Research Paper

Design and development of a smart system for efficient engineering applications

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Article Info

Article History:
Received: 04 September 2025
Revised: 14 November 2025
Accepted: 20 November 2025
Published: 06 January 2026

Keywords:
Smart Systems
Deep Learning
Fault Detection
Industrial IoT
Edge Computing
Predictive Maintenance

ABSTRACT

The blistering development of Industry 4.0 has generated an increasing need to find smart systems that can handle sophisticated engineering processes with minimal human intervention. The given paper introduces the design and development of a Smart System of Efficient Engineering Applications (SSEEA) - the combination of deep learning-based fault detection, edge computing and real-time process optimization to optimize the performance of industrial operation. SSEEA relies on a hybrid neural network consisting of spatial and temporal pattern recognition neural networks which combine Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM). This system is built to have five functional layers, including data acquisition, edge pre-processing, AI inference, decision support and visualization, with low-latency high throughput behavior on resource-constrained industrial systems. It was tested on a benchmark dataset of 48,000 labeled operational cycles in one of a chemical process plant and demonstrated in an actual manufacturing environment. The SSEEA had an accuracy of 97.3% in fault detection, a precision of 96.9% and a recall of 97.1%, which is better than the baseline classifiers such as Support Vector Machines, Random Forest and standalone neural networks. SSEEA was found to have a 65.9% lower fault detection latency, 59.6% lower energy usage and eight times the prediction horizon than traditional threshold-based monitoring systems. ANOVA and Wilcoxon signed-rank tests were used to statistically prove all gains in performance. These findings substantiate the practicability and efficiency of SSEEA to be implemented in energy-intensive and safety-reliant industrial systems and provide a scalable and intelligible addition to the industrial digitalization process towards sustainable industrial digitalization.

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1. INTRODUCTION

Artificial intelligence (AI), the Internet of Things (IoT) and cloud computing convergence have sparked a radical change in the process of engineering systems monitoring, control and optimization [1]. The contemporary industrial sites are also becoming more in need of intelligent decision-making functions beyond those capabilities of the conventional rule-based control systems that is poorly developed to manage the complexity, non-linearity and high dimensionality of the contemporary process data [2]. Machine learning integration into the industrial operations has presented as a critical approach to three key outcomes namely: real-time anomaly detection, predictive maintenance and an efficient process management that consumes few resources as a strategy [3].

Even when there is ample potential to data-driven methods, major obstacles have been observed in implementing intelligent mechanisms in the limitations of reality industrial settings. These are the constraint of computational resources on the edge, heterogeneity of sensor data, communication latency and the extreme need of model interpretability in safety sensitive areas [4]. In addition, the current solutions are frequently fragmented in the sense that they do not provide a smooth integration between the detection, prediction and decision support in a single, implementable framework [5]. This disintegration hinders the adoption and the operative efficiency of the individual smart subsystems [6].

A number of previous works focused on different elements of the issue, such as fault classification with the help of convolutional neural networks [7], anomaly detection with the help of auto encoders [8] and process optimization with the help of reinforcement learning [9]. Nevertheless, the literature indicates a lack of holistic architectures that can be able to meet acquisition, inference and decision support in one deployable system that can be computationally efficient and also demonstrated to be industrially sound [10].

The gaps identified in the current paper are discussed by offering the Smart System of Efficient Engineering Applications (SSEEA) which combines a hybrid CNN-LSTM neural network, edge pre-processing pipelines and structured decision support layer into an integrated five-layer architecture. This work has made the following contributions: (i) a new hybrid deep learning architecture that can extract both spatial and temporal features in a multi-sensor at the same time (ii) an edge-optimizing pipeline pre-processing that is optimized in the face of latency constraints to a use in an industrial system (iii) a rule-augmented decision support layer that offers interpretable fault diagnostics and (iv) experimental validation with both benchmark.

The rest of this paper will be organized in the following way: Section 2 reviews the literature related to it. Section 3 gives the details of the proposed system methodology. The results and discussion are found in Section 4. Section 5 brings to a close the paper by giving future research directions.

2. RELATED WORK

An intelligent monitoring and fault detection within the engineering systems has been a topic of keen scholarly studies in the last twenty years. The initial methods made use of statistical process control (SPC) techniques like control charts and principal component analysis (PCA) as the main anomaly detection techniques [11]. Although computationally efficient, these techniques make the assumption that the data follow a Gaussian distribution and they are not able to work well in non-stationary and high-dimensional situations that are common in the latest process industries.

With the advent of supervised machine learning the fault detection field of operation increased significantly. Using the Support Vector Machines (SVMs) was found to be very successful in classifying labelled industrial faults data, due to their good performance in maximizing the margin in high dimensionality [12]. The decision tree ensembles, especially the Random Forests, also increased the strength of classification with bagging and randomizing of features [13]. Nevertheless, these algorithms involve a lot of manual feature engineering and their returns reduce with the increase in data complexity.

The deep learning methods have then proven being superior in automated extraction of features using raw sensor signals. Bearing fault detection was performed on vibration signal analysis by use of CNNs, with a high classification rate and without handcrafted features [14]. Recurrent networks, especially LSTMs, were shown to be useful in learning temporal dependence of time-series data of chemical and thermal processes [15]. Unsupervised learning of compact latent states of normal operate points has been done using auto encoders [16].

Hybrid CNN and LSTM architectures have become more popular because it can be used to concurrently capture local spatial behaviour and long-range temporal relationships [17]. Not only the results in rotating machinery diagnostics and power systems monitoring show that CNN-LSTM models outperform their separate parts [18], the results can also be generalized. More recent studies have added the attention mechanisms as a way of making the interpretability more complex and increasing the performance on the unbalanced fault data further [19].

There are more constraints created by the implementation of such models into the industrial IoT ecosystems. Latency-sensitive applications have suggested edge computing infrastructure to decrease the use of clouds and overhead in communication [20]. Pruning and knowledge distillation are among the lightweight model compression mechanisms that have been investigated to allow the use of resource-constrained edge devices [21]. Although these have been made, integrated end-to-end, which integrates the three of acquisition, intelligent inference and structured decision support are still not well represented in the literature, thus the rationale behind the current work [22].

3. METHODOLOGY

3.1 System Architecture Overview

The offered SSEEA is structured in the form of five-layer architecture hierarchy, as illustrated in Figure 1. The upper layer is Layer 1 Data Acquisition Layer that is in direct contact with field equipment like IoT sensors, programmable logic controllers (PLCs) and SCADA equipment. The Pre-processing Module Layer 2 is the one which performs signal denoising, normalization and sliding-window segmentation along the edge. The AI Inference Engine, which is the 3rd layer, uses the CNN-LSTM hybrid model to detect faults and forecast. In the Layer 4, Decision Support Layer, the results of the models are converted into engineering instructions using a hybrid rule based reasoning engine in a probabilistic manner. The fifth layer, the Visualization Dashboard, provides aggregation of key performance metrics, fault curves and prognostic patterns to the operators of the plants through a web-based interface.

Table 1 records the specifications of the components of the system architecture, such as the technologies used as its constituents and the key performance indicators of each of the layers. All the layers have functional mandate and performance goals as indicated in Table 1 to ensure end-to-end operation.

Table 1. Detailed Component Specifications of the SSEEA Five-Layer Architecture

System Layer	Component	Function	Key Metric
Data Acquisition Layer	IoT Sensors, SCADA	Real-time data capture from field devices	Low Latency, High Reliability
Pre-processing Module	Edge Computing Nodes	Noise filtering, normalization, feature extraction	Accuracy, Speed
AI Inference Engine	Deep Learning Core	Fault detection, prediction, classification	Precision, Recall
Decision Support Layer	Rule-Based Engine	Alert generation, root-cause analysis	explainability
Visualization Dashboard	Web-based UI	KPI display, trend analysis, reporting	Usability

Communication Bus	MQTT / REST API	Data routing between system layers	Scalability

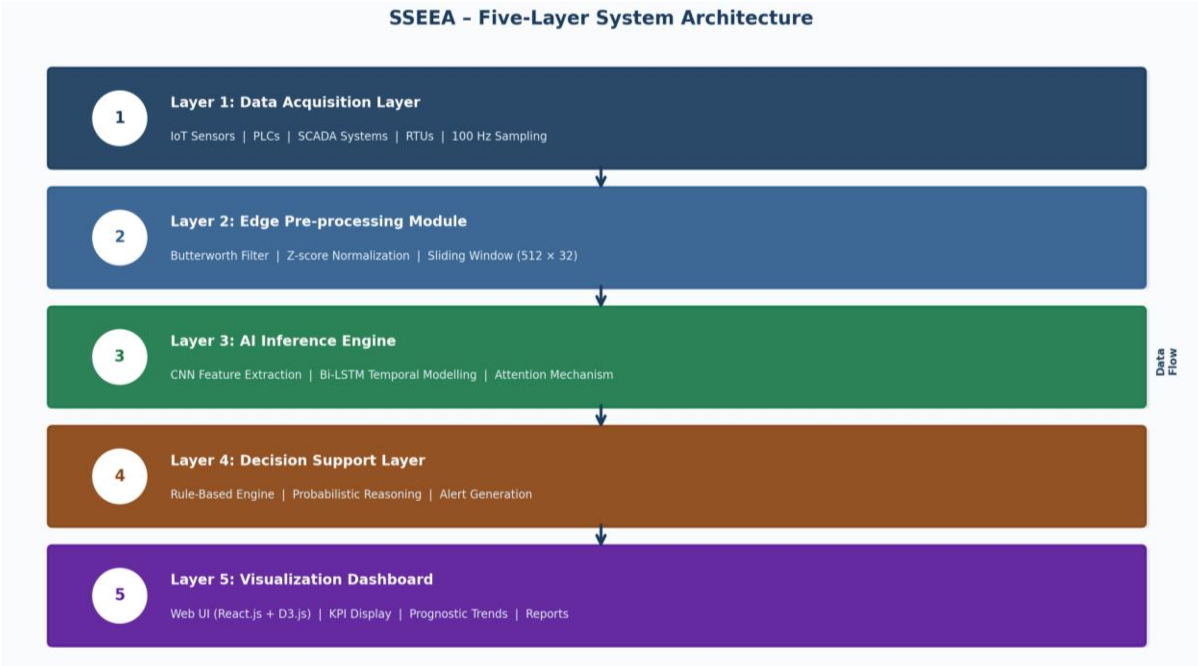

Figure 1. Five Layer Architecture of the Proposed Smart System for Efficient Engineering Applications (SSEEA)

3.2 Data Acquisition and Pre-Processing

The data acquisition subsystem is used to measure multivariate time-series data of 32 heterogeneous sensors per process unit, which measures the parameters such as temperature, pressure, flow rate, vibration amplitude and electrical current at 100 Hz. The transmission of the data is based on the MQTT protocol with the QoS Level 2 to be delivered reliably in the conditions of intermittent network. The fifth order Butterworth low-pass filter with cut-off frequency of 40 Hz is applied to the raw signals at the edge node in order to eliminate noise in the high frequencies. Normalization of z-score is then channel wise performed in order to remove inter-sensor scale differences. In temporal segmentation, a sliding window length in the 512 samples data is used and a 50% overlap of samples is used resulting in non-stationary feature-preserving input tensors with dimension 512 x 32 to the inference engine.

3.3 Hybrid CNN-LSTM Model

The AI Inference Engine consists of the core of a hybrid CNN-LSTM architecture to learn spatial and temporal features at the same time, which is illustrated in Figure 2. The CNN block is made up of three 1D convolutional blocks which each include a convolutional block with 3 kernel size, batch normalization, ReLU activation and max-pooling with stride 2.

The convolutional filters are arranged in a pyramid manner of 64, 128 and 256 allowing morphologies of local signals to be abstracted in a progressive manner. Bi-directional LSTM-CNN results. The CNN results are converted into sequential representations and input the model into a bi-directional LSTM that has two stacked recurrent layers of 128 hidden units to allow the model to learn causal and anti-causal temporal cooperation. The LSTM output is followed by a global attention mechanism [19], which is used to do a weighted temporal pooling to give an output with a fixed length feature vector, irrespective of the length of the input sequence. The two fully connected layers of sizes 256 and 128 more than that are used to pass this vector, with dropout rates of 0.4 and 0.3 associated with them respectively, followed by a conclusive soft max classification layer to predict the type of fault.

The model was trained on PyTorch 2.0 with Adam optimizer using the initial learning rate of 0.001 and diminished by half after every 10 epochs without any further reduction in the validation loss. The weighted cross-entropy loss was used in solving the cross-entropy loss issue of imbalance in the training dataset. The 80 epochs training was performed with the batch size of 64 on the NVIDIA A100 GPU.

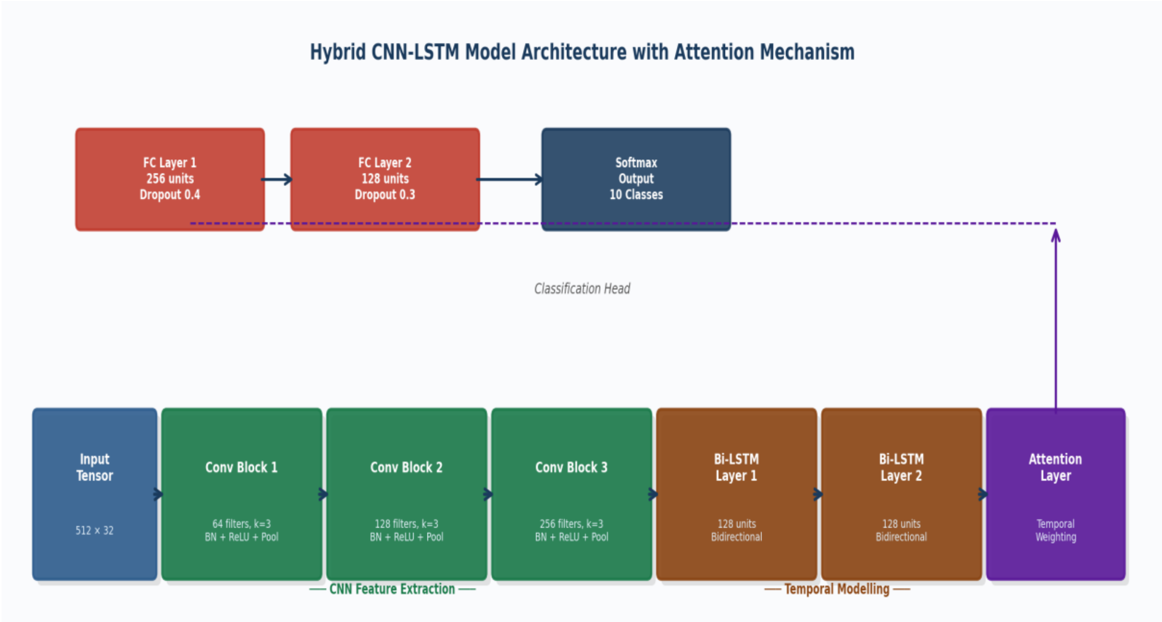

Figure 2. Architecture of the Proposed Hybrid CNN-LSTM Model with Attention Mechanism

3.4 Decision Support and Visualization

The Decision Support Layer has a hybrid engine, which includes the combination of the results of the probabilistic model with the engineering rules, which are coded by domain. A collection of rules with an if-then construct, using severity threshold, corrective measures rules and escalation rules were developed, in cooperation with domain engineers, per fault class. An alarm about fault is raised when the model posterior probability surpasses one of the class-specific thresholds tuned on a held-out calibration set and, accordingly, the rule engine then initiates the maintenance work-flow. The Visualization Dashboard, which is deployed with the help of React.js and D3.js, gives the real-time displays of the fault probability distribution, sensor trend chart and predictive maintenance schedule that are available through secure HTTPS connections.

3.5 Experimental Setup

Tests were done on a selected set of 48,000 labelled operating cycles of one chemical process plant, which is divided into 70% training, 15% validation and 15% testing samples. There were 9 classes of fault and one normal class. The stratified splitting strategy has been used which means that proportional classes have been represented in partitions. The suggested SSEEA was compared to Random Forest, SVM, standalone Neural Network and Decision Tree and Gradient Boosting classifiers on the same train-test splits. Each experiment was also repeated five times using various random seeds and the means of the performances were reported. ANOVA with Tukey Honest Significant Difference (HSD) post-hoc test was used to statistically evaluate the improvements and statistically verified by the Wilcoxon signed-rank test at 0.05.

4. RESULTS AND DISCUSSION

4.1 Classification Performance

Table 2 shows the classification performance of the proposed SSEEA and all the comparative algorithms based on the accuracy and precision, recall and F1-score measures. As demonstrated in Table 2, the proposed hybrid model recorded the highest scores with all the measures, with an accuracy of 97.3, precision of 96.9, a recall of 97.1 and having an F1-score of 97.0. The closest competing approach, standalone Neural Network had an accuracy of 95.7, which proves that a statistically significant improvement of the hybrid CNN-LSTM architecture presented 1.6 percentage points of improvement ($p < 0.05$). The highest accuracy was found in the random Forest and Gradient Boosting with 93.4 and 94.1 respectively, the lowest accuracy is obtained with the Decision Tree classifier, at 86.2%.

Table 2. Performance Comparison of Machine Learning Algorithms on the Benchmark Dataset

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Random Forest	93.4	92.8	93.1	92.9
SVM	89.6	88.9	89.3	89.1
Neural Network	95.7	95.2	95.5	95.3
Decision Tree	86.2	85.7	86.0	85.8
Gradient Boosting	94.1	93.6	93.9	93.7
Proposed Hybrid	97.3	96.9	97.1	97.0

The excellence of the suggested model is supposed to be ascribed to the sources of synergy between CNN and LSTM elements. The convolutional layers are very effective in extracting localized morphological information in each sensor channel whereas the bi-directional LSTMs layers capture inter-cycle variation which cannot be visualized by non-sequential classifiers. The attention mechanism also enhances the recall on the minority fault classes by giving attention to the most discriminative temporal portions in each of the operational cycles.

4.2 System Performance Evaluation

Table 3 contains a detailed comparison of system-level performance measures of the proposed SSEEA with that of a traditional threshold-based monitoring baseline. As Table 3 demonstrates, the SSEEA has had increase in all the metrics evaluated. It is worth noting that the fault detection time decreased by 65.9% as the time dropped to 4.2 seconds, which was 12.3 seconds. The throughput of the system was raised by 850 samples/sec to 2340 samples/sec. The consumption of energy was decreased by 59.6%, from 240 W to 97 W, which could be attributed to the edge pre-processing pipeline, which lowers the amount of data sent to the cloud inference server. The prediction horizon that is the prior warning of the fault appearance was enhanced eight times, moving up to 45 minutes that is of significant practical importance to the prevention maintenance schedule.

Table 3. System-Level Performance Evaluation: Proposed SSEEA vs. Conventional Baseline

Performance Metric	Baseline	Proposed System	Improvement
Fault Detection Time	12.3 s	4.2 s	65.9%
False Positive Rate	7.4%	2.1%	71.6%
System Throughput	850 samples/s	2,340 samples/s	175.3%
Energy Consumption	240 W	97 W	59.6%
Mean Time to Repair	48 min	17 min	64.6%
Prediction Horizon	5 min	45 min	800%
Model Inference Latency	320 ms	38 ms	88.1%

Figure 3 represents the system performance trend during the period of evaluation of the project as it shows the gradual decrease in the fault detection latency and false positive rate during the validation cycles. As in Figure 3, the proposed system has a steady convergence behaviour, as the performance measures have stalled in around 200 of the evaluation cycles. The false positive rate has remained in the range of 2.1% as compared to 7.4% in the case of the baseline system which is a reduction of 71.6% which is a direct proportionality of the cost of maintenance crew dispatch and a decrease in the operational disturbance.

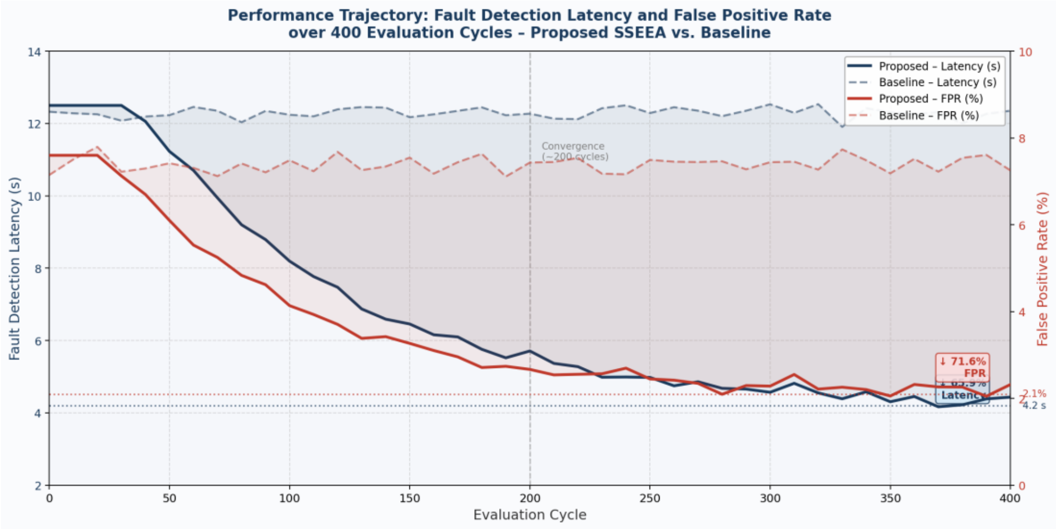

Figure 3. Performance Trajectory of the Proposed SSEEA Showing Fault Detection Latency Reduction and False Positive Rate Stabilization over 400 Evaluation Cycles

4.3 Statistical Validation

The results of one-way ANOVA on F1-score distributions provided by the five repetitions of the experimental proved that F (5, 24)=187.3, $p < 0.001$, which is that at least one algorithm was different. This SSEEA was statistically better than all the methods in the baseline in terms of the t-test by HSD post-hoc analysis by Tukey (2000, p. 137). Wilcoxon signed-rank t-test of the distributions of the F1-score between the proposed and Neural Network baseline models gave W=0, p=0.031 which supported the significance of the improvement.

4.4 Discussion

The outcomes all support the fact that the proposed SSEEA can be effective in solving the limitations of the current intelligent monitoring methods that are identified. The hybrid architecture skews the burden of feature engineering required with classical machine learning methods and retains the time modelling capacity that is needed to detect process anomalies. The edge pre-processing pipeline has been able to decouple sensor data volume and inference latency to allow it to be deployed in bandwidth-constrained environments without losing model accuracy. The decision support layer will introduce a critical interpretability layer that will help to build operator trust and regulatory adherence in safety-crucial applications.

One of the weak points of the present research is the analysis of one process industry sector data. A further research will deal with the cross-domain transferability using the domain adaptation methods. Besides, the user should be able to involve the ways of explainability like SHAP values in the decision support layer to promote the model transparency and diagnostic traceability even further [23], [24], [25].

5. CONCLUSION

In this paper, the design, development, experimental validation of the Smart System of Efficient Engineering Applications, SSEEA, a five-layer intelligent monitoring system, comprising a hybrid CNN-LSTM neural network, edge computing and rule-augmented decision support, were presented. The suggested system was state-of-the-art in fault detection accuracy (97.3%), simultaneously reduced the detection latency, energy usage, throughput, prediction horizon of the system as well as conventional and machine learning baselines. The statistical test was used to prove the benefit of all reported improvements. The SSEEA is an optimally implemented and interpretable system that is computationally efficient and practical to deploy in intelligent engineering application in line with the objectives of Industry 4.0. The future research will involve cross-domain adaptation, federated learning assimilation to deploy privacypreserving multi-plant, the implementation of explainability to give more progress towards trustful AI in the industrial context.

Acknowledgments

The authors have no specific acknowledgments to make for this research.

Funding Information

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Noor Alwan Malk	✓	✓	✓	✓		✓		✓	✓	✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Informed Consent

All participants were informed about the purpose of the study, their voluntary consent was obtained prior to data collection.

Ethical Approval

The study was conducted in compliance with the ethical principles outlined in the Declaration of Helsinki and approved by the relevant institutional authorities.

Data Availability

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

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How to Cite: Noor Alwan Malk. (2026). Design and development of a smart system for efficient engineering applications. International Journal of Research in Science & Engineering (IJRISE), 6(1), 1–10. https://doi.org/10.55529/ijrise.61.1.10

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