Development of AI Modeling for Implementation of Agricultural Product Price Information Prediction System

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As smart farm is currently designated as one of the government's seven key tasks, it is an industry that is important in agriculture and has a lot of potential for development. It is very important to manage and utilize the data generated by these smart farms. In addition, it is essential to make smart farm big data information a new growth engine for agriculture and an industry that creates added value. However, the technology that can use agricultural data is still lacking, and the direction of the data utilization is still ambiguous. Therefore, in this paper, big data analysis necessary for predicting market price information on agricultural product prices among smart farm support factors was performed. To this end, supervised learning, regression analysis, and classification were performed, and finally, a study was conducted to develop a predictive model. Through this, it is possible to prepare a basis for discovering services such as production environment and price compared to grade quality by synthesizing it with data produced in the future smart farm.

Keywords: Price prediction, Agricultural information, AI modelling, Smart farm, CNN, RNN.

1. Introduction

Smart farm refers to an agricultural system using the latest IT technologies (big data, artificial intelligence, Internet of Things, etc.). Recently, through smart farm technology incorporating ICT technology, precise crop and livestock management is possible based on accurate data based on environmental and growth information, and productivity is increased by improving yield and quality. Although the initial cost of building a smart farm is high, on the other hand, unnecessary labor costs and energy savings can be expected. In particular, I don't think there is any business item as good as a smart farm now that food imports are delayed due to Corona 19 and agricultural workers are banned from entering the country. Since the smart farm has a short history, it is mainly led by start-up companies, and the number of young entrepreneurs is increasing (Han & Joo, 2022; Cho et al., 2024; AlZubi, 2023).

Smart farm is composed of sensor node, controller, environment manager, and operating program. The sensor node digitally transmits real-time status such as weather, wind

direction, wind speed, insolation, rainfall, indoor temperature and humidity, CO2, soil temperature and humidity, light intensity, and illuminance. The controller collects information from sensors, stores and transmits data, and judges information analysis so that crops can grow in the optimal environment (Hashem & Gonzalez-Bulnes, 2020). In addition, it transmits a control command to the environment manager to control the environment. The environmental manager executes the contents commanded by the controller for switchgear, ventilation windows, curtains, water curtains, exhaust fans, flow fans, air conditioners, CO2 control, irrigation pumps, unmanned control systems, nutrient solutions, and irrigation equipment (Choudhari & Chauhan, 2018). Finally, the smart farm operation program to be monitored checks and controls the control status of various controllers and managers, and plays a role in configuring it.

These smart farms have data on agricultural production, management, shipment, and prices through smart farms, not just the creation of new added value in agriculture and smart farm facilities. Through this, we are laying the groundwork for providing insight into agricultural product shipment management based on the derivation of valuable data and information (Yoo. 2016; Jeong et al., 2019; Wasik and Pattinson, 2024; Porwal, 2024).

However, there are many problems in the construction and utilization of smart farms, which is a groundbreaking technology for such agricultural development. There are difficulties in deriving problems and maintaining the company swarming due to large budget input. In addition, since the smart farm is focused only on productivity improvement and production cost reduction, its application to other fields is insufficient. Therefore, it is necessary to find a solution from the perspective of big data through IoT sensor data. In addition, it is necessary to explore the development direction of smart farms should be presented from the perspective of overall agricultural income increase, and a new solution in the agricultural distribution field, the flexible price policy has a great influence on the improvement of agricultural productivity. Therefore, it is very important to predict market price information through analysis of agricultural product distribution information and reflect it in real time (Ullah & Kim, 2018; Kim & Han, 2017).

However, in the case of the current distribution of agricultural products, there are problems such as small-scale production and small-scale distribution, seasonality of production and flood shipments, supply-demand imbalance and price instability. In addition, problems such as multi-level distribution, excessive distribution margin, high loss rate in the distribution process, large volume/weight compared to price, and loss due to decay/reduction, etc. are appearing. In addition, problems such as dispersed production/consumption entities, high-end consumption, lack of competition between distribution channels, and inefficiency at each distribution stage are also being raised. In conclusion, since a large number of producers and consumers are involved and logistics costs are high, the cost of collecting and distributing is high and several stages of distribution are in progress. In addition, the distribution of agricultural products is easily perishable, bulky, and the distribution cost is very high due to the small-scale production structure. For this reason, agricultural products have low price elasticity and there is a problem that the price amplitude is very large (Park, 2021; Moon et al., 2020).

Therefore, in this paper, we developed an AI predictive modeling for agricultural product prices among factors for the efficient support of smart farms. By applying AI predictive modeling, the predicted market price can be applied to the price that is a problem in the distribution of agricultural products. In addition, it is possible to implement a system capable of controlling the harvest time of agricultural products and the time of production and shipment within a certain range.

2. AGRICULTURAL PRODUCTS DISTRIBUTION MEGA TREND

As the quality of life is improved due to the increase in income following the development of the national economy, society is developing into a high-level mass consumption society. At the same time, members of society seek diversity in their daily life and at the same time seek diversity in food consumption, so that various demands are increasing in terms of where to buy agricultural products and how to purchase them (O'Grady & O'Hare, 2017; Jang & Shin, 2021).

The diversity of consumers' consumption behavior requires various functions in the distribution of agricultural products. In particular, the utility (place utility, time utility, form utility, possession utility) through distribution is being improved. In addition, various compositional functions such as selective packaging, commercialization, storage, and processing are required from farmers who produce and sell agricultural products and intermediate distributors (Bang & Lee, 2022; Mythili et al., 2019). In addition, farms and producer organizations that produce agricultural products in production areas are pursuing various sales channels and sales methods such as direct sales from production areas, wholesale market shipments, direct retail transactions, and cyber transactions, at a backward level where agricultural products were simply sold to traveling collectors in the past (Jeong, 2022; Shin et al., 2022; Wiliam et al., 2022).

As shown in Table 1, the distribution of agricultural products from producers to consumers is expected to show a megatrend of distribution of agricultural products.

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Division	Changes in major distribution systems and distribution environments						
	- Intensifying sales competition between production areas and existing wholesale distributors						
Production & Supply	- Promoting continuous organization/scale-up of mountain areas						
	- Improving responsiveness to various transaction methods						
	- Progress in standardization and branding						
Consumption & Demand	- Changes in the propensity to purchase agricultural products by value, trust in purchasing, etc.						
	- Personalization of consumption						

Table 1: Mega trend of agricultural products distribution

	propensity/convenience/safety emphasis					
	- Expansion of processed food/dining out consumption according to lifestyle changes					
	- Generalization of purchases of unique brands of agricultural products					
	- Changes in the purchase of agricultural products according to socio-demographic tendencies					
	- Intensifying competition among various wholesale and distribution industries					
	- Gradual reduction of the wholesale market-oriented transaction system					
Wholesale	- Strengthening the market power of distribution organizations					
distribution	- The rapid progress of the multipolarization of the wholesale distribution system					
	- Promoting the government's strong wholesale market distribution system improvement policy					
Retail distribution	- Rapid progress in diversification of consumer retail distribution					
	- Strengthening market dominance through scale-up of retail distribution					
	- The rapid decline of traditional retail outlets					
	Weakening of the dependence of retailers on the wholesale market					
	- Focus on the government's direct transaction revitalization policy projects					

3. AI MODELING

In this paper, the basis for providing users with an insight into crop recommendation and agricultural product shipment management has been laid by providing AI-based estimated prices for smart farm production and shipment distribution prices. In addition, data on the distribution price of crops is required to provide AI-based predicted prices, and an AI prediction model was designed and developed using this data.

The entire system process proceeded to the stages of data collection, data preprocessing, learning dataset construction, AI modeling and learning, AI analysis result provision, AI-based service construction, and user service execution. Figure 1 shows the process name and service establishment and execution contents for each step.

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Fig. 1: AI modelling steps and contents

The necessary data used in the thesis was applied to production area information, wholesale stage information, agricultural product distribution information, and meteorological/climate information. The information used for data collection was from the present to the past 10 years. In addition, data properties were applied as structured data and time series data. Finally, the data utilization method was designed by dividing the source data and statistical data.

4. SIMULATION

First, pre-processing of the collected data must be performed before proceeding with the simulation. Data pre-processing is performed to increase model learning efficiency and efficiency with refined data, and is a very important task to ensure the accuracy and reliability of prediction. Data preprocessing in this paper was performed in a total of six steps.

Step 1: Data Preparation

- Refined data after quality control

Step 2: Data Exploration

- Understanding the characteristics of data

Step 3: Calibration of data

- Reinforcement of missing values
- Remove anomaly & singular number
- Step 4: Data Integration
- Expressed by integrating multiple corrected data

Step 5: Data Conversion

- Transformation and transformation for data mining
- Data labeling
- create dummy variable

Step 6: Data Cleanup

- Reduction of data size to prevent changes in the nature of data

Next, a plan was established to apply the AI analysis model. Preprocessed data (wholesale market distribution information, origin information, wholesale stage information, agricultural product distribution information, weather information, climate information, etc.) was prepared as a preliminary preparation for AI analysis model learning, and data vectorization conversion was performed.

As an AI analysis model, Supervised Leaning, Regression/Classification, and Prediction Model were applied. A supervised leaning model is a method of learning with a training pattern pair when training a model. At this time, an input variable (x) and a pair of target values (x, d) are required.

Regression/Classification model is a learning method using Supervised Learning. Regression Model predicts continuous/discrete output variable y for input variable x, and predicts continuous values (graph, class) based on data features. In addition, the classification model predicts the discrete/continuous output variable y (class) for the input variable x, and classifies the given data according to a predetermined category.

Prediction Model applied four methods as follows.

- ARIMA (Auto Regressive Integrated Moving Average): A model created by adding the AR (Auto Regressive) model and MA (Moving Average) model and introducing the difference.

- SARIMA (Seasonal ARIMA): A model that adds a periodic factor to the ARIMA model that combines the AR model and the MA model and introduces the difference.

- RNN (Recurrent Neural Network): A network that receives an input (x) and creates an output (y), and receives this output as an input again. It spreads recurrent neurons at each time step, and the input (x) for each time step and the previous time $\text{Step}(t_{-1})$ as input and output as input. It represents the output (y_t), and models such as LSTM, GRU, and STCNN-LSTM exist as derivative models of RNN.

- CNN (Convolutional Neural Network): CNN is a useful model for extracting features from vectorized images. It learns directly from data and classifies images using patterns.

A mock test simulation was performed to improve the accuracy of agricultural product prediction prices by applying these AI analysis models. First, the AI mid-term prediction results were verified. Using the existing data as a sample, the average for 3 months from June 2021 was predicted. Figure 2 shows the 3-month average prediction result screen. It was confirmed that the prediction for 3 months was relatively accurate, and it could be verified primarily in the predictive power part.



Fig. 2: 3-month average forecast result

In addition, the results of artificial intelligence short-term prediction were verified. In the short-term prediction simulation, existing data was used as a sample and cumulative data from 2018 to 2022 were used. As a result of checking the short-term prediction results of some items, the average accuracy was 80.25% to 91.08%, as shown in Table 2, and although there were yearly variations, relatively high accuracy was predicted.

Table 2: Results of short-term	prediction	of average	meridian	price of	agricultural	products
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Year	Very accurate	Nicety	Relatively accurate	Inaccuracy	Accuracy
2018	70	43	28	16	89.80%
2019	69	50	24	14	91.08%
2020	56	42	28	31	80.25%
2021	65	44	25	23	85.35%
2022	75	36	32	14	91.08%

5. CONCLUSION

Smart farm agriculture is being used in the overall part of smart farms, not just new added

value creation and smart farm facilities. In particular, it is possible to provide insight into agricultural product shipment management based on valuable data and information by securing data on agricultural production, shipment, and price.

Currently, 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 enables producers to receive the highest price. However, as a counterbalance, it also causes a great amplitude for the collapse and fluctuation of agricultural product prices. As a result, the government is implementing policies to promote fixed-price, private sales and electronic transactions in the wholesale market.

Therefore, in this paper, big data analysis necessary for predicting market price information on agricultural product prices among smart farm support factors was performed. To this end, supervised learning, regression analysis, and classification were performed, and finally, a study was conducted to develop a predictive model. Through this, it is possible to prepare a basis for discovering services such as production environment and price compared to grade quality by synthesizing it with data produced in the future smart farm.

As a result of the simulation, the average price of agricultural products for three months was predicted to be relatively consistent with the actual data and the predicted data. In addition, an average accuracy of 87.512% was derived from the 5-year data prediction.

References

- AlZubi, A.A. (2023). Artificial Intelligence and its Application in the Prediction and Diagnosis of Animal Diseases: A Review. Indian Journal of Animal Research. 57(10): 1265-1271. https://doi.org/10.18805/IJAR.BF-1684
- 2. Cho, O.H., Na, I.S. and Koh, J.G. (2024). Exploring Advanced Machine Learning Techniques for Swift Legume Disease Detection. Legume Research. https://doi.org/10.18805/LRF-789
- 3. S. H. Han & H. K. Joo (2022). Smart farm development strategy suitable for domestic situation -Focusing on ICT technical characteristics for the development of the industry6.0. Journal of Digital Convergence, 20(4), 147-157. DOI: 10.14400/JDC.2022.20.4.147
- N. M. Hashem & A. Gonzalez-Bulnes. (2020). State-of-the-Art and Prospective of Nanotechnologies for Smart Reproductive Management of Farm Animals. Animals, 10(5), 840. DOI: 10.3390/ani10050840
- P. Choudhari, A. Borse & H. Chauhan. (2018). Smart Irrigation and Remote Farm Monitoring System. International Journal of Computer Applications, 180(38), 24-26. DOI: 10.5120/ijca2018917011
- N. H. Yoo (2016). Development of Smart Farm System for Minimizing Carbon Emissions. The Journal of the Korea institute of electronic communication sciences, 11(12), 1231-1236. DOI: 10.13067/JKIECS.2016.11.12.1231
- J. H. Jeong, C. M. Lim, J. H. Jo, J. H. Kim, S. H. Kim, K. Y. Lee & S. S. Lee (2019). A Study on the Monitoring System of Growing Environment Department for Smart Farm. The Journal of Korea Institute of Information, Electronics, and Communication Technology, 12(3), 290-298. DOI: 10.17661/JKIIECT.2019.12.3.290
- I. Ullah & D. H. Kim. (2018). An Optimization Scheme for Water Pump Control in Smart Fish Farm with Efficient Energy Consumption. Processes, 6(6), 65. DOI: 10.3390/pr6060065
- 9. J. T. Kim & J. S. Han (2017). Agricultural Management Innovation through the Adoption

of Internet of Things: Case of Smart Farm. Journal of Digital Convergence, 15(3), 65-75. DOI: 10.14400/JDC.2017.15.3.65

- H. D. Park (2021). An Intelligent Edge Computing-based Scalable Architecture for Largescale Smart Farm System. Journal of System and Management Sciences, 11(3), 119-139. DOI: 10.33168/JSMS.2021.0307
- J. Y. Moon, G. E. Gwon, H. Y. Kim & J. H. Moon (2020). Building a Smart Farm in the House using Artificial Intelligence and IoT Technology. Proceedings of the Korea Information Processing Society Conference, 818-821. DOI: 10.3745/PKIPS.Y2020M11A.818
- 12. M. J. O'Grady & G. M. P. O'Hare. (2017). Modelling the smart farm. Information Processing in Agriculture, 4(3), 179-187. DOI: 10.1016/j.inpa.2017.05.001
- 13. Porwal, S., Majid, M., Desai, S. C. Vaishnav, J. & Alam, S. (2024). Recent advances, Challenges in Applying Artificial Intelligence and Deep Learning in the Manufacturing Industry. Pacific Business Review (International), 16(7), 143-152.
- 14. E. J. Jang & S. J. Shin (2021). Proposal of An Artificial Intelligence Farm Income Prediction Algorithm based on Time Series Analysis. International journal of advanced smart convergence, 10(4), 98-103. DOI: 10.7236/IJASC.2021.10.4.98
- C. W. Bang & B. K. Lee (2022). Design of Emergency Notification Smart Farm Service Model based on Data Service for Facility Cultivation Farms Management. Journal of Advanced Technology Convergence, 1(1), 1-6. DOI: 10.23152/JATC.2022.01.01.001
- R. Mythili, M. Kumari, A. Tripathi & N. Pal. (2019). IoT Based Smart Farm Monitoring System. International Journal of Recent Technology and Engineering, 8(4), 5490-5494. DOI: 10.35940/ijrte.D8806.118419
- Y. S. Jeong (2022). IoT Data Processing Model of Smart Farm Based on Machine Learning. Advanced Industrial SCIence, 1(2), 24-29. DOI: 10.23153/AI-SCIENCE.2022.1.2.024
- S. Shin, S. Eom & M. Choi (2022). Implementation of Edge Computing Platform for Smart Farm using MQTT and Kafka. Journal of System and Management Sciences, 12(1), 158-174. DOI: 10.33168/JSMS.2022.0112
- Wiliam, A., Arief, M., Bandur, A., Tjhin, V.U. (2022). Farmers' intention as mediator: does government social power predict real use behavior of smart-farming technology? Journal of Logistics, Informatics and Service Science, 9(3), 328-346. DOI: 10.33168/LISS.2022.0322
- 20. Wasik, S. and Pattinson, R. (2024). Artificial Intelligence Applications in Fish Classification and Taxonomy: Advancing Our Understanding of Aquatic Biodiversity. FishTaxa, 31: 11-21.