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Analyzing Heat Conduction in a Semi-Infinite Medium: Machine Learning Approach Based on Fourier Transform

Nimmy Pullare, T. V. Smitha* and Kallur Venkat Nagaraja*

Abstract

The prediction of heat transmission will be beneficial in the areas of frost protection, subterranean cables, slab thermal performance, and soil temperature management, all of which include the use of a semi-infinite medium. The conduction of heat through a semi-infinite medium has now become a prominent problem and can be analyzed mathematically through traditional methods. For describing the distribution of temperature, many analytical methods, together with machine learning (ML) techniques that will enhance the efficiency and accuracy of the scenario, have been implemented. Following this, an ML technique based on the Fourier transform method is proposed here for the investigation of heat conduction in a semi-infinite medium. In accordance with the literature survey conducted, no prior study is juxtaposed based on these two methodologies. The Fourier transform method serves precisely for solving heat conduction problems, while ML techniques provide a cutting-edge, data-driven method that could identify nonlinearities and intricate patterns in thermal management. Numerous ML techniques are employed for analyzing the heat conduction problem and are compared with the solution of the Fourier transform method. From the evaluation metrics employed, the unit R-squared (R^2) value, mean squared error (MSE), root mean square error (RMSE), and mean absolute error (MAE) values approaching 0 demonstrate that the decision tree model outperforms other ML techniques better and is highly predictive for heat conduction problems.

Keywords: Heat conduction; Semi-infinite medium; Fourier transform; Machine learning.
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1. Introduction

At the macroscopic level, everything that exists comprises a certain type of energy. The thermodynamic energy function may be used to quantify this type of energy state by dividing it into atomic-level states, such as rotational, electronic, and vibrational. Temperature is a measured scalar value that describes the energy function in a local equilibrium condition. The energy that molecules, atoms, or electrons transfer from a high-temperature area to a lower-temperature zone is called heat. Although heat transfer problems are more related to mechanical engineering, numerous works have been done in metallurgical, chemical, nuclear, electrical engineering, and many other domains.[1-6] Heat transfer is considered through three different modes: radiation, conduction, and convection. In high-temperature environments, such as in space applications and furnaces, the transmission of heat occurs through radiation by electromagnetic waves, which does not depend upon any medium. When the transference of heat is carried by fluid particles from a high region to a low region of temperature differential, convection occurs, which is applicable in the fluid mechanism, including natural processes, heat exchangers, and heating, ventilation, and air conditioning (HVAC) systems. Heat is transferred between solids or liquids through conduction, where a temperature gradient causes energy to move from higher to lower temperatures. Upon determining the temperature distribution inside the medium based on the position vector and time, the heat flow is calculated using the heat transfer laws. The exploration of heat transfer offers an intriguing synthesis of quantitative concepts and basic scientific principles.

To make calculations easier, a semi-infinite medium is considered in many heat transfer problems. A semi-infinite medium is one that stretches infinitely in one direction while being finite in the other dimensions. A plethora of researchers have made use of the semi-infinite medium in various applications.[7-12] Using a semi-infinite flat plate, Kesavaiah *et al*.[13] examined the convective flow of a viscoelastic dusty gas past a porous medium. Duan *et al*.[14] analyzed the unsteady

Computational Science Lab, Amrita School of Engineering, Amrita Vishwa Vidyapeetham, Bengaluru, 560035, India
**Email:* tv_smitha@blr.amrita.edu (T. V. Smitha);
kv_nagarja@blr.amrita.edu (K. V. Nagaraja)

heat transfer in a cone-shaped shell surrounded by a semi-infinite medium. They truncated the semi-infinite domain to twice the radius and height of the cylindrical geometry. Matta *et al*.[15] elucidated the impact of dissipation on magnetohydrodynamic (MHD) flow across a semi-infinite plate integrated with a chemical reaction. In a semi-infinite domain, Beybalaev *et al*.[16] examined the transient heat conduction.

The Fourier series is a crucial mathematical tool that helps to understand the structure and behavior of functions. Named after 18th-century mathematician Joseph Fourier, it decomposes periodic functions into simple oscillating functions like sines and cosines. This approach is applicable to various mathematical and physical problems, including linear differential equations with constant coefficients. The Fourier series is essential in fields like differential equations and harmonic analysis, providing a systematic approach to solving these problems. In order to solve heat equations in metal plates and explain complicated heat sources, one systematic way to express periodic functions as a sum of smaller trigonometric functions is achieved by utilizing the Fourier series. It exhibits a wide range of applications in image processing, vibration analysis, econometrics, signal processing, electrical engineering, acoustics, quantum physics, and optics. The Fourier transform is a prolongation of the Fourier series that occurs when the period of the function is extended and enabled to reach infinity.

The Fourier transform is frequently utilized in the domains of practical mathematics, wave propagation, communication theory, and electromagnetic fields. For the cooling process of radiators, the thermal performance of ternary hybrid nanofluid was investigated, and the corresponding governing partial differential equations were solved using the Fourier transform by Arif *et al*.[17] and Nuaimi *et al*.[18] They solved the inverse boundary value problem for the heat conduction equation and applied the Fourier transform to obtain the estimated solution. By applying the Fourier sine transform, Lisha and Vijayakumar obtained the exact solutions for temperature distribution and flow transport for investigating the effects of heat transfer of a hybrid nanofluid in MHD flow over an upright plate.[19] To reduce the complex boundary value problem into a singular integral equation, Yang *et al*.[20] utilized the Fourier transform to investigate a heat conduction problem. By employing the Fourier transform approach, Bonnet solved the frequency-dependent heat transport problem.[21]

For examining and predicting the heat transfer mechanisms in heat transfer system design structures, as well as to optimize heat transmission processes, machine learning (ML) techniques are extensively utilized. Many engineering fields, including heat transfer, have experienced a surge in the application of ML approaches. ML models may quickly comprehend complex relationships and serve as a prediction tool when integrated with an existing database. The enormous data generated by simulation results, experiments, and field observations is analyzed using ML models. The study of Anooj *et al*.[22] provides an ML-based diagnosis approach for thermal management systems that predicts liquid percentage based on surface temperature data. The application of nine ML techniques in the prediction of bubble condensation was investigated by Tang *et al*.[23] For predicting the heat transfer of the wavy porous fin, Kumar *et al*.[24] employed an artificial neural network (ANN). Bhattacharya and Majumdar explored the development of an ML model for studying the predictive and design analysis of an internal combustion engine.[25] Panimathi *et al*.[26] presented an ML-based model that analyses the impedance of the battery at various charge levels and temperatures in order to accurately predict the capacity of the battery. Reddy *et al*.[27] used ML regression models for the prediction of lithium-cell batteries' remaining useful life (RUL). The fluid flow characteristics and heat transfer efficacy of a double-pipe heat exchanger with T-W tape inserts were predicted using support vector regression by Rodrigues *et al*.[28] For modeling the characteristics of power amplifiers, Chandana *et al*.[29] employed support vector regression and kernel regression ML models. Chandan *et al*.[30] implemented three ML algorithms to predict the friction factor for the flow in micro/mini channels containing fins.

It is evident from the continuing literature research that no attempts have been made to investigate the analysis of heat conduction in a semi-infinite domain using ML techniques based on the Fourier transform approach. In light of this, the current study reflects the outcomes of the Fourier transform method with the ML methodology while examining heat conduction in a semi-infinite medium.

2. Methodology

2.1 Material preparation

Consider a one-dimensional conduction heat transfer through a semi-infinite medium along the x direction in which at large distances, the temperature $\hat{u}$ and its gradient along the x direction approach zero as x tends to infinity. The aforementioned assumptions are given mathematically in Eq. (1):[31]

$$k\frac{\partial^2\hat{u}}{\partial x^2}-\frac{\partial\hat{u}}{\partial t}=0,\ t>0, 0<x<\infty \tag{1}$$

Together with the boundary conditions (BC) in Eq. (2) and initial conditions (IC) in Eq. (3).

$$\text{BC: } \hat{u}(0,t)=\hat{u}_0, \text{for } t\geq 0 \tag{2}$$

$$\text{IC: } \hat{u}(x,0)=0, \text{when } 0<x<\infty \tag{3}$$

where $\frac{\partial\hat{u}}{\partial x}$ and $\hat{u}$ both tend to zero as $x\to\infty$ is depicted in Fig. 1. Here, k is defined as the ratio of specific heat capacity and density at constant pressure to thermal conductivity, which measures the pace at which heat diffuses through an object, and t is the time.

Since $\hat{u}$ is specified at $x=0$, the Fourier sine transform is applied to the given partial differential equation and is given as Eqs. (4) and (5):

$$\frac{dU_s}{dt} + k\alpha^2 U_s = \sqrt{\frac{2}{\pi}} k\alpha\hat{u}_0 \tag{4}$$

where

$$U_S(\alpha,t) = \left(\frac{2}{\pi}\right)^{\frac{1}{2}} \int_0^\infty \sin\alpha x \hat{u}(x,t)dx \tag{5}$$

The general solution is provided by Eq. (6):

$$U_s(\alpha,t) = -\frac{\hat{u}_0}{\alpha}\left(\frac{2}{\pi}\right)^{\frac{1}{2}} (e^{-k\alpha^2 t} - 1) \tag{6}$$

Inverting Eq. (4) by using the Fourier inverse sine transform, the solution of the heat conduction problem is in Eq. (7):

$$\hat{u}(x,t) = -\frac{2}{\pi}\hat{u}_0 \int_0^\infty \frac{\sin\alpha x}{\alpha}(e^{-k\alpha^2 t} - 1)\, d\alpha \tag{7}$$

Substituting Eqs. (8) and (9):

$$erf(y) = \frac{2}{\sqrt{\pi}}\int_0^y e^{-u^2} du \tag{8}$$

$$erfc(y) = 1 - erf(y) \tag{9}$$

The final solution is attained in Eq. (10):

$$\hat{u}(x,t) = \hat{u}_0 erfc\left(\frac{x}{\sqrt{2kt}}\right) \tag{10}$$

For the same problem mentioned in Eq. (1), the boundary and initial conditions are taken respectively as in Eq. (11):

$$BCs: \hat{u}(x,t) = 0 \text{ as} x \to \infty$$

$$\hat{u}_x(x,t) = 0 \text{ as} x \to \infty$$

$$IC: \hat{u}(x,0) = f(x) \tag{11}$$

where *f(x)* is an arbitrary function.

Using the Fourier transform approach, the solution is obtained as Eq. (12):

$$\hat{u}(x,t) = \frac{1}{2\sqrt{\pi kt}}\int_{-\infty}^{\infty} f(s)e^{\frac{-(x-s)^2}{4kt}} ds \tag{12}$$

Consider the initial condition where $f(x) = e^{-x^2}$ is a Gaussian function. Then, after applying the Fourier transform, the obtained solution is in Eq. (13):

$$\hat{u}(x,t) = \frac{e^{-\frac{\omega^2}{4}}}{4kt}\sqrt{\pi} \tag{13}$$

A mathematical link between the input and output variables must be established in order to fully analyze the experimental results. This involves executing a regression or curve-fitting process on the data using an array of techniques. In order to predict a continuous target variable from one or more predictor variables, supervised learning algorithms are utilized, such as ML regressors. The dataset is created by simulating Eqs. (10) and (13). The numerical and continuous dataset consists of 100 instances and three features with respect to Eq. (10). The values of x ranges from 1 to 100, $\hat{u}_0$ from 10 to 1000 in increments of 10 units, k from 2 to 200 in increments of 2 units and the value of t is set to be 1. Based on these inputs, the actual values of $\hat{u}$ were computed using the Fourier sine transform method. For Eq. (13), the value of k is set to range from 2 to 200 with an increment of 2 units. Here, 20% of the dataset is set aside for testing, and 80% is used for training.

For selecting the model, the Python library is utilized, Matplotlib is employed for creating graphs and visualizing the data, and for evaluating the models using statistical measures, sklearn metrics is used. The regressors work by calculating the correlation between the predictor and the target variables using the training dataset. The dataset includes nonlinear data; thus, to perform regression operations, a total of six regressors: K-nearest neighbor (KNN), linear regression (LR), gradient boosting (GB), decision tree (DT), support vector regression (SVR), and random forest (RF) are employed. The mean absolute error (MAE), root mean square error (RMSE), and R-squared (R^2) metrics are utilized to compare the ML models, as presented in Eqs. (14)-(16):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\varsigma_i - \hat{\varsigma}| \tag{14}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\varsigma_i - \hat{\varsigma})^2} \tag{15}$$

$$R^2 = 1 - \frac{\sum(\varsigma_i - \hat{\varsigma})^2}{\sum(\varsigma_i - \bar{\varsigma})^2} \tag{16}$$

where *N* is the sample size and $\hat{\varsigma}$, $\bar{\varsigma}$ are the predicted and the mean value of ς.

3. Results and discussion

This section offers a thorough synopsis of the primary findings from the present investigation. Here, the solution for the heat conduction problem is analyzed using different parameters utilizing ML models, namely the KNN, SVR, LR, GB, RF, and DT. For each model, the values of the R^2, MSE, RMSE, and MAE are computed and shown in Tables 1 and 2 for both the target values $\hat{u}$ represented as in Eqs. (10) and (13). In a statistical model, the R^2 shows how well the independent variable or factors explain changes in the dependent variable. Its range is 0 to 1, where 1 represents an ideal fit between the data and the model. The average difference between a model's predicted and actual values is represented by the standard deviation of residuals or RMSE. The MAE evaluates the average deviation between the actual and predicted values, irrespective of the error direction.

For comparing the actual values of $\hat{u}$ with the predicted values, comparison graphs are plotted and are displayed in Figs. 2 and 3 and the parity plot for each model is given in Figs. 4 and 5 for both the values of $\hat{u}$.

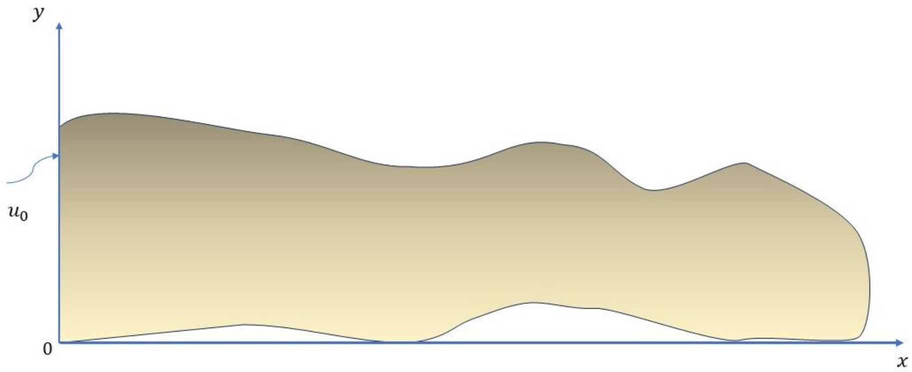

Fig. 1: The semi-infinite medium.

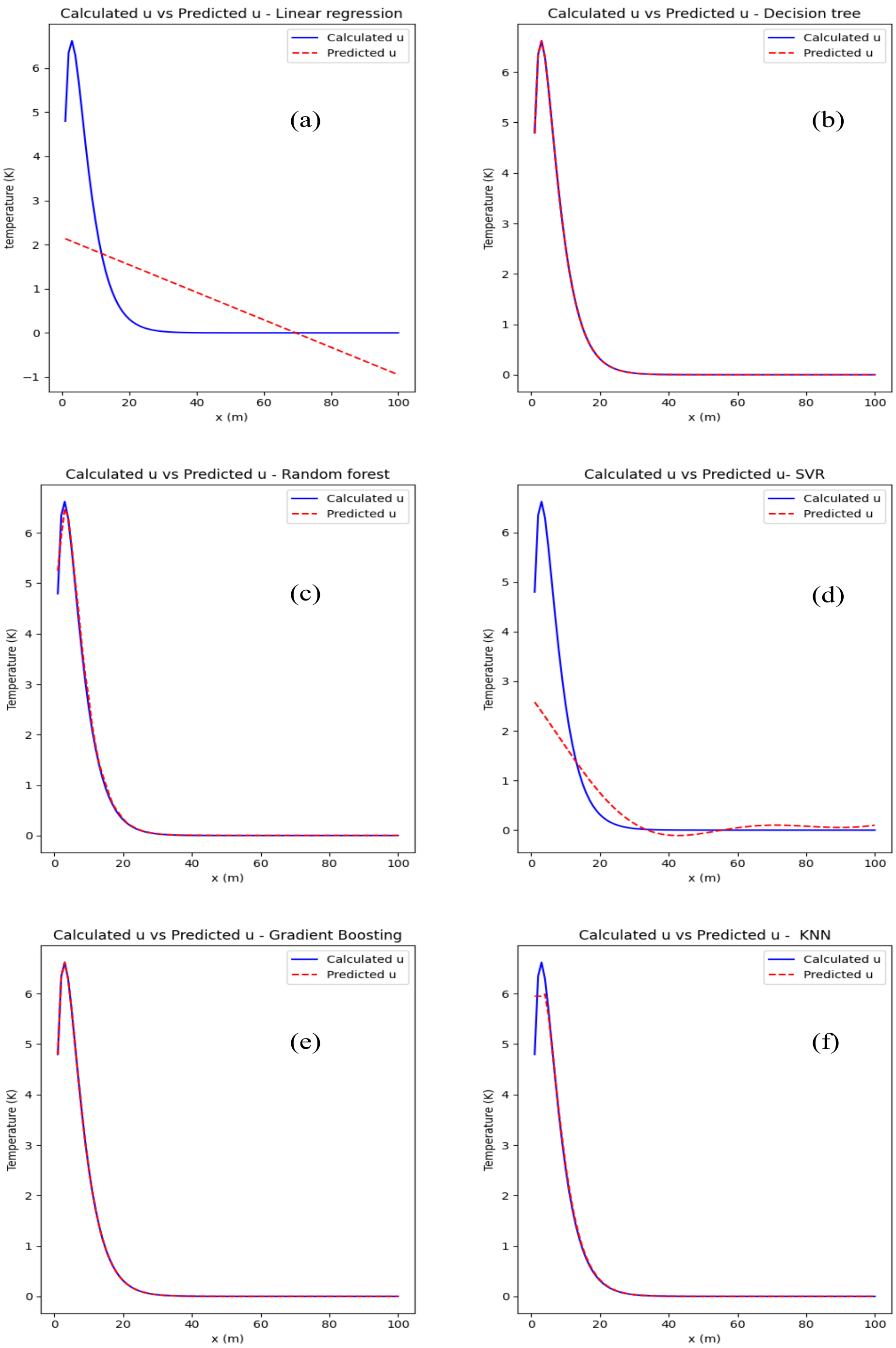

Fig. 2: The comparison plot of the models (a) LR, (b) DT, (c) RF, (d) SVR, (e) GB, and (f) KNN.

Table 1: The evaluation metrics for the ML models.

Model	MSE	RMSE	MAE	R^2
LR	1.48485360	1.21854569	0.8701669	0.3525190
DT	1.3E-17	3.572E-09	1.274E-09	1
RF	0.00519377	0.07206782	0.0226539	0.9965736
SVR	0.87693701	0.93644915	0.3774786	0.6176053
GB	6.6748E-08	0.00025835	0.00011832	0.9999999
KNN	0.02078344	0.14416464	0.03341135	0.9909372

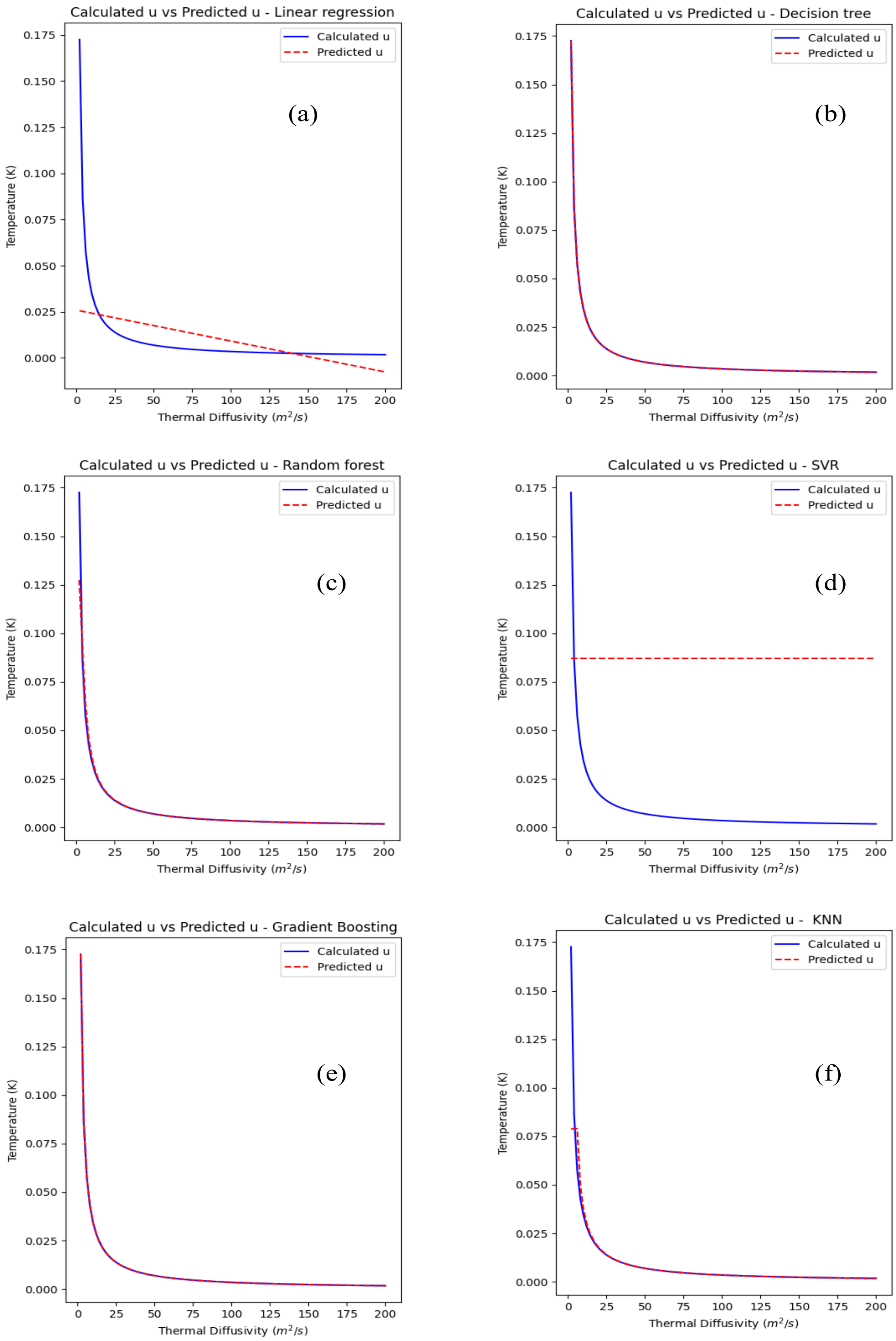

Fig. 3: The comparison plot of the models (a) LR, (b) DT, (c) RF, (d) SVR, (e) GB, and (f) KNN.

Table 2: The evaluation metrics for the ML models.

Model	MSE	RMSE	MAE	R^2
LR	0.000312938	0.017690065	0.008408727	0.2304818006
DT	0	0	1.274E-09	1
RF	0.956017889	1.78861E-05	0.004229198	0.0007168618
SVR	0.001136153	0.033706881	0.013387925	0.1655482391
GB	0.999995345	1.89270E-09	4.35052E-05	2.631826E-05
KNN	0.769802895	9.36137E-05	0.00967542	0.0013864995

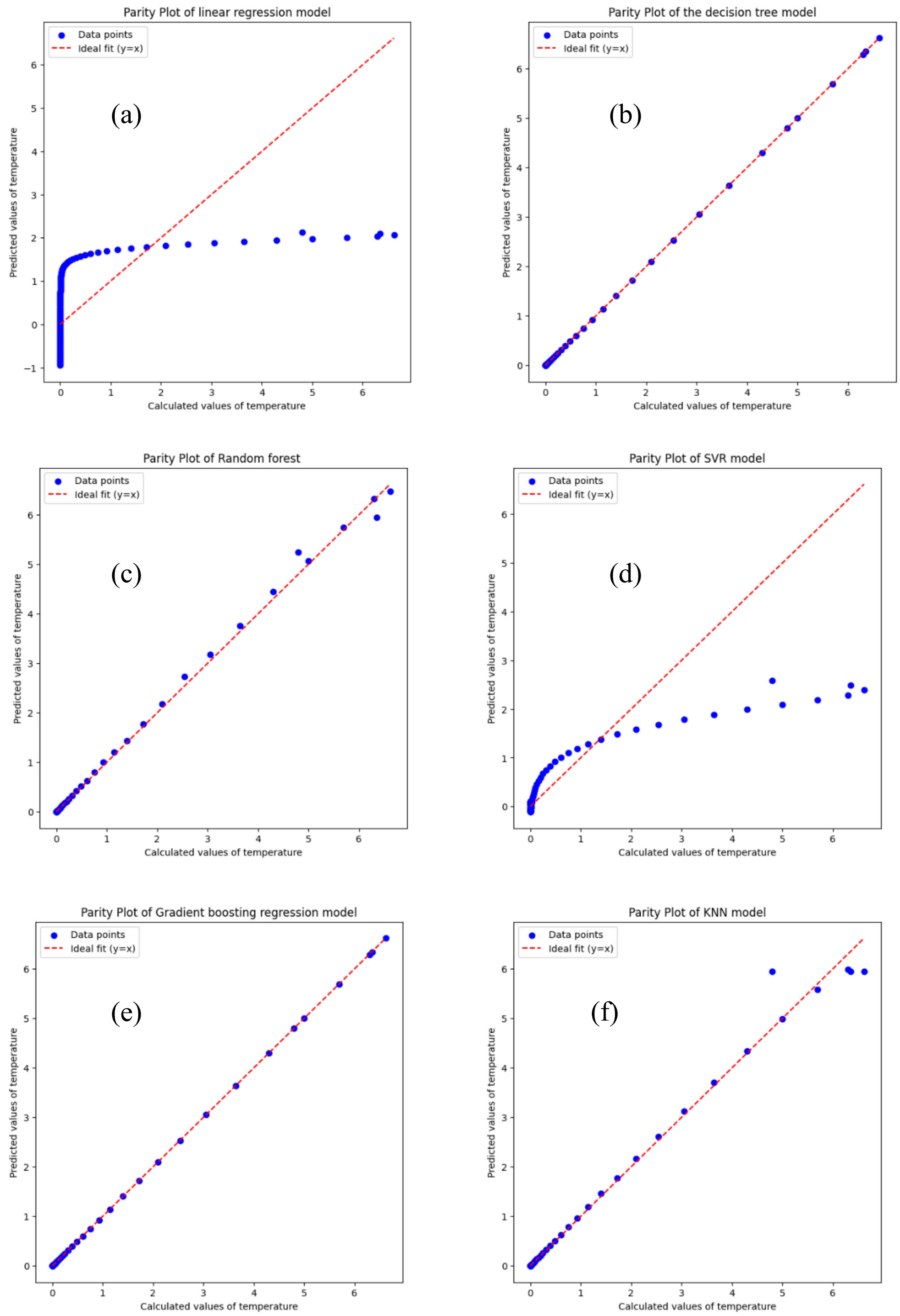

Fig. 4: The parity plot of the models (a) LR, (b) DT, (c) RF, (d) SVR, (e) GB, and (f) KNN.

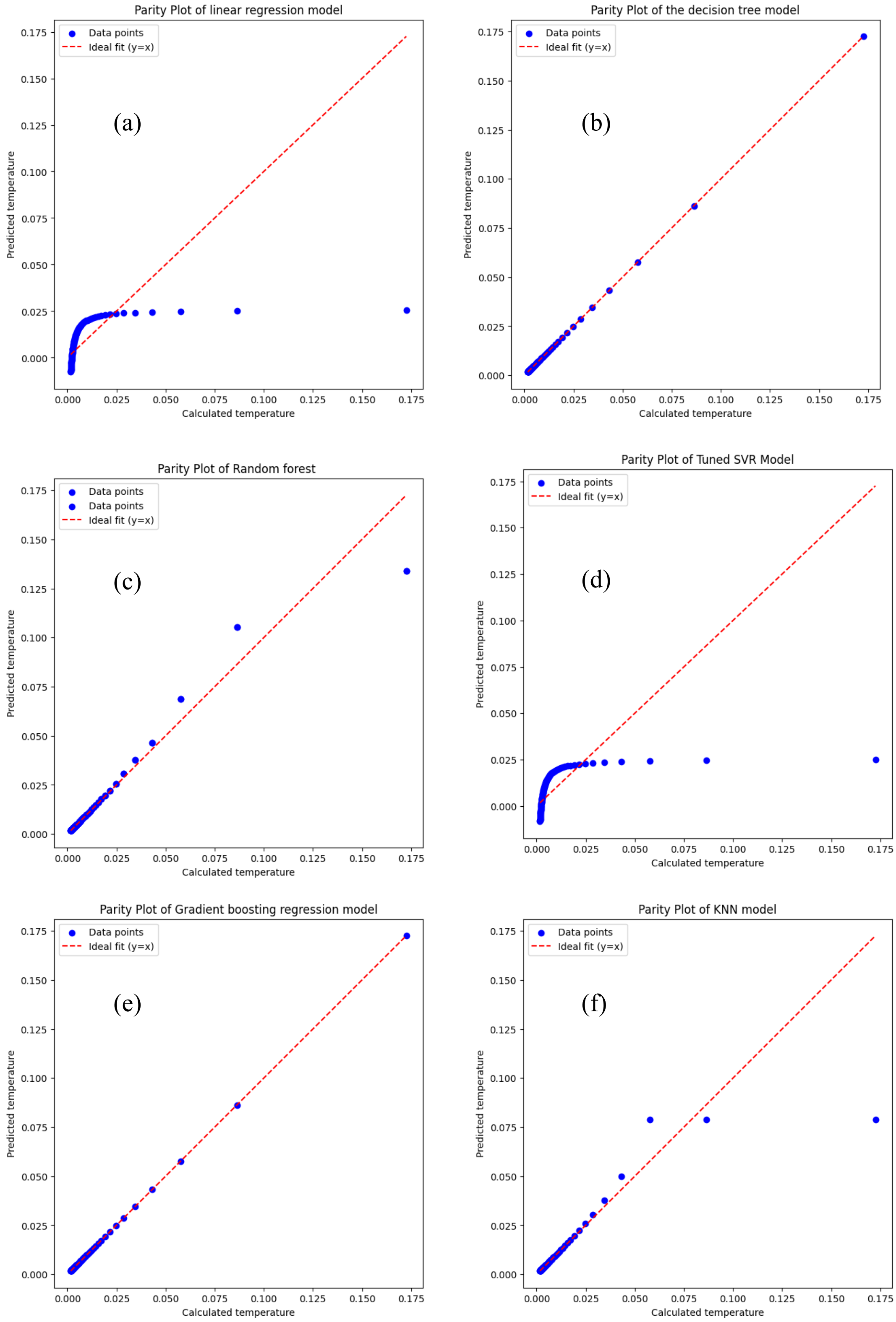

Fig. 5: The parity plot of the models (a) LR, (b) DT, (c) RF, (d) SVR, (e) GB, and (f) KNN.

From Tables 1 and 2, RMSE, MSE, and MAE values of the decision tree model converge to zero, implying that the predicted values are very adjacent to the actual values, thereby indicating the model's high accuracy. The dataset used has a simple structure and minimum noise which lacks the complexity of the data. Thus, k-fold cross validation is employed to evaluate this with k value equals 5 and the consistency in R^2 values for each of the fold indicates the simplicity of the data. Thus, in comparison with other models, the R^2 value for the DR model is 1, which signifies a perfect fit of the model in explaining the variability of the data about its mean. From Figs. 2-5, it is evident that the DT and GB models perform well. However, concerning the evaluation metrics, the DT model outperforms the GB approach.

4. Conclusion

Understanding how heat energy propagates through materials is made possible by heat transfer analysis, which is essential in both environmental and engineering scenarios. Engineers can forecast the temperature distribution and heat flow rate inside objects by using heat transfer analysis. There are many real-world uses for them, from developing effective cooling systems for electrical components to furnishing buildings with cozy living spaces. In order to explain how heat transfers throughout materials, heat transfer analysis uses mathematical models, most often differential equations. This is where more straightforward models, like the semi-infinite medium assumption, come in handy, particularly when working with big objects where heat flows in one direction mostly. Thus, an ML technique based on the Fourier transform method is proposed for the investigation of heat conduction in a semi-infinite medium. From the evaluation metrics and graphical representations, it can be concluded that the decision tree model fits the data rather well and is highly predictive for heat conduction problems. Thus, predicting the heat transfer will be beneficial in the field of thermal performance of slabs, underground cables, ground-source heat pumps, frost protection, and regulation of soil temperature, which all incorporate the usage of a semi-infinite medium.

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Conflict of Interest

There is no conflict of interest.

Supporting Information

Not applicable.

References

[1] K. R. Diller, Heat transfer in health and healing, *Journal of Heat Transfer*, 2015, **137**, 103001, doi: 10.1115/1.4030424.

[2] A. Rahimi, A. Dehghan Saee, A. Kasaeipoor, E. Hasani Malekshah, A comprehensive review on natural convection flow and heat transfer, *International Journal of Numerical Methods for Heat & Fluid Flow*, 2019, **29**, 834-877, doi: 10.1108/hff-06-2018-0272.

[3] W. Lipiński, E. Abbasi-Shavazi, J. Chen, J. Coventry, M. Hangi, S. Iyer, A. Kumar, L. Li, S. Li, J. Pye, J. F. Torres, B. Wang, Y. Wang, V. M. Wheeler, Progress in heat transfer research for high-temperature solar thermal applications, *Applied Thermal Engineering*, 2021, **184**, 116137, doi: 10.1016/j.applthermaleng.2020.116137.

[4] M. Lilly Clarance Mary, R. Saravanakumar, D. Lakshmanaraj, L. Rajendran, M. E. G. Lyons, Mathematical modelling of unsteady flow of gas in a semi-infinite porous medium, *International Journal of Electrochemical Science*, 2022, **17**, 220619, doi: 10.20964/2022.06.05.

[5] K. Kasim, A. Muley, M. Stoia, F. Ladeinde, Advanced heat transfer devices for aerospace applications, *ASME 2017 International Mechanical Engineering Congress and Exposition*, November 3-9, 2017, Tampa, Florida, USA, 2018 doi: 10.1115/IMECE2017-72382.

[6] Q. Li, L. Chen, H. Ma, C. Huang, Enhanced heat transfer characteristics of graphite concrete and its application in energy piles, *Advances in Materials Science and Engineering*, 2018, **2018**, 8142392, doi: 10.1155/2018/8142392.

[7] G. Nie, Z. Lei, J. Liu, L. Zhang, Bending waves localized along the edge of a semi-infinite piezoelectric plate with orthogonal symmetry, *Frontiers in Materials*, 2022, **9**, 1031538, doi: 10.3389/fmats.2022.1031538.

[8] R. Piscoya, M. Ochmann, Sound radiation of a line source with general time dependence moving above an interface between two homogeneous semi-infinite fluid media, *Journal of Theoretical and Computational Acoustics*, 2022, **30**, 2240003, doi: 10.1142/s2591728522400035.

[9] S. Sarma, N. Ahmed, Thermal diffusion effect on unsteady MHD free convective flow past a semi-infinite exponentially accelerated vertical plate in a porous medium, *Canadian Journal of Physics*, 2022, **100**, 437-451, doi: 10.1139/cjp-2021-0361.

[10] E. Deliktas-Ozdemir, Nonlinear Love-type waves in a heterogeneous layer sandwiched between two semi-infinite media, *Zeitschrift Für Angewandte Mathematik und Physik*, 2022, **74**, 7, doi: 10.1007/s00033-022-01895-6.

[11] A. U. Shirsat, A. Kumar, P. V. P. Moorthi, A. Gopinath, A. Sridharan, S. Karagadde, P. Nanthagopalan, P. K. Baburajan, R. S. Rao, A. Kumar Deo, S. V. Prabhu, Measurement of thermal properties of Ferro siliceous sacrificial radiation shielding concrete using semi-infinite transient heat conduction model, *Construction and Building Materials*, 2023, **388**, 131713, doi: 10.1016/j.conbuildmat.2023.131713.

[12] V. D. Beybalaev, A. A. Aliverdiev, A. Z. Yakubov, S. A. Ninalalov, A. A. Amirova, Mathematical model of heat conduction for a semi-infinite body, taking into account memory effects and spatial correlations, *Fractal and Fractional*, 2023, **7**, 265, doi: 10.3390/fractalfract7030265.

[13] D. C. Kesavaiah, P. G. Chowdary, M. Chitra, D. N. Venu, Chemical reaction and MHD effects on free convection flow of a viscoelastic dusty gas through a semi infinite plate moving with radiative heat transfer, *NeuroQuantology*, 2022, **20**, 9425-9434, doi: 10.14704/NQ.2022.20.8.NQ44962.

[14] X. Duan, W. Zhang, C. Chi, L. Li, S. Jiang, G. Chi, Analysis of transient heat conduction within semi-infinite medium surrounding heated conical shell, *International Journal of Thermal Sciences*, 2023, **185**, 108028, doi: 10.1016/j.ijthermalsci.2022.108028.

[15] S. Matta, B. Siddulu Malga, G. Rameshwar Goud, L. Appidi, P. Pramod Kumar, Effects of viscous dissipation on MHD free convection flow past a semi-infinite moving vertical porous plate with heat sink and chemical reaction, *Materials Today:*

Proceedings, 2023, **92**, 1629-1636, doi: 10.1016/j.matpr.2023.06.108.
[16] V. D. Beybalaev, A. A. Aliverdiev, J. Hristov, Transient heat conduction in a semi-infinite domain with a memory effect: analytical solutions with a robin boundary condition, *Fractal and Fractional*, 2023, **7**, 770, doi: 10.3390/fractalfract7100770.
[17] M. Arif, P. Kumam, W. Kumam, Z. Mostafa, Heat transfer analysis of radiator using different shaped nanoparticles water-based ternary hybrid nanofluid with applications: A fractional model, *Case Studies in Thermal Engineering*, 2022, **31**, 101837, doi: 10.1016/j.csite.2022.101837.
[18] B. T. Al-Nuaimi, H. K. Al-Mahdawi, Z. Albadran, H. Alkattan, M. Abotaleb, E. M. El-kenawy, Solving of the inverse boundary value problem for the heat conduction equation in two intervals of time, *Algorithms*, 2023, **16**, 33, doi: 10.3390/a16010033.
[19] N. M. Lisha, A. G. Vijayakumar, Analytical investigation of the heat transfer effects of non-Newtonian hybrid nanofluid in MHD flow past an upright plate using the caputo fractional order derivative, *Symmetry*, 2023, **15**, 399, doi: 10.3390/sym15020399.
[20] W. Yang, A. Pourasghar, Y. Cui, L. Wang, Z. Chen, Transient heat transfer analysis of a cracked strip irradiated by ultrafast Gaussian laser beam using dual-phase-lag theory, *International Journal of Heat and Mass Transfer*, 2023, **203**, 123771, doi: 10.1016/j.ijheatmasstransfer.2022.123771.
[21] Q. D. To, G. Bonnet, Fourier transform approach to homogenization of frequency-dependent heat transfer in porous media, *International Journal of Numerical Methods for Heat & Fluid Flow*, 2023, **33**, 2023-2048, doi: 10.1108/hff-03-2022-0198.
[22] G. V. S. Anooj, G. K. Marri, C. Balaji, A machine learning methodology for the diagnosis of phase change material-based thermal management systems, *Applied Thermal Engineering*, 2023, **222**, 119864, doi: 10.1016/j.applthermaleng.2022.119864.
[23] J. Tang, S. Yu, C. Meng, H. Liu, Z. Mo, Prediction of heat transfer of bubble condensation in subcooled liquid using machine learning methods, *Chemical Engineering Science*, 2023, **271**, 118578, doi: 10.1016/j.ces.2023.118578.
[24] C. Kumar, P. Nimmy, K. V. Nagaraja, R. S. Varun Kumar, A. Verma, S. Alkarni, N. Ali Shah, Analysis of heat transfer behavior of porous wavy fin with radiation and convection by using a machine learning technique, *Symmetry*, 2023, **15**, 1601, doi: 10.3390/sym15081601.
[25] A. Bhattacharya, P. Majumdar, Artificial intelligence-machine learning algorithms for the simulation of combustion thermal analysis, *Heat Transfer Engineering*, 2024, **45**, 176-193, doi: 10.1080/01457632.2023.2178282.
[26] B. Panimathi, K. Chandan, P. Nimmy, T. V. Smitha, An Efficient Prediction of battery capacity based on temperature and state of charge using impedance, *4th International Conference on Advances in Electrical, Computing, Communication and Sustainable Technologies*, January 11-12, Bhilai, India, IEEE, 2024, 1-5, doi: 10.1109/icaect60202.2024.10469137.
[27] P. S. Reddy, K. Deepa, S. T. Sangeetha, Case study on predictive modeling of UAV battery remaining useful life using machine learning regression techniques, *International Conference on E-mobility, Power Control and Smart Systems*, April 18-20, Thiruvananthapuram, India, IEEE, 2024, 1-5, doi: 10.1109/icemps60684.2024.10559377.
[28] G. Rodrigues, N. Srivastava, P. B. Pati, Investigation of Heat exchanger performance with delta-wing tape inserts for high Reynolds Number using various machine learning techniques, *14th International Conference on Computing Communication and Networking Technologies*, July 6-8, Delhi, India, IEEE, 2023, 1-7, doi: 10.1109/icccnt56998.2023.10307183.
[29] G. N. Chandana, G. H. Varma, J. V. Dheeraj, R. V. Sanjika Devi, D. G. Kurup, Modeling and linearization of radio frequency power amplifiers using machine learning approaches, *7th International Conference on Electronics, Materials Engineering & Nano-Technology*, December 18-20, Kolkata, India, IEEE, 2023, 1-5, doi: 10.1109/iementech60402.2023.10423509.
[30] K. Chandan, K. V. Nagaraja, F. Gamaoun, T. V. Smitha, N. Neelima, U. Khan, A. M Hassan, Improving flow efficiency in micro and mini-channels with offset strip fins: A stacking ensemble technique for Accurate friction factor prediction in steady periodically developed flow, *Case Studies in Thermal Engineering*, 2024, **56**, 104232, doi: 10.1016/j.csite.2024.104232.
[31] J. Yu, Y. Yang, A. Campo, Approximate solution of the nonlinear heat conduction equation in a semi-infinite domain, *Mathematical Problems in Engineering*, 2010, **2010**, 421657, doi: 10.1155/2010/421657.