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ARTIFICIAL NEURAL NETWORK-BASED MILK PASTEURIZATION QUALITY PREDICTION SYSTEM

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Abstract. *Quality of product is always one of the top concerns in manufacturing and production lines. The assessment and classification of product quality can be done by many different methods, such as using manual employment or through the evaluation of machines and equipment. In recent years, with the growth and development of artificial intelligence (AI) and deep learning (DL), applying DL algorithms in automatically evaluating and classifying product quality in factories is a trend and gradually becoming more popular. This paper proposes an approach to apply artificial neural network (ANN) in predicting the quality of milk pasteurization. We applied this approach on a real data set and got an accuracy of prediction at 97.83% compared to 92.90% using the decision tree algorithm. Furthermore, based on the trained ANN model, we develop a flexible predictive system for predicting the quality of the pasteurization process under different temperature conditions. This system will assist workers and machine operators in controlling the temperature of the pasteurizer to achieve the best product quality.*
Keywords: Pasteurization quality prediction, Artificial neural network, Deep learning, Flexible predictive system

1. **Introduction.** In recent years, with the significant development of science and technology, the production lines in factories have been continuously improved, developed, and invested in modern equipment to enhance the production process [2]. In smart factories, the production line is managed consistently and synchronously from the supply chain of production materials to assess supply quality and product quality management. It helps to increase operation productivity, reduce product costs, and free up human labor [3-5].

However, not all enterprises can immediately make investments in modern machinery and equipment to improve their production capacity in a short time, especially for small and medium-sized manufacturing enterprises. It often requires an enormous amount of money and time to upgrade existing production lines. Applying technology to the production process with existing equipment without replacing current machinery is always a matter of interest to researchers [6-9]. Accompanying with the development of science is the strong growth of AI and DL. In 1943, McCulloch and Pitts [10] introduced the simple model of the biological neuron, which is now popularly known as the ANN [11,12]. ANN has been developed, improved, and applied in many fields of research, production, and daily life.

In this study, we propose an approach to applying multilayer perceptron (MLP), a feed-forward ANN, in predicting the quality of the milk pasteurization process. The dataset is derived from a real factory in Korea and provided through the Korea AI Manufacturing Platform [13]. Using the MLP approach, we received the prediction accuracy at 97.83%, whereas using the decision tree approach got the accuracy at 92.90% (described in [14]).

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Furthermore, based on the trained model, we create a system that flexibly predicts the quality of the pasteurization process with different input parameters. In particular, the system promises to help the operator control the temperature of the pasteurizer to achieve the best product quality.

In the remainder, we organize the content of this paper as follows. We discuss works related to predicting product quality and defects in Section 2. We then explain some of the necessary background and our approach to building the model and creating a flexible prediction system in Section 3 and Section 4, respectively. In Section 5, we present the implementation of our method and evaluate its results. We create a system for recommending workers in operating the pasteurizers in Section 6. Finally, the final section gives some conclusions and future work.

2. **Related Works.** Karayel presented an approach using ANN for predicting and controlling the surface roughness in a computer numerical control (CNC) lathe [15]. In the method, they used the MLP model and trained the network with the scaled conjugate gradient algorithm. The experiments indicated that using their control algorithm with the trained network, the actual surface roughness values were closed to the reference surface roughness values. Consequently, by using MLP in predicting the quality of the surface roughness, the authors could use it to control the CNC lathe to achieve the best product quality.

Fakhr and Elsayad described and compared steel plate faults prediction with three different algorithms, i.e., C5.0 decision tree (DT), MLP, and logistic regression (LR) [16]. They used the data set from the University of California at Irvine machine learning repository to predict the regularly happening faults in the steel plate. The study results showed that using the C5.0 DT algorithm yielded the best performance with 98.09% accuracy on the test subset. Meanwhile, using the MLP and LR algorithms yielded accuracy at 79.14% and 62.99%, respectively.

Ren et al. proposed the wide-deep-sequence (WDS) model to provide a reliable quality prediction method for industrial processes with different types of industrial data [17]. The proposed WDS model is an upgraded version from the wide-deep model introduced by Google. In the study, they improved the model by combining an additional representation layer and using the long short-term memory (LSTM), a type of ANN, for examining quality information from time-domain characteristics. The outcomes intimated that their proposed methods helped improve the correctness of the predictions, got decent generalization performances on most samples, and ensured the sensitivity to defective products.

Park et al. proposed a data clustering-based machine learning (DC-ML) method for predicting plate thickness in the steel plate rolling mill operation to produce high-quality steel plates [18]. The proposal described combining clustering algorithms and supervised learning algorithms. By using the DC-ML method, the study achieved acceptable outcomes for the plate thickness prediction in manufacturing.

Su et al. introduced an approach using ANN for predicting the quality of wafer dicing saw in the semiconductor integrated circuit assembly manufacturing [19]. In the study, they applied MLP with the error backpropagation algorithm for creating a model to learning and analyzing data transferred from the machine sensors for prediction. The model achieved an accuracy of 75% for predicting abnormalities in wafer dicing saw operations.

Mentioned studies have shown that using deep learning models to predict product quality achieved high accuracy results (62.99%, 75%, or even 98.09%). It indicates that the application of deep learning in product quality prediction in production lines yields excellent results. In addition, at present, research often focuses on production and manufacturing; there are not many studies on the application of deep learning in the field of food processing and food quality prediction in factories. Hence, in this paper, we propose an approach using deep learning in predicting milk pasteurization quality, an essential step in dairy food processing in factories. Consequently, we apply the MLP model in predicting the milk pasteurization process's quality and build a comprehensive system for predicting the quality with flexible input parameters. The reason why we choose MLP in our approach is that, the data collected from the milk pasteurization process is characterized as a collection of input parameters (temperature, machine state) to predict the output value (milk quality label). These features are suitable for using the MLP model for supervised learning.

3. Background.

3.1. **Perceptron.** Perceptron is an algorithm invented by Rosenblatt and introduced in 1958. It is used for supervised learning of binary classifiers for deciding whether an input, represented by a series of vectors, belongs to a particular class [20]. A perceptron consists of input values, weights, weighted sum, step function, and output. Figure 1 illustrates an example of perception that has three input parameters.

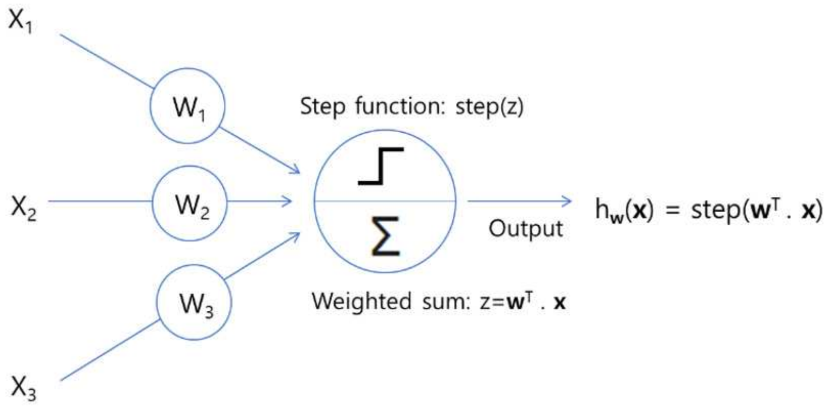

FIGURE 1. Perceptron (reproduced from [21])

3.2. **Multilayer perceptron (MLP).** MLP, a class of feed-forward ANN, contains many perceptrons and is composed of one input layer, one or more hidden layers, and one output layer (see Figure 2). In the MLP, every layer is fully connected to the next

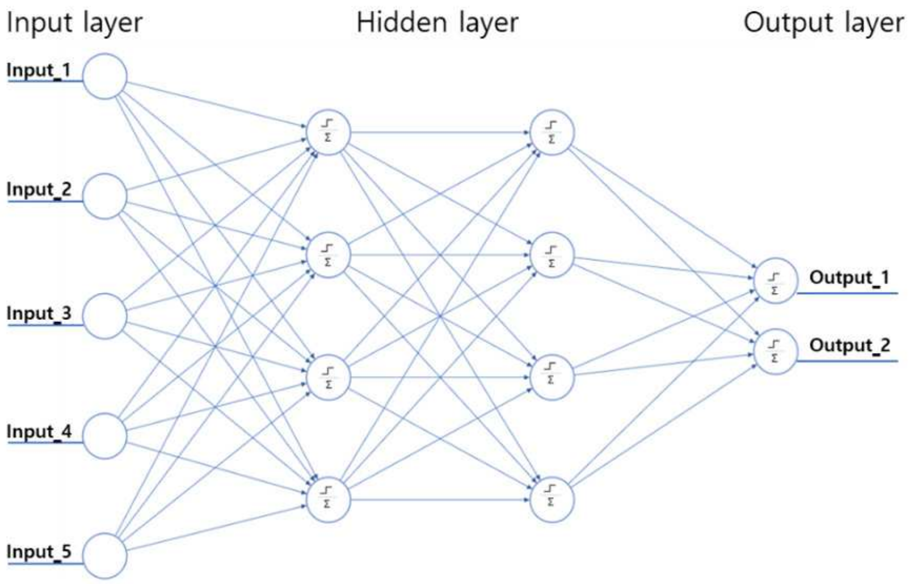

FIGURE 2. Multilayer perceptron (reproduced from [21])

layer, except the output layer. Each node is a neuron that uses an activation function for producing the output, except the input nodes [22].

4. **Milk Pasteurization Quality Prediction.** In the milk pasteurization process, the raw materials (fresh milk) were mixed in the liquid state in the dissolution process at a temperature of 100°C or less for 30 minutes or more. The quality of the process is necessary to eliminate or deactivate organisms and enzymes that contribute to spoilage or risk of disease.

In the pasteurization operating, as the pasteurizer machine adjusts the temperature, there is a difference in the time it takes for the temperature change to affect the entire liquid, especially with old pasteurizers that are not stable about the temperature sensor function. Therefore, it is not easy to maintain the appropriate temperature. Consequently, workers need to monitor the temperature of the machine and adjust the temperature accordingly. Adjusting the pasteurizer temperature often depends on the worker's experience and intuition, which affects the quality of the product. To overcome the limitations of these problems, we use the MLP model for predicting the quality of the pasteurization process.

Figure 3 describes the methodology predicting the milk pasteurization quality by using the MLP model. In this figure, the raw data collected in machine A (M1) and machine B (M2) is scaled and then transformed to the MLP model using the *data scaling and transformation* module. Subsequently, we transform pasteurized milk quality labels to vectors with the *one-hot-encoding* module and then put it into the model as the output. During the training phase, the weights and biases in the MLP model will be improved through the epochs to predict the labeled output. The best parameters will be used in the prediction phase.

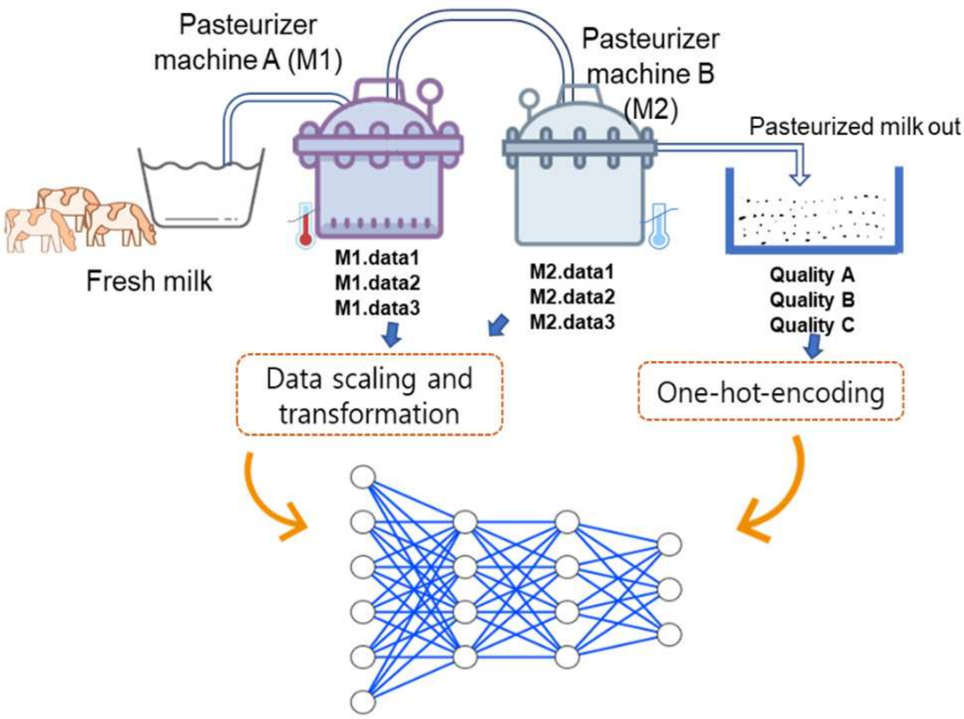

FIGURE 3. Milk pasteurization quality prediction using MLP

For evaluating the prediction values, we use the mean squared error (MSE) function as follows. In this equation, the predicted value $\left(\hat{Y}_t\right)$ is compared with the original value (Y_t). Then we take its sum divided by the total number of samples to get MSE value.

$$MSE = \frac{1}{n}\sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right)^2$$

5. **Experimental Results.** In this section, we conduct applying our method with the Sterilizer AI dataset [14] provided through the Korea AI Manufacturing Platform. The summary information of the data set is described in Table 1. In this data set, two pasteurizer machines are named *MixA* and *MixB*. Each machine has information about its *temperature* (*TEMP*) and state (*STATE*). The last field (*INSP*) in the data set describes the quality of each pasteurization process. The process quality has two labels, i.e., *OK* and *NG* (not good).

Table 1. Summary of the data set

Field	**Data type**	**Min**	**Max**	**Count**	**Description**
STD_DT	Date time	3 Apr 2020	11 Nov 2020	210,794	Time of process
MixA_TEMP	Float64	0	77.2	201,423	Temperature of machine A
MixB_TEMP	Float64	0	76.5	198,802	Temperature of machine B
MixA_STATE	Boolean			11,135	State of machine A
MixB_STATE	Boolean			10,255	State of machine B
INSP	String			210,794	Quality label

As we can see in Table 1, different fields have different count values, so that there are several missing values when the sensors record values into the data set. Therefore, we need to remove the records that do not contain complete information about machine A and machine B before fitting them to the MLP. To build and train the MLP, we use the open-source Keras library version 2.4.3 [23]. For measuring the training accuracy value, we use the built-in function in Keras (dividing the total by count).

After removing incomplete rows data, we separate the data set into two sets, 2/3 as the training set and 1/3 as the testing set. The one-hot-encoding function will be used for encoding the quality labels to vectors. Next, we fit the training set into the MLP model and get the model training accuracy as described in Figure 4.

Intuitively, the training achieved reliable values with this dataset. Its accuracy quickly converged to a value of over 95% after about 50 epochs. Using this MLP trained model, we get the prediction accuracy for the testing set at 97.83%. Meanwhile, using the decision tree algorithm with this data set, the prediction accuracy is 92.90%. In the decision tree approach, the authors analyzed the raw data by graphing decision rules that focus on essential variables as a tree structure and could be used by dividing the target variable into categorical and continuous cases [13].

6. **System Development.** Based on the trained MLP model in Section 4, we create a system for recommending workers in operating the pasteurizers. At the beginning, the state of M1 or/and M2 is read. Then the system generates a range of values setting of M1 or/and M2. After that, it predicts the quality of the process and recommends setting up the M1 or/and M2 to the workers (in particular, see Figure 5).

For helping the workers in operating the pasteurizer machine to make good quality, we create a system as shown in Figure 6. The system uses a flexible input function to predict the pasteurization quality with different machine temperature values and state values. The workers can operate the machines based on these recommendations setting.

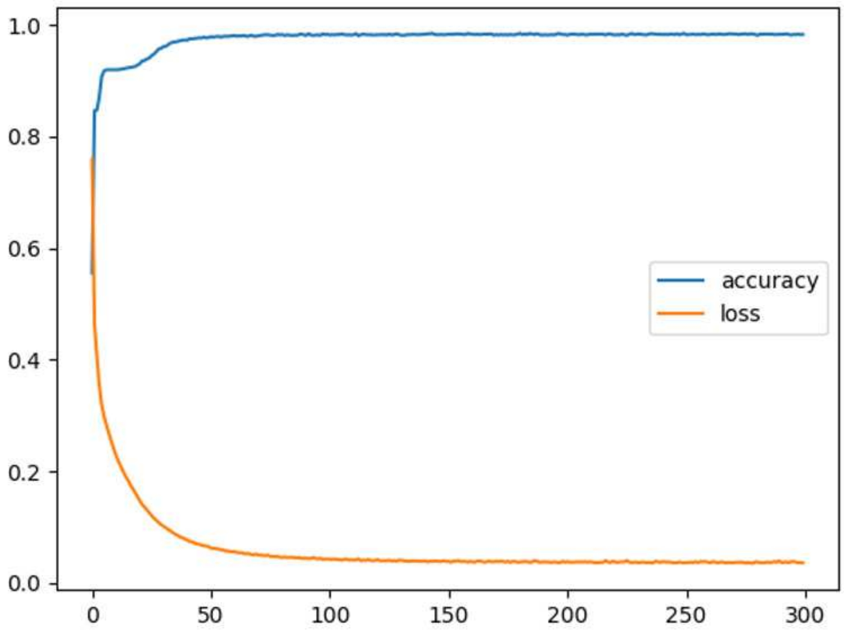

FIGURE 4. The training accuracy on the data set

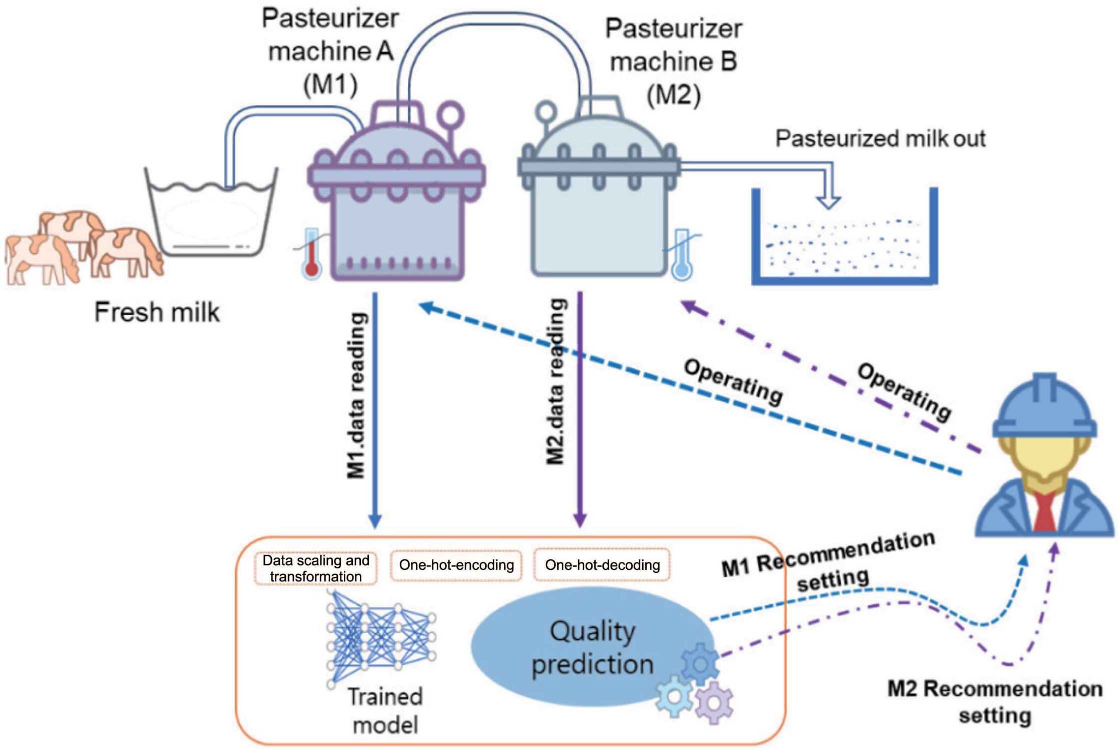

FIGURE 5. Milk pasteurizer operating recommendation system

One illustrative result of a recommendation setting for machine operating is shown in Figure 7. In this case, the state value of pasteurizer machine A is 1, and the state value of pasteurizer machine B is 0. The different quality labels of the process are predicted with different temperatures of machine A and machine B. The source code, system, and related resources to produce the experiments can be downloaded at https://github.com/vuthithuhuyen/milk-pasteurization-prediction.

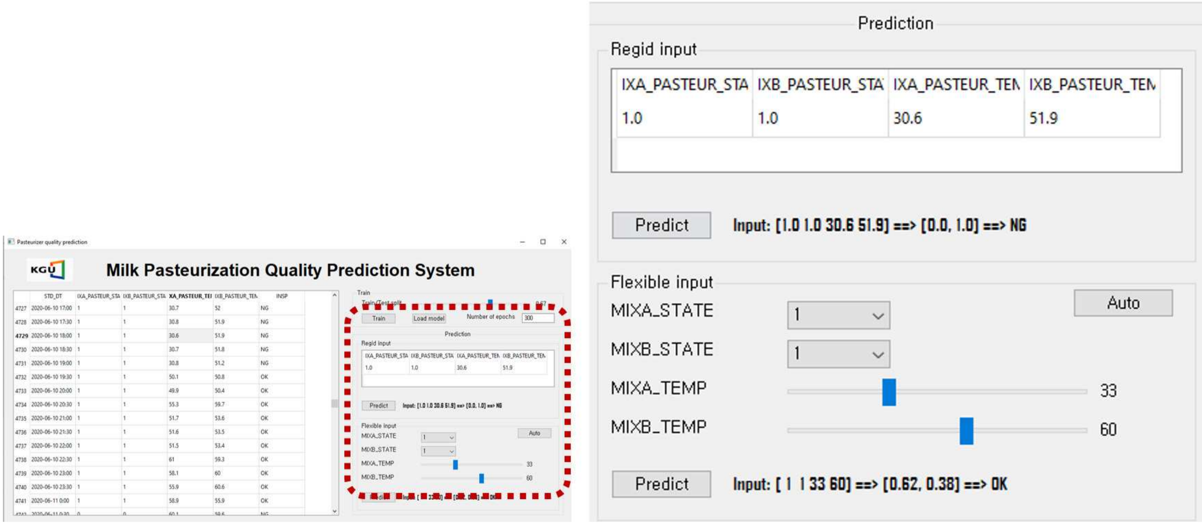

FIGURE 6. The milk pasteurization quality prediction system

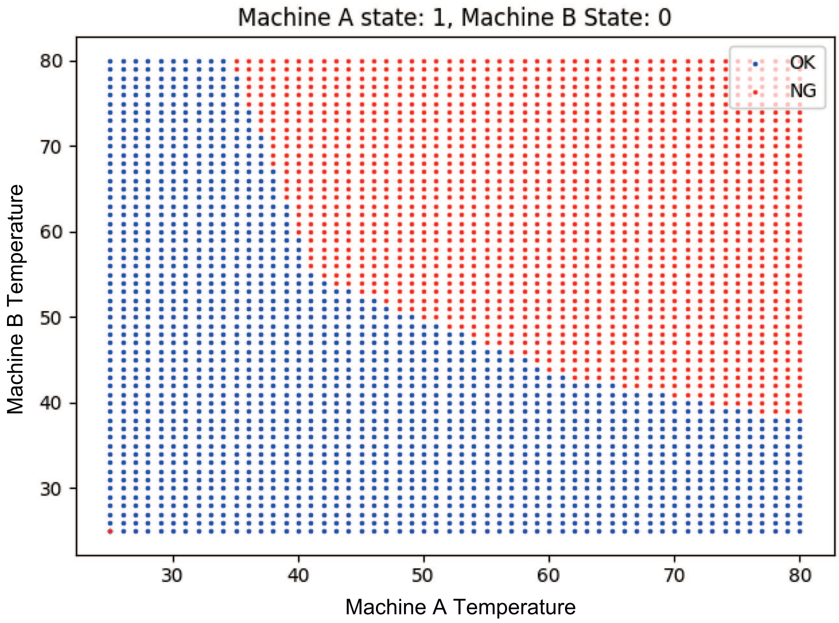

FIGURE 7. The prediction quality labels with different temperatures of machine A and machine B

7. **Conclusions.** In this paper, we proposed an approach using the MLP model for predicting milk pasteurization process quality. A real data set was applied and got an accuracy of prediction at 97.83% compared to 92.90% using the decision tree algorithm. Subsequently, based on the trained model, we create a system for supporting workers in operating the pasteurizer machines to get good quality. In the future study, we will conduct experiments with more samples, especially data sets with more quality labels. Furthermore, we will integrate the function of reading data directly from the pasteurizers' sensors to the system.

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