Prediction Analysis of Heat Penetration in Ohmic Heating using Multivariate Long Short-Term Memory Networks

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Received: 28 December 2024 | Revised: 14 February 2025 and 17 March 2025 | Accepted: 13 March 2025

ABSTRACT

Heat penetration significantly influences the efficiency and sustainability of various thermal systems. The development of a heat penetration prediction model using Artificial Intelligence (AI) aims to understand and optimize heat transfer processes to maintain honey quality during ohmic heating. The utilization of Neural Network (NN) methods, particularly Long Short-Term Memory (LSTM), for time-series data processing involves key processing variables, such as time, frequency, initial temperature, final temperature, current, and heat rate values. By applying multivariate LSTM for prediction, three data models were developed, each consisting of three submodels. Additionally, parameter tuning was performed, including the number of training data points, the number of neurons in the hidden layer, density, the number of epochs, and batch size. Models B1 and B3, with their specific parameters, demonstrated the best performance in predicting heat penetration, characterized by optimal error functions and minimal error propagation. These models successfully identified data patterns for predicting heat penetration, proving their effectiveness.

Keywords-honey quality; penetration; prediction; multivariate; LSTM

I. INTRODUCTION

Honey is a highly complex food substance and is one of the few man-made foods that can be consumed without processing. The region of production and the terrain influence the properties, chemical composition, and physical characteristics of honey [1-3]. Honey, a thick and sweet liquid, contains monosaccharides such as fructose and glucose [4]. The type of nectar determines the type of honey produced, and each has its benefits [5, 6]. However, honey can crystallize during storage, affecting its color, taste, and aroma [7]. Incorrect storage processes can cause changes in texture, taste, and granulation, and reduce honey quality [8]. Honey management that does not meet standards can also decrease honey quality [6]. During honey processing, all the requirements set by the Indonesian National Standard for Honey must be met [9].

The heating process is one of the most critical stages in honey management and often damages its quality [10]. This stage can destroy sugar crystal cores and sugar-tolerant osmophilic yeasts, extending the shelf life of honey [11]. Conventional pasteurization techniques generally cause unstable heat rates and the risk of damage to the honey content when temperatures exceed 70°C. Uncontrolled heating can alter honey parameters, such as damaging the enzymes within. Amylase enzymes are indicators of honey quality due to their heat sensitivity.

This study investigates the prediction of heat penetration values from the pasteurization process using an Ohmic Heating (OH) system. The method used is a Long Short-Term Memory (LSTM) Neural Network (NN), utilizing Trigona SP honey derived from freshly harvested coconut and palm flower nectar bees. This honey is then pasteurized at a temperature of 63°C with a holding time of 30 minutes using a specific electronic circuit. Several parameters that affect the pasteurization process are time (t), initial temperature, final temperature, electric current, and honey heat rate, all of which play a role in determining the characteristics of honey. This research predicts the heat transfer rate in honey as a time series problem. Each data point corresponds to the honey's initial temperature, the final temperature, the electric current, and the heat transfer rate. The initial and final temperature conditions of the honey during pasteurization provide context for honey quality and important information for a more accurate prediction. Traditional NN architectures, consisting of interconnected layers of weighted nodes, capture complex relationships. Recurrent Neural Networks (RNN) maintain an internal hidden state that is updated with each input and used in the output calculation of each node [12]. In [13], an NN was used to predict the value of the East Java Regional Government website. NN methods, such as LSTM, have been used to predict bee foraging activity under different climatic conditions that affect the accuracy of bees in food search [14]. LSTM, an effective RNN architecture, uses gating mechanisms to control previously stored information and calculate the output [15-17]. In [18], LSTM was used to predict rainfall by analyzing time series data to assess the severity of potential drought and flood risks in a region. In [19], RNNs were used to predict website access speed based on time series data from site traffic.

LSTM, a type of RNN, models time-series data with long-term dependencies. The advantage of LSTM lies in its ability to overcome the vanishing gradient and exploding gradient problems that often occur in standard RNNs. Additionally, LSTM captures non-linear patterns and models complex data based on time series. Various studies have shown that LSTM provides more accurate forecasting results compared to statistical methods for nonstationary, nonlinear, and complex time series data. Applications include forecasting bee activity [14], patterns of rat feeding behavior [20], authentication of different honeys [21], stock prices [22], and lifespan [23]. The reason for using LSTM to predict the rate of honey heat penetration is its capability to model time series data with long-term dependencies and fluctuating variables such as temperature and flow. LSTM retains important information from past data and discards irrelevant information, capturing nonlinear and complex patterns in time series data.

TABLE I. RELATED WORKS USING MULTIVARIATE LSTM

Ref.	Topic	Method	Subject
[14]	Predicting bee activity	LSTM and Gated Recurrent Unit (GRU)	Predict bee foraging activity based on different climate changes.
[20]	Predicting the type of food pattern for mice	Random Forest-Extra Trees	Predict the honey diet and distinguish it from the mixed sugar diet in mice.
[21]	Separating types of honey	LDA and PCA	Separate the types of honey using LDA and PCA methods.
[22]	Predicting stock prices	LSTM	Use multivariate time series data to predict stock prices.
[23]	Predicting transformer life	Deep Learning-LSTM	Predict transformer life based on operating and environmental conditions.
This study	Predicting the heat rate of honey	Multivariate LSTM	Predict the heat rate of honey to determine the quality of honey.

This study utilized an electronic circuit to collect real-time data, including the initial temperature, the final temperature, and the heat rate of honey. This study also aimed to optimize the LSTM architecture to predict the honey heat rate over time by optimizing time steps, the initial honey temperature, the final honey temperature, the electric current, and the honey heat rate, allowing the prediction of the honey heat rate at a specific time.

- This study predicts the honey heat rate at a specific time based on time, initial honey temperature, final honey temperature, and honey heat rate.
- This approach can save costs and time in determining the value of the honey heat rate using pasteurization techniques.
- The honey heat rates can determine its characterization after pasteurization.

II. METHODOLOGY

A. *Long-Short-Term Memory (LSTM)*

LSTM can be highly beneficial in forecasting the OH process. LSTM is well-suited for handling sequential data, such as temperature and electric current over time. The following LSTM was used to predict the heat penetration rate in honey and generate a heat path at a specific time. Figure 1 illustrates the steps of this study.

1) *Data Preprocessing*

Data preprocessing was performed as described in [24] to extract valuable information from the dataset, including time, initial honey temperature, electric current, and final honey temperature during the OH process. Preprocessing steps included data normalization and splitting them into training and test sets.

2) *LSTM Architecture*

An LSTM model was constructed following [25]. LSTM has dense layers with hyperbolic tangent activation and softmax layers. The appropriate sequence for the data was determined.

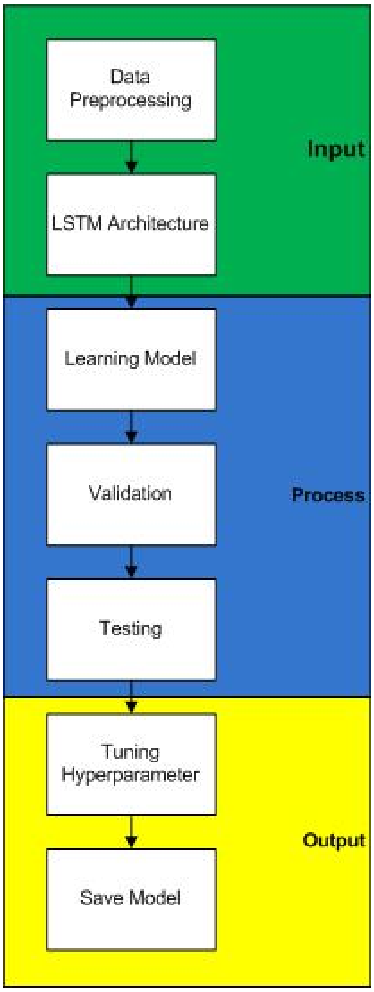


Fig. 1. Method.

3) Learning Model

In line with [26], training data were used to train the LSTM model. Mean Squared Error (MSE) was employed as the loss function, along with the Adam or SGD optimization algorithms to optimize the model.

4) Validation

Validation is a key step in determining the suitability of the model. Validation data were used to measure model performance using metrics such as MSE, MAE, or R^2 [27, 28].

5) Testing

There are three types of architectures for the LSTM method [29]. This study used a sequential model embedding layer architecture followed by LSTM layers and dense layers to test the model [30].

6) Hyperparameter Tuning

Hyperparameter tuning in LSTM can optimize values of MSE, MAE, or R^2 [25]. Hyperparameters such as the number of LSTM neurons, the number of LSTM layers, the dropout rate, the learning rate, and the number of training epochs were further tuned if the test results were unsatisfactory.

7) Implementation and Forecasting

Forecasting issues represent both opportunities and challenges [31-33]. LSTM was used to predict the final honey temperature in the OH process.

8) Save Model

The model was documented well, including architecture, hyperparameters, and evaluation results, to ensure that it can be stored and reused efficiently in future forecasting.

B. Data Preparation

This approach determines the characteristics of honey through the OH process using parameters from a special electronic circuit or device for honey pasteurization. This device separates harmful particles and identifies the characteristics of honey. The honey pasteurization process is influenced by several parameters: time (t), initial temperature, final temperature, electric current, and the rate of honey calorie consumption. However, each pasteurization process requires a specific and expensive electronic circuit that is time-consuming to create. The pasteurization results provide a value for the honey calorie consumption rate that indicates the honey quality. Therefore, this approach predicts the rate of honey calorie consumption using historical data from the pasteurization process with the LSTM method. The data used in this study are available in [34].

Figure 2 shows an electronic circuit for the pasteurization of honey to determine its characterization through the OH process. The aim was to incorporate Trigona SP honey produced by bees from coconut and palm flower nectar freshly harvested from Nusa Barat Tenggara, Indonesia, into the ohmic chamber treatment using a voltage gradient of 60 V/cm. Next, a heating or pasteurization process is carried out until the temperature reaches 63°C. The pasteurization process of honey is influenced by several parameters, namely time, initial temperature, final temperature, strong electric current, and heat rate in honey. Obtaining the optimal heat diversity at heat penetration will require a lot of trials and a long time and cost. This study predicts the most optimal heat penetration rate in honey using historical data from the pasteurization process using the LSTM method.

III. RESULTS AND DISCUSSION

The aim was to reduce MSE and MAPE values by combining changes in the LSTM variables, including the number of training data, the number of neurons, the number of epochs (iterations), and the batch size. In [35], an NN was applied by tuning the learning rate, epochs (iterations), and data training and testing to obtain a predictive data pattern model with a small MAPE and high accuracy. This study uses a total of 158 bacillus data from a series of honey pasteurization tools with different frequencies, namely 50 Hz, 300 Hz, 1 KHz, and 3 KHz, and each frequency has different values of time, initial temperature, final temperature, current, and heat rate. Each change in each variable forms three data pattern models, namely models A, B, and C. Tables II-IV show details on the variable changes for each model A, B, and C, respectively [33].

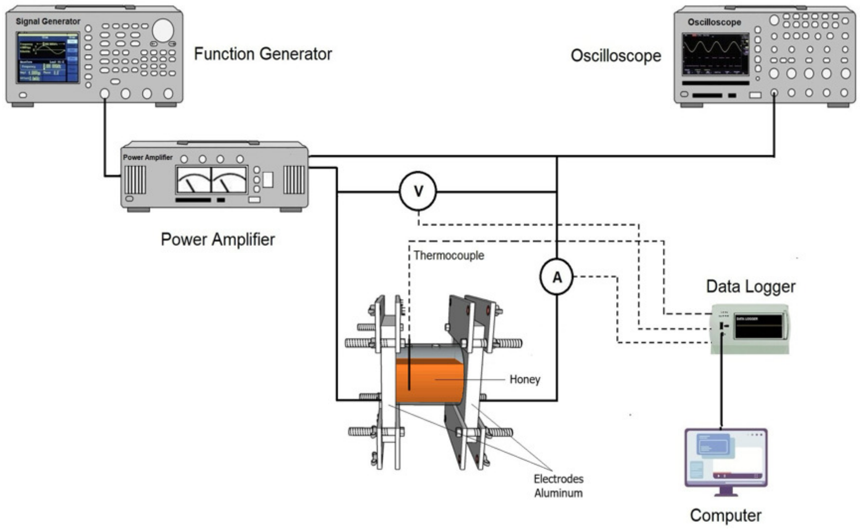


Fig. 2. Electronic circuits for honey pasteurization.

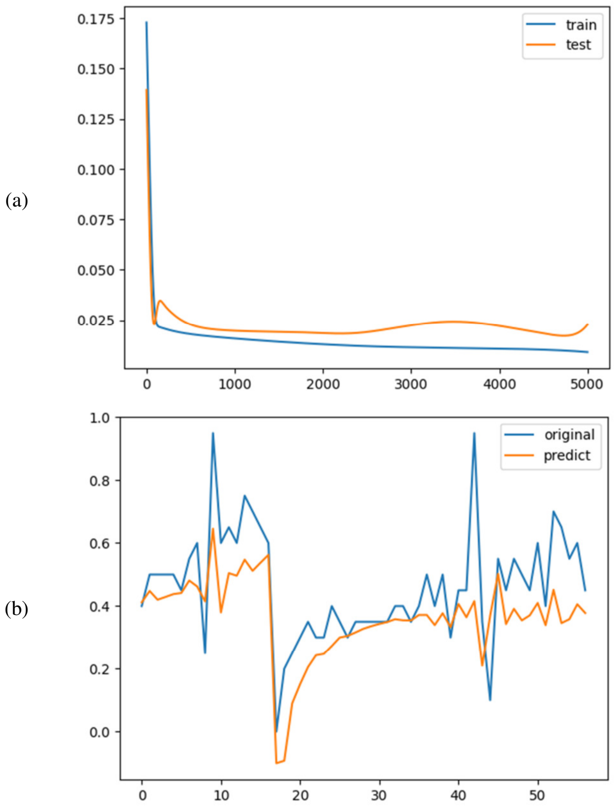


Fig. 3. Model A1: Graph of training/test results and actual/prediction data.

A. *Model A*

Model A1 utilizes 100 training data points, which is 70% of the total 158 data points, with 3 neurons in the hidden layer, a density of 1, 5000 epochs, and a batch size of 100. This is evident in Table II, where the model generates training and testing data patterns as shown in Figure 3(a). Additionally, this model has a prediction data pattern that matches the actual data in Figure 3(b). However, based on Figures 3(a) and 3(b), there is still a high loss error and instability between the predicted and the actual data.

TABLE II. VARIABLES FOR MODEL A

Model	Training data	Hidden layer neurons	Dense	Epoch	Batch size
A1	100	3	1	5000	100
A2	100	4	1	5000	200
A3	100	5	1	3000	200

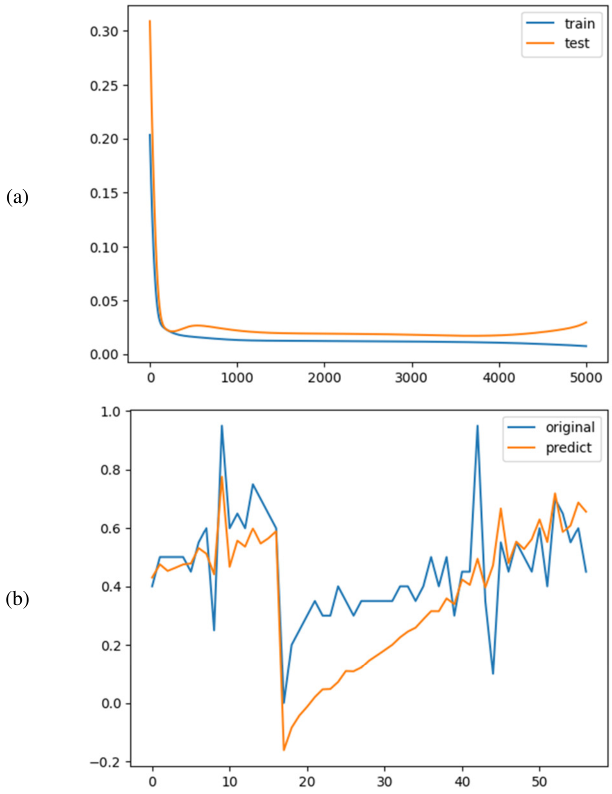


Fig. 4. Model A2: Graph of training/test results and actual/prediction data.

Model A2 employs 100 training data points, with 4 neurons in the hidden layer, a density of 1, 5000 epochs, and a batch size of 100. Figure 4 shows the model's training and testing data patterns and a comparison of the prediction with the actual data. Figures 4(a) and 4(b) indicate a relatively low loss error and fairly good stability between the predicted data and the actual data compared to model A1. Model A3, comprising 100 training data points, 5 neurons in the hidden layer, a density value of 1, 5000 epochs, and a batch size of 100, exhibits a relatively low loss error. This can be observed in Figure 5, where the comparison of training and test data shows a very narrow line gap. Similarly, the comparison of the predicted with the actual data indicates a very small loss error.

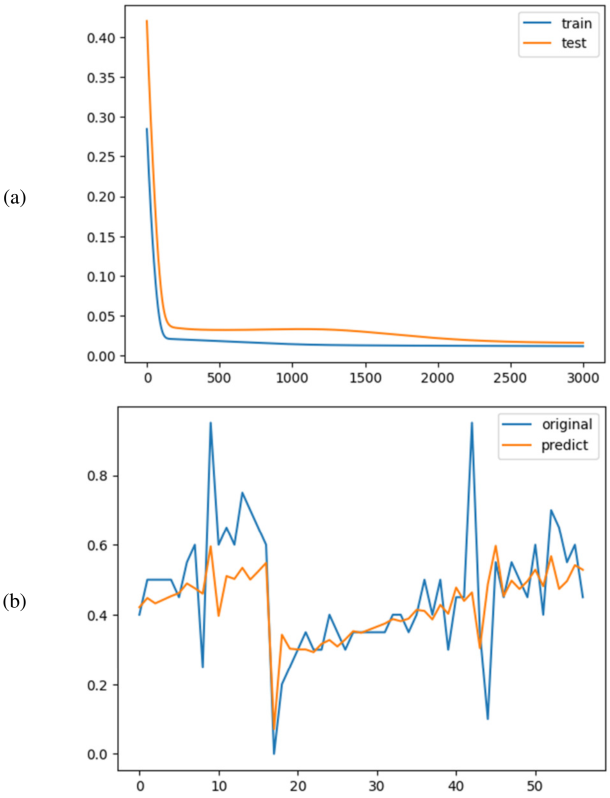


Fig. 5. Model A3: Graph of training/test results and actual/prediction data.

B. Model B

Model B employs 125 training data points, which constitute 80% of the total 157 data points, with a varying number of hidden layers. The hyperparameters are a dense value of 1, 3000 epochs, and a batch size of 200. Table III shows details for Model B. The visualization of each Model B is presented in Figures 6-8 as follows.

TABLE III. VARIABLES FOR MODEL B

Model	Training data	Hidden layer neurons	Dense	Epochs	Batch size
B1	125	5	1	3 000	200
B2	125	10	1	3000	200
B3	125	15	1	3000	200

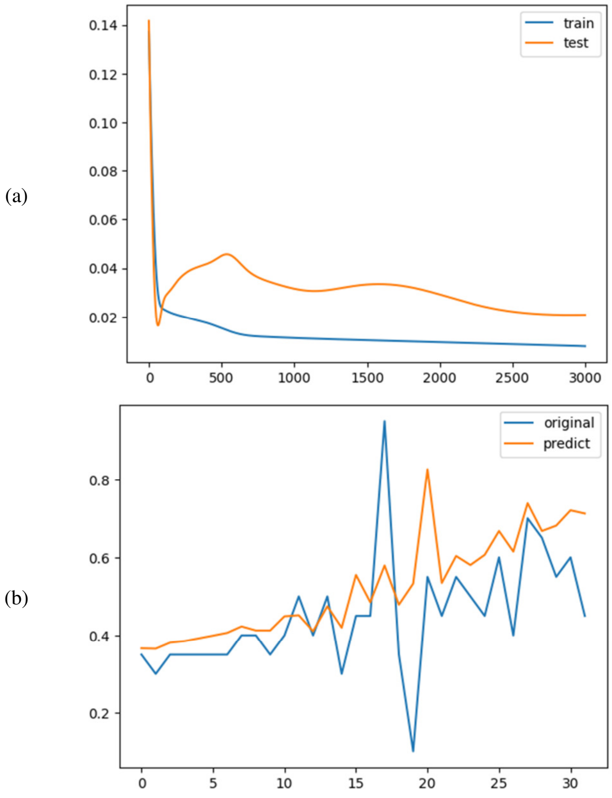


Fig. 6. Model B1: Graph of training/test results and actual/prediction data.

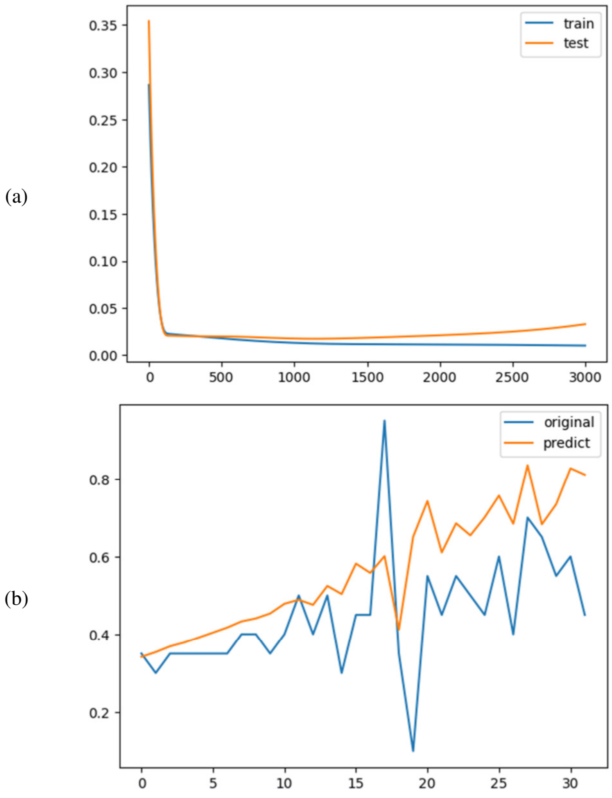


Fig. 7. Model B2: Graph of training/test results and actual/prediction data.

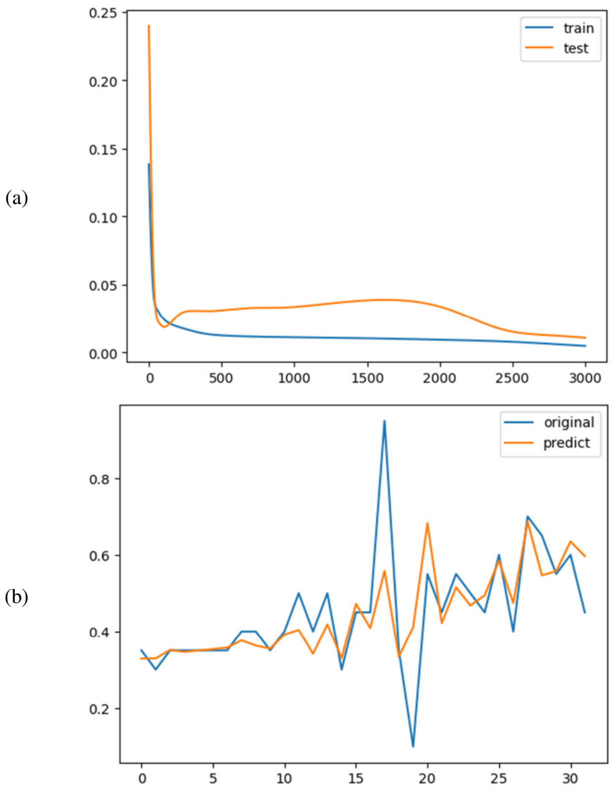


Fig. 8. Model B3: Graph of training/test results and actual/prediction data.

Model B1 utilizes 125 training data points (80% of the total data), has 5 neurons in the hidden layer, a density of 1, 3000 epochs, and a batch size of 200, resulting in a still high level of loss error. The training and testing data results graph in Figure 6(a) shows a significant gap between them, indicating a considerably high loss error. Model B2 is superior to model B1. This is due to the use of a greater number of neurons in the hidden layer, specifically 10 neurons. Although the number of training data, dense value, number of epochs, and batch size remain the same as in model B1, the increased number of neurons yields better results. Figure 7(a) shows a graph of training and testing results for Model B2, while Figure 7(b) shows a comparative graph between the predicted and actual data. Model B3 was superior to model B2, as can be observed in Figure 8. Although the values of all variables in Model B3 are identical to models B1 and B2, the significant difference lies in the number of neurons in the hidden layer, which is 15.

C. Model C

In model C, 90% of the total data was used for training, amounting to 142 data points. Table IV displays the values for each variable.

TABLE IV. VARIABLES FOR MODEL C

Model	**Training data**	**Hidden layer neurons**	**Dense**	**Epoch**	**Batch size**
C1	142	10	1	3 000	100
C2	142	30	1	3000	100
C3	142	30	1	3000	50

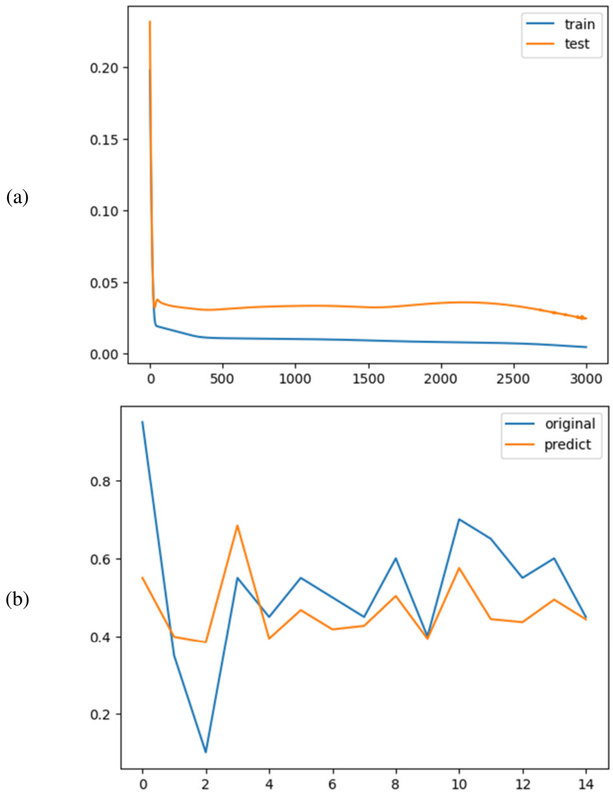


Fig. 9. Model C1: Graph of training/test results and actual/prediction data.

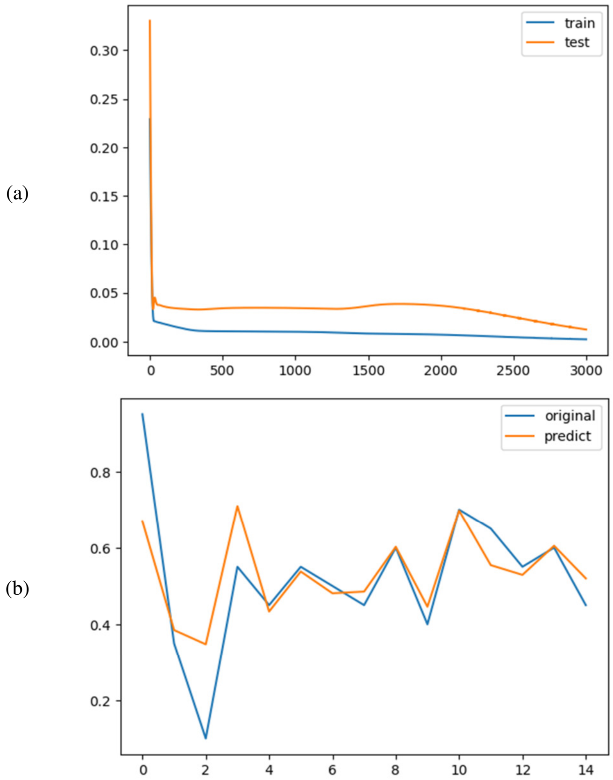


Fig. 10. Model C2: Graph of training/test results and actual/prediction data.

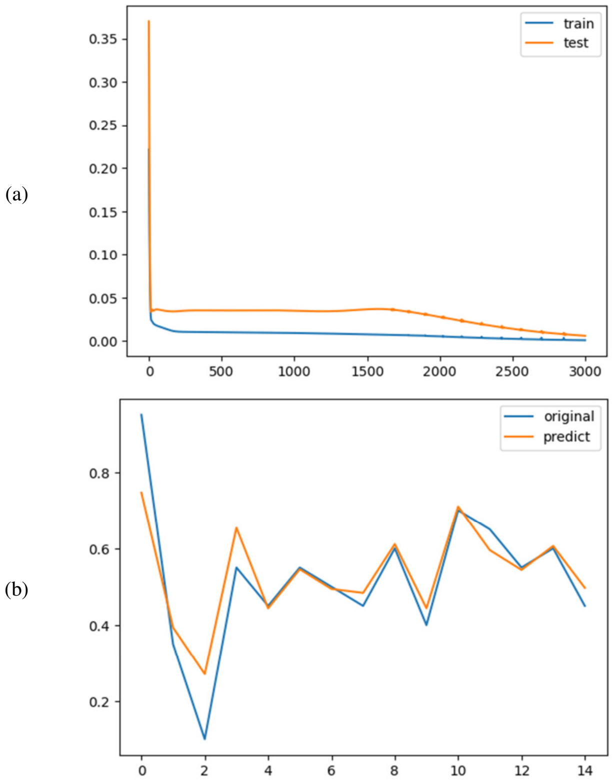


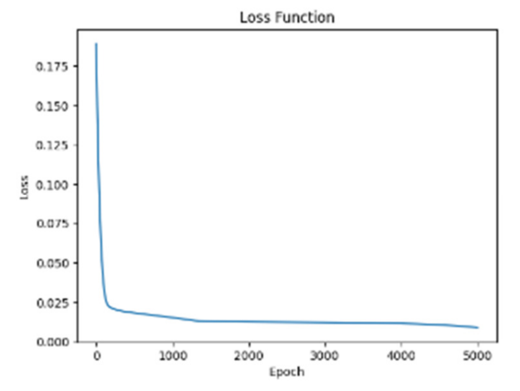
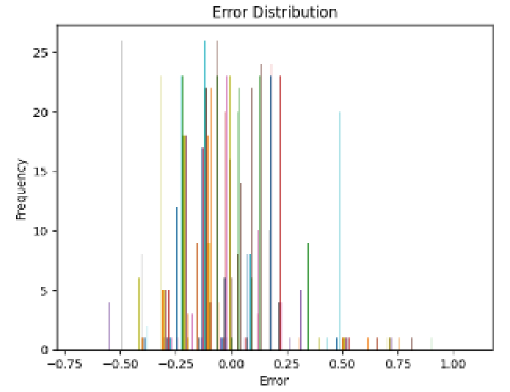
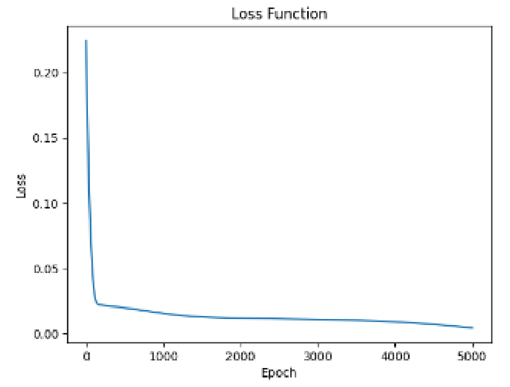
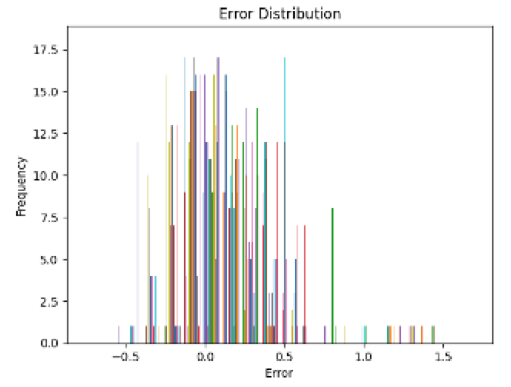
Fig. 11. Model C3: Graph of training/test results and actual/prediction data.

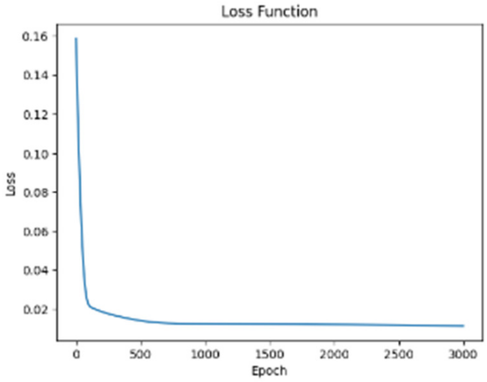
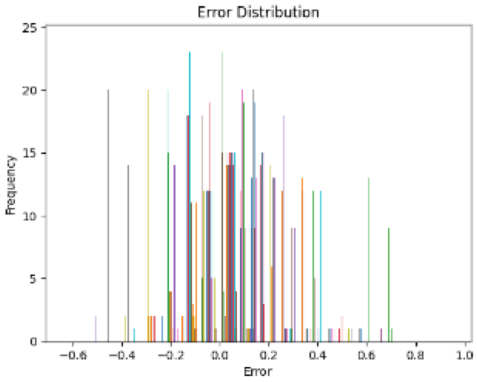
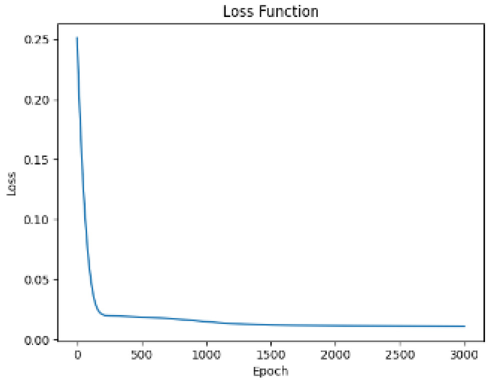
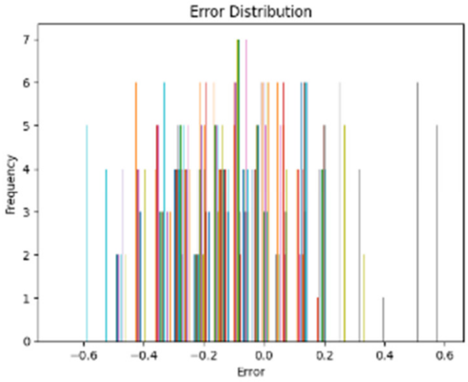
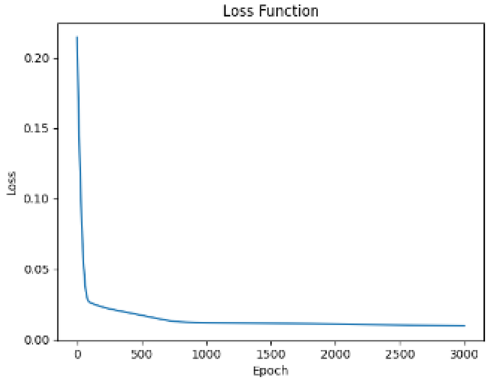
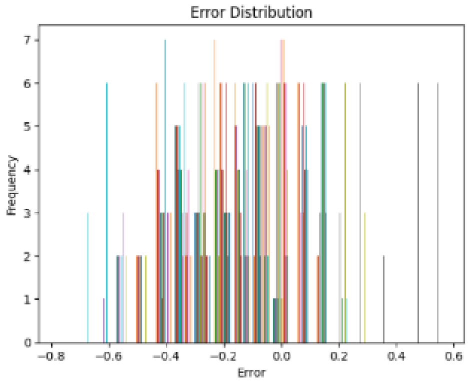
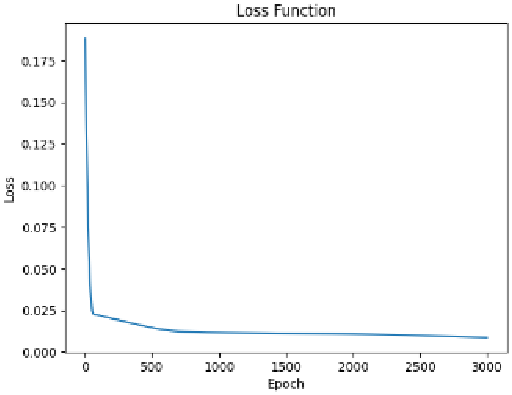
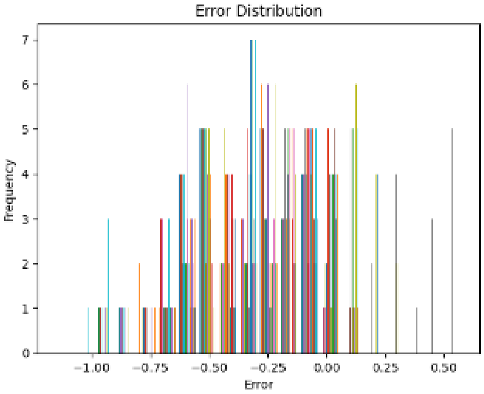
Model C1 employed 142 training data points, with 10 neurons in the hidden layer, a density of 1, 3000 epochs, and a batch size of 100. The results of this model, shown in Figure 9, indicate a high error rate. Model C2, utilizing 40 neurons in the hidden layer, was better than model C1, as shown in Figure 10. Although the data quantity, density value, number of epochs, and batch size remain the same as in model C1, the increase in the number of neurons in the hidden layer resulted in better outcomes. Model C3 was the best, with a very small difference between the training and testing data, to the extent that the training and testing data lines almost coincide. Similarly, the modeling between the prediction results and the actual data shows a high degree of conformity, with a very small discrepancy between them, as shown in Figure 11. To achieve data patterns with a very low error rate, model C3 utilized 142 training data points, 30 neurons in the hidden layer, a density value of 1, 300 epochs, and a batch size of 50.

IV. EVALUATION OF LSTM MODEL RESULTS

This study evaluated the results of three types of LSTM models. Each model had sub-models that served to fine-tune in the quest for optimal data patterns. Table V shows a comparative evaluation to determine the level of the loss function and the frequency of errors in each model.

TABLE V. GRAPH COMPARISON OF LOSS FUNCTION AND ERROR DISTRIBUTION FOR EACH MODEL

A1		
A2		

A3	Loss Function Loss Epoch 0.16 0.14 0.12 0.10 0.08 0.06 0.04 0.02 0 500 1000 1500 2000 2500 3000	Error Distribution Frequency Error 25 20 15 10 5 0 −0.6 −0.4 −0.2 0.0 0.2 0.4 0.6 0.8 1.0
B1	Loss Function Loss Epoch 0.25 0.20 0.15 0.10 0.05 0.00 0 500 1000 1500 2000 2500 3000	Error Distribution Frequency Error 7 6 5 4 3 2 1 0 −0.6 −0.4 −0.2 0.0 0.2 0.4 0.6
B2	Loss Function Loss Epoch 0.20 0.15 0.10 0.05 0.00 0 500 1000 1500 2000 2500 3000	Error Distribution Frequency Error 7 6 5 4 3 2 1 0 −0.8 −0.6 −0.4 −0.2 0.0 0.2 0.4 0.6
B3	Loss Function Loss Epoch 0.175 0.150 0.125 0.100 0.075 0.050 0.025 0.000 0 500 1000 1500 2000 2500 3000	Error Distribution Frequency Error 7 6 5 4 3 2 1 0 −1.00 −0.75 −0.50 −0.25 0.00 0.25 0.50

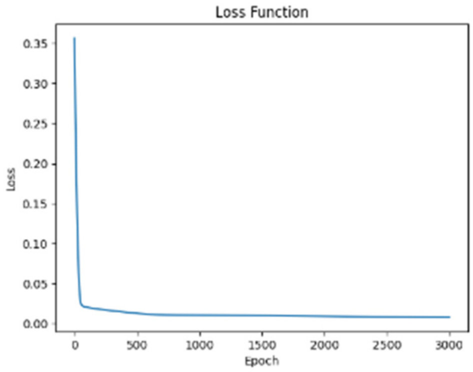
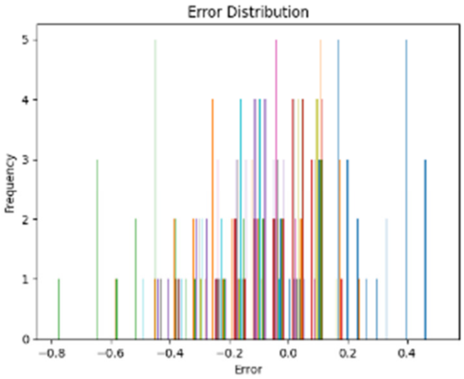
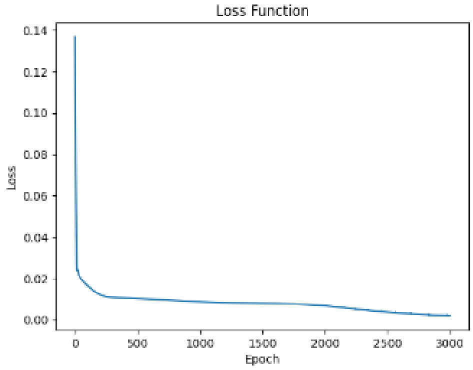
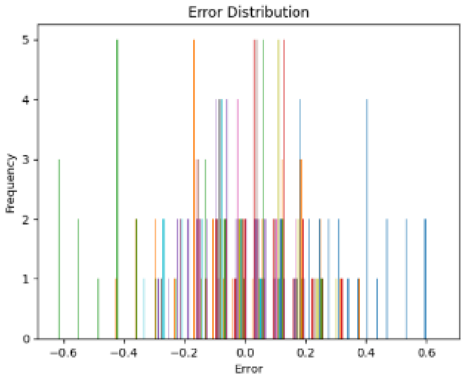
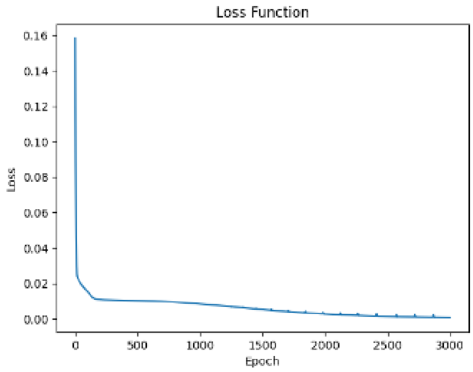
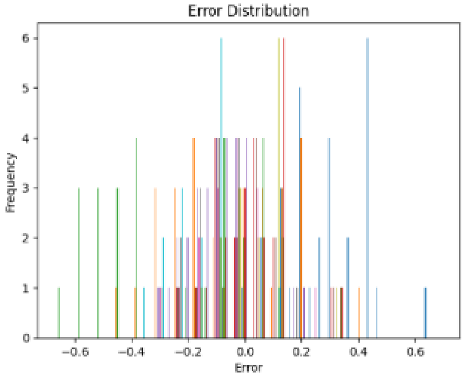
C1		
C2		
C3		

Figure 12 presents a visualization of model A3, which featured 5 neurons in the hidden layer, 3000 epochs, a batch size of 200, and 100 training data points and achieved an optimal RMSE of 0.41. For clarity in visualization, RMSE is multiplied by 100.

Figure 13 shows the optimal RMSE values for models B1 and B3, both of which have 10 neurons in the hidden layer, 3000 epochs, and 125 training data points, with the best RMSE being 0.171. Similarly to Model A, its RMSE is also multiplied by 100.

Fig. 12. Model A details and results.

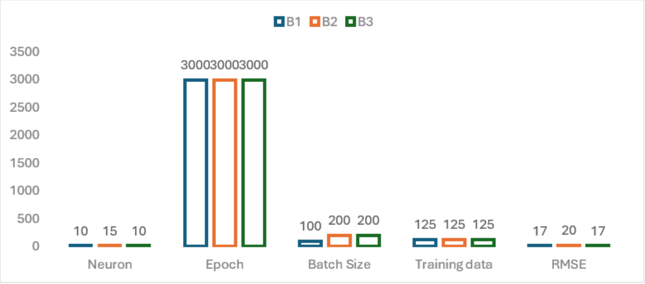


Fig. 13. Model B details and results.

Model C1 achieved an optimal RMSE of 0.20 with 10 neurons in the hidden layer, 3000 epochs, a batch size of 100, and 142 training data points. This value is once again multiplied by 100 for visualization purposes in Figure 14.

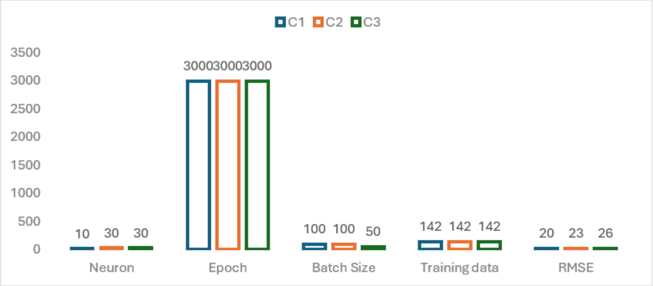


Fig. 14. Model C details and results.

In [35], OH was used to accelerate the reduction of water resistance in shellfish, aiding their longevity in restaurants without altering their energy and protein content. This study highlights a gap due to the absence of subsequent studies applying AI to make the OH process faster and more precise. ML includes specialized models to handle regression, including prediction or forecasting. This study advances the OH process with ML techniques, employing a multivariate LSTM architecture, an evolution of the standard LSTM, to predict the heat rate of the OH process using honey as the subject. The prediction of OH outcomes aims to improve the honey penetration process with OH techniques without the need for expensive equipment and extensive time.

V. CONCLUSION

This research concludes with two main findings. First, the honey heat penetration process is not limited to the use of electronic device arrays but can be effectively performed using a multivariate LSTM prediction model. Second, this study introduces a novel approach to the prediction of honey heat penetration, as no previous research has addressed this specific application. The study employs unique multivariate parameters, including time, frequency, initial temperature, final temperature, current, and heat rate, distinguishing it from previous LSTM studies that focused primarily on time series data and labeled results. This advancement signifies the evolution of LSTM into a multivariate framework, marking a significant contribution to the field of AI-driven food processing.

To predict honey penetration, three primary data models were developed, each comprising submodels with varying parameter configurations. Experimental results demonstrated that submodels B1 and B3, with specific parameter settings (training data count: 125, hidden layer neurons: 5 and 15, dense value: 1, epochs: 3000, and batch size: 200), achieved superior performance in terms of optimization and minimal error propagation. These findings suggest that the parameter configurations of submodels B1 and B3 are optimal for predicting honey heat penetration.

The primary contribution of this study lies in the development of a multivariate LSTM model specifically tailored for honey processing, a novel application that has not been explored in previous research. Furthermore, this study paves the way for future advancements, such as generating thermal images from honey penetration results to post-process thermal outcomes. By offering an innovative solution to maintain honey quality and optimize processing efficiency, this research expands the scope of AI applications in the food industry and provides a foundation for further exploration in this domain.

ACKNOWLEDGMENT

This research was supported by Universitas Brawijaya Malang, Indonesia. We would like to express our thanks to colleagues in the Department of Agricultural Technology, Universitas Brawijaya, Malang, Indonesia, and the Department of Information Engineering, University 17 Agustus 1945 Surabaya, Indonesia, for their assistance and cooperation in developing this paper.

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