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Artificial Neural Network Modeling to Predict Electrical Conductivity and Moisture Content of Milk During Non-Thermal Pasteurization: New Application of Artificial Intelligence (AI) in Food Processing

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Abstract: This study proposed applying artificial intelligence (AI) to predict the actual electrical conductivity (EC) of raw and pasteurized milk using moderate electric field (MEF) based on the electric field strength (EFS) and mass flow rate (MFR) along with modeling moisture content (MC) based on the EC. To this end, an artificial neural network (ANN) was implemented for conventionally (CP) and non-thermally (NP) pasteurized milk. The findings indicated no significant difference ($p > 0.05$) between the experimental and predicted data for EC and MC. The MFR and EFS affected the actual EC. The raw milk samples had an EC of 0.468812–0.46913 S/m and MC of 87.3218–87.35941%, while these values in NP pasteurized milk were 0.457441–0.638224 S/m and 87.33986–87.40851%. With correlation coefficients (R) of 0.736478106–0.951840323 and mean square errors (MSE) of 0.005539–0.0064, the ANN accurately predicted the raw and pasteurized milk MC based on the EC using the sixth-order polynomial model and the EC based on the EFS and MFR using a quadratic model. The EC of pasteurized milk by NP was significantly ($p < 0.05$) lower than that of CP and raw dairy by 15.44% and 11.30%, respectively. The results show that the EFS and MFR might be used for the online assessment of milk's physical attributes (e.g., EC), followed by using the assessed parameter to determine other properties (e.g., MC) by developing AI approaches based on optimized models. These observations showcase the innovative use of ANN-based AI to predict milk's EC and MC accurately. Integrating such AI platforms into non-thermal food processing could eventually develop more sustainable food production and enhance food security and quality through process innovation and sustainable manufacturing, contributing to the industrial revolution and sustainable development goals.

Keywords: emerging technologies; electrical conductivity; moisture content; milk; ANN; moderate electric field; dairy processing; non-thermal technologies; food production

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1. Introduction

Milk is a water-based fluid containing dissolved protein aggregates, carbs, and minerals. It is an emulsion or colloid of butterfat globules [1]. Milk is nature's most comprehensive food, providing energy, protein, vitamins, and minerals in nutrient-dense meals and milk products [2,3]. Milk's resistance to the passage of electricity is measured by its electric conductivity, which depends on the concentration and presence of specific ions, mainly sodium, potassium, and chloride ions [4]. Foods' physical properties are of enormous importance regarding consumer acceptance [5,6]. Electrical conductivity is needed for accurate electrical heating process modeling, electrical tomography research, and quality assurance [7], especially for electrical-based food processing, as it might be affected by temperature and composition [8].

In nonlinear optimization, neural networks are utilized to tackle complicated problems. The biological inspiration comes from the procedures employed, which are based on how neurons function in the brains of humans and animals. Currently, most ANN applications in food science allow problem-solving or assistance with problem-solving, improved design processes, and machine learning design limits [9]. This originated from research on artificial intelligence (AI) that focused on applying the proper training method and providing adequate data to effectively describe multivariate nonlinear processes [10].

An artificial neural network (ANN) typically consists of an output layer (the output), hidden layers (neurons), and an input layer (the input variables). Because ANNs are stable, effective, and uniquely able to explain nonlinear relationships between independent and dependent variables through input–output system training and retraining, they are typically used in complex systems [10]. The main advantage of artificial neural network modeling—essentially a black box—is that it uses several input variables to predict output variables even without prior knowledge about the links between the processes [11]. Furthermore, an ANN in agriculture engineering is a better alternative to traditional empirical modeling based on linear and polynomial regressions [12]. ANNs have gained popularity and are essential to the advancement of modern technology. Due to the growth in industrial automation and the Internet of Things, gathering data and monitoring food drying, extrusion, sterilization, and other processes are more accessible than ever. In the modern industrial revolution, ANNs have proven helpful in food processing tasks such as food grading, safety, and quality inspection [13].

Artificial neural networks (ANNs) are gaining popularity in food process engineering because they can model large datasets with complexity and nonlinear relationships. Compared to other perdition methodologies, such as Multiple Linear Regression (MLR) and Decision Trees, ANNs can capture complex patterns and interactions more than conventional techniques [14]. ANNs can predict food quality parameters more accurately than MLR, which assumes linear connections [15]. At the same time, although the Decision Tree methodology is easier to understand and train, it frequently needs to improve in dealing with highly variable data [16]. However, ANNs may show limitations in situations with little data because they necessitate significant computing power and larger training datasets than Decision Trees, where the correlations between variables are more prominent; its "black box" character also makes it difficult to interpret the results. Combining AI and ANN could boost the capability of this perdition methodology, which has been assessed in a present study for milk processing.

Leveraging AI-based ANNs is new to emerging food processing research, especially those aimed at the industrial scale. A previous work applied AI-based modeling for non-thermally processed milk to optimize color during storage [17]. Another recently published study explored the possibility of using AI to predict the aroma of dairy [18]. There is also a published manuscript on utilizing machine learning algorithms to predict clinical mastitis in dairy cows according to the electrical conductivity of milk [19]. Moreover, sesame milk yield was predicted using an ANN [20]. However, AI could provide further benefits to food processing by providing online data on other physical properties of products, such as electrical conductivity, which is a crucial parameter in electrical-based processing. There are no published papers on modeling electric conductivity based on the electrical field and mass flow rate for non-thermal pasteurized milk and the prediction of moisture content of milk based on electric conductivity using ANNs.

This study aimed to model the electric conductivity of pasteurized milk based on the electrical field and mass flow rate using ANNs. It also predicted the moisture content of non-thermal pasteurized milk based on electric conductivity using ANNs.

2. Materials and Methods

2.1. Milk

Fresh whole bovine milk was procured from Breeding and Market Beef in Kadhemia Town (Baghdad, Iraq) and refrigerated at 5 °C until further use.

2.2. Non-Thermal and Conventional Pasteurization

The milk pasteurizer systems (NP and CP) were the same as those reported in a previous study [17]. The milk was homogenized when the mixer was present in the milk tank. A mass flow rate (MFR) of 0.0167–0.0333 kg/s and electric field strength (EFS) of 25–35 V/cm were the process variables. Conventional milk pasteurization was performed at 63 °C for 0.5 h for 0.25 L sample in a 0.26 L stainless steel cylinder. The sample was then cooled to 5 °C and refrigerated until the upcoming analysis.

2.3. Electrical Conductivity

The movement of charges across a material is known as EC. EC during NP pasteurization is given by the following equation, according to the literature [21]:

$$\mathrm{EC} = \frac{I\,L}{U\,A} \tag{1}$$

In Equation (1), EC is the electrical conductivity (S/m), I is the current (A), L is the distance between the electrodes (m), U is the voltage (V), and A is the cross-section area of the electrodes (m^2).

The EC of milk after pasteurization by NP and CP was measured at a temperature of 25 °C using a conductivity meter (model 3510, Jenway Co., Chelmsford, UK).

2.4. Moisture Content

The MC of treated and fresh milk was determined using an ultrasonic analyzer (LAC-SA–50 Milk Analyzer, BOECO company, Hamburg, Germany). At 25 °C, the samples were examined. The milk analyzer was calibrated for the milk according to the supplier's protocol to ensure the accuracy and dependability of the results. Testing was carried out on each sample, which was three replicates.

2.5. Artificial Neural Network Modeling

The matrix laboratory (MATLAB)'s artificial neural network fitting (R2014a, MathWorks Inc., MA, Portola Valley, CA, USA) was utilized to model experimental data generated by the ANNs during the non-thermal milk pasteurization using a moderate electric field. Multilayer perception comprised the feedforward backpropagation of the algorithm input layer (moderate electric field and mass flow rate in case of electrical conductivity prediction, and electrical conductivity in case of moisture content prediction) in the neural network, ten hidden layers for training on data, and an output layer (electrical conductivity (case 1) (Figure 1a), moisture content of pasteurized milk (case 2) (Figure 1b), and moisture content of raw milk (case 2) (Figure 1c)). The training function was TRAUNLM, the adaption learning function was LEARINGDM, and the performance function was mean square error (MSE). Two layers, ten neurons, and the transfer function of TANSIG (used between input and hidden layers and between the hidden layer and output layer) were used [22].

The ANN models were trained until the error between the predicted and experimental response values was as small as possible. The Levenberg–Marquardt training algorithm was used for the dataset. The neural network parameters were all the weights and bias together. The experimental data were split into three groups to create the ANN model: 70% for training, 15% for testing, and 15% for validation. The total number of data points used for ANN training and testing was 33 for every property (99 for all properties). The generated ANN model's performance was evaluated using the coefficient of correlation. The correlation coefficient and MSE were calculated from the following equations (Equations (2) and (3)):

$$R = \sqrt{\frac{\sum_{i=1}^{n}\left(x_p - \overline{x_p}\right)^2}{\sum_{i=1}^{n}\left(x_e - \overline{x_e}\right)^2}} \tag{2}$$

$$MSE = \frac{\sum_{i=1}^{n} (x_p - x_e)^2}{n} \quad (3)$$

where R is the correlation coefficient, x_p is the predicted data, x_e is the experimental data, MSE is the mean square error, and n is the observation number.

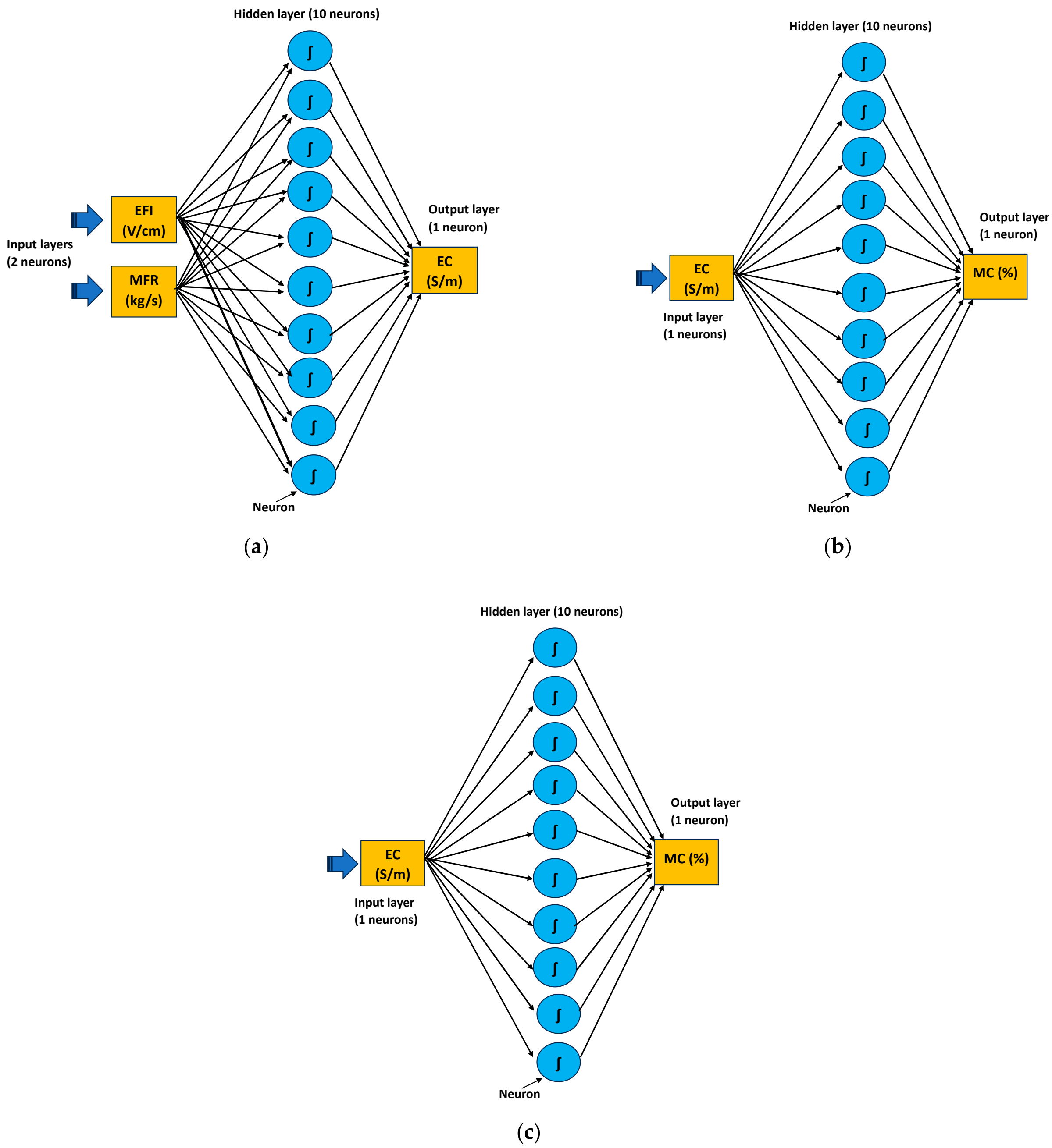


Figure 1. The feedforward neural network with multilayers: (**a**) prediction of electrical conductivity, (**b**) prediction of moisture content of pasteurized milk, (**c**) prediction of moisture content of raw milk. EFS: electric field strength, MFR: mass flow rate, EC: electric conductivity.

3. Results and Discussion

3.1. Experimental Electrical Conductivity

Table 1 shows the effect of the EFS and MFR on the EC during milk pasteurization by NP at 35 °C. The results reveal that the EC increased as the MFR decreased. When the MFR was reduced from 0.0333 to 0.0167 kg/s, the EC rose from 0.457441 to 0.638224 S/m, respectively. This is because of the increase in the residence time due to the decreased speed of milk at a lower MFR, which permits the passage of higher current, leading to a rise in EC according to Equation (1). The residence period of milk in the MEF was found to be significantly shortened with an increase in MFR at all EFS values [23]. The researchers also found that this result was associated with increased milk speed at a higher MFR. EC changed with the increasing EFS. For instance, EC increased from 0.457441 to 0.503529 when the EFS rose from 25 to 31 V/cm at a 0.0333 kg/s MFR, and then decreased to 0.501187, 0.497532, and 0.49191 S/m at 32, 33, and 34 V/cm, respectively. The maximum value of EC reached 0.596071 at an EFS of 35 V/cm and MFR of 0.0167 kg/s. The change in EC with the EFS is because pasteurized milk's conductivity can rise as the strength of the electric field increases because of temperature effects and increased ionic mobility.

Table 1. Effect of EFS and MFR on EC and MC during milk pasteurization by MEF at 35 °C.

EFS (V/cm)	MFR (kg/s)	EC (S/m)	
		Experimental	Predicted (ANN)
25	0.0333	0.457441	0.461948
25	0.025	0.550797	0.550661
25	0.0167	0.638224	0.637768
26	0.0333	0.465563	0.466968
26	0.025	0.51969	0.519654
26	0.0167	0.628994	0.635771
27	0.0333	0.479948	0.480037
27	0.025	0.492711	0.492596
27	0.0167	0.614899	0.626663
28	0.0333	0.491014	0.491003
28	0.025	0.473658	0.472494
28	0.0167	0.604849	0.611522
29	0.0333	0.496947	0.496733
29	0.025	0.46098	0.461157
29	0.0167	0.598337	0.597816
30	0.0333	0.500368	0.500604
30	0.025	0.458289	0.458693
30	0.0167	0.587987	0.586851
31	0.0333	0.503621	0.503529
31	0.025	0.459238	0.458872
31	0.0167	0.585201	0.584777
32	0.0333	0.501187	0.501768
32	0.025	0.46421	0.462115
32	0.0167	0.587152	0.585988
33	0.0333	0.497532	0.49737
33	0.025	0.479747	0.474522
33	0.0167	0.588196	0.588431
34	0.0333	0.49191	0.491741
34	0.025	0.499972	0.499811
34	0.0167	0.593931	0.593675
35	0.0333	0.479895	0.479877
35	0.025	0.52742	0.527145
35	0.0167	0.59541	0.596071
SSE *			0.01011
R			0.9546
RMSE			0.01935

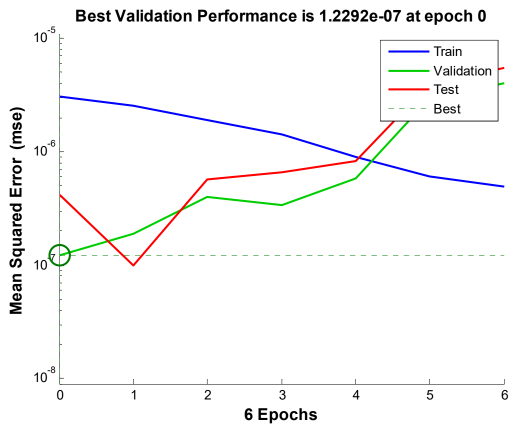
* SSE: sum of square error; RMSE: root mean square error; EFS: electric field strength; R: correlation coefficient; and MFR: mass flow rate.

On the other hand, it may drop due to desalination procedures that reduce ionic concentration and the presence of fat, which obstructs ionic mobility. The interaction of these variables results in a complex correlation between pasteurized milk's conductivity and the strength of the electric field, and the mean EC of milk ranged between 4.66 and 4.90 mS/m (0.466–0.490 S/m) [4,24,25]. Hwang et al. [26] depicted that the electric conductivity of raw milk was 0.45 S/m.

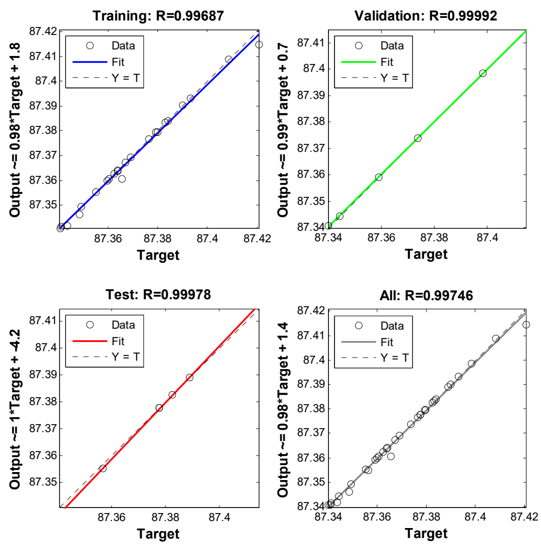
3.2. Modeling Electrical Conductivity Using Artificial Neural Network

The results in Table 1 reveal that the experimental and predicted ANNs converged, the SSE and RMSE were reduced, and the value of R^2 was high (0.9114). For the ANN performance (Figure 2), the best validation performance was 1.2292×10^{-7} at epoch zero, and the R values for training, validation, and testing all ranged between 0.99687 and 0.99992. Because ANNs can correlate various nonlinear relationships without requiring the specification of an appropriate fitting function beforehand, they hold great promise for modeling various applications of developing technologies in the food processing industry [22]. Therefore, EC can be predicted using the quadratic model based on the EFS and MFR as illustrated in Equation (4):

$$EC = 2.547 - 64.1MFR - 0.07916EFS + 868MFR^2 + 0.461MFR \times EFS + 0.001101EFS^2 \quad (4)$$



(**a**)



(**b**)

Figure 2. ANN performance: (**a**) mean square error (MSE) and (**b**) correlation coefficients (R) for training, validation, test, and all while the target and the output are the experimental and predicted EC, respectively).

Here, EFS is the electric field strength, MFR is the mass flow rate, and EC is the electric conductivity.

The three-dimensional plot in Figure 3a and the contour in Figure 3b depict the effect of the EFS and MFR on the predicted EC by the ANNs. The EC was reduced as the MFR increased at all EFS values. For example, when the MFR rose from 0.0167 to 0.0333 kg/s, the EC decreased from 0.596071 to 0.479877 S/m, respectively, at an EFS of 35 V/cm. The residence time decreases due to increased milk velocity at a higher MFR, allowing for lower current passage and a decline in EC. The change in EC during the increase in EFS was limited. For example, the EC declined from 0.588431 at an MFR of 0.0167 kg/s and EFS of 34 V/cm to 0.491741 at an MFR of 0.00333 kg/s and EFS of 34 V/cm. The MFR is of higher importance in the EC's effect than EFS. Sun et al. [27] stated that at 15 °C, milk had an electrical conductivity of 0.409–0.431 S/m. It grew practically linearly from 15 °C to around 80 °C, then sharply decreased at 83 °C. The increase in ionic mobility brought on by the rise in temperature and the decrease in viscosity may cause a surge in electrical conductivity [28].

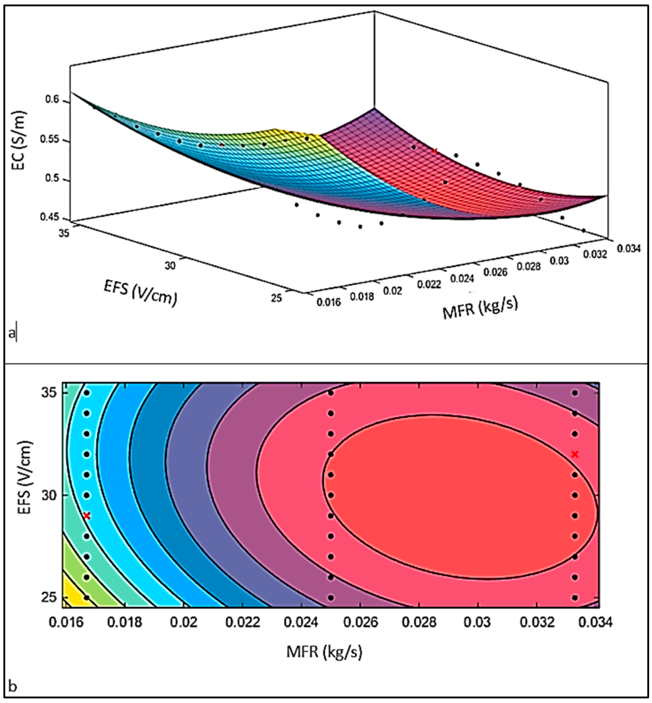


Figure 3. The effect of EFS and MFR on EC predicted by ANNs: (**a**) 3D plot, (**b**) contour plot.

3.3. Modeling Moisture Content of Pasteurized and Raw Milk Using Artificial Neural Network

The results are shown in Table 2. They reveal that the MC changed with a changing EC. The maximum experimental MC was 87.40851% at an EC of 0.588196 S/m—higher electrical conductivity results from more free ions being available for conduction when moisture rises. Also, Table 2 depicts that the experimental and predicted MCs using ANNs converged, and the SSE and RMSE were inclined. The ANN is superior to other modeling methods because it uses experimental data to create a highly accurate model and address issues associated with the food processing industry [22]. At the same time, an R^2 value of 0.906 was observed. For the ANN performance (Figure 4), the best validation performance was 2.1437×10^{-5} at epoch one, and the R values for training, validation, and testing all ranged between 0.8402 and 0.99452. Therefore, the MC of pasteurized milk can be predicted by a sixth-order polynomial model based on the EC as given in Equation (5):

$$\begin{aligned} MC = \ & -0.0001034EC^6 - 0.0002869EC^5 - 0.0006483EC^4 + 0.001566EC^3 + \\ & 0.004171EC^2 + 0.002973EC + 87.34 \end{aligned} \tag{5}$$

where EC is the electrical conductivity (S/m), and MC is the moisture content (%).

Table 2. Correlations between EC and MC during NP and raw milk pasteurization.

NP * Pasteurized Milk			Raw Milk		
EC (S/m)	MC (%)		EC (S/m)	MC (%)	
	Experimental	Predicted (ANNs)		Experimental	Predicted (ANNs)
0.457441	87.36405	87.38058445	0.469055	87.35254	87.35257
0.550797	87.37655	87.38484013	0.469035	87.35223	87.35161
0.638224	87.38905	87.38836818	0.469172	87.35141	87.35136
0.465563	87.35521	87.38096934	0.468955	87.33368	87.33983
0.51969	87.36921	87.38346795	0.469101	87.35001	87.34997
0.628994	87.38321	87.3880219	0.468855	87.3218	87.3264
0.479948	87.34838	87.38164526	0.469016	87.34387	87.34446
0.492711	87.36388	87.3822382	0.468987	87.34827	87.34011
0.614899	87.37937	87.38748033	0.469008	87.32943	87.34182
0.491014	87.34354	87.38215975	0.468912	87.35541	87.35531
0.473658	87.36054	87.38135066	0.469032	87.35555	87.35091
0.604849	87.37754	87.38708506	0.468898	87.34207	87.34651
0.496947	87.3407	87.38243349	0.468981	87.35032	87.34005
0.46098	87.3592	87.38075243	0.468996	87.34166	87.34036
0.598337	87.3777	87.38682502	0.469092	87.32527	87.32712
0.500368	87.33986	87.38259062	0.468962	87.33915	87.33997
0.458289	87.35986	87.38062474	0.468979	87.33819	87.34004
0.587987	87.37986	87.38640558	0.46913	87.35807	87.35872
0.503621	87.34102	87.38273956	0.469129	87.35941	87.35887
0.459238	87.36252	87.3806698	0.469003	87.35455	87.34095
0.585201	87.38402	87.38629141	0.468987	87.32812	87.34011
0.501187	87.34419	87.38262816	0.468865	87.35374	87.33886
0.46421	87.36719	87.38090538	0.468862	87.3364	87.3364
0.587152	87.39018	87.38637142	0.468866	87.33104	87.3395
0.497532	87.34935	87.38246039	0.468963	87.34581	87.33998
0.479747	87.37385	87.38163587	0.468979	87.32842	87.34004
0.588196	87.39835	87.38641412	0.468812	87.33366	87.33366
0.49191	87.35651	87.38220119	0.468916	87.33057	87.3306
0.499972	87.38251	87.38257246	0.469183	87.34883	87.34885
0.593931	87.40851	87.38664738	0.468972	87.33272	87.34001
0.479895	87.36567	87.38164279	0.469091	87.32882	87.32699
0.52742	87.39317	87.38381379	0.468961	87.35346	87.33996
0.59541	87.386707	87.38670716	0.468824	87.34658	87.34743
SSE		0.0007977			0.0011
R		0.951840323			0.736478106
RMSE		0.005539			0.0064

* NP: non-thermal pasteurization; SSE: sum of square error; RMSE: root mean square error; R: correlation coefficient; EC: electric conductivity; MC: moisture content.

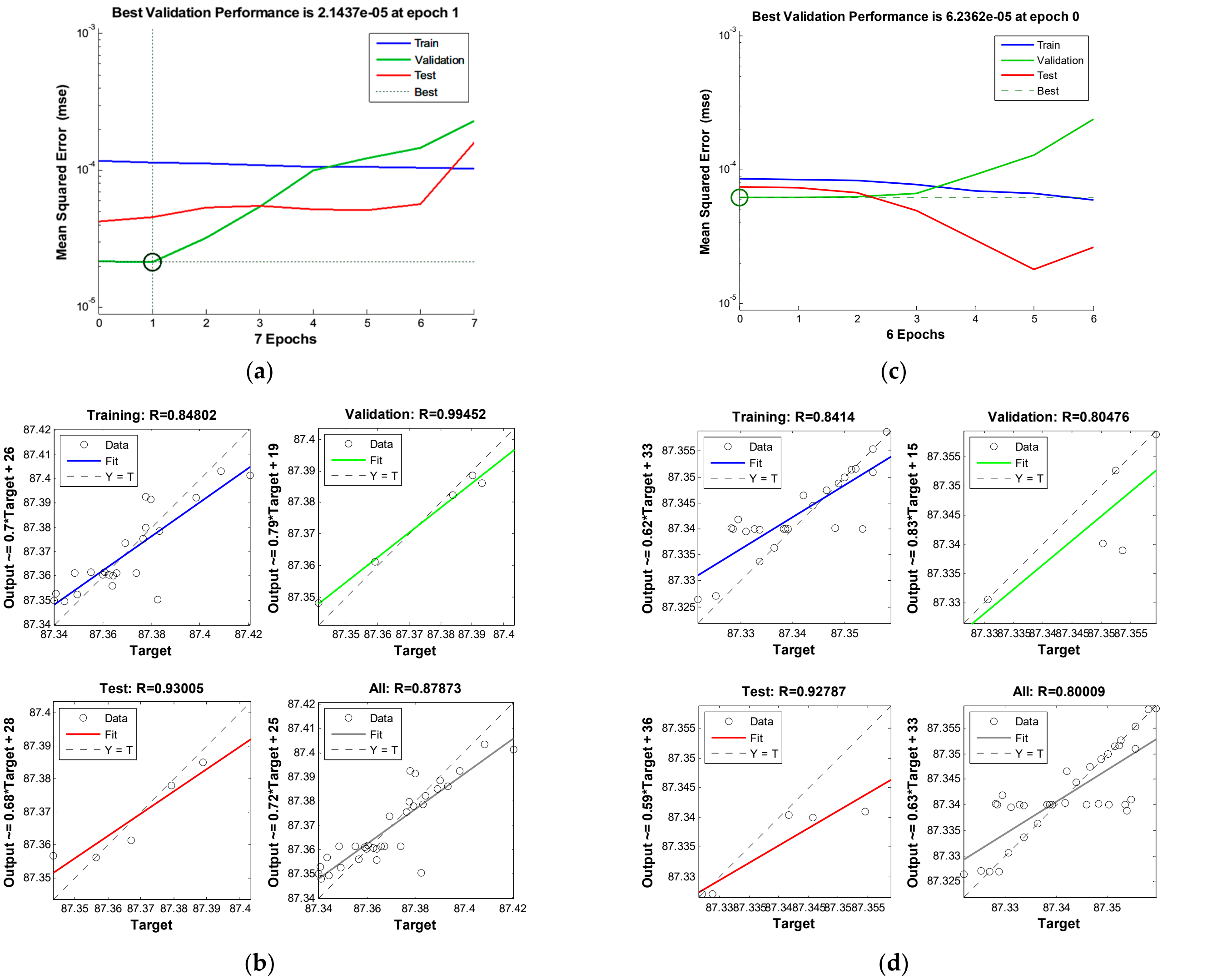


Figure 4. Visual representation of ANN performance; (**a**): mean square error (MSE) of pasteurized milk; (**b**): correlation coefficients (R) of pasteurized milk; (**c**): MES of raw milk; (**d**): R of raw milk. The target is the experimental MC, and the output is the predicted MC.

Figure 5 presents the relationship between EC and MC. The MC changed as the EC changed. This change is attributed to the milk's moisture content, which affects its electrical conductivity since it contains dissolved ions. Higher conductivity is usually the result of a rise in the concentration of these ions with increasing moisture content [29]. Understanding the correlation between EC and MC measurements is crucial for food quality evaluation, enhancing processing conditions, quality control, shelf-life management, and manufacturing, thereby improving consumer satisfaction and safety [24,29,30].

For raw milk, the sixth-order polynomial model was used to predict MC as given in Equation (6):

$$\begin{aligned} \mathrm{MC} = &-0.0001034\mathrm{EC}^6 - 0.0002869\mathrm{EC}^5 - 0.0006483\mathrm{EC}^4 + 0.001566\mathrm{EC}^3 + \\ &0.004171\mathrm{EC}^2 + 0.002973\mathrm{EC} + 87.34 \end{aligned} \quad (6)$$

where EC is the electrical conductivity (S/m), and MC is the moisture content (%).

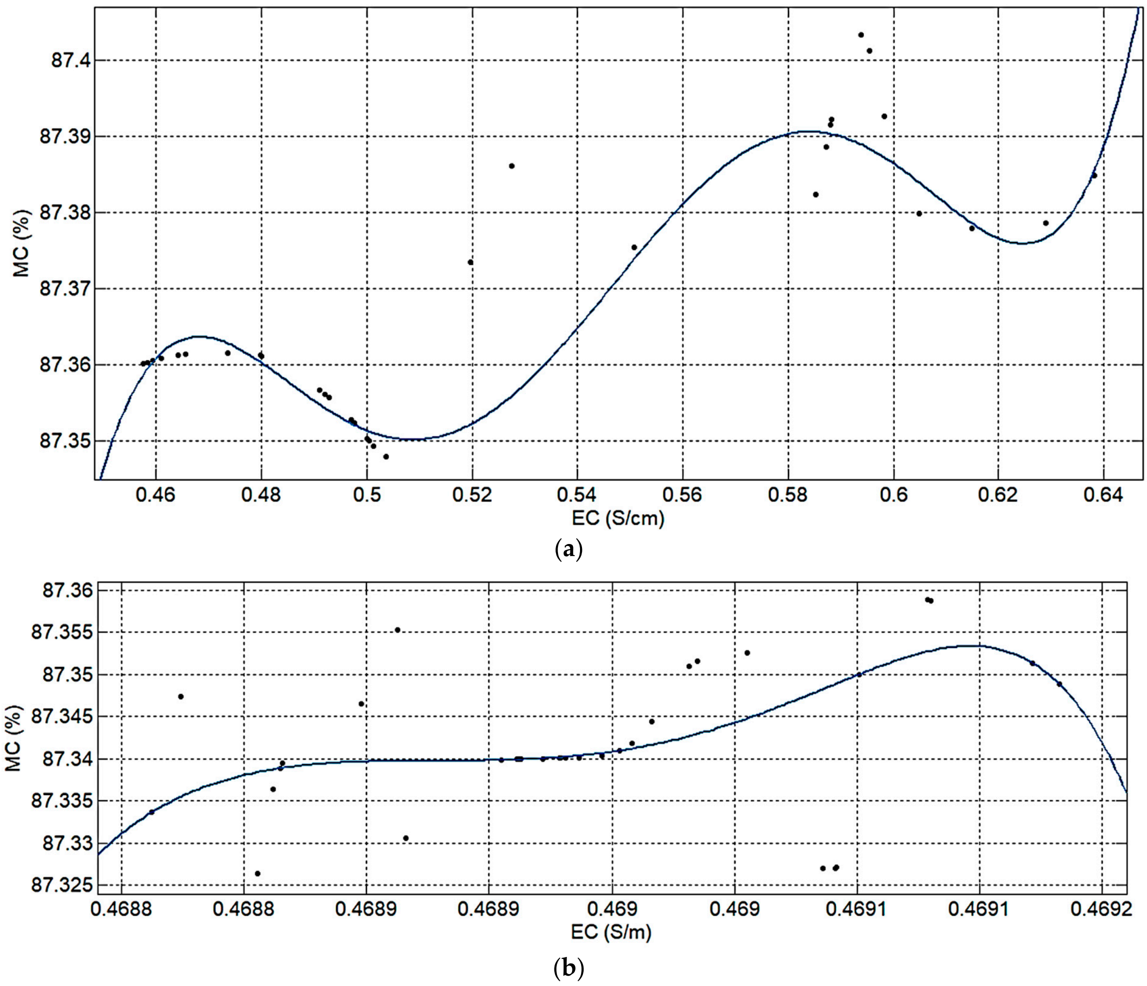


Figure 5. The predicted moisture content (MC) vs. electrical conductivity (EC) curves of pasteurized (**a**) and raw milk (**b**).

3.4. Effect of the Pasteurization Method on the Milk's Electrical Conductivity and Moisture Content

Table 3 illustrates the mean values of the EC and MC of pasteurized milk (after pasteurization) by NP, CP, and raw milk at laboratory temperature. The results reveal that NP's EC of pasteurized milk was significantly ($p < 0.05$) lower than that of the CP and raw milk by 15.44, and 11.30%, respectively. Hwang et al. [26] stated that the milk EC reached 0.505 and 0.806 S/m for raw milk at 5 and 20 °C temperatures, respectively. A previous study [31] revealed that the electric conductivity of raw milk reached 5.39 mS/cm (0.539 S/m). It was reported that the EC of an evaporated milk sample by ohmic heating (MEF) ranged between 0.41 and 1.89 S/m [32]. The differences between MC treatments were insignificant ($p > 0.05$). Also, a report [33] stated that the MC of raw cow milk was 87.392%.

Table 3. Electric conductivity and moisture content of pasteurized milk samples at laboratory temperature compared to raw milk.

Sample Type	EC (S/m)	MC (%)
NP *	0.416 ± 0.003^{a}	87.37 ± 2.01^{a}
CP	0.492 ± 0.001^{c}	87.39 ± 5.23^{a}
Raw milk	0.469 ± 0.005^{b}	87.32 ± 3.28^{a}

* NP: non-thermal pasteurization, CP: conventional pasteurization, EC: electric conductivity, MC: moisture content. Different letters in the rows refer to significant differences at 0.05.

There are also recent studies on the effects of electrical-based non-thermal pasteurization on the EC of other foods. For example, researchers applied electrical field-induced beef tenderization and observed an increase in EC [34]. The authors explained that the observed rise in EC could be linked to electricity-induced changes in cells' permeability and drip loss, allowing ions to move more freely and increase current flow. Similarly, in non-thermal milk pasteurization based on a moderate electric field, which is explored in the present study, electricity could alter electrical conductivity by affecting the permeability of milk components, possible electricity-induced protein denaturation, or component precipitation, promoting ion transport and potentially influencing the milk's physical properties. The above hypothesis needs further verifications in future "mechanism-focused studies".

4. Limitations

While the present study demonstrated the effectiveness of ANN applications in raw and pasteurized milk with potential contributions to sustainable development goals (e.g., enhancing food security, process innovation, and sustainable manufacturing), it also helped identify some of ANN's limitations. An ANN integrated with machine learning can be a valuable alternative to regression for milk data or design and control space data interpolations. Still, it requires careful evaluation due to potential overfitting. An ANN is valid for the regression of model parameters in manufacturing digital twin data adjustments, but it cannot prove root causes mathematically, making it unsuitable in regulatory environments. High data amounts are required, and hybrid models with isothermal ANNs can circumvent this but still require mechanistic models. Applications based on EC and MC are the most efficient. Standard operation mode data may not provide the necessary information for training ANNs, and relying on validated mechanistic models is often used with prejudice in industry. Standard control methods can fulfill computationally demanding tasks in process control, leading to economical business case-derived decisions. However, the benefits and effort of machine learning must be evaluated individually at each application and project step, as they are not general problem solvers and require expert knowledge for result evaluation. Also, it should be mentioned that the present study indicated the possibility of applying AI integrated with ANN for MC and EC of milk samples, while larger data sizes are required to be considered in future consecutive studies for practical contribution to industrial revolution.

5. Conclusions

The findings illustrate the successful application of artificial neural network (ANN) modeling in predicting EC and MC in raw and pasteurized milk samples, with the electric field strength and mass flow rate identified as key influencing factors. According to the observations, non-thermal pasteurization significantly reduced EC compared to conventional pasteurization and raw milk, while differences in MC between treatments were insignificant. ANN models effectively predicted EC and MC with minimal error, underscoring the potential for integrating AI into the real-time monitoring and optimization of non-thermal processing. This approach can be assessed for possible extension beyond EC and MC, including other quality indicators such as microbial activity, total soluble solids, and fraud detection. Future research should further focus on using deep machine learning to enhance the estimation of milk's quality attributes, building a broader database by examining milk from diverse sources. This work signals a shift toward more sustainable, efficient, and data-driven approaches in food production to achieve a more sustainable production based on emerging non-thermal processing technologies. Future studies might use adaptive neuro-fuzzy inference systems (ANFISs) to predict raw and pasteurized milk's EC, MC, and other properties. Moreover, ANNs can predict raw and non-thermal pasteurized milk fraud—practical applications. For practical applications, the prediction of EC and MC using ANNs can be used in food industries to determine EC and MC to detect milk fraud (e.g., adding water).

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