Heat and Fluid Flow Analysis and ANN-Based Prediction of a Novel Spring Corrugated Tape

Basma Souayeh 1,2,*, Suvanjan Bhattacharyya 3, Najib Hdhiri 2 and Mir Waqas Alam 1

Abstract: A circular tube fitted with novel corrugated spring tape inserts has been investigated. Air was used as the working fluid. A thorough literature review has been done and this geometry has not been studied previously, neither experimentally nor theoretically. A novel experimental investigation of this enhanced geometry can, therefore, be treated as a new substantial contribution in the open literature. Three different spring ratio and depth ratio has been used in this study. Increase in thermal energy transport coefficient is noticed with increase in depth ratio. Corrugated spring tape shows promising results towards heat transfer enhancement. This geometry performs significantly better (60% to 75% increase in heat duty at constant pumping power and 20% to 31% reduction in pumping power at constant heat duty) than simple spring tape. This paper also presented a statistical analysis of the heat transfer and fluid flow by developing an artificial neural network (ANN)-based machine learning (ML) model. The model is evaluated to have an accuracy of 98.00% on unknown test data. These models will help the researchers working in heat transfer enhancement-based experiments to understand and predict the output. As a result, the time and cost of the experiments will reduce. The results of this investigation can be used in designing heat exchangers.

Keywords: heat transfer; tape inserts; corrugation; heat exchanger; machine learning; prediction

1. Introduction

Energy is the essence of today’s world. The entire world is run by the force of energy. The advancement and innovations in the last two decades make life easier as never before. With the rise of technology usage, the need for energy is also rising. As per the report of VGB Powertech [1], the energy consumption has increased by 66% in the past two decades. The drastic increase in the demand for energy enhanced the consumption of non-renewable fuel, which led to an increase in the pollution as well as cost of fuel. This has caused researchers around the world to concentrate on energy conservation. One of the easiest ways of energy conservation is to increase the efficiencies of various equipment by employing the various techniques (passive and active) to increase the efficacy and reduce the losses.

A heat exchanger (HE) is a device which can exchange the energy between multiple fluids by direct or indirect contact. The fluids at different temperature transfer the energy between them, and hence, the energy exchange takes place. To further increase the heat transfer rate between the fluids, some additional attachment in the form of swirl generators [2–10], surface roughness [11–17] and other modifications [18–22] in the design of the heat exchangers are required. The purpose of using such a modification is to enhance the
turbulence in the flow field, which leads to a disturbance in the boundary layer, promotion of secondary flow and better mixing of hot elements with cold field elements [5,23–26]. These modifications also reduce the size of heat exchangers for the same heat exchange capacity. Moreover, the use of materials with higher thermal conductivity, such as steel, copper, brass, aluminum, etc., also promotes the heat transfer rate.

Rashidi et al. [27] reviewed various articles related to enhanced techniques which employed inserts with nanofluids for heat transfer (HT) enhancement and concluded that combined techniques are more effective over single techniques with a slight increase in the pressure drop (PD). Silva and Salviano [28] reported on the solar water heater with longitudinal vortex generator to enhance the thermal performance. They found that at a 30° angle of attack, the thermal enhancement factor is highest while the maximum heat transfer was reported with 45°. Gorjai and Shahidian [29] experimentally explored the thermal enhancement in a tube fitted with twisted tapes and nanofluid and reported an increase in the heat transfer rate as well as Darcy friction inside the tube. Dadvand et al. [30] employed a flexible beam kind of vortex generator in the downstream of the fluid domain having a cylindrical obstruction and reported an approximately 18% increase in the Nusselt number (Nu), while a 42% decrease in the Darcy friction was reported. The overall thermal performance was also enhanced. Arulprakashajothi et al. [31] conducted experiments in the transitional flow regime with conical inserts of different twist ratios fitted inside a cylindrical tube and found that conical strip with a twist ratio of 2 introduced more swirls when compared with other twist ratio inserts. Gnanavel et al. [32] investigated the thermal performance of a double pipe heat exchanger fitted with rectangular cut twisted tape inserts with different nanofluid flowing through it and reported an enhancement in the thermal performance of the heat exchanger with an increase in the flow velocity. In another numerical investigation by Gnanavel et al. [33], a similar kind of study was done with circular fin inserts. Keklikcioglu et al. [34] performed experiments with small length spring tapes coiled conically and welded to a wire fitted inside a cylindrical duct in which an ethylene glycol–water mixture flowed. The study was focused on the turbulent flow regime and results revealed that spring tapes introduced more irreversibility inside the fluid domain as a result enhancement in thermal performance. Klemes et al. [35] reviewed the various articles on the heat transfer improvement in heat exchangers and the optimization tools used. They concluded that there is a need to investigate the gap between theoretical approach and practical implementation. Saffarian et al. [36] conducted a numerical investigation on the different flow paths of a flat plate collector and Al2O3 and CuO with water as the working nanofluid. It was found that a wavy and spiral flow path shows maximum enhancement in heat transfer rate while the pressure drop was observed to be maximum with the wavy path. Sheikhholeslami et al. [37] computationally explained the impact of twisted tape within twisted tape for heat transfer augmentation in a cylindrical duct. It is revealed that introduction of secondary tape inside the fluid domain promotes the secondary flow, which result in enhanced entropy in the flow field, and hence, a higher heat transfer rate. Gholami et al. [38] investigated the influence of adding nanofluid and dimples on the free convective heat transfer in a vertical channel. The results obtained from the investigation revealed augmentation in the thermal performance. Li et al. [39] reported on the heat transfer enhancement in a microchannel using a shark-skin bionic modified surface and reported an increase in the thermal performance with an increase in the Reynolds number. Yu et al. [40] investigated the influence of triangular baffles on the thermal performance of the air-based PVT collector and reported an increase in both the outlet temperature as well as heat gain at the outlet of the collector. Chen et al. [41] reported on the factor influencing the heat transfer in ground water heat exchanger and found that an increase in the inlet temperature resulted in a higher heat transfer rate. Giwa et al. [42] studied the influence of thermo-physical properties, temperature and volume concentration of nanoparticle on the thermal and flow behavior and employed difficult machine learning techniques to predict the thermo-phys-
ical properties of nanofluid. Osman et al. [43] conducted experimental assessment to evaluate the convective heat transfer coefficient in transitional flow regimes. Alumina-water was employed as the working fluid. The results obtained from the investigation shows enhancement in Nu and the heat transfer coefficient. Other, similar investigations include [44–48].

A new technique known as machine learning has evolved in recent times which is very helpful in the field of predicting the results with accuracy. It is defined as the method of data analysis that allows the computer to automate the model building. Machine learning is a system that learns from its past data to predict future results and to improve the accuracy using the previous predictions. Machine learning has applications in various industries and is proving its caliber with predicting the results with higher accuracy [49–54]. For example, ML is used to analyze a vast volume of data derived from experiments, field measurements and numerical simulations in the field of fluid mechanics [55,56]. A data analysis based on machine learning not only increases the throughput and precision of the flow interpretation, but also opens up new possibilities, such as flow property prediction using quality data and past experiences [57].

The field of thermal science and engineering has also discussed how machine learning is used to promote data processing. Machine learning will act as a useful tool for predicting the results for the complex heat transfer and fluid flow problem in transitional and turbulent flow regimes. Researchers across the globe have found machine learning to be very useful. Lindqvist et al. [58], Baghban et al. [59], Kwon et al. [60] and Krishnayatra et al. [61] employed a machine learning approach for the development of correlations and predicting the thermal performance for heat exchangers. Baghban et al. [59] employed the machine learning approach for predicting the thermal performance of a coiled heat exchanger. The multilayer perceptron artificial neural network, adaptive neuro-fuzzy inference system and least squares support vector machine model were employed to predict the Nusselt number; they reported that the least squares support vector machine model predicted the results with the best accuracy. Kwon et al. [60] employed a random forest algorithm for predicting the heat transfer coefficient by training and testing the machine learning model and reported that the machine learning model predicts the heat transfer coefficient with a high accuracy, i.e., of 96.6%. Ahmadi et al. [62] employed neural networking for predicting the friction factor in a car radiator while using CuO-water nanofluid as a working agent. Golzar et al. [63] utilized the machine learning-based technique of artificial neural networking and Monte-Carlo sensitivity analysis for predicting the temperature of wastewater. Koroleva et al. [64] applied artificial neural networking for optimizing the rib roughness parameters in an internally roughened circular tube. Abdollahi and Shams [65] engaged the Pareto optimal strategy to optimize the design parameters of a winglet vortex generator to achieve the highest heat transfer enhancement at the lowest pressure drop condition. Sotiui et al. [66] employed machine learning for predicting the turbulent heat fluxes in the Reynolds-averaged Navier-Stokes equations and reported that initial results are appreciable, predicting the heat fluxes in a more complex flow. Karkaba et al. [67] employed large space exploration applications to optimize the design of vortex generators for maximum performance and heat transfer enhancement. Gerdroodbary [68] formulated a model using neural networking to predict the heat flux for magnetohydrodynamic nanofluid flow. Jovic et al. [69] explored the potentiality of adaptive neuro-fuzzy methodology in the predicting of heat transfer enhancement for the mini channel heat sink with higher accuracy. Machine learning techniques, such as fuzzy inference system (FIS), support vector machine (SVM) and artificial neural network (ANN), have found application in predicting thermal properties, such as effective thermal conductivity [70–73], thermal boundary resistance [74], recapitulate entropy [75], specific heat [76], dynamic viscosity [77–80] etc.

A thorough literature review has been done, and this geometry, as shown in Figure 1, has not been studied previously, neither experimentally nor numerically. A novel experimental investigation of this enhanced geometry can, therefore, be treated as a new
substantial contribution in the open literature. This paper also presented a statistical analysis of the heat transfer and fluid flow by developing an artificial neural network (ANN)-based machine learning (ML) model. The model is trained based on the features of experimental data, which provides an estimation of the experimental output based on user-defined input parameters. These models will help the researchers working in heat transfer enhancement-based experiments to understand and predict the output. As a result, the time and cost of the experiments will reduce.

**Figure 1.** (a) Schematic diagram of corrugated spring tape and (b) photographic view of the spring tape.
2. Experimental Setup, Procedure and Data Reduction

Figure 2 shows the pictographic representation of the experimental test rig employed for the experimental assessment. All the important parts have been leveled in Figure 2 for ease of understanding. Air enters the test section with the help of a blower of 7 kW capacity, which then travels through the calming section and enters the test section with uniform distribution. A rotameter with a range of 120 to 540 l/h is employed to measure the mass flow rate of the working fluid. A calibrated U-tube manometer with a measuring range of 0–150 mm of Hg is used to measure the pressure difference in the test section. The measuring range of the major measuring instruments is given in Table 1. The test section is made of a long circular metallic tube with a diameter of 20 mm and a length of 2 m. The outer surface of the test section is properly insulated to ensure no heat loss to the environment. A total of 36 thermocouples are attached to the surface of the test section at seven equidistant stations to measure the surface temperature of the test section. The system takes approximately 2 h to reach a steady-state condition. The steady state is assumed when fluctuations in the reading were negligible. Further details regarding the experimental setup and produce can be found in the authors’ previous work [6,8,10,18–21].

![Figure 2. Schematic diagram of the experimental setup.](image)

Table 1. Measuring range of instruments.

| Instrument       | Range            |
|------------------|------------------|
| DC power supply  | 0–1 500 W        |
| Thermocouples    | −100–350 °C      |
| Rotameter        | (i) 0–120 l/h,   |
|                  | (ii) 0–540 l/h   |
| U-tube Manometer | 0–150 mm Hg      |

Experimental investigation has been done for various configurations of hybrid tapes, as given in Table 2.

Table 2. Various configurations of hybrid tapes.

| Spring ratios (t = P/D) = 1.0, 2.0, and 3.0. |
|---------------------------------------------|
| Depth ratio: (h = e/W) = 0.16, and 0.25.    |
| Channel Diameter (D) = 0.02 m               |
| Length of Channel (L) = 2.00 m              |
| Tube thickness (δ) = 2.00 mm                |
| Reynolds number: (Re) = 10,000 to 71,000.  |
The Nusselt number ($Nu$) can be calculated as follows, where $k$ denotes the thermal conductivity of air [61]:

$$Nu = \frac{hD}{k}$$  \hspace{1cm} (1)

The Darcy friction coefficient, $f$, is further evaluated using the following formula [62,63]:

$$f = \frac{\Delta p}{\frac{1}{2} \rho v^2}$$  \hspace{1cm} (2)

For calculating the $Re_{dh}$, the authors referred to Bhattacharyya et al. [21]:

$$Re_{dh} = \frac{4\times m}{\pi\times D \times \mu}$$  \hspace{1cm} (3)

The thermo-hydraulic performance factor ($\eta$) was calculated as per Bhattacharyya et al. [20], which gave an understanding of the combined performance increases:

$$\eta = \frac{Nu/Nu_0}{(f/f_0)^{0.33}}$$  \hspace{1cm} (4)

3. Results and Discussion

The results obtained for the smooth tube for the Nusselt number and friction factor are validated with the well-established correlations of the Dittus-Boelter correlation [81], the Meyer et al. [82] correlation was used for the Nusselt number and Blasius Correlation [82] for the friction factor.

The Dittus-Boelter correlation [81] expressed the Nusselt number as follows:

$$Nu = 0.023 \times Re_{dh}^{0.8} \times Pr^{0.4}$$  \hspace{1cm} (5)

Range: 3000 < Re < 10^5; 0.7 < Pr < 120

Moreover, Meyer et al. [82] correlated the Nusselt number as follows:

$$Nu = 0.013 \times Re_{dh}^{0.867} \times Pr^{1.1}$$  \hspace{1cm} (6)

Range: 2445 < Re < 410,600; 0.5 < Pr < 276

The correlation for the friction factor given by Blasius [82] is given by:

$$f = \frac{0.3164}{Re_{dh}^{0.5}}$$  \hspace{1cm} (7)

Range: 4000 < Re < 10^5

Figures 3 and 4 show the validation analysis of the present study with previously established and acclaimed correlations for the Nusselt number [81,82] and friction factor [82]. The results obtained for the smooth tube for the Nusselt number and friction factor are in good accordance with previous studies. The Nusselt number deviates only 6% with the Dittus-Boelter correlation and 4% with the Meyer et al. correlation, while the friction factor differs only 4% from the data obtained using the Blasius Correlation.
3.1. Influence on the Nusselt Number

The Nusselt number is a dimensionless parameter which gives the ratio of convection and conductive heat transfer for the fluid. Increase in the value of Nusselt number represents the enhancement in the convective heat transfer.

Figure 5a depicts the relationship of Nusselt number (Nu) and Reynolds number (Re) in a conduit fitted with novel spring corrugated tape for fixed ‘t’ and variable ‘h.’ It is clear from Figure 5a that an increase in Re results in a higher Nu value. Further enhancement in the average Nusselt number is visible when inserts (spring tape) are employed for the investigation. For a given Reynolds number, the value of the Nusselt number is higher for the channel fitted with inserts than that of a smooth channel, which depicts augmentation of heat transfer in the presence of inserts. The maximum enhancement in the Nusselt number is reported for tape, with t = 1.0 and h = 0.25. For a fixed spring ratio ‘t,’ decreasing the value of depth ratio ‘h’ results in a decreased Nusselt number.
Figure 5. The Nusselt number as a function of the Reynolds number: (a) corrugated spring tapes for varying depth ratios while keeping the spring ratio fixed at 1.0, (b) corrugated spring tapes for varying spring ratios while keeping the depth ratio fixed at 0.25 and (c) comparison between all the tested configured parameters.

Figure 5b depicts that the Nusselt number is the function of the Reynolds number in a conduit fitted with novel spring corrugated tape for a fixed ‘h’ and variable ‘t.’ Once again, one can see from Figure 5b that an increase in the Reynolds number results in the higher Nusselt number value. For a given Reynolds number, the value of the Nusselt number is higher for the channel fitted with inserts than that of the smooth channel which
depicts augmentation of heat transfer in the presence of inserts. The maximum enhancement in the Nusselt number is reported for twisted tape with $t = 1.0$ and $h = 0.25$. For a fixed $h = 0.25$, increasing the value of ‘$t$’ results in a decreased Nusselt number.

Figure 5c depicts the relationship of Nusselt number and Reynolds number in a conduit fitted with novel spring corrugated tape for all possible cases. As expected, the maximum enhancement in Nusselt number is reported for spring tape with $t = 1.0$ and $h = 0.25$, while minimum enhancement is noted for spring tape with $t = 2.0$ and $h = 0$.

In conclusion, the grooved surface introduced disturbance in the flow field. The depth of the groove brings in irregular disturbance in the flow field. The grooved surface also disrupts the boundary layer, which results in a higher heat transfer rate. The further enhancement in heat transfer is due to the complexity in the flow field due to the presence of spring tape, which makes the flow more complex by generating secondary flow, recirculation and swirls, thereby enhancing the heat transfer rate.

3.2. Influence on the Friction Factor

The thermal performance of the thermal flow system also depends upon the friction factor. Higher friction factor results in a low thermal performance. Hence, one should consider the frictional losses seriously. The presence of inserts (corrugated spring tape) in the flow field helps in the augmentation of heat transfer, but it will also escalate the friction factor. The resulting pressure drop directly led to enhanced power for the same output. The various causes of pressure drops are enhanced contact between fluid and insert, reduction in dynamic pressure, formation of vortices in the flow field, generation of secondary vortex, etc. Figure 6a–c show that the friction factor ($f$) is the function of Re for different combinations of configuration and parameters. As expected in the turbulent flow regime, the friction factor shows a decreasing trend with an increase in the Re.
Figure 6. Friction factor as a function of the Reynolds number: (a) corrugated spring tapes for varying depth ratios while keeping the spring ratio fixed at 1.0, (b) corrugated spring tapes for varying spring ratios while keeping the depth ratio fixed at 0.25 and (c) comparison between all the tested configured parameters.

Figure 6a presented the plot for the friction factor as a function of Re for corrugated spring tape having a fixed spring ratio ‘t’ and variable depth ratio ‘h.’ Increase in the friction factor is noticed when the spring tape is employed. The highest friction factor has been noticed for t = 1.0 and h = 0.25. For a fixed t = 1.0, decreasing the value of h results in decreased friction factor.

Figure 6b shows the plot for friction factor (f) versus Re for corrugated spring tape having a fixed ‘h’ and variable ‘t.’ Increase in friction factor is noticed when spring tape is employed. The highest friction factor has been noticed for t = 1.0 and h = 0.25. For a fixed h = 0.25, increasing the value of ‘t’ results in a decreased friction factor.

Figure 6c depicts the relationship of friction factor and Reynolds number in a conduit fitted with novel spring corrugated tape for all possible cases. The maximum friction factor is reported for spring tape having t = 1.0 and h = 0.25, while the minimum friction factor is noted for spring tape having t = 2.0 and h = 0.
3.3. Influence on the Thermal Performance Factor

Thermo-hydraulic performance factor symbolized by ‘\( \eta \)’ is represented by Equation (4) and is defined as the ratio of the Nusselt number enhancement (\( \text{Nu}/\text{Nu}_0 \)) and friction factor enhancement (\( \text{f}/\text{f}_0 \)). This factor is the best parameter to evaluate the actual enhancement in the thermal performance of a heat exchanger [20,21]. Figure 7a–c shows the various plot for thermo-hydraulic performance as a function of \( \text{Re} \) for different combinations of parameters.

Figure 7. Thermohydraulic efficiency as a function of Reynolds number: (a) corrugated spring
tapes for varying depth ratios while keeping the spring ratio fixed at 1.0, (b) corrugated spring tapes for varying spring ratios while keeping the depth ratio fixed at 0.25 and (c) comparison between all the tested configured parameters.

Figure 7a shows the plot for the thermal performance factor ($\eta$) as a function of $Re$ for corrugated spring tape with a fixed spring ratio $t$ and variable depth ratio $h$. It is clear from Figure 7a that $\eta$ is above unity for all the cases, which prove the applicability of the present enhanced geometry. It is also clear from Figure 7a that an increase in the Reynolds number results in a diminishing thermal performance factor. The highest $\eta$ is noted for $t = 1.0$ and $h = 0.25$ for all $Re$. A decrease in the value of $h$ results in a decreased value of $\eta$.

Figure 7b shows the thermal performance factor ($\eta$) as a function of $Re$ for corrugated spring tape having fixed ‘h’ and variable ‘t’. The highest $\eta$ is noted for $t = 1.0$ and $h = 0.25$ for all $Re$. Increase in the value of ‘t’ result in decreased value of $\eta$.

Figure 7c depicts the relationship of $\eta$ and Reynolds number in a conduit fitted with novel spring corrugated tape for all possible cases. The highest $\eta$ is noted for $t = 1.0$ and $h = 0.25$ for all $Re$, while the smallest $\eta$ is noted for spring tape with $t = 2.0$ and $h = 0$. The hydro-thermal characteristics depend on fluid properties, flow conditions as well as geometric parameters of the fin geometry.

It is very important to compare the present geometry with the previously published geometry performance. Thus, the thermohydraulic performance of the present configurations is compared with previously studied geometries [83–87] and plotted in the Figure 8. By looking into Figure 8 one can easily understand that the present geometry offered superiority over other studied geometries.

Figure 8. Plot showing the comparability of thermo-hydraulic performance ($\eta$) of the present investigation with previous studies.

4. ANN-Based Heat Transfer Prediction

In this section, the influence of using ANN is described exhaustively. After the experiment, we have received a good amount of data to be considered for future prediction generalization. The generated data were used to train an ANN model which afterward provided us a prediction of new inputs. The user-defined model architecture is discussed in Section 4.1 and the computational environment is described in Section 4.2.
4.1. Model

The initial step of the ANN-based approach is collecting and analyzing the experimental data that were taken to train the model. The architecture of the ANN-based approach for prediction was used. To understand the detailed architecture of the ANN-based model, let us first walk through the workflow of ANN.

4.1.1. Workflow of ANN

At the initial stage, the dataset is divided into three categories: training data, validation data and test data. A “neuron” in ANN is a single computing cell and the model is composed of several neurons. Each neuron has activation functions that are mathematical equations of the weighted sum of the outputs of the previous layer with a bias added to it. Different types of activation functions are binary-step functions, linear and non-linear activation functions are analyzed. The activation functions which are chosen in this work are as follows:

- **Linear**: A straight line function where activation is proportional to the input (which is the weighted sum from the neuron). It can be written as:
  \[ A(x) = cx. \]  
  \( (8) \)

- **Relu**: It stands for Rectified Linear Units. The formula is deceptively simple: \( \max(0, z) \). Despite its name and appearance, it is not linear and provides the same benefits as Sigmoid but with better performance. It can be written as:
  \[ A(z) = \begin{cases} z & \text{if } z > 0 \\ 0 & \text{if } z \leq 0 \end{cases} \]
  \( (9) \)

The detailed workflow of ANN is described in the following five steps:

- The training and validation set is imported as the input layer. The validation set is used to tune the parameters of a classifier, for example, to choose the number of hidden units in a neural network.
- The input vector \( \mathbf{x} = (x_1^{(0)}, x_2^{(0)}, \ldots, x_n^{(0)}) \) is passed through the hidden layers of the neural network to produce an output:
  \[ y^k = f(z^k) \]
  \( (10) \)
  for an \( L \) layered neural network with \( 1 \leq k < L \). Here, \( f(x) \) is a nonlinear function, also known as the activation function.

\[
Z^k = \sum_{i=1}^{n} W_i^{(k-1)} X_i^{(k-1)} + b^{(k-1)}
\]  \( (11) \)

is a weighted input signal for a layer where \( 1 \leq k < L \) and \( b^k \) is the bias obtained from the previous layer. After computation of \( (L-1) \) hidden layers, the final output i.e., the \( L^{th} \) layer’s output, is calculated as:

\[ y^L = w^{(L-1)} y^{(L-1)} \]
  \( (12) \)

The choice of the activation function is variable depending on the required problem to be solved.

- Subsequently, the error is measured using the predicted value and the real available value. The error is calculated as:
  \[ e = a - y^L \]
  \[ (13) \]

where \( a \) is the real value and \( y^L \) is the predicted value. This is also known as the cost function. A variety of cost functions are available like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), etc. Choices are made based on the type of problem being
solved. Barron [88] investigated various error functions to show how they affect the performance of a model.

- Next, backpropagation is used, which is an important mathematical tool for improving the accuracy of predictions in ML. ANN uses backpropagation to compute a gradient descent with respect to the weights and biases of the connections with every neuron. For all weights of neurons in a level $k$, the gradient descent is updated as:

$$\text{w}_i^k (\text{new}) = \text{w}_i^k (\text{old}) - \alpha \frac{g'(e)}{g(w)}$$  \hspace{1cm} \text{(14)}

$$\text{b}_i^k (\text{new}) = \text{b}_i^k (\text{old}) - \alpha \frac{g'(e)}{g(w)}$$  \hspace{1cm} \text{(15)}

where $1 \leq k < L$ and $1 \leq i \leq n$ and $\alpha$ is the convergence factor. $g'(x)$ is the first order derivation of function $g(x)$.

- The above steps are repeated until the error is minimized sufficiently and this is done by finding the optimal weights and biases.

4.1.2. Full NN Model Architecture

This is a five-layered neural network-based ML model to predict the Nusselt number, friction factor and thermohydraulic efficiency. Several tests are done using different numbers of neurons and hidden layers. Among them, a model with four hidden layers, each having 30–40 neurons, is determined to have good accuracy. The neural network with four hidden layers with 40 neurons in each hidden layer has the best accuracy, and hence, this configuration is suggested for comparison of the accuracy and calculation speed. The result is being shown in Table 3. To run the training, the batch size is taken as 12 and epoch size as 200. The change in training loss with an increase in epoch numbers is shown in Figure 9a,b. For leverage validation, the values from the test set are considered. Corresponding outputs are predicted and are shown with the actual experimental output values (Table 4). The values that are considered for this validation are mainly the lower and upper bounds values of the actual experimental inputs.
Figure 9. Mean squared error as the function of epochs: (a) Nu, (b) \( f \) and (c) \( \eta \).

Table 3. Training accuracy.

| Output Parameters                  | Test Error (%) |
|------------------------------------|----------------|
| Nusselt Number                     | 98.25          |
| Friction Factor                    | 97.89          |
| Thermohydraulic Efficiency         | 98.74          |
Table 4. Leverage Validation.

| Actual Nusselt Number | Predicted Nusselt Number | Spring Ratios | Depth Ratio | Reynolds Number |
|-----------------------|--------------------------|---------------|-------------|----------------|
| 137.729               | 134.226                  | 1             | 0.000       | 56,647.063     |
| 104.401               | 103.048                  | 1             | 0.250       | 13,657.714     |
| 46.669                | 45.724                   | 2             | 0.000       | 13,932.029     |
| 171.270               | 173.049                  | 2             | 0.250       | 56,530.302     |

| Actual Friction Factor | Predicted Friction Factor | Spring Ratios | Depth Ratio | Reynolds Number |
|------------------------|---------------------------|---------------|-------------|----------------|
| 0.025                  | 0.024                     | 1             | 0.000       | 70,670.947     |
| 0.052                  | 0.052                     | 1             | 0.250       | 10,100.000     |
| 0.033                  | 0.034                     | 2             | 0.000       | 10,325.645     |
| 0.040                  | 0.041                     | 2             | 0.250       | 70,759.913     |

| Actual Thermo-hydraulic Efficiency | Predicted Thermo-hydraulic Efficiency | Spring Ratios | Depth Ratio | Reynolds Number |
|------------------------------------|--------------------------------------|---------------|-------------|----------------|
| 1.086                              | 1.083                                | 1             | 0.000       | 20,280.421     |
| 1.085                              | 1.085                                | 1             | 0.250       | 68,287.116     |
| 1.058                              | 1.058                                | 2             | 0.000       | 10,325.645     |
| 1.040                              | 1.035                                | 2             | 0.250       | 68,613.056     |

4.2. Computational Situation

All the experiments were run on Google Colab Notebook with an Nvidia GPU version 1.4.0 enabled, and Keras 2.4.0 was used as an API to train and test the neural network models, thus favoring a way to clone hardware configuration. The best model is reported after experimenting with different configuration of the models.

4.3. Predictions Using ANN

Figure 10a–c shows the assessment between the predicted and actual experimental value of the test data for $Nu$, $f$ and $\eta$, respectively. From Figure 10a–c, one can understand that the ANN model fits the dataset acceptably. The performance of the models has reported an accuracy of more than 97% on the test dataset.
The detailed statistical analysis of the generated data is shown in Table 5, which includes a count of the data, mean, and standard deviation that elaborates the range or the distribution of the generated data.

The newly generated parameters for prediction are shown in Table 6. The Nusselt number, friction factor and thermohydraulic efficiency results of generated data are shown in Tables 7–10. The inputs are new to the model, and hence, the accuracy is measured to their outcomes.

The present model for \( Nu, f \) and \( \eta \) will ease a huge workload by determining the required outputs. With given test data as mentioned in Tables 7–10, the researchers working with some similar experimental work will get help to tune their parameters according to their needs and get their required result. It is important to note and consider an error factor of ±3–5% while considering the results.
Table 5. Analysis of the generated data.

|                         | Spring Ratio | Depth Ratio | Reynolds Number |
|-------------------------|--------------|-------------|-----------------|
| **Count**               | 776          | 776         | 776             |
| **Mean**                | 1.85         | 0.19        | 31,428.57       |
| **Standard Deviation**  | 0.61         | 0.073       | 19,798.55       |

Table 6. New generated parameters for prediction.

| Sl. No. | Parameters         | Values                                                                 |
|---------|--------------------|------------------------------------------------------------------------|
| 1       | Spring Ratios      | 0.5, 0.75, 1.25, 1.75, 2.25, 2.5, 2.75, and 3                         |
| 2       | Depth Ratio        | 0.1, 0.12, 0.17, 0.22, 0.27 and 0.30                                  |
| 3       | Reynolds number (Re) | 10,000, 15,000, 20,000, 25,000, 30,000, 50,000 and 70,000             |

Table 7. Predicted result of $Nu$, $f$ and $\eta$ with the generated data at a constant spring ratio of 0.5.

| Sl. No | Spring Ratios | Depth Ratio | Nusselt Number | Reynolds Number | Friction Factor | Efficiency   |
|--------|---------------|-------------|----------------|-----------------|-----------------|--------------|
| 1      | 0.5           | 0.1         | 15,000         | 79.37996        | 0.0352221/7     | 1.1265842    |
| 2      | 0.5           | 0.1         | 20,000         | 90.3596         | 0.0336314/14    | 1.0964329    |
| 3      | 0.5           | 0.1         | 50,000         | 151.32751       | 0.0285426/83    | 0.9894652/4  |
| 4      | 0.5           | 0.1         | 70,000         | 188.50266       | 0.0285585/15    | 0.9411039/4  |
| 5      | 0.5           | 0.12        | 10,000         | 76.44916        | 0.0410028/03    | 1.2566105    |
| 6      | 0.5           | 0.12        | 15,000         | 87.77288        | 0.0392107/2     | 1.1936426    |
| 7      | 0.5           | 0.12        | 50,000         | 161.64597       | 0.0319917/24    | 1.0116853    |
| 8      | 0.5           | 0.12        | 70,000         | 195.88791       | 0.0320048/9     | 0.9546453    |
| 9      | 0.5           | 0.27        | 10,000         | 117.5347        | 0.0525790/53    | 1.731573     |
| 10     | 0.5           | 0.27        | 15,000         | 128.20746       | 0.0513205/27    | 1.5592642    |
| Sl. No | Spring Ratios | Depth Ratio | Nusselt Number | Reynolds Number | Friction Factor | Efficiency |
|-------|---------------|-------------|----------------|----------------|----------------|------------|
| 1     | 0.75          | 0.1         | 10,000         | 67.99744       | 0.036494925    | 1.1545019  |
| 2     | 0.75          | 0.1         | 15,000         | 78.82527       | 0.034750223    | 1.1164212  |
| 3     | 0.75          | 0.1         | 50,000         | 150.75844      | 0.028146021    | 0.9856459  |
| 4     | 0.75          | 0.1         | 70,000         | 187.99026      | 0.028218526    | 0.93835825 |
| 5     | 0.75          | 0.12        | 10,000         | 75.708496      | 0.040506277    | 1.2372814  |
| 6     | 0.75          | 0.12        | 15,000         | 87.06183       | 0.0386977      | 1.1797061  |
| 7     | 0.75          | 0.12        | 50,000         | 160.94188      | 0.03156229     | 1.0071446  |
| 8     | 0.75          | 0.12        | 70,000         | 195.30498      | 0.031639773    | 0.951452   |
| 9     | 0.75          | 0.27        | 10,000         | 115.3594       | 0.05216585     | 1.7006153  |
| 10    | 0.75          | 0.27        | 15,000         | 126.030235     | 0.050907873    | 1.5363052  |
| 11    | 0.75          | 0.27        | 50,000         | 193.65616      | 0.04535187     | 1.0875276  |
| 12    | 0.75          | 0.27        | 70,000         | 220.56442      | 0.045359384    | 0.9855498  |
| 13    | 0.75          | 0.3         | 10,000         | 115.87105      | 0.051728677    | 1.6873885  |
| 14    | 0.75          | 0.3         | 15,000         | 125.895035     | 0.0504768      | 1.5236944  |
| 15    | 0.75          | 0.3         | 50,000         | 193.47389      | 0.044995386    | 1.0782328  |
| 16    | 0.75          | 0.3         | 70,000         | 221.02788      | 0.04499829     | 0.9740696  |

**Table 8.** Predicted result of $Nu$, $f$ and $\eta$ with the generated data at a constant spring ratio of 0.75.
**Table 9.** Predicted result of $Nu$, $f$ and $\eta$ with the generated data at a constant spring ratio of 2.75.

| Sl. No | Spring Ratios | Depth Ratio | Nusselt Number | Reynolds Number | Friction Factor | Efficiency  |
|-------|---------------|-------------|----------------|-----------------|----------------|------------|
| 1     | 2.75          | 0.1         | 10,000         | 64.38968        | 0.032834537    | 1.0981691  |
| 2     | 2.75          | 0.1         | 15,000         | 75.11141        | 0.03136564     | 1.0711987  |
| 3     | 2.75          | 0.1         | 50,000         | 146.70876       | 0.025430866    | 0.9651202  |
| 4     | 2.75          | 0.1         | 70,000         | 183.03188       | 0.025414007    | 0.9223864  |
| 5     | 2.75          | 0.12        | 10,000         | 71.10724        | 0.03624366     | 1.1564618  |
| 6     | 2.75          | 0.12        | 15,000         | 82.24923        | 0.034679912    | 1.1184247  |
| 7     | 2.75          | 0.12        | 50,000         | 155.22401       | 0.028402777    | 0.9830122  |
| 8     | 2.75          | 0.12        | 70,000         | 189.7021        | 0.028389916    | 0.9336427  |
| 9     | 2.75          | 0.27        | 10,000         | 101.19361       | 0.048271976    | 1.5135043  |
| 10    | 2.75          | 0.27        | 15,000         | 111.37276       | 0.046978466    | 1.3949823  |
| 11    | 2.75          | 0.27        | 50,000         | 180.69826       | 0.040935393    | 1.0376029  |
| 12    | 2.75          | 0.27        | 70,000         | 210.35638       | 0.040666554    | 0.9524145  |
| 13    | 2.75          | 0.3         | 10,000         | 101.36578       | 0.04800595     | 1.5002298  |
| 14    | 2.75          | 0.3         | 15,000         | 110.75813       | 0.046733737    | 1.380851   |
| 15    | 2.75          | 0.3         | 50,000         | 179.58052       | 0.040895592    | 1.0287775  |
| 16    | 2.75          | 0.3         | 70,000         | 210.03546       | 0.0405635      | 0.9411752  |

**Table 10.** Predicted result of $Nu$, $f$ and $\eta$ with the generated data at a constant spring ratio of 3.0.

| Sl. No | Spring Ratios | Depth Ratio | Nusselt Number | Reynolds Number | Friction Factor | Efficiency  |
|-------|---------------|-------------|----------------|-----------------|----------------|------------|
| 1     | 3             | 0.1         | 10,000         | 64.024864       | 0.03240527     | 1.0953414  |
| 2     | 3             | 0.1         | 15,000         | 74.69814        | 0.030972851    | 1.0688862  |
| 3     | 3             | 0.1         | 50,000         | 146.40587       | 0.025158633    | 0.96376675 |
| 4     | 3             | 0.1         | 70,000         | 182.36119       | 0.025060937    | 0.9221999  |
| 5     | 3             | 0.12        | 10,000         | 70.68053        | 0.035722174    | 1.1523054  |
| 6     | 3             | 0.12        | 15,000         | 81.739815       | 0.034201264    | 1.1152515  |
| 7     | 3             | 0.12        | 50,000         | 154.66966       | 0.02805507     | 0.9813919  |
8 3 0.12 70,000 188.9134 0.02796031 0.93236125
9 3 0.27 10,000 99.77054 0.0477052 1.4983823
10 3 0.27 15,000 109.91505 0.046400424 1.3836051
11 3 0.27 50,000 179.01501 0.04038874 1.0341384
12 3 0.27 70,000 208.94516 0.04003634 0.9498908
13 3 0.3 10,000 99.937706 0.047467355 1.48402
14 3 0.3 15,000 109.26468 0.046184637 1.3687065
15 3 0.3 50,000 177.78868 0.040400542 1.0253074
16 3 0.3 70,000 208.54733 0.03999533 0.93863714

5. Conclusions
The experiment was conducted to investigate the thermal performance of a circular channel with corrugated spring tape inserts. For this study, the following conclusions were drawn:

1. An enhancement in $Nu$ was recorded with an increase of $Re$ for all the cases.
2. The heat transfer was found to rise with an increased depth ratio. Likewise, the average $Nu$ declined with a rise in the spring ratio.
3. The present geometrical configuration significantly better than the simple spring tape (60% to 75% increase in heat duty at constant pumping power and 20% to 31% reduction in pumping power at constant heat duty, without corrugation).
4. An ANN model was used for the regression analysis to predict the thermal energy transport coefficient, pressure penalty and thermohydraulic efficiency.
5. The models were evaluated to have an accuracy of 97.00% on unknown test data and the proposed model was able to reasonably forecast the $Nu$, $f$ and $\eta$. The results obtained from the analysis can be conveniently used to design highly efficient tube type heat exchangers.
6. From the above results, it can be concluded that the use of corrugated spring tape is an effective technique to enhance the thermal energy transport coefficient.
7. These models will help the investigators working in heat transfer enhancement-based experiments to understand and predict the output.

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Nomenclature

- $A$: tube inner wall surface area, m$^2$
- $b$: breadth, m
- $c_p$: heat capacity, J/kgK
- $D$: inner diameter of test tube, m
- $f$: Darcy friction factor
- $h_c$: convective heat transfer coefficient, W/m$^2$K
- $h$: depth ratio
- $k$: fluid thermal conductivity, W/mK
- $L$: tube length, m
- $m$: mass flow rate, kg/s
- $Nu$: Nusselt number
- $\Delta p$: pressure drop, N/m$^2$
- $Pr$: Prandtl number
- $R_w$: Wall thermal resistance, K/W
- $q_w$: Wall heat flux
- $Re$: Reynolds number
- $T$: temperature, K
- $t$: Spring ratios
- $\delta$: tape thickness, m
- $V$: bulk velocity for plain tube, m/s; voltage V

Greek Symbols

- $\rho$: fluid density, kg/m$^3$

Subscripts

- $b$: bulk
- $i$: inlet
- $o$: outlet
- $ow$: outer wall
- $w$: inner wall
- $0$: plain tube (turbulator free)

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