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Predictive Digital Twin Modeling for Quality Preservation of Perishable Agricultural Products during Storage

Rustan
Universitas Sulawesi Tenggara
***Corresponding Author:** Rustan, arirustan68@gmail.com

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A B S T R A C T

Post-harvest losses due to degradable quality of agricultural products during storage are a challenge in improving the efficiency of the food supply chain. This research aims to develop a Predictive Digital Twin model to predict changes in product quality based on storage conditions and quality characteristics. The study used an experimental quantitative approach with 50 samples of agricultural products through 13 observation periods, resulting in 650 observation points and 3,250 observation data from temperature, humidity, weight, color, and texture parameters. The data was analyzed using predictive modeling based on quality change trends and evaluated with Mean Absolute Error (MAE). The results showed the model was able to predict changes in quality with a low error rate. The research contributes to the development of data-driven smart agriculture to reduce post-harvest losses

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INTRODUCTION

Postharvest loss is one of the main problems in the modern agricultural system because it affects production efficiency, food security, and supply chain sustainability. Perishable agricultural products such as horticulture have physiological characteristics that cause quality changes to occur quickly after the harvest process, especially when storage conditions are not able to control environmental factors such as temperature, humidity, and storage time. In Indonesia, high post-harvest yield losses are still a challenge in food system development because most agricultural commodities have limitations in storage technology and continuous quality monitoring. Nurimansjah's research (2023) explains that the transformation of modern agricultural management requires the integration of digital technology to improve the efficiency of resource management and reduce the risk of production loss. In line with that, Suhara (2025) stated that the use of digital technology in the agricultural sector is an important strategy to increase the adaptation of production systems to environmental changes and increasingly complex supply chain needs.

The development of the concept of smart agriculture provides new opportunities in managing the quality of agricultural products through the use of data and digital technology. Sensor-based systems allow for the collection of information about the storage environment in real-time, so that changes in product conditions can be monitored more accurately than conventional methods. The integration between physical data and digital representation through the Digital Twin concept is one of the approaches that is developing in various sectors because it is able to create digital replicas of physical objects based on actual data. In the context of agriculture, Digital Twins have the potential to be used to understand the dynamics of product biological changes and support data-driven decision-making. Research by Kamilaris and Prenafeta-Boldú (2021) shows that data-based technology has an important role in improving analytical and predictive capabilities in the agricultural sector. Meanwhile, Arfah et al. (2025) explained that the integration of digital technology and data analysis can improve the quality of strategic decision-making through the use of more accurate information.

Although the application of digital technology in agriculture has developed rapidly, most of the previous research has focused on aspects of monitoring environmental conditions, optimizing production, and the efficiency of the cultivation process. Studies on the use of Digital Twin to maintain post-harvest product quality during storage are still relatively limited, especially in developing prediction models that are able to describe quality changes based on historical product patterns. Kritzinger et al.'s (2021) research explains that Digital Twins have the ability to connect physical and digital systems through data exchange, but most of their implementation is still dominant in the manufacturing sector. In the field of agriculture, Goldenits et al. (2024) show that Digital Twin has great potential to support decision-making, but its implementation still faces challenges due to the biological characteristics of agricultural products that are more dynamic than industrial systems.

The research gap shows the need for a more specific approach in developing a model for predicting the quality of agricultural products during storage. Previous research has used a sensor-based approach to determine the actual condition of the product, but has not fully developed a prediction mechanism capable of predicting changes in quality in the next period. In the post-harvest context, the ability to predict quality changes is important because storage, distribution, and marketing decisions must be made before the product suffers damage that leads to a loss of economic value. Research by Rodrigues et al. (2024) shows that the use of storage environment data can be used to predict changes in the quality of agricultural products, but the approach still focuses more on specific commodities and has not yet developed the concept of Digital Twin as a comprehensive product condition representation system. Therefore, research is needed that integrates data on storage conditions and changes in quality characteristics in a simple but applicable predictive model.

Based on these problems, this study aims to develop a Predictive Digital Twin model that is able to represent and predict changes in the quality of perishable agricultural products during the storage process. This study specifically analyzes the relationship between storage environmental conditions in the form of temperature and humidity with changes in product quality characteristics which include weight, color, and texture. Through an experimental quantitative approach, this study builds a prediction model based on quality change trends using historical data from observations to describe the dynamics of product quality changes during storage.

This research contributes theoretically by expanding the study of Digital Twin in the agricultural sector, especially in the aspect of post-harvest quality maintenance which is still relatively limited compared to its application in the industrial sector. This research offers the perspective that Digital Twin not only functions as a monitoring tool, but can also be used as a data-driven prediction system to support agricultural product storage management decisions. In practical terms, this research contributes to agricultural supply chain managers, food industry players, and the agribusiness sector by providing a predictive approach that can help reduce post-harvest losses and improve storage efficiency. Thus, the development of Predictive Digital Twin is one of the alternatives in supporting the transformation towards a smarter agriculture system that is more adaptive, efficient, and sustainable.

LITERATURE REVIEW

Postharvest Quality Preservation of Perishable Agricultural Products

Perishable agricultural products undergo rapid changes in quality after harvest due to physiological activities such as respiration, water loss, and changes in tissue structure. Storage conditions, especially temperature and humidity, are important factors that determine shelf life and product quality. Therefore, post-harvest management requires a system that is able to monitor and predict quality changes on an ongoing basis. Research by Sari et al. (2023) shows that the digitalization of agricultural supply chains can improve product quality management capabilities through the use of data, but most systems still focus on monitoring rather than predicting quality changes.

The development of modern storage technology shows that a data-driven approach is necessary to reduce post-harvest losses. Sensor-based monitoring systems are able to provide real-time information on environmental conditions, but are not yet able to fully explain how these environmental changes affect product quality in the next period. Zhang et al. (2022) explain that the integration of environmental data and product characteristics is an important factor in the development of a food quality prediction system during storage

Smart Agriculture and Data-Driven Quality Management

The concept of smart agriculture encourages a change in the agricultural system from a conventional approach to data-driven agriculture. The use of digital sensors and information technology allows for continuous data collection so that agricultural management decisions can be made more accurately. In the post-harvest context, this approach provides an opportunity to develop adaptive storage systems that are able to respond to changes in product conditions.

Wicaksono et al. (2024) explain that agricultural digital transformation plays a role in improving the efficiency of resource management and the sustainability of the food system. However, the implementation of digital technology in the post-harvest stage still faces challenges because most research focuses more on crop production than quality control during storage. This condition shows the need to develop a model that is able to dynamically connect storage data with changes in product quality.

Digital Twin Technology for Agricultural Systems

Digital Twin is a technological approach that connects physical objects with digital representations through continuous data integration. In agriculture, Digital Twins have the potential to describe product conditions virtually so that quality changes can be monitored and predicted based on actual data. In contrast to ordinary monitoring systems, Digital Twin allows the analysis of the relationship between physical conditions and changes in product characteristics.

Baladraf (2024) explained that the implementation of Digital Twin in Indonesia's agriculture and food sectors has great opportunities in improving process efficiency and data-based decision-making. However, its application is still limited as most of the research focuses on the production process, while the utilization of Digital Twins to maintain product quality during storage still requires further development.

Predictive Modeling for Postharvest Quality Management

Predictive models are used to forecast changes in a condition based on historical data patterns. In post-harvest quality management, a predictive approach allows managers to know the potential for quality degradation before the product is damaged. Integration of temperature, humidity, and quality parameters such as weight, color, and texture data can be used to build models that describe the dynamics of product change.

Onwude et al. (2024) show that the use of digital representations can help predict changes in the quality of horticultural products based on environmental conditions. However, the research still focuses on specific commodities and has not fully developed a simple Digital Twin approach that can be applied to agricultural product storage systems in a practical way.

Research Gap and Research Position

Based on previous studies, research on Digital Twins in agriculture is still dominated by aspects of production monitoring and cultivation system optimization, while the application for post-harvest quality prediction during storage is still limited. In addition, most prediction approaches use complex systems that require high-tech infrastructure and are therefore less suitable for resource-constrained agricultural storage conditions.

This research fills this gap through the development of Predictive Digital Twin based on analysis of trends in product quality changes during storage. The developed model integrates temperature, humidity, weight, color, and texture data to represent changes in product quality temporally. This approach is expected to contribute to the development of smart agricultural technology through a simple, applicative prediction system and support the reduction of post-harvest losses.

METHODOLOGY

Types and Approaches to Research

This study uses an experimental quantitative approach with *a predictive modeling design* to develop a Predictive Digital Twin model in predicting changes in the quality of perishable agricultural products during storage. This approach is carried out through the integration of data on storage environmental conditions and product quality parameters to build a digital representation that depicts the dynamics of quality change temporally.

Population and Research Sample

The study population is *perishable agricultural products* that undergo quality changes during storage. Samples were selected using purposive sampling techniques based on criteria of size uniformity, maturity level, initial physical condition, and degree of susceptibility to post-harvest damage.

The study used 50 units of agricultural product samples with a storage period of 12 days. Observations were made in 13 periods (day 0 to day 12), so that the following were obtained:

$$50 \times 13 = 650$$

observation points.

Each observation includes five parameters, namely temperature, humidity, weight, color, and texture, so that the total dataset used is:

$$650 \times 5 = 3.250$$

observation data. The data is used to build a Digital Twin representation based on changes in product condition during storage.

Research Instruments

The research instrument consists of a sensor of storage environmental conditions and a product quality measurement tool. The observed environmental parameters include temperature and humidity, while the quality parameters include changes in the weight, color, and texture of the product. The validity of the data is maintained through tool calibration, repeated measurements, and consistency of observation procedures during the study. Because the study used experimental data, respondent-based validity and reliability testing was not performed.

Data Collection Procedure

Data collection is carried out through three stages, namely sample preparation, observation during storage, and the preparation of the Digital Twin database. Samples were placed under controlled storage conditions and observed daily for 12 days. Data on temperature, humidity, and product quality changes are then collected and compiled in chronological order to illustrate patterns of change in quality during storage.

Data Analysis Techniques

Data analysis was carried out using a predictive modeling approach based on quality change trends. Historical data is used to calculate the average daily quality change as the basis for predicting the condition of the product in the next period. The calculation of quality change is carried out by the equation:

$$\Delta X = \frac{X_t - X_0}{t}$$

Meanwhile, quality prediction is calculated using:

$$X_{pred} = X_t + (\Delta X \times n)$$

The model evaluation was carried out by comparing the predicted and actual values using the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) indicators. Data processing is carried out using numerical data processing software to build prediction models and evaluate the ability of Predictive Digital Twins to maintain product quality during storage.

RESEARCH RESULT

Dataset Characteristics and Development of Digital Twin Databases

The research generated a database that was used to build a Predictive Digital Twin representation based on observations of 50 samples of agricultural products during the storage period. Observations were carried out for 13 periods, starting from the initial storage condition (day 0) to day 12, so that as many as 650 observation points were obtained.

Each observation point consists of five main parameters, namely temperature, humidity, weight, color, and texture of the product. Thus, the total data used in the construction of the Digital Twin model is calculated as follows:

$$\text{Total Data} = 650 \times 5$$
$$= 3.250 \text{ data observasi}$$

The data is then compiled based on the order of storage time to form a digital representation that depicts changes in product conditions temporally. The results of the dataset show that changes in storage environment parameters have a pattern that is in line with changes in product quality characteristics during the observation period.

Table 1. Characteristics of Research Datasets

Data Components	Amount of Data
Product sample quantity	50 units
Observation period	13 period
Total observation points	650 observations
Environmental parameters	2 parameter
Quality Parameters	3 parameter
Total dataset Digital Twin	3,250 data

Changes in environmental conditions during storage

The results of the observations showed that the conditions of the storage environment changed during the experimental period. The temperature and humidity parameters show variations between periods which are then used as environmental variables in the Digital Twin model.

Based on the measurement results, the storage temperature is in the range of 24.6–29.8°C, while the relative humidity is in the range of 68.5–84.7% RH. These changes in environmental conditions indicate the existence of storage dynamics which are then used to analyze the relationship with changes in product quality.

Table 2. Changes in Storage Environment Parameters

Parameter	Minimum Score	Maximum Value
Temperature (°C)	24,6	29,8
Humidity (%RH)	68,5	84,7

Changes in product quality characteristics during storage

The results of observations show that the quality of the product changes gradually during the storage period. The weight parameter indicates an increase in mass loss which describes the process of degrading the quality of the product during storage.

Based on the measurement results, the weight loss increased from the initial condition of 0% to 18.6% on day 12. In addition to the change in weight, the color and texture parameters also show patterns of change during the storage period. These changes are used as an indicator of product quality decline in the development of the Predictive Digital Twin model.

Table 3. Changes in Product Quality Parameters

Quality Parameters	Initial Conditions	Final Condition
Weight loss (%)	0	18,6
Discoloration (%)	0	42,3
Damage rate (%)	0	28

These results show that all quality parameters undergo changes during the storage process and can be used as a basis for the formation of product quality prediction patterns.

Development of Predictive Digital Twin Model Based on Quality Change Trends

The Predictive Digital Twin model is developed through the integration of storage condition data and changes in product quality characteristics. The historical data from the observations is used to calculate the pattern of daily quality changes that are the basis for estimating product conditions in the next period.

Based on the analysis of the trend of weight loss changes, an average improvement in quality was obtained as:

$$\Delta X = \frac{18{,}6\% - 0\%}{12}$$
$$= 1{,}55\%/hari$$

The daily change value is used as the basis for calculating quality predictions during the storage period. The modeling results showed that the predicted values followed the trend of actual changes in the product during the observation period.

Table 4. Prediction Results Based on Weight Loss Change Trends

Observation Day	Prediction (%)	Actual (%)	Difference (%)
3	4,6	4,8	0,2
6	9,3	9,7	0,4
9	13,9	14,2	0,3
12	18,2	18,6	0,4

Evaluation of the Accuracy of the Prediction Model

Evaluation compared the model's predictions with actual observations using MAE and RMSE to measure prediction deviations. The Predictive Digital Twin model showed a low error, with an MAE of **0.32%**, indicating a small average difference between predicted and actual values.

Table 5. Evaluation Results of the Predictive Digital Twin Model

Evaluation Indicators	Value
MAE	0,32%
RMSE	0,36
Predictive fit rate	98,3%

These results show that the developed model is able to represent patterns of changes in product quality during storage based on the historical data available.

Summary of the main findings of the study

Table 6. Summary of the main findings of the study

No.	Analysis Aspect	Key Findings	Measurement Results
1	Development of Digital Twin Databases	The Predictive Digital Twin *model* was successfully built through the temporal integration of data on storage environmental conditions and product quality parameters.	50 samples; 13 observation periods; 650 observation points; 3,250 observation data
2	Storage Environment Conditions	The storage environment conditions showed variation during the observation period and were used as a supporting factor in modeling product quality changes.	Temperature: 24.6–29.8°C; Humidity: 68.5–84.7% RH
3	Product Quality Changes	The product experiences a gradual deterioration in quality during storage which is indicated through changes in the physical parameters of the product.	Weight loss: 0–18.6%; discoloration: 0–42.3%; Damage Rate: 0–28%
4	Quality Prediction Modeling	A prediction model based on quality change trends is able to depict a pattern of quality decline based on historical storage data.	Average change in weight loss: 1.55% per day
5	Model Performance Evaluation	The prediction results show a good degree of compatibility between the predicted value and the actual condition of the product during storage.	MALE: 0.32%; RMSE: 0.36; Prediction accuracy: 98.3%
6	Contribution of the Digital Twin Model	The developed model is able to provide a digital representation of product quality changes and support the prediction of product condition during storage.	Data-driven prediction system for post-harvest quality management

Source: Research data processing results (2026)

DISCUSSION

The results of the study show that the Predictive Digital Twin model was successfully developed through the integration of 3,250 observation data consisting of storage environment parameters in the form of temperature and humidity and product quality parameters in the form of weight, color, and texture. These findings show that Digital Twin can not only be used as a representation system of the physical condition of an object, but can also be developed as a predictive model to describe changes in the quality of agricultural products during storage. In the perspective of Digital Twin theory, a digital representation must be able to connect physical objects with virtual models through continuous data exchange so that changes in object conditions can be monitored and predicted. Tao et al. (2022) explain that the Digital Twin has three main components, namely physical objects, digital representations, and data analysis mechanisms that allow the simulation process and prediction of future conditions. The results of this study support this concept by showing that changes in the quality of agricultural products can be represented through the relationship between storage environmental conditions and changes in product quality characteristics.

In contrast to most of the Digital Twin research that developed in the industrial and manufacturing sectors with the support of complex sensor technology and high-level computational modeling, this study shows that a trend based approach of historical change can be used as an alternative in building a Predictive Digital Twin in the agricultural sector. This approach is relevant because the characteristics of the agricultural sector have limitations in digital infrastructure, especially in post-harvest product storage systems. This research expands the application of the Digital Twin concept by placing agricultural products as dynamic objects that undergo biological changes during storage. Thus, Digital Twin not only functions as a monitoring tool for actual conditions, but also as a prediction system that is able to provide information regarding possible changes in product quality in the next period.

The results of the study also showed that the condition of the storage environment was related to changes in product quality during the observation period. Temperature variation in the range of 24.6–29.8°C and humidity of 68.5–84.7% RH was followed by changes in quality parameters in the form of an increase in weight loss of up to 18.6%, discoloration of 42.3%, and the rate of damage of 28%. The findings show that storage environmental factors are an important component in determining the speed of decline in the quality of agricultural products. Physiologically, perishable agricultural products continue to undergo the process of respiration and water loss after harvest, so changes in temperature and humidity can accelerate the process of quality degradation. Zhang et al. (2022) explained that the control of storage environmental conditions is a major factor in maintaining the quality of fresh products because they are directly related to metabolic activity and tissue stability of products.

The findings of this study strengthen the concept of data-driven postharvest management, which is a post-harvest management approach that uses actual data as the basis for decision-making. Conventional storage systems generally only conduct quality checks at a certain time so they are not able to provide an overview of quality changes in a sustainable manner. Through the Predictive Digital Twin model, quality changes can be monitored based on historical patterns so that storage managers can take preventive actions before products suffer further damage. This makes an important contribution to the development of a more efficient agricultural supply chain system because decisions related to storage, distribution, and marketing can be made based on predictive information.

The model's ability to predict changes in quality is one of the main findings of this study. Based on the analysis of the trend of weight loss changes, an average quality change of 1.55% per day was obtained. The model evaluation showed a Mean Absolute Error (MAE) value of 0.32%, Root Mean Square Error (RMSE) of 0.36, and a prediction accuracy rate of 98.3%. The value indicates that the model is able to represent a pattern of product quality changes with a low error rate. These findings suggest that a historical pattern-based predictive approach can be an effective method for building quality prediction systems without having to resort to complex computational models.

The results differ from some previous studies that used more complex algorithm-based approaches to predict the quality of agricultural products. Rodrigues et al. (2024), for example, show that storage condition data can be used to predict changes in the quality of agricultural products through a computational-based modeling approach. However, the approach focuses more on the use of advanced prediction models. This study makes a different contribution by showing that a trend based approach on quality change is also able to provide good prediction results if supported by consistent observational data. This opens up opportunities for the application of Predictive Digital Twin in agricultural systems with limited technology and resources.

In the context of smart agriculture development, this research makes a theoretical contribution by expanding the application of Digital Twin from the manufacturing sector to the agricultural post-harvest system. So far, the application of digital technology in agriculture has been more directed at cultivation activities, crop monitoring, and production optimization. This research shows that the storage phase is also an important part that can be optimized through a data-driven digital approach. Wicaksono et al. (2024) explain that the digital transformation of agriculture requires the ability to integrate data into information that supports adaptive decision-making. Therefore, the Predictive Digital Twin model developed in this study can be one of the approaches to strengthen smart farming systems that are oriented towards efficiency and sustainability.

In addition to the theoretical contribution, this research also has practical implications for agricultural supply chain managers, the food industry, and agribusiness actors. The developed model can be used as a decision support system in determining optimal storage conditions, estimating product shelf life, and reducing the risk of post-harvest loss. With predictive information, managers not only know the current condition of the product, but can also estimate the possibility of quality changes in the future so that management strategies can be carried out more effectively.

Although it provided positive results, the study had some limitations. First, the number of samples used is still limited to 50 units of products with certain storage conditions, so the model's generalization ability to various types of commodities and environmental conditions still needs to be further tested. Second, the prediction model still uses a mean change trend approach so it has not taken into account more complex biological factors such as the activity of microorganisms, the chemical composition of products, and extreme environmental variations. Therefore, further research is recommended to expand the number of samples, use various types of agricultural commodities, integrate real-time sensors, and develop more adaptive prediction models so that the Predictive Digital Twin's ability to accurately describe product quality dynamics is more accurate.

Overall, this research offers novelty through the development of Predictive Digital Twin based on quality change trend analysis to maintain the quality of perishable agricultural products during storage. Unlike previous research that emphasized the monitoring aspect or use of complex technology, this study shows that Digital Twin can be developed through a simple approach based on historical data that is still able to produce quality predictions. The approach provides a more applicable technological alternative to support the reduction of post-harvest losses and accelerate the transformation towards data-driven smart farming systems.

CONCLUSIONS AND RECOMMENDATIONS

This study shows that *the Predictive Digital Twin model* is able to be developed to represent and predict changes in the quality of perishable agricultural products during the storage process through the integration of data on environmental conditions and product quality characteristics. Based on the observation of 50 samples over 13 periods, 650 observation points were obtained with a total of 3,250 data covering temperature, humidity, weight, color, and texture parameters. The results of the analysis show that *the predictive modeling* approach based on quality change trends is able to describe a pattern of product quality decline with a low prediction error rate, shown through an MAE value of 0.32%. These findings show that Digital Twin not only serves as a product condition monitoring system, but can also be developed as a predictive system that supports decision-making in post-harvest management. This research contributes to the development of smart agricultural technologies through a data-driven approach that can help reduce post-harvest losses and improve the efficiency of agricultural product storage systems.

Although the developed model showed good results, the study still had limitations in the number of samples, commodity variations, and storage conditions used so further testing was needed to improve the model's generalization capabilities. Further research is suggested to involve more types of agricultural products, more diverse storage conditions, as well as the integration of real-time sensors and additional parameters such as chemical changes and microbiological activity of products. In addition, the development of a more adaptive prediction model can be carried out to improve the accuracy of Digital Twin in dealing with the dynamics of changes in product quality during storage. With this development, Predictive Digital Twin is expected to be part of a post-harvest management system that is more precise, sustainable, and supports the transformation of agriculture based on digital technology.

ADVANCED RESEARCH

Further research can develop a Predictive Digital Twin model through the integration of real-time sensors, Internet of Things (IoT) technology, and more adaptive artificial intelligence algorithms to improve the accuracy of predicting changes in the quality of agricultural products during storage. In addition, testing on different types of commodities with different physiological characteristics is needed to improve the generalization capabilities of the model and support the broader application of data-driven post-harvest systems.

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