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Predicting Energy Load of L-Shaped Courtyard Buildings in Malaysia Using Machine Learning

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Abstract— Building's account for a substantial share of global energy consumption, with cooling demand dominating in hot and humid tropical climates such as Malaysia. Although dynamic simulation tools such as EnergyPlus and TRNSYS provide accurate performance evaluation, their high computational cost and reliance on specialised expertise limit their application during early-stage design. This study develops a machine learning-based surrogate modelling framework to predict the cooling load, heating load, and total energy load of L-shaped courtyard buildings in Kuala Lumpur. A validated parametric simulation dataset was generated using key architectural and geometric variables, including WIDTH, LENGTH, HEIGHT, ORIENTATION, WINDOWS_RATIO, FORM_FACTOR, and S_V_RATIO. Three supervised regression models, Random Forest (RF), Gradient Boosting (GB), and Artificial Neural Network (ANN-MLP), were evaluated using Root Mean Square Error (RMSE) and Coefficient of Determination (R^2). The results show that ensemble learning models consistently outperform ANN, with Gradient Boosting achieving the highest predictive accuracy across all energy outputs. For cooling load prediction, GB achieved an RMSE of 0.0188 and an R^2 of 0.9997, while also producing the best performance for heating load and total energy load. The findings further indicate that envelope-related variables, particularly the window-to-wall ratio, have a significant influence on cooling and overall energy demand in tropical courtyard buildings. By integrating climate-specific parametric simulation with ensemble machine learning, the proposed framework accurately reproduces simulation-derived energy loads while reducing the need for repeated simulation during early-stage design. The developed surrogate model provides a reliable decision-support tool for rapid performance assessment during early-stage architectural design and contributes a validated predictive framework for energy-efficient tropical courtyard buildings in Malaysia.

Keywords— Building energy prediction, courtyard buildings, tropical climate, machine learning, Gradient Boosting

I. Introduction

The building sector remains one of the largest consumers of global energy, accounting for nearly 40% of total final energy demand and a significant share of greenhouse gas emissions [1], [10]. In tropical climates, such as Malaysia, building energy consumption is predominantly driven by cooling demand rather than heating, due to persistently high temperatures and humidity throughout the year [11], [18]. As urbanisation accelerates and indoor comfort expectations increase, electricity consumption in residential and commercial buildings continues to rise, placing additional pressure on national energy systems and carbon reduction targets [10], [26]. Improving building energy efficiency, particularly during the early design stage, has therefore become a critical strategy for sustainable development.

Architectural design decisions made during conceptual planning have long-term consequences for operational energy performance. Parameters such as building geometry, façade transparency, orientation, and compactness directly influence solar heat gain, surface heat transfer, and internal thermal behaviour [5], [18], [25]. In tropical contexts, envelope-related factors such as window-to-wall ratio (WWR) play a particularly significant role in determining cooling load [5]. Among passive design typologies courtyard architecture has historically demonstrated climatic responsiveness through enhanced natural ventilation, shading, and daylight distribution [8], [15], [16]. In Malaysia, L-shaped courtyard configurations are commonly adopted in educational institutions, commercial developments, and residential projects due to their spatial flexibility and environmental performance potential [9].

Despite the recognised climatic benefits of courtyard typologies, quantitative frameworks linking courtyard geometry to whole-building energy performance remain limited. Traditional approaches for evaluating building energy demand rely heavily on dynamic simulation tools such as EnergyPlus and TRNSYS [2], [4], [12]. While these tools provide detailed transient heat balance modelling, they require extensive input parameters, calibration, and computational time. Comparative studies have shown that

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simulation outputs may vary depending on modelling assumptions and software configurations [4], [13]. Consequently, architects often face practical constraints in testing multiple design alternatives during early-stage development, where rapid iteration is essential.

Simplified analytical methods such as the Cooling Load Temperature Difference (CLTD) method and Radiant Time Series Method (RTSM) offer faster approximations but rely on steady-state assumptions and tabulated correction factors, limiting their ability to capture nonlinear interactions between geometry and climatic variables [2], [14]. These deterministic approaches are not well suited for complex forms such as L-shaped courtyard buildings, where surface exposure, orientation, and enclosure degree interact dynamically.

Recent advances in machine learning (ML) provide an alternative paradigm for building energy prediction. Rather than explicitly solving thermodynamic equations, ML models learn nonlinear relationships directly from structured datasets [3], [6]. Ensemble learning techniques such as Random Forest and Gradient Boosting have demonstrated strong predictive performance in heating and cooling load estimation tasks [7], [20], [21]. Surrogate modelling frameworks, where ML models are trained on simulation-generated datasets, enable near-instantaneous prediction of new design configurations while maintaining high accuracy [6], [22]. This capability is particularly valuable for early-stage architectural design, where numerous parametric variations must be evaluated efficiently.

Although machine learning applications in building energy research have expanded globally, relatively few studies focus specifically on tropical courtyard geometries under Malaysian climatic conditions [9], [17]. Most existing ML-based energy studies utilise generic building archetypes or temperate climate datasets, limiting their contextual relevance to cooling-dominated environments [18], [23]. Furthermore, the integration of ensemble machine learning techniques with courtyard-specific parametric variables remains underexplored.

To address this gap, this study develops and evaluates a machine learning-based predictive framework for estimating cooling load, heating load, and total load of L-shaped courtyard buildings in Kuala Lumpur. Using a validated parametric simulation dataset, the study compares three supervised regression algorithms: Random Forest, Gradient Boosting, and Artificial Neural Network (MLP). Model performance is assessed using Root Mean Square Error (RMSE) and Coefficient of Determination (R^2), enabling rigorous comparison of predictive accuracy.

By integrating climate-specific architectural parameters with advanced ensemble learning techniques, this research contributes a high-accuracy surrogate modelling approach tailored to Malaysian tropical conditions. The findings aim to support performance-driven architectural decision-making, reduce reliance on repeated dynamic simulations, and promote energy-efficient courtyard design aligned with national sustainability objectives [1], [10], [26].

II. LITERATURE REVIEW

The building sector remains one of the largest contributors to global energy consumption, accounting for nearly forty percent of total final energy demand worldwide [1]. In tropical regions such as Malaysia, energy consumption is predominantly cooling-driven due to high temperature and humidity throughout the year. Consequently, reducing cooling load has become central to achieving sustainability and carbon reduction targets [1].

Architectural design parameters, particularly geometry and façade configuration, significantly influence cooling demand in hot–humid climates. However, the methodologies used to evaluate building energy performance vary in complexity, accuracy, and computational demand. The literature can broadly be categorised into three methodological streams: traditional analytical methods, dynamic simulation approaches, and machine learning-based predictive modelling.

Table 1 shows the traditional cooling and heating load estimation techniques were developed to simplify thermal load calculations during early engineering design. Among the most commonly applied analytical methods are the Cooling Load Temperature Difference (CLTD) method, Total Equivalent Temperature Difference (TETD), and the Radiant Time Series Method (RTSM) [2], [14]. These approaches rely on predefined correction factors and simplified heat balance assumptions derived from standard climatic conditions.

The CLTD method estimates peak cooling loads by adjusting temperature differences based on construction type and solar exposure. While straightforward and computationally efficient, it assumes steady-state conditions and limited dynamic interaction between building components [2]. TETD expands this by incorporating equivalent temperature adjustments to better represent solar gains, yet it remains manual and sensitive to tabulated values. RTSM improves temporal representation by separating radiant and convective heat components; however, it assumes periodic load patterns and simplified occupancy behaviour [14].

Although these techniques remain useful for quick approximations, their deterministic nature restricts their applicability to complex geometries such as courtyard buildings. They cannot effectively capture nonlinear interactions between geometric compactness, façade transparency, and climatic variability.

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TABLE I
TRADITIONAL METHODS USED FOR COOLING LOAD AND HEATING LOAD PREDICTION

Method	Core Principle	Strengths	Limitations	Key Source
CLTD	Tabulated temperature differences to estimate peak cooling	Simple and fast	Assumes steady-state; limited climate adaptability	[2]
TETD	Equivalent temperature difference incorporating solar gains	Improved solar correction	Manual and time-intensive	[2]
RTSM	Time-series heat balance simplification	Accounts for radiant and convective split	Assumes periodic conditions; limited annual accuracy	[2]

Dynamic simulation tools such as EnergyPlus, TRNSYS, IDA ICE, and Ecotect as shown in Table 2 represent the industry standard for detailed building energy modelling [4], [12], [13]. These tools solve transient heat balance equations using hourly weather data, material properties, occupancy schedules, and HVAC system parameters.

Dynamic simulation allows accurate modelling of solar radiation, shading devices, thermal mass effects, and ventilation behaviour, making it suitable for complex building forms such as courtyard typologies. However, modelling accuracy depends heavily on input assumptions and calibration processes. Comparative analyses have reported discrepancies in predicted energy loads between software platforms even when modelling identical geometries [4].

Moreover, simulation-based parametric exploration requires significant computational time. Testing multiple architectural variations during conceptual design can be impractical, particularly in professional practice where time constraints are strict.

TABLEII
THE INDUSTRY STANDARD FOR DETAILED BUILDING ENERGY MODELLING

Tool	Capability	Advantages	Limitations	Key Source
EnergyPlus	Detailed transient simulation	High accuracy; industry standard	Time-intensive; complex input setup	[4]
TRNSYS	Modular system simulation	Flexible HVAC modelling	High computational cost	[4]
IDA ICE	Whole-building simulation	Integrated airflow modelling	Software variability in results	[4]
Ecotect	Concept-stage environmental analysis	Faster modelling	Less detailed physics modelling	[4]

A. *Machine Learning in Building Energy Prediction*

Machine learning (ML) has gained attention as an alternative to physics-based modelling due to its ability to learn nonlinear relationships directly from data [3], [6]. Supervised regression algorithms are commonly used to predict heating and cooling loads based on geometric and envelope features.

Based on Table 3, Artificial Neural Networks (ANN) were among the earliest ML models applied in energy research. While capable of modelling complex nonlinear behaviour, ANNs require careful hyperparameter tuning and may overfit small datasets [3].

Ensemble learning methods such as Random Forest (RF) and Gradient Boosting (GB) have demonstrated superior predictive performance in structured tabular datasets typical of building energy modelling [7], [20], [21]. RF reduces variance through bagging, while GB improves accuracy by sequentially correcting residual errors. These methods are particularly effective in capturing interactions among façade transparency, surface exposure, and orientation.

TABLE III
MACHINE LEARNING ALGORITHM AND THE MODEL STRENGTH AND WEAKNESS IN ENERGY LOAD PREDICTION.

Algorithm	Model Type	Strengths	Weaknesses	Key Sources
ANN (MLP)	Neural Network	Captures nonlinear relationships	Sensitive to hyperparameters; risk of overfitting	[3]
Random Forest	Ensemble (Bagging)	Robust; reduces variance	Slightly less interpretable	[7]
Gradient Boosting	Ensemble (Boosting)	High accuracy; strong generalisation	Computationally heavier than RF	[7]

B. *Surrogate Modelling for Early-Stage Design*

As shown in Table 4, Surrogate modelling integrates machine learning with dynamic simulation outputs to enable rapid prediction of building performance [6], [22]. In this framework, ML models are trained on simulation-generated datasets and subsequently used to provide near-instantaneous predictions for new design configurations.

This approach significantly reduces computational burden and supports rapid parametric exploration during conceptual design. Rather than replacing simulation tools entirely, surrogate models serve as decision-support systems. Promising configurations identified through ML prediction can later be validated using high-fidelity simulation. In cooling-dominated climates, early design decisions related to envelope transparency and compactness strongly influence operational performance

[5], [20]. Surrogate modelling therefore enhances the feasibility of performance-driven architectural optimisation.

TABLE IV
THE ASPECT OF MACHINE LEARNING SURROGATE MODEL.

Aspect	Dynamic Simulation	ML Surrogate Model
Computational Time	High	Very low after training
Accuracy	High (physics-based)	High (data-driven approximation)
Early-Stage Suitability	Limited	Highly suitable
Parametric Exploration	Time-intensive	Rapid iteration possible
Design Decision Support	Detailed validation	Fast screening tool

C. *Courtyard Architecture and Energy Performance*

Courtyard architecture is widely recognised as a climate-responsive typology in tropical regions. Traditional Malaysian shophouses use air-well courtyards to enhance stack ventilation and daylight penetration [8], [15]. Contemporary buildings continue to adopt courtyard forms due to their passive cooling potential referring to Table 5.

Courtyard geometry influences solar exposure, airflow patterns, and surface heat transfer. Studies show that compact forms and reduced façade transparency significantly reduce cooling demand in hot–humid climates [5], [18], [25]. Envelope-related parameters, particularly window-to-wall ratio, are consistently identified as dominant predictors of cooling load.

Despite its environmental relevance, quantitative energy modelling of L-shaped courtyard buildings under Malaysian climate conditions remains limited [9], [17]. Most courtyard studies focus on microclimate or thermal comfort rather than multi-output energy load prediction. Integrating courtyard-specific geometric parameters with machine learning techniques therefore provides a novel contribution to tropical building performance modelling.

The literature reveals three critical gaps:

- Limited machine learning studies focused specifically on tropical courtyard geometry
- Insufficient integration of courtyard morphology with surrogate modelling frameworks
- Lack of climate-specific predictive tools tailored to Malaysian design practice

The validated L-shaped courtyard dataset used in this study enables systematic evaluation of geometric and envelope variables under Kuala Lumpur weather conditions. By integrating ensemble machine learning techniques with courtyard design parameters, this research addresses the identified methodological and contextual gaps.

TABLE V
FOCUS OF THE STUDY, KEY FINDING AND GAP IDENTIFIED BASED FROM PREVIOUS STUDY.

Study Focus	Climate Context	Key Finding	Gap Identified	Key Source
Traditional Malaysian courtyards	Hot–humid	Improved natural ventilation	No quantitative cooling load modelling	[8]
Parametric courtyard simulations	Hot–dry	Courtyard geometry reduces cooling load	Limited tropical validation	[4]
Envelope optimisation	Tropical	WWR strongly influences cooling	Not courtyard-specific	[5]

III. METHODOLOGY

This study adopts a structured machine learning framework to predict cooling load, heating load, and total load of L-shaped courtyard buildings under Malaysia's hot–humid tropical climate. The methodological approach follows the CRISP-DM (Cross Industry Standard Process for Data Mining) framework The workflow progresses systematically from problem definition to deployment of the best-performing predictive model.

The first stage is business understanding. The primary objective of the study is to develop predictive models capable of estimating three energy performance indicators: cooling load, heating load, and total load. These outputs are derived from a validated parametric simulation dataset of L-shaped courtyard buildings located in Kuala Lumpur. The aim is to create a surrogate modelling tool that reduces dependence on repeated dynamic simulations while maintaining high predictive accuracy for early-stage architectural design decisions.

The second stage is data understanding and pre-processing. The dataset used in this study was derived from a validated parametric simulation dataset of L-shaped courtyard buildings developed in [9]. The dataset represents building energy performance under Kuala Lumpur weather conditions and consists of architectural variables describing building geometry, façade transparency, orientation, and compactness. Compared with operational datasets collected from existing buildings, the simulation-based dataset provides a controlled environment for systematically evaluating the influence of individual design parameters on building energy performance while eliminating variations caused by occupant behaviour and operational uncertainties (see Table 6).

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TABLE VI
DATASET UNDERSTANDING

Variable	Description	Unit
WIDTH	Building width	m
LENGTH	Building length	m
HEIGHT	Building height	m
ORIENTATION	Building orientation relative to north	Degree
WINDOWS_RATIO	Window-to-wall ratio	Ratio
FORM_FACTOR	Building compactness indicator	Dimensionless
S_V_RATIO	Surface-to-volume ratio	Dimensionless
COOLING_LOAD	Annual cooling energy demand	kWh/m²
HEATING_LOAD	Annual heating energy demand	kWh/m²
TOTAL_LOAD	Sum of annual cooling and heating energy demand	kWh/m²

Seven architectural input variables were considered, namely WIDTH, LENGTH, HEIGHT, ORIENTATION, WINDOWS_RATIO, FORM_FACTOR, and S_V_RATIO. These variables represent building dimensions, façade characteristics, and geometric compactness that directly influence solar heat gain, heat transfer, and thermal behaviour. The corresponding output variables consist of COOLING_LOAD, HEATING_LOAD, and TOTAL_LOAD, representing the annual building energy demand expressed in kWh/m².

Prior to model development, the dataset underwent a structured data quality assessment. The original dataset was inspected for missing values, inconsistent variable names, incorrect data types, and statistical outliers. A typographical inconsistency in the original dataset was corrected by renaming the variable "HIGHT" to "HEIGHT" to ensure semantic consistency throughout the analytical workflow. Missing value analysis confirmed that the dataset contained no null observations, eliminating the need for data imputation. Outlier detection using the Interquartile Range (IQR) method further confirmed that all predictor and target variables were within acceptable statistical limits, indicating a high-quality simulation dataset suitable for machine learning modelling.

Following data quality assessment, the dataset was divided into training (70%) and testing (30%) subsets to evaluate model generalisation performance. Continuous variables were standardised where appropriate to improve optimisation stability, particularly for the Artificial Neural Network model. Exploratory Data Analysis (EDA) was subsequently conducted to examine statistical distributions, identify relationships among variables, and evaluate correlation patterns prior to model training. The analysis consistently indicated that envelope-related variables, particularly WINDOWS_RATIO, exhibited the strongest relationship with cooling load and total energy demand.

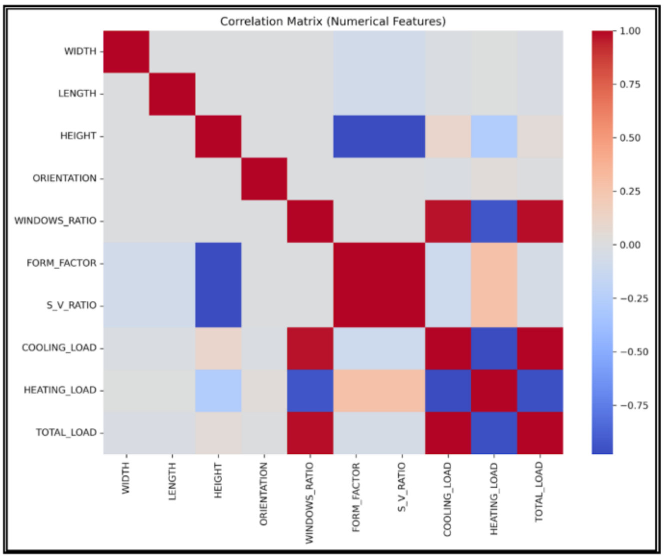

Fig 1 – Correlation Matrix between architectural design variables and target energy load during EDA.

Figure 1 illustrates the correlation matrix between the architectural design variables and the target energy loads. Among all input variables, Window-to-Wall Ratio (WINDOWS_RATIO) exhibits the strongest positive correlation with both Cooling Load and Total Load, indicating that increasing façade glazing substantially increases energy demand in Malaysia's hot-humid climate. Conversely, WINDOWS_RATIO shows a strong negative correlation with Heating Load, reflecting the inverse relationship between glazing and heating energy requirements.

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FORM_FACTOR and S_V_RATIO demonstrate moderate relationships with the energy loads, suggesting that building compactness also contributes to thermal performance. In contrast, WIDTH, LENGTH, HEIGHT, and ORIENTATION exhibit relatively weak correlations, indicating that their independent influence on energy demand is less significant than façade transparency. These observations support the subsequent machine learning results, where Gradient Boosting successfully captured the dominant influence of envelope-related variables in predicting building energy performance.

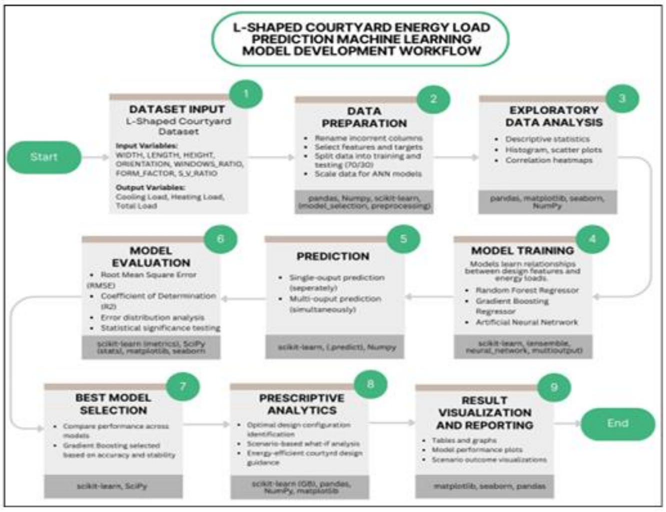

Fig 2 - Detailed Machine Learning Development Process for L-Shaped Courtyard Energy Load Prediction.

Figure 2, supports the explanation of dataset input, data preparation, exploratory analysis, model training, evaluation, best model selection, prescriptive analytics, and result visualisation.

The third stage is model development. Three supervised regression algorithms were implemented: Random Forest (RF), Gradient Boosting (GB), and Artificial Neural Network (ANN – Multilayer Perceptron). Random Forest constructs multiple decision trees using bootstrapped sampling and averages their predictions to reduce variance and improve robustness [7]. Gradient Boosting builds models sequentially, where each new tree corrects the residual errors of the previous one, resulting in high predictive accuracy and strong generalisation performance [7]. The ANN model captures nonlinear relationships through hidden layers and backpropagation optimisation [3].

The machine learning models were configured using predefined hyperparameter settings as shown in Table 7 selected to provide stable predictive performance. For the Random Forest model, the number of decision trees (n_estimators) and random state were specified prior to training. The Gradient Boosting model was configured using predefined values for the number of estimators, learning rate, and random state. For the Artificial Neural Network (ANN), the network architecture, activation function, optimisation algorithm, maximum number of iterations, and early stopping parameters were specified before model training. Using fixed hyperparameter settings ensured a consistent and reproducible modelling framework for comparing the predictive performance of the three machine learning algorithms.

TABLE VII
HYPERPARAMETER THAT IS USED BASED ON THE MACHINE LEARNING MODEL.

Model	Hyperparameter	Value
Random Forest	Number of estimators (n_estimators)	200
	Random state	42
Gradient Boosting	Number of estimators (n_estimators)	200
	Learning rate	0.1
	Random state	42
Artificial Neural Network	Hidden layer sizes	(64, 32)
	Activation function	ReLU
	Solver	Adam
	Maximum iterations	1000
	Early stopping	TRUE
	Validation fraction	0.1
	n_iter_no_change	20
	Random state	42

The fourth stage is model evaluation. Model performance was assessed using Root Mean Square Error (RMSE) and Coefficient of Determination (R^2). RMSE measures the magnitude of prediction error, while R^2 indicates how well the model explains variance in the target variable. Lower RMSE and higher R^2 values indicate better predictive performance. Residual analysis and comparative evaluation across the three models were conducted separately for cooling load, heating load, and total load. The model demonstrating the lowest prediction error and highest stability across outputs was selected as the best-performing algorithm.

The final stage involves deployment and application. The selected model functions as a surrogate predictive engine capable of providing near-instantaneous energy load predictions for new L-shaped courtyard configurations. This enables rapid parametric exploration during early-stage

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architectural design without repeatedly running computationally intensive dynamic simulations [6]. Rather than replacing physics-based simulation entirely, the model serves as a decision-support layer that accelerates conceptual evaluation while preserving the option for final simulation-based validation.

Overall, the methodology integrates climate-specific parametric simulation data with ensemble machine learning techniques to produce a reliable, efficient, and scalable predictive framework tailored to tropical courtyard buildings in Malaysia

IV. RESULTS

This section presents the predictive performance of the three machine learning models, namely Gradient Boosting (GB), Random Forest (RF), and Artificial Neural Network (ANN), for estimating cooling load, heating load, and total load of L-shaped courtyard buildings. Model evaluation was conducted using Root Mean Square Error (RMSE) and Coefficient of Determination (R^2). Lower RMSE and higher R^2 indicate superior predictive accuracy.

A. *Cooling Load Prediction Performance*

The results shown Table 8 that Gradient Boosting achieved the highest predictive performance for cooling load estimation. The model recorded an RMSE of 0.0188 and an R^2 value of 0.9997, indicating near-perfect prediction accuracy. Random Forest also performed strongly, with an RMSE of 0.0374 and R^2 of 0.9989. In contrast, the ANN model demonstrated lower predictive stability, with a higher RMSE of 0.2685 and R^2 of 0.9412.

TABLE VIII
COOLING LOAD PREDICTION PERFORMANCE

Model	RMSE	R^2	Performance Rank
Gradient Boosting	**0.0188**	**0.9997**	1 (Best)
Random Forest	0.0374	0.9989	2
ANN (MLP)	0.2685	0.9412	3

The results demonstrate that ensemble learning algorithms outperform the Artificial Neural Network (ANN) in predicting cooling load for L-shaped courtyard buildings. Among the evaluated models, Gradient Boosting achieved the lowest prediction error (RMSE = 0.0188) and the highest coefficient of determination (R^2 = 0.9997), indicating excellent agreement between predicted and simulated cooling loads. Random Forest also produced highly accurate predictions but exhibited slightly higher prediction errors than Gradient Boosting, whereas ANN showed substantially larger error dispersion and lower predictive stability.

The superior performance of Gradient Boosting can be attributed to its sequential residual-learning mechanism. Unlike Random Forest, which constructs multiple independent decision trees and averages their predictions, Gradient Boosting iteratively builds new trees that specifically correct the prediction errors generated by previous trees. This sequential optimisation enables the model to capture subtle nonlinear relationships between architectural parameters, façade characteristics, and energy performance more effectively. The comparatively lower performance of ANN may be explained by the characteristics of the simulation dataset. Although multilayer perceptron are capable of modelling highly complex nonlinear relationships, they generally require careful hyperparameter optimisation and large training datasets to achieve stable generalisation. For structured tabular datasets with a limited number of design variables, tree-based ensemble methods frequently demonstrate superior prediction accuracy and robustness.

These findings are consistent with previous building energy prediction studies. Divina et al. (2022) reported that Gradient Boosting outperformed deep learning approaches for structured building energy datasets, while Zhang et al. (2021) similarly identified tree-based ensemble models as highly effective surrogate models for building energy prediction. The present findings therefore reinforce previous evidence that Gradient Boosting provides an appropriate balance between predictive accuracy, model stability, and computational efficiency for simulation-based building energy datasets.

B. *Heating Load Prediction Performance*

Although heating demand is minimal in Malaysia's tropical climate, predictive modelling was conducted to maintain methodological completeness. Gradient Boosting again achieved the best performance referring to Table 9, with RMSE of 0.0095 and R^2 of 0.9989. Random Forest followed with RMSE of 0.0202 and R^2 of 0.9952, while ANN produced RMSE of 0.0527 and R^2 of 0.9673.

TABLE IX
HEATING LOAD PREDICTION PERFORMANCE

Model	RMSE	R^2	Performance Rank
Gradient Boosting	**0.0095**	**0.9989**	1 (Best)
Random Forest	0.0202	0.9952	2
ANN (MLP)	0.0527	0.9673	3

The consistently strong performance of Gradient Boosting across outputs suggests high model generalisation and robustness. The low prediction error for heating load

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reflects the model's ability to learn small-scale variations within a cooling-dominated climate.

Although annual heating demand is relatively insignificant in Malaysia's hot-humid climate, including heating load prediction provides a comprehensive assessment of model performance across multiple energy outputs. Gradient Boosting consistently achieved the lowest prediction error, demonstrating that the model can accurately capture even small variations within the simulation dataset. The consistent ranking of Gradient Boosting, Random Forest, and ANN across cooling and heating loads further indicates that the observed performance differences are attributable to the modelling capability of each algorithm rather than the characteristics of a specific target variable.

C. *Total Load Prediction Performance*

For total load prediction can be seen in Table 10, Gradient Boosting remained the best-performing model, achieving RMSE of 0.0143 and R^2 of 0.9997. Random Forest produced RMSE of 0.0223 and R^2 of 0.9993, while ANN recorded RMSE of 0.2339 and R^2 of 0.9192.

The results demonstrate that ensemble learning techniques consistently outperform ANN in this dataset. The superior accuracy of Gradient Boosting confirms its suitability as the final surrogate model for courtyard energy load prediction.

The consistently strong predictive performance observed for total energy load indicates that Gradient Boosting effectively captures the combined influence of multiple architectural parameters on building energy performance in Table 10. Since total load integrates both cooling and heating demand, accurate prediction requires the model to simultaneously learn complex interactions among geometric configuration, façade transparency, and compactness indicators. The near-perfect R^2 achieved by Gradient Boosting demonstrates that the surrogate model successfully approximates the dynamic simulation outputs while maintaining excellent predictive stability.

TABLE X
TOTAL LOAD PREDICTION PERFORMANCE

Model	RMSE	R^2	Performance Rank
Gradient Boosting	**0.0143**	**0.997**	1 (Best)
Random Forest	0.0223	0.9993	2
ANN (MLP)	0.2339	0.9192	3

D. *Overall Comparative Summary Across Energy Outputs*

Residual distribution analysis indicated that Gradient Boosting and Random Forest produced tightly clustered residuals around zero, demonstrating minimal bias and strong stability. ANN exhibited wider error dispersion, particularly for extreme values of cooling and total loads (see Table 11).

TABLE XI
OVERALL COMPARATIVE SUMMARY

Energy Output	Best Model	Lowest RMSE	Highest R^2	Conclusion
Cooling Load	Gradient Boosting	0.0188	0.9997	Excellent predictive accuracy
Heating Load	Gradient Boosting	0.0095	0.9989	Very stable and precise
Total Load	Gradient Boosting	0.0143	0.9997	Strong generalization

Figure 3,4 and 5 illustrates the residual distributions of the three machine learning models for cooling load, heating load, and total load prediction. Across all target variables, Gradient Boosting exhibits the narrowest residual distribution around the zero-error line, indicating consistently small prediction errors and minimal systematic bias. Random Forest demonstrates similarly stable behaviour but with slightly larger residual variation, whereas ANN produces substantially wider error dispersion and several extreme residuals, particularly for cooling load and total load prediction.

These observations are consistent with the RMSE and R^2 values reported in Tables I–III, confirming that Gradient Boosting provides the most accurate and reliable predictions among the evaluated models. The residual analysis further demonstrates the strong generalisation capability of the ensemble learning approach for simulation-based building energy prediction.

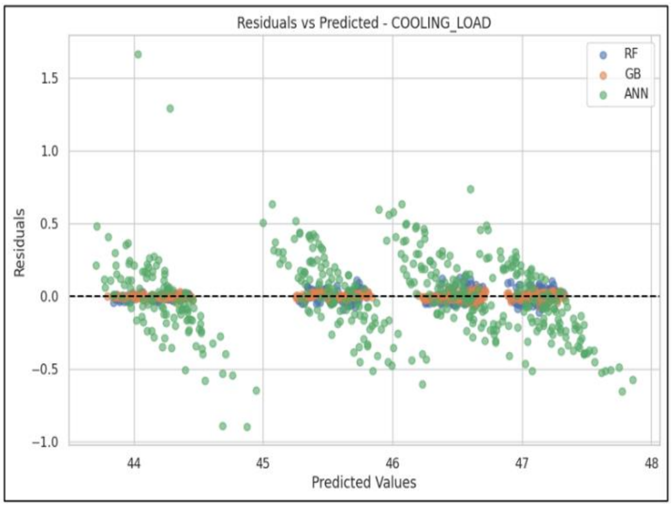

Fig 3 – Residual distribution and predicted for Cooling load

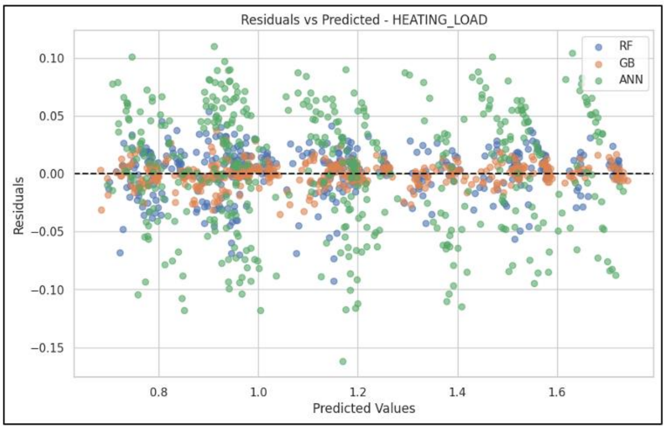

Fig 4. Residual distribution and predicted for Heating Load

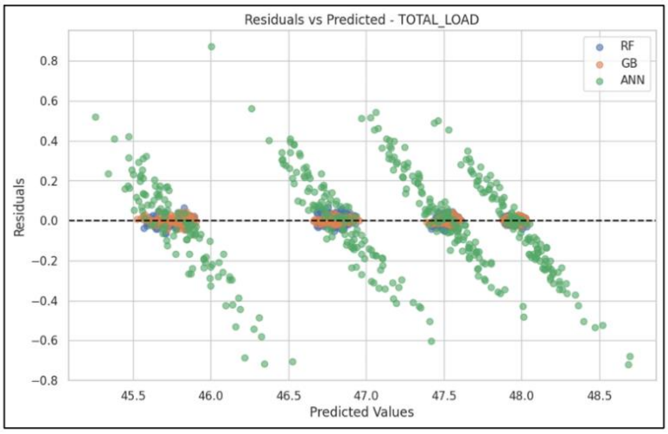

Fig. 5 - Residual distribution and predicted for Total Load

The statistical consistency across all three target outputs supports the hypothesis that ensemble-based machine learning algorithms provide superior predictive accuracy compared to standalone neural network models [3], [7].

Based on RMSE, R^2, and residual stability, Gradient Boosting was selected as the best-performing model. The model demonstrates:

- Highest predictive accuracy across all outputs
- Lowest prediction error
- Strong generalisation capability
- Stable residual distribution

The selected model serves as the final surrogate predictive engine for L-shaped courtyard energy load estimation. The high R^2 values (greater than 0.998 for ensemble models) indicate that machine learning can replicate simulation-derived energy loads with very high fidelity. This confirms that the trained model can replace repeated simulation runs during early-stage architectural design exploration.

The results validate the feasibility of integrating machine learning into tropical courtyard building design workflows, supporting rapid optimisation and energy-efficient configuration selection.

Methodologically, this research demonstrates that machine learning can function effectively as a surrogate modelling tool. The trained model enables near-instantaneous prediction of energy loads for new L-shaped courtyard configurations, significantly reducing reliance on computationally intensive dynamic simulations. Rather than replacing simulation entirely, the developed framework complements existing tools by accelerating early-stage design exploration and enabling rapid parametric assessment.

From a practical perspective, the proposed predictive framework supports architects and engineers in making data-informed design decisions during conceptual stages. By identifying high-performing geometric configurations and minimizing cooling demand, the approach contributes to energy-efficient tropical building design and aligns with Malaysia's broader sustainability and low-carbon objectives.

Overall, the results demonstrate that Gradient Boosting provides the performed best among the evaluated models for predicting building energy performance of L-shaped courtyard buildings in Malaysia. Its consistently superior performance across cooling load, heating load, and total load suggests that boosting-based ensemble learning is particularly well suited for structured simulation datasets characterised by nonlinear interactions among architectural variables.

The results also indicate that window-to-wall ratio is the dominant architectural parameter influencing cooling and total energy demand, followed by geometric compactness indicators such as FORM_FACTOR and S_V_RATIO. These findings are consistent with recent studies on tropical building envelopes, which identify façade transparency as one of the primary drivers of cooling energy consumption in hot-humid climates. Consequently, reducing excessive glazing while maintaining compact building geometry represents an effective passive design strategy for improving energy performance during the early stages of architectural design.

V. Conclusions

This study developed and evaluated a machine learning-based predictive framework for estimating cooling load, heating load, and total load of L-shaped courtyard buildings under Malaysia's hot–humid tropical climate. Using a validated parametric simulation dataset, three supervised regression models Gradient Boosting (GB), Random Forest (RF), and Artificial Neural Network (ANN) were compared to determine the most accurate and stable predictive approach.

The results demonstrate that ensemble-based models consistently outperform neural network models in this structured architectural dataset.

Among the three algorithms tested, Gradient Boosting achieved the highest predictive accuracy across all energy outputs, with R^2 values exceeding 0.998 and the lowest RMSE values for cooling, heating, and total loads. These findings confirm that Gradient Boosting provides superior generalization performance and stability for tropical building energy prediction tasks.

Although the proposed models achieved high predictive accuracy, the study has several limitations. The models were developed using a simulation-generated dataset representing L-shaped courtyard buildings under Kuala Lumpur climatic conditions. Consequently, the findings may not be directly generalisable to other building typologies, climatic regions, or operational building datasets without further validation. Future work should evaluate the proposed framework using measured building data and additional cross-validation strategies to improve robustness and generalisability.

The study also suggests that envelope-related parameters, particularly window-to-wall ratio, exert strong influence on cooling and total energy demand in courtyard buildings. Geometric compactness indicators such as form factor and surface-to-volume ratio further contribute to performance variation. These findings reinforce the importance of façade design and massing strategies in reducing cooling loads within tropical climates.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR(S) CONTRIBUTION STATEMENT

All authors contributed equally to this work.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ETHICS STATEMENT

This study did not require ethical approval.

REFERENCES

[1] A. Aldhshan, K. Maulud, O. Jaafar, H. Karim, and B. Pradhan, "Building energy consumption trends in tropical climates," Sustainable Cities and Society, vol. 72, pp. 103–118, 2021.

[2] R. Al Shawa, "Assessing the validity of simplified heating and cooling demand calculation methods: The case of Passive House Planning Package (PHPP) and Radiant Time Series Method (RTSM)," Frontiers in Built Environment, vol. 10, pp. 1–15, 2024.

[3] X. Chen, Y. Xiao, Y. Guo, and D. Yan, "Machine learning approaches for building energy prediction: A review," Energy and Buildings, vol. 279, pp. 112–130, 2023.

[4] A. Garcia-Ballesta, J. Perez-Fadon, and J. Almendros-Ibanez, "Assessment of building energy simulation tools to predict heating and cooling energy consumption at early design stages," Sustainability, vol. 15, no. 4, pp. 3450–3465, 2023.

[5] R. Gupta and C. Deb, "Envelope optimisation for cooling load reduction in tropical buildings," Building and Environment, vol. 228, pp. 109–124, 2023.

[6] P. Westermann and R. Evins, "Surrogate modelling for sustainable building design: A review," Renewable and Sustainable Energy Reviews, vol. 134, pp. 110–130, 2021.

[7] Y. Zhang, J. Wen, H. Chen, Y. Ye, and W. Livingood, "Tree-based ensemble learning for building energy prediction," Applied Energy, vol. 285, pp. 116–134, 2021.

[8] I. Zwain and A. Bahauddin, "Thermal performance of courtyard shophouses in Malaysian hot-humid climate," Journal of Asian Architecture and Building Engineering, vol. 14, no. 3, pp. 541–548, 2015.

[9] A. Almhafdy, N. Ibrahim, M. Ahmad, M. Almahmoud, and M. Alashwal, "Dataset on energy consumption in buildings within tropical climate based on design aspects of courtyards," Data in Brief, vol. 61, Art. no. 111834, Aug. 2025, doi: 10.1016/j.dib.2025.111834.

[10] International Energy Agency, Energy Efficiency 2023. Paris, France: International Energy Agency, 2023.

[11] ASEAN Centre for Energy, Southeast Asia Energy Outlook 2024. Jakarta, Indonesia: ASEAN Centre for Energy, 2024.

[12] D. Zhou, Y. Zhang, X. Li, X. Huai, and M. Xu, "Energy, environmental, and economic feasibility assessment of solar adsorption cooling system under different climate conditions in China," International Journal of Energy Research, vol. 2025, Art. no. 5377062, 2025, doi: 10.1155/ER/5377062.gap between predicted and measured energy performance of buildings: A review," Building Research & Information, vol. 52, no. 2, pp. 180–196, 2023.

[14] Y. Ren, Z. Chen, H. Zhang, and L. Liu, "Optimal classification of radiant time series for cooling load calculation," Energy and Buildings, vol. 290, pp. 113–129, 2024.

[15] G. Gunasagaran, N. Ibrahim, and A. Bahauddin, "Environmental performance of traditional Malaysian courtyard houses," Journal of Design and Built Environment, vol. 22, pp. 75–89, 2021.

[16] M. Diz-Mellado, S. Barreneche, and L. Cabeza, "Impact of courtyard geometry on building energy performance," Energy Reports, vol. 9, pp. 520–532, 2023.

[17] A. Al-Fayyad, M. Al-Mamoori, and S. Al-Shimmary, "The impact of courtyard geometry on energy efficiency in hot-dry climates," Journal of Engineering, vol. 29, no. 3, pp. 140–154, 2023.

[18] L. Liu, H. Zhang, C. Hu, Y. Tang, X. Wu, and J. Wang, "Influence of building form and envelope on cooling energy demand in hot-humid climates," Energy and Buildings, vol. 250, pp. 111–126, 2021.

https://doi.org/10.31436/ijpcc.v12i2.713

[19] Z. Zhu, H. Feng, and Y. Li, “Courtyard morphology and microclimate performance in warm regions,” Building and Environment, vol. 216, pp. 108–122, 2022.
[20] Y. Ali, X. Zhou, and T. Hong, “Artificial intelligence applications in building energy modelling: A systematic review,” Energy and AI, vol. 7, pp. 100–118, 2023.
[21] T. Kaghembega, X. Chen, and R. Tchewafei, “Optimisation of building envelope parameters using gradient boosting models,” Applied Energy, vol. 332, pp. 120–138, 2024.
[22] D. Balmer, M. Kuhn, B. Bischof, D. Salamanca, J. Kaufmann, F. Perez-Cruz, and M. Kraus, “Machine learning surrogates for parametric building performance exploration,” Building Simulation, vol. 17, pp. 345–360, 2024.
[23] J. Bekdaş, B. Duta, and A. Baki, “Comparison of ANN and ensemble learning models for energy load prediction,” Journal of Building Engineering, vol. 66, pp. 105–118, 2023.
[24] L. Breiman, “Random forests,” Machine Learning, vol. 45, no. 1, pp. 5–32, 2001.
[25] R. Ouf, M. Gohary, and V. Ugursal, “Energy efficiency strategies in hot-humid climates: A review,” Renewable and Sustainable Energy Reviews, vol. 132, pp. 110–125, 2020.
[26] Government of Malaysia, National Energy Transition Roadmap (NETR), Putrajaya, Malaysia, 2023.