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Research Article

Artificial Intelligence-Based Modeling of Boiling Heat Transfer: Current Approaches and Future Perspectives

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Keywords

Critical heat flux,
Machine learning,
Boiling heat transfer,
Artificial intelligence,
Heat transfer coefficient.

Abstract

Boiling offers a compact route for removing large heat loads in power systems, electronics cooling, batteries, and other thermal devices, yet its prediction is still difficult because the wall, liquid, vapor phase, and operating conditions evolve together. Classical correlations remain useful engineering tools, especially within the ranges for which they were developed. Their reliability may decrease, however, when they are applied to coated, roughened, micro/nano-structured, or nanofluid-based surfaces where surface morphology, wettability, particle deposition, and bubble dynamics are coupled. This narrative review examines how artificial intelligence methods have been used to model boiling heat transfer, including ANN, fuzzy logic, ANFIS, RBF/GRNN, SVR, GPR, deep learning, probabilistic approaches, explainable AI, and optimization-assisted frameworks. The discussion does not treat AI as a universal substitute for mechanistic or empirical correlations. Instead, it evaluates the conditions under which data-driven models can be useful and the situations in which their predictions should be interpreted cautiously. The review focuses on input selection with physical meaning, boiling-regime dependence, surface characterization, input-output dependency and data leakage, validation practice, model interpretability, uncertainty quantification, and optimization potential. Overall, AI-based models can assist boiling prediction and design when trained on representative data and evaluated within their domain of validity, but their usefulness depends on physical consistency, transparent reporting, and experimental verification.

1. Introduction

Boiling heat transfer, which converts liquid into vapor at a heated surface, is widely used when large thermal loads must be removed over a small temperature difference. It is therefore relevant to nuclear and conventional power systems, heating and cooling units, high-performance computing hardware, battery thermal management, and aerospace applications [1]. In such systems, the design target is not only to increase heat removal, but also to keep operation safely below the critical heat flux (CHF). CHF is a safety boundary in heat-flux-controlled boiling because crossing it can move the surface from efficient nucleate boiling toward a poorly cooled film-boiling state, with a sudden rise in wall temperature [2]. The difficulty is that boiling response is not controlled by fluid properties alone; surface texture, roughness, wettability, pressure, heat flux, geometry, and bubble dynamics act together [1,3].

At the heated wall, several processes occur at the same time: bubbles appear at active nucleation sites, grow, detach, merge, leave dry or partially dry zones, and are followed by liquid rewetting. These events determine the heat transfer coefficient (HTC), the approach to CHF, and the shape of the boiling curve. Surface roughness, contact angle, and surface morphology are especially influential because they affect nucleation-site density, bubble departure, and capillary liquid supply [3,4]. For this reason, coatings, roughened surfaces, micro/nano-textures, and nanoparticle deposition are frequently used to improve boiling performance. Recent reviews of additive- and nanofluid-assisted pool boiling also show that surfactants, polymers, nanoparticles, roughness, and deposition can interact in non-uniform ways, so HTC and CHF trends may change with the particular fluid-surface pair and operating range [5]. Surface modification is therefore not automatically beneficial. Moderate modification may increase nucleation activity, whereas excessive coating, dense particle layers, or thick porous deposits can add thermal resistance and reduce performance [4,6].

Boiling models have traditionally relied on empirical or semi-empirical correlations, including well-known formulations such as Rohsenow and Zuber. These correlations are valuable when the fluid, surface, and pressure range are close to the data from which they were derived. Their limitations become more visible when surface morphology, wettability, capillary transport, material properties, and nanofluid effects must be represented simultaneously. This gap has encouraged the use of data-driven models in boiling heat transfer. Artificial intelligence methods can map complex input-output relations from experimental, numerical, or literature-compiled data, and in selected cases they can outperform a single classical correlation within the investigated domain [7]. ANN, fuzzy logic, ANFIS, RBF, support vector methods, GPR, deep learning, and optimization-assisted approaches have therefore been applied to estimate HTC, CHF, wall superheat, Nusselt number, and minimum film boiling temperature [8-25].

The early literature mainly employed ANN, fuzzy logic, and ANFIS models to demonstrate that data-driven tools could reproduce boiling behavior and HTC trends [8-11]. Later work added RBF networks, genetic-algorithm-supported models, and broader ANN architectures, while also including variables such as roughness, nanoparticle concentration, pressure, heat flux, and thermophysical properties [12-16]. More recent studies have moved toward deep learning, GPR, probabilistic learning, and multi-objective optimization, expanding the discussion from prediction alone to uncertainty, model selection, and operating-condition design [17-19,25].

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Even with these developments, the literature still contains important weaknesses. High reported accuracy does not necessarily mean that a model has learned the underlying boiling physics. Many datasets cover only one fluid family, one surface type, one material group, or a narrow range of heat flux and pressure, which limits transfer to new fluids, surfaces, or regimes [7,19]. For this reason, AI-based boiling models should be judged not only by error values, but also by physical consistency, validation outside the training domain, and their ability to provide interpretable information about the controlling heat-transfer mechanisms [7,19,24,25].

This study examines when artificial intelligence can contribute meaningfully to boiling heat transfer modeling and where its use remains limited. The discussion first explains why purely correlation-based approaches may be insufficient for some modified surfaces and multiparameter boiling datasets. It then reviews ANN, ANFIS, RBF, SVM/SVR, GPR, DNN, CNN, BNN, and optimization-supported models. Particular attention is given to input-output selection, dataset structure, physical interpretability, uncertainty analysis, and future research needs. The article is written as a narrative review, not as a systematic review or meta-analysis. It does not attempt a formal database-screening procedure. Instead, it brings together representative studies in AI-based boiling heat transfer to compare their methodological strengths, limitations, and physical reliability. Compared with broader reviews of AI applications or CHF prediction, the emphasis here is narrower: physically meaningful input selection, mathematically dependent variables and data leakage, surface characterization, explainable and uncertainty-aware AI, boiling-regime dependence, and optimization-supported modeling. This framing is intended to support more reliable and interpretable AI models rather than simply to catalogue algorithms.

2. Why is Artificial Intelligence Needed in Boiling Heat Transfer?

The motivation for using artificial intelligence in boiling heat transfer follows from the way boiling experiments combine surface effects, fluid response, operating conditions, and bubble-scale events. Nucleation, bubble growth, coalescence, detachment, microlayer evaporation, and rewetting occur together rather than as isolated steps. Their influence depends on the heating surface as much as on the liquid properties. A useful model must therefore be able to represent surface-fluid-operation coupling rather than treating boiling as a function of a single variable [1,7].

Surface features provide a clear example of this coupling. Roughness and wettability may increase the number of active nucleation sites and improve liquid supply, while morphology, porosity, and coating architecture can change bubble motion near the wall. The same surface treatment, however, can also become harmful if it forms an overly thick or dense layer that introduces additional thermal resistance [3,4,6]. Thus, boiling performance depends on how the surface, working fluid, and operating condition interact in a specific domain.

This domain dependence explains why classical correlations may lose accuracy when they are used far from their original calibration range. Nanofluids, coated surfaces, micro/nano-structured surfaces, and material-dependent effects introduce variables such as contact angle, roughness, coating thickness, porosity, morphology, and capillary behavior that are difficult to include in a single fixed-form correlation. AI models can be useful in such cases because they can handle several measured variables at once. This usefulness is conditional, however. It depends on data quality, physically independent inputs, validation strategy, and the model's ability to operate beyond the training domain. Since the meaning of inputs and outputs also changes with the boiling domain, Table 1 summarizes the major boiling regimes and their modeling implications for AI-based heat transfer studies.

Experimental investigation remains essential for boiling research, but it is expensive, time-consuming, and sensitive to measurement and reproducibility issues. Each new fluid, surface material, coating procedure, particle concentration, or heat-flux range may require a separate experimental campaign. Temperature measurement, heat-flux calculation, wall-temperature estimation, and surface characterization also introduce uncertainty [7,19]. Data-driven models provide a way to extract additional value from existing experimental and numerical datasets. ANN, ANFIS, RBF, SVR, GPR, DNN, and related methods have been used to estimate HTC, CHF, wall superheat, and Nusselt number [8-19]. Their main practical advantage is the ability to combine thermal variables with surface roughness, contact angle, coating thickness, nanoparticle concentration, particle size, pressure, and thermophysical properties in the same framework [6,7,13,16,19]. When linked to GA, PSO, or MOGA, these models may also support design choices such as increasing HTC while limiting wall superheat [12,25].

Table 1. Boiling-domain considerations for AI-based heat transfer modeling.

Boiling domain	Typical physical meaning	AI-modeling implication	Reason for inclusion
Pool boiling	Bubble nucleation, growth, departure, coalescence, and surface rewetting under a quiescent bulk liquid.	Surface roughness, contact angle, heat flux, pressure, and fluid properties should be defined consistently.	Most reviewed datasets and surface-modification studies are pool-boiling oriented.
Flow boiling	Phase change under forced flow with coupled effects of mass flux, quality, channel geometry, and pressure drop.	Inputs such as mass flux, vapor quality, hydraulic diameter, and flow orientation are needed in addition to thermal variables.	Models trained only on pool-boiling data should not be generalized directly to flow boiling.
Film boiling/minimum film boiling temperature	Vapor film stability and transition from film boiling to rewetting dominate heat transfer.	Output targets and input variables differ from nucleate boiling HTC prediction.	This distinction prevents physically inconsistent model comparisons.
Nanofluid boiling	Particle concentration, particle size, deposition, and base-fluid properties affect surface-fluid interactions.	Nanoparticle variables must be separated from surface-aging and deposition effects where possible.	Several reviewed AI studies focus on nanofluids and nanorefrigerants.
Coated or micro/nano-structured surfaces	Surface morphology, porosity, coating thickness, wettability, and capillary transport influence nucleation and rewetting.	Surface characterization data should be included, but coupled variables require careful validation to avoid overfitting.	This is central to the review's discussion of physical input selection.
CHF-oriented datasets	Safe operating limits are governed by dryout, hydrodynamic instability, surface wettability, and heat-flux history.	CHF models require validation against unseen operating ranges and should not be judged only by random train/test splits.	CHF prediction has different physical and safety implications than HTC prediction.

The usefulness of these models is limited by the dataset on which they are trained. Small or narrow datasets can give accurate predictions inside the sampled range but unreliable behavior outside it. In addition, many AI architectures behave as black boxes; a low prediction error may not explain why a surface or operating condition improves boiling. Future use of AI in this field therefore requires more careful input selection, transparent validation, uncertainty assessment, and explainability tools, together with experimental confirmation [19,25].

3. Major Artificial Intelligence Models Used in Boiling Heat Transfer and Their Comparative Evaluation

3.1. Artificial Neural Networks

Artificial neural networks (ANNs) are one of the most widely used artificial intelligence models in boiling heat transfer studies. These models are particularly successful in predicting heat transfer coefficient, critical heat flux, and wall superheat thanks to their ability to learn nonlinear relationships between input and output variables. In the literature, the multilayer perceptron (MLP) structure is the most frequently preferred ANN model. Gajghate et al. (2020) [15] modeled the boiling behavior on graphene-coated surfaces with the help of ANNs. Zarei et al. (2020) [16] predicted the boiling performance of nanocoolants with high accuracy using large datasets.

The most important advantage of ANN models is their ability to evaluate numerous physical parameters simultaneously. Heat flux, surface roughness, contact angle, nanoparticle concentration, and thermophysical properties can be used within the same model [6,13]. However, ANN predictions should be supported by sensitivity or feature-importance analyses when physical interpretation is required. In addition, model success largely depends on the quality of the dataset and the correct selection of input parameters [7].

3.2. Fuzzy Logic and Anfis Models

Fuzzy logic-based models can provide effective results in systems with uncertain and complex relationships. Due to the scattered and nonlinear nature of experimental data in boiling heat transfer, fuzzy logic and ANFIS models are among the important alternatives [9,10]. In studies by Das and Kishor (2010) [9], it was shown that the fuzzy logic approach gave successful results in estimating the pool boiling heat transfer coefficient. ANFIS models combine the learning ability of artificial neural networks with the interpretability of fuzzy logic. Therefore, they are considered more advantageous than ANN models in terms of interpreting physical behavior [10,11]. However, determining membership functions and adjusting model parameters requires expertise. In addition, the training process can become complex with large datasets.

3.3. Radial Basis Function Networks and GRNN

Radial basis function networks (RBF) and generalized regression neural networks (GRNN) are preferred, especially in small and medium-sized datasets, due to their fast-learning capabilities. These models can learn complex relationships between input parameters and output variables at high processing speed. Zendehboudi et al. (2017) [12] successfully predicted the boiling behavior of nanofluids using an RBF model optimized with a genetic algorithm. In another RBF-based study, Zendehboudi and Tatar (2017) [26] modeled the nucleate pool boiling heat transfer of refrigerant-oil mixtures with nanoparticles and predicted both the heat transfer coefficient and the nanoparticle-related heat transfer enhancement factor using 360 data samples for each parameter; the study also used the leverage algorithm to evaluate the applicability domain of the developed models and to identify doubtful data samples. The most important advantage of RBF-based models is their fast-training process and high convergence performance. However, the generalization success of the model is quite sensitive to the dataset used. In cases where the data distribution is uneven, a decrease in prediction performance can be observed. In addition, computational costs can increase in large datasets [12].

3.4. Support Vector Machines/Support Vector Regression

Support vector machines (SVM) and support vector regression (SVR) are among the artificial intelligence methods that offer strong generalization capabilities, especially in limited datasets. These models can model nonlinear relationships by transferring them to high-dimensional spaces with the help of kernel functions. In boiling heat transfer, SVR models are used in boiling heat transfer coefficient, critical heat flux and temperature predictions. One of the most important advantages of SVR methods is their robustness against overfitting. They can produce successful results, especially in experimental studies where the number of data is limited. However, model performance is quite sensitive to the type of kernel used and hyperparameter selections. If the appropriate parameters are not selected, the prediction success can decrease significantly [7].

3.5. Gaussian Process Regression

Gaussian process regression (GPR) is one of the powerful regression models that has attracted attention in boiling heat transfer studies in recent years. GPR models can not only make predictions but also calculate the prediction uncertainty. Kumar et al. (2024) [18] compared different artificial intelligence methods and showed that the GPR model provided the highest accuracy. The most important advantage of GPR models is that they can offer a confidence interval along with high accuracy. This feature provides a significant advantage in boiling studies where experimental uncertainties are high. However, computational costs can increase significantly in large datasets. Therefore, GPR models are mostly preferred in small and medium-sized datasets [18].

3.6. Deep Learning Models

Deep learning models have the capacity to learn complex data relationships thanks to their multi-layered structures. DNNs and CNNs have begun to be used in boiling heat transfer modeling, especially in studies with large datasets. Sajjad et al. (2021) [17] have shown that deep learning-based models provide high accuracy in multi-parameter boiling problems. The most important advantage of deep learning models is their ability to automatically extract features from complex data structures. They have significant potential, especially in image-based boiling regime classification and high-dimensional data analysis. For example, Liu et al. (2018) [27] used deep feedforward neural networks trained on high-fidelity pool boiling simulation data and near-wall local flow features to predict heat transfer components, wall superheat, and near-wall void fraction, showing that DNNs can support data-driven closure modeling when physically meaningful local inputs are available. However, their study also indicates that models trained on pool boiling data should not be directly transferred to flow boiling without caution because the underlying flow and boiling patterns may differ substantially [27]. Nevertheless, their high data demand, long training time, and limited transparency may restrict their practical use in experimentally constrained boiling studies [7,17].

3.7. Probabilistic and Explainable Artificial Intelligence Models

Recent studies have increasingly focused on AI models that can quantify prediction confidence and reveal the relative influence of input variables. In this context, BNN, NGBoost, and explainable artificial intelligence approaches have begun to be used in boiling heat transfer studies. Mehdi et al. (2024) [19] have shown that probabilistic machine learning methods offer significant advantages in terms of uncertainty analysis.

Uncertainty-aware models are especially important in boiling heat transfer because experimental measurements may include uncertainties associated with wall temperature, heat flux calculation, surface aging, contact angle variation, and coating morphology. Therefore, probabilistic models such as GPR, BNN, and NGBoost can provide additional reliability by estimating not only the predicted value but also the uncertainty associated with the prediction. Explainable AI techniques such as SHAP analysis, feature importance ranking, sensitivity analysis, and permutation importance can help identify the relative contribution of input parameters. In boiling heat transfer, these methods are useful for understanding whether heat flux, wall superheat, surface roughness, contact angle, pressure, or coating-related parameters dominate the prediction. Methods such as SHAP analysis, feature importance ranking, and sensitivity analysis facilitate the physical interpretation of model results. However, the application of these methods may require higher computational costs and expertise.

3.8. Optimization-Supported Artificial Intelligence Models

Artificial intelligence models are often used in combination with optimization algorithms in boiling heat transfer studies. Optimal operating conditions can be determined through methods such as genetic algorithm (GA), particle swarm optimization (PSO) and multi-objective genetic algorithm (MOGA) [12,25]. In particular, ANN-GA and ANN-MOGA combinations are widely used in the literature.

Ghahnaviyeh et al. (2025) [25] aimed to both increase the heat transfer coefficient and reduce the wall superheat in Fe_3O_4/water nanofluid using the ANN-MOGA approach. Such hybrid models offer significant advantages not only in making predictions but also in terms of optimum design and performance analysis. For example, ANN-GA or ANN-MOGA frameworks can simultaneously evaluate competing objectives such as increasing HTC, reducing wall superheat, and maintaining safe CHF margins. Therefore, these hybrid approaches can support experimental design and thermal system optimization. However, the success of optimization directly depends on the reliability of the artificial intelligence model used [25].

The AI models reviewed in this section differ not only in their learning mechanisms but also in their data requirements, interpretability, uncertainty-handling capacity, and suitability for specific boiling heat transfer targets. Model selection varies depending on the size of the dataset, the type of input parameters, the output variable to be predicted, the expectation of physical interpretability, and the computational cost. Therefore, models should be evaluated not only in terms of prediction accuracy but also in terms of generalization ability, explainability, data requirements, and optimization potential [7,19].

As shown in Table 2, ANN and DNN models stand out in terms of high prediction accuracy, while fuzzy logic and ANFIS models offer a more interpretable structure. GPR and probabilistic models provide significant advantages in evaluating prediction uncertainty; optimization-supported models can be used in boiling heat transfer studies not only for prediction but also for design and performance improvement [18,19,25]. Therefore, the appropriate model selection in boiling heat transfer should be made not only according to error values but also by considering the data structure, physical problem, explainability of the model and the purpose of the study [7].

Model selection in boiling heat transfer prediction should be made according to dataset size, model objective, expected interpretability, and uncertainty requirements. ANN and DNN models are generally more suitable for large and highly nonlinear datasets, whereas SVR and GPR models may be more effective for limited datasets due to their generalization ability. GPR is particularly useful when prediction uncertainty is important, while optimization-supported models are more appropriate for design and operating-condition optimization.

Table 2. Strengths and weaknesses of artificial intelligence models used in boiling heat transfer.

Model	Application	Strengths	Limitations
ANN/MLP	HTC, CHF, wall superheat and Nusselt number estimation.	It can learn nonlinear relationships and provide high accuracy with multivariate data.	Black box structure High dependence on data quality and input selection.
Fuzzy Logic/ANFIS	Prediction of HTC based on uncertain and complex experimental data.	More interpretable than ANN. It offers a rule-based structure.	Membership function and rule selection sensitive. It can get complicated with large datasets.
RBF/GRNN	HTC/Nu prediction in small to medium-sized datasets	Fast learning Good convergence performance.	Data distribution is sensitive; generalization may be limited.
SVM/SVR	HTC, CHF, or temperature estimation on limited datasets.	Resistant to overfitting It can provide strong predictions with limited data.	Kernel and hyperparameter selection sensitive
GPR	HTC forecast and uncertainty assessment.	Can provide an uncertainty range together with the prediction. Advantageous for experimental uncertainty assessment.	Computational costs increase with large datasets.
DNN/CNN	Multiparameter datasets and image-based boiling regime analysis.	Can learn complex data relationships. Strong with large datasets.	It requires a lot of data and high computing power. Its interpretability is limited.
BNN/NGBoost/Explainable AI	Uncertainty analysis and parameter significance assessment.	The model improves reliability and physical interpretability.	Its implementation is more complex. It requires expertise.
ANN-GA/ANN-PSO/ANN-MOGA	Determining optimum working conditions.	Provides prediction + optimization. It is effective in multi-objective problems.	Optimization success depends on the accuracy of the underlying model.

4. Input and Output Parameters Used in the Literature

The success of the model used depends not only on the algorithm applied but also on the physical meaning of the input and output parameters given to the model. In the literature, different input parameters such as heat flux, pressure, wall superheat, fluid properties, surface roughness, contact angle, nanoparticle concentration, particle size, coating thickness and dimensionless numbers are used (see Fig. 1) [6,7,13,16,19].

Heat flux and wall superheat are fundamental variables that directly determine the boiling curve and boiling regime. Therefore, heat transfer coefficient, Nusselt number, or surface temperature have been used as input variables for estimation in many studies [16,17]. Special care must be taken to avoid data leakage and circular logic in AI-based boiling models. For example, since the heat transfer coefficient is commonly calculated from heat flux and wall superheat, using both heat flux and wall superheat as input variables to predict HTC may artificially increase model accuracy. Therefore, physically dependent variables should be carefully controlled when defining input–output combinations. Surface parameters such as surface roughness, contact angle, porosity, and coating thickness affect active nucleation points, bubble separation behavior, and liquid transport back to the surface, thereby altering boiling performance [3,4,6]. Among surface-related input parameters, surface roughness, contact angle, porosity, coating thickness, SEM-based morphology, and wettability are particularly important because they directly influence active nucleation site density, bubble departure behavior, liquid rewetting, and capillary transport. This is supported by the high-fidelity DNN-based study of Sajjad et al. (2021) [28], who used a large roughened-surface pool boiling dataset and incorporated surface roughness, roughness fabrication method, surface material, surface inclination, saturation temperature, pressure, and liquid thermophysical properties to predict nucleate boiling heat transfer performance. Their correlation analysis also identified heat flux, surface inclination, surface roughness, surface-material thermal conductivity, saturation temperature, and pressure as influential factors affecting the nucleate pool boiling heat transfer coefficient [28]. In particular, studies in which roughness, nanoparticle concentration, and coating properties are included in ANN models have shown that HTC and wall superheat can be predicted with high accuracy [6,15].

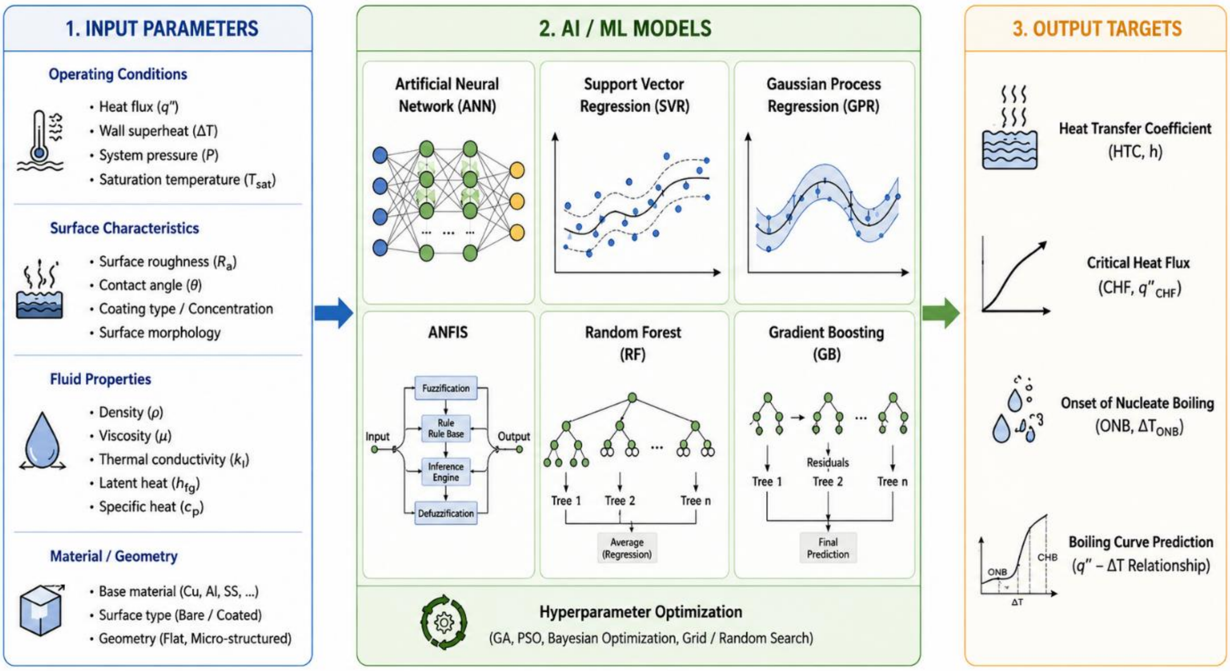

Figure 1. Main input parameters used in artificial intelligence-based boiling heat transfer modeling. Note: This figure is an original schematic prepared by the author to summarize the input groups, AI/ML model families, and output targets discussed in this study. It is not reproduced or adapted from another published source

In nanofluid studies, particle concentration, particle size, particle thermal conductivity, and base fluid properties are frequently used input parameters. Zarei et al. (2020) [16] used variables such as heat flux, saturation pressure, nanoparticle properties, base fluid properties, and oil content to predict the boiling performance of nano coolant fluids. Hassanpour et al. (2018) [13] showed that particle diameter, concentration, wall superheat, and pressure affect the model performance in Al_2O_3/water nanofluids. In some studies, dimensionless parameters such as Reynolds, Prandtl, and Nusselt numbers have been used instead of direct physical variables. This approach helps to represent different fluid and operating conditions in a more general way and can increase the generalization ability of the model [19].

In terms of output parameters, the most commonly estimated quantity in the literature is the heat transfer coefficient. In addition, critical heat flux, wall superheat temperature, Nusselt number and minimum film boiling temperature have been used as outputs [7,17,19,21]. Especially CHF is an important output parameter in high heat flux applications as it determines the safe operating limit.

In conclusion, the selection of input and output parameters is important not only in terms of statistical accuracy but also in terms of physical interpretability. Using parameters that are physically meaningful, independently and reliably measured increases the generalizability of the model, while using directly related variables in the same model without control may limit the scientific value of the model [7,15]. To move beyond a general model-based discussion and provide a study-level methodological synthesis, representative AI-based boiling heat transfer studies are summarized in Table 3 with respect to boiling type, fluid/surface characteristics, dataset structure, input–output variables, benchmark models or correlations, validation strategy, and key limitations.

5. Advantages and Limitations of Artificial Intelligence Approaches

AI-based boiling models are useful only when their predictions can be interpreted in relation to the data and physics from which they were built. ANN, ANFIS, GPR, DNN, and related methods have reproduced HTC, CHF, wall superheat, and Nusselt number trends in a variety of experimental and literature-based datasets [8,13,15-19]. Their value is not simply that they reduce statistical error; they can also organize multiparameter boiling data and provide preliminary estimates before additional experiments are performed. Coupling these models with optimization algorithms can help identify promising surface conditions, nanoparticle concentrations, or operating parameters [7,12,25]. This benefit is reliable only when the training data cover the relevant boiling domain and when the selected variables represent independent physical effects. Models built from narrow datasets may fail for new fluids, unseen surfaces, or different boiling regimes. For this reason, sensitivity analysis, uncertainty estimation, and explainable AI tools should accompany prediction results whenever the model is used to support physical interpretation [5,7,17-19].

Table 3. Study-level methodological synthesis of representative AI-based boiling heat transfer studies.

Study	Boiling/domain	Fluid/surface focus	Inputs and outputs	Model/validation emphasis	Key limitation for interpretation
Liang and Mudawar [2]	Pool boiling CHF	Flat surfaces; effects of pressure, surface size, roughness, orientation, and contact angle	Mechanistic and parametric CHF variables → critical heat flux	Review of CHF mechanisms, models, and correlations	CHF is governed by multiple competing mechanisms; AI-based CHF models should preserve regime-specific physical constraints and should not rely only on aggregate error metrics
Das and Kishor [9,10]; Swain and Das [11]	Pool or flow boiling HTC	Organic liquids, distilled water, or tube-bundle configurations	Thermal/operating variables -> HTC	Fuzzy logic / ANFIS; useful for uncertain experimental data	Membership functions and rule structure are problem dependent; external generalization is limited.
Zendehboudi et al. [12]	Nanorefrigerant pool boiling	Nanoparticle migration and refrigerant-related properties	Nanofluid descriptors and operating variables -> boiling response	RBF optimized with GA	Performance is sensitive to dataset distribution and optimization choices.
Hassanpour et al. [13]; Zarei et al. [16]	Nanofluid / nanorefrigerant pool boiling	Al_2O_3/water or nanorefrigerant systems	Particle size/concentration, pressure, heat flux, wall superheat -> HTC	ANN and related AI models; random train/test validation commonly used	Potential circular dependency must be controlled when HTC is calculated from heat flux and wall superheat.
Gajghate et al. [15]; Kumar et al. [18]	Coated-surface pool boiling	Graphene, CNT+GO, or nanoparticle-coated surfaces	Surface characteristics and operating variables -> HTC/boiling performance	ANN or GPR; GPR is useful when uncertainty intervals are needed	Surface variables are coupled; coating thickness, morphology, and wettability cannot always be isolated.
Sajjad et al. [17]	Porous or structured-surface boiling	Porous surfaces and multiparameter boiling data	Surface/thermal descriptors -> HTC	Deep learning for nonlinear patterns	Requires larger datasets and remains less transparent without explainability tools.
Mehdi et al. [19]	Micro-structured pool boiling	Micro-structured surfaces	Surface and operating descriptors -> HTC with uncertainty	Probabilistic machine learning and uncertainty-aware prediction	Uncertainty improves reliability but does not replace external validation on unseen surfaces.
Ghahnaviyeh et al. [25]	Nanofluid pool boiling optimization	Fe_3O_4/water on copper heating surface	Concentration and operating variables -> HTC/wall superheat	ANN-MOGA for prediction and multi-objective optimization	Optimization reliability depends on the accuracy and domain validity of the underlying ANN.
Liu et al. [27]	Pool boiling/high-fidelity simulation-based boiling closure	Simulation-derived local near-wall boiling features	Local momentum and energy transport, pressure gradients, turbulent viscosity, surface information → heat transfer components, wall superheat, near-wall void fraction	Deep feedforward neural network; interpolation and extrapolation tests against high-fidelity simulation data	Transferability from pool boiling to flow boiling remains uncertain; feature selection and coupling with CFD solvers require careful validation.

6. Future Research Directions

Future AI-based boiling studies need datasets in which the input variables are both measurable and physically meaningful. Operating parameters such as pressure, heat flux, and fluid properties are not sufficient when surface engineering is central to the problem. Roughness, contact angle, porosity, coating thickness, capillary transport indicators, SEM-based morphology, profilometer data, and coating descriptors should be reported more systematically. A persistent difficulty is that coating thickness, porosity, roughness, and wettability are rarely independent in real surfaces; they are coupled through fabrication method, aging, capillary transport, and nucleation behavior. SVR, GPR, and probabilistic methods may be useful for limited experimental datasets, but no universally validated framework has yet shown that these coupled effects can be fully separated without overfitting. Open and standardized databases covering different fluids, surfaces, coatings, and operating ranges would greatly improve model generalization.

A second need is to connect AI predictions more closely with physical interpretation. Explainable AI can help identify whether a model is driven by meaningful variables such as roughness, contact angle, pressure, heat flux, or coating morphology, rather than by hidden correlations in the dataset. Although ANN and DNN models can achieve high accuracy, their black-box nature limits mechanistic insight unless they are combined with SHAP, sensitivity analysis, feature ranking, uncertainty quantification, or physics-informed constraints [17,19]. Visual and spatial data also deserve more attention. High-speed images, IR thermography, and SEM data, when analyzed with CNN or image-processing-based learning, could support boiling-regime classification, bubble-dynamics monitoring, and quantitative surface representation [7]. Future work should therefore combine surface characterization, external validation, uncertainty reporting, and physically constrained learning in the same modeling workflow.

7. Conclusion

Boiling heat transfer depends on the joint behavior of the surface, the working fluid, and the operating condition. Empirical correlations remain important for well-defined cases, but their transferability is limited when surfaces are coated, roughened, micro/nano-structured, or used with nanofluids over wide operating ranges. The studies reviewed here show that ANN, ANFIS, RBF, SVR, GPR, DNN, probabilistic models, and optimization-supported AI have been applied to HTC, CHF, wall superheat, Nusselt number, and minimum film boiling temperature prediction. These approaches can assist interpretation and design when the training data are representative and the validation strategy is appropriate.

The central message is that accuracy alone is not enough. A boiling model is useful only if its inputs are physically meaningful, its output is not inflated by circular dependencies, and its predictions remain credible outside a narrow training set. Future progress will depend on hybrid and physics-consistent AI frameworks that include surface characterization, report validation procedures clearly, quantify uncertainty, and avoid relying only on aggregate error metrics.

Declaration of Conflict of Interests

The author declares that there is no conflict of interest. They have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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