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Stacked Heterogeneous Ensemble Learning Model in Mixed Convection Heat Transfer from a Vertically Oscillating Flat Plate

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ABSTRACT

This study analyses the effects of mixed convection heat transfer from a moving vertical flat plate with an experimental and stacked heterogeneous ensemble learning approach. In the experimental work, the effects on both natural and forced convection of dimensionless oscillation amplitude (A_o), dimensionless oscillation frequency (Wo) and Rayleigh number (Ra) are investigated. In the experiments, the vertical movement of the plate is provided by a flywheel-motor assembly. The average Nusselt numbers (Nu) on the fixed plate and the moving plate surface were obtained. Additionally, this study is focused on predicting heat transfer of a moving flat plate using single-based algorithms (Gradient Boosting, AdaBoost, Multilayer Perceptron) and a stacked heterogeneous ensemble learning model. The statistical performance of the single-based algorithms and the stacked ensemble model is measured in the prediction of mixed convection heat transfer. The results show that the stacked-based ensemble learning model yielded the MSE = 2.01, RMSE = 1.42, MAE = 1.1 and R2 = 0.99 values. Overall, this study reveals that the proposed stacked ensemble machine learning model can be used successfully for modelling the convection heat transfer of a moving plate.

Dikey Salınımlı Düz Bir Levhadan Karışık Taşınım Isı Transferinde Yığılmış Heterojen Topluluk Öğrenme Modeli

Araştırma Makalesi

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Makine öğrenmesi

ÖZ

Bu çalışmada, hareketli dikey düz bir levhadan karışık taşınım ısı transferinin etkileri deneysel ve yığılmış heterojen topluluk öğrenme yaklaşımı ile analiz edildi. Deneysel çalışmada, boyutsuz salınım genliği (A_o), boyutsuz salınım frekansı (Wo) ve Rayleigh sayısının (Ra) doğal ve zorlanmış taşınım üzerindeki etkileri incelendi. Deneylerde, levhanın dikey hareketi volan-motor düzeneği ile sağlandı. Hareketli levha ve sabit levha yüzeyi üzerinde ortalama Nusselt sayıları (Nu) elde edildi. Ayrıca, bu çalışma, tek tabanlı algoritmalar (Gradient Boosting, AdaBoost, Multilayer Perceptron) ve yığılmış heterojen topluluk öğrenme modeli kullanarak hareketli bir düz plakanın ısı transfer tahminine odaklanmıştır. Tek tabanlı algoritmaların ve yığılmış topluluk modelinin istatistiksel performansı karışık taşınım ısı transferi tahmininde ölçülmüştür. Sonuçlar, yığılmış topluluk modelinin MSE = 2.01, RMSE = 1.42, MAE = 1.1 ve R2 = 0.99 değerlerini verdiğini göstermektedir. Genel olarak, bu çalışma, önerilen yığılmış topluluk makine öğrenme modelinin, hareketli bir levhanın taşınım ısı transferini modellemek için başarıyla kullanılabileceğini ortaya koymaktadır.

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1. Introduction

Recently, the exploration of heat transfer improvement methods has been the focus of attention for many researchers due to the increasing energy demand of the industry. Therefore, passive and active heat transfer improvement methods are often used. Application arrangements such as wavy surfaces, the addition of baffles/fins into the channel, the use of nanofluids, and the use of a vortex generator to create a turbulator effect are passive methods. This method is cheap and simple as it does not require additional power but provides limited heat transfer. In cases where higher heat transfer is required, active techniques such as electric and magnetic field applications, boundary layer suction, boundary layer injection, oscillating/pulsating flows, and moving surfaces are preferred. It has been proven that all active methods improve heat transfer. Several researchers have studied experimental, numerical and mathematical analysis to enhance convection heat transfer (Cortell, 2007; Akdag et al., 2014; Khalid et al., 2017; Koffi et al., 2017; Pradhan et al., 2017; Shah et al., 2019).

Oscillatory flows and moving surfaces are commonly used active heat transfer improvement methods since these applications are known to cause high mass and heat transfer. Oscillatory flow applications are encountered in nature and biological systems, engineering implementations, industrial, nuclear, aerospace and military fields. It is possible to encounter applications in which oscillating flows are used in many industrial fields such as chemistry, food, and nuclear, especially in the energy field such as heating and cooling. Many researchers have recently focused on oscillating flows and moving surfaces (Subhashini and Sumathi, 2014; Ashafa et al., 2017; Patil et al., 2018; Lee et al., 2019; Sarhan et al., 2019). The effects on heat transfer of the oscillations of a vertical plate were analyzed analytically (Gomaa and Al Taweel, 2005) and numerically (Uddin et al., 2015). As a result of these studies, they declared that periodic surface movements increase the heat transfer rate depending on the oscillation parameters. Khan et al. (2019) presented an analytical study investigating free convection on a perpendicular moving cylinder surface and reported that the surface temperature declined with the rising Prandtl number and Nusselt number. Neethu et al. (2021) analytically and statistically analyzed the magnetic field flow of the nanofluid passing between perpendicular porous plates moving in opposite directions. Mehta et al. (2021) experimentally studied the effects of different parameters on the thermal efficiency of closed-loop flat-plate oscillating heat pipe.

There are experimental studies in the literature for solutions to complicated heat transfer problems. Experimental studies require a very long time, and devices are pretty expensive. For this reason, numerical and analytical methods are preferred as alternative solutions. However, complex thermal problems are challenging to solve analytically. Another alternative method is to use machine learning models. One of the most popular machine learning models is artificial neural networks (ANN). ANN has been used in different studies relating to the prediction of heat transfer (Akdag et al., 2009;

Ghritlahre and Prasad, 2018). Their study focuses on ANN applications and their success in dealing with complicated thermal systems. In another study, performance parameters of flat plate solar collectors were predicted by employing an ANN, and 96.3% R2 value was obtained (Kalogirou, 2006). Sozen and Arcaklioglu (2007) investigated the exergy analysis of an ejector absorption heat transformer employing ANN. This study achieved to provide 99% R2 statistical result. Yang (2008) presented a review study about ANN approach for various thermal applications. Khalaj et al. (2014) measured the effect of thermohydraulic performance on passive heat transfer using an ANN approach. Mohanraj et al. (2015) presented a literature survey considering the applications of ANN for the thermal behaviour of heat exchangers. In a different study, heat transfer on a flat plate was predicted by employing ANN, and this study yielded a 0.363 MAE score (Akdag et al., 2016). The proposed ANN also provided a convincing R2 score (99%). An ANN approach was also created to investigate the nanofluids flow in a microchannel heat sink (Tafarroj et al., 2017) and the ANN provided a 99% R2 score. Ghritlahre and Prasad (2018) presented a comparative study to predict the heat transfer from roughened absorber plate to air passing using the ANN and Linear Regressor. The used ANN provided a better MAE (0.316) score than the Linear Regressor. Koroleva et al. (2020) investigated heat transfer enhancement performance using computational fluid dynamics and artificial neural networks. 5.17×10^{-5} MSE score is obtained through the proposed approach. Akhgar et al. (2019) realized a study using ANNs to estimate the thermal conductivity of hybrid nanofluids (MWCNT-TiO_2). Abdelatief et al. (2019) investigated the natural convection on the outer surface of an elliptical tube at varying inclination angle and heat flux with experimental and ANN approach and compared the results with the literature studies. Serrano et al. (2020) examined the effect of bed materials in bubbling fluidized bed gasification using ANN method. Mirzaei and Mohiabadi (2021) studied the thermal behaviour of the flat plate solar collector with different nanofluids using ANN approach and estimated the system's performance with a deviation less than ± 2% method. Alkanhan (2021) conducted a study to examine the thermal conductivity of graphene oxide with ANNs approach, and the results were found to have an error range 2.27%. Malika and Sonawane (2021) carried out a study to estimate the thermal conductivity of hybrid nanofluids (Fe_2O_3-SiC) using an artificial neural network approach and response surface methodology (RSM) modelling method, and the results of the ANN method were reported to be more accurate. Pare and Ghosh (2021) used the ANN approach to estimate the thermal conductivity of Al_2O_3, CuO and ZnO nanoparticles and reported that the ANN approach's results agree with the experimental study. In another study, support vector regression (SVR), random forest (RF), and ANN were used to predict the condensation frictional pressure drop and heat transfer coefficient for horizontal microchannel and macro channel flows (Hughes et al., 2021). The random forest provided the best performance with an absolute average deviation of about 4% for both models. The literature study indicates that ANNs ensure plausible results for many engineering applications.

The studies mentioned above successfully obtained convincing statistical scores based on their aim and objectives by employing ANN, support vector regression and random forest. However, the literature study shows that the Stacked Heterogeneous Ensemble Learning model has never been used in studies related to heat transfer, to the best of the authors' knowledge. Thus, this study aims to propose a Stacked Het-erogeneous Ensemble Learning model for the prediction of heat transfer with mixed convection on an oscillating plate. The effects of the different parameters such as oscillating frequency (Wo), oscillating amplitude (A_o) and Rayleigh number (Ra) on the mixed convection are examined, and the estimated results from the ANN model and the test results are given comparatively. A detailed explanation for the stacked ensemble approach is given in Section 3. The objectives of this study based on the aim are listed below with bullet points.

- To determine the optimal single-based algorithms to be used in the level-0 of the stacked ensemble approach.
- To determine the optimal meta-learner algorithm for the level-1of the stacked approach.
- To compare the performance of the singe-based algorithms and the proposed Stacked Heterogeneous Ensemble model in terms of RMSE, MSE, MAE and R2.

The structure of this paper is organized as follows. The experimental study is presented in the second section. In the third section, detailed information about the proposed stacked heterogeneous ensemble model is given. Results and discussion are demonstrated in the fourth section. Conclusion and future directions are given in the final section

2. Experimental Study

2.1. Experimental Schema

The schema used for the experimental study is shown in Figure 1. The experimental model consists of two flat square copper plates dimension 210 mm in thickness of 1.5 mm. The thermocouples are placed along the vertical axis on both copper plates.

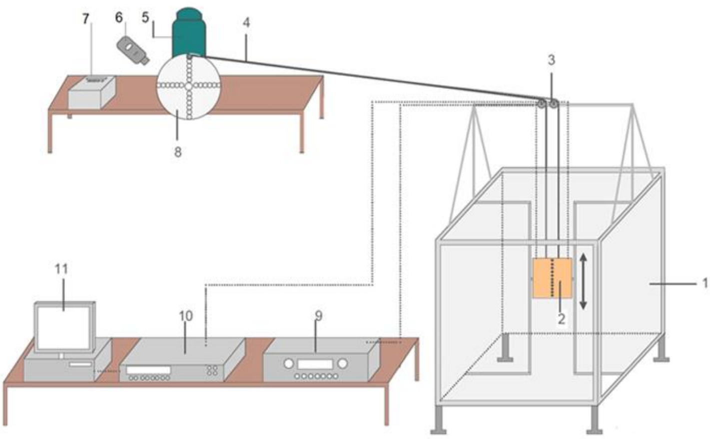


Figure 1. Experimental schema.

(1-Glass enclosure, 2- Vertical flat plate, 3- Reel system, 4- Hanger connection system, 5- Electric motor, 6- Digital speed indicator, 7- Frequency controller, 8-Fly-wheel, 9- Power unit, 10-Data acquisition system, 11- Computer).

The experimental setup and experimental model are shown in Figure 2. The thermocouples (K-type, Omega) on copper plates were attached along the perpendicular axis. The temperature data measured with thermocouples were collected by a computer-based data collection system (Keithley 2750). A specially manufactured flywheel was used for the oscillation amplitude. The flywheel was driven by a DC motor (2.4 kW). The oscillation frequency was controlled by the speed regulating unit of the motor. A detailed description of the experimental setup and evaluation method of the data are available in (Akcay et al., 2020).

a b

Figure 2a. Experimental setup, **b.** Experimental model.

2.2. Experimental Procedure

The heater block is assembled with copper plates and heated by Kapton heaters fed from an adjustable power supply. Three different heat fluxes, 20W, 40W, and 50W, were applied to the copper plate and the Rayleigh numbers (Ra) obtained according to these heat fluxes are 1.17×10^7, 2.94×10^7 and 3.6×10^7, respectively. In this study, the Rayleigh number was used to represent the heat flux applied to the plate. The heat transfer with free convection from the fixed flat plate is calculated. The temperatures on the surface are compared with open literature (Akcay et al., 2020). Then, the flat plate moves periodically within the enclosure at a specific Ra, Wo, and A_o. The plate continued its periodic motion for a specific time (3600s), after calculating the heat transfer with mixed convection from the moving surface. In the study, 60 experiments were carried out for different parameters and the used parameters are given in Table 1. The related parameters of the experimental study were explained in detail in the Reference (Akcay et al., 2020).

Table 1. Experimental parameters.

Rayleigh number (Ra)	Oscillation amplitude (A_o)	Oscillation frequency (Wo)
1.17×10^{7}	0.40, 0.75, 1.10, 1.40	65, 92, 113, 131, 146
2.94×10^{7}	0.40, 0.75, 1.10, 1.40	65, 92, 113, 131, 146
3.60×10^{7}	0.40, 0.75, 1.10, 1.40	65, 92, 113, 131, 146

The continuity, momentum, and energy equations for the heat transfer with mixed convection from the fixed flat plate are written as in Eqs. (1)-(3).

$$\frac{\partial u}{\partial x} + \frac{\partial u}{\partial y} = 0 \tag{1}$$

$$\frac{\partial u}{\partial t} + u\frac{\partial u}{\partial x} + v\frac{\partial u}{\partial y} = \vartheta\left(\frac{\partial^2 u}{\partial y^2}\right) + g\beta(T - T_\infty) \tag{2}$$

$$\frac{\partial T}{\partial t} + \mathrm{u}\frac{\partial T}{\partial x} + \mathrm{v}\frac{\partial T}{\partial y} = \alpha\frac{\partial^2 T}{\partial y^2} \tag{3}$$

Due to the vertical oscillation of the plate, the surface temperatures change periodically. Using the measured temperatures over time, the average temperatures are obtained as follows;

$$T_{w,x} = \frac{1}{\mathrm{N}\Delta\mathrm{t}} \sum_{i=1}^{N} T_{w,x}(x,t)\,\Delta\mathrm{t} \tag{4}$$

where, N, Δt, and T_w represent the data number, the time interval, and the instantaneous surface temperature, respectively. The average temperature on the plate is calculated as follows;

$$\overline{T}_w = \frac{T_{w1}+T_{w2}+T_{w3}+\dots\dots+T_{w11}}{11} \tag{5}$$

The spatio-temporally averaged Nusselt number (Nu_ω) is given by

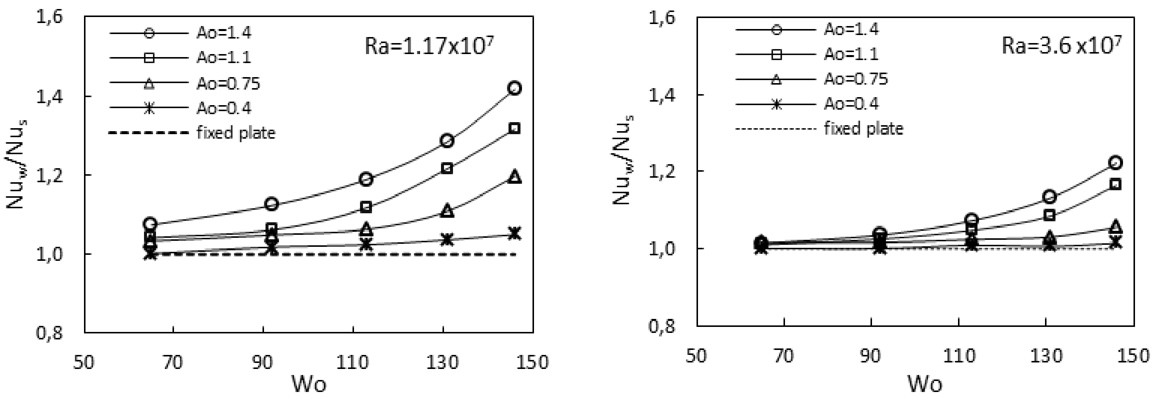
$$Nu_\omega = \frac{1}{\tau \mathrm{L}} \int_{\mathrm{x_0}}^{\mathrm{L}} \int_0^{\tau} \mathrm{Nu(x,t)\,dtdx} \tag{6}$$

where, τ is the cycle time and L shows the length of the plate. Furthermore, the cycle-averaged Nusselt number is obtained as follows

$$Nu_{\omega} = \frac{q''L}{k(\overline{T_w} - T_{\infty})} \tag{7}$$

where, $\overline{T}_w$(°C) is the average surface temperature and T_∞ (°C) is the free temperature, q″ (W/m^2) is the heat flux, k (W/mK) is the thermal conductivity. Moreover, the ratio of the heat transfer of the moving plate (Nu_ω) to the heat transfer of the fixed plate (Nu_s) is described as thermal effectiveness (η).

$$\eta = \frac{Nu_\omega}{Nu_s} \tag{8}$$



a b

Figure 3. Variation of the thermal effectiveness for two different Rayleigh numbers.

Figure 3 shows the effects of the oscillating parameters on the effectiveness of different Rayleigh numbers. It is observed that the thermal performance factor of moving plate rises with rising oscillation parameters for all Rayleigh numbers compared to the fixed plate. Nonetheless, this rising is detected to increase with decreasing Rayleigh number. Due to the high Rayleigh number, the free convection effects are more dominant in mixed convection on the surface. The physical meanings of the experimental study were explained in detail in the Reference (Akcay et al., 2020). The present study focused on the applicability of the stacked heterogeneous ensemble learning model for the prediction of mixed convection heat transfer.

In this study, the uncertainty analysis method was applied, and the total average uncertainty of Nu is calculated to be 4.25% (Akcay et al., 2020; Holman, 2001).

3. Heterogeneous Ensemble Learning Model

This study presents a new Stacked Heterogeneous Ensemble Learning approach. The structure of the proposed stacked approach is presented in Figure 4. The rest of this section gives information about the dataset, stacked ensemble approach and scoring metrics. Initially, the dataset is split into training (80%) and test (20%) sets. Then, 10-fold cross-validation was used to evaluate the proposed model using the training set. Additionally, the proposed model's performance estimation is obtained based on unseen (test) data.

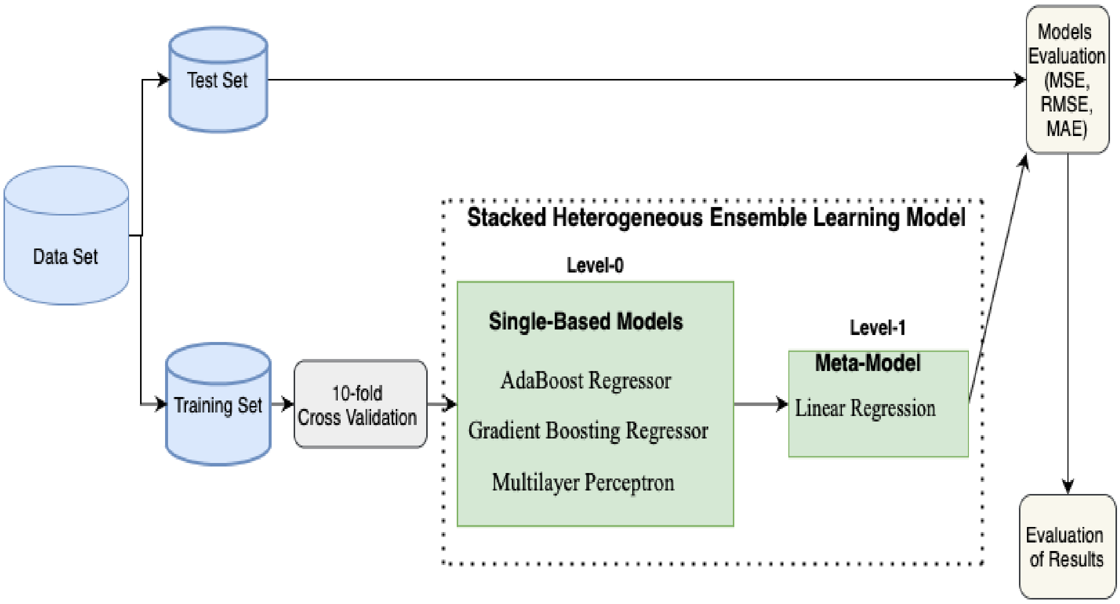


Figure 4. Proposed Stacked Heterogeneous Ensemble Learning Model.

3.1. Dataset

This study uses a dataset to determine the employed stacked ensemble model's efficiency in predicting mixed convection heat transfer for the oscillating vertical plate. The dataset consists of 60 samples and three parameters. These parameters are pulsating amplitude (A_o), pulsating frequency (Wo) and Rayleigh number (Ra). Detailed experimental data are given in Table 1.

3.2. Stacked Ensemble Approach

A stacked ensemble learning model means the combination of two levels (level-0 and level-1) to obtain a convincing performance compared to the single-based learning models. Machine learning algorithms are used in these two levels (Zhou, 2021; Buyrukoglu and Savas, 2022). Single-based models are used in level-0, and the algorithm used in level-1 is named a meta-model. There should be used only one machine learning algorithm in level-1 as a meta model. In the background of any stacked ensemble learning algorithm, the meta model uses the outputs of the single-based models as an input in level-1. In the end, the meta-model enables a final regression or classification score.

In this study, two different boosting ensemble learning models and multilayer perceptron (MLP) are employed in level-0 as single-based ensemble learning models. The employed boosting ensemble learning algorithms are AdaBoost Regressor, and Gradient Boosting Regressor. Then, Linear Regression is used as a meta-model in level-1. Different machine learning algorithms were tried to use the optimum model in level-1. Linear regression, MLP, and random forest models were used, and the best performance was obtained through linear regression. Thus, Linear Regression was used in level-1 in the proposed Stacked Heterogeneous Boosting Ensemble approach. The rest of this section gives information about the employed models in the proposed approach.

3.2.1. AdaBoost Regressor

The AdaBoost algorithm has two types which are AdaBoost. R1 and AdaBoost. R2. AdaBoost. R1 is proposed for the classification problems, while AdaBoost. R2 is proposed for the regression problems. It means that it can be used for classification and regression (Buyrukoglu and Akbas, 2022). In this study, AdaBoost. R2 is used for the prediction of mixed convection heat transfer. In the training process, only one decision stump is initially used as a weak learner. This algorithm aims to find misclassified data and add more weights to be used in the subsequent decision stump. Then, the same process is carried out in the second decision stump. This process is repeated until to obtain the desired result from the AdaBoost algorithm (Buyrukoglu et al., 2021). Finally, we created the AdaBoost model with 60 estimators in this study to predict mixed convection heat transfer.

3.2.2. Gradient Boosting Regressor

Gradient Boosting algorithm is developed for classification and regression issues like the AdaBoost. In the gradient boosting ensemble learning algorithm, the processes of the AdaBoost and Gradient Boosting ensembles learning algorithms are the same. However, there is a difference in the use of the loss function. The AdaBoost algorithm is sensitive to outliers because the exponential loss function is minimized in this algorithm. In contrast to AdaBoost, the Gradient Boosting ensemble learning algorithm is more robust to outliers than AdaBoost. The reason is that any differentiable loss function can be used in gradient boosting ensemble learning (Natekin and Knoll, 2013). In this case, the Gradient Boosting ensemble algorithm can be considered more flexible than the AdaBoost. In our case, the proposed Gradient Boosting regressor structure includes the following hyperparameters. The number of estimators is 60, and the learning rate of the model is 0.1.

3.2.3. Multilayer Perceptron

Multilayer perceptron (MLP) is a feed-forward neural network consisting of several layers, including input, hidden and output. Backpropagation is used in the training process of an MLP network. Also, if an MLP network includes more than one hidden layer, it is considered a deep neural network. It is used to solve different problems requiring supervised learning (Tang et al., 2015; Buyrukoğlu, 2022). Figure 5 illustrates the proposed MLP network structure. As shown in Figure 5, two hidden layers are used, and the number of neurons for these hidden layers are 6 and 3 respectively. In creating the proposed MLP network, 3000 iterations were used as a result of a case study to obtain the optimal result. Sigmoid activation function has been used in these hidden layers. Also, the dropout method is used because it effectively reduces the overfitting in neural networks. In other words, randomly selected neurons are dropped during the training process when the dropout method is used (Srivastava et al., 2014). It can be used for both input and any hidden layers. This study uses the dropout method only for the first hidden layer, and the value is determined as 0.5.

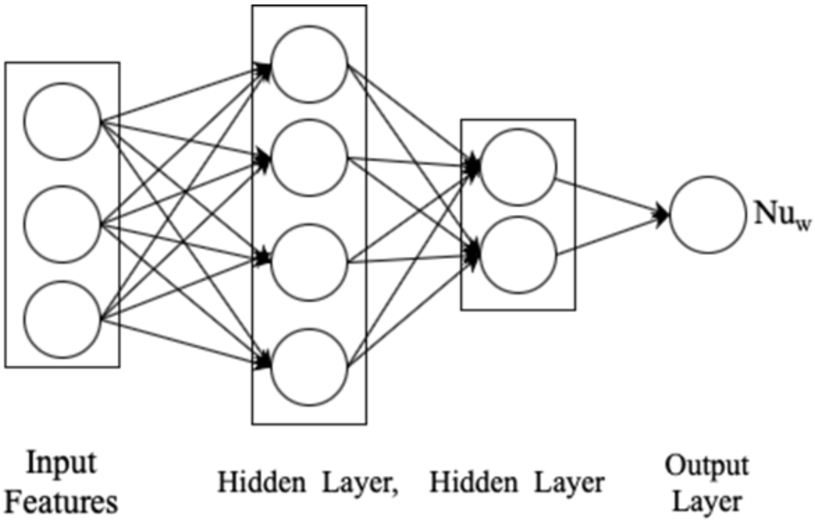


Figure 5. Structure of the proposed Multilayer Perceptron.

3.2.4. Linear Regressor

Linear Regression is used as a meta-model (level-1) in this study. Linear Regression has two types of regressions, which are simple and multi-linear regression (Buyrukoglu, 2021). A single predictor is used in simple linear regression, while more than one predictor is used in multiple linear regression. Due to the usage of more than one predictor in the prediction of mixed convection heat transfer, multi-linear regression is used in this study.

3.3. Scoring Metrics

Three different scoring metrics are used to evaluate the success of the employed models presented in the previous section. These metrics are mean squared error (MSE), root mean square error (RMSE) and mean absolute error (MAE) (Chicco et al., 2021). These metrics are calculated as

$$MSE = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2 \tag{9}$$

$$RMSE = \sqrt{\frac{1}{\mathrm{n}}\sum_{i=1}^{n}(P_i - \hat{P}_i)^2} \tag{10}$$

$$MAE = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}\left|\mathrm{P_i} - \hat{\mathrm{P}}_\mathrm{i}\right| \tag{11}$$

where P_i is the actual value, $\hat{P}_i$ is the predicted value from the model and n is the number of observations.

4. Results and Discussion

This section initially provides information about the evaluation performance of the employed algorithms (Section 4.1). Then, results about the AdaBoost and MLP models' efficiency in creating the stacked ensemble model are given in Section 4.2, separately. Moreover, actual and predicted values obtained through the employed models are compared in Section 4.3. Then, a comparison of previous studies and current models is presented to reveal the efficiency of the stacked ensemble learning model in Section 4.4. Finally, the result of the scoring metrics of the proposed stacked ensemble learning is given based on a different dataset in Section 4.5.

4.1. Evaluation Results of the Employed Studies

Table 2 presents the statistical performance of the employed single-based models and the stacked-based ensemble learning algorithms. It is noted that the presented scores are test scores of these models. As seen in Table 2, the best performance in predicting heat transfer of a moving flat plate is obtained through the proposed heterogeneous stacked ensemble learning model (MAE:1.1, RMSE:1.42, MSE:2.01, and R2:0.99). On the other hand, the Gradient Boosting algorithm provided the worst performance in the prediction of heat transfer of a moving flat plate.

Table 2. Statistical performance measures for the ANN approach.

Model	**MSE**	**RMSE**	**MAE**	**R2**
Stack	2.016	1.420	1.106	0.998
MLP	3.518	1.876	1.398	0.996
AdaBoost	18.756	4.331	1.837	0.979
Gradient Boosting	14.636	3.826	2.851	0.983

Creating the MLP, AdaBoost and Gradient Boosting models is essential to obtain a convincing result using the stacked ensemble learning model. In this sense, different iterations in MLP and estimators in AdaBoost are tried to obtain an optimal Stacked Ensemble Learning Model. The following section gives information about the efficiency of the iterations (in MLP) and estimators (in AdaBoost) in creating an effective stacked model in the prediction issues.

4.2. Use of MLP and AdaBoost in the Creation of an Effective Stacked Ensemble Model

Figures 6 and 7 illustrate the MAE scores of the stacked ensemble learning model based on the used different number of iterations in MLP (Figure 6) and estimators in AdaBoost (Figure 7). As presented in Figure 6, the lowest MAE score (1.1) for the stacked model is obtained using the 3000 iterations in MLP. On the other hand, the worst MAE performance (1.69) is obtained when the used number of iterations is 500. The MAE scores between the used 500 and 3000 iterations were slightly reduced from 1.69 to 1.1. Also, the MAE score remained stable when more iterations were used from the 3000 iterations. Hence, 3000 iterations are used in the MLP to obtain the optimal MAE value from the stacked model.

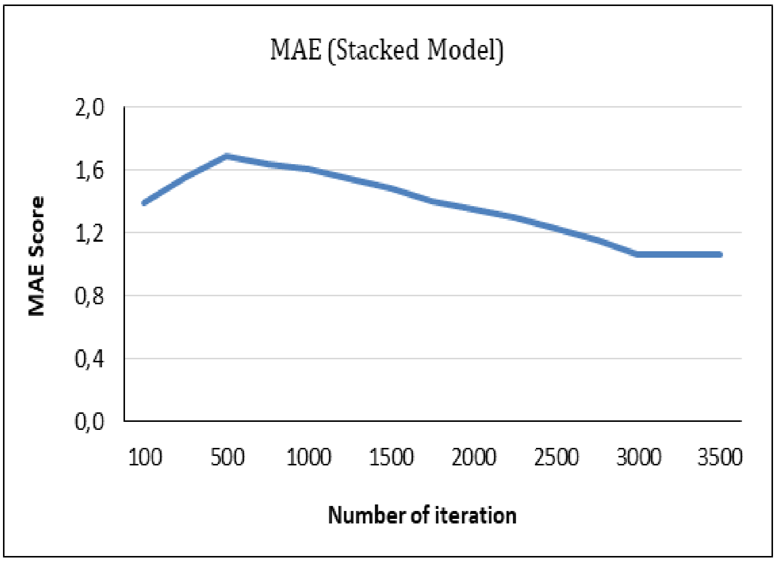


Figure 6. MAE scores of Stacked Model based on different iterations used in MLP.

It should be highlighted that the number of estimators is kept as 60 in the AdaBoost while the number of different iterations in the MLP were trying to get the best MAE score from the stacked ensemble model. This is because the best MAE score is obtained from the stacked models when the 60 estimators are used in the AdaBoost. However, different estimators in AdaBoost were tired in determining the optimal number of estimators, as illustrated in Figure 7. The worst MAE score (1.25) for the stacked ensemble model was obtained when AdaBoost's used number of estimators is between 10 and 40. It means that the MAE score of the stacked model remained stable when the used number of estimators was 10, 20, 30, and 40, respectively. The MAE score of the stacked model is slightly reduced when the number of iterations is increased from 40 to 60. Then, the best MAE score (1.1) of the stacked model is obtained using 60 estimators in AdaBoost. However, the MAE score of the stacked model remained stable even if the used number of estimators was increased from 60 to 100. Thus, the optimal estimator number used in AdaBoost is accepted as 60. Moreover, the number of iterations used in MLP was kept at 3000 while the number of different estimators in AdaBoost tried to get the best MAE score from the stacked ensemble model.

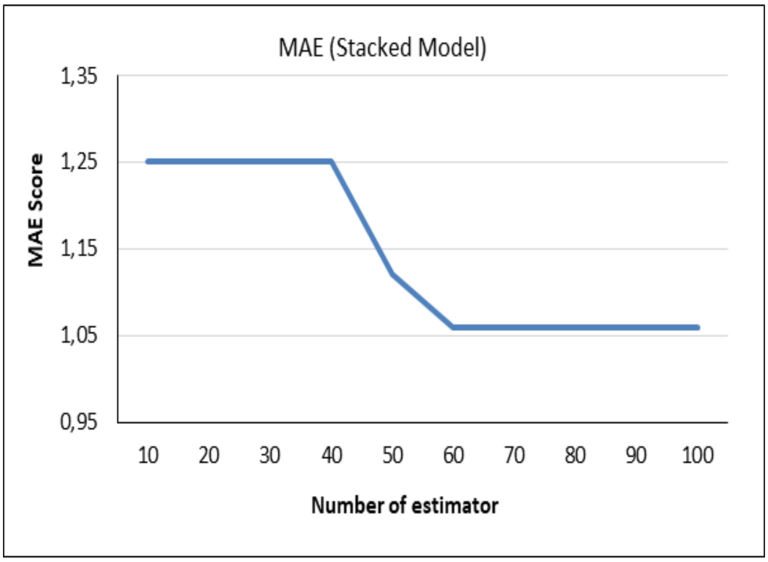


Figure 7. MAE scores of Stacked Model based on different estimators used in AdaBoost.

4.3. Results on the Actual and Predicted Value from the Employed Models

Actual and the predicted values obtained from the employed MLP, AdaBoost, Gradient Boosting, and Stacked Heterogeneous Ensemble Learning model are given in Figure 8. Figure 8 shows that the lowest differences between the actual and predicted were observed with the Stacked Ensemble Learning model. However, some of the employed algorithms (especially MLP and AdaBoost) have less difference between the actual and predicted value compared to the stacked ensemble in some points. For example, MLP provided better results for the samples numbered from 28-31 and 49-51 compared to the stacked ensemble. AdaBoost was also achieved to provide better results for the samples numbered between 31-33 compared to the stacked ensemble. Significantly, the AdaBoost algorithm has the worst performance between the actual and the predicted data points for the samples numbered from 1-18 compared to the samples numbered from 18-60. It can be considered as a usual situation because of the working principle of the AdaBoost presented in Section 3.2.1.

Overall, even if the MLP and AdaBoost provided better performances for the samples in some points compared to the stacked model, as shown in Figure 8, the stacked ensemble learning model outperformed the others in general. The results show that the proposed stacked ensemble learning model can be used to predict heat transfer of a moving flat plate.

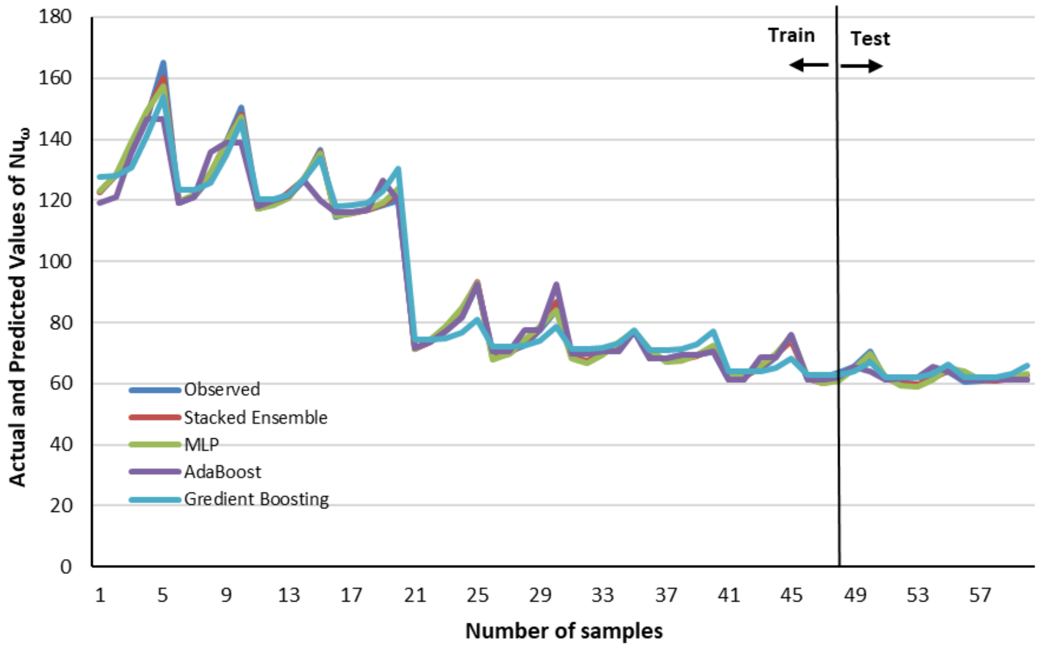


Figure 8. Actual and the predicted values obtained from the employed MLP, AdaBoost, Gradient Boosting, and Stacked Heterogeneous Ensemble Learning model.

4.4. Comparison of Previous Studies and Current Models

As highlighted in Section 1, many studies about the prediction of heat transfer have been proposed using machine learning algorithms. Also, most of these studies were created using ANN, while some of the studies created different machine learning algorithms. Table 3 shows the studies with similar aims and objectives to ours.

A study proposed by Akdag et al. (2016). is developed to predict heat transfer on a flat plate using ANN. In this study, a single hidden layer was used to create the ANN, which can be considered a limitation. More than one single hidden layer could be used behind the use of a single hidden layer to determine the optimal neural structure. Also, many researchers have specified that the use of more than one hidden layer in the classification and regression problems may accelerate the ANN accuracy performance. Not using the proposed neural structure's dropout method can be considered a second limitation. Instead, it could be used to obtain better statistical results. This study provided a 0.363 MAE value. In a different study (Ghritlahre and Prasad, 2018), Artificial Neural Networks and Linear regressors were developed to predict the heat transfer from roughened absorber plate to air passing. Even if the ANN provided better MAE performance (MAE: 0.316) than the linear regressor, there are some limitations in the creation of ANN. The limitations are the same as those of ANN created by Akdag et al. (2016). Another study was also proposed by Koroleva et al. (2020) to investigate heat transfer enhancement performance using computational fluid dynamics and artificial neural networks. 5.17×10^{-5} MSE score is obtained through the proposed approach. Even if more than one hidden layer was used in the creation of the ANN, the dropout method has not been used to improve the performance of the proposed ANN model, and Kalogirou (2006) employed ANN, including three hidden layers without using the dropout method in the prediction of the performance parameters of flat plate solar collectors. This model achieved to obtain a 96.3% R2 value.

Table 3. Previous studies and the proposed approach.

Literature	Method	Aim	Result
Akdag et al., (2016)	ANN	Estimate of the heat transfer for pulsating flow using ANN	MAE: 0.363
Ghritlahre and Prasad, (2018)	MLP	Prediction of the thermal performance from roughened absorber plate to air passing	MAE: 0.316
Koroleva et al., (2020)	CFD + ANN	Analysis of heat transfer improvement using CFD and ANN	MSE: $5.17 \cdot 10^{-5}$
Kalogirou, (2016)	ANN	The prediction of the performance parameters of flat plate solar collectors using ANN	R2: 0.963
The proposed approach	Stacked Approach Level 1: MLP AdaBoost, Gradient Boosting Level 2: Linear Regressor	Prediction of mixed convection heat transfer on oscillating plate	MAE: 1.1

Even if the studies mentioned above achieved convincing results based on their aim and objectives, they employed single-based machine learning algorithms. However, the efficiency of the stacked ensemble learning model has never been measured in the prediction of mixed convection heat transfer (in the literature), to the best of our knowledge. Thus, we proposed a stacked ensemble learning model for the prediction of mixed convection heat transfer, which is the main contribution of this study. Finally, the proposed stacked model provided convincing statistical scores, as shown in Table 3. In other words, this study reveals the applicability of the stacked heterogeneous ensemble learning model for the prediction of mixed convection heat transfer.

4.5. Efficiency of the Proposed Stacked Model Using a Different Dataset

A different dataset is used to justify the employed stacked ensemble model's efficiency in predicting heat transfer for pulsating flow. The dataset consists of 96 samples and four parameters. These parameters are pulsating amplitude (A_o), Pulsating frequency (Wo), blowing ratio (M) and Reynolds number (Re) (Akdag et al., 2018). Statistical scores of the employed stacked ensemble model and single-based models are given in Table 4. As seen in Table 4, the employed stacked ensemble model provided the best statistical scores among the others. This result justifies the stacked ensemble learning model's efficiency for predicting heat transfer using pulsating jet at the flat plate and mixed convection heat transfer for the oscillating vertical plate.

Table 4. Stacked model performances

Model	MSE	RMSE	MAE	R2
Stack	0.623	0.789	0.610	0.998
Neural Network	3.111	1.764	1.423	0.996
AdaBoost	7.927	2.815	1.361	0.996
Gradient Boosting	34.440	5.869	4.305	0.995

5. Conclusion and Future Directions

This study examines the effects of the oscillation parameters on the mixed convection heat transfer of a moving vertical plate with an experimental and a stacked heterogeneous ensemble learning model. Firstly, experimentally obtained the heat transfer for oscillation parameters and Rayleigh number on the moving plate surface. The Nusselt number increased with increasing Rayleigh number and oscillation parameters. Then, the proposed stacked heterogeneous ensemble learning model is created to estimate the mixed convection heat transfer of the plate. Some statistical scoring metrics interpret the effectiveness of the stacked model. The results showed that the stacked ensemble learning model could effectively estimate the Nusselt number on a moving flat plate. The stacked model achieved to obtain convincing statistical scores (MSE = 2.01, RMSE = 1.42, MAE = 1.10, R2 = 0.99). Also, the proposed stacked model is used for predicting mixed convection heat transfer using a different dataset, and the stacked model is again achieved to provide the best statistical scores. This study reveals that the Stacked Heterogeneous Ensemble Learning model can be safely used to predict mixed convection heat transfer the average Nusselt number with high accuracy. As a further study, complex heat transfer problems can be examined by employing stacked ensemble learning or deep learning models.

Conflict of Interest: The authors declared that there is no conflict of interest.

Author’s Contributions: S. Akcay: Conducting, interpreting and writing of the experimental study; S. Buyrukoglu: Conducting, interpreting and writing of Stacked Heterogeneous Ensemble Learning model approach; U. Akdag: Supervision of the experimental study.

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