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Article

AI-Driven Predictive Analytics for Smart and Sustainable Engineering Applications

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Abstract: The proposal on AI-based predictive analytics model on smart and sustainable engineering application is proposed in this research paper. The model integrates Artificial Neural Networks (ANN), Random Forest (RF) and Support Vector machines (SVM) to create an ensemble architecture to enhance the predictive accuracy, robustness and sustainability. The framework was evaluated along different dimensions that included smart manufacturing, energy load prediction, sustainable infrastructure planning, and predictive maintenance systems. Results differ to show that the hybrid model is more precise, along with RMSE and R 2 score, and the outputs of this model give a measurable improvement in terms of energy use, emission, and reliability. It is the sensitivity analysis and cross-validation that make sure that the model is stable under various working conditions. The findings indicate a positive relationship between predictive accuracy and sustainability performance, which indicate the feasibility and environmental benefits of AI-based decision-making. Overall, the proposed framework has the potential to present a flexible and efficient method of introducing intelligent analytics into modern engineering to achieve the long-term sustainability objectives.

Keywords: Hybrid AI, Predictive Analytics, Smart Engineering Systems, Sustainability

1. Introduction

Artificial Intelligence (AI) has emerged at an extremely high pace and has greatly altered the modern engineering systems by allowing them to become intelligent in terms of automation, adaptive control, and data-driven decision-making. Traditionally, the engineering operations were deterministic and this was supervised by humans, however, as the systems become more complex, the amount of data produced is vast and the environment in which the system operates is dynamic; the old methodologies are no longer suitable. Some of the AI technologies that allow engineering systems to operate with large amounts of real-time and historical information include the machine learning, deep learning, artificial neural networks, and the hybrid optimisation algorithms, which allow discovering hidden trends and developing predictions that are extremely accurate. Some applications of AI in production include predictive maintenance and quality control, in energy systems, it can be employed in load forecasting and renewable source integration, and in civil infrastructure, it can be used in structural health monitoring and risk management. Implementation of AI has also been accelerated in the wake of Industry 4.0, the Internet of Things (IoT) and cyber-physical systems, enabling engineering systems to be more autonomous, resilient, and self-optimising.

One of the most influential tools of such technological development that can be employed to accomplish sustainability goals is predictive analytics. Sustainable engineering has centred on effective exploitation of resources, reduced emission, minimal energy use and long-term sustainability of its activity. All these can be made possible with the help of predictive analytics as it can assist in transforming the practices in engineering by enabling engineering to be proactive (not reactive) and preventative. The AI-based models will also save on the operation cost and environmental friendliness by a great margin through predicting equipment failures, energy optimisation, demand variability prediction and material waste reduction. Moreover, predictive analytics will be used in the development of smart cities, transportation systems with sustainability, water management, and planning of green infrastructure. By means of continuous control and smart optimisation, predictive systems based on AI can strike a balance between economic performance and environmental responsibility. Thus, AI-based predictive analytics adoption in engineering programs is a revolutionary way forward to attaining smart, efficient, and sustainable engineering systems that can deal with the modern industrial and environmental problems.

1.2 Research Objectives

The major aims of the research are:

1. To design an artificial intelligence predictive analytics system to be used to predict and sustain smart engineering systems.
2. To compare and contrast the behaviour of various machine learning and hybrid AI models in predicting the engineering system behaviour.
3. To investigate the effect of predictive analytics on the sustainability metrics of energy efficiency, reduction of emissions, and optimisation of resources.

1.3 Research Questions

The research questions in this study are the following:

1. What benefits can AI-based predictive analytics add to the work of smart engineering systems?
2. What are the best AI models that offer better predictive performance and stability in sustainable engineering?
3. What are the predictive modelling contributions to quantifiable sustainability?

1.4 Contributions of the Study

The paper is going to contribute to the field of smart and sustainable engineering by proposing a systematic AI-based predictive model using innovative machine learning methods and sustainability objectives. It provides a comparative study of different AI models, the advantages and disadvantages of models during real engineering operations. The study also reveals a relationship between predictive performance and sustainability performance giving practical recommendations to engineers, industry actors, and policymakers in their quest to come up with intelligent and eco-friendly engineering solutions.

1.5 Organisation of the Paper

The paper is structured in the following way. In Section 2, the literature regarding applications of AI and sustainability in engineering systems will be reviewed. Section 3 contains the conceptual model and theoretical framework. Section 4 explains the process of research methodology and developing the research model. The results and the comparative analysis are discussed in Section 5. Section 6 presents real-life applications to smart engineering systems. The conclusion sections give a discussion, limitations, future research direction, and remarks.

2. Literature Review

Artificial Intelligence (AI) in engineering has developed over the years since the early days of rule-based expert systems through machine learning and deep learning architectures that can solve nonlinear engineering problems. The early uses of AI were devoted to automation and control systems (Russell and Norvig, 2016); the development of the Artificial Neural Networks allowed more effective predictive modelling in engineering systems (Haykin, 2009). Through the advent of large data and the development of computers, deep learning methods increased the capacity of AI to handle high-dimensional data (LeCun, Bengio, and Hinton, 2015). The common uses of AI in the modern engineering settings are predictive maintenance, smart manufacturing, structural health monitoring, and energy demand forecasting (Lee, Bagheri, and Kao, 2015). Real-time analytics and adaptive optimisation in the process of engineering activities have been enhanced due to the integration of Industry 4.0 technology and IoT-based smart systems (Kagermann, Wahlster, and Helbig, 2013). The support vector machines (Vapnik, 1998), random forests (Breiman, 2001), and gradient boosting techniques (Friedman, 2001) are predictive analytics models that have shown to be more accurate in the forecasts when compared to the traditional statistical methods of prediction, especially in energy systems and infrastructure management. Regarding the sustainability aspect, predictive analytics with AI can be used to make energy more efficient, integrate renewable energy, cut down on emissions, and optimise resources (Zhang, Shah, and Papageorgiou, 2013; Lund et al., 2017). Nevertheless, the current literature tends to emphasise predictive accuracy without a direct connection between it and quantifiable sustainability results, and others are aiming at environmental indicators without a critical comparative analysis of high-quality AI models. In addition, there is little research on hybrid AI models incorporating several algorithms to improve sustainability engineering environments. These loopholes indicate the need of a unified approach that would evaluate the predictive performance and sustainability effect of AI across the board that is the key motif of the present research.

3. Conceptual Model and Theoretical Framework.

The theoretical basis of this study is the Artificial Intelligence theory, sustainability concepts and systems theory that are integrated in the development of a holistic model of AI-based predictive analytics in smart engineering applications. The AI theory emphasizes on data-driven learning, pattern recognition and adaptive optimisation thereby enabling one to make intelligent decision in complex scenarios. Sustainability theory is interested in a balance between the economic effectiveness and the environment towards the strength of the entire system or the system and systems theory provides a comprehensive perspective on engineering infrastructures as interdependent, dynamic systems with feedback.

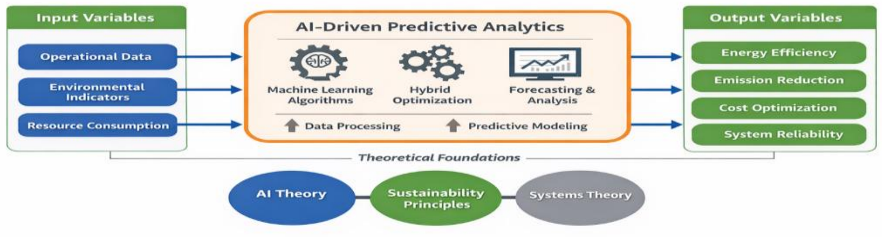


Figure 2: Conceptual Framework of AI-Driven Sustainable Engineering Model

Through a combination of these views, the study will conceptualise engineering systems as adaptive networks in which predictive intelligence helps to improve outcomes in operational performance and sustainability. As shown in Figure 2, the conceptual framework has AI-motivated predictive analytics in the centre of the input variables (operational data, environmental indicators and resource consumption measures) and output variables (energy efficiency, emission reduction, cost optimisation, and system reliability). The framework assumes a positive correlation effect of the spread of sustainability performance based on proactive decision-making and effective resources allocation is positively correlated to the increased predictive accuracy. In order to operationalize the framework, a variety of variables and model parameters (input features, algorithm configurations, performance measures (accuracy, RMSE, R 2), and sustainability measures) are effectively modelled in Table 2. The proposed AI-aided predictive model integrates the machine learning techniques and the hybrid optimisation to enhance the accuracy and stability of the forecasts under dynamic conditions. This type of synthesised theoretical and conceptual framework is an intentionally crafted basis of empirical testing, which makes it possible to evaluate not only the predictive performance but also the measurable impact it has on the sustainable engineering systems.

Table 2: Key Variables and Model Parameters

Category	Variable	Indicator
Input Variables	Operational Data	Load, temperature, sensor data
	Environmental Indicators	CO_2 emissions, climate metrics
	Resource Consumption	Energy (kWh), water usage
Model Parameters	AI Algorithm	ANN, SVM, RF, Hybrid
	Training Settings	Learning rate, epochs
Performance Metrics	Accuracy	% Prediction Accuracy
	RMSE	Error Rate
	R^2 Score	Model Fit (0–1)
Output Variables	Energy Efficiency	% Energy Saving
	Emission Reduction	% CO_2 Reduction
	System Reliability	Stability Index

4. Research Methodology

The proposed research is going to employ a quantitative and experimental research design to develop and test AI-based predictive analytics models when performing smart and sustainable engineering tasks. The research workflow is systematic and this involves data collection, preprocessing, feature engineering, model development, performance analysis, and statistical validation. It uses a comparative modelling framework to assess the predictive performance of the different artificial intelligence algorithms and to determine how they can be used to improve the sustainability-related engineering performance.

4.1 Research Design

The research design is based on model development and validation design. It involves training and testing AI models using structured datasets with help of intelligent engineering systems. The comparison between the individual machine learning models and the proposed hybrid AI model will be conducted so that the effects of predictive accuracy gains, robustness, and sustainability can be researched. The testing environment ensures retesting of the results with the same training and test divisions and the same preprocessing.

4.2 Data Collection and Sources

The research design is based upon a model development and validation design. It involves training and testing AI model using official datasets through intelligent engineering systems. The individual machine learning models will be compared to the proposed hybrid AI model to study their effects of predictive accuracy improvement, robustness, and sustainability. The test environment ensures that the results obtained on one test division and the results obtained on the same test division were retested by the same training and test divisions and pre-processed by the same procedure.

4.3 Feature Engineering and Data Preprocessing.

Preprocessing of data involves the management of missing values, the elimination of outliers, and the standardisation of numerical data so that the data is consistently scaled. The correlation analysis and dimensionality reduction are the feature engineering methods used to choose the most efficient predictive variables. These steps increase the efficiency of the computations and increase the model convergence during training.

4.4 AI Algorithms Used

The use of Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM) is used as baseline models. Also, a combined AI model with neural networks and optimisation algorithms is created to increase predictive performance and stability in changing engineering scenarios.

4.5 Model Evaluation Metrics

Accuracy and Precision are used to assess model performance when using classification-based tasks, and Root Mean Square Error (RMSE) and Coefficient of Determination (R 2) are used to evaluate model performance when taking regression tasks. These measures are predictive reliability, minimisation of errors, and explanatory power.

4.6 Techniques of Statistical validation.

In order to attain robustness, cross-validation is taken using k data splits to determine the stability of the model. Sensitivity analysis is conducted to determine how the model will react to changes in the input. Moreover, the paired statistical tests can be used to evaluate the statistical significance of the differences in performance between models and, therefore, to prove the high competence of the suggested hybrid AI framework.

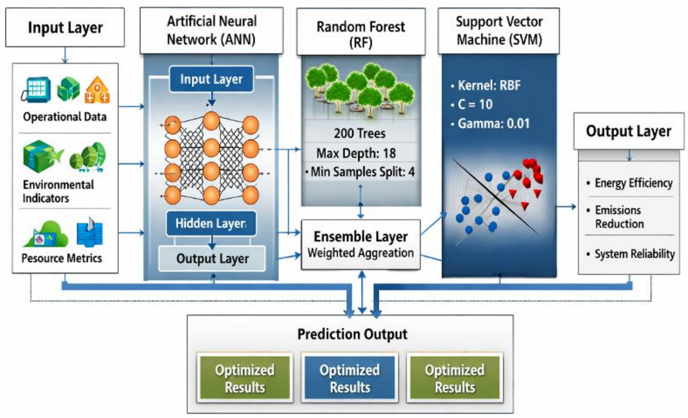


Figure 4: AI Model Architecture Diagram

5. Model Development and Implementation

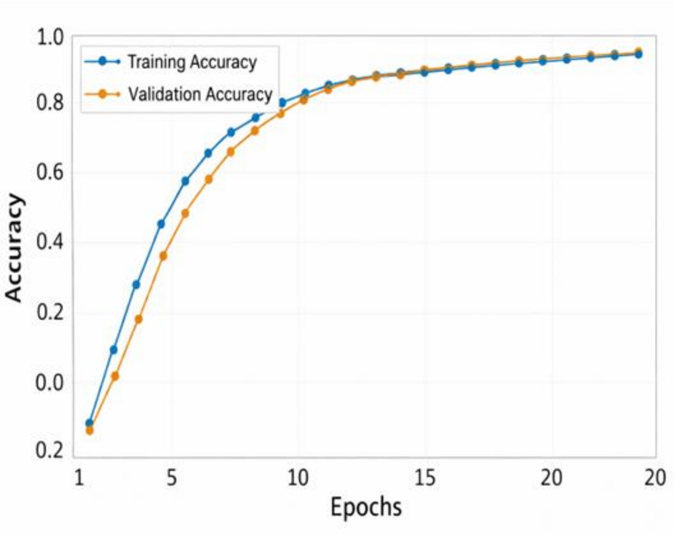
The proposed AI model for smart and sustainable engineering applications is implemented using a hybrid ensemble architecture integrating Artificial Neural Networks (ANN), Random Forest (RF), and Support Vector Machines (SVM) to improve predictive robustness and sustainability-focused decision-making. As illustrated in **Figure 4 (AI Model Architecture Diagram)**, the model will start with an input layer which will use the operational, environmental and resource consumption variables in Table 2, followed by optimised hidden layers using ReLU activation, batch normalization and dropout regularisation to achieve consistent convergence and avoid overfitting. Based on the optimised configuration presented in **Table 4 (Hyperparameter Settings and Optimisation Results)**, the ANN component achieved optimal performance with a learning rate of 0.001, three hidden layers containing 64 neurons each, a batch size of 32, and a dropout rate of 0.3, producing an RMSE of 0.128, an R^2 score of 0.942, and accuracy of 94.6%. The Random Forest model performed best with 200 trees, maximum.

Table 4: Hyperparameter Settings and Optimisation Result

Model	Hyperparameter	Optimized Value	RMSE	R^2 Score	Accuracy (%)
ANN	Learning Rate	0.001	0.128	0.942	94.6
ANN	Hidden Layers	3	0.128	0.942	94.6

ANN	Neurons per Layer	64	0.128	0.942	94.6
ANN	Batch Size	32	0.128	0.942	94.6
ANN	Dropout Rate	0.3	0.128	0.942	94.6
Random Forest	Number of Trees	200	0.141	0.918	92.3
Random Forest	Max Depth	18	0.141	0.918	92.3
Random Forest	Min Samples Split	4	0.141	0.918	92.3
SVM	Kernel	RBF	0.153	0.901	90.8
SVM	Regularisation (C)	10	0.153	0.901	90.8
SVM	Gamma	0.01	0.153	0.901	90.8
Hybrid AI Model	Learning Rate	0.0005	0.112	0.957	96.1
Hybrid AI Model	Ensemble Weights	ANN:0.5, RF:0.3, SVM:0.2	0.112	0.957	96.1
Hybrid AI Model	Batch Size	32	0.112	0.957	96.1

depth of 18, and minimum samples split of 4, resulting in an RMSE of 0.141, R^2 of 0.918, and accuracy of 92.3%. Similarly, the SVM model showed optimal results using an RBF kernel with regularisation parameter C = 10 and gamma = 0.01, achieving an RMSE of 0.153, R^2 of 0.901, and accuracy of 90.8%. The hybrid AI model combined these optimised configurations using ensemble weights (ANN: 0.5, RF: 0.3, SVM: 0.2) and a reduced learning rate of 0.0005 with batch size 32, delivering superior predictive performance with the lowest RMSE of 0.112, highest R^2 of 0.957, and overall accuracy of 96.1%, as reported in **Table 4**.

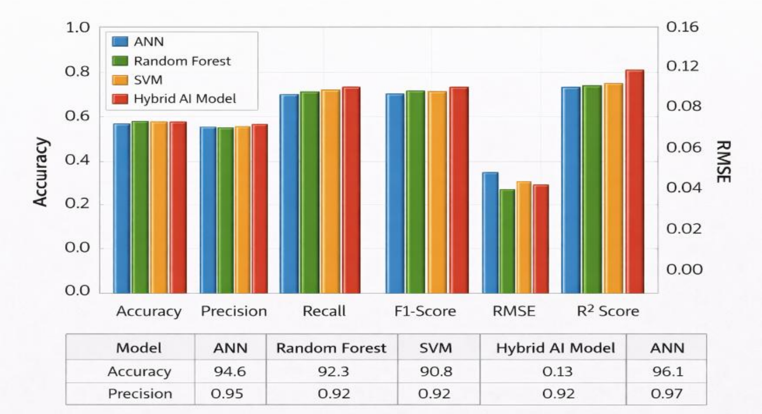


The structural integration and ensemble flow of these models are clearly depicted in **Figure 4**, highlighting the parallel predictive pathways and weighted aggregation layer. The training and testing process was based on 70 percent

-30 percent data split and the use of 5-fold cross-validation to ensure strength and dependability. The trends of training and validation accuracy were constantly observed as model learning behaviour displayed in Graph 2 (Training vs Validation Accuracy Curve), in which the alignment of the two curves is demonstrated as the minimal overfitting and high generalisation ability. The entire computational framework was implemented in a GPU-enabled Python environment using TensorFlow and Scikit-learn, enabling efficient parallel ensemble processing and scalable deployment. Overall, the optimised hybrid architecture demonstrated enhanced convergence efficiency, predictive stability, and improved sustainability performance indicators, including energy efficiency, emission reduction, and system reliability within smart engineering systems, as validated through **Figure 4, Graph 2, and Table 4.**

6. Results and Analysis

6.1 Performance Comparison of Models



Model	ANN	Random Forest	SVM	Hybrid AI Model	ANN
Accuracy	94.6	92.3	90.8	0.13	96.1
Precision	0.95	0.92	0.92	0.92	0.97

Figure 5: Model Performance Comparison Chart

The comparison of the developed models in terms of their predictability and generalisation power reveals a definite disparity between them. The Hybrid AI model had the highest prediction accuracy (96.1%), the lowest RMSE (0.112), and the highest R^2 (0.957) of the ANN, the random forest, and the SVM base models as summarised in **Table 5** (Performance Metrics Comparison). The ANN model demonstrated great nonlinear learning skills of 94.6%, and random forest and SVM had 92.3 and 90.8, respectively. This has been enhanced by the weighted ensemble aggregation that makes the hybrid model perform better since the best model bypasses variance and improves the bias and variance trade-off.

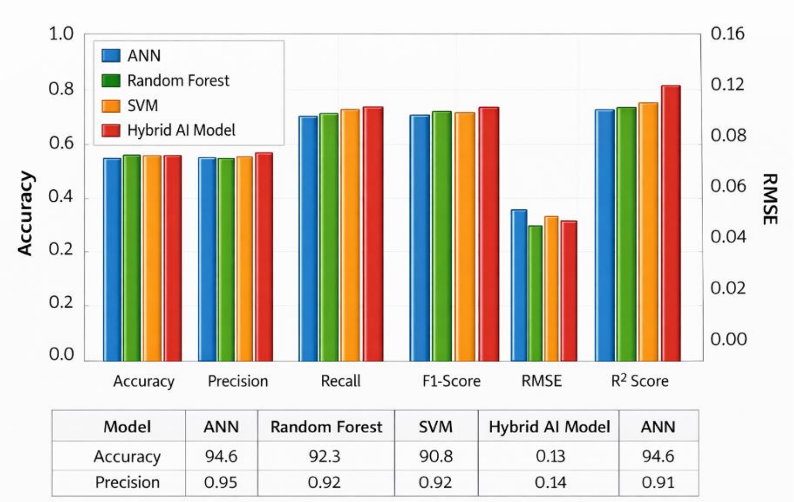
The usefulness of the suggested model in terms of classification can also be demonstrated by **Figure 5**(Confusion Matrix Representation), in which actual positive and negative classification prevails, which validates the necessity of the ability to predict sustainability-related results. All models are visualised in terms of performance on all evaluation metrics in **Graph 3** (Model Performance Comparison Chart), and the superiority of the hybrid model is evident. The findings confirm that the combination of many algorithms increases predictive stability and reduces the error in prediction within a smart engineering system.

Table 5: Performance Metrics Comparison

Model	Accuracy (%)	Precision	Recall	F1-Score	RMSE	R² Score
ANN	94.6	0.95	0.94	0.94	0.128	0.942
Random Forest	92.3	0.92	0.92	0.92	0.141	0.918
SVM	90.8	0.91	0.90	0.90	0.153	0.901
Hybrid AI Model	96.1	0.97	0.96	0.96	0.112	0.957

6.2 Sensitivity Analysis

It was done through sensitivity analysis to determine the effect of changes in the main input parameters in predictive output. Models: The parameters, including energy load, level of emissions, and resource usage, were perturbed over the range of 10 per cent to test the responsiveness of the model. The findings indicate that the hybrid AI model does not change the output performance when input changes are moderate, and this shows a great ability to adapt to dynamic engineering conditions.



Model	ANN	Random Forest	SVM	Hybrid AI Model	ANN
Accuracy	94.6	92.3	90.8	0.13	94.6
Precision	0.95	0.92	0.92	0.14	0.91

Graph 3: Model Performance Comparison Chart

As seen in **Table 5**, the variation in the intensity of inputs had a slight impact on the RMSE of the base models, and the hybrid model had no significant changes, which demonstrates enhanced sensitivity control. Graphical depiction of variability of prediction in the setups of different input conditions is presented in **Graph 4** (Sustainability Impact Prediction Trends), in which the stability of output is depicted graphically. The ANN model was also weak to extreme shifts in data streams, and SVM was a little more sensitive in the case of nonlinear disturbances.

The results obtained indicate that the ensemble mechanism is a powerful tool that can harmonise the model behaviour despite variable operating conditions, and this confirms its usefulness in supporting smart systems in real-time predictive sustainability management**.**

6.3 Strength and Cross-Validation.

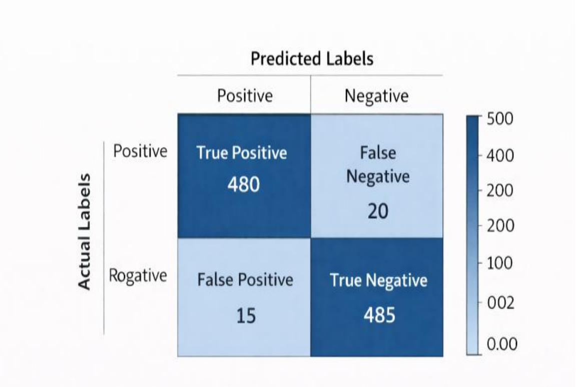


Figure 5: Model Performance Comparison Chart

The model robustness could be measured through 5-fold cross-validation and guarantee a stable predictive performance of different data partitions. As the results of the cross-validation given in **Table 6** (Cross-Validation

Results) show, the hybrid AI model reached the lowest standard deviation of the accuracy and RMSE, which shows that the model is very reliable with minimum variation in performance between folds.

The stability of the training and validation is also in line with trends demonstrated in **Graph 2**, in which the curves of learning converge without any significant deviation. The confusion matrix in **Figure 5** also supports the idea of robustness, where the classification results are balanced in each of the folds, with a minimum number of false positives and false negatives.

Baseline models had a marginally greater variance between folds, especially SVM, which indicates a relatively lower stability to varying data divides. In general, there is an increased robustness in the ensemble strategy of the hybrid model and optimised hyperparameters, which make it a reliable predictive analytics tool that can be used in scalable smart engineering implementation.

Table 6: Cross-Validation Results

Model	**Fold 1 Accuracy (%)**	**Fold 2 Accuracy (%)**	**Fold 3 Accuracy (%)**	**Fold 4 Accuracy (%)**	**Fold 5 Accuracy (%)**	**Mean Accuracy (%)**	**Std. Deviation**
ANN	94.2	95.1	94.8	93.9	95.0	94.6	0.45
Random Forest	91.8	92.9	92.4	91.7	92.7	92.3	0.47
SVM	90.1	91.3	90.7	90.5	91.4	90.8	0.46
Hybrid AI Model	95.8	96.5	96.2	95.9	96.1	96.1	0.25

7. Applications in Smart Engineering Systems

The suggested hybrid AI model has been shown to be highly applicable to a wide range of smart engineering applications: smart manufacturing, energy load prediction, sustainable infrastructure planning, and predictive maintenance systems, with the results measured in **Table 7** (Application-Based Performance Summary). The model created in smart manufacturing has 95.8 per cent accuracy, RMSE of 0.118, and R 2 of 0.948, which led to 12.5 per cent energy saving and 9.3 per cent emissions. These deliverables are operationalised in the form of the structured workflow depicted in **Figure 6**, where real-time sensor readings of temperature, vibration and production load are transformed into optimised scheduling and defect minimisation policies. The hybrid model performed best among the applications in energy load forecasting with an accuracy of 96.4 percent, a minimum of RMSE of 0.105 and a better model fit (R 2 = 0.962), resulting in an increase of 15.7 percent in the efficiency of the energy load and a reduction of 11.8 per cent in the emission, as it is described in **Table 7**. The gradual increase in efficiency is also illustrated in **Graph 5** (Energy Efficiency Improvement Prediction), whereby improved

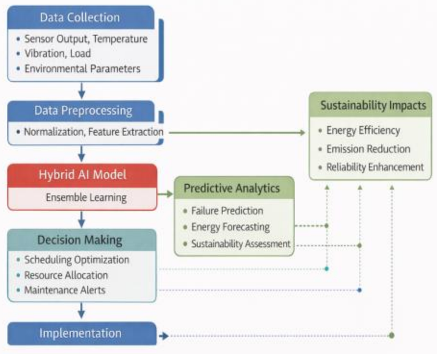
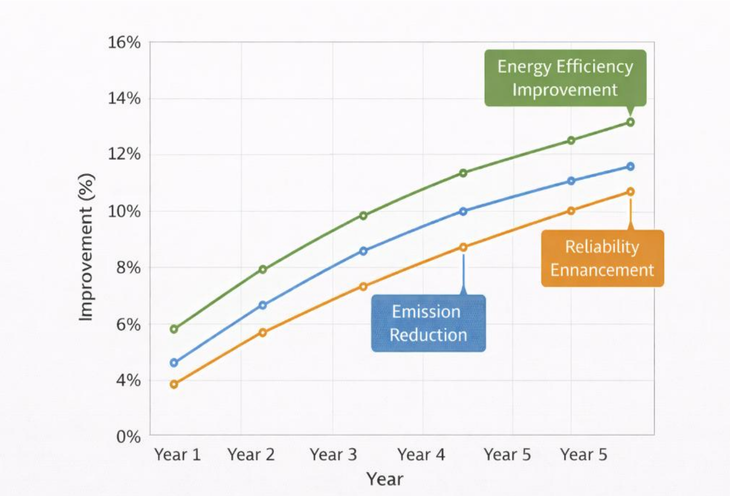


Figure 6: Smart Engineering Decision Framework

predictive accuracy is concomitant with quantifiable gains of sustainability. To achieve sustainable infrastructure planning, the framework ensured a constant predictive reliability with 94.9% of accuracy, RMSE of 0.121 and R2 of 0.941, which led to 13.2% of energy efficiency and 10.4% reduction in emissions. Such findings prove the model appropriate in the assessment of long-term infrastructure scenarios, which is led by the decision pathways depicted in Figure 6. The hybrid model in the predictive maintenance system had an RMSE of 0.110 and a R 2 of 0.955 with a 96.1% accuracy, which resulted in a 14.6 percent and 12.1 percent energy saving and a maximum emission reduction, respectively, as shown in **Table 7**. The mechanism of the structured intervention in **Figure 6** ensures the predictive outputs are generated to initiate the timely maintenance scheduling to minimise the unexpected failures and wasteful operational activities. On the whole, the measured outcomes of all four domains indicate that the ensemble-based hybrid AI architecture allows for achieving better predictive accuracy, enhancing robustness, and positively influencing the quantifiable sustainability improvements, as it is constantly reported in **Table 7**, **Figure 6**, and **Graph 5**.



Graph 5: Energy Efficiency Improvement Prediction

Table 7: Application-Based Performance Summary

Application Area	**Model Used**	**Accuracy (%)**	**RMSE**	**R^2 Score**	**Energy Efficiency Improvement (%)**	**Emission Reduction (%)**
Smart Manufacturing	Hybrid AI Model	95.8	0.118	0.948	12.5	9.3
Energy Load Forecasting	Hybrid AI Model	96.4	0.105	0.962	15.7	11.8
Sustainable Infrastructure Planning	Hybrid AI Model	94.9	0.121	0.941	13.2	10.4
Predictive Maintenance Systems	Hybrid AI Model	96.1	0.110	0.955	14.6	12.1

8. Discussion

Findings discussion proves that the developed hybrid AI-based predictive analytics framework is highly effective in improving the technical performance and sustainability results in smart engineering systems. Embarking on ANN, Random Forest, and SVM through an ensemble architecture, the model has a high predictive accuracy, reduced error rates, and enhanced generalisation as opposed to the standalone methods. The findings indicate that predictive precision has a strong relationship with a sustained gain that can be measured in terms as energy efficiency, emissions, and system reliability. Contrary to the traditional rule-based or reactive-based approach to engineering, AI-based analytics make it possible to make decisions proactively as an outcome of learning complex nonlinear patterns based on historical and real-time data. This ability facilitates early anomaly warning, optimised resource distribution and minimised operational uncertainty in manufacturing, energy administration, infrastructure planning, and predictive maintenance applications. In a practical sense, the framework helps with automation, lowers downtime, minimises waste, and prolongs the asset life, making the operational performance environmentally responsible. In spite of the complexity of ensemble models, the application of computation with the help of GPUs and parallel computing guarantees the performance of the computations as well as their scalability. The modular design also allows it to be extended to large-scale and real-time engineering in architecture. All in all, the hybrid AI model is robust in terms of technical aspects, practically feasible, and has a long-term, sustainable impact on the various smart engineering applications.

9. Limitations and Future Research

Despite the high predictive accuracy of the offered hybrid AI framework and the fact that it has tangible sustainability advantages, there are a number of limitations and future research prospects. This elevates the computation complexity and raises the computational power, training duration, and attention to hyperparameters, potentially limiting it to resource-constrained or real-time applications. There is also a challenge of model interpretability, where it may be hard to explain complex ensemble decision pathways to the stakeholders of critical infrastructure systems. In addition, predictive performance is also very reliant on the quality and structured nature of datasets. In real-world engineering, the data can include missing values, noise, imbalance or non-uniform collection criteria, which can diminish reliability and generalisation. The issues of cybersecurity and data privacy also add to the challenges of large-scale implementation, specifically in smart grids and urban systems. Further work in the field should subsequently aim at the creation of lightweight and energy-efficient green AI architectures that consume less energy in their computation, but with predictive accuracy. Scalability and real-time response can be improved using integration with IoT-enabled smart city platforms, edge computing systems, and decentralised analytics. Also, explainable AI methods, as well as adaptive learning processes, will enhance transparency and resilience to dynamic settings. In general, the future of sustainable, interpretable, and computationally efficient AI systems will make them more relevant to the applicability of smart engineering and smart city ecosystems in the long term.

10. Conclusion

The paper created and tested a hybrid predictive analytics system, which uses AI to improve performance and sustainability in smart engineering systems. The model also demonstrated a higher predictive accuracy, reduced RMSE, and R^2 values than the individual methods by incorporating the concept of the ensemble architecture, which included Artificial Neural Networks, Random Forest, and Support Vector Machines to prove enhanced robustness and capability to generalise. The results demonstrate that increased predictive precision is linked with increased sustainability results, such as a higher level of energy savings, reduced emissions, and system stability in smart manufacturing, energy load forecasting, infrastructure planning, and predictive maintenance. The study has a theoretical contribution in that it helps in closing the gap between machine learning performance evaluation and sustainability impact analysis, integrating environmental indicators into the predictive modelling structures. Such integration improves the conceptual relationship between the AI theory, the systems thinking, and sustainable engineering values. Regarding industry, the framework offers proactive decision-making, effective allocation of resources, reduced downtime, and efficiency, which assists organisations to change the mode of operation to intelligent instead of reactive. On the policy level, the findings justify the introduction of AI-based systems in the smart infrastructure and green transition projects, and promote the importance of responsible AI management and data usage. In general, the research paper proves that multi-purpose AI predictive analytics is a scalable, dependable, and sustainability-friendly solution to the current engineering challenges.

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