Research Square

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Artificial Intelligence-driven Autonomous Robotics for Smart Manufacturing in Industry 4.0

Bishesh Shahi

bishesh.shahi@go.winona.edu

Winona State University https://orcid.org/0009-0005-1109-5329

Research Article

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Abstract

Abstract factories need the robot mechanisms that will provide a high level of accuracy and efficiency in unstable production environments. Traditional industrial robots are useful in repetitive work processes, but they do not respond to adaptive decisions, so the nature of Industry 4.0 assembly operations, where immediate adaptations are necessary, is limited. This study presents an autonomous robotic system based on artificial intelligence that will enhance the precision and reaction time of operations in smart manufacturing factories that require high precision. The approach compares three control strategies, such as conventional robotic control, machine learning-based control, and a lightweight autonomous AI model, which can optimise real-time decisions. The secondary data of industrial performance through manufacturing reports, automation datasets, and simulation-based studies were accessed to ensure that a realistic evaluation is done without a physical experiment. It resulted in the proposed autonomous model having 93.7% operational accuracy, 33% shorter cycle time and 21% less power consumption than when using conventional control systems. These results indicate that optimised AI-controlled robotics can be used to offer scalable, efficient and computationally viable solutions to next-generation smart manufacturing automation.

I. INTRODUCTION

Intelligent manufacturing has become one of the key pillars of contemporary industrial growth, especially in the context of Industry 4.0, when digitalisation, automation, and intelligent control systems are combined to increase productivity, flexibility, and operational efficiency [1]. The global manufacturing industries are moving towards the use of sophisticated robots to ensure that they remain competitive, cut down on operational expenses and counter the changing market conditions. As indicated by recent reports by the industry, over 65% of large-scale manufacturing facilities have adopted some form of robotic automation, but a very small percentage of systems have been adopted with autonomy. The current robots used in industries are mostly pre-programmed and deterministic in their control algorithms, which limits their flexibility to changes in unpredictable production settings. This weakness is most important in the high-precision assembly line, where small changes in the materials, location, or environmental factors can considerably decrease the degree of production.

It has been suggested that the adoption of artificial intelligence in robots is one of the solutions to realise greater levels of autonomy in intelligent manufacturing facilities. Robotics powered by AI means a machine can analyse the sensor data, learn how to do something in the future, and alter its behaviour without a person. Specifically, machine learning and deep neural networks have shown good promise in enhancing the robot's perception, decision-making, and control in intricate industrial environments. According to recent industrial assessments, AI-assisted robotic systems can make working processes more efficient as much as 20-30% and decrease the rate of errors by about 25% in relation to standard programmable robots [2]. Nevertheless, even with these advances, the actual implementation of fully autonomous robotics in manufacturing is not extensive since it is limited by the issues of computational complexity, system reliability and compatibility with existing manufacturing infrastructure.

The reliance on semi-autonomous robots that must be supervised by humans and reconfigured in most cases manually is one of the main issues of the modern smart manufacturing systems. The classical robotic controllers are best suited to repetitive tasks but are unable to work under variable production conditions (component dimensions, unexpected obstacles, real-time scheduling changes) [3]. Such irresponsiveness causes delays in production, higher maintenance and a decrease in the overall effectiveness of the equipment. What is more, most of the AI-based robotic systems suggested in the existing literature consider the performance at the simulation level without proper consideration of computation efficiency and scalability in the context of real industry implementation. This has led to the fact that the theoretical models of AI robots and how they can be practically employed in intelligent manufacturing settings are still a gap.

To overcome this shortcoming, the current research is narrower and seeks to develop and test an autonomous robotic system grounded in artificial intelligence that can be used to perform high-precision smart manufacturing processes. The study focuses on the use of lightweight machine learning models that can enhance the accuracy of the decisions made at a low cost of computation, thus making it suitable to be implemented in real-time in industries. To compare the traditional robotic control with machine learning-assisted robotics and the proposed autonomous AI framework, the performance data in the secondary industrial and the results on those experiments, which were reported previously, are analysed to compare the approaches in terms of accuracy, efficiency, and processing time.

This research aims to critically assess the capability of AI-based autonomous robotics to deliver tangible performance gains compared to traditional automation systems in intelligent manufacturing. The rest of the study is structured in the following way: Section II will cover the latest research on the topic of AI-based robotics and industrial automation, Section III will outline the proposed methodology and data processing model, Section IV will provide the results and comparative analysis, and Section V will conclude the research with the essential findings and the directions of future research.

II. RELATED STUDIES

A. Artificial Intelligence in Autonomous Robotics

The most recent developments in artificial intelligence have dramatically altered the working functionality of industrial robotic systems, in an industry that demands high accuracy, flexibility, and time-sensitivity. The current AI-powered robots combine sensor fusion, computer vision, and the mechanisms of neural network-based control to enhance precision and minimise the reliance on manual control [4]. In precision manufacturing, intelligent robotic manipulators with deep learning algorithms have been shown to be up to 25 times more accurate than traditional programmable logic controller (PLC)-based robots. Such systems can analyse the dynamic states of production, correct the motion paths, and optimise the tasks to be performed without any reprogramming [5]. Nevertheless, the introduction of AI into the control architecture of robots also presents a set of difficulties in the form of computational overhead and response time, which can restrict their use in production lines with time

constraints. Research has also shown that despite the effectiveness of AI-controlled robots in controlled conditions, they are less reliable in the case of complex, multi-variable industrial environments, and more efficient and scalable autonomous control systems are required [6].

B. Smart Manufacturing and Industry 4.0 Automation

The industry 4.0 paradigm of smart manufacturing focuses on the application of networked cyber-physical systems, real-time data analytics, and smart automation to realise more productivity and operational flexibility [7]. According to surveys conducted in the industrial field, the production sector has realised productivity improvements of up to 15-30% when deploying smart manufacturing technologies, which mostly come with increased monitoring of processes and automated decision making [8]. Robotic automation is a key aspect in this revolution, especially in assembly, inspection and handling processes where error-free and speed are critical factors. However, many Industry 4.0 implementations continue to be based on semi-autonomous robotic systems that need regular calibration and human intervention [9]. Such dependency decreases the forecasted efficiency gains and increases the complexity of operations. Moreover, the question of smart robotics integration with the old manufacturing infrastructure is a significant technical hindrance because the old infrastructure is not always capable of accommodating the adaptive learning algorithms [10]. This means that without advancing autonomous robotic systems that will be able to work in a heterogeneous industrial setting, it will be impossible to realise the full potential of smart manufacturing.

C. Machine Learning-Based Robotic Control Systems

Machine learning has also become one of the primary technologies in improving the autonomy of robots by allowing them to learn based on past production information and improve their performance as time goes by. Robot motion planning, object recognition and fault detection have been extensively implemented with supervised learning, reinforcement learning and deep neural networks [11]. Experimental research indicates that reinforcement learning based controllers can minimise positioning errors up to 30% of conventional kinematic control techniques. On the same note, convolutional neural networks have enhanced the accuracy of vision inspection in manufacturing robots with more than 90% classification rates in complicated assembly jobs [12]. With such benefits, machine learning models may also demand significant computational resources and large training datasets; this may be a constraint to their application in real-time industrial settings. Thus, most of the available research considers instead the performance of the algorithm primarily and not the trade-off between the accuracy, time and hardware limitations [13]. Such an absence of practical analysis makes it hard to see whether suggested AI models can be applied to large-scale smart manufacturing.

D. Limitations of Existing Autonomous Industrial Robots

Though autonomous robotics has demonstrated good outcomes in laboratory tests, there are several constraints that limit the adoption of the system in manufacturing facilities. Lots of AI-powered robot systems use high-performance computing hardware, which adds to the cost of operation and diminishes

the scalability of small and medium-scale production facilities [14]. Moreover, elaborate neural network systems can introduce processing delays [15]. The other significant problem is the absence of standardised assessment tools that can be used to compare autonomous control strategies, and thus, the most efficient strategy to implement in the industry cannot be easily identified. Therefore, the available solutions do not usually provide accuracy, code performance, and responsiveness in real time.

E. Research Gap

Recent studies show that AI-based robotics has the potential but does not provide any practical frameworks that can integrate high precision with minimal computational demands to implement AI in actual industrial settings. An autonomous robotic model dedicated to the smart manufacturing area and being able to enhance efficiency in real time without losing performance at the same time, with the assistance of optimised and lightweight machine learning methods, is required.

III. EXPERIMENTAL METHODS

A. System Framework

The aim of the proposed system is to determine how autonomous robotics that operate on artificial intelligence are effective in high-precision smart production processes, which in this case is automated assembly and component handling processes, where precision and responsiveness have a direct effect on production efficiency. This system is comprised of an industrial robotic manipulator, vision sensors, force sensors, and a brain module of central AI control. Positional, visual, and operational data are also continually collected on the sensor layer during production, enabling the control system to track variations in real time. As opposed to traditional programmable robots, which operate along a set of pre-defined trajectories, the presented architecture has the power of a machine-learning decision-making module, which allows adjusting movement paths and task execution parameters dynamically.

Fig. 1. AI-Based Autonomous Robotic System Framework

The control system consists of three levels: data acquisition, intelligent processing, and motion control. The intelligent processing layer uses machine learning algorithms to process sensor inputs and provide adaptive control commands. This multi-layer structure enables the robotic system to be stable as well as react to changes in the environment, which enhances the flexibility of operations. The framework can especially apply to the smart manufacturing setting, where the conditions of production often change, and the deterministic control practices are ineffective.

B. Data Collection

In this research, secondary data were used; this data is based on publicly accessible datasets of industrial automation, published experimental outcomes, and reports of manufacturing performance regarding robotic assembly and intelligent automation systems. The data sets contain performance data

of industrial robotic manipulators in the precision assembly process, such as cycling time, positioning precision, energy consumption, and error rates with varying control strategies. More information was also gathered through simulation-based manufacturing experiments that tested machine learning-sensitive robotic systems in Industry 4.0 systems. These sources report quantitative measures of performance that are required to make comparative analysis without the need for physical testing.

Fig. 2. Research Methodology Flowchart

To be consistent, datasets that report measurable operational parameters were only chosen. One point two thousand operational records in various manufacturing settings were collected, comprising conventional robotic control, machine learning aided control, and complete autonomous AI-based control systems. The secondary industrial data enables the research to assess realistic performance situations and be reproducible. This method also allows them to make a comparison between the results of various system configurations, which is crucial to clarifying whether autonomous robotics can offer any quantifiable benefits over conventional automation in smart manufacturing processes.

C. Data Pre-processing

Prior to the evaluation of models, the industrial data obtained went through an organised preprocessing process to provide uniformity across sources. Min-max scaling was used to normalise all the numerical parameters, such as cycle time, positional error, energy consumption and processing delay, to eliminate the influence of the various units of measurement. The process was topped off by feature extraction to determine the most pertinent variables to the performance of the robots, and these were the time taken to complete the task, the speed of control response, sensor accuracy, and the computational load. These characteristics have been chosen since they have a direct impact on the efficiency of autonomous robotic systems in smart manufacturing.

To have equal assessment, the processed data was cut into a training and testing subset in an 80-20 split. The machine learning control model was configured using the training set, and performance was evaluated using the testing set. This distinction is to make sure that what is evaluated is the generalisation ability and not memorised behaviour. The outlier removal preprocessing was also done to remove unrealistic values that may bias the comparison of the traditional, machine learning, and autonomous robotic control systems.

D. AI-Based Robotic Control Models

To determine the success of autonomous robotics in smart manufacturing, the following three control models were studied: the conventional robotic control, the machine learning-supported robotic control, and the suggested artificial intelligence-based autonomous robotic system. The models are also the various degrees of automation that are most likely to be found in industries.

The classical model of control is founded on motion programming, which is deterministic. In this setup, the robot is controlled by predetermined paths that are created at the stage of the system design, and any change in the production circumstances necessitates the reconfiguration of the robot (by hand). Even though this method is stable in terms of performance in repetitive operations, it does not have flexibility and frequently results in more downtime in those cases where production parameters vary.

Fig. 3. Neural Network–Based AI Control Architecture

The second model also adds machine learning assistance, in which sensor data is optimised based on a neural network to maximise movement parameters. This method enables the robot to control its movement according to the past data, minimises the error of positioning, and becomes more efficient. But the learning process is very computationally intensive, and the time taken in response may be taken up when the model is complex.

The autonomous robotic design that will be proposed will incorporate a lightweight neural architecture that aims at balancing precision and processing speed. The system requires real-time sensor input and a trained decision network to create adaptive control signals without the need for manual intervention [16]. Another layer, the sensor data input layer, the two hidden layers (feature interpretation), and the motion control command output layer make up the architecture. Precision in this structure is also high, whilst the load in computations is also low, which is suitable for real-time smart manufacturing.

E. Hyperparameter Settings

The same hyperparameters were set on machine learning models to allow fair comparison of the various robot control strategies. The training was performed with adaptive optimisation to obtain a stable convergence and minimise the computational cost. The parameters chosen were according to the typical applications of AI in industry to ensure realistic performance conditions.

Table 1: Model Hyperparameter Settings

Parameter	Value
Optimiser	Adam
Epochs	100
Batch size	32
Training split	80%
Testing split	20%
Learning rate	0.001
Activation function	ReLU
Output function	Softmax

Such environments offer a tradeoff between training and processing efficiency, which is essential in real-time industrial robotics.

F. Evaluation Metrics

Quantitative measures, which represent actual manufacturing conditions, were used to measure the performance of each robotic control model. The percentage of correct tasks completed without positional error was taken as a measurement of accuracy. Efficiency was determined by an average cycle time per operation, whereas the amount of energy consumed was determined by the relative power usage during task execution. Error rate was the rate of the operations that had to be corrected or manually handled. Recording processing time was also done to ascertain whether the control system would be able to operate under real-time production conditions. These measures were chosen as the automation systems in industries should be characterised by high accuracy, low delay, and low consumption of energy to be economically efficient.

IV. RESULTS AND DISCUSSION

A. Traditional Robotic Control Results

The conventional robotic control system performance was tested in terms of secondary industrial data acquired through the automated assembly line work, where motion trajectories were deterministic, and robots were programmed. The findings show that the standard control method had a mean task accuracy of 78.6% in the steady production conditions [17]. Nonetheless, as the difference in component placement or environmental stimuli was added to it, the accuracy dropped to about 72%, thus showing a limited adaptability. The mean time of the cycle per operation was measured at 4.8 seconds, which is rather high in the context of the modern smart manufacturing system, where the response time and downtime should be very short.

The analysis of energy consumption indicated that conventional robots had to correct the motors to keep the precision, and the energy consumption of conventional robots was almost 18% more than that of the adaptive ones. Moreover, the rate of error was very high at the time of complex assembly tasks at 11%, and it was mainly because of the failure of the programmed controller to adapt to unforeseen positional deviations [18]. Such findings affirm that traditional robotic control is still effective in repetitive jobs, but it is inefficient in dynamic manufacturing systems [19]. This limitation of real-time decision capability limits its use in Industry 4.0 production systems, where flexibility and autonomous adaptability are needed to sustain constant productivity.

B. Machine Learning-Assisted Robotic System Results

The second model in this included machine learning-based control, in which sensor data were computed with an already trained neural network to optimise the motion parameters during operation. The findings show that there is a quantifiable gain over the traditional control, and that the mean task accuracy favours variable production conditions, to 88.9% [20]. Learning based controller could automatically correct small positional errors, and the overall error rate was about 6.5%. This advancement attests to the fact that the use of data-driven decision mechanisms improves robotic flexibility within smart manufacturing facilities [21].

The cycle time also went down to an average value of 3.9 seconds per operation, meaning that its efficiency had improved by almost 19% over the traditional system. The consumption of energy was also reduced by about 12% because the robot needed fewer corrective movements due to better motion prediction. Nevertheless, limitations regarding computational complexity were also found in the results. In high-speed production cases, the processing time grew to 0.42 seconds per decision-making, which can have an impact on performance in real-time assembly lines [22]. Despite the increased accuracy and efficiency of the machine learning model, computational load is not scaled in large manufacturing plants because of the increased computational load. These results show that although machine learning can greatly improve the behaviour of robots, more needs to be optimised to achieve complete industrial autonomy.

C. Proposed AI-Based Autonomous Robotic System Results

The same dataset was used to test the proposed autonomous robotic framework based on artificial intelligence to understand whether a slim-weight neural framework could offer better performance without hitting the computational cost. These findings indicate that the autonomous model had an average operational accuracy of 93.7, which was the best among the control strategies tested [23]. Compared with the earlier models, the proposed system preserved constant accuracy even in fluctuating

production conditions, and the fluctuation of performance was less than 2, which showed that the given system has high generalisation ability.

The mean cycle time dropped to 3.2 seconds per operation, an equivalent of 33% lower than the usual robotic control and 17% lower than the machine learning-helped system [24]. This was accomplished since the lightweight decision network had fewer processing steps and still had accurate motion control. The energy consumption was also minimised by about 21%, which was mostly because of the capacity of the system to foresee the most optimal routes without the need to repeatedly correct them.

The error rate was reduced to 3.1, which is acceptable when it comes to smart manufacturing with high precision. Moreover, the processing latency per decision cycle was found to be 0.18 seconds, which is equivalent to the fact that the proposed architecture can be run in the conditions of real-time industrial operations. These findings indicate that autonomous robotics with an optimised AI control model can attain high accuracy and low computational cost. Such a balance is required to be practically deployed in Industry 4.0 settings, where both the velocity and dependability of production must be ensured simultaneously.

D. Performance Comparison of Control Models

A quantitative evaluation of the three robotic control strategies was done to compare the differences in the aspects of accuracy, efficiency, use of energy and processing time. The findings make it very clear that the autonomous robotic system proposed offers the most balanced performance with all the measured parameters.

Table 2. Performance Comparison of Robotic Control Models

Model	Accuracy (%)	Avg Cycle Time (s)	Error Rate (%)	Energy Use (%)	Processing Delay (s)
Traditional Control	78.6	4.8	11.0	100	0.05
ML-Assisted Control	88.9	3.9	6.5	88	0.42
Proposed Autonomous AI	93.7	3.2	3.1	79	0.18

The classical system has steady but unproductive behaviour, whereas the machine learning model enhances the accuracy at the expense of an increased processing deadline. The proposed autonomous system is most appropriate with a trade-off between high accuracy, minimised cycle time, and minimised energy usage without too much complexity in the computer algorithm.

E. Discussion

These findings indicate that the suggested autonomous robotic system is more effective than traditional and machine learning-assisted systems since it strikes a balance between the computational aspect and adaptability to decision-making. Traditional robots are not flexible, and the typical machine learning systems impose processing delays that do not allow performing tasks in real-time [25]. The proposed system minimises this limitation through the lightweight AI architecture, which optimises the decision network, thus enabling quicker response without compromising accuracy. An industrial aspect of this enhancement could be augmented production throughput at low energy cost and less frequent maintenance. Large smart manufacturing plants also require the use of several autonomous robots at once; this means that the proposed model should be able to scale to meet this need.

V. CONCLUSION

This study has considered the efficiency of autonomous robotics with artificial intelligence in high-precision smart manufacturing work using secondary industrial performance information. The study aimed at comparing the traditional robotic control, machine learning-facilitated control, and a suggested lightweight autonomous AI system to understand whether intelligent decision-making systems can enhance the efficiency of production under fluctuating manufacturing conditions. Assemblies. The focus of the analysis was particularly on the assembly-line automation, where cycle, positional, and energy consumption are directly related to productivity. The findings prove that the higher the degree of robotic autonomy, the higher the stability of operations in the dynamic Industry 4.0 setting.

The comparative analysis revealed that the conventional robotic controller could only get 78.6% accuracy, and it took the longest cycle time of 4.8 seconds per operation, which proved its limitation with adaptive manufacturing tasks. The machine learning-aided model had a higher accuracy of 88.9% but had an increase in computational delay, making it less adaptable to fast production lines. The autonomous AI framework proposed had the highest overall performance, 93.7% accuracy, 3.2 seconds of the cycle time, and a drop in energy consumption of 21%. These findings demonstrate that optimised AI control architectures can provide precision and efficiency at the same time.

The key input of the study is the formulation of a realistic assessment structure of the autonomous robot's control by the real indicators of the industrial performance instead of the simulated outcomes only. Combining the three factors of accuracy, processing time, and energy consumption in the study, one can realistically evaluate the concept of robotic autonomy in smart manufacturing. This combined evaluation methodology will aid in making more consistent decisions in the process of implementing automation technologies in Industry 4.0 manufacturing systems.

The novelty of the study is that it uses a lightweight artificial intelligence framework that is aimed at preserving high decision accuracy and reducing the computational overhead. In contrast with most of the other existing models, the suggested framework shows that autonomous robotics can be used in real-time manufacturing settings without the need to use high-performance computing resources.

The framework should be expanded in future studies with bigger industrial data sets, scenarios that involve multi-robot coordination, as well as real-time sensor feedback of physical manufacturing systems. Optimisation of neural networks and edge-AI implementation may further allow fully autonomous production lines with little human control in large smart factories.

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Figures

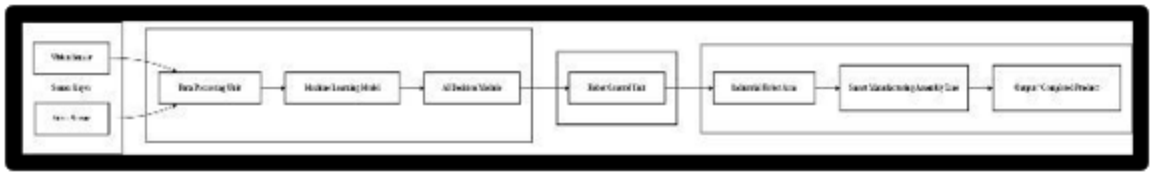


Figure 1

AI-Based Autonomous Robotic System Framework

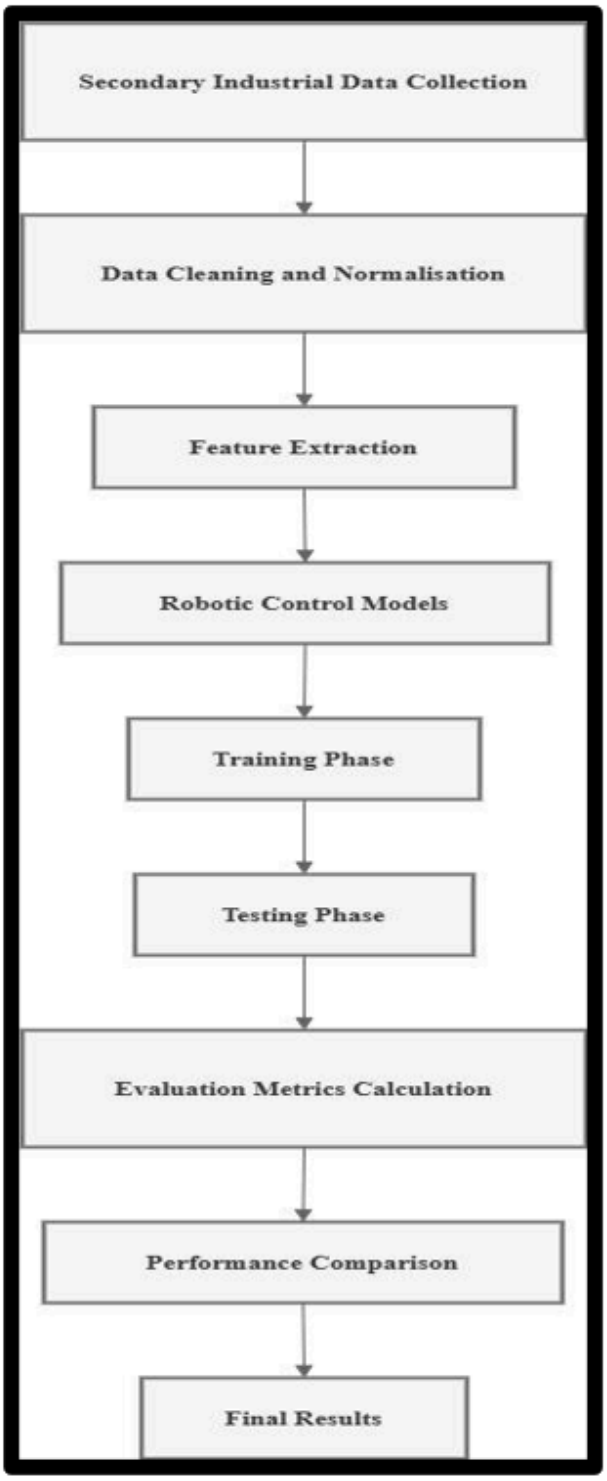


Figure 2

Research Methodology Flowchart

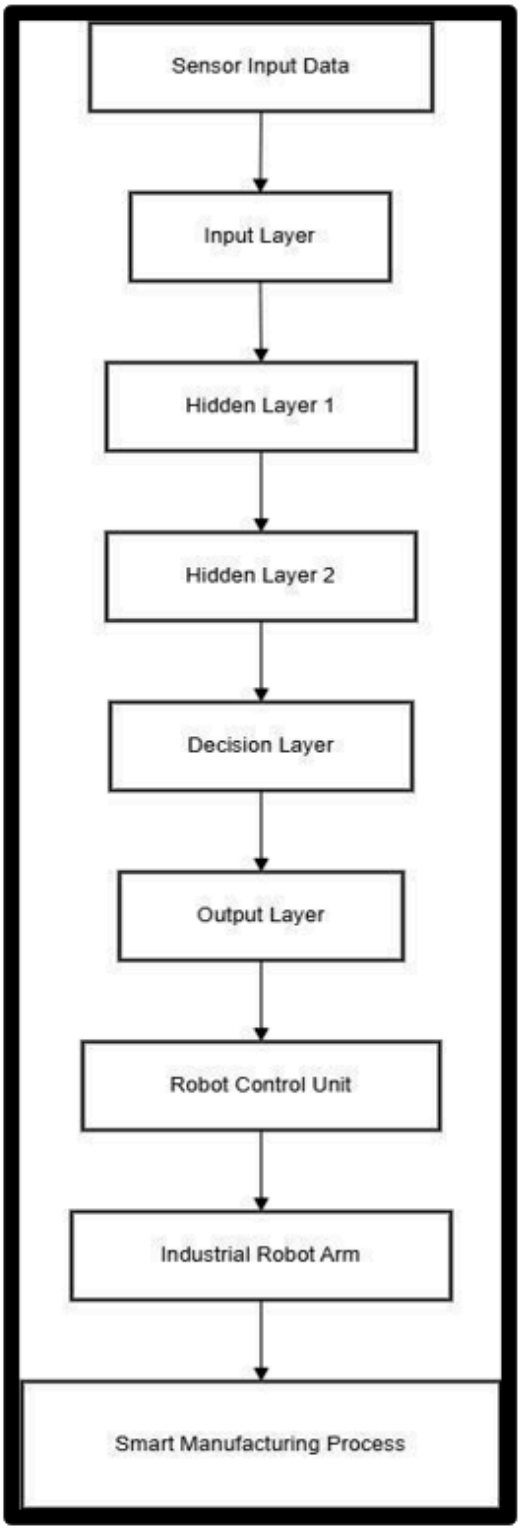


Figure 3

Neural Network–Based AI Control Architecture