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Research Article

Predicting heat transfer performance of Fe_3O_4-Cu/water hybrid nanofluid under constant magnetic field using ANN

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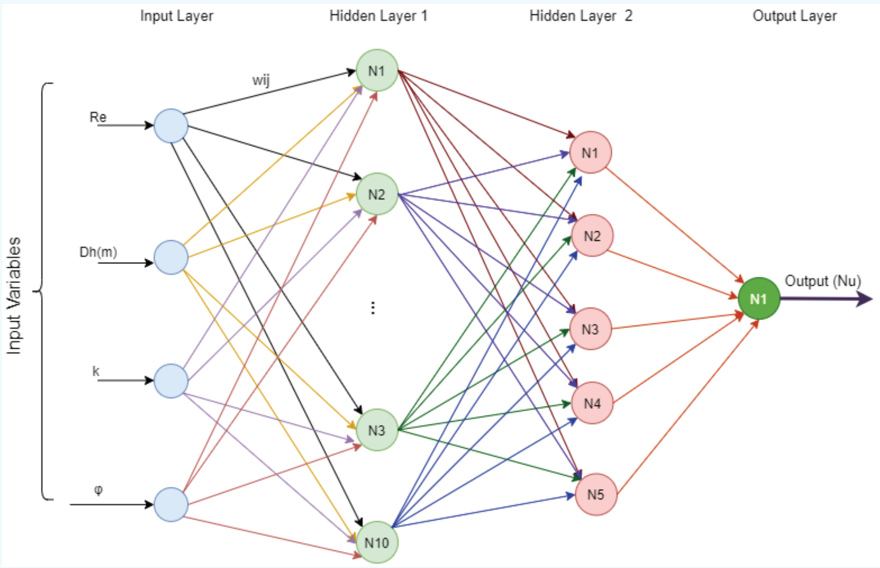
GRAPHICAL ABSTRACT



ABSTRACT

In this study, the experimental results using mono (Fe_3O_4/water and Cu/water) and hybrid (Fe_3O_4-Cu/water) type nanofluid with nanoparticle volume concentrations of ($0 \leq \varphi \leq 0.02$) under laminar flow conditions ($994 \leq Re \leq 2337$) were compared with the results obtained by ANN. While the Reynolds number (Re), hydraulic diameter (D_h), thermal conductivity (k) of

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working fluid, and volume concentration of the nanoparticles (φ) were selected as input layers, the Nusselt number (*Nu*) were considered as output layers. The %75 of the findings obtained from experiments were used to train Artificial Neural Network (*ANN*). The estimated data by *ANN* is in perfect agreement with the experimental data. The success of *ANN* was determined by comparing it with *SVM*, Dec Tree, and their variations. Mean square error (*MSE*), root mean square error (*RMSE*), R-sq (R^2), and mean absolute error (*MEA*) were considered in evaluating the results obtained. According to findings, *MAE* 0.00088274, *MSE* 1.4106e^{-06}, *RMSE* 0.0011877 and R^2 1.00 were measured. These findings show that the use of *ANN* is a feasible way to predict the convective heat transfer performance of hybrid nanofluid under a magnetic field (*MF*).

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INTRODUCTION

In the last decades, heat transfer enhancement studies have been the priority for many researchers to increase the energy efficiency of the systems. To enhance heat transfer, many applications have been utilized [1]. Nanofluids have been studied numerously to understand the physical mechanism behind the heat transfer enhancement phenomena [2]. One of the novel methods is to combine multiple solutions. Using nanofluids consisting of ferro nanoparticles and a MF further enhances convective heat transfer due to Lorentz and Kelvin force mechanisms which are associated with MF [3–5]. Tekir et al. [6] did an experimental investigation to determine the alternating MF effect on convective heat transfer of nanofluid under laminar flow regime (1120≤Re≤2120) using the alternating MF consisting of three different wave types (sinus, triangle, and square). The square wave type with a lower frequency shows better behavior. Also, priority of use of non-uniform MF has been reported by different author [7]. Zhang and Zhang [8] numerically studied to examine the behaviur of ferronanofluid flowing inside square channel under MF effect and turbulent regime. While the MF has been performed between 0.01T and 0.09T, the nanofluid volumetric concentration has been 0.01≤φ≤0.05. It was observed that the highest MF shows better enhancement by 44% compared to non-MF condition. In recent years, researchers have widely discussed the time and cost of the experiments. Therefore, a new method to decrease the need for experiments has been researched. For this purpose, attention has been attracted to the use of ANN since it can reduce the number of experiments and gain time to more focus on research subjects. In literature, studies on obtaining the thermophysical properties of nanofluids are on the frontline [9, 10]. Whereas, studies on obtaining the heat transfer performance of the nanofluids are limited [11]. Esfe et al. [12] studied to predict the heat transfer performance of MgO/water nanofluid under different Re (1000≤Re≤15000). The prediction method was selected as ANN. As a result of ANN, the use of 0.5 vol.% nanofluid presents optimum behavior in all Re. Zolghadri et al. [13] experimentally studied shell-tube heat exchanger using alumina nanofluid (0.02≤φ≤0.04) under laminar flow regime (150≤Re≤350) at different temperature ratings of working fluid (70 K-90 K). After the experiments, the ANN was developed to predict and compare with experimental results. As a result of ANN, it was observed that the mean square model shows 0.23% deviation compared to experimental results. Esfe [14] experimentally investigated to determine hydrothermal characteristics of Ag/water nanofluid flow inside double-pipe heat exchanger under turbulent flow regime (2500≤Re≤30000). After experiments, the ANN method was applied to predict and elucidate its performance. The ANN results were compared with experimental Nu and the average Darcy friction factor (f). It was reached that 99.76% and 99.54% agreements, in Nu and f respectively, were achieved between experimental results and ANN results. Baghban et al. [15] did an experimental and ANN study to estimate convective heat transfer performance of working fluid utilized in the experiments. The results obtained from experiments and ANN show better agreement with each other, so the prediction method can be used in engineering applications. On the other hand, the use of hybrid nanofluid, which shows better thermal performance than mono type nanofluid [16], can be predict by using ANN. This type of study can be really cheaper and easy reaching the data needed. Vaferi et al. [17] investigated to predict experimental results with the highest convergence rate using ANN. The hydrothermal characteristics of nanoparticles (Al_2O_3 and CuO) were experimentally determined and estimated using ANN in terms of convective heat transfer rate. The findings show that the use of ANN is good preferring in determining nanofluid hydrothermal characteristics study.

As seen from the literature, the comparison of ANN methods hasn't been utilized in heat transfer enhancement applications in which hybrid nanofluids or magnetic field effect are involved. In this study, the thermal performance of Fe_3O_4-Cu/water hybrid nanofluid, and Fe_3O_4/water, Cu/water mono nanofluids obtained by experimental dataset

[18] has been compared with the results of developed ANN methods. ANN is used to estimate the heat transfer performance of the hybrid nanofluid in the proposed model. The performance of this model was compared with that of several other variants of ANN (see Table 2).

EXPERIMENTAL SETUP

In this study, the effect of hybrid nanofluid (Fe_3O_4-Cu/water) in the circular tube was experimentally investigated before conducting *ANN*. The schematic and real photography of the experimental setup can be seen in Figure 1. The circular tube of D_h=16 mm is the length of 1500 *mm*.

Table 1. Thermophysical properties of nanoparticles and fluids at 293K [18].

Materials	DW	Fe_3O_4	Cu
Density (kg/m³)	998	5172	8940
C_p (J/kg.K)	4182	663	390
Conductivity (W/m.K)	0,598	9,6	400

To provide *B*=0.3T *MF* at 1.2≤*X*≤1.3 *m* of the test tube, the coil wrapped on an iron bar was utilized. The coil's

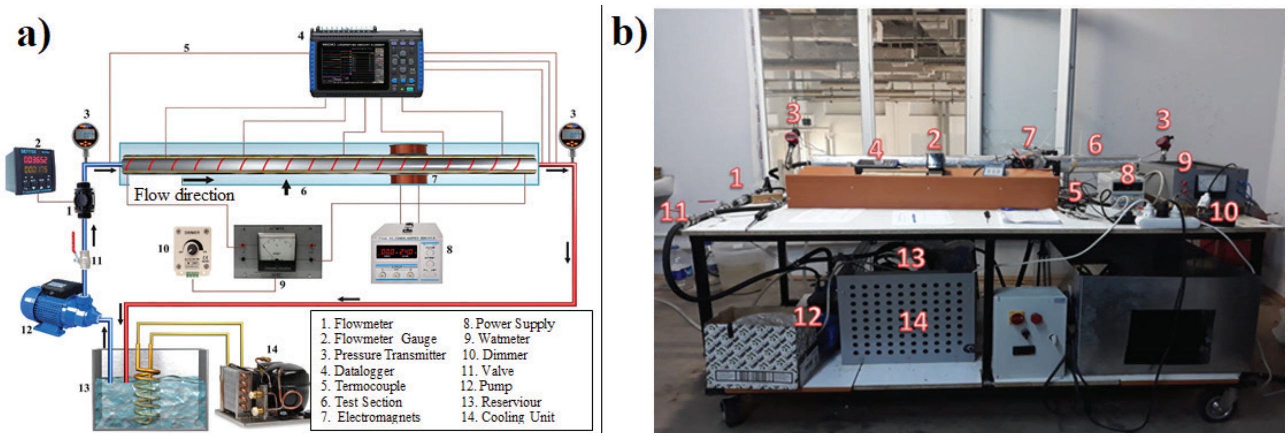

Figure1. a) Schematic view and b) photograph of the experimental setup.

The working fluid was firstly reached to flowmeter by centrifugal pump (P=1.5 *kW*). The volumetric flow rate was changed by flowmeter and passed to the test section. The test section was subjected to constant heat flux by a heater cable having a power of 50 *W/m*. The temperature changes on the tube were monitored by 5 thermo-couples. While 1 thermo-couple was placed at inlet, 3 of them were placed at outlet section. The data taken from the experimental setup by thermo-couples were transferred to datalogger at 1-sec. interval. The pressure drop was examined by pressure transducers placed inlet and outlet section of the test section. To minimize heat loss, glass wool was covered on the tube. By the way, to provide constant inlet temperature, the heat exchanger was used at the entrance of the test section. Also, all the tests were repeated three times and average results were taken into consideration.

The nanoparticles (Fe_3O_4 and Cu) were purchased from Nanografi Company in Turkey. The average size of nanoparticles is 20 *nm*. The SEM images of nanoparticles and XRD analysis of Fe_3O_4 are shown in Figure 2. Also, the thermo-physical properties of nanoparticles can be seen in Table 1.

resistance is 28 *Ω* and it was wrapped 3000 times around the iron bar. *MF* is measured by a gaussmeter. The *MF* application position and the gaussmeter can be seen in Figure 3.

The uncertainties due to experimental tools and measurement error are important parameters in evaluating findings from experiments. In the present study, the uncertainties were determined using the below formulation [19]:

$$\delta U=\sqrt{\left(\frac{\partial U}{\partial W_1}\delta W_1\right)^2+\left(\frac{\partial U}{\partial W_2}\delta W_2\right)^2+\ldots+\left(\frac{\partial U}{\partial W_n}\delta W_n\right)^2} \quad (1)$$

The uncertainties calculated using the formulation above-mentioned are found as 2%, 0.4%, 0.9%, and 0.9% for thermocouple, pressure transducers, flow meter, and heater, respectively. Also, it was determined as 0.61%, 1.4%, 1.20%, and 1.02% for *h, Nu, Re, f*, respectively.

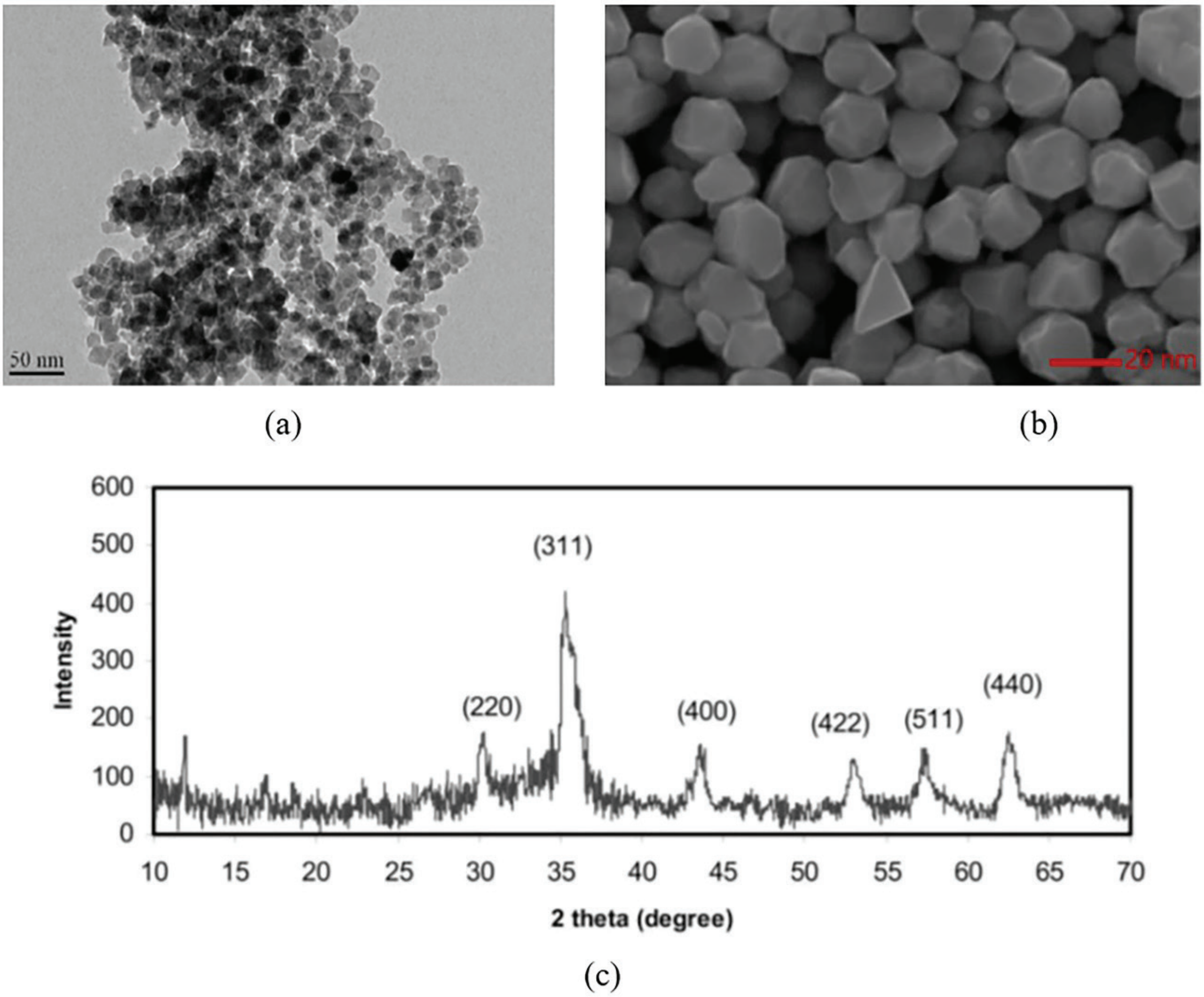

Figure 2. SEM images of (a) Fe_3O_4 (b) Cu, and (c) XRD.

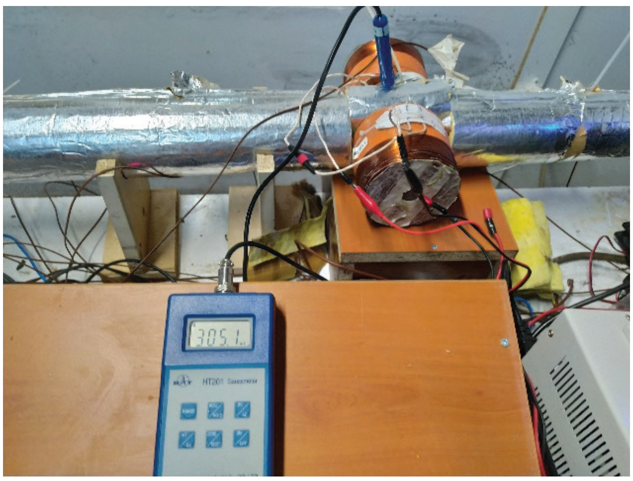

Figure 3. *MF* location and gaussmeter.

ARTIFICIAL NEURAL NETWORK (ANN)

ANN is mathematical function using neurons to assist complex or non-linear engineering problems [20]. The neurons work as a system of the human brain. In this study, MATLAB program was used for ANN. The ANN script and program used are given below.

Some of the commands used are summarized here. “newfit” was used to create a new model (network), “train” was used to train the created model, and “sim” was used to simulate. See [21–24] for more information.

The ANN’s neurons make a relationship between input layers and training values. By using this neural information obtained from input and training layers, the target data is estimated. It incorporates the philosophy of reducing the sum of squared errors between the target data estimated by ANN and output obtained from the training data and

```
%% Load data
 data=load('data.mat');
 %%
%Train data
traininputs=data.traininput';
traintarget=data.trainoutput';
%Test data
testinputs=data.testinput';
testtarget=data.testoutput_Real';
%% Creat Network
layers=[20 10 5];
transferfun={'tansig','purelin','purelin'};
trainFcn='trainbr';
ag=newfit(traininputs,traintarget,layers,transferfun,trainFcn);
enetwork=train(ag,traininputs,traintarget);
%% simulation
sinavtr=sim(enetwork,traininputs);
hatatr=sinavtr-traintarget;
sinavts=sim(enetwork,testinputs);
hatats=sinavts-testtarget;
%% Graph
figure;
subplot(2,2,[1 2])
```

constantly updating the weights connecting the neurons in the associative layers to bring them closer to the optimum [25, 26]. The training case is to arrange the parameters of ANN such as connection weights. The training process should not be contained less than 75% of the total results to provide a better training process for ANN. The training process is done to minimize the deviation rate in the estimating process of ANN. After the training process, the target data, which is estimated by ANN, was predicted. While the Re, Dh, k, and φ are selected as input layers, the Nu is selected as output layer. The input layer of the model contains 4 neurons for 4 inputs, 10 neurons for the first hidden layer, and 5 neurons for the second hidden layer. The experimental results were compared with the proposed method, and it was found that the results of the proposed methods were compatible with the experimental results. The proposed structure of the created ANN model is shown in Figure 4.

The performance of the proposed correlation was evaluated using the statistical analysis of mean square error (MSE), root mean square error (RMSE), R-sq (R2), and mean absolute error (MAE) for both the prediction dataset and the real experimental dataset. As indicated in Figure 6, these metric calculations of MAE confirm the accuracy of the correlation over the experimental dataset evaluated

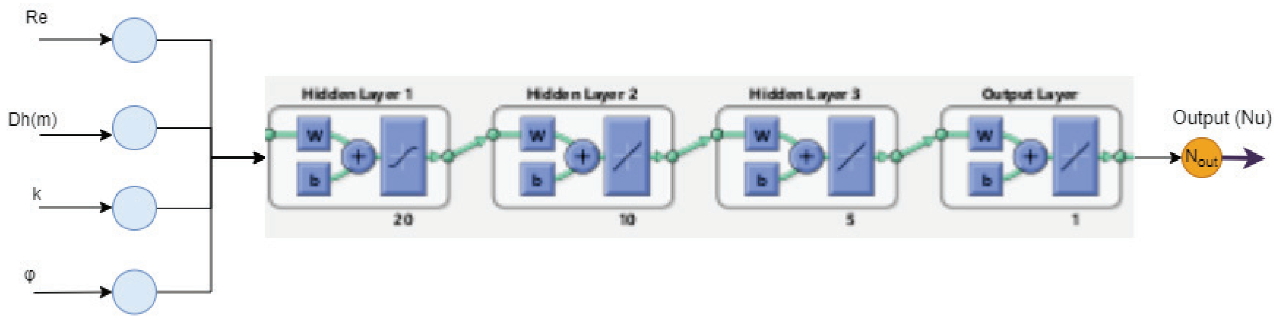

Figure 4. Configuration system for multi-layer ANN.

using ANN. The above-mentioned parameters can be calculated using Eq. (2)-(5).

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2 \quad (2)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2} \quad (3)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}| \quad (4)$$

$$R^2 = 1 - \frac{\Sigma(y_i - \hat{y})^2}{\Sigma(y_i - \bar{y})^2} \quad (5)$$

where N is the number of data, $\bar{y}$ is the average of the predicted, y_i and $\hat{y}$ are the predicted and actual values, respectively. Let us briefly explain these calculations.

Mean Square Error (MSE)

A mean squared error [27] is a statistical method for determining the closeness of a regression line to a set of data points. The MSE is a metric that quantifies the performance of an estimator in a machine learning model.

Root Mean Square Error (RMSE)

Calculating the difference between predicted and actual values is a common application of a quadratic metric known as Root Mean Square Error (RMSE) [28][29]. This metric determines how significant an error is in a machine learning model. The Root Mean Square Error (RMSE) gives an indication of how well the data fits the optimal line. An RMSE value of 0 means that the model contains no errors. The RMSE has the advantage of penalizing large errors more heavily, which can sometimes lead to a better fit between the two variables. Root Mean Square Error (RMSE) is a statistic that can be used in a variety of mathematical processes to remove absolute values that are not required.

Mean Absolute Error (MAE)

Mean absolute error (MAE) [28, 29] is a statistical measure used to quantify the difference between two continuous variables. MAE refers to the vertical distance averaged between each actual value and the line that provides the closest fit to the data. It is a linear variable that determines the average number of errors in a group of predictions, without considering the direction in which the errors go, with each error contributing the same amount to the mean.

R squared

R^2, also known as the coefficient of determination, measures the proportion of variation in the dependent variable that can be predicted based on the values of the independent variable(s). It is a statistic used in the context of statistical models whose main objective is to test hypotheses based on either the prediction of future events or other relevant information. It is a measure of how well observed outcomes are reproduced by the model, based on the overall rate of variation in the outcomes described by the model. This measure results from the fact that it compares observed outcomes with outcomes described by the model [30–32].

In these experiments, *ANN* was compared to many machine learning algorithms. For all experiments, the dataset was split into 75% for training and the rest for testing. The tests were performed 10 times and all measurements are shown as average values in Table 2 and Figure 5, respectively.

To estimate the *Nu*, a correlation was established using *ANN*, *SVM*, *Dec Tree* regression analysis, and the results are shown in Table 2.

ANN have been developed based on the operating principle of the human brain. This structure, based on communication between neurons, has connections between nodes with different weights. They are distributed and parallel information processing architectures consisting of processing components, each with its own memory and coupled by these connections. Using computer programmes, artificial neural networks attempt to mimic the organisation of organic neural networks in the human brain. In general, artificial neural networks consist of three layers: the input layer, the hidden layer and the output layer. Consequently, the input of a neuron within the structure is represented as the output of another neuron within the structure. The transmission of these outputs takes place via connections. The connections are represented by weights, which are numerical numbers placed between neurons. When a neuron i. sends a signal to its neuron j., the weight of the synapse multiplies the signal that i. received. The number resulting from this process represents the total activity of the neuron. After determining the activation value, the neuron's signal transfer functions are used to calculate the output.

SVM is a supervised machine learning method usually used for classification operations, although they are used in both classification and regression analysis. They are based on the idea of finding non-linear bounds by creating a linear boundary in a large, transformed version of the feature space. Specifies that for a non-linearly separable data set containing values from two classes, there are lines separating the classes. The selection of a line that best separates the two classes is done using only a subset of the training samples called support vectors. For problems where the classes cannot be decomposed linearly, SVM uses an implicit transformation of the input variables using the kernel function. Kernel functions allow SVM to separate non-linear separable support vectors using a linear plane.

The decision tree algorithm is one of the classification algorithms used in data mining. A decision tree is a structure used to divide a large collection of data into smaller subsets by applying a set of decision rules. In other words, it is a structure that divides large data sets into very small groups of data sets by applying basic decision levels. When developing a tree structure using a top-down technique, the class labels are specified at the leaf level of the tree and

Table 2. The results of *RMSE*, R^2, *MSE*, and *MAE* for training and testing data using different algorithms.

Algorithms		Training Results	Test Results
Fine Tree	***RMSE***	0.018287	0.046412
	R^2	1.00	0.99
	MSE	0.00033441	0.0021877
	MAE	0.01059	0.034307
Medium Tree	***RMSE***	0.077058	0.10085
	R^2	0.98	0.96
	MSE	0.005938	0.01017
	MAE	0.077421	0.060277
Coarse Tree	***RMSE***	0.16913	0.20281
	R^2	0.90	0.85
	MSE	0.028606	0.038755
	MAE	0.028606	0.15699
Linear SVM	***RMSE***	0.038408	0.039244
	R^2	0.99	0.99
	MSE	0.0014752	0.0015401
	MAE	0.035949	0.036608
Quadratic SVM	***RMSE***	0.036437	0.037107
	R^2	1.00	1.00
	MSE	0.0013277	0.0013769
	MAE	0.033225	0.033751
Cubic SVM	***RMSE***	0.037426	0.038223
	R^2	0.99	0.99
	MSE	0.0014007	0.001461
	MAE	0.032707	0.033455
Fine Gaussian SVM	***RMSE***	0.044602	0.053093
	R^2	0.99	0.99
	MSE	0.0019894	0.0028189
	MAE	0.041686	0.044914
Medium Gaussian SVM	***RMSE***	0.03272	0.036459
	R^2	1.00	1.00
	MSE	0.0010706	0.0013293
	MAE	0.028105	0.030749
Coarse Gaussian SVM	***RMSE***	0.041518	0.047402
	R^2	0.99	0.99
	MSE	0.0017238	0.0022469
	MAE	0.036984	0.041611
ANN	***RMSE***	***0.00099246***	***0.0011877***
	R^2	***1.00***	***1.00***
	MSE	***9.85E-03***	***1.41E-02***
	MAE	***0.00078213***	***0.00088274***

the feature operations are expressed by the branches that extend from these leaves to the top of the tree.

The correlation was proposed to predict the *Nu* of target data in terms of *Re*, D_h, k, and φ by using an optimized neural network with a varying number of neurons using two hidden layers in a selected *ANN* structure. The *MLP*-based *ANN* analysis was selected to be suitable to predict the *Nu* of the target data. The graphical representations of the regression results obtained from *Dec Tree, SVM,* and their variants with algorithms at different k and φ are shown in Figure 5 to demonstrate the agreement between experimental and correlation results. It can be seen in all the graphs that the experimental data and the correlation results are close to each other. This agreement shows that the proposed equations could predict the *Nu* accurately.

ANALYSIS OF PROPOSED METHODS

To build an optimum ANN model, training, testing, and all data were used to analyze the performance of the ANN. The results in Table 2 show that ANN has the lowest MSE and suitable correlation coefficients for data validation making it the best choice. The comparison between observed and expected values for Nu is shown in Figure 6. The results of the training, test, and overall data sets are shown in this figure. By the way, each data set contains regression coefficients. When the regression coefficients are close to 1, it indicates a strong association between the

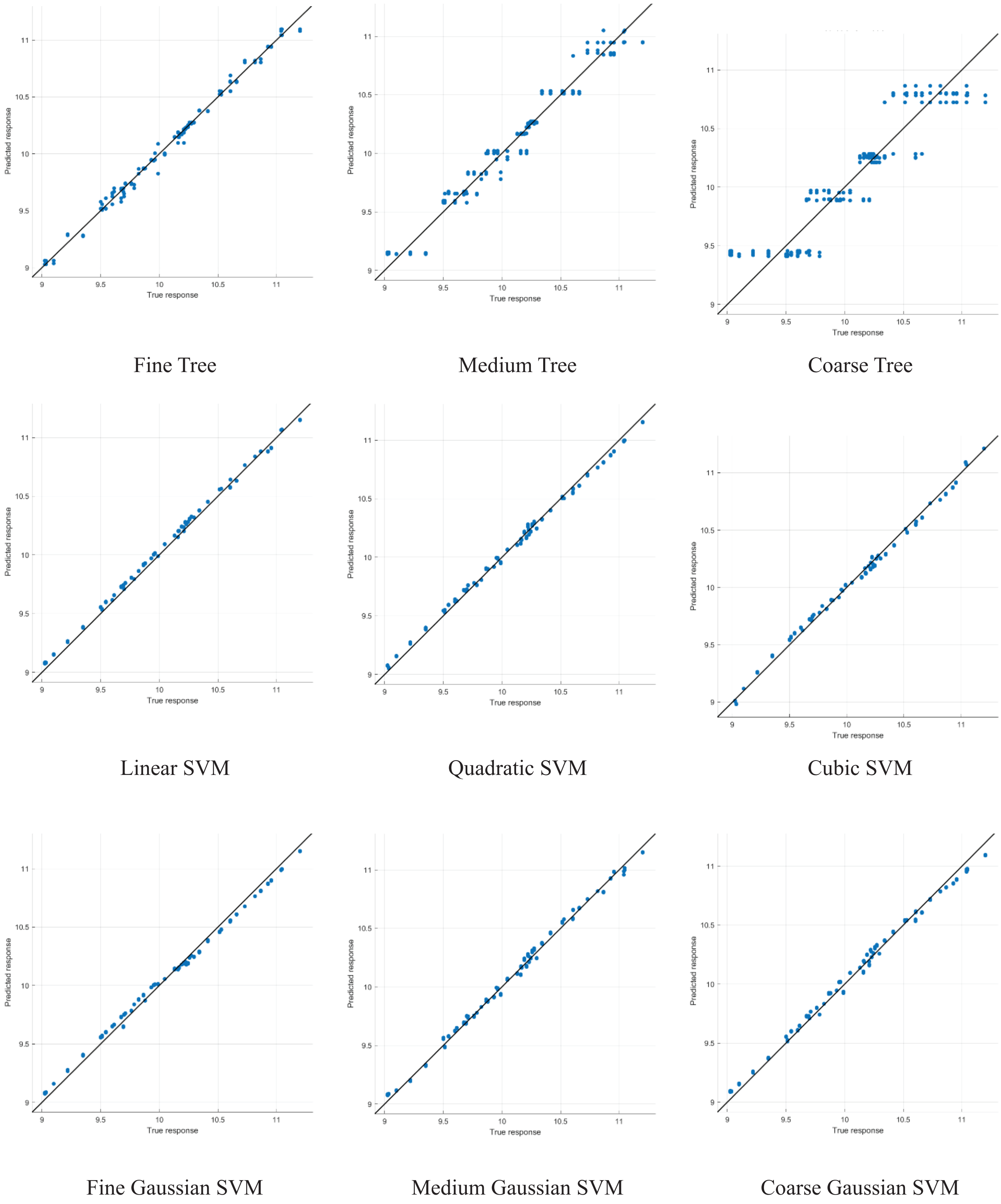

Figure 5. Predicted vs. actual plot of test data for different machine learning algorithms.

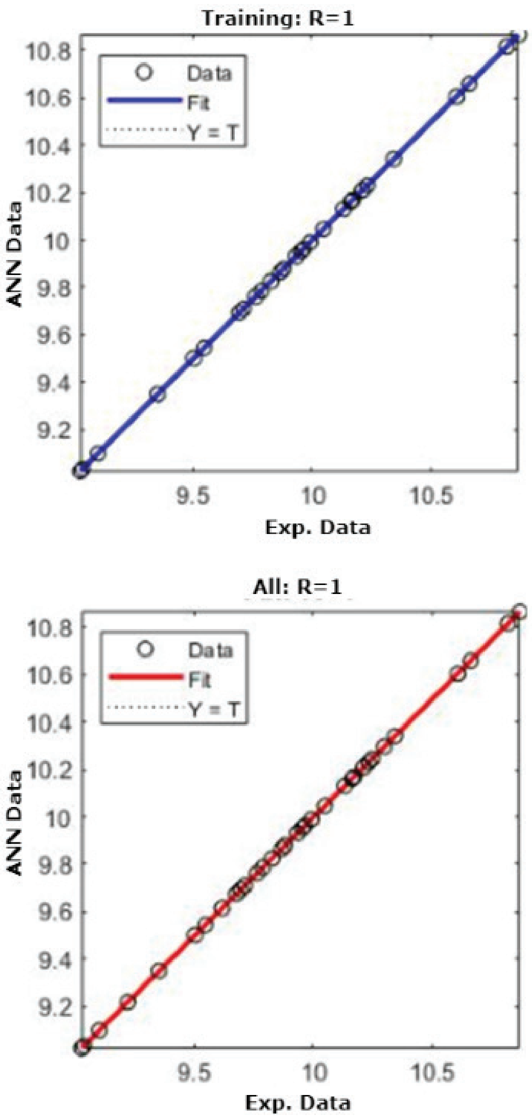

Figure 6. Regression of proposed ANN.

experimental and the ANN estimated data. As you can see, the regression coefficients are above 1 for all data sets included in the present model.

Figure 7 illustrates the performance of the training data including the results of the test and the best data. The MSE values decrease as the number of periods increases and become constant. This shows that the ANN was well trained. The consistent pattern of MSE values with an increasing number of periods shows the overfitting nature of the model. At 321 epochs, the MSE of the validation dataset was $5.874e^{-13}$.

In Figure 8, the red lines represent ANN predicted data, whereas the blue lines indicate actual data. The error histogram represents the differences between the target and predicted values during the training of the feed-forward neural network. These error counts may be negative to indicate how many the expected values deviate from the target values.

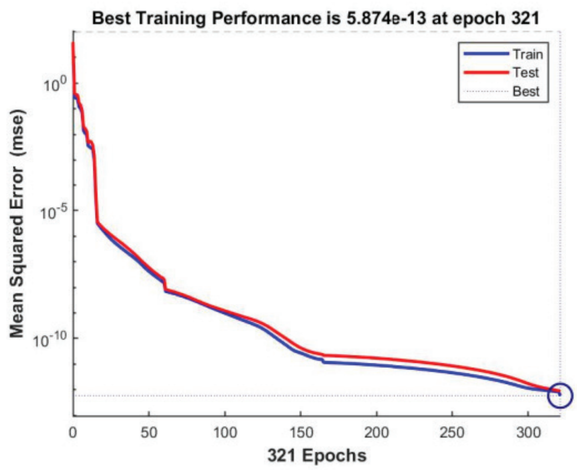

Figure 7. Training performance and state.

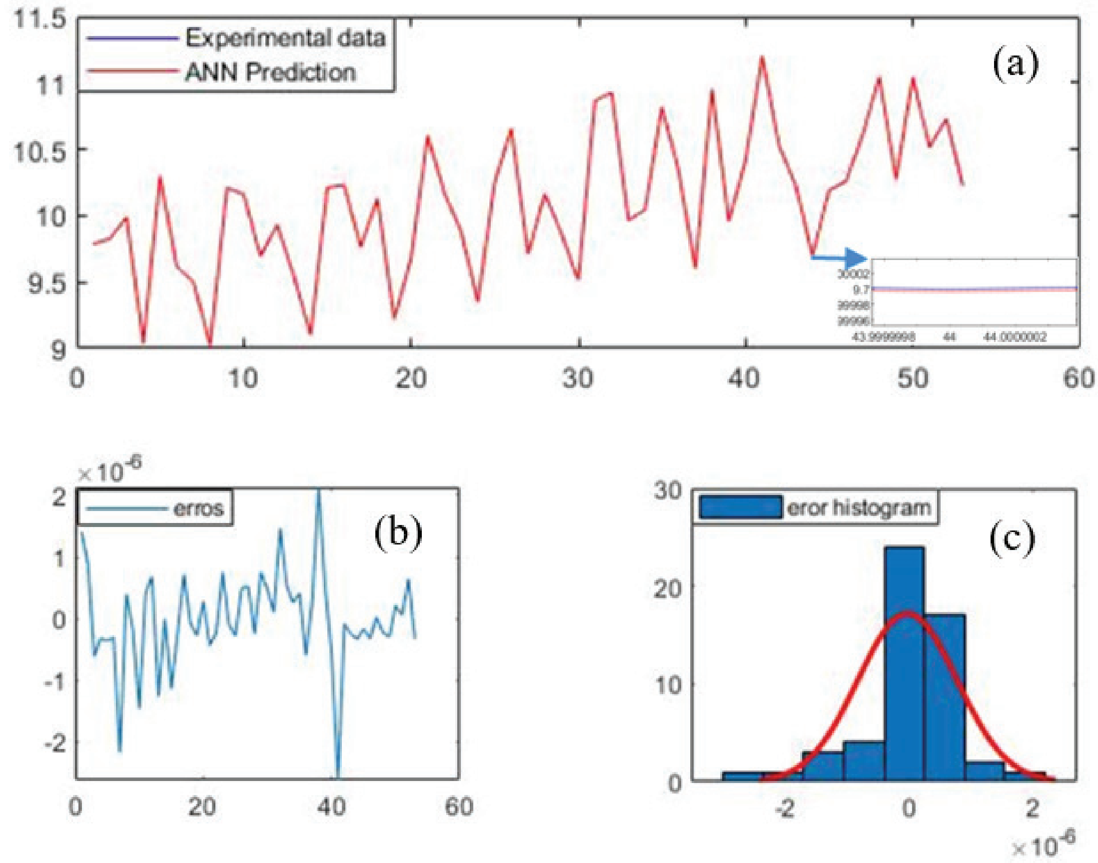

Figure 8. Graphical representation of a) predicted ANN results, b) errors, and c) error histogram for test data.

As the error range (maximum negative error to maximum positive error) approaches the normal distribution and the zero point of the Gaussian curve, the error value decreases. The histogram can be used to identify outliers. It can be seen in Figure 8 that the largest error values are between -1 and 1, showing that overestimates and underestimates are acceptable. Moreover, it follows a normal distribution pattern around the standard deviation of the error and the zero point of the error histogram, resulting in low error values close to zero for the sum of the overestimated positive and underestimated negative values. The result is that the data points to places where the fit is much worse than the fit for most of the data, which is called an outlier. As seen in this case, the ANN technique works effectively with the data experimentally obtained using Fe_3O_4-Cu/water hybrid nanofluid.

CONCLUSIONS

Heat transfer in a circular tube is an important research area in the gas and oil industry. This study presents a relationship among experimental findings, *ANN*, and *SVM*. The results of the proposed *ANN* model are in complete agreement with the experimental data. *SVM, Dec Tree*, and their derivatives have been compared to each other to see how *ANN* works well. *MSE*, *RMSE*, R^2, and *MEA* were used to check the results. From the test data for these metrics, *MAE* 0.00088274, *MSE* 1.4106e^{-06}, *RMSE* 0.0011877, and R^2 1.00 were obtained.

The performance of the proposed model was compared with that of several other variants of *ANN*. The results of the model proved to be better than the results of the other *ANN* variants. The artificial neural network approach offers both advantages and disadvantages. Advantages: Neural networks can gain knowledge from previous experiences. After training, they can react quickly to a new set of data. Artificially created neural networks do not require a mathematical model. Artificial neural networks can quickly and intelligently discover unexpected relationships in data. Conventional computer systems are very susceptible to potential system errors. It can adapt to solve a particular problem if its properties, such as the weighting coefficient and network topology, vary. Not all networks are linear. Therefore, they can solve complicated problems with greater precision than linear methods. Non-linear behaviour can be perceived, detected and sensed. However, these problems and behaviours are difficult to capture quantitatively.

Disadvantage: It is unclear what is inside the system. In certain cases, it can be difficult to assess the performance of networks. When they solve a problem, they may not find a particularly acceptable answer or they may make mistakes. Since there is no function to train the network, this is the case. In other cases, even if the function is discovered, the data is insufficient. Training them is very time-consuming and costly. It can be a challenge to adapt it to different systems. The quality and capacity of the network is related to its usage rate. Even doubling the number of nodes can lead to a much longer duration.

For future scope, ANN model can be developed for different concentrations of the hybrid nanofluids to determine the optimum concentration. Also, the studies can be conducted for nanofluids with different nanoparticles and different shapes.

NOMENCLATURE

ANN	Artificial neural network
D	Diameter *(m)*
h	Average convective heat transfer coefficient (W/m^2·˚C)
k	Thermal conductivity (W/m˚C)
L	Length of the pipe (m)
μ	Dynamic viscosity (kg/m.s)
MSE	Mean square error
Nu	Average Nusselt number
q˝	Heat flux (W/m^2)
Re	Reynolds number
RMSE	Root mean square error
ρ	Density (kg/m^3)
T	Magnetic field magnitude (Tesla)

DECLARATIONS

Conflict of interest on behalf of all authors, the corresponding author states that there is no conflict of interest. The authors declare that they have no interest in competition or controversy.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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