, the forecast of companies and governments always has a fundamental weakness. That is, they do not take into account the possible error rates in their models. Even if they do, their models are only compatible with past data and cannot make accurate forecasts with future data. Although reducing the error and increasing the accuracy of the models in forecasting is very important, it should be noted that not all features can be entered into the forecasting models. There are always some features that we do not know about them.

On the other hand, there is no denying the enormous change that artificial intelligence has made in the modern world. Artificial intelligence is a factor that is widely used by both leading companies and small sectors of the economy around the world. It is also widely used as a factor of growth and competition in the modern world. Unlike classical statistical models that find linear relationships between data in time series, deep learning can find nonlinear and complex relationships and model them. Moreover, linear or classical models are weaker than deep learning in multivariate models. It has been observed that markdown-pricing policies resulting from the interplay between the time-varying fresh product quality and the time-varying price significantly impact the choice of the cooperation mode. (Xu, Fan, Zheng, & Song, 2021). A 2020 study shows that we can use artificial intelligence to perform large-scale strategic planning and forecast aggregate supply and demand (Abdulov, 2020). But the reason that shows the importance of the use and popularity of artificial intelligence is the deep learning and high speed in performing analyzes.

In the first part of this article, by examining the literature on the subject, the features that have a significant impact on food prices have been identified. Then the historical data of these variables were collected. These data is time series and multivariate. In the next step, the proposed model is presented using a combination of optimized Neural Networks. The proposed model is combination of a Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM) and Genetic Algorithm (GA) that is called CNN-LSTM-GA. This network can extract complex properties of different variables. The CNN layer can extract features between several variables affecting food prices, and the LSTM layer is suitable for modeling time information from irregular trends in time series components. Next, the CNN-LSTM model's Hyper-parameters were Tune to reduce possible errors and optimize the model by using a Genetic algorithm. After that, we compare the proposed method CNN-LSTM-GA with other deep learning models by validation metrics like Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Error (MSE), and R-square (R^2). Using the proposed method (CNN-LSTM-GA) the price was forecasted.

Various factors such as brand value, product pricing of other manufacturers, corruption, demand rate, etc., can affect perishable food sales. That's why we try to use artificial intelligence and deep learning to predict the pricing of other manufacturers. The products produced in these factories are perishable food, and their prices are set in the production factory. So, the retailers are not able to change the price and if they are not sold before their expiration date, in addition to imposing huge costs on the supply chain, they also increase environmental pollution. Therefore, one of the most practical approaches that can be used in green supply chain management is the use of game theory, which can lead to a constructive interaction. On the other hand, due to the increasing awareness about environmental protection, currently, academics and professionals have shown great interest in green marketing and green supply chain management. (Agi, Faramarzi-Oghani, & Hazır, 2021; Mathiyazhagan, Govindan, & Noorul Haq, 2014). In the second part of this article, the game theory approach is used to present the pricing model. The manufacturer, retailer, and customers are three participants in this model. The brand value of each manufacturer has been considered a variable in this model. Because the brand is a factor to having brand loyalty, it can play a significant role in customer behavior (Bhattacharya & Sen, 2003). In other words, the brand can be recognized as an important factor in customers' decisions to choose and buy products. Finally, providing the right price for the products along with predicting the price of other manufacturers is the goal of this article to get a favorable price to maximize product demand. To achieve the above goals, the following steps have been performed.

1. First, we examine the factors that play a significant role in the price of food. We found various factors that can affect the price of food in the literature.
2. In the second stage, the CNN-LSTM algorithm in the deep learning approach is proposed.
3. Next, we try to Tune CNN-LSTM model's Hyper-parameters to reduce possible errors and optimize the model by using a Genetic Algorithm.
4. After that, the proposed method was validated by comparing the CNN-LSTM-GA with other deep learning models.
5. After that, we forecast the step prices using the proposed method CNN-LSTM-GA.
6. Finally, we present a game theory model for a 2-echelon green supply chain with a supplier and two retailers. In this model, the brand value of manufacturers, the price of

products, corruption, and the demand rate have an attributive impact. These factors are significant factors that influence customers' decisions to choose different products.

This model can be used by managers as a decision support system for pricing perishable food that is priced in factories. This model can also be used for goods that are sold periodically. It refers to goods that become obsolete after a while or whose technology becomes antiquated. Other uses of this model include seasonal goods, which, even if not perishable, have a high storage cost. In general, presenting a game theory pricing model for perishable food, taking into account the prices of other competitors and their brand value, is a major contribution of this article.

We will briefly do the following in the sections of this article. Section 2 is devoted to a review of the literature. Section 3 deals with product price forecasting. In Section 4, we create a game theory model. In Section 5, we examine the low forecast error of that model. Section 6 deals with the results, and Section 7 are devoted to resources. Figure 1 shows the steps we take to achieve these goals.

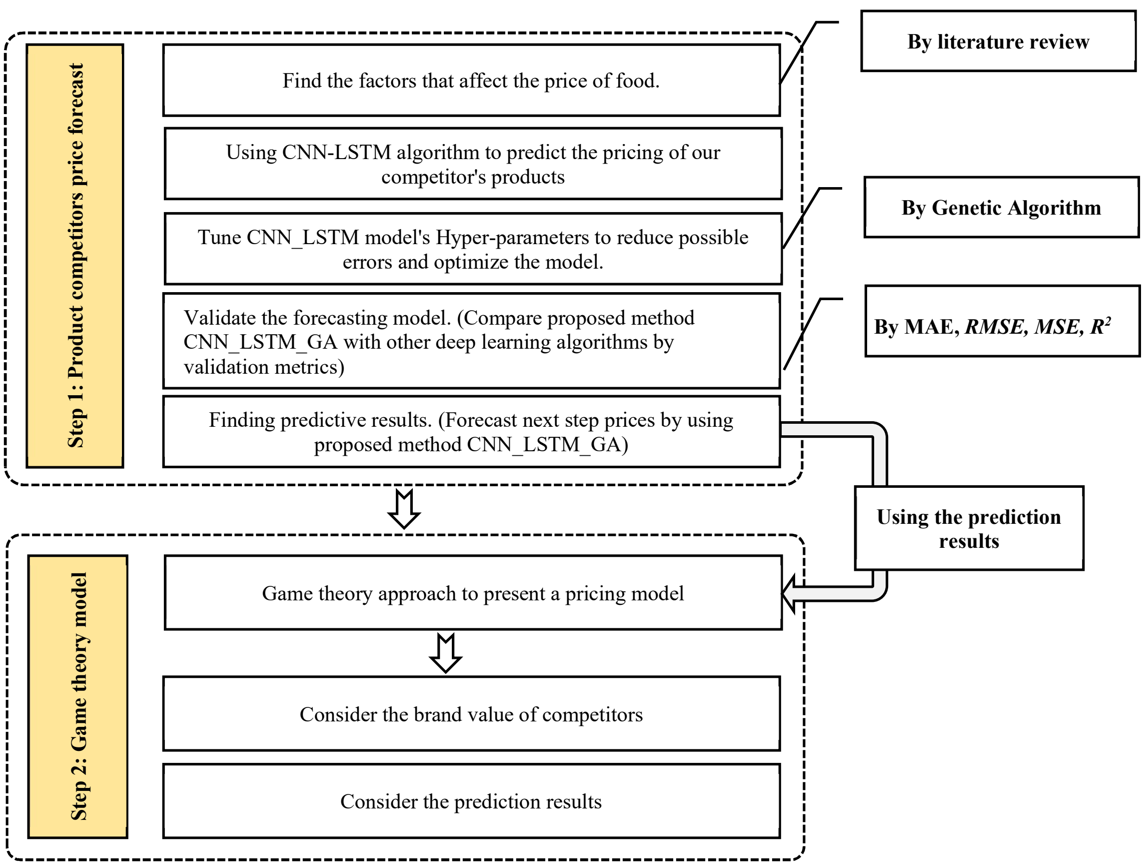

Figure 1 Steps implemented in this article

2. literature Review

In the first section of the literature review, we examine the food price forecast and perishable food pricing. The second part is dedicated to using the game theory approach in identifying food prices.

2.1 Food Price Forecasting

Food price forecasting is very important for the academic community and politicians because it can lead to food security. So much research has been done in this area and many models have been developed to increase the accuracy of predictions. Vector Auto Regression (VAR) is one of the traditional methods that is used for time series forecasting problems. The VAR model needs to be measured by the rate of another product or a base product, which is why most of the relevant literature in food price forecasting has examined the relationship between global crude oil prices and food prices. For example, researchers have recently concluded a nonlinear causal relationship between food prices and crude oil prices (Chatziantoniou, Degiannakis, Delis, & Filis, 2020). Other researchers concluded by predicting food prices that there is a relationship between the price of biofuels and food, both in the short and long term. In this paper, oil prices and population-related variables were considered as control variables to analyze these relationships (Bilgili, Koçak, Kuşkaya, & Bulut, 2020). Rising oil prices could have a direct impact on agricultural production costs (Fowowe, 2016). Following the relationship between energy prices and food prices, we could conclude that food responds positively to any shock from oil prices (Taghizadeh-Hesary, Rasoulinezhad, & Yoshino, 2019). With all these interpretations, what is clear is the impact of these costs on the lives of individuals, businesses, and vulnerable segments of society because rising food prices can reduce the supply of cheap food (Okimoto, 2015). Hanif, Areola Hernandez, Shahzad, and Yoon (2021) examined the dynamics between oil and world food prices as measured by the World Food Price Index. Olayungbo (2021) explored the relationship between oil and food prices in countries that are both importers and exporters of oil by merging causal links. Amolegbe, Upton, Bageant, and Blom (2021) Examined food price volatility due to food insecurity by using the VAR algorithm.

2.1.1 Deep learning and CNN-LSTM Algorithm in Forecasting

Deep learning has recently attracted the attention of many researchers. One of the most important reasons for the popularity of deep learning is its high processing speed and greater low forecast error than traditional algorithms. These reasons have led researchers to use it in various fields. Given the importance and superiority of deep learning over traditional algorithms, we review the literature on the use of deep learning in this section. Recently, researchers from Egypt used deep learning algorithms to predict the prevalence of coronavirus in Egypt (Marzouk, Elshaboury, Abdel-Latif, & Azab, 2021). Bi, Li, and Fan (2021) proposed a deep learning model to improve the low forecast error of tourism demand forecasting. X. Chen et al. (2022) used deep learning to predict wind speeds to improve energy efficiency. Lower forecast error prediction of air pollutant concentrations using deep learning is another area that can refer to (J. Kim, Wang, Kang, Yu, & Li, 2021). Increasing competition and revenue management practices in the hotel industry increase the need for lower forecast error forecasting to maximize profits and optimization. For this reason, Huang and Zheng (2021) used in-depth learning to forecast daily hotel demand.

There are many studies that have used this method to predict different subjects. For example, Zhou, Feng, and Li (2021) used the CNN-LSTM method to improve the performance of non-intrusive load decomposition. Other researchers used this algorithm to predict housing energy consumption (T.-Y. Kim & Cho, 2019). Other researchers used the CNN-LSTM algorithm to predict the patient's condition and estimate the disease severity of Covid-19 (Dastider, Sadik, & Fattah, 2021). Lu, Li, Li, Sun, and Wang (2020) used CNN-LSTM to predict the Stock prices because these data have the characteristics of time series.

2.2 Perishable Food Pricing

Product prices can increase consumers' willingness to use a new brand, which in the long run will lead to customer loyalty (Alvarez Alvarez & Vázquez Casielles, 2005; Cui, Yang, & Chou, 2016; Santini, Vieira, Sampaio, & Perin, 2016). Chew, Lee, and Liu (2009) developed a dynamic planning model to prevent price extraction and capacity allocation for a perishable product. Begum, Sahoo, and Sahu (2012) noted that the longevity of many perishable goods follows Weibull distribution. In the same vein, X. Wang and Li (2012) proposed a model to reduce food spoilage and maximize food retailer profits. This model was dynamically examined through pricing and based on food shelf life. Avinadav et al. (2013) developed a model to determine the correct price, order quantity, and payback period for perishable items with demand dependent on price and time. To maximize retailer profits, Herbon, Levner, and Cheng (2014) developed a dynamic pricing model to entice customers to buy items that are approaching expiration dates. Rana and Oliveira (2015) used the Q-learning algorithm to present a dynamic pricing model. Using a Q-learning algorithm allows them to learn pricing strategies together without explicitly modifying consumer behavior. In this year, a theoretical game model for joint pricing and measurement decisions was made by retailers of perishable goods (Rana & Oliveira, 2015)

Since Typology and/or taxonomy plays a significant role in the development of social science theories, Kumar et al. (2015) aimed to develop a decision support system based on structural equation modeling and sought to taxonomy of green supply chain management for managers in order to better understand the complex relationships between external and internal factors.
In 2017, other researchers presented a dynamic mathematical model to examine dynamic pricing strategies to reduce food spoilage and perishable products (Adenso-Díaz, Lozano, & Palacio, 2017). R. Li and Teng (2018) proposed a pricing model for perishable products retailers because the reference price influences consumer decisions. In this model, the demand depends on the selling price and the freshness of the product. By examining the trend of stock price changes, common problems of pricing, advertising, and inventory control for a company that sells perishable products have been examined (Ryan & Casidy, 2018). Many factors, such as competitors' prices for alternative services or demand, influence the prices of services and products and make the pricing problems a large-scale random issue. The price of services and products is the main factor of demand based on marketing and economic theory. In addition, the demand for perishable products depends on their freshness (Konuk, 2018). In 2020 an investigation was done on joint decisions regarding the pricing of perishable goods retailers

(Hendalianpour, 2020). In this study, numerical tests confirm the optimal consistency of prices and inventory strategies. It also shows with different demand scenarios the system will be in equilibrium. Goodarzian and Fakhrzad (2020) used A Mixed Integer Non-Linear Programming (MINLP) model to minimize the total cost and maximize the total profit of the four-echelon supply chain network.

In 2021, a one-population evolutionary game model was proposed to investigate different strategies of producers regarding sustainability and their evolutionary behavior with financial constraints, so that with the increase of global warming, grain producers may pursue emission reduction in their production activities and contribute to the sustainable development goals (Hosseini-Motlagh, Johari, & Zirakpourdehkordi, 2021). In the same year, a mathematical model was developed to demonstrate the optimal inventory system strategy for perishable goods with a combination of selling price-dependent demand and stocks under partial backlog (Sadikur Rahman et al., 2021). In the COVID-19 pandemic, a game theory model was developed. In this model, the government and interdictor are the main players in suggesting the best location, routing and allocation of medical centers to distribution warehouses during the outbreak of Covid-19 (Gunasekaran, Ghasemi, Goodarzian, & Abraham, 2021). Liu, Zhao, and Goh (2021) modeled a binary relationship as a Stuckberg game to determine whether product corruption and price-sensitive demand for perishable products could affect buying, production, and sales. In 2022 to locate distribution centers, vehicle routing, and inventory problems under earthquake conditions, a game theory model has been described (Ghasemi, Goodarzian, Muñuzuri, & Abraham, 2022). According to climate changes and environmental conditions, researchers are always trying to reduce pollutants, i.e, the importance of re-designing logistics networks has been studied at different levels (E, Panicker, & Sridharan, 2022). Mogale, Ghadge, Cheikhrouhou, and Tiwari (2022) developed a mathematical model to improve overall sustainability in the food grain supply chain by considering logistics, transportation, inventory and location issues.

Game theory is one of the most widely used techniques in the literature for pricing perishable food. There is also a lot of research that has been done to predict food prices. Among the proposed models, there have been limited efforts to take into account the brand value of food. Although many researchers have used these techniques in research, the combination of the two approaches has so far been a research gap and has not been investigated in the extant literature. In this way, perishable food manufacturers need to provide an appropriate pricing model to optimize the sales volume of their products. It is also very difficult to compete with manufacturers who have well-established brands. Therefore, there is a need to forecasting the pricing strategy in order to provide appropriate pricing. Hence, this article covers this research gap using two approaches of forecasting and the Game Theory model.

3. Problem Description and Methodology

One of the most significant environmental pollutants is food production, which leaves pollutants at every level of a supply chain. Perishable foods remain on store shelves, and as we get closer to their expiration date, their sales decrease until they eventually reach zero. It means that the tendency to buy products whose expiration date is near decreases among customers. Failure to sell perishable products before their expiration date expires can incur costs for manufacturers and retailers. Also, it is not possible to store these products, or their storage life is short. On the other hand, discount strategies for such goods do not work well and may question the quality of products. Research also shows that consumers may be hesitant to buy perishable and discounted food products (Konuk, 2018), undermining consumer confidence in product quality (Z. Li, Yada, & Zennyo, 2021). That is why pricing strategies for perishable goods are so important.

A new company recently wants to enter the market for processed protein products. These products have an expiration date, and the consumer attaches great importance to the brand produced. Research shows that brand-related factors affect the consumer's willingness to buy perishable goods. Because consumers are aware of the quality of products whose brand is well-known and advertises more. Thus, advertising policies must be done properly, because they may hurt customers' behavior and instilling low-quality products in customers. In such a situation, it can be difficult for new companies to compete with established brands. In this situation, the newly established company needs to price its products by taking into account the prices that other manufacturers set for their products. To find the pricing strategy of other manufacturers, we first predict the pricing of manufacturers. The forecast results are used to present the pricing model in the two-tier supply chain. Offering a reasonable price for products and creating policies and interactions with retailers can significantly reduce this competition.

There are two well-known food manufacturers with the two brands A and B. The price of one of the products produced by these two manufacturers has been examined for a year. The prices of these products are recorded daily to be used in the forecasting process. On the other hand, several factors positively and directly impact food prices. In other words, food prices respond positively to any shock of change. We have obtained some of these factors by reviewing the literature, including the price of foreign currencies, gold, oil, and the price of the commodity produced (for example, meat or poultry). After obtaining their data over a period of one year, we examined whether these factors affect the product price of these two manufacturers under a well-known brand. Then, using the proposed CNN-LSTM-GA algorithm, we predicted the price of this product for each manufacturer. To show that our proposed algorithm has acceptable performance, we predicted the price of the product for two manufacturers using several other deep learning algorithms, namely Simple RNN, Gated Recurrent Unit (GRU), LSTM, CNN and CNN-LSTM. By using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Error (MSE), and R-square (R^2), the validation of these models have been compared. The results show that our proposed algorithm CNN-LSTM-GA is better than other algorithms.

In the second part, considering the brand value of other manufacturers, the prices of other manufacturers' products, advertising, and the perishability of goods, we present a game theory model. We develop this model under two scenarios of discount and no discount in a two-tier supply chain that includes one manufacturer and a large number of retailers. Manufacturers, retailers, and buyers are our main actors in this model. The manufacturer seeks to increase sales volume, increase profits, and brand value. Retailers have a very important role to play in this. In addition to communicating with producers, they also deal directly with buyers. In other words, the retailer can draw consumers' attention to their specific brands through various advertisements, product displays, and better processes. Because retailers are looking to retain customers and make more profit, the quality and price of products are very important to retailers. In order to maintain its brand, the retailer must offer the best product to the customers, and if the supplier fails to provide the quality required by the retailer, he will lose his customers. This creates an interactive collaboration between the manufacturer and the retailer. By creating sales contracts, a win-win result can be achieved between the supplier and the retailer to increase the performance and satisfaction of both parties.

Consumers interact directly with retailers, and retailers' behavior creates a connection that the customer interacts with the brand and influences customer preferences. On the other hand, satisfaction with one brand increases the demand for products compared to other brands. The interaction between producer and consumer is also determined by product quality and brand value. Consumer satisfaction with a product is directly related to the price paid for the product purchased. In addition, price is one of the most significant factors that can attract customers.

In the third step of this article, we provide a managerial insight into the interaction between producer, retailer, and consumer, which depends on product quality, pricing decisions, and willingness to cooperate between retailer and manufacturer, taking into account the brand value of the manufacturer.

3.1 Forecasting Approach

3.1.1 Data Description

As mentioned earlier, we have obtained the factors that affect food prices by reviewing the literature. These factors include the price of the dollar, the price of oil, the price of gold, the price of chicken, and the price of products brand A and brand B. It is not possible for us to mention the names of these manufacturers and we display their names under the titles of brand A and brand B. The data set used in this article is time series and multivariate. In this article, we used these factors to be able to forecast the prices of products from brand A and brand B. The foods are identical and perishable. We collected the prices of the mentioned items on a daily basis in Iran for a year. The data are collected daily for a year from March 2020 to March 2021. We intend to predict the price of brand A, and the price of brand B, and these two variables are our target variables. We examined the correlation of the variables with each other. In both brand A and brand B variables, the highest correlation is related to the price of the other brand, then the price of oil, the price of the dollar, and finally, the price of gold and the price of chicken. We split the first 80 percent of the Dataset to train of the model and the remaining 20 percent to test and evaluate the model.

3.1.2 Convolutional Neural Network

In the 1960s, Hubel et al. conducted biological research. Their research showed that the transmission of visual information from the retina to the brain was complemented by multiple levels of receptive field excitation, which eventually suggested a Convolutional Neural Network (CNN). CNN algorithm is a leading neural network with a deep structure (LeCun, Bengio, & Hinton, 2015). The main structure of CNN consists of the input layer, convolution layer, pooling layer, fully connected layer, and output layer. Information in the input layer process through feature transformation and extraction in the convolution layer and pooling layer. This local information of the convolution layer and the pooling layer is further integrated from the fully connected layers and mapped to the output signals by the output layer. The output layer generates output after receiving the properties. Equation 1 also shows the CNN calculation formula. In Equation 1, N shows the output size, W: input size, F: the size of the convolution kernel, P: padding value size, S: step size.

$$N = (W - F - 2P)/S + 1 \quad [1]$$

The convolution layer is responsible for extracting features from the input data (H. Wang et al., 2017). It includes the convolution kernel, the convolutional layer parameters, and the activation function. The convolution layer is the most significant and unique layer on CNN. The convolution layer can extract features of input variables by convolution kernels. In other words, we can say that the extraction of properties is the convolution kernel's essence. The scale of convolution kernels is smaller than the input matrix. The convolution layer uses convergence operations to output the feature map instead of the general matrix operation. The calculation of each element in the feature map is in the form of Equation 2. In Equation 2, $x_{i,j}^{out}$: is the output value in row i and column j of the feature map. $x_{i+m,j+n}^{in}$: is the value in row i and column j of the input matrix. $f_{cov}(0)$: is the selected activation function. $w_{m,n}$: shows the weight in row m and column n for the convolution kernel. b: shows the bias of the convolution kernel.

$$x_{i.j}^{out} = f_{cov}(\sum_{m=0}^{k}\sum_{n=0}^{k} w_{m,n}\, x_{i+m,j+n}^{in} + b) \quad [2]$$

In general, the input matrix uses multiple kernels for convolution layer. Each convolution kernel extracts a feature from the input matrix and creates a feature map. After that, the pooling layer reduces the length and width of the previous feature map and improves the computational efficiency with down-sampling. The output of feature vectors by the convolutional layer can be reduced through pooling layer. Also, the results can be improved at the same time. Because CNN has a good ability to extract grid data features, m variables of any type were expanded to n stations to obtain a matrix of m rows and n columns. We can say that CNN as a whole, the fully connected layer is a classifier. It is located at the end of the network and performs regression classification on the extracted features. Thus, we can compose CNN in two parts. The first part includes feature extraction (convolution, activation function, pooling), and the second part includes classification and recognition (fully connected layer) (Yao, Xu, & Ramezani, 2021).

3.1.3 Long Short-Term Memory

A Recurrent Neural Network (RNN) has the functions of data learning, classification, prediction, etc., which, at the same time, has a time-series characteristic. This feature has made it able to have high efficiency in predicting time series. This network can evolve and predict data. However, memorizing input information too far apart is a problem for the RNN. Because, by increasing the network layers and iterations, the subsequent nodes of the RNN will gradually forget the previous information, resulting in gradient diminishing or gradient explosion problems. Thus the long-term dependency problem is the fatal injury of traditional RNN (Srivastava & Lessmann, 2018). To solve this problem in RNN, Long Short-Term Memory (LSTM) was developed. LSTM mainly solves the problem of gradient disappearance. This feature can make the network remember the content for a longer time and make the network more reliable (Ko et al., 2021; Zhang, Li, Li, & Xu, 2021). LSTM has also achieved exceptional success due to its ability to learn short-term and long-term dependencies on the problem.

''cells'' are the main information-processing units in LSTM. These cells are more sophisticated neurons in typical MLP. LSTM cells, like neurons, can be connected and stacked to transmit temporal information. LSTM can turn information into a cellular state. This feature is called a gate. There are three gates in LSTM possesses: input gate, forget gate, and output gate. These gates are used to provide read, write and reset functions respectively. Cell mode is the path of information transfer that allows the transfer of information in order. Gates are used to updating or discarding historical information. This feature helps the LSTM to decide which information is useful in the long term. In Equations of LSTM, C_{t-1}: is the cell state from the previous module, d_{t-1}: is the output of the previous module, X_t: is the current input, used to generate new memory, and the output information includes the cell state C_t transmitted later, new output d_t.

The forgetting gate in LSTM is a valve. A lot of information will flood into the memory when the input gate is always open. At this time, a forgetting mechanism needs will add to remove the information in the memory. We call this forgetting gate. It looks at d_{t-1}(previous output) and X_t(current input) and outputs a number among 0 with 1 for every digit in the cell state C_{t-1}(previous state) that 1 shows completely saved, and 0 shows fully deleted. The calculation formula is shown in Equation 3. In Equation 3, W_f: is the weight matrix, b_f: is the bias term, and F: is the output through this network with a number in the range (0, 1) that indicates the probability of the previous cell state being forgotten. 1 means ''completely reserved'', and 0 means ''completely discarded''.

$$f_t = sigmoid(W_f[d_{t-1}, X_t] + b_f) \tag{3}$$

In LSTM, after the circulating neural network ''forgets'' part of the previous state the input gate requires supplementing the newest memory from the current input. This process could be fulfilled by the ''input gate''. In LSTM, the input gate consists of two parts. The first part is about, a sigmoid layer named the ''input threshold layer'' that decides which values we need to renew. The second part is about, a $tanh$ layer, that establishes a new candidate vector $\widetilde{C}_t$, which will be increased to this state. This relation shows in Equations 4, 5, and 6.

$$h_t = \sigma(W_n.[d_{t-1}, X_t] + b_n) \tag{4}$$

$$\widetilde{C_t} = \tanh(W_m.[d_{t-1}, X_t] + b_m) \quad [5]$$

$$C_t = F_t * C_{t-1} + h_t * \widetilde{C_t} \quad [6]$$

In Equations 4, 5, and 6, W_n: represents the weight matrix, b_n: represents the deviation element, W_m: represents the weight matrix to update the unit status, b_m: represents the offset element to update the unit status (W. Wang et al., 2019), and C_t: represents the status of the updated memory unit. In Equation 7, enter the gate h_t and $\widetilde{C_t}$, run the dot product to decide whether to update the state of the time step memory unit; the forgetting gate F_t takes the scalar product with $C_{t-1}$to decide whether it is necessary to keep the initial state of the unit memory of the time step.

The output gate in LSTM is the current time output that must be generated after calculating the new status. Also, it uses to control the level of filtering of the storage unit status in this layer. The output gate sets the output at this time based on the last state, the last time output, and the current input. Its calculation formula is as Equations 7 and 8. First of all, we have to use the sigmoid activation function to get an O_t whose value is in the range [0, 1]. Then multiply the state of the memory cell C_t by the $tanh$ activation function then multiplies by O_t, this is the output of this layer. d_t is not only associated with the input X_t in time step t and with the activation value d_{t-1} of the hidden layer at the previous time step but also with the state of the memory unit $C_t$under the time step.

$$d_t = O_t * \tanh(C_t) \quad [7]$$

$$O_t = \sigma(W_o[d_{t-1}, X_t] + b_o) \quad [8]$$

3.1.4 CNN-LSTM Approach

In most machine learning applications, feature extraction is a significant step in generating meaningful information for the predictive model to enable it to make lower forecast error predictions (Sharma, Zhang, & Rai, 2021). Time series problems are no exception in this respect. Time series problems include many dynamics that need to be clarified and tailored to fit a regression/classification model, often with the integration of expert opinion. Furthermore, feature extraction is not only a lengthy procedure, but the methodologies vary widely from application to application.

CNN and LSTM are both traditional algorithms that used in deep learning. CNNs are good at extracting local characteristics from data and acting on spatial generalizations and abstractions. The LSTM network can extend the transient function and process the data information with the sequence function. The combination of CNN and LSTM models is more stable and useful than using CNN and LSTM models separately (Guo, Zhao, Zheng, Ning, & Gao, 2020). Therefore, in this article, we combine the properties of the CNN network with the LSTM network. For this work, we use the parallel connection of the network to achieve the CNN-LSTM network model, which takes advantage of the time and capacity of the net. Expression of the spatial characteristics of the two networks. The CNN-LSTM diagram is shown in Figure 2. This figure shows that, first of all, data will be preprocessed. After that, the processed data are used to form the CNN and LSTM network respectively. Then, the feature information extracted from the CNN and the feature information extracted from the LSTM are processed in the same dimension, respectively, through the map layer. Also, the outputs of the CNN and LSTM are processed in parallel connection by concatenation. Finally, it is classified by output layer activation function.

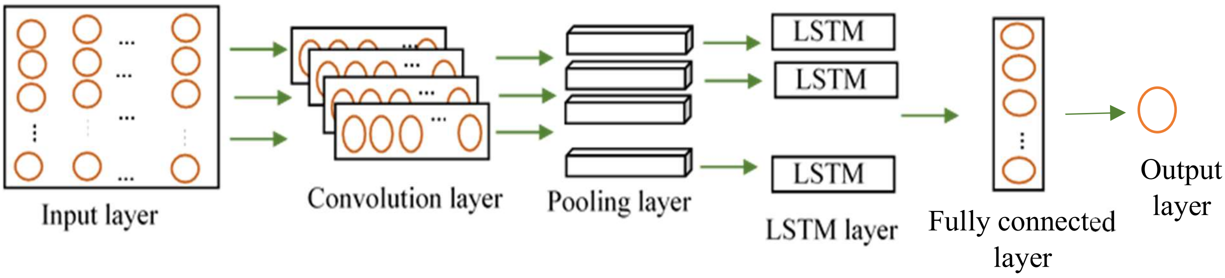

Figure 2 CNN-LSTM structure

3.1.5 Genetic Algorithm

Genetic Algorithm is a special type of Meta-Heuristic Algorithm that uses biological techniques such as inheritance, biological mutation, and Darwin's principles of choice to find the optimal formula for predicting or matching the pattern. Genetic Algorithms are a good choice for regression-based prediction techniques. This algorithm uses Genetic evolution as a model for problem solving and optimization. In this study, the Genetic Algorithm would obtain an integer number of kernel size, number of neurons, and type of activation function, which would then be used to train the models. They also include selection, mutation, and crossover, that iteratively be used until the convergence criteria are satisfied. We used the Genetic Algorithm to optimize and find the optimal CNN-LSTM Hyper-parameters, such as number of kernels of CNN layer, the number of neurons of LSTM layer and layer's activation function.

In this study, we used population size = 50, cross-over rate = 0.4, and mutation rate = 0.1. Search space for the number of kernels and neurons is [2,128], and Activation Function is [relu, selu, tanh, linear]. The number of kernels selected by the Genetic Algorithm for the Convolution layers is 4. The number of neurons selected for the LSTM layers is 7, and the activation function that is selected for the layers is relu.

3.1.6 CNN-LSTM-GA

Tuning the structure and harness Hyper-parameters of CNN-LSTM will be very difficult if done using trial and error. Although we optimized the structure of CNN, LSTM, CNN-LSTM, RNN, MLP, and GRU Algorithms as much as possible by using this method, it is very time-consuming to do, and we cannot guarantee that we have achieved the optimal structure. For this reason, we use the Meta-Heuristic Genetic Algorithm to find the optimal CNN-LSTM. Genetic Algorithm (GA) is an optimization method for solving complex problems by repeating different possible solutions. In this work, GA is used to find the optimal CNN-LSTM Hyper-parameters. The purpose of the CNN-LSTM-GA algorithm is to demonstrate the efficiency of the Genetic Algorithm, which works as follows. The first part deals with the initial regulation of population genes. The second part is related to genetic operations, and the third part will be related to chromosome evaluation.

The process begins with initialization, population size, and number of Generation. The Genetic Algorithm applies a series of evolutionary operators until obtained the best CNN-LSTM architecture and structure to predict product prices for brands A and B. Figure 3 shows how we optimize our Hyper-parameters using a Genetic Algorithm.

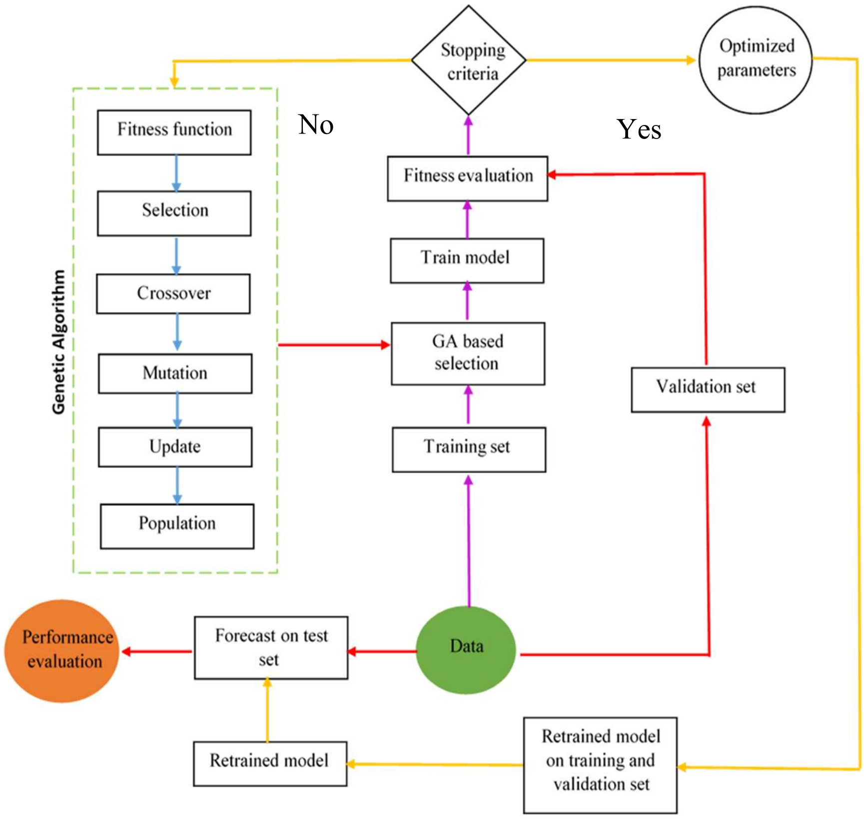

Figure 3 Genetic Algorithm and neural network model

Normally, RNN networks are used for time series data so that time dependencies patterns can be learned by these types of networks. In this research, we used the combination of CNN and LSTM so that, in addition to identifying temporal continuity patterns by RNN, feature extraction was first performed by CNN in order to extract more important information from the data, and this work reduced the model error and increased its performance. Also, the correct selection of network Hyper-parameters has a direct effect on increasing performance and reducing model error. Searching and selecting these Hyper-parameters manually and by trial and error is very exhausting and time-consuming. It does not guarantee the optimality of the obtained Hyper-parameters. On the other hand, one of the weaknesses of Neural Networks is that Hyper-parameters of these networks are performed as Random Search and Grid Search. Due to the Random Search of the search space, Random Search cannot find the optimal Hyper-parameters, and the Grid Search the entire search space to find the optimal Hyper-parameters, which will take a lot of time. To solve this problem, we used the Genetic Algorithm to find the optimal Hyper-parameters to reduce the search time in addition to finding the optimal values.

3.1.7 Experiments and Evaluation

As mentioned earlier, we use the Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Square Error (MSE), and R-square (R^2) methods to evaluate performance and predictive effects, which we address, respectively. The MAE calculation formula is shown in Equation 9. In Equation 9, y_i :is the predictive value, and x_i :is the true value. The smaller the MAE value, we have better forecasting.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - x_i| \quad [9]$$

The RMSE calculation formula is shown in Equation 10. In Equation 10, y_i: is the predictive value, and x_i : is the true value. The smaller the RMSE value, we have better forecasting.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \quad [10]$$

The MSE calculation formula is shown in Equation 11. In Equation 11, y_i: is the predictive value, and x_i : is the true value. The smaller the MSE value, we have better forecasting.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2 \quad [11]$$

The R^2 calculation formula is shown in Equation 12. In Equation 12, y_i: is the predictive value, and x_i : is the true value, and $\overline{y_i}$: is the average value. The R^2's value range is (0, 1).

$$R^2 = 1 - \frac{(\sum_{i=1}^{n}(y_i - x_i)^2)/n}{(\sum_{i=1}^{n}(\overline{y_i} - x_i)^2)/n} \quad [12]$$

3.1.8 Implementation

Our research relied on open-source libraries in the Python environment. Python is a high-level interpreted programming language that can be used for a variety of applications, including research. Our models were implemented using the Keras Toolkit written in Python and TensorFlow, an open-source software library that was provided by Google. For Genetic Algorithm implementation, we use sklear-deap package and evolutionary search library.

In addition, other important packages such as NumPy, Pandas, and Matplotlib were also used to process, manipulate and visualize data.

3.1.9 Data Preprocessing

Data preprocessing is a significant step in achieving better performance and low forecast error in machine learning models and deep learning-based models. Data preprocessing is about dealing with inconsistent, missing, and noisy data. The database used in this article does not contain this type of data. In addition, data preprocessing included data cleansing, normalization, and restructuring. Because machine learning models and CNN-LSTM-GA are sensitive to the scale of the inputs, the data is normalized using feature scaling in the range [0, 1]. The normalization method is shown in Equation 13. In this Equation, $x_{min}$and x_{max} are the minimal and maximal value of each import data series.

$$z = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad [13]$$

We consider the first 70% of the Dataset to train the model (training set) 10% of the Dataset to Hyper-parameter tuning and model optimization (validation set), and the remaining 20% to test and evaluate the model (test set).

3.1.10 Implement Model

The proposed model for this paper is CNN-LSTM-GA. This algorithm is a CNN-LSTM model in which some of its Hyper-parameters had tuned by a Genetic Algorithm. Hyper-parameters tuned by the Genetic Algorithm includes the number of kernels (filters) in the Convolution layers, the number of neurons in the LSTM layers, and the type of Activation Function in the layers.

Genetic Algorithm parameters such as cross-over rate, mutation rate, and population size can influence the result to obtain the optimal solution. In this study, we used population size = 50, cross-over rate = 0.4, and mutation rate = 0.1.

Search space for the number of kernels and neurons is [2,128] and Activation Function is [relu, selu, tanh, linear]. The number of kernels selected by the Genetic Algorithm for the Convolution layers is 4. The number of neurons selected for the LSTM layers is 7, and the activation function that is selected for the layers is relu.

The Hyper-parameters used in the proposed CNN-LSTM-GA algorithm in this experiment is shown in Table 1. The input training set data is a three-dimensional vector with dimensions (None, 14.6) which 14 is the time step sizes, and 6 is the number of input features.

First, the data enter the one-dimensional convolution layer to further extract features and obtain a three-dimensional output vector (None, 12, 4), in which 4 is the size of the convolution layer filters.

Next, the vector enters the pooling layer, and a three-dimensional output vector (None, 6, 4) has also obtained. Then, the output vector enters another convolution layer with 4 filters and another pooling layer. The other three layers are Flatten layer, Repeat Vector layer, and Time Distributed layer. Two LSTM layers with 7 hidden units and the output data (None, 7) after training, enter other layers of the entire connection layer to get the output layer. The output layer has three units because the prices of brands A and B will be forecast for the next three days.

Table 1 Hyper-parameters used in the proposed CNN-LSTM-GA algorithm

Parameters	Value
Convolution layer filters	4
Convolution layer kernel_size	4
Convolution layer activation function	relu
Pooling layer pool_size	2
Number of hidden units in LSTM layer	7
LSTM layer activation function	relu
Number of hidden units in Output layer	3
Output layer activation function	linear
Number of hidden units in Output layer	3
Time_step	14
Batch size	8
Learning rate	0.001
Optimizer	Adam
Loss function	mean square error
Epochs	100

3.2 Game Theory Model

3.2.1 Problem Definition

We assume a two-tier supply chain with one supplier and a large number of retailers. The stores in this network buy fresh goods from the supplier. The ordering cycle is determined by the retailers. The supplier demands that the retailers modify their existing order size when they sign the quantity discount contract and compensate them with a quantity discount at a low selling price. From the standpoint of the retailers, they bargain together, establish a coalition to increase profits, and sensibly distribute the overall profit of their coalition. Retailers have no time to refill their inventory once the selling season begins.

3.2.2 Multi Retailer- one Supplier and Price-sensitive Demand of Perishable product

In this section, we first present the notations used in this model.

K_m Supplier fixed ordering cost

K_r retailers fixed ordering cost

D_i retailer demand rate

h_i inventory holding cost

$I(t)$ inventory level in period t

β fresh product deterioration rate

c supplier's production cost

Q_{Ri} ordering quantity of retailer i

$x_i(\alpha)$ profit allocation to retailer i

Π_m supplier profit

π_{ri} Retailer profit

α Supplier selling price

O ordering cycle

3.2.3 Model formulation

The supply chain in this article comprises one supplier and n distinct retailers. assume $N = \{1,2,\dots,n\}$, denote a group of retailers in the game, with n being the number of stores in the coalition. We assume the following to simplify the mathematical model without losing generality: The supplier plays the role of the leader, while the retailers play the role of the followers. Unsold items have no salvage value at the end of the selling period. The demand is always there. Stock-outs are not permitted. The supplier has the capability of promptly delivering fresh produce to the merchants.

Under various scenarios, we create a mathematical model for an FPSC with one supplier and many retailers. The inventory level at time t falls owing to demand and degradation. As a result, the following equation satisfies the inventory changes with respect to time, I(t), according to this description:

$$\frac{dI_i(t)}{dt} = -\beta I_i(t) - D_i, 0 \leqslant t \leqslant T_i \qquad [14]$$

The boundary condition here will be $I_i(T_i) = 0$. the inventory level is $I(t)$, D_i is the demand rate of retailer. Hence Eq. (14) continues to be solved using following equation (the ordering cycle length of retailer is T_i).

$$I_i(t) = \frac{D_i}{\beta}(e^{\theta(T_i - t)} - 1), 0 \leqslant t \leqslant T_i \qquad [15]$$

The primary goal of this research is to obtain fresh insights into successful collaborative procurement, with goal of lowering overall costs while increasing total profit.

Coordination of the FPSC under independent procurement

In this part, we scrutinize over the coordination of an FPSC with and without a quantity discount contract under independent procurement.

3.2.4 Stage I: without consideration of a quantity discount contract

In this case, the supplier and the retailer separately try to maximize the profit without considering the profit of others. Retailer i's ordering quantity is set to the same as the starting inventory level of fresh produce $Q_i(T_{Di}^{w}) = I_i(0)$ (Zheng, Zhou, Fan, & Ieromonachou, 2019). Assume w and D signify the situation of independent procurement without a quantity discount. As a result, the retailer's ordering quantity $Q_i(T_{Di}^{w})$, is as followings:

$$Q_{ri}(T_{Di}^{w}) = \frac{D_i}{\theta}(e^{\beta T_{Di}^{w}} - 1) \quad [16]$$

Retailer total costs are procurement cost, $\alpha_{Di}^{w} D_i \frac{e^{\theta T_{Di-1}^{w}}}{\theta}$, holding costs of inventory and at last k_r which is as followings:

$$h_i \int_0^{T_{Di}^{w}} \frac{D_i}{\beta}(e^{\beta(T_{Di}^{w}-t)} - 1)dt = h_i D_i \frac{e^{\beta T_{Di}^{w}} - \beta T_{Di}^{w} - 1}{\theta^2}$$

Retailer's earned profit can be shown in equation17.

$$\pi_{Dri}^{w}(\alpha_{Di}^{w}, T_{Di}^{w}) = p_i D_i - \frac{K_r}{T_{Di}^{w}} - h_i D_i \frac{e^{\beta T_{Di}^{w}} - \beta T_{Di}^{w} - 1}{\beta^2 T_{Di}^{w}} - \alpha_{Di}^{w} D_i \frac{e^{\beta T_{Di}^{w}} - 1}{\beta T_{Di}^{w}} \quad [17]$$

The profit of retailer i per unit of time in Eq. (17) may be summarized as follows:

$$\pi_{Dri}^{w}(\alpha_{Di}^{w}, T_{Di}^{w}) = (p_i - \alpha_{Di}^{w})D_i - \frac{K_r}{T_{Di}^{w}} - \frac{T_{Di}^{w}}{2}(h_i + \alpha_{Di}^{w}\beta)D_i \quad [18]$$

As a baseline for an FPSC without a contract, we use the supplier's selling price for retailer α_{Di}^{w}. For retailers with a quantity discount contract, we specify α_{Di}^{w}as a parameter for the ideal supplier's selling price. Consider the circumstance where the FPSC is coordinating without a contract through independent procurement.

Taking the first derivative of Eq. (14) with regard to the ordering cycle T_{Di}^{w}, we set it equal to 0 for a given α_{Di}^{w}; hence, $\frac{d\pi_{Dr}^{w}(\alpha_{Di}^{w}T_{Di}^{w})}{dT_{Di}^{w}} = \frac{K_r}{(T_{Di}^{w})^2} - \frac{(h_i+\alpha_{Di}^{w.\beta)D_i}}{2} = 0$. Taking the second derivative of Eq. (14) with regard to T_{Di}^{w}, we get $\frac{d^2\pi_{Di}^{ij}(\alpha_{Di}^{w},T_{Di}^{w})}{d(T_{Di}^{w})^2} = -\frac{2K_r}{(T_{Di}^{w})^3} < 0$,, demonstrating that the retailer's profit function $\pi_{Dri}(\alpha_{Di}^{w}, T_{Di}^{w})$ is concave to T_{Di}^{w}. As a result, we discover that the best ordering cycle is as following:

$$T_{Di}^{w*} = \sqrt{\frac{2K_r}{(h_i + \alpha_{Di}^{w}\beta)D_i}} \quad [19]$$

Substituting T_{Di}^{w*} into Eq. (14), we obtain the retailer's optimal profit in the decentralized FPSC as follows:

$$\pi_{Dri}^{w}(\alpha_{Di}^{w}, T_{Di}^{w*}) = (p_i - \alpha_{Di}^{w})D_i - \sqrt{2K_r(h_i + \alpha_{Di}^{w}\beta)D_i} \quad [20]$$

Therefore, the supplier's optimal profit is:

$$\pi_{Ds}^{w} = \sum_{i=1}^{n} (\alpha_{Di}^{w} D_i - cD_i - \frac{K_m}{T_{Di}^{w*}}) \quad [21]$$

3.2.5 stage II: with consideration of a quantity discount contract

In this stage, the study examines if an FPSC can be coordinated by a quantity discount contract under independent procurement. The supplier's goal is to make more money by persuading merchants to order more fresh food. The assumption is that the supplier is in charge of the SC and that maximizes the manufacturer's profit. The problem may be represented in terms of two decision variables, $(\alpha_{Di}^{cw}, T_{Di}^{cw})$, based on the foregoing understanding of system functioning. As a result, the FPSC coordination optimization issue under a quantity discount contract can be stated as followings:

$$max \qquad \pi_{D_5}^{w}(\alpha_{Di}^{\infty}, T_{Di}^{w}) = \sum_{i=1}^{n} (\alpha_{Di}^{\infty} - c)\, D_i - \frac{K_m}{T_{Di}^{\infty}} \quad [22]$$

$$\text{s.t.} \quad \pi_{Dri}^{\omega w}(\alpha_{Di}^{\infty}, T_{Di}^{\infty}) = (p_i - \alpha_{Di}^{\infty}) D_i - \frac{K_r}{T_N^{\infty}} - \frac{T_{Di}^{\infty}}{2}(h_i + \alpha_{Di}^{\infty}\theta) D_i \geqslant \pi_{Di}^{w}(\alpha_{Di}^{w}, T_{Di}^{w*}) \quad [23]$$

According to Eq. (19), the merchants will only accept the contract if their individual profit is higher than it would be if the contract did not include a quantity discount (stage I). $\alpha_{Df}^{\alpha*}$ is an endogenous variable, but $\alpha_{D'}^{\mathrm{we}}$ is an exogenously provided variable in this case?

We have the supplier's optimal selling price that it charges the retailers by solving the constraint condition:

$$\alpha_{Di}^{\omega v*} = (\alpha_{Di}^{w} + \sqrt{\frac{2K_r(h_i + \alpha_{Di}^{w}\beta)}{D_i}} - \frac{K_r}{D_i T_{Di}^{\alpha w}} - \frac{T_{Di}^{\infty}}{2} h_i), (1 + \frac{T_{Di}^{cw}}{2}\theta) \quad [24]$$

Considering previous equations, the optimal profit of the supplier is:

$$\pi_{Ds}^{cw*}(T_{Di}^{cw}) = \sum_{i=1}^{n} \frac{\alpha_{Di}^{w} D_i + \sqrt{2K_r D_i (h_i + \alpha_{Di}^{w}\beta)} - \frac{K_r}{T_{Di}^{w}} - \frac{D_i T_{Di}^{cw}}{2} h_i}{1 + \frac{T_{Di}^{cw}}{2}\beta} - \frac{K_m}{T_{Di}^{cw}} - \sum_{i=1}^{n} cD_i \quad [25]$$

Considering equation 25 to the ordering cycle T_{Di}^{cw}, next equation will be as followings:

$$\frac{d\pi_{Ds}^{cw*}(T_{Di}^{cw})}{dT_{Di}^{cw}} = \frac{-A(T_{Di}^{cw})^2 + (K_m + nK_r) + (K_m + nK_r)\beta T_{Di}^{cw}}{\left(1 + \frac{T_{Di}^{cw}}{2}\beta\right)^2 (T_{Di}^{cw})^2} \quad [26]$$

$$A = \sum_{i=1}^{n} \frac{D_i h_i}{2} + \frac{\beta}{2} \sum_{i=1}^{n} (\alpha_{Di}^{w} D_i + \sqrt{2K_r D_i (h_i + \alpha_{Di}^{w} \beta)}) - \frac{K_s \beta^2}{4}$$

Solving $\frac{d\tau_{Ds}^{\mathrm{ar}}(T_{\mathrm{P}}^{\mathrm{og}})}{dT_{\mathrm{B}}} = 0$, we obtain the ordering cycle as follows:

$$T_{Di}^{\mathrm{cw}^*} = \frac{(K_m + nK_r)\theta + \sqrt{(K_m + nK_r)^2 \beta^2 + 4A(K_m + nK_r)}}{2A}$$

Taking into account ordering cycle T_{Di}^{cw}, we come to next equation:

$$\frac{d^2 \pi_{Ds}^{\mathrm{cow}}(T_D^{\mathrm{ow}})}{d(T_D^{\mathrm{ov}})^2} = -2A(T_{Di}^{\mathrm{cw}})^3 [(1 + \frac{\beta}{2} T_{Di}^{\mathrm{cw}})^2 + (1 + \frac{3}{2} \beta T_{Di}^{\mathrm{cw}} + \frac{\beta^2}{2} (T_{Di}^{\mathrm{cw}})^2)] \quad [27]$$
$$-(K_m + nK_r)[2T_{Di}^{\mathrm{cw}} + 4\beta (T_{Di}^{\mathrm{cw}})^2 + 3\beta^2 (T_{Di}^{\mathrm{cw}})^3 + \frac{3}{4} \beta^3 (T_{Di}^{\mathrm{co}})^4]$$

If $\frac{d^2 \pi_{Ds}^{\mathrm{cow}}(T_D^{\mathrm{ow}})}{d(T_D^{\mathrm{ov}})^2} < 0$, $T_{Di}^{\mathrm{cw}^*}$ is the optimal order.

4. Numerical Example

This section provides numerical examples to illustrate our results in the previous sections. We will use Malaysia’s durian supply as an example. In China, many supermarkets get durians from a Malaysian supplier. The impact of different policies is carefully examined.

Because of the favourable weather, closeness to China, and preferential tariff regulations, Southeast Asian nations have continued to export tropical fruit to China. Durians are a fruit that might be difficult to export internationally. While vehicles may transport durian across the Causeway over shorter distances, such as from Kuala Lumpur to Singapore, transporting durian by marine freight needs quick refrigeration due to its high respiration rate.

Due to the availability of durian fruit in Malaysia, it is one of the world’s major growers and exporters. Hong Kong, China, and Greater China are the most important markets for Malaysian durian export in terms of size and prospective growth. The durian export pilot showed that utilizing standards backed by the EPCIS visibility platform, cross-border traceability is viable. Overall, supply chain performance and integrity improved significantly as a result of the trial. The amount of time it took to trace the whereabouts of consignments in the supply chain was cut in half. Authorities were confronted with new obstacles in enabling and managing rising durian commerce. Authorities are required to put in place a system that allows makers, merchants, and end-users to seamlessly connect with governments in order to efficiently safeguard and monitor the market or, if necessary, restrict items from being supplied.

This section will be of great help in the case of the differences depending on the parameters of the system. Based on this assumption, there is one supplier handling the durian and four retailers in China in the FPSC. The data used for the selected FPSC comes from a dataset that includes four supermarkets. β=0.03, Km=100 (CNY) in fixed order cost for the supplier, Kr=60 for the retailer, and c=1.5 in procurement (or production) costs for the supplier. Retailers’ parameters are shown in Table 2.

Table 2 Parameters of retailer I

Retailer	1	2	3	4
Di	90	140	110	128
hi	0.7	0.4	0.6	0.8
pi	3.0	4.6	4.9	6.2

5. Result and discussion

5.1 Results of forecasting

To confirm the usefulness of our proposed algorithm (CNN-LSTM-GA) in predicting the price of goods of brands A and B, we experimented with several other deep learning algorithms. The Hyper-parameters of these algorithms are optimized as possible by using trial and error. Therefore, these algorithms have the lowest possible error rate. We once consider the price of brands A and B as target variables separately in these algorithms. It should be noted that the structure of the algorithms is fixed for both brands and does not change. The forecast is in the form of a 3_day_ahead prediction, and we intend to forecast the prices of brands A and B for the next three days.

In order to select the best model from the tested models and use it in the next phase (game theory), we compared their performance with each other. For this purpose, regression evaluation criteria were used. These criteria include MSE, MAE, RMSE and R2 score. MSE, MAE and RMSE indicate the amount of error in the forecast, and the lower the value, the less error and the better the model performance. R2 score also indicates the fit of the model, the closer it is to 1, the better the fit and the better the performance of the model.

To compare the performance of the experiments, we used 5_fold cross-validation. Tables 3 include the performance of deep learning models for predicting the prices of brand A and B products, respectively. Results are evaluated in four metrics, namely MSE, RMSE, MAE, and R2 score.

Experimental results show that the proposed CNN-LSTM-GA algorithm performed better than the other algorithms for both the price of brands A and B.

In Table 3, the MSE value of the proposed algorithm is 0.0023, MAE is 0.0396, and RMSE is 0.05, which are the lowest compared to other models. The value of R2 of the proposed algorithm is 0.9378, which is more than other models and shows that the proposed model CNN-LSTM-GA has more performance than other models and is the most suitable model for predicting the price of brand A.

Table 3 Comparison results for brand A

	Brand A				Brand B			
Model	MSE	MAE	RMSE	R2score	MSE	MAE	RMSE	R2score
CNN-LSTM	0.0024	0.0389	0.0492	0.9378	0.0026	0.043	0.0513	0.9321
CNN	0.0028	0.0447	0.0529	0.9226	0.0032	0.0458	0.0568	0.8855
GRU	0.0044	0.0553	0.0662	0.8736	0.0033	0.0449	0.0576	0.8761

LSTM	0.0056	0.0592	0.0749	0.8075	0.0036	0.045	0.0603	0.8463
MLP	0.0067	0.0685	0.08	0.7136	0.002	0.038	0.04	0.9017
CNN-LSTM-GA	0.0023	0.0396	0.05	0.9632	0.0012	0.0295	0.03	0.9612
RNN	0.0035	0.0507	0.06	0.8843	0.003	0.0477	0.05	0.8612

In Table 3, the MSE value of the proposed algorithm is 0.0012, MAE is 0.0295, and RMSE is 0.03, which are the lowest compared to other models. The value of R^2 for the proposed algorithm is 0.9378, which is more than other models and shows that the proposed model CNN-LSTM-GA has more performance than other models and is the most suitable model for forecasting the price of B brand.

5.2 Result of Game Theory

We apply the settings in Table 2 to the previously examined cases. Then we look at how the supplier's selling price and the retailers' ordering cycle affect both the supplier's and retailers' earnings.

The highest value of the supplier's profit happens when the supplier charges the retailers a selling price of α_{max}^{cw} =2.7651, whereas the maximum value of the retailers' profit occurs when the supplier charges a selling price of α_{min}^{cw}==2.2342. When α^{cw}=2.8, it denotes a situation in which the supplier and retailers are unable to coordinate their supply chains. The retailers are hesitant to work with the supplier in this circumstance, and the supplier's profit is reduced as a result of the higher selling price and lower order quantity. When the provider's best-selling price fulfils $\alpha_{min}^{cw}* \leqslant \alpha^{cw}* \leqslant \alpha_{max}^{cw}*$., the supplier and retailers can gain greater profit than in the absence of a contract, whereα^{cw}=2.8. In conclusion,

The food supply chain will be optimized with a quantity discount contract. Table 4 is a good indicator of obtained profits.

Table4 independent procurement- obtained profits by actors (price units are US dollars and it has been scaled)

α^{cw}	**Profit**				
	Supplier	**Retailer 1**	**Retailer 2**	**Retailer 3**	**Retailer 4**
2.79	289	117.6	189.6	98.6	185.5
2.76	556.1	120.7	215.5	112.3	188.2
2.6	502.4	134.4	220.7	118.7	197.1
2.5	467.6	147.7	230.6	129.6	206.7
2.4	423.9	149.8	249.4	145.2	214.1
2.3	362.72	167.2	278.9	157.0	224.6
2.2	298.9	177.1	288.4	177.2	248.8

Table 5 joint procurement- obtained profits by actors (price units are US dollars and it has been scaled)

α^{cw}	**Profit**				
	Supplier	**Retailer 1**	**Retailer 2**	**Retailer 3**	**Retailer 4**
2.79	475.7	176.7	261.8	157.8	237.4
2.76	519.1	176.1	261.6	157.3	237.5

2.74	507.6	178.8	265.5	162.3	242.4
2.73	494.1	181.9	265.3	164.3	245.4
2.72	457.1	181.6	269.8	164.3	245.9
2.68	466.4	186.7	272.9	168.4	248.3
2.67	468.7	188.2	275.2	170.8	253.3

The profits of the supplier and retailers under joint procurement are shown in the results. According to Table 5, merchants may make more money through cooperative procurement than independent buying. Furthermore, the supplier's profit under collaborative procurement is higher than the supplier's profit under independent procurement. After the retailers participate in cooperative procurement, the threshold of the supplier's selling price is lower (Table 6 vs. Table 5).

Table 7 indicates that when the degradation rate grows, the supplier's selling price lowers, the retailer's ordering cycle shortens, and the ordering frequency increases.

Table 6 impact of various deterioration rates on different stages of programming (price units are US dollars and it has been scaled)

β	**Independent procurement**		**Joint procurement**	
	α_{Di}^{cw}	T_{Di}^{cw}	α_{Di}^{cw}	T_{Di}^{cw}
0.02	2.59	1.565	2.655	0.807
0.03	2.48	1.542	2.604	0.802
0.04	2.47	1.419	2.614	0.807
0.05	2.46	1.391	2.548	0.720

When comparing independent and collaborative procurement, the supplier's selling price is greater, and the retailer's buying cycle is shorter in joint procurement.

Tables 7, 8, and 9 show that when the degradation rate rises, both the supplier and the retailer's earnings drop, regardless of whether they use independent or collaborative procurement.

Table 7 understanding the impact of different deterioration rates on profit- independent procurement (price units are US dollars and it has been scaled)

β	**Supplier**	**Retailer 1**	**Retailer 2**	**Retailer 3**	**Retailer 4**
0.02	422.2	149.5	247.0	136.3	214.7
0.03	418.0	148.5	245.42	135.2	213.5
0.04	415.0	147.6	243.89	134.1	212.6
0.05	411.8	146.7	242.41	133.1	211.5

Table 8 understanding the impact of different deterioration rates on profit- joint procurement

β	**Supplier**	**Retailer 1**	**Retailer 2**	**Retailer 3**	**Retailer 4**
0.03	491.6	195.2	288.4	175.3	265.3
0.04	486.2	193.5	287.8	174.6	264.9
0.05	485.4	191.0	286.4	173.5	264.4

0.06	407.7	178.6	227.4	155.3	209.1

When comparing Tables 9 and 10, it is evident that cooperative procurement generates higher profit for both the supplier and the store than independent procurement.

Regardless of how much the parameters vary, the numerical analysis shows that coordinating FPSCs through quantity discount contracts is optimal. In cases where the selling price and ordering cycle are based on the contract, the supplier's and retailer's profits are much higher than if the contract were not in place. Table 7 illustrates that it would be easier to coordinate the FPSC if (C_{Di}^{cw},T_{Di}^{cw}) is close to ($C_{Di}^{cw^*}$,$T_{Di}^{cw^*}$), Furthermore, when the parameters are in the range of (c^{cw*}, TC^{cw*}), the whole supply chain, the provider, and the retailers are all more lucrative.

When the coordination cost is taken into account, the fixed ordering cost N is estimated as indicated in Table 9.

Table 9 fixed ordering costs in coalition N

N	**2**	**3**	**4**	**1,2**
Kr+cN	65	65	65	75.78
N	1,4	2,3	2,4	3,4
Kr+cN	92.63	66.26	75.47	84.44
N	1,2,4	1,3,4	2,3,4	1,2,3,4
Kr+cN	94.80	109.54	99.86	112.62

Table 10 shows the features of (N, π^{cw*}).

Table 10 Parameters of the characteristic function values of π^{cw*}

N	**2**	**3**	**4**	**1,2**
πCrcw*N	0.895	0.845	0.977	1.035
N	1,4	2,3	2,4	3,4
πCrcw*N	1.024	1.074	1.132	1.060
N	1,2,4	1,3,4	2,3,4	1,2,3,4
πCrcw*N	1.192	1.127	1.171	1.254

We apply the settings from Tables 10 and 9 to the previously examined cases. Under joint procurement, we may now acquire the earnings of both the supplier and the retailers while accounting for coordination costs. Table 11 indicates the impact of coordination costs on the FPSC in collaborative procurement.

Table 11 joint procurement supplier and retailer profit (price units are US dollars and it has been scaled)

αCew	Profit				
	Supplier	**Retailer 1**	**Retailer 2**	**Retailer 3**	**Retailer 4**
2.9	479.04	156.76	238	137	210
2.8799	566.87	156.76	238.27	137	210
2.7794	541.54	168.55	243601	145.44	222.41
2.7489	526.96	170.61	254.60	152.51	228.73
2.7213	488.09	183.40	269.29	163.66	250.97

Clearly, profit is higher when procurement is done independently and lower when coordination is not taken into account. When the coordination cost is taken into account, the ordering cycle lengthens, and the ordering frequency reduces, yielding these findings. Furthermore, the supplier's ideal selling price fluctuates due to the coordination cost and the ordering cycle of the retailers. The managerial complexity of an FPSC with one supplier and several retailers is exemplified by this arrangement. Table 11 shows that an FPSC's overall profit is larger under a quantity discount contract than it is without one. This finding suggests that quantity discount contracts are effective and important in organizing an FPSC under joint procurement.

One of the most extensively utilized strategies in the literature for pricing perishable foods is game theory. There has also been a lot of study on predicting food costs. There are fewer articles that address the brand value of food in the model among the presented models. In this approach, perishable food makers must supply an acceptable price plan in order to maximize product sales volume. It is also quite tough to compete with well-known firms. As a result, to give a suitable price, it is necessary to foresee the pricing strategy of other manufacturers. Thus, the study addresses this knowledge gap by utilizing two forecasting methodologies and a Game Theory model.

Consumers engage directly with merchants, and retailers' conduct impacts customer preferences by creating a relationship between the customer and the brand. Considering the branding, happiness with one brand improves product demand. Product quality and brand value also influence the connection between manufacturer and consumer. Consumer satisfaction with a product is inversely proportional to the price paid for it. Furthermore, one of the most important things that might attract buyers is pricing.

6. Conclusion and Managerial Insight

In food retail, studies of pricing outcomes have been complicated by the fact that transactions may include multiple products, as well as by the presence of a highly concentrated food processing and retailing industry, which mediates between a competitive farm product market as well as a consumer market. In this study, we examine the relationship between retailers, food manufacturers, and farmers through the lens of theoretical and empirical evidence.

Farmers are increasingly linked to consumers through downstream food retail markets as global food value chains transform; meanwhile, market concentration has been growing globally due to the dominance of major supermarket chains in food retail.

This study presents a pricing strategy for the food supply chain. In doing so, we first identified competitors' prices based on historical data and then we implemented a game theory mathematical model to have the best pricing actions. In the game theory approach, we presented two models; with and without quantity discount contracts. These contracts help decision-makers to compare different results and pinpoint the best solution for their companies.

Prices in retail markets with several products often involve not only selecting multiple prices, but also choosing other competitive variables. Among complementary product categories, retailers set relative price levels, while within product categories they set individual prices for highly substitutable brands. A retail-pricing strategy encompasses both price discrimination across products as well as across time, vertical contracting decisions and wholesale pricing between manufacturers and retailers, co-manufacturing decisions, price decisions resulting in different product assortments for milk and breakfast cereal, or price and quality decisions made simultaneously. Multiproduct retailers are faced with the challenge of making decisions about entire product lines as well as presenting a desirable mix of attributes within each product line.

When a product is priced in the factory and it is not possible to change its price by the retailer, this product is under competition with other manufacturers, which according to the brand value of the manufacturers and their prices, the demand for the products can be different. This model can be used by managers and manufacturers as a decision support system for pricing perishable food that is priced in factories, in addition to considering the policies of producers for pricing, the prices of other producers and Consider their brand value as well. It means that, by predicting the pricing of otherand considering the value of their brand, the producers can have the best pricing for their products to maximize their profit and sales.This model can also be used for goods that are sold periodically. It refers to goods that become obsolete after a while or whose technology becomes antiquated. Other uses of this model include seasonal goods, which, even if not perishable, have a high storage cost. In general, presenting a game theory pricing model for perishable food, taking into account the prices of other competitors and their brand value, is a major contribution of this article.

Several other deep learning algorithms have been tested to confirm the usefulness of the proposed method (CNN-LSTM-GA) in forecasting. The Hyper-parameters of these algorithms are optimized as possible by using trial and error. The results show that the proposed method has been able to show better results and make more accurate in forecasting than other algorithms. The price of brands A and B were considered as a target variable separately in these algorithms. It should be noted that the structure of the algorithms is fixed for both brands and does not change. This approach is based on a 3_day_ahead prediction and the price of brands are forecast for the next three days.

In order to select the best model from the tested models and use it in the next phase (game theory), the performance of these algorithms were compared with each other by using regression evaluation criteria. such as MSE, MAE, RMSE and R2 score. MSE, MAE and RMSE. These criteria show the amount of error in the forecast, and the lower the value, the better the performance of the model. R2 score also indicates the fit of the model, the closer it is to 1, the better the fit and the better the performance of the model.

According to insights, merchants may make more money through cooperative procurement than they can through independent buying. Furthermore, the supplier's profit under collaborative procurement is higher than the supplier's profit under independent procurement. After the retailers participate in cooperative procurement, the threshold of the supplier's selling price is lower. When comparing independent and collaborative procurement, the supplier's selling price is greater and the retailer's buying cycle is shorter in joint procurement. It is evident that cooperative procurement generates higher profit for the supplier and the store than independent procurement.

Regardless of how much the parameters vary, the numerical analysis shows that coordinating FPSCs through quantity discount contracts is optimal. If in cases selling price and ordering cycle are on the basis of the contract, the supplier's and retailer's profits are much higher than if the contract were not in place.

We should consider two concerns that highlight the limitations of complex system models like this study in terms of prediction. The first is the question of emergence, which is intimately related to size and space in data by demonstrating that models of local activity may give birth to global order. This brings us to the second issue that restricts our ability to forecast. Most of the models to which we are referring here have methods for selecting growth drivers through random processes. For example, selecting cells for development is frequently a process of assessing the likelihood that they will be developed and then selecting actual allocations to these cells based on these values with using Monte Carlo techniques. Although it is feasible to arrange these sorts of models in a deterministic framework, most would agree that the certainty suggested by this is problematic. Furthermore, if the standard approach of random simulation is taken, there is the issue of determining what real simulations mean when they change from run to run. Taking some central limiting simulation is also troublesome because decisions inside these structures are invariably decided by discrete thresholding.

Future studies should focus on increasing digitization and developing robust tracking systems that can manage food advocacy, source, and safety during this epidemic, where counterfeiting and adulteration may be more prevalent than normal. Furthermore, digitization provides a comprehensive audit trail of reliable information, allowing suppliers to enter the supply chain with the ability to check the quality of manufacturing and operations at all stages, from farm to retailer. More research should be done on conventional food procurement systems, which have given rise to both consumer expectations and misunderstandings. Consumers should be better informed and educated about food quality and its implications for health. The application of technology tools decreases waste, boosts resilience, and promotes viability in FSC. The evolving end-to-end business model is mostly dependent on revolutionary innovation in the food sector. As a result of adopting digitization, food safety and advocacy will increase, allowing the market to democratize accessibility and experiment. All of this is made feasible by the industry's automation, increasing efficiency, better customer understanding, and support for significant food production and consumption shifts. Furthermore, completing food system reform will need a considerable shift in mindsets, as well as the roles and responsibilities of public sector actors against companies in setting food demand. This may be accomplished in FSC by carefully developing horizontal cooperation procedures. Food systems are essential for economic prosperity, human health, and planetary health, and getting all three correctly is vital. They are inextricably linked and have a considerable influence on one another. Every nation must imagine probable future possibilities in which everyone consumes properly, based on environmentally, economically, and socially sustainable food systems. Local and national perspectives on how such food systems can manifest in greater predominance should lead to policy aims aimed at the long-term transformation.

In general, the approach in this study can help producers as a decision support tool to make better decisions about the proper pricing of perishable food products. It is therefore suggested that future researchers examine the impact of more features on food price forecasts and use those features to predict the pricing of other producers. These features can be different in different societies. Also, to improve the performance of the prediction model, it is suggested to use other meta-heuristic algorithms and compare the results with each other. Incorporating other factors that can affect the demand for perishable food products in the game theory model can seemingly improve the results and provide a more accurate model. It is worthy to mark that the contracts which are applied for the above-mentioned pricing formulation can be expanded. Some other contracts can also be applied and compared with the presented one (e.g. revenue-sharing contracts, cost-sharing contracts).

Refernces:

Abdulov, R. (2020). Artificial Intelligence as an Important Factor of Sustainable and Crisis-Free Economic Growth. *Procedia Computer Science, 169*, 468-472. doi:https://doi.org/10.1016/j.procs.2020.02.223

Adenso-Díaz, B., Lozano, S., & Palacio, A. (2017). Effects of dynamic pricing of perishable products on revenue and waste. *Applied Mathematical Modelling, 45*, 148-164. doi:https://doi.org/10.1016/j.apm.2016.12.024

Agi, M. A. N., Faramarzi-Oghani, S., & Hazır, Ö. (2021). Game theory-based models in green supply chain management: a review of the literature. *International Journal of Production Research, 59*(15), 4736-4755. doi:10.1080/00207543.2020.1770893

Alvarez Alvarez, B., & Vázquez Casielles, R. (2005). Consumer evaluations of sales promotion: the effect on brand choice. *European Journal of Marketing, 39*(1/2), 54-70. doi:10.1108/03090560510572016

Amolegbe, K. B., Upton, J., Bageant, E., & Blom, S. (2021). Food price volatility and household food security: Evidence from Nigeria. *Food Policy*, 102061. doi:https://doi.org/10.1016/j.foodpol.2021.102061

Andreyeva, T., Long, M., & Brownell, K. (2009). The Impact of Food Prices on Consumption: A Systematic Review of Research on the Price Elasticity of Demand for Food. *American journal of public health, 100*, 216-222. doi:10.2105/AJPH.2008.151415

Avinadav, T., Herbon, A., & Spiegel, U. (2013). Optimal inventory policy for a perishable item with demand function sensitive to price and time. *International Journal of Production Economics, 144*(2), 497-506. doi:https://doi.org/10.1016/j.ijpe.2013.03.022

Azadi, Z., Eksioglu, S. D., Eksioglu, B., & Palak, G. (2019). Stochastic optimization models for joint pricing and inventory replenishment of perishable products. *Computers & Industrial Engineering, 127*, 625-642. doi:https://doi.org/10.1016/j.cie.2018.11.004

Begum, R., Sahoo, R. R., & Sahu, S. K. (2012). A replenishment policy for items with price-dependent demand, time-proportional deterioration and no shortages. *International Journal of Systems Science, 43*(5), 903-910. doi:10.1080/00207721.2010.543481

Bhattacharya, C. B., & Sen, S. (2003). Consumer–company identification: A framework for understanding consumers’ relationships with companies. *Journal of marketing, 67*(2), 76-88.

Bi, J.-W., Li, H., & Fan, Z.-P. (2021). Tourism demand forecasting with time series imaging: A deep learning model. *Annals of Tourism Research, 90*, 103255. doi:https://doi.org/10.1016/j.annals.2021.103255

Bilgili, F., Koçak, E., Kuşkaya, S., & Bulut, Ü. (2020). Estimation of the co-movements between biofuel production and food prices: A wavelet-based analysis. *Energy, 213*, 118777. doi:https://doi.org/10.1016/j.energy.2020.118777

Chatziantoniou, I., Degiannakis, S., Delis, P., & Filis, G. (2020). Forecasting oil price volatility using spillover effects from uncertainty indices. *Finance Research Letters*, 101885. doi:https://doi.org/10.1016/j.frl.2020.101885

Chen, S.-C., Min, J., Teng, J.-T., & Li, F. (2016). Inventory and shelf-space optimization for fresh produce with expiration date under freshness-and-stock-dependent demand rate. *Journal of the Operational Research Society, 67*(6), 884-896. doi:10.1057/jors.2015.100

Chen, X., Yu, R., Ullah, S., Wu, D., Li, Z., Li, Q., . . . Zhang, Y. (2022). A novel loss function of deep learning in wind speed forecasting. *Energy, 238*, 121808. doi:https://doi.org/10.1016/j.energy.2021.121808

Chew, E. P., Lee, C., & Liu, R. (2009). Joint inventory allocation and pricing decisions for perishable products. *International Journal of Production Economics, 120*(1), 139-150. doi:https://doi.org/10.1016/j.ijpe.2008.07.018

Chung, J., & Li, D. (2013). The prospective impact of a multi-period pricing strategy on consumer perceptions for perishable foods. *British Food Journal, 115*(3), 377-393. doi:10.1108/00070701311314200

Cui, B., Yang, K., & Chou, T. (2016). Analyzing the Impact of Price Promotion Strategies on Manufacturer Sales Performance. *Journal of Service Science and Management, 09*, 182-187. doi:10.4236/jssm.2016.92022

Dastider, A. G., Sadik, F., & Fattah, S. A. (2021). An integrated autoencoder-based hybrid CNN-LSTM model for COVID-19 severity prediction from lung ultrasound. *Computers in Biology and Medicine, 132*, 104296. doi:https://doi.org/10.1016/j.compbiomed.2021.104296

E, J., Panicker, V. V., & Sridharan, R. (2022). Environmental friendly route design for a milk collection problem: the case of an Indian dairy. *International Journal of Production Research, 60*(3), 912-941. doi:10.1080/00207543.2020.1846219

Fowowe, B. (2016). Do oil prices drive agricultural commodity prices? Evidence from South Africa. *Energy, 104*, 149-157. doi:https://doi.org/10.1016/j.energy.2016.03.101

Ghasemi, P., Goodarzian, F., Muñuzuri, J., & Abraham, A. (2022). A cooperative game theory approach for location-routing-inventory decisions in humanitarian relief chain incorporating stochastic planning. *Applied Mathematical Modelling, 104*, 750-781. doi:https://doi.org/10.1016/j.apm.2021.12.023

Goodarzian, F., & Fakhrzad, M. (2020). A New Multi-Objective Mathematical Model for A Citrus Supply Chain Network Design: Metaheuristic Algorithms. *International Journal of Industrial Engineering*. doi:10.22094/JOIE.2020.570636.1571

Gunasekaran, A., Ghasemi, P., Goodarzian, F., & Abraham, A. (2021). A bi-level mathematical model for logistic management considering the evolutionary game with environmental feedbacks. *The International Journal of Logistics Management, ahead-of-print*. doi:10.1108/IJLM-04-2021-0199

Guo, X., Zhao, Q., Zheng, D., Ning, Y., & Gao, Y. (2020). A short-term load forecasting model of multi-scale CNN-LSTM hybrid neural network considering the real-time electricity price. *Energy Reports, 6*, 1046-1053. doi:https://doi.org/10.1016/j.egyr.2020.11.078

Hanif, W., Areola Hernandez, J., Shahzad, S. J. H., & Yoon, S.-M. (2021). Tail dependence risk and spillovers between oil and food prices. *The Quarterly Review of Economics and Finance, 80*, 195-209. doi:https://doi.org/10.1016/j.qref.2021.01.019

Hendalianpour, A. (2020). Optimal lot-size and Price of Perishable Goods: A novel Game-Theoretic Model using Double Interval Grey Numbers. *Computers & Industrial Engineering, 149*, 106780. doi:https://doi.org/10.1016/j.cie.2020.106780

Herbon, A., Levner, E., & Cheng, T. C. E. (2014). Perishable inventory management with dynamic pricing using time–temperature indicators linked to automatic detecting devices. *International Journal of Production Economics, 147*, 605-613. doi:https://doi.org/10.1016/j.ijpe.2013.07.021

Hosseini-Motlagh, S.-M., Johari, M., & Zirakpourdehkordi, R. (2021). Grain production management to reduce global warming potential under financial constraints and time value of money using evolutionary game theory. *International Journal of Production Research, 59*(17), 5108-5129. doi:10.1080/00207543.2020.1773562

Huang, L., & Zheng, W. (2021). Novel deep learning approach for forecasting daily hotel demand with agglomeration effect. *International Journal of Hospitality Management, 98*, 103038. doi:https://doi.org/10.1016/j.ijhm.2021.103038

Karakotsios, A., Katrakilidis, C., & Kroupis, N. (2021). The dynamic linkages between food prices and oil prices. Does asymmetry matter? *The Journal of Economic Asymmetries, 23*, e00203. doi:https://doi.org/10.1016/j.jeca.2021.e00203

Kim, J., Wang, X., Kang, C., Yu, J., & Li, P. (2021). Forecasting air pollutant concentration using a novel spatiotemporal deep learning model based on clustering, feature selection and empirical wavelet transform. *Science of The Total Environment, 801*, 149654. doi:https://doi.org/10.1016/j.scitotenv.2021.149654

Kim, T.-Y., & Cho, S.-B. (2019). Predicting residential energy consumption using CNN-LSTM neural networks. *Energy, 182*, 72-81. doi:https://doi.org/10.1016/j.energy.2019.05.230

Ko, M. S., Lee, K., Kim, J. K., Hong, C. W., Dong, Z. Y., & Hur, K. (2021). Deep Concatenated Residual Network With Bidirectional LSTM for One-Hour-Ahead Wind Power Forecasting. *IEEE Transactions on Sustainable Energy, 12*(2), 1321-1335. doi:10.1109/TSTE.2020.3043884

Konuk, F. A. (2018). The role of risk aversion and brand-related factors in predicting consumers' willingness to buy expiration date-based priced perishable food products. *Food Research International, 112*, 312-318. doi:https://doi.org/10.1016/j.foodres.2018.06.009

Kumar, V., Holt, D., Ghobadian, A., & Garza-Reyes, J. A. (2015). Developing green supply chain management taxonomy-based decision support system. *International Journal of Production Research, 53*(21), 6372-6389.

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature, 521*(7553), 436-444. doi:10.1038/nature14539

Li, K., Lee, J.-Y., & Gharehgozli, A. (2021). Blockchain in food supply chains: a literature review and synthesis analysis of platforms, benefits and challenges. *International Journal of Production Research*, 1-20. doi:10.1080/00207543.2021.1970849

Li, R., & Teng, J.-T. (2018). Pricing and lot-sizing decisions for perishable goods when demand depends on selling price, reference price, product freshness, and displayed stocks. *European Journal of Operational Research, 270*(3), 1099-1108. doi:https://doi.org/10.1016/j.ejor.2018.04.029

Li, Z., Yada, K., & Zennyo, Y. (2021). Duration of price promotion and product profit: An in-depth study based on point-of-sale data. *Journal of Retailing and Consumer Services, 58*, 102277. doi:https://doi.org/10.1016/j.jretconser.2020.102277

Liu, L., Zhao, Q., & Goh, M. (2021). Perishable material sourcing and final product pricing decisions for two-echelon supply chain under price-sensitive demand. *Computers & Industrial Engineering, 156*, 107260. doi:https://doi.org/10.1016/j.cie.2021.107260

Lu, W., Li, J., Li, Y., Sun, A., & Wang, J. (2020). A CNN-LSTM-Based Model to Forecast Stock Prices. *Complexity, 2020*, 6622927. doi:10.1155/2020/6622927

Mamoudan, M., Forouzanfar, D., Mohammadnazari, Z., Aghsami, A., & Jolai, F. (2021). Factor identification for insurance pricing mechanism using data mining and multi criteria decision

making. *Journal of Ambient Intelligence and Humanized Computing*. doi:10.1007/s12652-021-03585-z
Marzouk, M., Elshaboury, N., Abdel-Latif, A., & Azab, S. (2021). Deep learning model for forecasting COVID-19 outbreak in Egypt. *Process Safety and Environmental Protection, 153*, 363-375. doi:https://doi.org/10.1016/j.psep.2021.07.034
Mathiyazhagan, K., Govindan, K., & Noorul Haq, A. (2014). Pressure analysis for green supply chain management implementation in Indian industries using analytic hierarchy process. *International Journal of Production Research, 52*(1), 188-202.
Mogale, D. G., Ghadge, A., Cheikhrouhou, N., & Tiwari, M. K. (2022). Designing a food supply chain for enhanced social sustainability in developing countries. *International Journal of Production Research*, 1-21. doi:10.1080/00207543.2022.2078746
Okimoto, M. (2015). International price competition among food industries: The role of income, population and biased consumer preference. *Economic Modelling, 47*, 327-339. doi:https://doi.org/10.1016/j.econmod.2015.02.033
Olayungbo, D. O. (2021). Global oil price and food prices in food importing and oil exporting developing countries: A panel ARDL analysis. *Heliyon, 7*(3), e06357. doi:https://doi.org/10.1016/j.heliyon.2021.e06357
Rana, R., & Oliveira, F. S. (2015). Dynamic pricing policies for interdependent perishable products or services using reinforcement learning. *Expert Systems with Applications, 42*(1), 426-436. doi:https://doi.org/10.1016/j.eswa.2014.07.007
Ryan, J., & Casidy, R. (2018). The role of brand reputation in organic food consumption: A behavioral reasoning perspective. *Journal of Retailing and Consumer Services, 41*, 239-247. doi:https://doi.org/10.1016/j.jretconser.2018.01.002
Sadikur Rahman, M., Al-Amin Khan, M., Abdul Halim, M., Nofal, T. A., Akbar Shaikh, A., & Mahmoud, E. E. (2021). Hybrid price and stock dependent inventory model for perishable goods with advance payment related discount facilities under preservation technology. *Alexandria Engineering Journal, 60*(3), 3455-3465. doi:https://doi.org/10.1016/j.aej.2021.01.045
Santini, F. d. O., Vieira, V. A., Sampaio, C. H., & Perin, M. G. (2016). Meta-Analysis of the Long- and Short-Term Effects of Sales Promotions on Consumer Behavior. *Journal of Promotion Management, 22*(3), 425-442. doi:10.1080/10496491.2016.1154921
Sarker, B. R., Mukherjee, S., & Balan, C. V. (1997). An order-level lot size inventory model with inventory-level dependent demand and deterioration. *International Journal of Production Economics, 48*(3), 227-236. doi:https://doi.org/10.1016/S0925-5273(96)00107-7
Sebatjane, M., & Adetunji, O. (2020). A three-echelon supply chain for economic growing quantity model with price- and freshness-dependent demand: Pricing, ordering and shipment decisions. *Operations Research Perspectives, 7*, 100153. doi:https://doi.org/10.1016/j.orp.2020.100153
Sharma, A., Zhang, Z., & Rai, R. (2021). The interpretive model of manufacturing: a theoretical framework and research agenda for machine learning in manufacturing. *International Journal of Production Research, 59*(16), 4960-4994. doi:10.1080/00207543.2021.1930234
Srivastava, S., & Lessmann, S. (2018). A comparative study of LSTM neural networks in forecasting day-ahead global horizontal irradiance with satellite data. *Solar Energy, 162*, 232-247. doi:https://doi.org/10.1016/j.solener.2018.01.005
Taghizadeh-Hesary, F., Rasoulinezhad, E., & Yoshino, N. (2019). Energy and Food Security: Linkages through Price Volatility. *Energy Policy, 128*, 796-806. doi:https://doi.org/10.1016/j.enpol.2018.12.043
Tsiros, M., & Heilman, C. (2005). The Effect of Expiration Dates and Perceived Risk on Purchasing Behavior in Grocery Store Perishable Categories. *Journal of Marketing - J MARKETING, 69*, 114-129. doi:10.1509/jmkg.69.2.114.60762
Wang, H., Yi, H., Peng, J., Wang, G., Liu, Y., Jiang, H., & Liu, W. (2017). Deterministic and probabilistic forecasting of photovoltaic power based on deep convolutional neural network. *Energy*

Conversion and Management, 153, 409-422. doi:https://doi.org/10.1016/j.enconman.2017.10.008

Wang, W., Hong, T., Xu, X., Chen, J., Liu, Z., & Xu, N. (2019). Forecasting district-scale energy dynamics through integrating building network and long short-term memory learning algorithm. *Applied Energy, 248*, 217-230. doi:https://doi.org/10.1016/j.apenergy.2019.04.085

Wang, X., & Li, D. (2012). A dynamic product quality evaluation based pricing model for perishable food supply chains. *Omega, 40*(6), 906-917. doi:https://doi.org/10.1016/j.omega.2012.02.001

Xu, C., Fan, T., Zheng, Q., & Song, Y. (2021). Contract selection for fresh produce suppliers cooperating with a platform under a markdown-pricing policy. *International Journal of Production Research*, 1-25.

Yao, S., Xu, Y.-P., & Ramezani, E. (2021). Optimal long-term prediction of Taiwan's transport energy by convolutional neural network and wildebeest herd optimizer. *Energy Reports, 7*, 218-227. doi:https://doi.org/10.1016/j.egyr.2020.12.034

Zhang, M., Li, J., Li, Y., & Xu, R. (2021). Deep Learning for Short-Term Voltage Stability Assessment of Power Systems. *IEEE Access, 9*, 29711-29718. doi:10.1109/ACCESS.2021.3057659

Zheng, Q., Zhou, L., Fan, T., & Ieromonachou, P. (2019). Joint procurement and pricing of fresh produce for multiple retailers with a quantity discount contract. *Transportation Research Part E: Logistics and Transportation Review, 130*, 16-36.

Zhou, X., Feng, J., & Li, Y. (2021). Non-intrusive load decomposition based on CNN–LSTM hybrid deep learning model. *Energy Reports, 7*, 5762-5771. doi:https://doi.org/10.1016/j.egyr.2021.09.001