Design and Development of a Conventional Mechatronic System with Deep Learning–Based Industrial Applications

Sandi Yudha Barri Zaqy[1], Adi Febrianton[2]
[1]Lecture, Department of Mechanical Electrical Engineering
Polytechnic Jambi, Jambi, Indonesia.
[2]Assistant Professor, Department of Maintenance Machine
Politeknik Kampar, Bangkinang, Riau, Indonesia.
E-mail: sandi@politeknikjambi.ac.id[1], adifebrianton@gmail.com[2]

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ABSTRACT

The significance of incorporating deep learning methods into diverse fields has grown because of their transformative influence on resolving complex issues, improving efficiency, and unlocking new capabilities. By integrating deep learning, mechatronic devices and systems can become more intelligent, adaptive, and effective in their operations. Deep learning techniques enable these systems and devices to learn from data, identify patterns, and make decisions in real time, thereby improving their ability to adapt to changing environments and maximize performance. The proposed system combines mechanical components, electronic hardware, sensors, actuators, and embedded control units with advanced deep learning models to achieve intelligent decision-making and improved operational efficiency. Deep learning techniques are employed to analyze complex, high-dimensional sensor data for tasks such as system state estimation, performance optimization, fault detection, and predictive analysis in industrial environments. The developed framework supports adaptive learning capabilities, allowing the system to respond dynamically to changing operational conditions. The paper delineates the promising prospect for deep learning integration in mechatronics, emphasizing collaborative efforts among academia, industry, and regulators to ensure responsible deployment of these technologies. This paper serves as a guiding framework for researchers, engineers, and policymakers, facilitating the effective integration of deep learning methodologies in mechatronics devices and systems.

Corresponding Author:

Sandi Yudha Barri Zaqy,
Lecture, Department of Mechanical Electrical Engineering
Polytechnic Jambi, Jambi, Indonesia.
E-mail: sandi@politeknikjambi.ac.id

1. INTRODUCTION

The requirement for cognitive mechatronic solution that can function effectively in dynamic and data-intensive contexts has been fuelled by the growing complexity of industrial systems. Because of their dependability and deterministic behaviour, conventional mechatronic systems—which include mechanical parts, electronic devices, sensors, actuators, and controls units—are frequently utilised in industrial automation [1]. Nevertheless, these systems' capacity to adjust to nonlinear dynamics, uncertainties in the environment, and changing operational conditions is constrained by their frequent reliance on predetermined model and rule-based control procedures.

A potent data-driven method for simulating intricate relationships and deriving significant insights from extensive, high-dimensional sensor data is deep learning. Its ability to improve the intelligence and autonomous of engineering systems has been proven by its effective use in fields including pattern recognition, fault detection [2], and predictive analytics. Real-time learning, adaptable decision-making, and enhanced system performance without significant manual adjustment are made possible by integrating techniques from deep learning into mechatronic systems.

Despite these benefits, deep learning's practical integration into traditional mechatronic systems for use in industries is still difficult [3]. Effective deployment is hampered by obstacles pertaining to processing in real time, embedded hardware, data heterogeneity, as well as system reliability. Furthermore, adaptability and industrial adoption are limited by the absence of unified system structures that smoothly integrate mechatronic modules with deep learning models.

The development and design of a traditional mechatronic system combined with deep learning-based industrial applications is presented in this study. To enable effective sensor data collection, real-time processing, as well as intelligent decision-making, a modular architecture is suggested. The suggested system shows how deep learning can improve defect detection, performance optimisation, system state prediction, and predictive modelling in industrial settings.

Problem Statement

Even though conventional mechatronic systems are widely used in manufacturing automation, their reliance on pre-established mathematical equations and rule-based control techniques restricts their flexibility, scalability, and resilience in challenging and dynamic operating environments. Large amounts of heterogeneous data from sensors are produced in modern industrial settings, and these data are not efficiently processed by conventional methods, which results in inadequate system monitoring, delayed problem identification, and decreased operational efficiency. Deep learning has shown great promise in data-driven decision-making, but its practical integration into traditional mechatronic systems is still difficult because of embedded hardware limitations, real-time processing constraints, and the lack of unified design principles that seamlessly integrate sensing, control, and learning. A methodical framework that facilitates effective data collection, effective feature learning, and dependable real-time implementation of deep learning models into traditional mechatronic systems for use in industries is necessary to address these issues.

Main Contributions of This Paper

The following is a summary of this paper's primary contributions:

1. In order to enable real-time adaptive decision-making, this work describes the design and development of a traditional mechatronic system combined with deep learning-based intelligence for industrial applications.

2. To enable smooth multi-sensor data collection, effective data preparation, and deep learning model integration inside embedded control frameworks, modular hardware–software design is suggested.
3. Applying high-dimensional industrial sensor data, a data-driven deep learning method is used for defect detection, predictive analysis, and system status estimation.
4. Real-time experimental deployment and performance analysis under both normal and problematic operation situations confirm the efficacy of the suggested approach.
5. A comparison with traditional techniques shows that the suggested deep learning-enabled mechatronic system has better accuracy, quicker reaction times, and increased robustness.

This is how the rest of the paper is structured. A synopsis of relevant research on deep learning-based mechatronic systems and its industrial uses is provided in Section 2. The materials and procedures, such as system design, data collecting, extraction of features, and deep learning formulation, are covered in Section 3. The implementation specifics and experimental findings are covered in Section 4. The work is finally concluded and future research possibilities are outlined in Section 5.

2. LITERATURE REVIEW

The purpose of this study is to perform a Systematic Literature Review (SLR) in the application of machine learning (ML) methods in the field of PHM of commercial mechanical systems and equipment. 50 studies were found to be qualified for the aforementioned SLR. Key Performance Indicators (KPIs) utilised to validate the diagnostics and prognostics method, as well as the types of machine learning algorithms used in the 50 examined articles [4], have been examined. The most popular algorithms, according to the research, are Shallow Learning and Deep Learning (DL), although KPIs are utilised differently depending on whether the goal is regression or classification. Furthermore, the findings showed that many authors continue to evaluate their algorithms using synthetic datasets rather than datasets derived from actual data received by their components. In order to standardise the authors' methodical diagnostics and prognostics procedure for the final category of datasets, this research also presents a schematic framework.

Enhanced capabilities are needed to apply maintenance plans based on conventional data-driven fault diagnostic schemes across contemporary production systems in the present Industry 4.0 framework. In actuality, complex electromechanical systems needing sophisticated monitoring techniques result from the integration of many mechanical elements [5], considering of multiple operating situations, and the emergence of coupled fault patterns due to inevitable multi-fault scenarios. In this sense, a viable strategy for a big data paradigm utilising cloud-based software services is data fusion methods backed by cutting-edge deep learning technology. However, the primary restriction when using deep learning models is their structure and choice of hyper-parameters. Therefore, a novel deep-learning-based approach for electromechanical system defect identification is given in this study. The suggested methodology's primary advantages are its high degree of flexibility to given data and ease of application. A supervising discriminant analysis algorithm and an unsupervised stacking auto-encoder assist the methodology.

Enhanced robotics, the Internet of Things (IoT), artificial intelligence (AI), and big data analysis are just a few of the technologies that companies are using to create intelligent, networked systems that can communicate data in real time, make dispersed decisions, and automate tasks. Two case studies—one on a smart injection moulded machine and other on soft robots—are further examined in this study [6]. The synergies, advantages, difficulties, and promise for the future of combining mechatronics using Industry 4.0 technology are demonstrated by these examples. In the end, this convergence promotes the creation of smart workplaces and products, increasing manufacturing productivity, efficiency, and adaptability while also supporting sustainability through waste reduction, resource optimisation, and a reduction in the environmental effects of industrial production. This represents a major change in industrial manufacturing towards more environmentally friendly methods.

The study categorised five worldwide scenarios: practical methods to product development, research on engineering curriculum and education, studies on mechatronic system components, artificial intelligence applications, and mechatronic system design methodology. Not only does this highlight the fact that the term "innovation" in mechatronics is used in a significant number of publications, but it also characterises [7] a relationship to the term that always has to do with the implications, ramifications, and possibilities that a particular product, design, robot, or machine could offer to the marketplace or future research. In a similar vein, it was discovered that the results of numerous publications highlight the benefits of adopting technology for commercial purposes and link the term innovation to return on investment or operating expenses.

This study emphasises the significance of resolving these issues and suggests that future research endeavours focus on enhancing model generalisation, integrating explainable AI methods, and maximising DL [8] deployment in situations with limited data. Furthermore, a promising path for intelligent, real-time decision-making in mechanically powered systems is presented by the combination of DL with the latest Industry 4.0 technologies, including IoT, digital replicas, and cyber-physical systems. For scholars and practitioners looking to use or develop DL techniques in mechanical engineering situations, this review is an extensive resource.

3. METHODS AND MATERIALS

3.1 System Description and Data Collection

Mechanical subsystems, electrical circuits, sensors, actuators, and an integrated control unit are all incorporated into a modular design in the suggested conventional mechatronic system. Several industrial-grade sensors are used to continually track system behaviour under various operating situations [9]. These sensors include vibration, temperature, electrical current, and positional sensors. Analog-to-digital converters are used to obtain sensor signals, which are then sent to the embedding processing unit at a predetermined sampling frequency. Let's express the unprocessed sensor data gathered from NNN sensors as

$$X(t) = \{x_1(t), x_2(t), \dots, x_N(t)\} \qquad (1)$$

where the time-dependent signal from the $x_1(t), x_2(t), \dots, x_N(t)$ sensors is represented by $X(t)$. To guarantee adequate depiction of system dynamics, data collecting is carried out under normal, transitory, and malfunctioning operation situations. While certain features are analysed in real time for live decision-making, the gathered dataset is kept in a central repository for offline evaluation and model training.

3.2 Data Preprocessing and Extraction

Industrial settings frequently provide raw sensor data that is tainted by noise, outliers, and values that are missing [10]. Preprocessing techniques like segmentation, filtering, and normalisation are used before feature extraction to guarantee data dependability. A digitised low-pass filter is used to remove noise, and it is expressed as

$$\overline{x_i}(t) = x_i(t) * h(t) \qquad (2)$$

where $*$ indicates the convolution process and $x_i(t) * h(t)$ indicates the filter's impulse response. Next, each signal is normalised using min–max normalisation, which is described as

$$x_i^{norm}(t) = \frac{x_i(t) - min(x_i)}{max(x_i) - min(x_i)} \qquad (3)$$

To capture temporally patterns, the preprocessed impulses are divided into fixed-length intervals of size TTT, creating a collection of samples that are represented as

$$X_k = \{x_i^{norm}(t) | t \in [(k-1)T, kT]\} \qquad (4)$$

3.3 Feature Extraction and Representation

To transform highly dimensional time-series data from sensors into useful representations appropriate for deep learning models [11], feature extraction is carried out. Each segmented window is used to extract statistical and temporal data like variance, mean, root mean square (RMS), skewness, and kurtosis. The $x_i^2(t)$ sensor signal's RMS value is calculated as

$$RMS_i = \sqrt{\frac{1}{T}\sum_{t=1}^{T} x_i^2(t)} \qquad (5)$$

Each signal segment is subjected to a Fast Fourier Transform (FFT), which is defined as

$$X_i(f) = \sum_{t=0}^{T-1} x_i(t) e^{-j2\pi f t/T} \qquad (6)$$

A vector of characteristics, $X_i(f)$ in which ddd represents the total amount of features, is created by concatenating the attributes gathered from each sensor. Deep learning algorithms use these feature vectors as inputs [12]. For the purposes of automatic feature learning, raw segmentation signals are fed directly into machine learning architecture in addition to manually created features.

3.4 Deep Learning Model Formulation

Nonlinear interactions between sensor data and system states are modelled using a deep learning framework. Let f be the appropriate system state or output, and $\hat{y}_k$ be the input feature vector. A nonlinear map $(F_k; \theta)$ is learnt by the deep learning algorithm so that

$$\hat{y}_k = f(F_k; \theta) \qquad (7)$$

where $\frac{1}{K}$ denotes the model parameters. The learning process aims to minimize the loss function $(y_k - \hat{y}_k)^2$, defined as

$$L = \frac{1}{K}\sum_{k=1}^{K} (y_k - \hat{y}_k)^2 \qquad (8)$$

where KKK is the quantity of training samples. Gradient-based optimisation approaches are used to optimise model parameters [13], allowing the system to learn correlations from sensor data in an adaptable manner.

3.5 Real-Time Implementation

The learnt deep learning model is integrated into the mechatronic system's control architecture for real-time deployment. Real-time predictions are produced by preprocessing incoming sensor data and passing it through the trained network. The actuator interface is used to carry out the necessary control actions based on the anticipated state of the system [14]. This closed-loop integration improves the operational effectiveness and dependability of the suggested system by enabling adaptive control, fault identification, and predictive analysis.

3.6 Applications of Deep Learning in Mechatronics

By improving perception, intelligence, and adaptability, deep learning's incorporation with traditional mechatronic systems has made a variety of cutting-edge industrial applications possible. Deep learning models provide data-driven decision-making that outperforms conventional model-based methods by using high-dimensional sensor data obtained from electrical, mechanical, and control subsystems. The suggested mechatronic framework uses adaptive control, real-time learning, and prediction to serve a variety of industrial applications.

Intelligent condition surveillance and problem detection are two of the main uses of deep machine learning in mechatronics. Wear, environmental disruptions, and operational uncertainty frequently cause industrial mechatronic systems to gradually deteriorate or collapse unexpectedly. Deep learning models may learn complicated defect signs and differentiate among normal and unusual operating states when they are trained on multi-sensor data, such as vibration, temperatures, and current signals. This increases system reliability and lowers unexpected downtime as well as repair costs by enabling early fault identification and isolation.

Predictive maintenance, which uses deep learning algorithms to calculate the remaining lifespan of mechatronic components, is another important application. Deep learning algorithms can forecast future system behaviour and foresee possible faults before they happen by examining historical trends in sensor data. By scheduling maintenance tasks proactively rather than recurrently, this predictive capability maximises resource utilisation and prolongs the lifespan of equipment in industrial settings.

Additionally, deep learning is essential for performance optimisation and system state estimation. Traditional estimating methods frequently depend on oversimplified mathematical models that might not adequately represent the dynamics of nonlinear systems. Deep learning models, on the other hand, may accurately estimate state of systems that are challenging or impractical to physically monitor by directly learning complicated input-output correlations from data. Mechatronic systems become more efficient, precise, and stable as a result of this greater state awareness supporting optimised control strategies.

Deep learning makes it possible for electronic devices to dynamically modify control behaviours in response to shifting operating conditions in the field of adaptable and intelligent control. Deep learning-enabled controllers can automatically adjust to changes in load, speed, and ambient conditions by continually gaining insight from real-time sensor feedback. Applications like robotic manipulators, automated production systems, and intelligent machinery functioning in unpredictable or time-varying settings benefit greatly from this flexibility.

Additionally, deep learning improves perception and human-machine interaction in mechatronic systems via applications like vision-based monitoring and inspection. Automated inspection, item recognition, and identification of errors in manufacturing procedures are made possible by deep neural networks that are applied to scanned and sensory data. This increases productivity, accuracy, and consistency in quality assurance jobs while decreasing reliance on manual inspection.

All things considered, deep learning's mechatronics applications show how it may turn traditional systems into intelligent, self-sufficient, and durable industrial solutions. Deep learning greatly advances Industry 4.0 and smart production by allowing sophisticated monitoring, prediction, optimisation, and control capabilities [15]. The suggested architecture offers a workable basis for implementing these applications in actual mechatronic systems while preserving scalability and dependability.

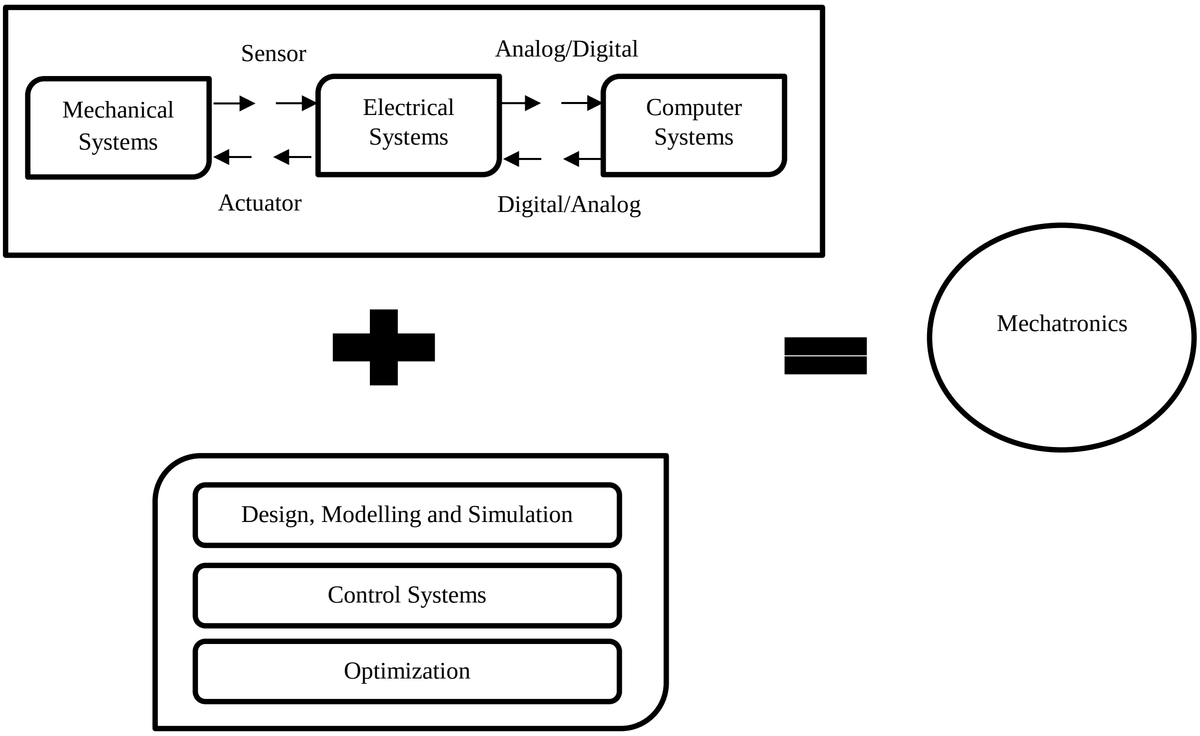

Figure 1. Mechatronics conventional design methodology

The fundamental distinctions between these approaches are that the Model-Based Design methodology is codified and supported by various modelling languages, whereas functional modelling approaches are informal and cannot produce repeatable functional technique models of a particular product (the identical good produced by two teams of designers has a small chance to accomplish the same results). Reusing well-established design ideas such as "Program Re-engineering" in a model-based approach is another significant distinction. The problem with functional modelling is that the maintained design model may only be utilised to the product model that serves as the model's focal point. The traditional mechatronic process design methodology is depicted in Figure 1.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

4.1 Implementation of the Proposed System

To ensure versatility and real-time operation, a modular hardware-software architecture was used to create the suggested deep learning-enabled mechatronic system. Industrial-grade sensors for registering vibration, temperature, electrical current, and positional data were integrated with the mechanical subsystem. Analog-to-digital conversion modules were used to interface sensor signals with an integrated controller, allowing synchronised multi-sensor data gathering. Higher-level processing of data and deep machine learning inference were carried out on a computer unit, while signal conditioning and initial preparation were handled by the embedded platform.

The gathered sensor dataset was used to train a deep learning algorithm offline before it was used for online inference. As mentioned in the techniques section, segmented time-series data was used for model training, and gradient-based learning was used for optimisation. Incoming sensor data was continually preprocessed, converted into feature representations and delivered to the trained model for fault classification and condition prediction during real-time operation. A tightly coupled intelligent control framework was created by generating and executing control signals and system warnings via the actuator interface based on the anticipated outputs.

4.2 Experimental Setup

To assess the efficacy of the suggested system, experiments were carried out under various operating settings, including as normal operation, variable load conditions, and provoked fault scenarios. To guarantee an objective assessment of performance, the dataset was split into testing, validation, and training sets. The deep learning algorithm and overall system behaviour were evaluated using performance metrics like precision, recall, accuracy, F1-score, and error in prediction. The main hardware and software elements utilised in the experiment implementation are listed in Table 1.

Table 1. Hardware and Software Configuration of the Proposed System

Component	Specification
Sensors	Vibration, temperature, current, position
Embedded Controller	Microcontroller-based embedded system
Sampling Frequency	1–5 kHz (depending on sensor type)
Processing Unit	CPU/GPU-based computational platform
Deep Learning Framework	Python-based deep learning library
Communication Interface	Serial / Ethernet

4.3 Performance Evaluation

By contrasting the deep learning-based technique with a traditional rule-based strategy, the suggested system's performance was assessed. The experimental findings show that integrating deep learning into the mechanical framework significantly increases system intelligence and dependability. The deep learning model's classification performance under various operating settings is shown in Table 2.

Table 2. Performance Comparison under Different Operating Conditions

Condition	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Normal Operation	98.6	98.2	98.9	98.5
Load Variation	96.8	96.1	97.2	96.6
Fault Condition	95.4	94.7	95.9	95.3

The findings show the resilience and adaptability of the suggested approach by showing that it retains excellent accuracy even in dynamic and defective settings.

4.4 Analysis of Experimental Results

The contrast of expected and genuine system states over real-time operation is shown in Figure 2. The deep learning model's ability to capture nonlinear system dynamics is confirmed by the projected output, which closely resembles the actual system behaviour.

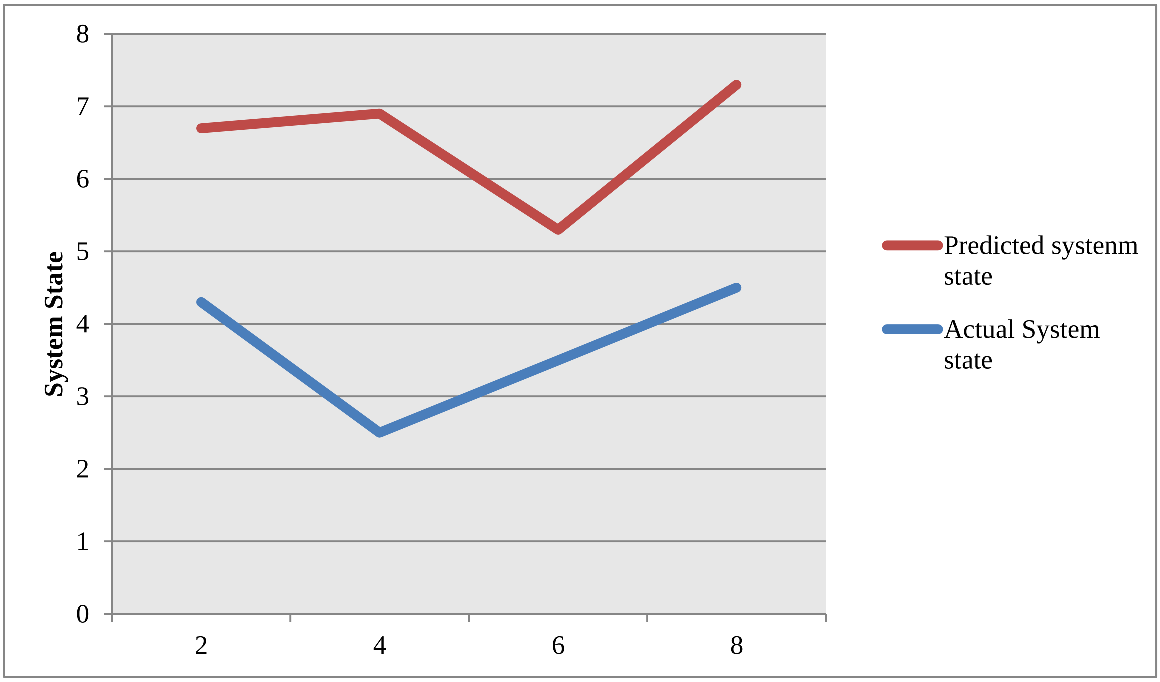

Figure 2. Comparison of actual and predicted system states during real-time operation

When an error is introduced during operation, the system's fault detection behaviour is shown in figure 3. The efficiency of the suggested deep learning-based framework in detecting aberrant system behaviour in real time while retaining low false rates of detection is demonstrated by the detected fault response, which closely tracks the actual fault situation with minimal delay.

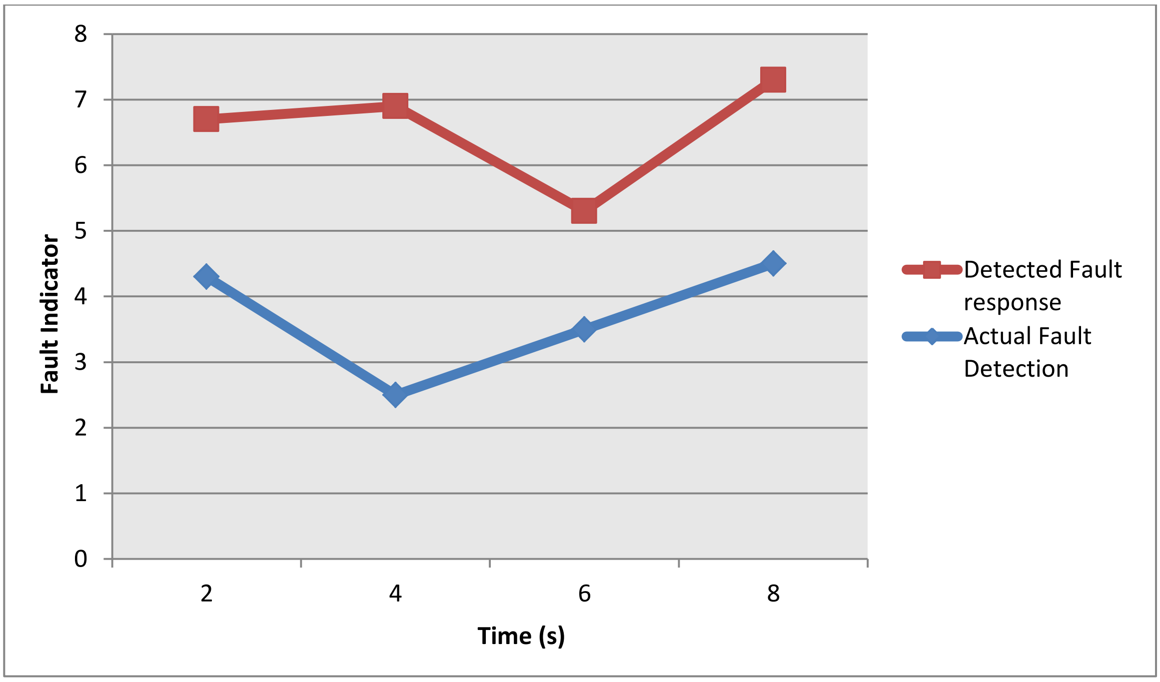

Figure 3. Fault detection response of the proposed system under different operating conditions

Response time and error in prediction were assessed and contrasted with a conventional method in order to further examine system efficiency. Table 3 provides a summary of the findings.

Table 3. Comparison of Proposed System with Conventional Method

Method	Average Response Time (ms)	Mean Prediction Error
Conventional Method	120	0.087
Proposed DL-Based System	65	0.032

The suggested system's appropriateness for real-time industrial uses is demonstrated by its shorter response time and decreased prediction error.

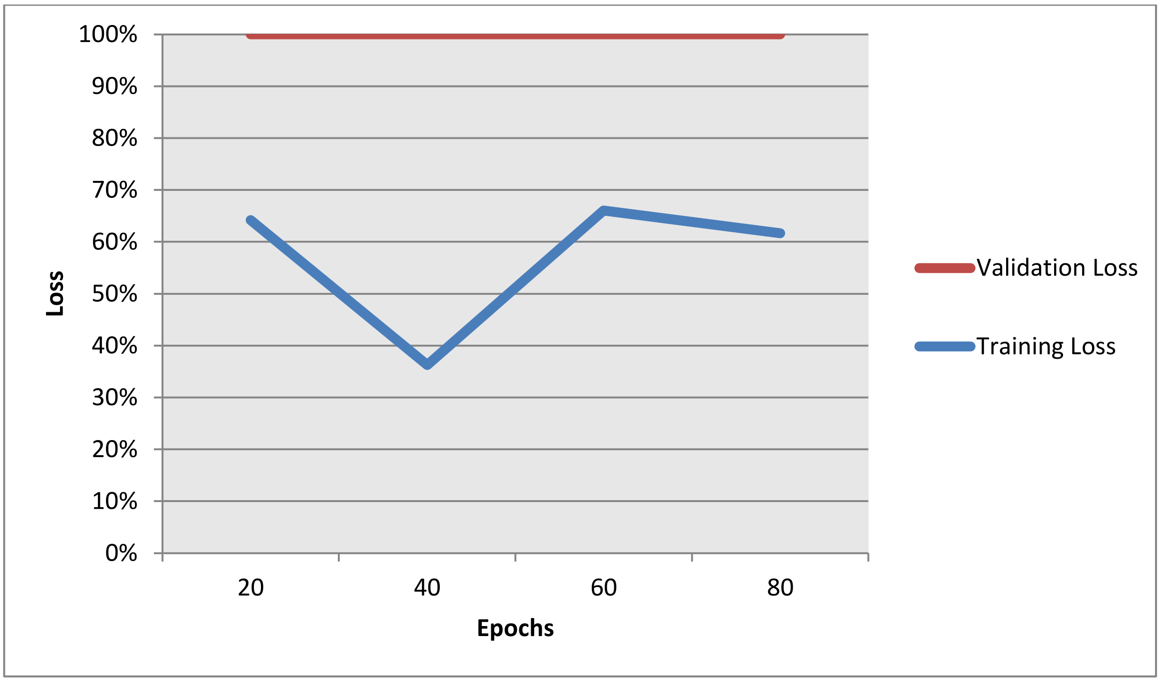

Figure 4. Training and validation loss convergence of the deep learning model

The convergence properties of the suggested deep learning network during training are depicted in figure 4. As the number of epochs increases, validation as well as training losses gradually decline, suggesting steady learning behaviour, efficient optimisation, and the lack of overfitting.

Discussion

The experimental findings verify that deep learning greatly improves the intelligence, flexibility, and performance of a traditional mechatronic system. Accurate state estimation, problem detection, and real-time predictive analysis are made possible by the suggested architecture's efficient processing of high-dimensional sensor input. The deep learning-enabled solution exhibits better scalability and resilience than conventional rule-based methods, making it appropriate for use in industrial settings.

5. CONCLUSION

The development and design of a traditional mechatronic system combined with deep learning-based industrial applications was discussed in this study. The suggested framework improves system intelligence, flexibility, and operational efficiency by fusing sophisticated deep learning models with mechanical parts, electronic hardware, actuators, sensors, and embedded control units. To enable smooth multi-sensor data collecting, processing in real time, and intelligent choice-making in industrial settings, a modular framework was chosen.

In comparison to traditional rule-based methods, experimental results showed that deep learning integration greatly enhances system performance. Under various operating situations, the suggested system produced accurate system state estimate, efficient fault detection, and trustworthy prediction analysis. The deep learning model's capacity to capture nonlinear system behaviour and function dependably in real time was confirmed by the strong agreement between projected and actual system states, quick fault detection reaction, and stable training convergence.

The results verify that deep learning is a potent enabler for converting traditional mechanical systems into adaptive and flexible industrial solutions. The suggested method offers a workable and expandable basis for Industry 4.0 and smart manufacturing applications. Future research will concentrate on expanding the framework to more intricate industrial systems, integrating edge-based learning to lower latency, and improving the resilience and interpretability of the model for safety-critical applications.

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