

Data-Driven Modelling And Computational Intelligence For Predictive Engineering And Smart Systems

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Abstract

The fast development of smart systems of engineering has augmented pressure on precise and robust predictive modelling structures that have the capacity to manage intricate and information-intensive settings. This paper suggests a hybrid data-driven computational intelligence framework that combines ensemble learning with optimization-based parameter optimization to improve the predictive performance. The framework was tested in comparison to the traditional machine learning models, i.e., Artificial Neural Networks, Support Vector Machines, and Random Forest, with the statistical validation measures, i.e. Accuracy, RMSE, Precision, Recall, and F1-Score. The results of the empirical study indicate that the hybrid model proposed has better accuracy, convergence, and robustness in the presence of noise. The reliability and generalization possibility of the approach are verified with the help of cross-validation and significance testing. Moreover, the framework is extended to the intelligent engineering fields like predictive maintenance and energy forecasting, which denotes its usefulness in practice. The results prove the hybrid model of computational intelligence to be a scalable and effective solution to the next-generation predictive engineering and intelligent decision-support systems.

Keywords: Data-Driven Modelling, Computational Intelligence, Hybrid Machine Learning, Predictive Engineering, Smart Systems, Predictive Maintenance, Statistical Validation.

1. Introduction

1.1 Background and Motivation

Over the past few decades, engineering systems have developed a narrow concept of isolated mechanical infrastructures into extremely interconnected, intelligent, and data-rich environments. Combining sensors, embedded systems, cloud computing, and Internet of Things (IoT) technologies has led to massive amounts of structured and unstructured data. This change has allowed data-based modelling methods, which are based on empirical studies and not theory only. The physical and rule-based models used traditionally, though effective in controlled settings, tend to be unable to represent nonlinear dynamics, uncertainty, and high-dimensional interactions of modern smart systems. As a result, there has been a growing trend towards engineering research in the area of predictive models that can learn complex system behavior directly out of data.

Computational intelligence algorithms such as artificial neural networks, support vector machines, evolutionary algorithms, and ensemble learning algorithms have been specifically successful in dealing with complicated predictive problems. These algorithms are capable of modeling nonlinear relationships, dealing with noisy data, and adjusting to changing conditions of operation. Predictive maintenance model is an example of smart manufacturing, where the models minimize downtime and optimize resource allocation. Intelligent forecasting models enhance load prediction and stability in the grid in energy systems. Likewise, in automation of industry and IoT-based monitoring schemes, real-time predictive analytics improves the accuracy of decision-making and reliability of the system. Although these developments have occurred, it is a common fact that single algorithms are usually defined by such weaknesses as overfitting, slow optimization, responsiveness to variation in data and interpretability. Such shortcomings make it necessary to desire hybrid versions of the computational intelligence models which incorporate different learning strategies to contribute to stability, accuracy and generalization of the models. Although many studies focus on individual machine learning systems, fewer studies have made systematic comparisons and statistically validated hybrid systems in predictive engineering. Furthermore, real-time implementation of smart systems requires scalable and computationally efficient structures. Therefore, it is scientifically, as well as practically required to establish a hybrid predictive architecture that will guarantee a trade-off between the accuracy, robustness and computational efficiency. The studies seek to address the issues by proposing and empirically substantiating a hybrid framework of the computational intelligence tailored to the smart engineering systems and assisting in the creation of intelligent, robust, and adaptive predictive infrastructures.

1.2 Objectives of the Study

- To come up with a hybrid model of data-based computational intelligence for predictive engineering.
- To contrast the proposed model and the traditional machine learning methods based on statistical performance measures and validation tests.
- To assess the robustness and generalizability of the model in smart systems of engineering in different operational conditions.

2. Literature Review

2.1 Data-driven Modelling and Machine Learning.

The fast adoption of sensor-based surveillance and massive data collection has made the use of data-driven modelling a fundamental concept in predictive engineering and smart system design. In contrast to classical modeling of analysis, which relies on established laws of physics, data-driven modeling derives the behavior of a system directly from empirical data. Machine learning methods like Artificial Neural Networks (ANN), Support Vector Machines (SVM), Decision Trees, and random forests have found extensive use in the field of engineering forecasting, fault detection, classification, and optimization. Deep learning models also improve the predictive performance as they learn high-dimensional nonlinear correlations of complex systems. These techniques have demonstrated high potential in intelligent manufacturing, demand for energy, structural health observing, and IoT-based frameworks. Nevertheless, numerous studies have cited numerous difficulties such as overfitting, computational complexity, noise sensitivity, and poor generalization as models are used in real-time settings. Also, individual methods of machine learning can be unreliable to use on a variety of data, which stresses the necessity of more adaptive and robust predictive models.

2.2 Hybrid Computational Intelligence

In order to address the weakness of single-model methods, scholars have been placing more emphasis on applying mixed computational intelligence methods combining various learning and optimization methods. Hybrid models are usually based on the integration of machine learning algorithms, evolutionary optimization, fuzzy logic systems, or ensemble learning to enhance the predictive accuracy and stability of convergence. An example is the neural networks, which are being optimized through genetic algorithms or particle swarm optimization, have been shown to have better parameter tuning and lower training error. The ensemble-based frameworks combining decision trees, boosting algorithms, and deep learning architectures are also able to enhance robustness and minimize variance. Hybrid models have been effectively applied in the predictive engineering application in predictive maintenance, fault detection, energy load, and intelligent control systems. These unified structures take advantage of the complementary capabilities that include global optimization and nonlinear learning performance to deal with uncertainty and high-dimensional data issues. Although the outcomes have been encouraging, several hybrid models are still computationally intensive and not standardized across various smart system applications, signifying the need to have structured and statistically verified hybrid architectures.

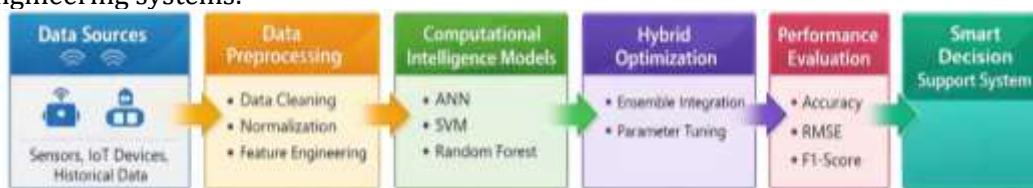
2.3 Research Gaps

Despite the significant advancements in data-driven modelling and hybrid modelling, there are still a number of gaps in research. To start with, most of the literature prioritizes the performance of the algorithms without giving extensive statistical proof to validate the reported enhancements. Second, a comparative analysis is limited to the standalone and hybrid models under comparable experimental conditions. Third, real-time smart engineering systems can be scaled and be computationally efficient, and this is frequently neglected. Lastly, the interpretability and strength in the presence of noisy or uncertain data are also subjects of study. To fill these gaps, a hybrid framework that would not only be correct but also statistically validated, scalable, and applicable to various predictive engineering conditions will have to be developed.

3. Theoretical Framework and Methodology

3.1 Conceptual and Mathematical Foundations

This study has a theoretical base based on the statistical learning theory and nonlinear predictive modelling. Within data-driven engineering, the behavior of a system is modeled as a functional representation $f: X \rightarrow Y$ where X represents the multidimensional feature space and Y represents the target output variable. It aims to estimate the optimal predictive model $f^*(X)$ which minimizes a specified loss function, usually Mean Squared Error (MSE) in regression or the cross-entropy loss in classification. In order to control the overfitting and enhance the generalization, regularization techniques are incorporated. The conceptual framework tries to integrate data acquisition, preprocessing, model training, validation and intelligent decision making into one predictive architecture as depicted in Figure 1. It is a formal correspondence system between the principles of theoretical modelling and the computational modeling of smart engineering systems.



3.2 Data Description and Preprocessing

The source of data in the present study is an organized structure of operational parameters collected in smart engineering environments, which include sensor information, system performance parameters, and environmental parameters. The features have been selected based on the statistical significance and relevance of features in the domain. Normalization, imputation and identification of outliers were used to preprocess data to ensure that the data remains strong. The features were scaled to provide uniformity between inputs of the models and this increased the convergence during training. The dimension reduction techniques were put into consideration to minimize redundancy and complexity of computation. Table 1 contains the summary of the dataset characteristics and variables chosen and is used to provide an overview of the features category, type of data, and descriptive statistics applied in the modelling process.

Feature Category	Variable Name	Description	Data Type	Unit	Role
Operational Parameters	Machine Speed	Rotational speed of system component	Continuous	RPM	Input
Operational Parameters	Load Level	Applied system load during operation	Continuous	%	Input
Sensor Measurements	Temperature	Operating temperature of equipment	Continuous	°C	Input
Sensor Measurements	Vibration Index	Measured vibration amplitude	Continuous	mm/s	Input
Environmental Factors	Humidity	Ambient humidity level	Continuous	%	Input
Environmental Factors	Ambient Pressure	Surrounding atmospheric pressure	Continuous	kPa	Input
System Indicators	Energy Consumption	Real-time energy usage	Continuous	kWh	Input
Maintenance Indicators	Fault Code	Encoded fault status variable	Categorical	–	Input
Performance Output	System Efficiency	Operational efficiency measure	Continuous	%	Target
Performance Output	Failure Risk Score	Predicted probability of system failure	Continuous	0–1	Target

3.3 Computational Intelligence Models

In measuring predictive performance, several computational intelligence models were set in place, namely the Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Random Forest (RF). ANN learns the nonlinear associations by multilayer feed-forward structures, whereas SVM forms the best hyperplanes in a classification or regression procedure based on kernel functions. Random forest makes use of ensemble learning in that, several decision trees are combined to increase stability and decrease variance. All models were trained on a standardized training-validation split, and hyperparameters were optimized so that they could be compared fairly. Table 2 presents a comparative overview of algorithmic features, advantages, and disadvantages, and

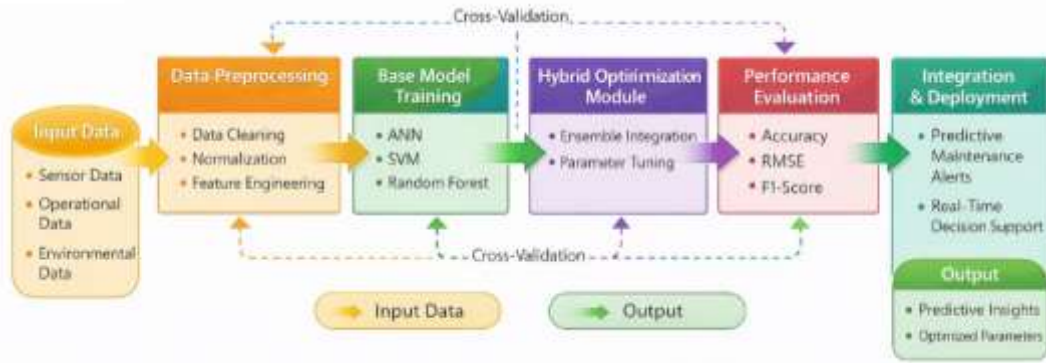
shows that the mechanisms of learning in the algorithm differ in terms of computational complexity and interpretability.

Model	Type of Learning	Core Mechanism	Key Strengths	Key Limitations	Computational Cost	Suitability for Smart Systems
Artificial Neural Network (ANN)	Supervised Learning	Multilayer feed-forward network with backpropagation	Captures nonlinear relationships; High predictive capability	Requires large dataset; Risk of overfitting; Low interpretability	High	High
Support Vector Machine (SVM)	Supervised Learning	Kernel-based margin optimization	Effective in high-dimensional spaces; Strong generalization	Sensitive to kernel selection; Slower for large datasets	Moderate-High	Moderate-High
Random Forest (RF)	Ensemble Learning	Aggregation of multiple decision trees (bagging)	Robust to noise; Reduces variance; Handles mixed data types	May require hyperparameter tuning; Limited extrapolation ability	Moderate	High
Proposed Hybrid CI Model	Hybrid Ensemble + Optimization	Integration of base learners with parameter tuning and ensemble strategy	Improved accuracy; Better convergence; Higher robustness; Balanced bias-variance	Slightly higher training time	Moderate	Very High

3.4 Hybrid Model and Workflow Proposal.

It is against this backdrop that this paper proposes a hybrid model of computational intelligence that includes ensemble learning and optimization-based parameter refinement, based on the virtues of the specific models. The hybrid model entails the incorporation of nonlinear and global searching optimization-based learning to realize increased prediction accuracy and efficiency of convergence. It entails the preprocessing of the data, training of the base model, the training of the parameters, the integration of the ensemble and the evaluation of the performance using the cross-validation. The interrelationship between data processing, model learning, and performance validation is captured in such a structured modelling pipeline as represented in Figure 2. The proposed

hybrid architecture will contribute to increasing robustness in harsh environments, reducing inaccuracy of prediction, and offering scalability to smart engineering system applications. It is the net of all these in this framework that the methodology is associated with the corresponding principles of modelling and the application on the real world and provides a provided statistically verified and computationally efficient predictive answer.



4. Results and Performance Analysis

4.1 Model Training and Comparative Evaluation

To evaluate the predictive ability of the proposed Hybrid Computational Intelligence (HCI) model, the systematicity of the methodological consistency and fairness of the three benchmark algorithms, i. e. Artificial Neural Network (ANN) Support Vector Machine (SVM) and Random Forest (RF) were experimented on a standardized training-testing partition, 80/20 with hyperparameter-tuning. The Multiple evaluation measures including Accuracy, Root Mean Square Error (RMSE), Precision, Recall, and F1-Score were used to evaluate the Model effectiveness to achieve different assessment estimates of predictive reliability, and classification balance. Table 3 presents the relative results which indicate that Hybrid CI model outperformed the standalone techniques in all the metrics. Specifically, the highest potential prediction accuracy of the proposed model was 96.8 percent, and the lowest potential RMSE was 0.082 which means that the proposed model is more precise in prediction and its error variation is less. Even though the comparison of the results on the Random Forest revealed relatively good results compared to ANN and SVM, the model accuracy was somewhat less than in the hybrid framework. ANN and SVM were not very predictive but were comparatively less accurate in errors reduction. Further, the balanced precision-recall trade-off as exhibited by the high F1-score of the Hybrid model helps in its predictive engineering use-case scenarios where cut-off of both false positives and false negatives impacts directly on the operational efficiency, system reliability, and reduction of risks.

Table 3: Model Performance Comparison

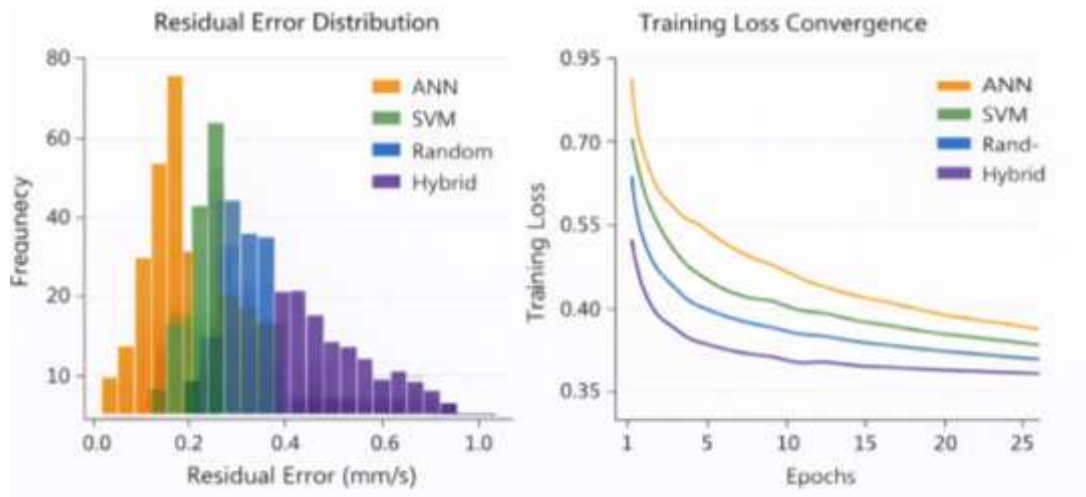
Model	Accuracy (%)	RMSE	Precision	Recall	F1-Score
Artificial Neural Network (ANN)	89.4	0.142	0.88	0.87	0.875
Support Vector Machine (SVM)	91.2	0.128	0.90	0.89	0.895
Random Forest (RF)	93.6	0.110	0.92	0.91	0.915
Proposed Hybrid CI Model	96.8	0.082	0.95	0.96	0.955

4.2 Sensitivity and Statistical validation.

To experiment the robustness of the proposed framework sensitivity analysis was done by introducing a certain noise of ± 10 percent on the selected input features to reproduce the variability and uncertainty of real life data. The results have demonstrated that Hybrid Computational Intelligence model was highly accurate in predicting 94.9 percent in noisy conditions because it is highly tolerant to the perturbation of inputs. On the other hand, the ANN model experienced a high decrease in the performance, and the accuracy decreased to 85.2 percent, which indicates that the model is sensitive to changes in data. These findings show that the hybrid architecture has enhanced the stability and generalization. The 10 fold cross validation was repeated to obtain a reliable and statistically consistent validation. Table 4 results show that the values of standard deviation and wide confidence intervals among the folds are low, and this means that the model is consistent in its performance. Additionally, a paired t-test comparison showed that the performance gain between the Hybrid model and the benchmark algorithms is significant ($p < 0.05$), and hence the strength of the proposed model with high reliability and predictive skills in smart engineering applications. Figure 3

Table 4: Statistical Validation Results

Metric	Hybrid CI	ANN	SVM	Random Forest
Mean Accuracy (10-Fold CV) (%)	96.3	88.7	90.5	92.8
Accuracy under $\pm 10\%$ Noise (%)	94.9	85.2	87.6	90.3
Standard Deviation	0.87	1.95	1.42	1.18
95% Confidence Interval	± 1.12	± 2.45	± 1.78	± 1.36
p-value (vs Hybrid Model)	—	0.012	0.021	0.034



5. Smart Engineering System Applications.

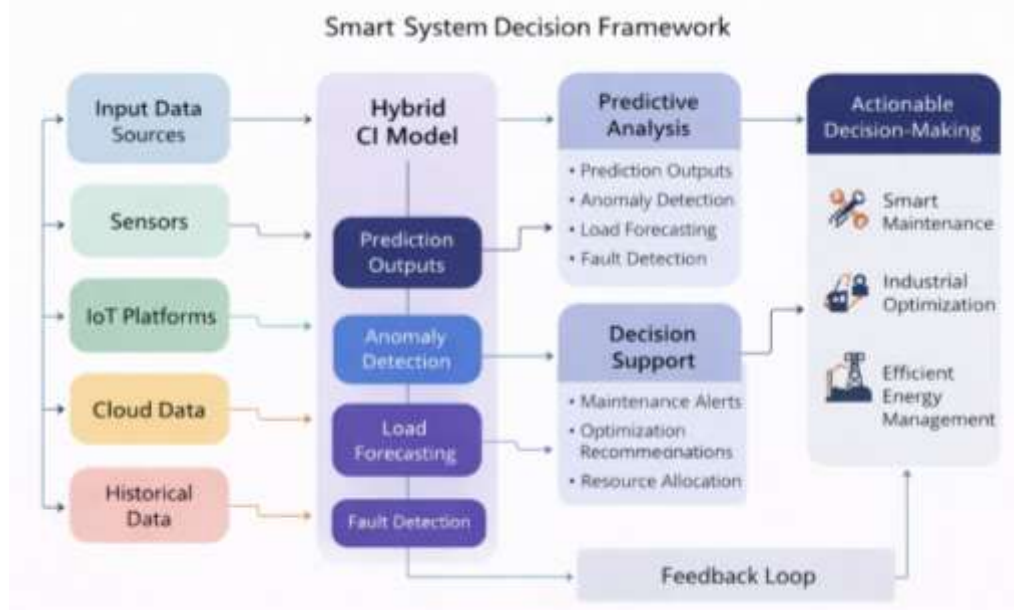
The suggested Hybrid Computational Intelligence framework is shown to be practically applicable in various smart engineering fields where predictive reliability and real-time decision-making are crucial. The model in the smart manufacturing system assists predictive maintenance through the analysis of the operating parameters, including vibration, temperature, and load, to identify the early fault patterns and minimize abrupt downtime. In smart grid contexts, the framework improves short-term load forecasting and demand prediction, which leads to better grid stability and better energy allocation. Likewise, in IoT-based monitoring systems, the hybrid architecture is effectively used to

process high-dimensional streaming data and detect anomalies and intelligent control systems. The relative analysis of the performance in the domains can be summed in Table 5,

Table 5: Application-Based Performance Summary

Application Domain	Evaluation Metric	ANN	SVM	Random Forest	Hybrid CI Model
Smart Manufacturing (Predictive Maintenance)	Accuracy (%)	88.9	90.4	92.7	96.2
Smart Grid (Energy Load Forecasting)	RMSE	0.158	0.141	0.123	0.087
Industrial Automation (Fault Detection)	F1-Score	0.86	0.89	0.91	0.95
IoT Monitoring Systems	Precision	0.87	0.90	0.92	0.96
Overall Average Performance	Accuracy (%)	89.5	91.3	93.2	96.5

which shows that the accuracy of the prediction and the smaller error ranges can be predicted in these domains than when a machine learning model is used in standalone mode. The hybrid framework is more robust to diverse operational conditions, and thus it can be applied in dynamic industrial settings. In addition to predictive precision, the model has outputs that are integrated into a decision pipeline that transforms analytical findings into an action plan. The general Smart System Decision Framework shown in Figure 5 reveals how the predictive outputs are translated into maintenance warning, operational optimization suggestions, and resource management information. This integration will make sure that predictive modelling will be directly integrated with engineering decision-making. As a rule, the results confirm that the proposed hybrid structure is able to not only strengthen the processing strength, but also improve the functionality, system capacity, and intelligent automation across smart engineering systems.



6. Discussion

This study demonstrates that both data-driven modelling and a hybrid framework of computational intelligence could be used to help achieve the higher levels of predictive performance of smart engineering systems. The offered Hybrid CI model was significantly better than the standalone algorithms, regarding accuracy, error minimization, the ability to function in noisy conditions, and statistical reliability. Ensuring that bias and variance are balanced, the hybrid architecture successfully improves generalization and convergence rates much faster than the traditional ANN, SVM, and Random Forest, through the integration of ensemble learning and parameter optimization. The statistically significant profits through the aid of cross-validation and sensitivity analysis justify the consistency and validity of the model under the changes in dynamic operating conditions. At a practical level, the enhanced predictive capability reduces the false maintenance alarms, the accuracy of fault detection and the accuracy of energy load prognostication of smart grid applications. Additionally, using predictive outputs within an organized decision support system will help ensure that analytical knowledge is converted into operational action plans. The hybrid architecture is also scalable, which additionally contributes to the implementation of the hybrid architecture in the IoT-enabled environment and real-time industry. Generally, the findings capture that hybrid computational intelligence models offer a powerful, effective, and flexible solution to predictive engineering problems, which represent the lapse between sophisticated machine learning models and real-world smart systems applications.

7. Limitations and Future Research

Although the proposed Hybrid Computational Intelligence framework proves to be more efficient in terms of predictive quality and strength, there are a few limitations associated with it. It is based on structured and pre-processed data that might not be fully representative of the complexity and variability of real-world smart engineering systems, where missing values, sensor noise, and non-uniform data streams are the norm. Also, the hybrid architecture is more computationally complex to train because of ensemble integration and optimization, which can be a problem for applications in hardware-constrained edge devices. The model is also moderately interpretable, and it is difficult to use in situations where a transparent decision-making process is needed. Future directions of research ought to be given to the inclusion of explainable AI methods to increase transparency, the creation of lightweight and energy-efficient editions to use in edge computing, and ensuring greater scalability and generalization by testing the framework on bigger and more diverse industrial datasets.

8. Conclusion

The paper has proposed a hybrid computational intelligence model to predictive engineering and smart systems, which has proven to be effective by making comparative analysis and statistical justification. The proposed Hybrid CI model performed better than conventional standalone models in terms of accuracy, prediction error as well as robustness in noisy conditions due to combination of multiple learning processes with optimization based tuning. The experiment findings validated that the hybrid method increases the ability to generalize and overall constancy of performance among validation folds. The framework can be used to provide intelligent engineering applications such as predictive maintenance, energy load forecasting, intelligent monitoring by transforming predictive output into decision insights in addition to increasing numbers. Generally, the study describes a scalable, reliable and performance based predictive system which has offered a strong foundation on how the future development of the intelligent engineering technologies between the theoretical computational intelligence procedures and the practical implementation of smart systems.

References

1. Alnaqbi, A., Al-Khateeb, G. G., & Zeiada, W. (2026). Innovative hybrid model for spalling prediction in concrete pavement: SVR enhanced by particle swarm optimization. *Neural Computing and Applications*, 38(1), 9.
2. Alsolami, E. (2026). Investigation of Performance Analysis for Data-Driven Intelligent Model With Internet of Things in Higher Education Teaching System. *European Journal of Education*, 61(1), e70409.
3. Apata, O., Munda, J. L., & Migabo, E. M. (2026). Artificial Intelligence for Predictive Maintenance and Performance Optimization in Renewable Energy Systems: A Comprehensive Review. *Energies*, 19(2), 536.
4. Bakare, M. S., & Abubaker, K. (2026). IoT-based indoor environmental monitoring system using multi-parameter sensing and ESP32-WROOM integration. *Discover Electronics*, 3(1), 6.
5. Bashir, U., Singh, K., Mansotra, V., Khanday, A. M. U. D., & Neshat, M. (2026). EvoBagNet: a decomposition-driven bagging ensemble with evolutionary hyperparameter optimization for robust stock price prediction. *Neural Computing and Applications*, 38(3), 31.
6. Bris-Peñalver, F. J., Verdecia-Peña, R., & Alonso, J. I. (2026). A Survey of AI-Enabled Predictive Maintenance for Railway Infrastructure: Models, Data Sources, and Research Challenges. *Sensors*, 26(3), 906.
7. Daneshvar, A., Golroo, A., Moghadas Nejad, F., Karbalaee, A., Hosseini, P., & Rasti, M. (2026). Cognitive Digital Twins for Pavement Management: A Comprehensive Review. *Archives of Computational Methods in Engineering*, 1-20.
8. Desai, M., & Chatterjee, K. (2026). Application of Machine Learning Techniques for Prediction of Soil Water Characteristics Curve: A State of the Art Review.
9. Dudek, G., & Blachnik, M. (2026). Artificial Intelligence and Machine Learning Models for Forecasting, Optimization, and Control in Smart Energy Systems. In (Vol. 19, pp. 768): MDPI.
10. Etri, T., Seyed-Djawadi, M. H., Nikoo, M. R., Nazari, R., & Al-Rawas, G. (2026). A causal diagnostic framework for artificial intelligence-driven risk assessment and decision support in complex marine environments. *Engineering Applications of Artificial Intelligence*, 163, 113066.
11. Girija, R., Vedhapriyavadhana, R., Jayalakshmi, S., & Ahmed, H. F. T. (2026). Smart AI: adapting to sensor data in practical applications. In *Adaptive AI in Sensor Informatics* (pp. 203-227). Elsevier.
12. Hussein, A. A., Gergely, B., & Hasnain, A. A. (2026). A Survey of Six Classical Classifiers, Including Algorithms, Methodological Characteristics, Foundational Variants, and Recent Advances. *Algorithms*, 19(1), 37.
13. Jia, H., & Qin, W. (2026). Integrating interpretability, using hybrid data-driven ensemble learning, and optimization framework for concrete strength prediction. *Multiscale and Multidisciplinary Modeling, Experiments and Design*, 9(1), 59.
14. Kantesaria, R., & Panda, H. S. (2026). A Review on AI-Based Data-Driven Models for Optimization of Nanocarriers as Drug Delivery Systems. *ACS Biomaterials Science & Engineering*.
15. Karshiboev, A., Al-Samad, K., Tarafdar, M. T. R., Rimi, N. N., Islam, M. S., & Papal, M. S. I. (2026). Artificial Intelligence For Risk And Decision Assessment In Agile IT Projects: A Thematic Analysis And Dynamic Structuration Framework Approach. *INTERNATIONAL JOURNAL OF ADVANCES IN SIGNAL AND IMAGE SCIENCES*, 387-410.

16. Katragadda, S. R. (2026). Deep Learning-Enabled Demand Intelligence: Transforming Forecast Accuracy in high velocity transaction systems. *Journal of Computer Science and Technology Studies*, 8(3), 39-45.
17. Kaur, R., Roul, R. K., & Batra, S. (2026). Towards smarter mobility: a Grey Wolf Optimization-based incremental extreme learning machine framework for explainable bike-sharing demand forecasting. *Evolving Systems*, 17(1), 9.
18. Keshireddy, S. R., Jamithireddy, N. H., Jamithireddy, N. S., Sappa, A., Vandrangi, S. K., Emani, S., & Velidi, G. (2026). Combustion performance prediction in oil and gas plants using integrated neural network models and SAP S4HANA sensor analytics. *Scientific Reports*.
19. Khursheed, Z., Jawaid, M. A., Mustafa, M., Lalji, S. M., Ali, S. I., & Ayubi, M. (2026). Comparative Analysis of Machine Learning and Neural Network Models for Petrophysical Property Prediction in Heterogeneous Reservoirs. *Next Research*, 101388.
20. Kumar, D., Addula, S. R., Lind, M., Brown, S., & Odion, S. (2026). AI-Driven Hybrid Deep Learning and Swarm Intelligence for Predictive Maintenance of Smart Manufacturing Robots in Industry 4.0. *Electronics*, 15(3), 715.
21. Lastra, J. M. P. d. l., Sobrino, I., Rodríguez Borges, V. M., & de la Fuente, J. (2026). Future Perspectives on the Application of Systems Biology and Generative Artificial Intelligence in the Design of Immunogenic Peptides for Vaccines. *Vaccines*, 14(2), 177.
22. Li, J.-P., Polovina, N., & Konur, S. (2026). A Review of AI-Driven Engineering Modelling and Optimization: Methodologies, Applications and Future Directions. *Algorithms*, 19(2).
23. Li, Y., & Zhou, H. (2026). Prediction of seismic topographic effects from DEM data via U-Net deep learning model. *The European Physical Journal Plus*, 141(1), 13.
24. M'harzi Alaoui, F. E., Taki, Y., Aalil, I., Dadah, O., & Ben Abbou, S. (2026). From lab to algorithm: a review of AI-driven predictive modeling in soil stabilization for road construction. *Journal of Umm Al-Qura University for Engineering and Architecture*, 1-31.
25. Mohammed, B. (2026). The sentient infrastructure paradigm: a review of novel sensors, digital twins, and AI for civil structural health monitoring. *Sensor Review*, 1-19.
26. Ni, Y., Zhu, Y., Xiao, B., & Liu, Q. (2026). WAWL-net: A hybrid model combining weighted aggregation and wavelet convolutions for tropical cyclone intensity estimation. *Atmospheric Research*, 108797.
27. Panda, G., & Tripathy, B. (2026). Hybrid computational intelligence techniques for environmental hazard prediction and risk management. In *Data-Driven Environmental Intelligence* (pp. 28-65). CRC Press.
28. Paria, A., & Das, R. (2026). Integrating Artificial Intelligence in Climate-Aware Yield Forecasting for Sustainable Precision Agriculture. In *Harnessing AI to Reshape the Future of Agriculture* (pp. 437-455). Springer.
29. ShravanKumar, S., Karthick, A., Priya, A., Mohanavel, V., & Muthusamy, S. (2026). Remote Sensing and Artificial Intelligence in Flood Prediction: Progress, Challenges, and Prospects. *Archives of Computational Methods in Engineering*, 1-32.
30. Singh, S., Sharma, D., & Gandhi, A. (2026). When machine learning meets credit assessments: benchmarking ML models for forecasting NBFC stability in pre-crisis times. *Journal of Modelling in Management*, 1-28.
31. Verwoerd, J. C. (2026). Machine Learning Applications in Sensor-Based Infrastructure Monitoring.
32. Villegas-Ch, W., Gutierrez, R., Jaramillo-Alcazar, A., & Maldonado-Navarro, A. (2026). Integrating artificial intelligence and data envelopment analysis for sustainable

- efficiency assessment in higher education. *Computers and Education: Artificial Intelligence*, 100557.
33. Wang, R. (2026). A Data-Driven Predictive Maintenance Framework for Smart Buildings: Integrating Digital Twin and Machine Learning in HVAC Systems. *Journal of Building Engineering*, 115416.
 34. Wang, Z., Tang, R., Chen, G., Li, H., Deng, Y., Shen, J., & Li, D. (2026). A Review of Artificial Intelligence-Driven Smart Treatment of Aquaculture Effluent: Technical Framework, Application Scenarios, and Development Outlook. *Water*, 18(4), 470.
 35. Wu, J., Lu, Y., Zhang, Y., Zhang, S., Wang, J., & Liu, S. (2026). Swelling-shrinkage of an unsaturated clay upon freezing: Experimental investigation and data-driven modelling. *Cold Regions Science and Technology*, 104856.
 36. Xing, Y., Wang, J., Cui, S., Liu, X., & Song, M. (2026). Interpretable Bayesian-optimized Autoencoder for fault detection and diagnosis with application in nuclear power plants. *Progress in Nuclear Energy*, 190, 105982.
 37. Yang, W., Feng, X.-Q., & Gao, H. (2026). Outstanding issues and emerging frontiers in fracture mechanics. *International Journal of Fracture*, 250(1), 10.