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Design of e-commerce business model through AI price prediction of agricultural products

Nam-Gyu Han[1], Bong-Hyun Kim[2*]
[1]Student, Dept. of Computer Science, Washington State University
[2]Professor, Dept. of Computer Engineering, Seowon University

농산물 AI 가격 예측을 통한 전자거래 비즈니스 모델 설계

한남규[1], 김봉현[2*]
[1]워싱턴주립대학교 컴퓨터과학과 학생, [2]서원대학교 컴퓨터공학과 교수

Abstract For agricultural products, supply is irregular due to changes in meteorological conditions, and it has high price elasticity. For example, if the supply decreases by 10%, the price increases by 50%. Due to these fluctuations in the prices of agricultural products, the Korean government guarantees the safety of prices to producers through small merchants' auctions. However, when prices plummet due to overproduction, protection measures for producers are insufficient. Therefore, in this paper, we designed a business model that can be used in the electronic transaction system by predicting the price of agricultural products with an artificial intelligence algorithm. To this end, the trained model with the training pattern pairs and a predictive model was designed by applying ARIMA, SARIMA, RNN, and CNN. Finally, the agricultural product forecast price data was classified into short-term forecast and medium-term forecast and verified. As a result of verification, based on 2018 data, the actual price and predicted price showed an accuracy of 91.08%.

Key Words : Agricultural product price, AI prediction, e-Commerce, Prediction model, AI algorithms

요 약 농산물은 기상, 기후 등의 변화로 인해 공급이 불규칙하고, 공급량이 10% 하락하면 가격이 50% 상승하는 가격 탄력성이 매우 높다. 이러한 농산물 가격의 변동으로 인해 소상인의 경매를 통해 생산자에게 대금의 안전성을 보장하고 있다. 그러나, 과잉생산으로 가격이 폭락할 경우, 생산자에 대한 보호 조치는 미비한 실정이다. 따라서, 본 논문에서는 농산물에 대한 가격을 인공지능 알고리즘으로 예측하여 전자거래 시스템에 활용할 수 있는 비즈니스 모델을 설계하였다. 이를 위해, 학습 패턴 쌍으로 모델을 학습시키고, ARIMA, SARIMA, RNN, CNN을 적용하여 예측 모델을 설계하였다. 최종적으로, 농산물 예측가격 데이터를 단기예측과 중기예측으로 분류하여 검증하였다. 검증 결과, 2018년 데이터를 기반으로 실제 가격과 예측 가격이 91.08%의 정확도를 나타냈다.

주제어 : 농산물 가격, AI 예측, 전자거래, 예측 모델, 인공지능 알고리즘

*Corresponding Author : Bong-Hyun Kim(bhkim@seowon.ac.kr)
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1. Introduction

Agricultural products have a short distribution period, and there are many variables, such as a decrease in product value due to spoilage and deterioration in the distribution process. These agricultural products are characterized by complicated steps, high costs, and price amplitude. In addition, it involves a large number of producers and consumers, resulting in high logistics costs, and goes through several stages of distribution[1,2]. The distribution of agricultural products is perishable, bulky, and the distribution cost is very high due to the small-scale production structure. In particular, leaf root vegetables have the highest distribution costs, and food crops' distribution costs are the lowest. Due to this, agricultural products have low price elasticity, and the price amplitude is enormous. Depending on the crop, cabbage and radish prices fluctuate the most. In July 2020, the price of cabbage skyrocketed due to the increase in the number of days of precipitation, putting a burden on consumer prices, and in January 2021, there was a drop in the price of cabbage. Due to the price fluctuations of these agricultural products, producers have even discarded cabbage from their production areas. The fluctuations in the price of cabbage put a burden on food companies, and it passed on to consumers. In 2010, more than two-thirds of kimchi manufacturers went out of business due to a surge in the price of cabbage in high altitudes, and the price of kimchi rose. In addition, as of February 2019, the government spent about 19.4 billion won in the government budget for disposing of cabbages nationwide[3-5].

The current state of the agricultural product distribution structure is that more than 56% of agricultural products are traded through electronic auctions in public wholesale markets. In the wholesale market, the electronic auction is a device that allows producers to receive the highest price. However, on the contrary, it is also a cause of large fluctuations in the price of agricultural products. For this reason, the Ministry of Agriculture, Food and Rural Affairs is implementing policies to promote regular-price purchase trading and electronic trading in the wholesale market. Currently, regular-price purchases and electronic trading methods have low transaction rates due to the different expectations of producers' expectations for price increases and consumers' expectations for price declines. Even in this situation, the wholesale market has not undergone significant changes and development compared to 10 years ago. Even in this situation, the wholesale market has not undergone significant changes and development compared to 10 years ago[6]. There are few opportunities to access technology and development opportunities to the wholesale market, even if there is a need for a system and structural changes. In addition, although specialized processing is required to distribute agricultural products, it is difficult to practically apply AI technology to small and medium-sized enterprises due to the burden of professionalism and service costs. For the above reasons, data processing and service development are required based on data and AI knowledge based on domain knowledge on agricultural and fishery product distribution. Still, an actual system and business design and implementation are not progressing due to a lack of professional human resources for data and AI.

Therefore, in this paper, we designed a business model which can be used in the electronic transaction system by predicting the price of agricultural products with an artificial intelligence algorithm. To this end, we trained a model with the training pattern pairs, and a predictive model was designed by applying ARIMA, SARIMA, RNN, and CNN. Finally, we conducted a study to classify the agricultural product predicted price data into short-term and medium-term predictions and secure the result data.

2 Market and Technology Trends

2.1 Market Trends

We can identify the business trend of agricultural products distribution by dividing it into the production area sector, the agricultural product distribution wholesale sector, and the consumption area sector. First, in the case of business trends in the production area, scaling and organization are in progress, but the pace is slow, and the scale and organization are insufficient. Producing areas are trying to receive the full price of agricultural products and conduct to receive high farm households' receipts through the consignment-type joint accounting system. In addition, direct distribution cases are increasing for producers to increase farm household receipts[7].

Second, in the case of business trends in agricultural distribution and wholesale area, diversification of the transaction system is being sought, but no significant results are obtained. Related parties are discussing the importance of efficient logistics delivery for fair competition and transaction efficiency. They are trying to improve the wholesale market transaction system and promote direct transaction cyber transactions. In addition, policymakers are trying policies to improve the efficiency of local wholesale market operations. They are changing transaction methods such as regular price purchase electronic transactions from existing auction transactions[8].

Third, in the case of business trends in the consumer area, the proportion of large retailers is increasing, and the pace of change is rapidly developing. In addition, intending to improve quality and value, we are enhancing consumer convenience. Also, introducing a fair-trade system for agricultural products and the advancement of logistics systems lead to efficient delivery. Fig. 1 shows the changes and challenges of the agri-food distribution environment.

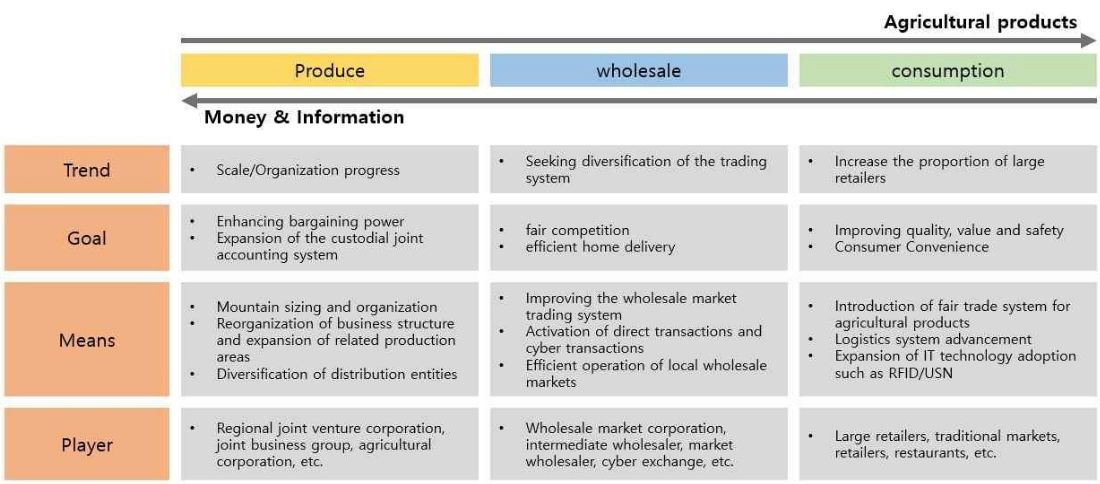

Fig. 1. Changes in the agricultural food distribution environment and challenges

2.2 Technology Trends

The industry uses various technology techniques for predicting agricultural product prices by applying artificial intelligence algorithms. Typically applied methods include reinforcement learning, LSTM, and ANN (Artificial Neural Networks). Reinforcement learning is a type of machine learning in which the learning subject interacts with the environment and selects the best behavior to achieve a given goal. Supervised learning learns the input and the result obtained for the input. In contrast, reinforcement learning is a method in which the learning subject takes an arbitrary action in a given environment and receives a reward for this action. The learning subjects learn how to act in a given state to maximize the reward. Here, the learning subject is called the agent, and the entire external environment interacting with the agent is called the environment. In addition, a reward is a scalar value that expresses the evaluation of the agent's behavior[9,10]. Fig. 2 shows the repetitive interaction between the agent and the environment in reinforcement learning.

A representative example of reinforcement learning is Q-learning. Q-Learning is an algorithm that continuously updates policy data on which decision in a specific state will give the highest future reward. The goal of Q-Learning is to learn the optimal policy for an agent to take a specific action in a particular situation in a finite Markov decision process (FMDP). It maximizes the predicted value of the overall reward starting from the current state and going through all successive steps. Q-learning can be applied without significant transformation, even in an environment where a transition from one state to another occurs stochastically or a reward is given probabilistically. Also, the word "Q" symbolizes the quality of the reward for the action taken in the current state[11-13].

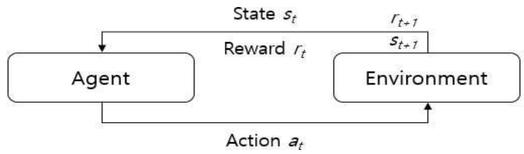

Fig. 2. Interaction between agent and environment

LSTM (Long-Short-Term Memory) refers to the structure of a neural network designed to enable long/short-term memory by compensating for the disadvantage that the traditional RNN cannot memorize information located far from the output. It is an algorithm mainly used for time series processing or natural language processing. LSTM erases unnecessary memories by adding an input gate, a forget gate, and an output gate to the memory cell of the hidden layer and decides what to remember. In other words, LSTM has a slightly more complicated formula for calculating the hidden state than traditional RNN and adds a value called cell state[14,15].

ANN (Artificial Neural Network) is the most core technology of deep learning, and it is a network composed of artificial neurons that abstract neurons. Just as neurons, which are the basic structures of the brain, process tasks by interconnecting them in the human brain, artificial neurons as a mathematical model are connected to form a network, which is called an artificial neural network. The primary functions of a neuron are arithmetic processing, information reception, and information output, and several neurons are combined to form a neural network. Similarly, artificial neural networks determine the output by a pre-determined non-linear function for many inputs. According to their functions, all neurons of a neural network model are usually divided into the input layer, the hidden layer, and the output layer, and each layer is organically connected. The input layer connects the external input module and sends it to the hidden layer according to the input unit. The hidden layer is a unit layer for the internal processing of the neural network, and the main role is to switch the mode of the neural network module. The output layer is used to create the output mode of the module. The advantage of neural networks is that they have enough nodes so that a few connections' faults do not cause the system to fail, i.e., high fault tolerance. In addition, the advantage of artificial neural networks is that they can learn in a new environment, and can generalize even if the input is incomplete and cannot be known in advance (generalization process). Finally, the advantage of artificial neural networks is their adaptability, which is used to maintain and update programs immediately[16]. The three characteristics of artificial neural networks are that, first, they are more favorable for prediction than interpretation of data, second, there is no need for a mathematical model, and third, the size of the data must be enormous.

ARIMA, SARIMA, RNN, CNN, etc. were used for the AI prediction model applied in this paper. The ARIMA (Autoregressive Integrated Moving Average) algorithm is a model created by adding the AR (Autoregressive) MA (Moving Average) model and the model and introducing the difference. The SARIMA (Seasonal ARIMA) algorithm is a model in which a periodic factor is added to an ARIMA model that combines an ARMA model and a model and introduces a difference. In addition, the Recurrent Neural Network (RNN) algorithm is a network that receives an input (x) to make an output (y), and receives an output again as an input, and there are derived models such as LSTM and GRU. Finally, CNN (Convolutional Neural Network) is a useful model for feature extraction from vectorized images, which is a model that learns directly from data and classifies images using patterns.

3 Business Model Design

The wholesale market has not undergone significant changes and development compared to a few years ago. Although there is a need for a system and structural changes, there were few opportunities to access technology and development. In addition, the lack of expertise in AI technology and high service costs were burdensome for companies related to the distribution of agricultural products. For this reason, it is necessary to process data and develop services based on knowledge of data and AI-based on domain knowledge on the distribution of agricultural and fishery products. However, the reality is that there is a shortage of professional human resources for data and AI.

Currently, the wholesale market for agricultural products is growing as a distribution base for agricultural and marine products due to the large-scale business promotion of the government and local governments. The need to strengthen competitiveness by applying AI price prediction data to the agricultural and fishery wholesale market is emerging. Therefore, in this paper, we designed a business model that can be used in the electronic transaction system by predicting the price of agricultural products with an artificial intelligence algorithm.

The business model design for agricultural market price prediction and price comparison with other regional wholesale markets applying AI algorithm was designed in the phase of applying the predicted market price in the electronic transaction system and the phase of using the comparison information of the auction in other regional wholesale markets during the auction. The goal of the prediction market application model in the electronic trading system is to activate electronic trading by applying the predicted market price to the price. And for all other matters (Logistics, transportation, consumers, quality during transportation, etc.) related to electronic transactions, the local agricultural and fishery market is self-solving. In addition, the auction comparison information utilization model in other regional wholesale markets provides favorable price conditions to distributors by suggesting good price conditions during the auction by comparing market prices in other regional wholesale markets. Figure 3 shows a business model for price prediction of agricultural products applied with an AI algorithm and price comparison with wholesale markets in other regions.

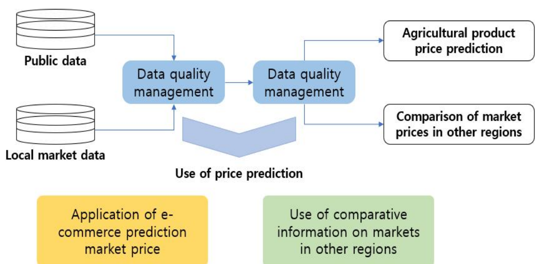

Fig. 3. AI algorithm applied price comparison business model

In applying the electronic transaction system using AI price prediction data, the agricultural product price distribution public data utilization phase, AI prediction data introduction phase, and electronic transaction and auction application phase were divided and designed. In the agricultural product price distribution public data utilization stage, we collect and use public data of real-time auction information and settlement information of the national wholesale market of the Ministry of Agriculture, Food and Rural Affairs. We also collect and use Korea Agro-Fisheries & Food Trade Corporation's public data of wholesale and retail survey prices. In addition, public data on retail survey prices by the Consumer Agency are collected and used. Next, in the AI prediction data introduction stage, the data is utilized through data quality management and data mining that refines the collected data, and the agricultural auction price prediction function is introduced through machine learning using artificial intelligence. Predictions are divided into short-term predictions and medium-term predictions. Short-term predictions are applied to electronic transactions and auctions, and mid-term predictions provide information to distributors through shipping options. In the electronic transaction and electronic auction application stage, we compare and apply the price data of the nationwide agricultural wholesale market, respectively. In the electronic transaction, we apply a short-term predicted price. In the electronic auction, we use the real-time processed data to form a better price by referring to the market price of other regional wholesale markets in related programs.

4. AI analytics model

In this paper, for the prediction and utilization of AI price data, it is designed to load the price data through data collection and modeling and use it in the system. Fig. 4 shows the step-by-step process of data application method.

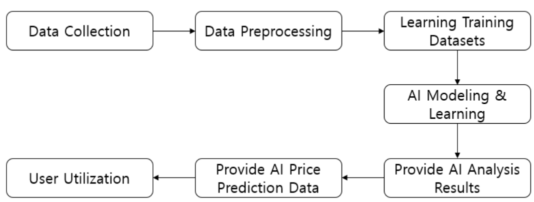

Fig. 4. Data application steps

In the data collection stage, we collect transaction data in the wholesale market and data provided by the supply corporations, and integrate additional necessary data with the supply corporations' data, and conduct mapping and linkage data between companies. The data pre-processing stage is a preparation stage for data quality inventory and processing learning data construction. Data quality rule application and quality management are performed, and the agricultural and fishery product price data quality problem of public data used for standards is managed through the supplier's data quality framework. At this time, data outliers are removed, and data labeling and dummy variables are created. Fig. 5 shows the data preprocessing steps.

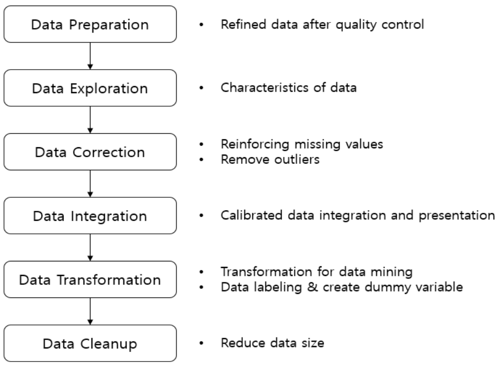

Fig. 5. Data preprocessing steps

In the training dataset construction stage, a dataset is built through processing to use the AI model, and a training dataset is built through data mining and preprocessing. Also, we derive data information and shape feature correlation for AI model candidate selection and conduct file conversion and DB linkage. In the AI modeling and learning stage, we select and test an AI model suitable for the data shape and characteristics, tune the AI model, learn from the data, and produce predictive data. In the AI analysis result provision stage, we provide an AI analysis data set is provided, a DB related to demanding companies is built, and AI-based derived results and data. In the stage of providing AI price prediction data, information and results using the AI analysis dataset are derived, and the DB of price prediction data is linked by providing the AI analysis dataset. In the user utilization stage, wholesalers and auctioneers apply and utilize the existing settlement program and auction program, and work for data output report preparation and data service. Fig. 6 shows the business model design through the application of the AI analysis model.

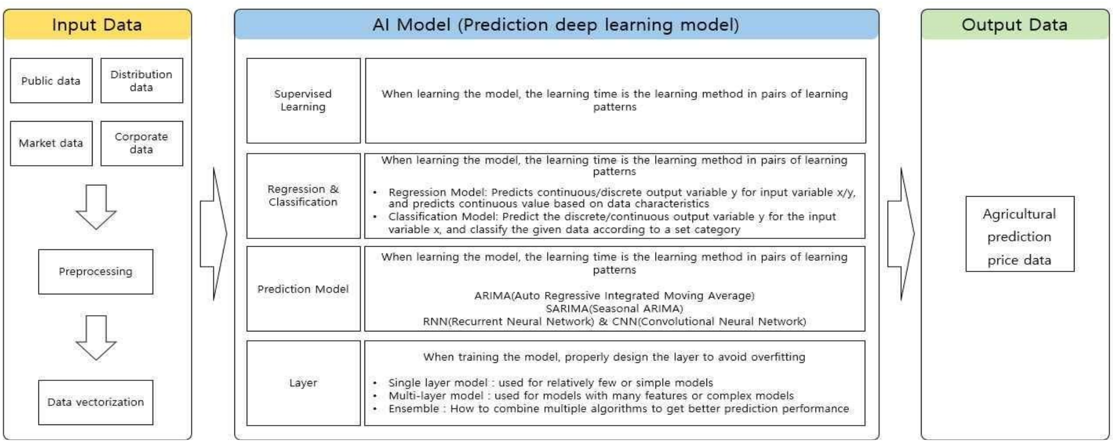

Fig. 6. AI analytic model-applied price prediction business model

Finally, Fig. 7 shows the agricultural price AI prediction model finally designed in the paper.

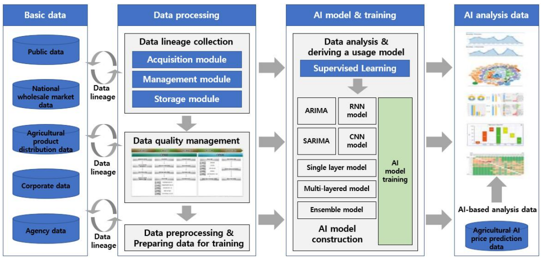

Fig. 7. Agricultural price AI prediction model

5 Conclusion

As the COVID-19 situation continues, the scale of agricultural trade is shrinking due to declining consumption, and the volume of sales in the wholesale market is declining. It is time to activate the agricultural product price prediction business model used in the electronic transaction system. However, expectations for the market price, e-commerce, and commerce do not reflect the market price on the day, but the predicted value, so conflicting expectations of consumers' and suppliers' work. As a result, e-commerce and e-commerce are not being conducted smoothly. Therefore, in this paper, we designed a business model that can be used in the electronic transaction system by predicting the price of agricultural products with an artificial intelligence algorithm. To this end, we trained a model with the training pattern pairs and designed a predictive model by applying ARIMA, SARIMA, RNN, and CNN. Finally, we conducted a study to classify the agricultural product predicted price data into short-term and medium-term predictions and secure the result data. By applying this, it is possible to break away from the inefficient traditional method and improve the reliability of agricultural trade through AI price prediction. In addition, the utilization of AI prediction data can reduce various costs and contribute to an increase in sales. Finally, we believe that it will be possible to improve confidence in the wholesale market by providing data to small and medium-sized merchants and distributors.

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한 남 규(Nam-Gyu Han) [학생회원]

· 2018년 2월 : 아주대학교 정보통신대학 소프트웨어학과(학사)
· 2019년 8월 ~ 현재 : 워싱턴주립대학교 컴퓨터과학과 석사과정
· 관심분야 : Machine Learning, Data Science
· E-mail : namgyu.han@wsu.edu

김 봉 현(Bong-Hyun Kim) [정회원]

· 2002년 2월 : 한밭대학교 전자계산학과(공학석사)
· 2009년 2월 : 한밭대학교 컴퓨터공학과(공학석사)
· 2012년 ~ 2015년 : 경남대학교 컴퓨터공학과 교수
· 2020년 3월 ~ 현재 : 서원대학교 컴퓨터공학과 교수
· 관심분야 : 빅데이터, 인공지능, IoT 서비스
· E-Mail : bhkim@seowon.ac.kr