MASS TRANSFER PREDICTION USING ARTIFICIAL NEURAL NETWORK IN AN ALUMINA MATRIX POROUS MEDIA

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Abstract: When it comes to the problem of expressing intricate non-linear interactions, one relatively recent development in the field of mathematical modelling is the application of artificial neural networks, which are also abbreviated as ANNs in some instances. In this paper, we develop a machine learning prediction model for predicting the flow of mass transfer in an alumina matrix porous media. Consider of a cylinder with a catalyst layer on its surface and a porous media surrounding it that is completely filled with fluid except for the one end. This cylindrical device is typical of a catalytic reactor. When the cylinder is heated to a constant temperature, the chemically reactive zeroth-order material is predicted to completely coat the outside of the vessel. Reinforced porous materials undergo a continual, temperature-dependent chemical reaction in their fluid phase. The model shows an improved predictive performance in all its experimentation.

Keywords: Mass Transfer, ANN, Machine Learning, Prediction

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INTRODUCTION

A significant variety of natural and man-made processes involve the movement of fluids across a body or across a stretched surface in some capacity. As a direct consequence of this, the stagnation-point flow has been the focus of a considerable amount of interest within the field of classical hydrodynamics [1]. However, a stagnation-point flow can be formed in porous media in a variety of different circumstances. One technique to increase heat transmission in microreactors that are hosting highly exothermic activities is to fill the pores of a porous medium that is hosting such activities [2].

Rarely is the topic of chemical systems, particularly those involving stagnation flows across a curved body that is enclosed by a porous substance, brought up for discussion. Solute diffusion, heat transmission by chemical radiation, hydrodynamics and chemical reaction of stagnation flows are some of the many factors that could be at play here. Electrochemical systems and thermochemical solar reactors are examples of industrial applications that make use of impinging flows in porous media [3].

As a result of this, it is absolutely necessary to research, enhance, and imitate them. The local thermal equilibrium (LTE) is widely used when talking about porous catalytic reactors due to the fact that it takes into account a thermally homogeneous mixture of fluid and solid. This assumption, however, is not valid in circumstances in which there are steep temperature gradients as a consequence of the existence of a major heat source or sink, in addition to the impacts of Soret and Dufour [4].

One technique that can be utilised in order to imitate the natural processes that take place inside of the brain is known as an artificial neural network, or ANN for short. This approach gets its cues from the neural system and is built upon its three fundamental components, which are the input data, the training process, and the output data. This method takes its cues from the neural system and is constructed upon its three primary components. Over the past few years, this method has evolved into a cutting-edge instrument that can optimise, forecast, and analyse a wide variety of complex engineering systems [5].

The conventional methods for modelling such a large data set call for an excessive amount of time and are prone to errors; ANN offers a novel option. The application of ANN to the management of energy has proven to be beneficial in the

resolution of a variety of challenging problems, including those that are encountered in multiphase flow. ANN has also been shown to be beneficial in the resolution of a number of other difficult problems [6].

It takes a lot of time and requires a lot of processing power to investigate many different fluid mechanics difficulties using typical methods. The examination of these difficulties is made more difficult as a result of the complexity that is brought about by the presence of a large number of characteristics that are interrelated. It is often necessary to perform a large number of calculations in order to accurately predict how an issue will behave in such a setting; however, machine-learning approaches such as ANN can be of assistance. In order to accurately predict how an issue will behave in such a setting, it is often necessary to perform a large number of calculations. It is self-evident that a modelling tool with a price point that is fair is required in order to properly handle the situation that is currently at hand [9].

In order to identify an algorithm that offers a high level of performance, we investigate a variety of ANNs to see what we can come up with. The use of non-linear heat transfer, which has been shown to improve both the accuracy of forecasts and the quality of studies, is the method that is applied in order to accomplish this goal. Additionally, utilising the thermal non-equilibrium hypothesis helps produce more detailed modelling of local heat transport than would otherwise be possible. This is because the hypothesis assumes that temperatures are not in equilibrium [10].

LITERATURE SURVEY

Sheri and Shamshuddin [11] analysed the boundary layer of a chemically reactive flow in the vicinity of a porous plate. It was hypothesised that there was also a magnetic field in the region, in addition to the radiation heat transfer and viscous dissipation that were already known to be there.

The first major efforts to discover a solution to this problem were performed by Chao et al. [12]. Their approach entailed the utilisation of a catalytic porous bed, a chemical reaction, and a stagnation-point flow. The governing equations could be solved by combining two distinct methods, namely the perturbation approach and the finite element methodology. Both of these methods are examples of how governing equations can be solved. As a result of a higher rate of conversion from reactants to products, it was found that the temperatures required to be higher, but the concentrations of the reactants needed to be lower. This was due to the fact that the activation energy and the solute diffusion rate were both decreased as a consequence of the increased conversion.

Pal and Biswas [13] used the singular perturbation method to carry out analytical research of double-diffusive transport. This study was an investigation of analytical behaviour. During the investigation, which took place in a porous media and involved oscillatory flow, it was carried out across a plate. When the response parameter was increased, there was a subsequent decrease in concentration, which was accompanied by an increase in the skin frictional coefficient.

Tlili et al. [14] conducted an investigation on the effects of chemical and thermal radiation on the magnetohydrodynamic (MHD) was surrounded by porous substance. It has been established that thermal slip, magnetic fields, a rise in the Reynolds number, and an increase in the proportion of solid volume all have a detrimental impact on the amount of heat that is transferred via convective means.

Khan et al. [15] conducted their research on a porous medium in order to investigate the convective heat transfer in an MHD flow over a stretched sheet. This type of heat transfer takes place during the stagnation point of the flow. The similarity technique, which was used to reduce the number of governing equations, was followed by the discovery of numerical solutions for the chemical process that was a part of the domain. This discovery came about as a result of the usage of the similarity method. In addition to this, it was demonstrated that an increase in the number of chemically reactive species, the Prandtl number, or the Lewis number all have the effect of dampening the temperature and concentration profiles.

Alizadeh et al. [16] focused their attention on the double diffusion that takes place in catalytic porous media when an impinging flow is applied to a cylinder. In order to get as close as possible to the underlying physics of the problem, mathematical modelling was done. The goal of this modelling was to get as close as possible to the underlying physics of the problem. They followed the lead of previous research in emphasising the preponderant influence of the Biot number. This was done to emphasise the relationship between the three numbers.

PROPOSED METHOD

Specific gravity of a porous medium can range anywhere from 2.45 to 19 gigapascals (GPa) in hardness. Specific gravity is determined by the soot content as well as the medium overall composition. If the bulk hardness of alumina needs to be preserved, the utilisation of fullerene soot comes highly suggested. By comparing these data to those for alumina, one may potentially get at the conclusion that the hardnesses of the materials listed here are up to 4.3 times higher than those stated for alumina. This is a plausible conclusion to arrive at. The comparison of the data presented here with those for alumina will lead to the discovery of this finding. The samples that have been sintered maintain the hardness of very pure and exceptionally dense alumina at a level that is within 97% of the level it was at when it was in its original state.

The most long-lasting samples were those that had been strengthened by one minute of heating at temperatures of 1300 and 1500 degrees Celsius with one weight percent fullerene soot. Testing for alumina is practically necessary because of the low levels of soot. This is because there is a relatively modest amount of soot. The problem is that doing so reduces resilience, and that where the challenge lies. In contrast, the samples that were reinforced with MWCNT soot have a higher porosity, which results in a reduced overall hardness which is shown in fig 1.

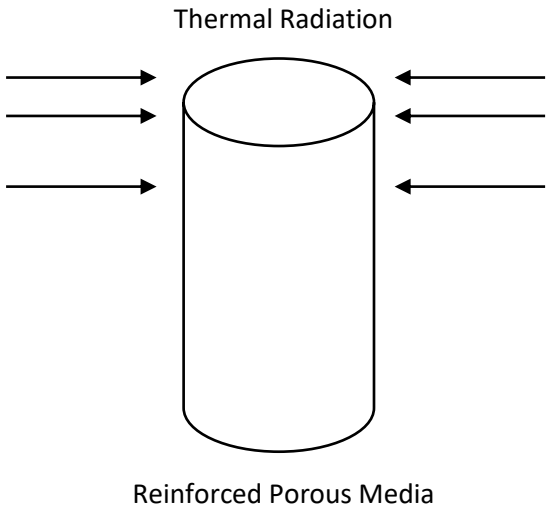

Figure 1: Reinforced Porous Material

Figure 1, which may be seen at this location, provides a concise representation of the conditions that have contributed to the current issue that we are dealing with. Consider a cylinder that is only open on one end, that has a catalyst layer on its surface, and that is surrounded on all sides by a porous media that is totally filled with fluid. This cylinder would be an example of a catalytic reactor. It is expected that the chemically reactive zeroth-order substance completely covers the exterior of the cylinder, which is heated to a constant temperature. There is a continuous chemical reaction going on in the fluid phase of the reinforced porous substance, and this reaction is dependent on the temperature.

In the following paragraph, we will go over the process by which the surface of the cylinder transforms into the position of a stagnation point flow that is uniform. In the equations, the terms solid and liquid are denoted by the s and f, respectively (8).

The following boundary conditions need to be satisfied in order to ensure that the equation for mass transfer can be completely solved:

$r=a: \partial C/\partial r = -kRD = \text{Constant}$; $r=\infty: C \rightarrow C\infty$

where,

kR - kinetic catalytic reaction,

D - molecular diffusion coefficient, and

C∞ - flow of mass concentration.

ANN

With the assistance of a type of artificial neural network called a Multilayer Perceptron, we generate forecasts in this investigation concerning the temperatures of non-dimensional solids (θs), fluids (θf), and concentrations (ϕ). This network is made up of many layers of neuronal connections. In general, people refer to the most frequent ones as the input, hidden, and output layers, in that particular sequence which is shown in fig 2.

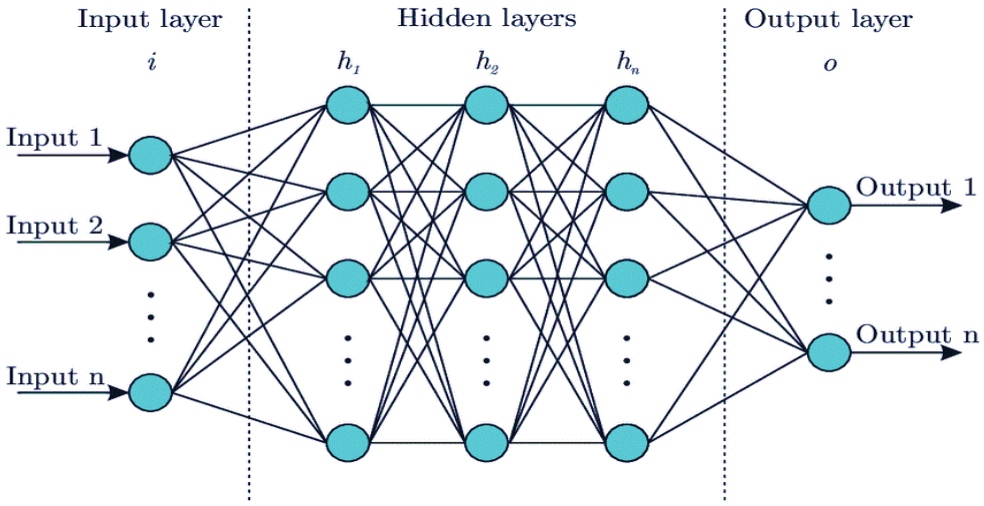

Figure 2: ANN

Figure 2 depicts an artificial neural network (ANN) in a simplified form of its architecture, which consists of n inputs, k hidden neurons, and a single output neuron. The ANN was designed to simulate natural neural networks. When a neuron connects to the neurons in the layer above it, it brings with it a weight coefficient that it uses to calculate the strength of the connection. Backpropagation of error is used during the training process to fine-tune the weights across a number of rounds. This is done over the course of several sessions. This procedure is repeated repeatedly until the required degree of precision is reached. An epoch or an iteration is a full forward-backward cycle that integrates new weight coefficients. In this context, either term can be used interchangeably. The accuracy of the algorithm forecasts is evaluated based on how closely they correspond to another collection of data referred to as benchmarking data.

ANNs are computational structures that, through an iterative learning process, are able to learn the link between a set of input variables and a set of output variables. Even the most complex and non-linear questions can be answered by these networks with nothing more than elementary mathematical operations like addition and multiplication. After a neural network has been trained, it can be used to make predictions about a target variable by drawing on the information contained in a separate dataset referred to as a holdout, with just a minimal amount of additional fine-tuning being necessary.

The vast majority of neural networks, which are often referred to as ANNs, are constructed up of neurons, which are weighted connections between successive layers of the network (edges). Each and every artificial neural network (ANN) has at least one hidden layer, along with at least one input layer and at least one output layer. A perceptron is a fundamental building element that is used in the construction of artificial neural networks. Each individual input in a perceptron is given a weight, and the sum is computed by using a function referred to as activation of the neuron.

A different function is utilised to perform the calculations necessary to determine the outcome. An artificial neural network, often known as an ANN, is a structure that consists of multiple layers and is built from stacked perceptrons. If we make the assumption that the outputs of the network, which are symbolised by the symbol zi, are decided by a summing function, then we obtain the following result if the inputs to the ith perceptron are as follows:

$zi = \sum xijwij+bi$

where

n - inputs;

m - neurons in a layer;

wij - jth neuron weight, and

bi - bias term.

It is possible to reduce the complexity of the zi matrix representation to the following:

$zi=wiTxi+bi$

where

$wi=[wi1,wi2, \ldots, win]T$

$bi=[bi1,bi2, \ldots, bin]T$

Iterative change of the weights and bias components of a perceptron can be used to improve the capacity of a perceptron to improve its estimates of the output values in response to a specific loss function. The approach corrects the network parameters in line with the errors that are computed with the help of observed and estimated data. This correction is based on the parameters of the network. The disparity between the expected value of the network output at iteration n (i.e., dn) and the actual value of the output is referred to as a loss term (yn).

$L(n)=Loss(dn, yn)$

where

Loss - function for the yn and dn, that quantifies the difference between the actual output values and the estimated values, and where yn and dn are the actual output values and the estimated values, respectively. In order to update the weights of the network based on this loss term, it is possible to utilise gradient descent learning at the neuron level.

$wij(n+1) = wij(n)-\eta\ (\partial L(n)/\partial wij(n)0$

where,

n - iteration,

wij - weight between j neuron to i,

η - step size, and

$\partial\ L(n)/\partial wij(n)$ - Loss gradient w.r.t wij.

Experimentation is the primary way for fine-tuning a network hyperparameters, including the step size, and is the one that is most commonly used. In the process of updating biassed terms, a methodologically analogous approach is utilised as part of the process.

The values of each neuron can be transformed from an unknown range using a non-linear function that is referred to as the activation function. This function is capable of converting values from a range such as [1, 1] or [0, 1], respectively. The sigmoid function, the hyperbolic tangent (tanh), and the rectified linear unit (ReLU) are the three activation functions that are most frequently used in artificial neural networks (ANNs). A summation term that reflects the activation function of the perceptron is included in the below equation.

$\sigma(z)=1/(1+e-z)$ (sigmoid)

$\tanh(z)=21+e-2z-1$

$ReLU(z)=\{z \quad if\ z>00 \quad if\ z\leq 0$

At this location, research is being conducted to investigate the efficacy of neural networks in accurately predicting the spread of disease across the United States. The ANN is a popular type of feedforward ANN that extends the (single) Perceptron model by including one or more hidden layers in the middle of the input and output layers. The ANN is put to use for classification and regression work during the supervised learning process.

RESULTS AND DISCUSSIONS

The use of artificial neural networks (ANN) should be avoided unless it can be shown that the numerical approach used to solve the governing equations adequately represents the physics that lies behind them. Until this can be proved, the use of ANN is not warranted. After that, the ANN algorithm is trained by employing the outcomes of the computations carried out on the set of equations. The materials and its configurations are shown in table 1, and the results achieved by performing several metrics are shown in fig 3- fig 7.

Table 1: Material and its configuration

Model	Algorithm structure	Functions
Porous Media	8:4:1	Gaussian
Reinforced Porous Media	8:4:1	Polynomial kernel
Reinforced Porous Media with ANN	8:100:1	Ensemble

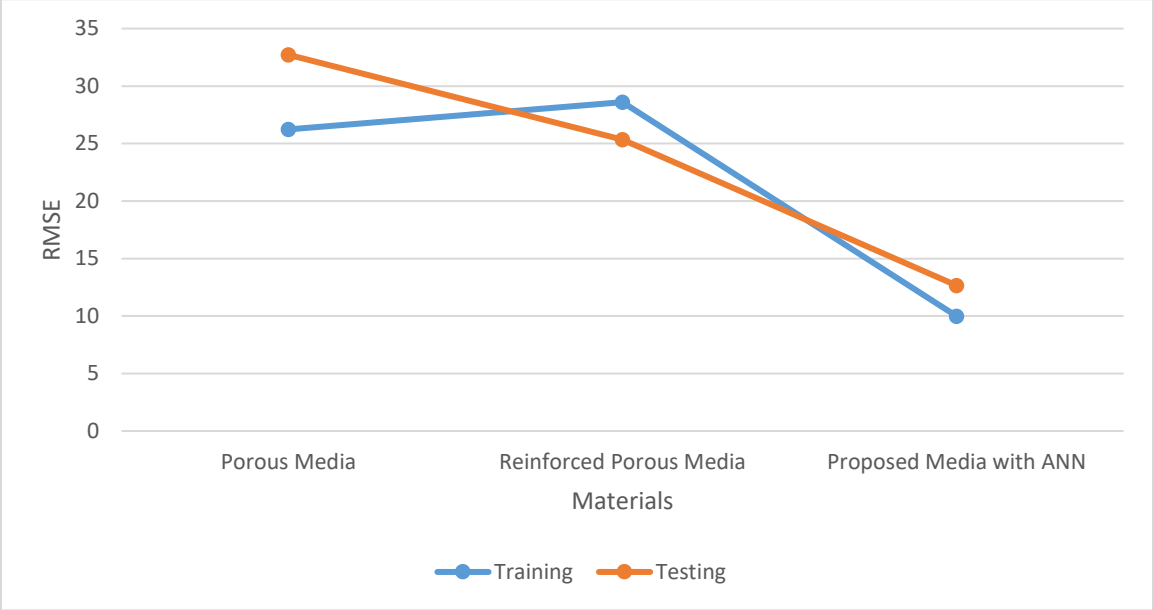

Figure 3: RMSE

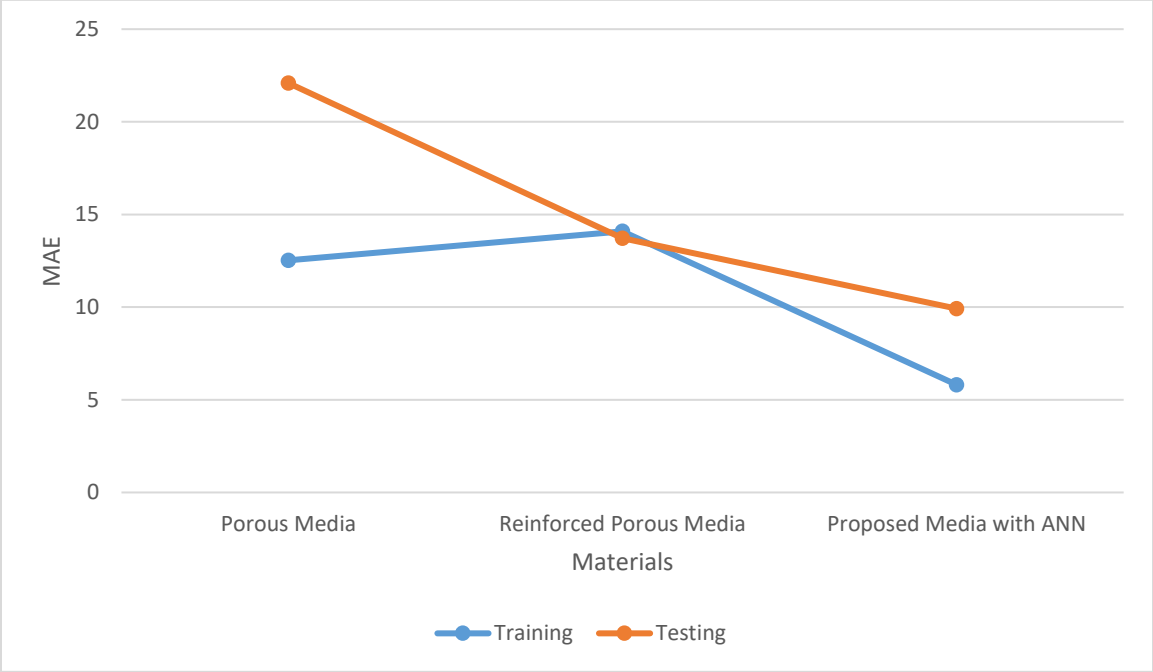

Figure 4: MAE

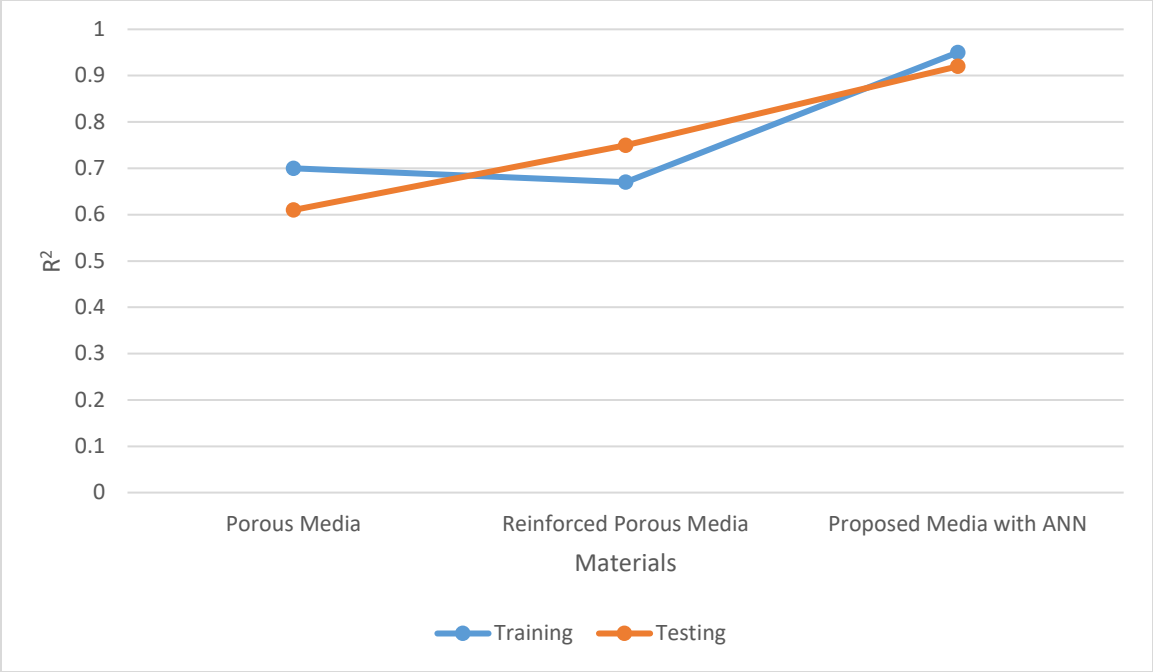

Figure 5: R2

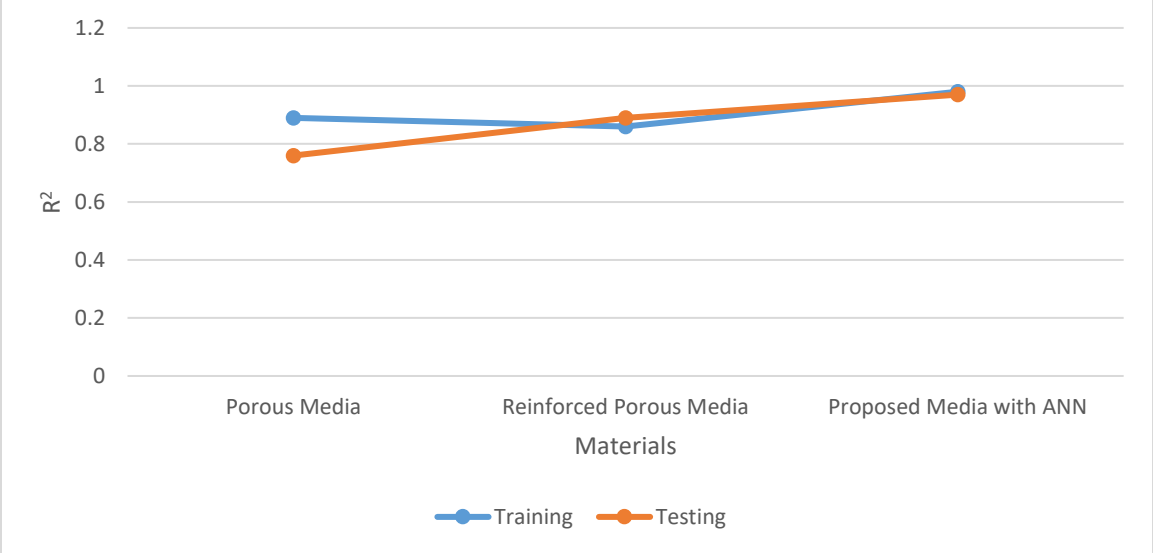

Figure 6: ROC

Figure 2-6 provides a comparison of the non-dimensional components of temperature with the non-dimensional components of velocity. The relative error of these findings, which were derived from the prior study, is often less than 0.1% of the time. The fact that this possibility already exists and that it has been properly investigated is very encouraging news. In addition, it was found that the results based on the current local thermal non-equilibrium and those of LTE reported demonstrate no noticeable difference in the limit of a large value of Biot numbers in the porous medium, which is physically expected.

The introduction of radiation into the flow field has the ability to bring about shifts in the way temperatures are distributed throughout the environment. Surprisingly, radiation does not have any effect whatsoever on the temperature of the fluid. This is because the temperatures of the fluid and the solid are different in a non-equilibrium thermal environment, which is essential for the radiation heat transfer mechanism to function properly. The condition must be non-equilibrium in order for the mechanism to work properly. However, if the value of the radiation parameter is increased to its maximum, the temperature of the solid will reach the temperature of the freestream over a shorter radial distance.

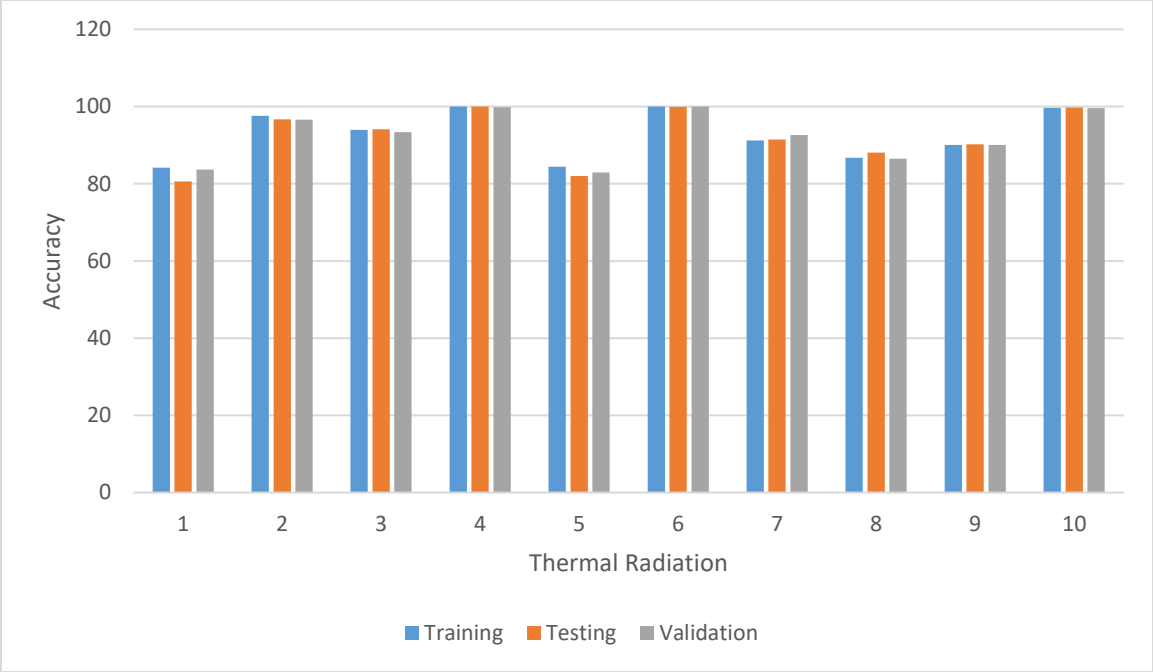

Figure 7: Accuracy

This occurs when the value of the radiation parameter is increased to its maximum. Because of this, we are aware that there is a limit to the extent to which radiation heat transport can have an impact on a porous domain. This came about as a direct result of the previous point. The study is able to see how the temperature of the wall effects the temperature distribution of the fluid and the porous solid. Find out how much of a role the temperature parameter has in determining the system's overall thermal response, and use this information to make decisions. Both convection and radiation are able to move heat more effectively when the temperature of the wall increases.

If the temperature does not influence the rate of the reaction, then the concentration must have a substantial impact on how the temperature is maintained. In order to accomplish the desired outcome of reducing the non-dimensional concentration by one order of magnitude near the cylinder wall, it is necessary to increase the reaction rate. This indicates that the mass boundary layer is becoming thinner as a result of greater species formation at the surface of the catalyst as a result of the increased reaction rate. This is because the increased reaction rate is the cause of the increased species formation at the surface of the catalyst. This is due to the fact that a higher reaction rate is the root cause of a greater number of species being created.

In addition, this image illustrates the impact that various values of the Soret number have on the mass distribution when applied to a variety of heat-generating intensities at a range of different levels. Because it is simpler for mass to migrate from the warm zone to the cold zone when the SORET number is negative, the mass boundary layer can be regarded complete at smaller radial distances. This allows for more efficient mass transfer from the warm zone to the cold zone. This is because when the Soret number is negative, heat transfer stimulates the transfer of mass, but when the Soret number is positive, heat transfer and mass transfer work in the opposite manner. The reason for this is that when the Soret number is negative, heat transfer stimulates the transfer of mass. Because of this, the mass boundary layer gets thicker as the SORET number goes up. This is a direct result of the situation.

Boosts that are applied to the Nusselt number are significantly influenced by increases in the heat source parameter, which can have a considerable multiplicative effect. This indicates that an increase in temperature differential, which can be induced either by an increase in the heat source or an increase in the response rate strength, is what makes the convective heat transfer more effective. This increase in temperature differential can be induced by either an increase in the heat source or an increase in the response rate strength.

Changes in the Damkohler number have a relatively minor impact on the Nusselt number. Because of this, it is possible to maximise the correspondingly negative value of the Nusselt number whenever the Soret number has a value that is in the negative. The absolute value of the Soret number will cause the Nusselt number to decrease. This is due to the fact that thermal diffusion will become more prevalent than convection as the Soret number grows. In spite of the fact that the activation energy might take on a variety of different values, the Nusselt number has a propensity to converge on a single maximum.

CONCLUSIONS

As part of this investigation, we develop a machine learning prediction model in order to compute an estimate of the rate of mass transfer in a porous medium whose foundation is an alumina matrix. This conclusion was reached after it was determined that both sets of results are based on the current local thermal non-equilibrium. After demonstrating that both sets of results were consistent with one another, this conclusion was reached as a result. These two comparisons show how trustworthy the equations that were selected and the numerical technique that was utilised are by demonstrating their dependability. In previous publications that they have authored,

the writers have provided a lengthy list of proofs and provided further depth of explanation regarding the numerical strategy that they applied.

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