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A MULTI-STEP MULTIVARIATE LSTM-BASED MODEL FOR QUALITY PREDICTION OF MELTING PROCESS

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Abstract. *Product quality is consistently the top concern of consumers, so that it determines the success of businesses. Product quality is constituted and specified by multiple factors in manufacturing factories, from the selection of production materials, operating machinery to the production and preservation of products to bring to consumers. In these stages, the melting and mixing of production materials in tanks plays an essential role in determining the quality in food manufacturing industry. In this paper, we introduce an approach based on the multi-step multivariate long short-term memory (LSTM) model to predict the melting and mixing quality of raw materials in tanks of food factory. By choosing multivariable and multi-step input, we present how to choose the parameters to predict the product quality from the tanks. Applying the approach, the accuracy was improved from 69% to 78% for predicting quality of product in a melt tank from a real factory in Korea. This approach benefits the operators, engineers to control and operate machinery to produce good quality products.*
Keywords: Multi-step multivariate long short-term memory, Product quality prediction, Melting process, Product quality in food manufacturing industry

1. **Introduction.** With the tremendous development of deep learning and machine learning in the recent decade, numerous algorithms are effectively applied, bringing significant benefits to the operations of manufacturing plants and factories. The production lines are automated, and machines gradually replace humans in the manufacturing stages of products used in our lives. Product quality assessment is a particular concern that ranks first in the production process of manufacturing products, especially in the food industry domain. In the past, if evaluating product quality was done manually by humans, more and more deep learning algorithms have been introduced, used, and applied to assess the quality of products, recently. By using algorithms and machines, it takes advantage of improving the operational efficiency of the production system, saves costs, and improves labor productivity, thereby yielding profits to businesses as well as benefits to consumers [1-4]. There are numerous solutions, and different approaches have been introduced to predict product quality in factories, production lines, such as prediction of the quality of steel plate rolling [5-8], manufacturing product quality prediction [9-12], or analyzing the quality of manufacturing product with deep learning [13-15].

One of the crucial stages of the food production process is mixing ingredients in the melt tanks. In this paper, we present an approach using the multi-step multivariate long short-term memory (LSTM) model to predict product quality from a melt tank system in a factory. More precisely, we describe how to choose the efficient parameters from the dataset generated from sensors to train and predict the product quality in a melt tank system. Based on the trained model, we create a GUI (graphical user interface) system

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for suggesting the machine operators to efficiently control melt tanks to produce good product quality.

In the rest of this paper, we organize content as follows. The next section discusses the related works about using the LSTM model and predicting melt tank product quality. Section 3 presents and explains the concept of the multi-step multivariate LSTM model. Section 4 and Section 5 describe our approach for applying the model in predicting melt tank product quality, choosing good parameters for inputting into the model, and building the GUI prediction system. Finally, Section 6 concludes the content of this paper.

2. **Related Works.** We review some recent studies related to using the LSTM model for prediction in manufacturing. In [16], Essien and his colleague introduced a deep learning model using the convolutional LSTM autoencoders network for smart manufacturing. In the study, they proposed a novel deep convolutional LSTM autoencoder architecture for predicting machine speed in a smart manufacturing process. The data was acquired from a metal packaging plant in the United Kingdom. By using a sliding window, they restructured the input sequence to a supervised learning method. Their method showed that the model outperformed the naive and statistical benchmark and improved prediction performance. Furthermore, the model required lower model training time, saved total duration, and was easy to adopt in real manufacturing processes.

In [17], Bai et al. presented the AdaBoost (adaptive boosting)-LSTM predictive model in manufacturing quality prediction. In the study, they proposed a model with four steps in the procedure, i.e., collect data, analyze the importance of parameters with rough set theory, run the AdaBoost-LSTM, and output the predicted values. The method was proven through a dataset provided from competition about the manufacturing quality prediction. Their proposed framework can improve the practical application and prediction performance in manufacturing quality.

In [18], Wang and his colleagues studied short-term cycle time forecasting in re-entrant manufacturing systems using a two-dimensional LSTM model with multiply memory units. The research proposed a method to forecast the short-term cycle time of wafer lots in wafer manufacturing. The method consists of a two-dimensional architecture to transfer the wafer and layer correlations, and a multiply memory structure used to boost the capacity of constant error carousel (CEC) in the LSTM model with the grid-like 2D-LSTM model and multi-CEC unit. They proved that their architecture could enhance prediction accuracy and forecasting strength for the short-term cycle time of wafer lots. The method could provide more timely guidance on managing the production, e.g., rebalancing work, changing dispatching controls, and job priorities.

In [19], Chan and his colleagues proposed using convolutional bidirectional LSTM networks to predict tool wear in machine health monitoring systems. The study suggested a deep learning approach, namely holistic-local long short-term memory (HLLSTM), that adopts the LSTM to predict tool wear with holistic and local features. In particular, they introduced the architecture for prediction with four layers, i.e., feature extraction, local feature, holistic feature, and fully connected layer. Their experimental results indicated that the mean absolute error value of real tool wear could reduce by using the HLLSTM and accurately predicting outcomes.

In [20], Yin et al. presented a method for predicting in a smart factory producing steels that combines deep learning and big data experience feedback. They used the "3-sigma" declaration and wavelet entry denoising to preprocess the raw data. After trying with CNN (convolutional neural network) for building the prediction model, they optimized the model by integrating CNN with the LSTM through the AdaBoost method. Their study took advantage of combining two types of networks and proved the prediction accuracy, and got high-precision prediction results.

The listed studies have shown that applying LSTM in manufacturing plants effectively predicts the output quality of production lines and products. Researchers consistently try to optimize and improve models to improve factory prediction results. In this paper, we propose to apply the multi-step multivariate LSTM model in predicting the quality of products produced from melt tanks in food factories. Using this model, we demonstrate choosing the number of inputs and the appropriate features to include in creating the model. The following section explains the concept of multi-step multivariate LSTM and its application in predicting product quality in the melt tank system.

3. Multi-Step Multivariate LSTM Model.

3.1. **LSTM model.** The LSTM model is a recurrent neural network that focuses on predicting sequences [21-23]. It learns and memorizes a series over time by connecting from output to input. The model performs the same function over time while learning sequences. It uses the output of the current step as the input of the following step, especially. For more details, Figure 1 represents a block in the LSTM model. It consists of input vector X_t, the output of the previous block h_{t-1}, memory of the previous block C_{t-1}, the memory of current block C_t, and the output of current block h_t. σ and tanh are sigmoid and hyperbolic tangent layers, respectively. f_t, i_t and O_t are the values calculated through the sigmoid layers, forget gate, input gate and output gate, respectively, and $\tilde{C}_t$ is the value calculated through the tanh layer.

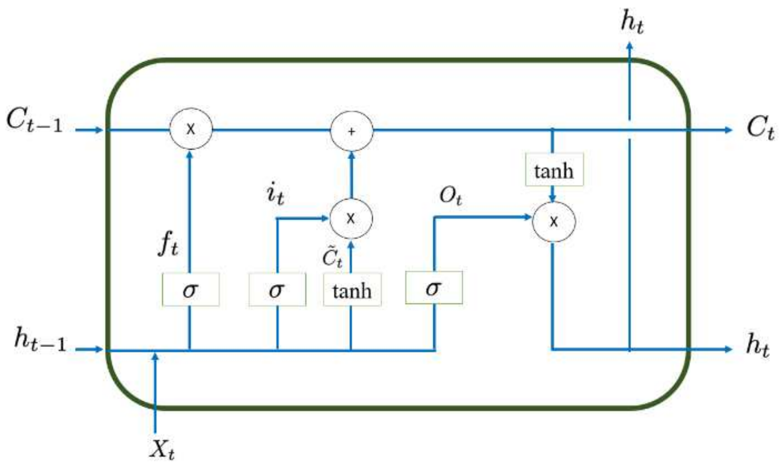

FIGURE 1. An LSTM block, reproduced from [24]

3.2. **Multi-step multivariate LSTM.** Multi-step is the process of using multiple steps of input for putting in the LSTM model. Meanwhile, multivariate is observing multi-features of the input to create the model [25]. The concept is explained with the example below.

Example 3.1. *We can consider a small dataset from a melt tank system in Table 1.*

TABLE 1. Example of a melt tank dataset

MELT_TEMP	MOTORSPEED	MELT_WEIGHT	INSP	TAG
489	116	631	3.19	OK
364	201	66	3.18	NG
495	167	75	3.20	OK
362	203	61	3.19	NG
464	154	608	3.19	OK

In case of observing both MELT_TEMP, MOTORSPEED, MELT_WEIGHT, INSP for predicting quality (TAG) with (input-step = 2, output-step = 1), we have

$$\left.\begin{matrix}(489, 116, 631, 3.19)\\(364, 201, 66, 3.18)\end{matrix}\right\} => NG \quad \left.\begin{matrix}(364, 201, 66, 3.18)\\(495, 167, 75, 3.2)\end{matrix}\right\} => OK$$

In case of observing MELT_TEMP, MOTORSPEED, INSP for predicting quality (TAG) with (input-step = 3, output-step = 1), we have

$$\left.\begin{matrix}(489, 116, 3.19)\\(364, 201, 3.18)\\(495, 167, 3.2)\end{matrix}\right\} => OK \quad \left.\begin{matrix}(364, 201, 3.18)\\(495, 167, 3.2)\\(362, 203, 3.19)\end{matrix}\right\} => NG$$

4. **Melt Tank Product Quality Prediction System.** In the mixing process of powdered raw ingredients in food processing, it is necessary that various powders and liquid raw materials become a uniform mixture in the compound process to ensure process quality for producing food products in the later processes. The quality of the mixing process is affected by the relative capacity of the raw ingredients, the dissolution temperature, speed of the motor, and moisture content of ingredients. During the operation of the equipment for incorporating ingredients in the storage tanks, although the operation process is carried out according to the standard regulations of each equipment, machine operators still have to depend on experience to perform. In particular, in the case of producing a large number of products or handling multiple ingredients, it is necessary to check the temperature, humidity, and related properties of the raw ingredients. In order to maintain good melt quality, it is essential to change the equipment operating value. Due to a lack of specific instruction, the output quality of the product depends mainly on the experience of the equipment operator. To overcome this concern, we use the multi-step multivariate LSTM model to predict the quality of the mixing ingredients in the melt tank. Predicting the quality of the product will help operate the machines efficiently.

Figure 2 describes our approach in detail. In the beginning, the raw materials are mixed and produce the melt tank operation data. After that, the data is processed and fed into the system to train the model. The product quality prediction results of the ingredient mixing process are sent to the machine operator, thereby helping to make appropriate adjustments.

As shown in the figure, we choose the different number of input steps and features with the data collected from sensors in the melt tank to build the model. With each parameter, we scale the input data with different input-steps and features, transform the quality label into vectors and then put it into the LSTM model for training. Then, the product quality prediction accuracy is compared to choose the best input parameter in model building. To compare results, we evaluate the effectiveness values of the accuracy, precision, recall, and F1 scores [26], which are calculated by the following formulas:

$$Accuracy = \frac{TN + TP}{TN + TP + FN + FP} \qquad Recall = \frac{TP}{TP + FN}$$

$$Precision = \frac{TP}{TP + FP} \qquad F1\ score = 2 * \frac{Precision * Recall}{Precision + Recall}$$

where TP: True positive; TN: True negative; FP: False positive; FN: False negative.

5. **Experimental Results.** This section applies our approach with a real-life dataset in a food factory provided on the Korea AI manufacturing platform [27]. The dataset contains 835,200 rows describing the information of manufacturing time (STD_DT), row index (NUM), the temperature of the melt in the tank (MELT_TEMP), the speed of the motor controlling the tank (MOTORSPEED), the weight (MELT_WEIGHT), the moisture content of products (INSP), and the product quality (TAG). Figure 3 depicts

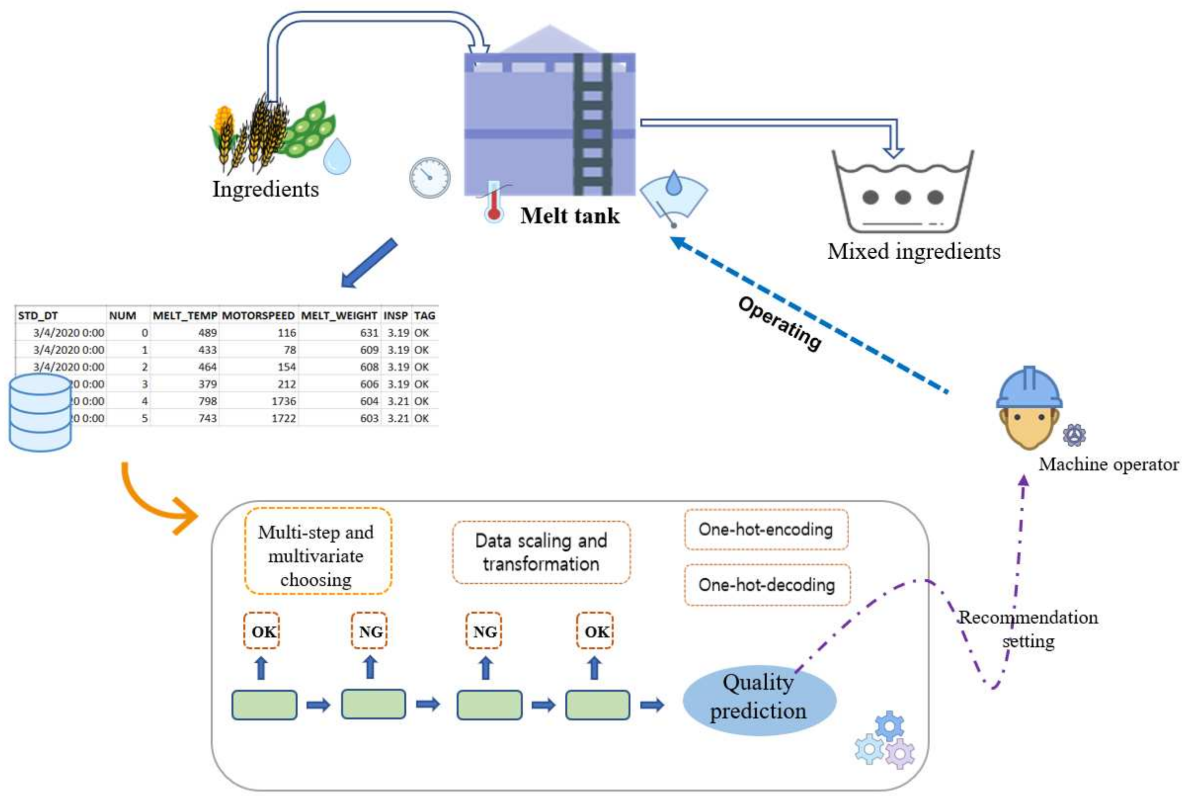

FIGURE 2. Melt tank product quality prediction approach using the multi-step multivariate LSTM model

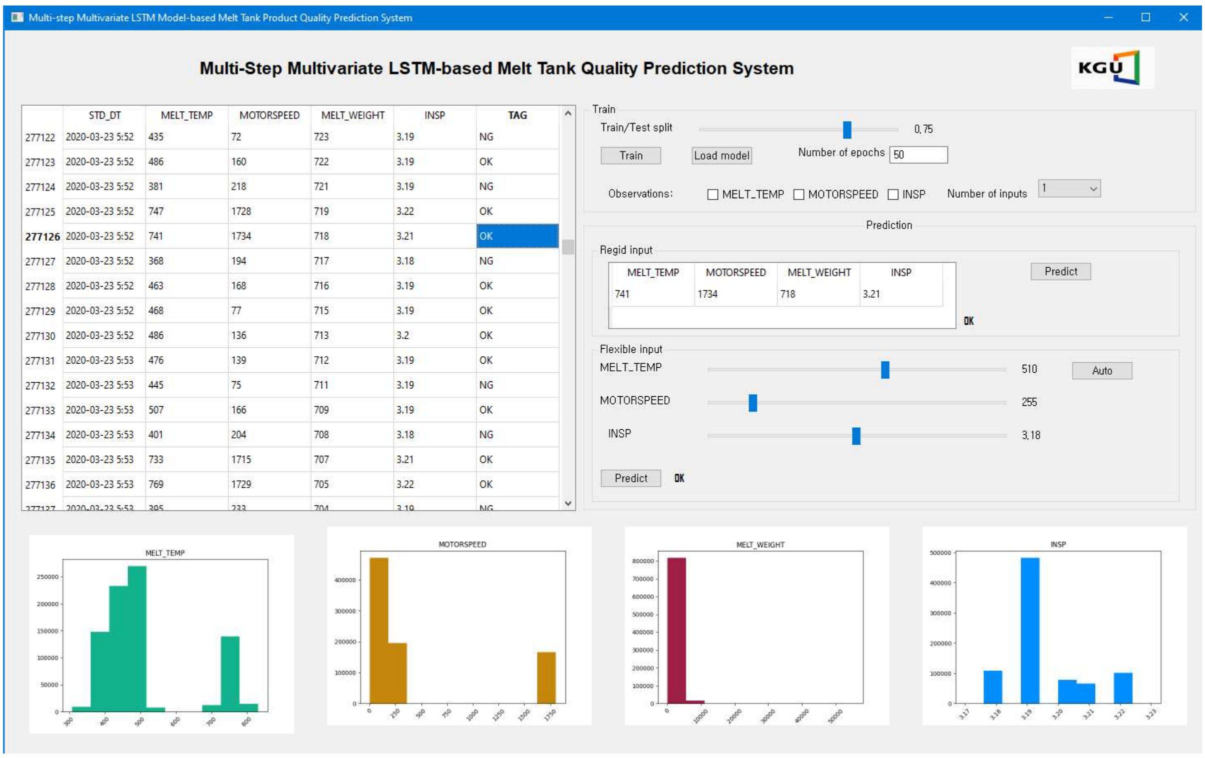

FIGURE 3. Multi-step multivariate LSTM-based melt tank quality prediction system

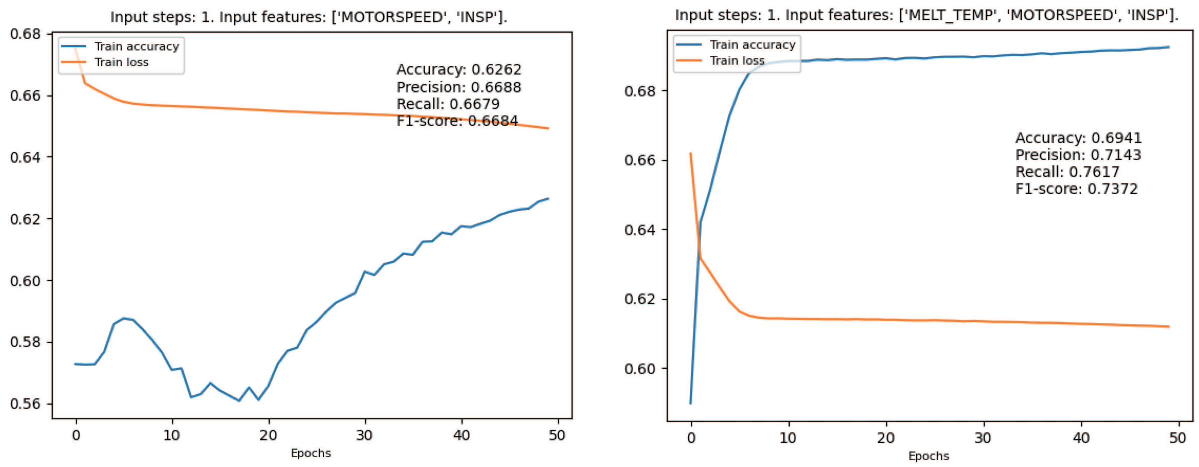

FIGURE 4. Evaluation of prediction results with 1 input-step

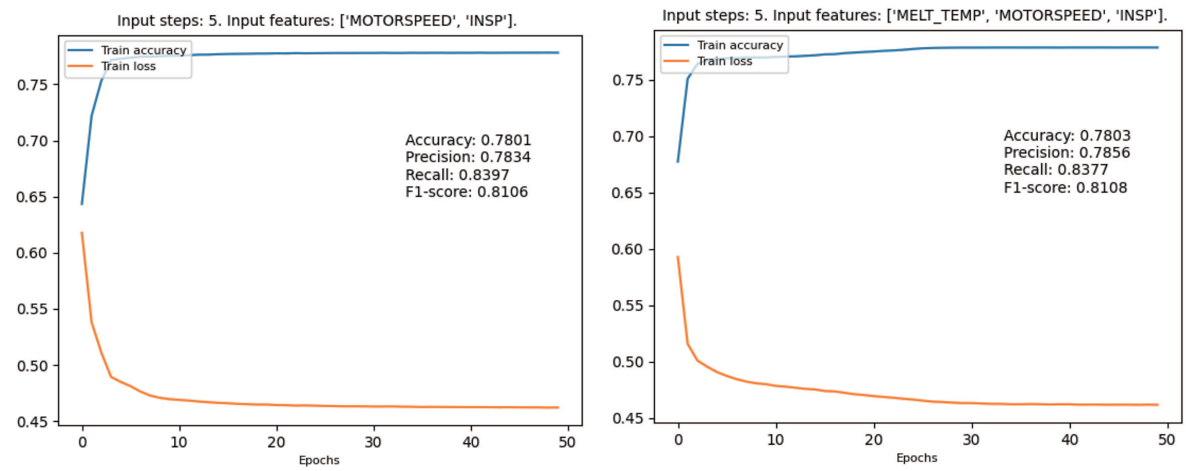

FIGURE 5. Evaluation of prediction results with 5 input-steps

the operating interface of the system. Through this interface, the machine operator can obtain the product quality prediction results with each parameter about MELT_TEMP, MOTORSPEED, MELT_WEIGHT, and INSP. At the same time, device operators can also set up flexible input with adjustable parameters to see the results of product quality prediction with these parameter sets. With each different set of input-step parameters and features, we trained and evaluated the model and got the results as shown in Figures 4 and 5.

Other evaluation results, source code, and related resources can be downloaded at https://github.com/vuthithuhuyen/melttankqualitypredictionwithLSTM.

Figure 6 depicts the comparison results between the different models. 1-TSI means prediction with 1 input-step; T: Temperature, S: Speed, I: INSP. This result shows that choosing 1 input step gives us the results with the lowest accuracy in the models. Choosing 5 input-steps, 10 input-steps, or 20 input-steps produces similar results. Using the multi-step multivariate method, the prediction accuracy is 78%, compared to 69% in [27].

6. Conclusions.

In this paper, we propose an approach using the multi-step multivariate LSTM model to predict the quality of the product in a melt tank system from a food factory in Korea. We have shown how to build an effective model in predicting product quality. With the created system, workers operating machinery in food factories using melt tank equipment will be able to easily refer to the operation of machinery to produce good product quality. In future work, we will evaluate the system with more datasets and

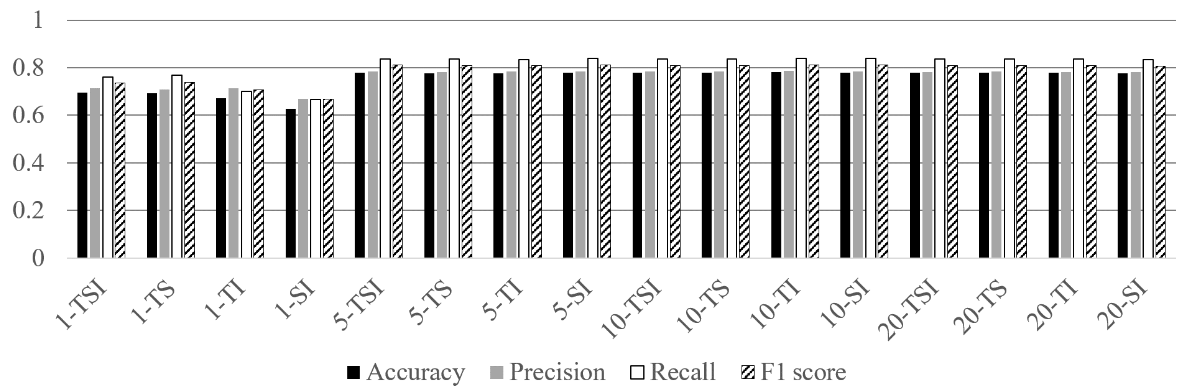

Figure 6. Comparison of predicting results between different LSTM models

more quality labels. Furthermore, we will work with some factories to bring our system to use in practice.

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