AI-ACCELERATED EMBEDDED SYSTEM PLATFORM WITH MICROWAVE TRANSCEIVER FRONT-END FOR PREDICTIVE MAINTENANCE IN INDUSTRIAL AUTOMATION APPLICATIONS

S. Karthika and B. Sathananth

Department of Electronics and Communication Engineering, College of Engineering, Anna University, Chennai, India
Department of Electronics and Communication Engineering, V.S.B. College of Engineering Technical Campus, India

Abstract

The study presented an AI-accelerated embedded system platform that supported predictive maintenance within industrial automation environments. The research addressed the increasing demand for intelligent monitoring systems that ensured reliable operation of industrial machinery and minimized unexpected downtime. The proposed framework employed a microwave transceiver front-end combined with a system-on-chip architecture that has integrated AI inference capability for real-time condition assessment of industrial assets. The method utilized a Convolutional Neural Network (CNN) based anomaly classification model that has processed sensor-derived microwave signal reflections to identify early-stage mechanical degradation. The system has captured high-frequency response patterns from industrial components and has translated them into diagnostic features through signal conditioning and feature extraction modules. The AI model has performed classification of normal and abnormal operational states with adaptive threshold mapping that has improved decision consistency under varying load conditions. The method processed microwave reflection signals captured from industrial components and extracted discriminative features for classification. The system achieved 94.5% accuracy, 94.0% precision, 94.2% recall, and 94.1% F1-score, while reducing inference latency to 62 ms.

Keywords:

Embedded System, Microwave Sensing, Predictive Maintenance, Industrial Automation, Convolutional Neural Network

1. INTRODUCTION

Industrial automation systems have become a central component of modern manufacturing ecosystems, where operational continuity and system reliability are critical requirements. The advancement of sensing technologies and computational intelligence has enabled industrial platforms to shift toward predictive maintenance strategies, which focus on early fault detection and system health monitoring. In this context, embedded system platforms with integrated sensing and AI capability have gained significant attention for real-time decision support [1]. These systems provide continuous monitoring of machine conditions and help reduce unexpected failures that often lead to production loss and safety risks.

Recent developments in microwave transceiver-based sensing have expanded the capability of non-invasive condition monitoring. Microwave signals offer strong penetration characteristics and sensitivity to material and structural variations, making them suitable for detecting subtle mechanical changes in industrial components [2]. At the same time, AI-accelerated hardware architectures have improved the ability to process high-dimensional sensor data directly at the edge, reducing dependency on centralized cloud infrastructure. The combination of embedded intelligence and advanced sensing has created new possibilities for industrial predictive maintenance systems [3].

However, several challenges remain in the design and deployment of such integrated systems. One major challenge is the accuracy of signal interpretation under noisy industrial environments, where electromagnetic interference and mechanical vibration distort sensor readings [4]. Another challenge is the limitation of power-efficient computation within embedded platforms, where real-time AI inference must be performed without excessive energy consumption. Additionally, synchronization between microwave sensing modules and AI processing units often lacks optimal coordination, which affects system responsiveness and stability [5].

The core problem addressed in this study lies in the absence of a unified embedded platform that effectively combines microwave transceiver sensing with AI-driven fault prediction in a compact and energy-efficient architecture. Existing solutions often rely on separate sensing and processing units, which increases latency and reduces system reliability. Furthermore, conventional maintenance approaches depend heavily on periodic inspection rather than continuous predictive analysis, which leads to delayed fault detection [6]. This gap becomes more critical in large-scale industrial environments where equipment failure can propagate system-wide disruptions [7]. Another issue is the lack of adaptive learning capability in traditional embedded monitoring systems, which limits their ability to generalize across different machine conditions and operational loads [8].

The primary objective of this research was to design and develop an AI-accelerated embedded system platform with integrated microwave transceiver capability for predictive maintenance applications. The study also aimed to enhance real-time fault detection accuracy, reduce computational overhead, and improve system responsiveness under industrial operating conditions. Another objective focused on achieving efficient edge-level intelligence without relying on continuous cloud communication.

The novelty of the proposed work lies in the integration of microwave sensing hardware with an AI-enabled system-on-chip architecture that supports real-time inference at the edge. Unlike traditional systems, the proposed platform has combined signal acquisition, preprocessing, and classification within a unified embedded framework. This integration has minimized latency and has improved fault detection efficiency in dynamic industrial environments.

The key contributions of this study include: first, the development of a microwave-based sensing architecture tailored for industrial condition monitoring; second, the implementation of an AI-accelerated SoC design that enables real-time predictive maintenance; third, the introduction of a CNN-based diagnostic model optimized for embedded deployment; and fourth, the validation of system performance under realistic industrial conditions demonstrating improved reliability and reduced downtime.

2. RELATED WORKS

Recent research has focused on improving predictive maintenance systems through advanced sensing technologies and artificial intelligence techniques. Several studies have explored the use of embedded systems for industrial monitoring, where sensor fusion and machine learning models have been employed to detect equipment anomalies. Early work has demonstrated that vibration and acoustic sensors can effectively capture mechanical irregularities, although their performance often degrades in noisy environments [9]. Another line of research has investigated microwave sensing techniques for non-contact condition monitoring. Microwave-based approaches have shown strong potential in detecting material deformation and structural changes in industrial components. These systems have provided higher penetration capability compared to optical sensors, making them suitable for enclosed industrial setups. However, many of these implementations have relied on standalone processing units, which have limited real-time responsiveness [10]. Machine learning methods such as Support Vector Machines (SVM) and Random Forest classifiers have been widely applied in predictive maintenance systems. These models have demonstrated reasonable accuracy in fault classification tasks, but they often require extensive feature engineering and lack adaptability to changing industrial conditions [11]. Deep learning models, particularly CNN-based architectures, have improved automatic feature extraction capability, reducing dependency on manual preprocessing steps. Nevertheless, their deployment in embedded environments remains challenging due to computational constraints [12].

3. PROPOSED METHOD

The proposed method presents an AI-accelerated embedded platform that combines a microwave transceiver front-end with a system-on-chip (SoC) based deep learning inference engine for predictive maintenance in industrial automation systems. The architecture operates through continuous microwave signal emission toward industrial equipment, followed by reflection capture that represents structural and operational variations. The embedded SoC performs real-time signal conditioning, feature computation, and convolutional neural network (CNN) based classification to detect early fault signatures. The system further maps classification outputs into predictive maintenance decisions that support timely intervention. The entire workflow operates at the edge level, which reduces communication delay and ensures continuous monitoring stability under industrial conditions.

3.1 OPERATIONAL FRAMEWORK

The proposed architecture consists of a microwave transceiver module, an analog front-end interface, an embedded system-on-chip, and an AI inference engine. The system operates in a closed-loop configuration where sensing, computation, and decision-making occur in a unified pipeline. The microwave transceiver emits a signal represented as:

$$s(t) = A_c \cos(2\pi f_c t + \phi) \tag{1}$$

where A_c denotes amplitude, f_c denotes carrier frequency, and ϕ denotes phase offset. The transmitted signal interacts with industrial equipment surfaces and returns as a reflected waveform $r(t)$, which carries structural information. The reflected signal is modeled as:

$$r(t) = \sum_{i=1}^{N} \alpha_i s(t - \tau_i) + n(t) \tag{2}$$

where α_i represents reflection coefficients, τ_i represents propagation delay, and $n(t)$ represents additive noise introduced by industrial electromagnetic interference. The SoC receives $r(t)$ through an analog-to-digital conversion stage that maps continuous signals into discrete samples: $x[n]=r(nT_s)$, where T_s denotes sampling interval.

The architecture operates in three sequential functional layers. The first layer performs signal normalization. The second layer performs feature computation. The third layer performs CNN-based inference. The decision output is generated as: $D=f_{CNN}(x[n])$, where D represents system health status.

The system ensures deterministic execution within embedded constraints by using pipeline scheduling within the SoC. This architecture improves temporal consistency and reduces latency between sensing and decision formation.

3.2 MICROWAVE SENSING AND SIGNAL PROPAGATION MODEL

The microwave sensing subsystem forms the physical foundation of the proposed system. It operates on electromagnetic wave interaction with industrial equipment surfaces, where structural variations modify reflection characteristics.

The transmitted electromagnetic field is expressed as:

$$E_t(t) = E_0 e^{j(2\pi f_c t)} \tag{3}$$

The reflected field from the target surface is expressed as:

$$E_r(t) = \Gamma \cdot E_t(t - \tau) \tag{4}$$

where Γ represents the reflection coefficient dependent on material impedance and surface deformation. The reflection coefficient is defined as:

$$\Gamma = \frac{Z_L - Z_0}{Z_L + Z_0} \tag{5}$$

where Z_L denotes load impedance of the industrial component and Z_0 denotes characteristic impedance of the transmission medium.

Mechanical degradation modifies impedance distribution, which causes variation in Γ. The system captures these variations through amplitude and phase distortion. The received signal power is expressed as:

$$P_r = P_t G_t G_r \left(\frac{\lambda}{4\pi d}\right)^2 |\Gamma|^2 \tag{6}$$

where P_t denotes transmitted power, G_t and G_r denote antenna gains, λ denotes wavelength, and d denotes distance between sensor and target. The system monitors temporal variation of P_r, which acts as an indicator of structural instability. The phase shift is represented as:

$$\Delta\phi = \frac{4\pi d}{\lambda} \tag{7}$$

Any deviation in phase stability indicates mechanical misalignment or fault initiation. This sensing mechanism provides high sensitivity toward micro-level structural changes, which makes it suitable for predictive maintenance applications. The signal acquisition module converts analog microwave reflections into digital representation suitable for AI inference. The analog signal $r(t)$ passes through amplification and filtering stages before digitization. The sampled signal is expressed as:

$$x[n] = r(nT_s) + w[n] \tag{8}$$

where $w[n]$ represents quantization noise. Normalization is performed to stabilize amplitude variation:

$$x_{norm}[n] = \frac{x[n] - \mu_x}{\sigma_x} \tag{9}$$

where μ_x represents mean value and σ_x represents standard deviation. To enhance signal quality, a band-pass filter is applied:

$$H(f) = \begin{cases} 1, & f_l \le f \le f_h \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

The filtered signal becomes:

$$x_f[n] = \mathcal{F}^{-1}\{\mathcal{F}(x_{norm}[n]) \cdot H(f)\} \tag{11}$$

where $\mathcal{F}$ represents Fourier transform. Noise suppression is achieved through adaptive smoothing:

$$x_s[n] = \alpha x_f[n] + (1-\alpha)x_s[n-1] \tag{12}$$

where α represents smoothing coefficient. The conditioning stage ensures that the signal retains fault-relevant frequency components while removing industrial noise artifacts.

3.3 REPRESENTATION LEARNING

The feature extraction module transforms conditioned signals into discriminative representations suitable for CNN processing. The system extracts both time-domain and frequency-domain features. Time-domain statistical features include:

$$\mu = \frac{1}{N}\sum_{n=1}^{N} x_s[n] \tag{13}$$

$$\sigma^2 = \frac{1}{N}\sum_{n=1}^{N} (x_s[n] - \mu)^2 \tag{14}$$

$$S_k = \frac{1}{N}\sum_{n=1}^{N} (x_s[n] - \mu)^k \tag{15}$$

where S_k represents higher-order statistical moments. Frequency-domain transformation is performed using Discrete Fourier Transform:

$$X[k] = \sum_{n=0}^{N-1} x_s[n] e^{-j(2\pi kn/N)} \tag{16}$$

Spectral energy distribution is computed as:

$$E_f = \sum_{k=0}^{N-1} |X[k]|^2 \tag{17}$$

The system also computes spectral entropy:

$$H = -\sum_k p_k \log(p_k) \tag{18}$$

where $p_k = \frac{|X[k]|^2}{\sum |X[k]|^2}$.

Feature vectors are concatenated as:

$$F = [\mu, \sigma^2, S_3, S_4, E_f, H, X[k]] \tag{19}$$

This representation enhances separability between normal and faulty states.

4. CNN-BASED AI MODEL ON EMBEDDED SOC

The embedded CNN model performs classification of feature vectors into operational states. The input tensor is denoted as: $F \in \mathbb{R}^{m\times 1}$. The convolution operation is defined as:

$$y_i^{(l)} = \sum_{j=0}^{k-1} w_j^{(l)} F_{i+j} + b^{(l)} \tag{20}$$

where $w_j^{(l)}$ represents kernel weights and $b^{(l)}$ represents bias.

The activation function is applied using ReLU: $a_i^{(l)} = \max(0, y_i^{(l)})$. Pooling operation reduces dimensionality: $p_i = \max(a_{i:i+s})$. The final dense layer computes classification probability:

$$P(y = c | F) = \frac{e^{z_c}}{\sum_{i=1}^{C} e^{z_i}} \tag{21}$$

where C denotes number of classes. The loss function is defined as cross-entropy:

$$\mathcal{L} = -\sum_{c=1}^{C} y_c \log(P(y = c | F)) \tag{22}$$

The SoC accelerates convolution operations using parallel compute units, which reduces inference latency significantly. Weight quantization is applied as:

$$w_q = \text{round}(w/s) \tag{23}$$

where s denotes scaling factor. This enables efficient execution under embedded constraints.

4.1 PREDICTIVE MAINTENANCE DECISION FRAMEWORK

The final module converts CNN outputs into actionable maintenance decisions. The system defines operational states as:

$$S = \{S_{normal}, S_{degraded}, S_{fault}\} \tag{24}$$

Decision rule is expressed as:

$$D = \begin{cases} S_{normal}, & P < \theta_1 \\ S_{degraded}, & \theta_1 \le P < \theta_2 \\ S_{fault}, & P \ge \theta_2 \end{cases} \tag{25}$$

where P represents fault probability output from CNN. A temporal degradation index is computed as:

$$I(t) = \beta I(t-1) + (1-\beta)P(t) \tag{26}$$

This index captures progressive deterioration trends. Remaining useful life (RUL) estimation is modeled as:

$$RUL = \int_{t}^{T_f} (1 - I(t))dt \tag{27}$$

The system triggers maintenance alerts when: $I(t) \geq \theta_c$. This decision mechanism ensures proactive intervention before catastrophic failure.

5. RESULTS AND DISCUSSION

The experimental environment uses MATLAB R2024a and Python-based TensorFlow 2.13 framework for CNN training and inference simulation. The embedded deployment is emulated using ARM Cortex-A72 based SoC architecture with 8 GB RAM.

The microwave sensing subsystem is simulated using CST Microwave Studio for signal propagation modeling. The system operates on Windows 11 workstation with Intel i7 10th Gen processor. The experiments execute in controlled industrial noise conditions with additive Gaussian interference to evaluate robustness.

Table.1. System and Simulation Parameters

Parameter	Description	Value
f_c	Carrier frequency	5.8 GHz
T_s	Sampling interval	1 μs
N	Signal length	2048 samples
SNR	Noise level	5–25 dB
CNN layers	Deep learning depth	5 layers
Batch size	Training batch	32
Learning rate	Optimization step	0.001
Epochs	Training cycles	50

The parameters in Table.6 define the operational configuration of the proposed system. The microwave frequency at 5.8 GHz ensures high-resolution reflection sensitivity for industrial equipment monitoring.

The sampling interval and signal length control temporal resolution and feature granularity. The CNN architecture with five layers balances computational efficiency and classification accuracy. Noise conditions between 5 dB and 25 dB simulate realistic industrial interference environments.

Table.8. Accuracy Comparison Across Methods

Iteration	SVM-SOM (%)	eHIPF (%)	PSO (%)	Proposed (%)
5	82.1	83.5	84.0	90.2
10	83.0	84.2	85.1	91.4
15	84.2	85.0	86.3	92.6
20	85.0	86.1	87.0	93.8
25	86.3	87.2	88.1	94.5

The Table.8 shows that the proposed method consistently achieves higher accuracy compared to SVM-SOM, eHIPF, and PSO across all iterations. At iteration 5, the proposed model reaches 90.2%, which already exceeds PSO by approximately 6.2%. As iterations increase, the performance gap remains stable, indicating consistent learning behavior. At iteration 25, the proposed system achieves 94.5%, while SVM-SOM reaches 86.3%, showing a difference of 8.2%. This improvement arises due to integrated microwave feature representation combined with CNN-based hierarchical learning, which captures subtle fault signatures more effectively. The traditional SVM-SOM model shows limited adaptability to nonlinear signal variations. The eHIPF model improves slightly due to filtering mechanisms, yet it lacks deep feature abstraction capability. PSO optimization improves parameter tuning but still depends on handcrafted features. The proposed architecture eliminates this limitation through end-to-end learning at the embedded SoC level. The results confirm that the fusion of microwave sensing and AI inference enhances classification reliability under noisy industrial conditions.

Table.9. Precision Comparison Across Methods

Iteration	SVM-SOM (%)	eHIPF (%)	PSO (%)	Proposed (%)
5	81.0	82.4	83.2	89.5
10	82.5	83.8	84.6	90.8
15	83.7	85.0	85.9	92.1
20	84.6	86.2	87.0	93.3
25	85.8	87.5	88.4	94.0

The Table.9 demonstrates that precision improves steadily across all methods, with the proposed model outperforming others significantly. At iteration 5, the proposed system records 89.5%, which is higher than PSO by 6.3%. The improvement indicates better reduction of false positives in fault detection. At iteration 25, precision reaches 94.0%, while SVM-SOM remains at 85.8%. The improvement is driven by CNN-based feature discrimination that separates fault and non-fault patterns more effectively than conventional classifiers. The eHIPF method improves precision through preprocessing but lacks adaptive learning capability. PSO shows moderate improvement due to optimized parameter tuning but still depends on static feature selection. The proposed system integrates real-time microwave signal adaptation with deep learning inference, which reduces misclassification under noisy environments. The consistent increase across iterations indicates stable convergence behavior of the embedded learning model.

Table.10. Recall Comparison Across Methods

Iteration	SVM-SOM (%)	eHIPF (%)	PSO (%)	Proposed (%)
5	80.2	81.9	82.7	88.8
10	81.6	83.1	84.0	90.3
15	82.8	84.5	85.6	91.7
20	83.9	85.7	86.9	93.0
25	85.0	86.8	88.0	94.2

The Table.10 indicates that recall improves consistently for all methods, with the proposed model achieving the highest detection capability. At iteration 5, recall reaches 88.8%, which exceeds

PSO by 6.1%. At iteration 25, the proposed method achieves 94.2%, while SVM-SOM records 85.0%. The improvement reflects enhanced sensitivity toward detecting true fault cases. The CNN-based architecture improves feature abstraction, which helps capture subtle degradation patterns in microwave reflections. The eHIPF system provides moderate improvement through filtering, but it does not fully capture nonlinear fault characteristics. PSO improves recall through optimized parameter tuning but still depends on limited feature representation. The proposed system improves detection consistency through joint optimization of sensing and AI inference layers, which reduces missed fault detection under noisy industrial conditions.

Table.11. F1-Score Comparison Across Methods

Iteration	SVM-SOM (%)	eHIPF (%)	PSO (%)	Proposed (%)
5	80.6	82.1	82.9	89.1
10	82.0	83.6	84.8	90.6
15	83.2	84.8	86.1	91.9
20	84.3	86.0	87.3	93.2
25	85.4	87.2	88.6	94.1

The Table.11 demonstrates that the proposed method achieves superior F1-score performance across all iterations. At iteration 5, the proposed system achieves 89.1%, which is higher than PSO by 6.2%. At iteration 25, the score increases to 94.1%, indicating balanced improvement in both precision and recall. The SVM-SOM method shows lower F1-score due to limited nonlinear modeling capability. The eHIPF method improves stability but lacks deep representation learning. PSO performs moderately well due to optimization but still depends on predefined feature structures. The proposed method achieves better balance through CNN-driven feature learning and microwave signal integration, which reduces classification bias and improves robustness.

Table.12. Latency Comparison Across Methods

Iteration	SVM-SOM (%)	eHIPF (%)	PSO (%)	Proposed (%)
5	120	110	105	70
10	118	108	102	68
15	115	106	100	66
20	112	104	98	64
25	110	102	95	62

The Table.12 indicates that the proposed system achieves the lowest latency among all methods. At iteration 5, latency reduces to 70 ms, which is significantly lower than SVM-SOM at 120 ms. At iteration 25, latency further reduces to 62 ms. The improvement results from SoC-level parallel processing and hardware-accelerated CNN inference. Traditional methods such as SVM-SOM and eHIPF rely on sequential processing, which increases computation time. PSO improves efficiency moderately through optimized computation but still depends on iterative search mechanisms. The proposed architecture minimizes processing overhead by integrating sensing and inference within a unified embedded pipeline, which reduces data transfer delay and improves real-time responsiveness.

5.1 DISCUSSION

The experimental evaluation across Tables 8 to 12 confirms that the proposed system consistently outperforms existing methods across all performance metrics. Accuracy improves up to 94.5%, precision reaches 94.0%, recall achieves 94.2%, and F1-score reaches 94.1%, while latency reduces to 62 ms. The SVM-SOM method shows lower performance due to limited feature representation capability. The eHIPF model improves performance moderately through filtering but lacks adaptive learning. The PSO-based system provides optimization benefits but does not fully capture complex microwave signal patterns. The proposed architecture achieves superior results due to integrated microwave sensing and CNN-based inference executed on an AI-accelerated SoC. The system demonstrates stable convergence across iterations and maintains robustness under noisy industrial conditions. The reduction in latency indicates effective hardware-software co-design. The results validate that edge-level intelligence significantly enhances predictive maintenance capability in industrial automation systems.

6. CONCLUSION

The study presents an AI-accelerated embedded platform integrated with microwave transceiver sensing for predictive maintenance in industrial automation. The proposed system achieves improved fault detection accuracy of 94.5%, precision of 94.0%, recall of 94.2%, and F1-score of 94.1%, while reducing inference latency to 62 ms. The system demonstrates strong robustness under industrial noise conditions due to effective signal conditioning and CNN-based feature learning. Compared to SVM-SOM, eHIPF, and PSO methods, the proposed architecture consistently performs better across all evaluation metrics. The integration of microwave sensing with embedded AI processing improves early fault detection capability and reduces system downtime. The SoC-based execution enables real-time inference, which enhances operational reliability in industrial environments. The results confirm that unified edge intelligence systems provide significant advantages over traditional separated sensing and processing frameworks. The study establishes a scalable foundation for future industrial predictive maintenance systems that require low-latency and high-accuracy decision-making.

REFERENCES

[1] B.P.R. Rella, A. Chakraborty, S.B. Shah, H. Ghosh, S. Gautam, B.A. Dhirwani and N. Mutyam, "AI-Engine-based Acceleration for High-Performance Programmable System-on-Chip Designs", *Journal of Computational Analysis and Applications*, Vol. 32, No. 1, pp. 894-906, 2024.

[2] X. Huang, H. Wang, Q. Shiyin and T. Su-Kit, "Embedded Artificial Intelligence: A Comprehensive Literature Review", *Electronics*, Vol. 14, No. 17, pp. 1-40, 2025.

[3] J. Ivkovic and J.L. Ivkovic, "Exploring the Potential of New AI-Enabled MCU/SOC Systems with Integrated NPU/GPU Accelerators for Disconnected Edge Computing Applications: Towards Cognitive SNN Neuromorphic Computing", *Proceedings of International Conference on LINK IT and EdTech Scientific*, pp. 12-22, 2023.

[4] H. Li, Z. Ling and C. Yang, "Software and Hardware Co-Design of AI High-Rate Chips for Parallel Training of Edge Intelligence", *Intelligent Decision Technologies*, Vol. 18, No. 4, pp. 3259-3276, 2024.

[5] B. Gayanath, G. Rathnasekara, K. Karunanayake and A. Madanayake, "Scalable AI+ DSP Compute Frameworks using AMD Xilinx RF-SoC ZCU/VCU Platforms for Wireless Testbeds for Scientific, Commercial Space and Defense Applications", *Electronics*, Vol. 15, No. 2, pp. 1-18, 2026.

[6] F. Montazer, B. Mehdikhani, N. Noroozi, R. Nezameslami, A. Nezameslami, A. Shahbazi and H. Nematzadeh, "GPU-Accelerated Artificial Intelligence Applications in Cancer Diagnosis, Imaging and Treatment Planning", *Asian Pacific Journal of Cancer Prevention: APJCP*, Vol. 26, No. 8, pp. 2725-2739, 2025.

[7] F. Yardımcı, D. Kose, A.A. Tarçın, Y. Koç and T. Kadıoglu, "Evaluation of Quantization Strategies for Lightweight CNN Inference on AI-Accelerated and Conventional Microcontrollers", *Proceedings of International Conference on Electrical and Electronics Engineering*, pp. 1-5, 2025.

[8] K. Halbiniak, K. Rojek, S. Iserte and R. Wyrzykowski, "Unleashing the Potential of Mixed Precision in AI-Accelerated CFD Simulation on Intel CPU/GPU Architectures", *Proceedings of International Conference on Computational Science*, pp. 203-217, 2024.

[9] J. Ivkovic, J.L. Ivkovic and V. Veljovic, "AI Equipped SoC/MCU Systems in IoT Edge Nodes", *Proceedings of International Conference on AI and Robotics*, pp. 1-17, 2019.

[10] M.R. Rezaee and N.A.W.A. Hamid, "Modern Tools, Languages and Systems Available for Implementing Artificial Intelligence Algorithms", *Artificial Intelligence for Computational Fluid Dynamics*, pp. 345-376, 2026.

[11] S. Son, Y.H. Cho, S.H. Kim, S. Kim, H. Kim and J. Choi, "Hyper-AI-Driven Acceleration of Multi-Database Integrated Genomic Analysis for Infectious Disease Response", *Proceedings of International Conference on Robotics, Automation and Artificial Intelligence*, pp. 548-552, 2025.

[12] T.T. Nguyen and D.R. Elmaleh, "LizAI XT-AI-Accelerated Management Platform for Complex Healthcare Data at Scale, Beyond EMR/EHR and Dashboards", *Big Data and Cognitive Computing*, Vol. 9, No. 11, pp. 1-18, 2025.