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PREDICTION OF NUCLEATE BOILING AND BURNOUT HEAT FLUX IN PRESSURIZED WATER REACTOR USING MACHINE LEARNING ALGORITHMS

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ABSTRACT

The accurate prediction of both nucleate boiling and burnout heat flux is crucial for enhancing the security and stability of a water-cooled pressurized reactor. Burnout phenomenon occurs when the heat transfer rate surpasses the critical heat flux (CHF), rapidly increasing fuel rod temperature due to a substantial drop in the convective heat exchange coefficient. This event can cause severe overheating and potential damage to the reactor core. Since no deterministic theory exists for predicting both heat fluxes, the process of obtaining accurate predictions is complex and not straightforward. To overcome this complexity we developed various machine learning (ML) algorithms for predicting boiling and burnout heat flux (BHF) in a reactor core. In this paper, three ML algorithms, k-nearest neighbors (KNN), Decision Tree (DT), and Artificial neural network (ANN) are developed, trained, and compared. The data were analyzed and processed by implementing an R programming environment by using different packages. The demonstrated model performance was evaluated using k-value, accuracy, cross-validation result, and confusion matrix. By comparing prediction efficiency and others parameter of three developed algorithms we finalize that ANN algorithm shows better performance than the DT and KNN algorithm regarding classification heat flux prediction problem. These findings are encouraging for the potential future implementation of machine learning techniques for heat flux along with reactor core diagnostics.

Keywords: *Nuclear Power Plant, Pressurized Water Reactor; Critical Heat Flux; KNN, Decision Tree; ANN.*

1. INTRODUCTION

The global reliance on nuclear power for electricity generation is growing significantly. At the end of 2022, an overall nuclear energy capability of about 393.8 GW(e) was achieved, with 438 reactors operational in 32 countries. Nuclear power provided 2486.8 terawatt-hours of electricity without generating greenhouse gases, accounting for approximately 10% of the world's total electricity generation and more than 25% of its low-carbon electricity (AA.VV., 2022). The workings of a nuclear power plant are vast and intricate, so identifying anomalies is too challenging, despite being monitored by a vast number of sensors and thousands of operating personnel. The main part of the nuclear power plant (NPP) is the reactor core where the nuclear fission and neutron scattering reaction takes place that contains many fuel assemblies. Since a nuclear fission reaction rate is triggered by the thermal neutrons, the reaction produces the heat flux. So, the reactor core monitoring techniques are of utmost importance to identify the core anomalies and to localize and classify the problem to provide impact for plant safety and reliability. In this context, a highly effective approach for reactor core surveillance focuses on monitoring the typical variation in neutron flux as well as the heat flux (Pázsit and Demazière, 2010).

This article offers an in-depth exploration of how ML techniques have the potential to update the predictive accuracy of critical heat transfer phenomena in pressurized water reactors (PWRs) for reliable plant operations. Two major aspects of the heat transfer process are boiling and departure from nucleate boiling or burnout heat flux. At the fuel rod surface, nucleate boiling occurs when the temperature is higher than saturation but lower than the critical heat flow and this heat flux is adequate to produce vapor bubbles. When the heat transfer surface experiences a considerable decline in heat transfer efficiency, it is referred to as being beyond the critical heat flux (CHF) or burnout heat flux, which can lead to overheating and potential damage to the fuel rod of the fuel assembly (Pázsit and Demazière, 2010).

Traditional methods for predicting nucleate boiling and burnout heat flux generally rely on empirical correlations and mechanistic models derived from experimental data and depend upon the plant condition and configuration. To address these challenges, this work investigates the prediction sensitivity of three machine learning algorithms KNN, DT, and ANN methods to deliver more accurate and reliable predictions for PWR's safe operation. An ML algorithm is a subset of artificial intelligence (AI) and is classified into two types of problems during data mining

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e.g. classification and regression (Morgan *et al.*, 2022). In this paper classification ML problem is implemented for heat flux prediction. The KNN algorithm predicts the output by finding the nearest data points by measuring Euclidian distance in the training set to the input data and utilizing their values. Decision trees (DT) partition data into branches according to feature values, resulting in predictions derived from a series of decision rules. Artificial Neural Network (ANN) models replicate the arrangement and operations of biological neural networks, comprising multiple layers of interconnected neurons that develop the capability to detect patterns within the data.

The article offers an in-depth comparison of the heat flux prediction performance exhibited by demonstrated models. These findings suggest that machine learning model especially artificial neural networks (ANN) and decision trees (DT) offers a significant improvement compared to conventional methods regarding predicting heat flux accuracy and plant reliability. The research also identifies prospective avenues for future exploration, such as incorporating real-time monitoring data to bolster model accuracy and extending the utilization of these methodologies to different types of reactor configurations.

2. RELATED WORKS

The authors (Zhao, Salko, and Shirvan) have introduced several ML techniques for forecasting the CHF in Sub-cooled and heat flux conditions in low-grade flow boiling regimes and identifying the optimum choice. In this paper (Zubair *et al.*, 2022) the authors have demonstrated the ANN and Random Forest (RF) algorithms in different operating conditions for predicting critical heat flux (CHF) and that the optimum performance is provided by the ANN algorithm. The authors (Naimi *et al.*, 2022) showed that the reactor fault diagnostics problems can be predicted more accurately by the KNN algorithm when they demonstrate ANN, KNN, and Support Vector Machine (SVM) techniques and use 15 different classifiers and ensembles. The authors (Demazière *et al.*, 2020) developed another machine-learning technique for neutron noise-based anomaly detection and localization due to the low error rate. (Kubinski, Darnowski and Palmi, 2022) Authors proposed an ML algorithm for forecasting how nuclear reactor core characteristics or parameters will change over time in different conditions. In contrast to the previously mentioned studies, this investigation provides new insights. This study introduces a unique predictive model employing ML techniques, specifically ANN, DT, and KNN classification, to forecast the nucleate heat flux core boiling and burnout in PWRs.

3. MAIN COMPONENTS OF PWRs

A typical PWR plant mainly consists of two circuits, which are named primary and secondary circuits or loops. The primary loop components are the reactor core, steam generator (SG), pressurizer, reactor coolant plant or main circulation pump, and several sets of hydro accumulators. The reactor core dynamics might be represented by a point kinetics approach. Additionally, the control rod is an essential part of the reactor core or actuators that control the nuclear fission reaction rate or power by absorbing thermal neutrons during the insertion into the core. In the primary circuit, the pressurizer is used to create the desired pressure into the core to avoid the boiling of coolant. Heated water is continuously transferred to the steam generator by the action of the reactor coolant pump to generate steam and finally supplied to the turbine in the secondary circuit. The major components of the secondary circuit are the turbine, generator, moisture separator, different reheaters, and feed water pump (Naimi *et al.*, 2022).

A vivid example of a PWR is the Russian design VVER-1000 and VVER-1200 reactor where the water is used as both moderator and coolant. A concise overview of the ideal reactor power core model is provided above table to keep it brief. For an extensive and grasped explanation of the NPP computational model, different actuators, and sensors, readers are encouraged to refer to (Vajpayee *et al.*, 2020) the article. An overview of the plant's main input and output components is provided in Table 1.

Table 1. The different variables defined for the PWR model

Variable	Definition
P_n	Thermal power of the reactor core
ρ_{rd}	Amount of reactivity
P_p	Actual pressure of the Pressurizer
Q_h	Reheater heat Addition Rate
L_w	The coolant level of the Pressurizer
m_{sur}	Mass flow rate
P_{sg}	The pressure of the Steam generator
C_{tg}	Factor affecting the turbine-governor valve
w_{tur}	Speed of the Turbine

3.1 Reactor Core Model

In order to simulate the reactor, a set of point kinetics equations containing thermal hydraulics parameters and six sets of delayed neutron precursors could be utilized. This is the overall mathematical representation of the reactor core model (Vajpayee *et al.*, 2020).

$$\frac{dP_n}{dt} = \frac{\rho_t - \sum_{i=1}^{6}\beta_i}{\Lambda} P_n + \sum_{i=1}^{6}\lambda_i C_{in}, \quad (1)$$

$$\frac{dC_{in}}{dt} = \lambda_i (P_n - C_{in}), \qquad i = 1 \text{ to } 6, \quad (2)$$

$$\frac{dT_f}{dt} = H_f P_n - \frac{1}{\tau_f}(T_f - T_{c1}), \quad (3)$$

$$\frac{dT_{c1}}{dt} = H_c P_n + \frac{1}{\tau_c}(T_f - T_{c1}) - \frac{2}{\tau_r}(T_{c1} - T_{cin}), \quad (4)$$

$$\frac{dT_{c2}}{dt} = H_c P_n + \frac{1}{\tau_c}(T_f - T_{c1}) - \frac{2}{\tau_r}(T_{c2} - T_{c1}), \quad (5)$$

$$\rho_t = \rho_{rd} + \alpha_f T_f + \alpha_c (T_{c1} + T_{c2}), \quad (6)$$

$$\frac{d\rho_{rd}}{dt} = G v_{rd}. \quad (7)$$

In the Equations (1)-(7) are given above, P_n indicates the normalization constant of the neutronic power; C_{in} denotes the concentrations of the normalized delayed neutron precursors, β_i is the effective delayed neutron fractions, and λ_i is the decay constant. In the aforementioned equation lifetime of the prompt neutron represented byΛ, ρ_t indicates the overall reactivity of the core and ρ_{rd} is the reactivity of the Boron control rod. Moreover, T_f, $T_{c1,}$ and T_{c2} represent the temperature of the fuel rod, and the temperatures in the coolant node 1 and 2 respectively. Also here, H_f and H_c are the two constant-coefficient values, $\tau_{c,}$ and τ_r represent the time constants parameter; α_f and α_c refer to the coefficients of reactivity for fuel and coolant at different temperatures, In addition, the reactivity worth denoted by G and finally, v_{rd} the velocity of the control rod.

3.2 Data Description and Partitioning

The heat flux acoustic spectrum data was generated from the thermal hydraulics laboratory at Obninsk Institute for Nuclear Power Engineering, (OINPE, Moscow, Obninsk, Russia) by implementing a simulation technique in normal and transient conditions due to the unavailability of real NPP operational data. This acoustics spectrum data consists of 173 rows and 201 columns. The 201 number columns indicate the real classification outcome of boiling and burnout heat flux data. This data spectrum depends upon the reactor core temperature (T), Pressure (P), and mass flow rate (G) in both normal and transient conditions. A variety of heat flux statistics were assessed in this paper and created for boiling and burnout heat flux prediction by implementing different machine learning algorithms for classification problems. This task was achieved by splitting the training and testing data set as one row is testing data and the rest of it evenly divided as training data and validation data and iterating all row data. Then compare the predicted data with the actual heat flux categorical data or column no 201 data. Finally, using different packages, confusion matrix, and several parameters the proposed machine learning (ML) algorithms predict the accurate heat flux and show their individual prediction accuracy and other parameters.

The study of nucleate boiling and burnout flux phenomenon of coolant in a reactor core is of utmost important work for fuel rod safety. The authors (Theofanous *et al.*, 2002) showed a detailed explanation of the boiling and burnout phenomenon of coolant in the case of pool boiling of fluid. Fig.1. shows the boiling and burnout heat flux scenario of liquid coolant.

4. PROGRAMMING ENVIRONMENT

The R programming environment was selected in this work to illustrate the machine learning techniques for heat flux prediction instead of Python and other cutting-edge equivalent languages. The reason behind choosing R programming due to its vast advantages compared to other languages. The main positive aspects of R language are the availability of its open source, this programming language is smart, simple, and effective, it can operate on all systems and has many loops, conditionals, and user-fixed recursive functions, and input and output features and it has splendid integration capabilities with other languages and there is big network support. Authors (Kaya *et al.*, 2019) showed Intrigued interest in using the R platform for spatial data analysis and described briefly the working procedure of the R studio platform.

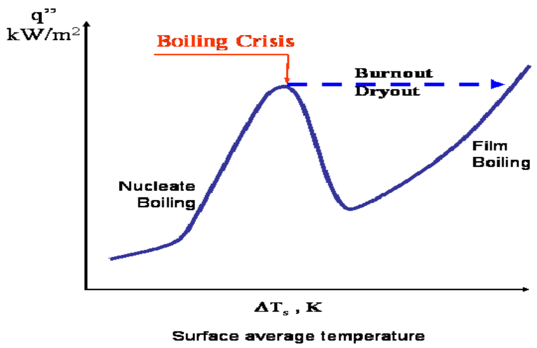

Figure 1: The pool boiling curve (Theofanous *et al.*, 2002).

5. CLASSIFICATION ALGORITHMS

Various ML methods are employed for both classification and regression tasks in the NPP diagnosis process. Three distinct families of machine learning classification algorithms from the R studio environment were presented in this paper to estimate their availability for the boiling and burnout classification heat flux of PWRs.

5.1 K-Nearest Neighbor (KNN) Algorithm

A well-known algorithm is the KNN which is a supervised or regulated ML algorithm. The K-Nearest Neighbors (KNN) algorithm, frequently employed in pattern identification classification tasks, determines the category of unknown parameters by calculating how far it is from the closest training data. This technique uses the similarity between an unlabeled and to classify it, labeled samples from the training set. This method has been extensively used in areas like visual data processing, statistical pattern identification, and data extraction. (Naimi *et al.*, 2022). Now day's KNN technique becoming more popular for fault diagnostics in the manufacturing industry (He and Wang, 2007, 2008). K-nearest neighbors (KNN) approaches find the k-nearest labeled samples in the training dataset for an unlabeled sample x by using distance metrics.

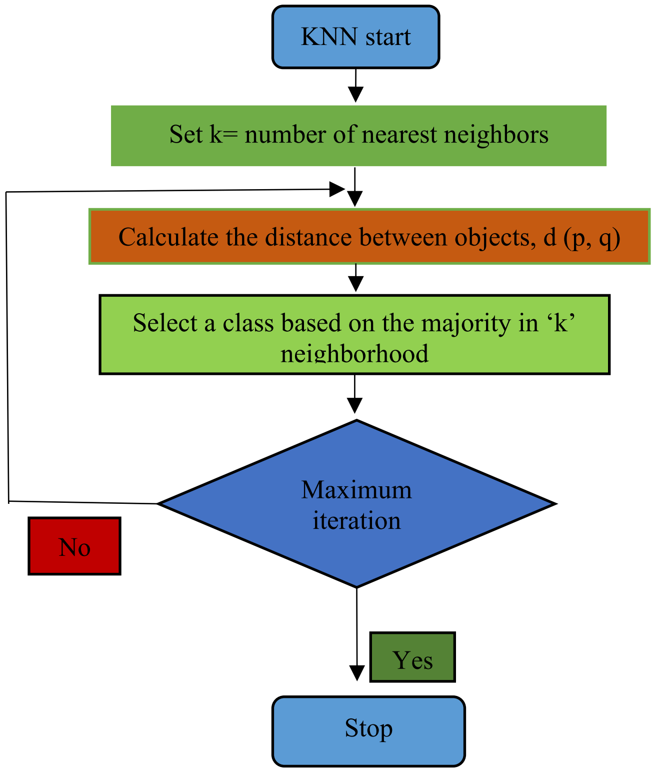

Figure 2: K-NN algorithm flowchart for the classification data prediction.

Generally, Euclidean distance metrics are utilized to evaluate the separation between two points in space. For instance, if p and q are Euclidean points, where $p = (p_1, p_2, \ldots, p_n)$ and $q = (q_1, q_2, \ldots, q_n)$, then the following method can be used to calculate the Euclidean distance (Chen *et al.*, 2020).

$$\text{Distance (p, q)} = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2}$$

$$\text{Distance (p, q)} = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \quad (8)$$

The Figure 2 in the following indicates the KNN classification algorithm flowchart for general data preparation and final outcomes heat flux prediction.

5.2 Decision Tree (DT)

Another machine learning technique that has been adopted here for heat flux classification problem prediction is the decision tree algorithm. To make decisions, this instance-based algorithm uses the concepts of inductive learning. A top-down recursive methodology is employed in the DT technique. Determine each non-leaf node's appropriate sample set's properties from the root node. Based on the test findings, several sub-sample sets are created from the training sample set.

Every subsample set creates a new root node, where the demarcation procedure described before is carried out once again. Repeat the process successively until the specific termination conditions are met. A rule in the DT is represented by the entire path that leads between a leaf node and the root node. There are various types of decision tree algorithms are popular in data science. Some of them are Iterative Dichotomies 3 (ID3) and Successor of ID3 (C4.5) methods are applied for fault diagnostics in NPPs (Mu and Xia, 2010). Additional popular decision tree algorithms are classification and regression trees in the data mining industry. The authors (Charbuty and Abdulazeez, 2021) presented a model for ML language's just classification based on the DT algorithm. This work established a classification-based DT algorithm technique for the prediction of reactor core heat flux.

For the decision tree algorithm, the Entropy function is introduced to evaluate a dataset's impurity or randomness, Entropy is 0 (pure) if the data is homogeneous, meaning that all of the elements are similar, if the elements are equally divided, however, entropy increases toward 1 (impure). The entropy of classifying set S concerning c asserts that if the target G displays variability with different attribute values *(*Xihui *et al. 2019)* as described in Equation (9).

$$\text{Entropy (S)} = \sum_{i=1}^{c} P_i \log_2(P_i) \quad (9)$$

Where P_i is the subset's sample number divided by the value of i-th attributes.

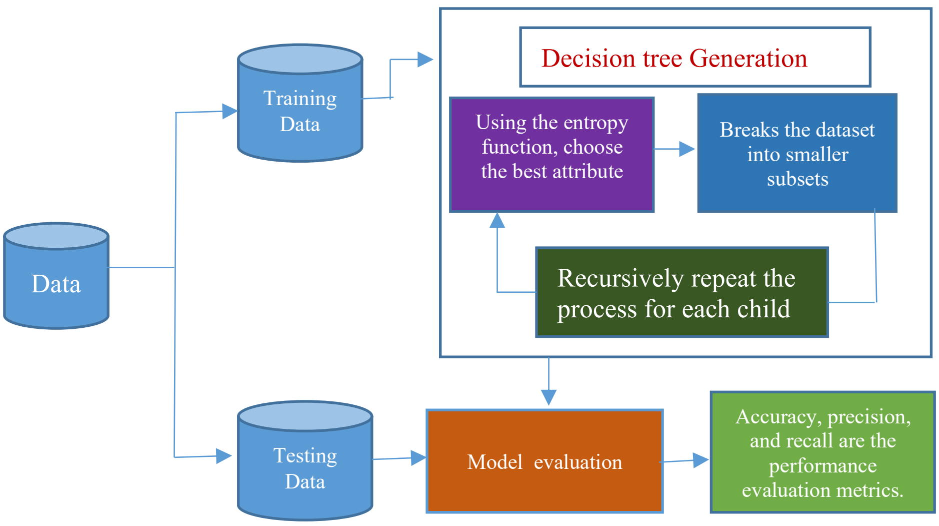

Figure 3: Decision Tree algorithm flowchart for the classification data prediction

5.3 Artificial Neural Network (ANN)

The human brain serves as the biological model for artificial neural networks, a unique and efficient type of machine-learning approach. In such a network, there are units known as neurons, which are interconnected akin to synapses transmitting data to additional natural neurons. The neurons are arranged into a minimum of three layers in a basic Multilayer Perceptron (MLP) neural network: input, one or more hidden layers, and output. The layer that takes input parameters and forwards them to a hidden layer is termed the input layer. Conversely, the output layer receives information from the hidden layer and generates the final output (Kubinski, Darnowski and Palmi, 2022), (Zubair *et al.*, 2022). The hidden layer also consists of several nonlinear activation functions that can conduct linear and nonlinear relations with input and output (Kalogirou, 2000), (Rodriguez-Galiano *et al.*, 2015).

Let us consider the function h $(h_1 \ldots h_n)$ defined as the hidden layer and y $(y_1 \ldots y_N)$ is the output layer and those are expressed by the following equations:

$$h_k = f^1 (w_{xh}x + b_h), \quad (10)$$

$$y_k = f^2 (w_{yh}\, h_k + b_y), \quad k = [1, \ldots, N] \quad (11)$$

In the following equations, x denotes the input vector and the weight matrix is w, for example w_{xh} is the weight matrix of the hidden layer input. The bias vector represent as b, For example b_h is called the hidden bias vector. And f^1, f^2 represents the sigmoid activation function and the linear activation function (Naimi *et al.*, 2022).

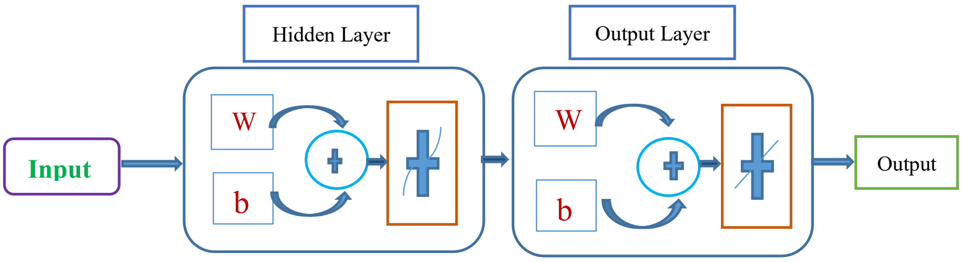

Figure 4: Working structure of Artificial Neural Network (ANN) Algorithm.

6. RESULTS AND DISCUSSION

In this work, an effective machine learning algorithm was developed and proposed for the heat flux prediction according to its higher prediction capacity. By analyzing different prediction parameters, we could propose that ANN algorithm has shown approximately 96% prediction performance for both heat flux prediction. The essential figure and different predicting parameters that are generated from the R language environment are described concisely for three proposed languages in below.

6.1 KNN Classifier

The first developed algorithm is a supervised language named as the KNN algorithm technique. It operates on a majority basis sample between training and testing data by measuring the Euclidean distances and indicating how far individuals are located from each other. In this study, a core heat flux dataset was studied for the boiling and burnout heat flux classification prediction by studying the KNN algorithm in R programming environment and achieved the following figure for model accuracy prediction with different k value (k=1 to 20).

6.2 Decision Tree (DT) Classifier

We have also demonstrated a decision tree (DT) algorithm in an R environment for predicting nucleate boiling and burnout heat flux. For assessing the predicting performance of a proposed algorithm it is important to ensure it can generalize effectively to new data. Cross-validation is a commonly utilized technique to accomplish this since it gives a projection of the model's performance on fresh, untested data (Nti et al. 2021). A more reliable performance estimate is produced as a result of the model's evaluation over many data subsets, which addresses the problem of variability in the training and validation data. It provides a more reliable evaluation of a model's performance than depending just on one train-test split.

Table 2: Different parametric values for tree construction Decision Tree (DT) classifier.

CP	NSPLIT REL	Rel Error	Xerror	Xstd
0.195312	0	1.00000	1.00000	0.099220
0.093750	2	0.60938	0.78125	0.093161
0.046875	4	0.42188	0.70312	0.090159
0.015625	7	0.28125	0.76562	0.092599
0.000100	8	0.26562	0.75000	0.092018

Each entry in the table at the bottom of the output corresponds to a tree in the sequence created by pruning. Now look at each column in the table below, where CP stands for the complexity parameter. For higher complexity parameters are associated with less complex models and vice versa. The quantity of splits in the tree is denoted by the term "nsplit". Keep in mind that 1 + nsplit equals the total number of tree terminal nodes. Additionally, the "rel" error is the tree's RSS training error, normalized by the total variance of the response. Lastly, the cross-validation standard error is denoted by "xstd" and the cross-validation error estimate by "xerror."

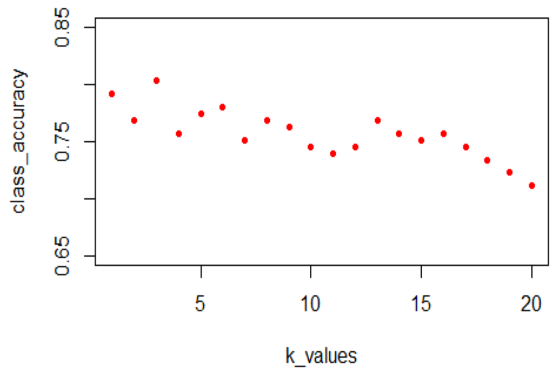

Figure 5: Graphical representation of KNN model accuracy for heat flux prediction with different 'K' values.

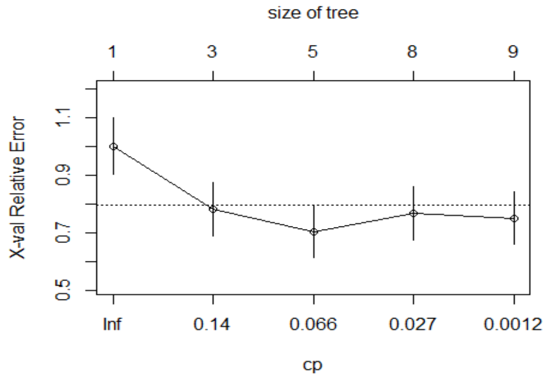

Figure 6: Cross-validation (CV) vs Complexity Parameter (CP) graph for DT model accuracy assessment.

Figure 6. Shows the cross-validation error versus complexity parameter (cp) graph for evaluating the performance of the DT algorithm for heat flux prediction. The horizontal braking line marks the average value of the CV curve.

6.2.1 *Tree Construction*

A DT is a flowchart-like model enabled for making decisions or predictions. There are multiple nodes representing decisions or attribute tests, branches representing the decisions' outcomes, and leaf nodes representing the conclusions or forecasts. Each leaf node represents a continuous value or a class label, each internal node represents an attribute test, and each branch represents the outcome of the test. The main components of an ideal decision tree figure are root nodes, internal nodes, branches, and leaf nodes. Where root nodes indicate the entire data set for starting tree, internal nodes show the test or decision on attributes and branches is the decision or outcome during prior to the final step. Finally, the leaf nodes suggest the final decision or prediction class. For the heat flux input data, the following variables are actually used in tree construction for boiling and burnout heat flux prediction. Those are, V109, V111, V142, V154, V19, V44, V60, and V80 with root node error: 64/173 = 0.36994 and n=173.

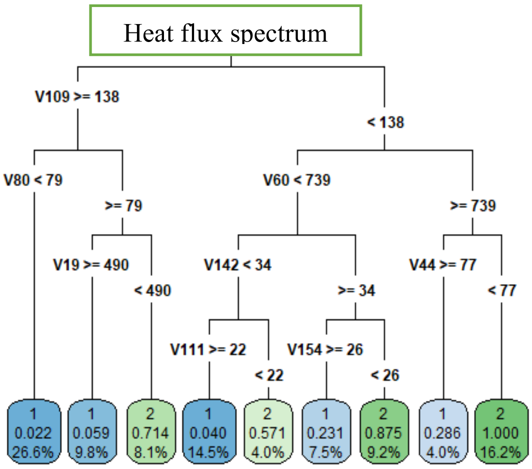

Figure 7. Construction tree for boiling and burnout heat flux prediction in DT model.

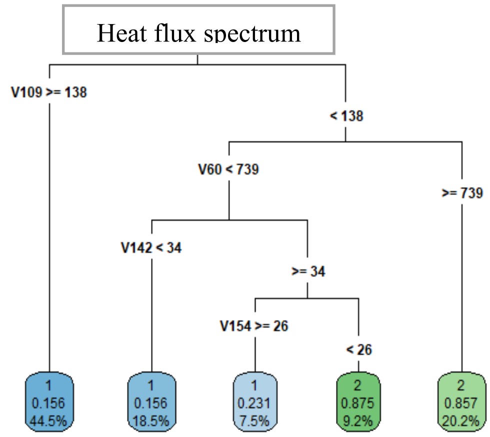

Figure 8. Construction pruned tree for boiling and burnout heat flux prediction in DT model.

6.2.2 *Pruning Tree*

Pruning is a method used in machine learning to compress data, specifically aimed at decreasing the size of decision trees. It achieves this by eliminating parts of the tree that are deemed non-critical or redundant for classifying instances. By simplifying the final classifier, pruning contributes to enhancing predictive accuracy through the reduction of over fitting and enhance the robustness. Finally, prune the aforementioned tree to the desired size using prune (fit, cp=) in R and obtained the following Figure.8. As can be seen from the figure, the heat flux prediction summary of the decision tree (DT) algorithm where two heat flux classifiers are predicted the satisfactory accuracy.

6.3 ANN Classifier

Lastly, another popular machine learning algorithm was proposed the Artificial Neural Network or ANN algorithm for reactor core boiling and burnout heat flux prediction due to its higher predicting accuracy. In essence, it behaves like a real neuron and divides into several layers, such as the input, hidden, and output layers. These layers are connected and exchange signals utilizing various activation functions, ultimately producing the intended output.

To train the heat flux data iterating a total of 173 rows of data is considered as one row is testing and the rest is training data for classification outcome prediction. The visual representation diagram of the proposed algorithm is shown below and it divided into input layer, hidden layer where weighting the input data by using activation functions and transmitting into the output layer for boiling and burnout heat flux prediction. The technique looks for a set of weights to make sure that the network's output vector for each input vector roughly reflects the intended output vector. If there is a well-defined and constrained set of input-output cases, or patterns, the total error in the network's performance with a given set of weights can be assessed by comparing the expected and actual output vectors for each pattern. One common method for this comparison is the least squares approach and a “neuralnet” package is used to complete this task.

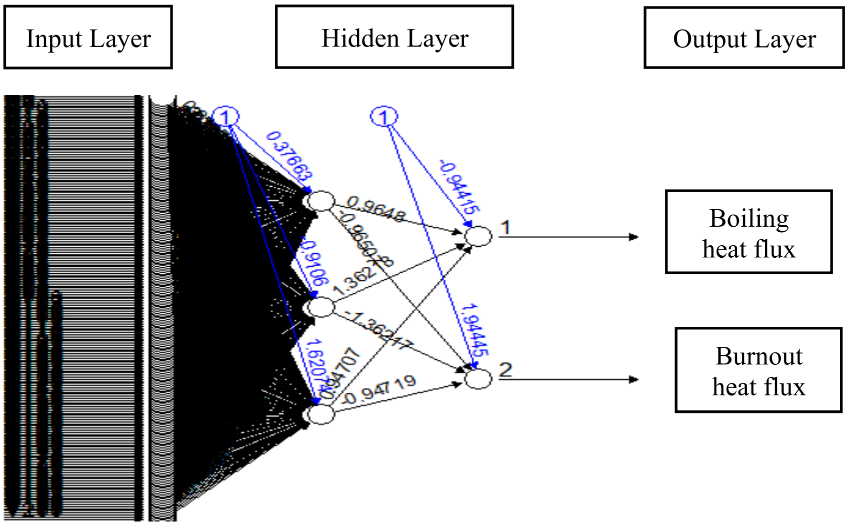

Figure 9. Visual representation of ANN algorithm working principle for heat flux prediction.

Creating an improved machine learning algorithm is the primary goal of this work for identifying both heat flux predictions. Although there are some usual techniques for heat flux prediction implementation of the machine learning technique is completely advanced and fruitful. In this study, three ML algorithms the KNN, DT, and ANN are developed to test the performance of heat flux data for boiling and burnout class prediction. Three algorithms are trained to classify the boiling and burnout heat data to assist reactor operational personnel for safe and reliable NPP operation.

In the R programming environment, a confusion matrix statistics technique was employed to assess the performance of the generated algorithms. A table that helps assess the efficiency of a classification technique by summarizing and illuminating its performance is called a confusion matrix. The following representations of accuracy, precision, and recall can be computed using the confusion matrix (Naimi, Deng et al. 2022).

$$\text{Predicted Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{12}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{13}$$

$$\text{Recall} = \frac{TP}{TP+FN} \tag{14}$$

Where, TP is the true positive, TN refers to the true negative, FP is the false positive, and FN, indicates the false negative.

Table 3 represents the different parametric values of the three developed algorithms for better prediction accuracy. Here CI- means the Confidence Interval parameter in the confusion matrix, it indicates a range where the true value is expected to be found, according to a specific level of confidence. In this study maximum CI is 95% was found for ANN and DT algorithms. If the null hypothesis is correct, the P-value indicates the probability that the alternative hypothesis will have an impact.

Table 3: Confusion matrix results parameter of the heat flux dataset for KNN, DT, and ANN classifiers.

Developed Algorithms	CI-Value (%)	P-Value	Kappa	Sensitivity/ Recall	Specificity	Precision (%)	Balanced Accuracy (%)	Total Accuracy (%)
KNN	90	1.6×10^{-5}	0.6188	0.7959	0.8213	86.00	80.82	80.35
DT	95	1.7×10^{-5}	0.6506	0.8361	0.8627	93.58	84.94	84.40
ANN	95	2×10^{-16}	0.9146	0.9450	0.9844	99.04	96.47	95.95

The minimum P value has been found here for the ANN algorithm, which means this algorithm is more accurate than others for class prediction. The Kappa coefficient assesses the alignment between classification outcomes and the true values, a kappa value of 1 indicates absolute agreement, whereas a value of 0 indicates no agreement. From table.3 we found that the Kappa value is less for KNN than DT and ANN algorithms. For ANN the Kappa coefficient is close to 1, which means the predicted class and the actual class are nearly the same. The ratio of true positive predictions to all positive cases is the definition of sensitivity. It is also called as the true positive rate (TPR) or recall (REC). The ideal sensitivity score is 1, while the worst score is 0. The best sensitivity or recall score has been found 0.9450 for the ANN algorithm than others. It depicts the fact that the ANN algorithm predicts more true positive classes for reactor core heat flux. The specificity of another parameter is determined by dividing the total number of real negative events by the ratio of true negative cases. It is also referred to as the true negative rate (TNR). The optimal specificity score is 1, and the lowest is 0. In this study, the lowest specificity has been found for the KNN algorithm and the highest for the ANN algorithm. These results also suggest that the ANN algorithm is better than other algorithms for classification cases.

Additionally, precision is a statistic that counts the percentage of accurately predicted positive instances among all positive predictions to determine how accurate positive predictions are. The ANN algorithm shows about 99.04% result for the prediction of true positive class. In addition, the balanced accuracy represents the arithmetic mean between sensitivity and specificity. As usual like the prior parameter, the balanced accuracy is low for the KNN algorithm and highest at 96.47% for the ANN algorithm. Finally, the most important indicator is accuracy, it calculates the percentage of cases that are correctly classified overall versus all cases. The KNN algorithm shows an accuracy is 80.35 for k=3, moreover, The DT and ANN algorithms show prediction accuracy of about 84.40% and 95.95% respectively for the two types of heat flux classification studies. So the ANN algorithm is unquestionably a superior performer compared to the other techniques. Although the DT classifier exhibits higher overall accuracy compared to the KNN classifier. Intersetingly, the 2024 Nobel Prize in Physics was achieved by John Hopfield and Geoffrey Hinton for the fundamental discoveries and inventions that enable machine learning with Artificial Neural Networks. Undoubtedly one can see that, the ANN algorithm is the best one for the nuclear reactor core heat flux prediction by comparing the different parametric values including the overall accuracy.

There is considerable scope for further research, by enhancing the training dataset to adding random heat flux and developed more ML algorithms to improve the prediction accuracy and also incorporating more detailed mathematical technique or by fluctuating temperature, pressure mass flow rate, etc. Additionally, the input database might contain more technological parameters. In the long run, these parameters could be utilized to enhance the prediction accuracy and calculate additional nuclear reactor core output parameters. This new technique might enable to enhance the safety of a reactor core to assist the NPP operational personnel in safe and reliable NPP operation.

7. CONCLUSIONS

In this work, it is aimed to develop an efficient AI-based machine learning algorithm for reactor core heat flux prediction from the acoustic heat flux spectrum dataset. In the diagnostic process, data was collected from the simulation technique of a PWR reactor and utilized for training the classifiers. The data set was split into training and testing set and finally the prediction performance was compared with the testing set. An in-depth analysis was conducted to compare classifier performance using the confusion matrices for KNN, CART and ANN algorithms. The proposed ANN classification methods shows robust performance and are highly effective in predicting the boiling and burnout heat flux in PWR systems. Thus it has been cleared that, the ANN algorithm technique is more benificial for heat flux prediction to enhance the safety and reliability of a reactor core by providing exact instruction to the NPP operaing personnels.

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