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DESIGN AND DEVELOPMENT OF A MOBILE ROBOTIC PLATFORM WITH FABRICATION OF A 4-DOF MANIPULATOR FOR CONDITION MONITORING AND WELD SEAM INSPECTION IN REACTOR PRESSURE VESSEL HEADS

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Abstract

Manual weld inspection in hazardous and confined industrial environments is time-consuming, inconsistent, and exposes human inspectors to significant safety risks. This study presents the design and development of a robotic weld inspection system integrated with a multi-sensor condition monitoring framework for automated detection of weld defects in complex confined structures such as Reactor Pressure Vessel (RPV) heads. The proposed system combines a mobile robotic platform with a 4-DOF manipulator, ultrasonic sensing, temperature and pressure monitoring, and real-time data visualization. The core contribution of this work lies in the integration of robotic inspection hardware with data-driven analysis implemented in R. Ultrasonic signals were processed using statistical threshold-based anomaly detection for defect identification, while environmental sensor data were analyzed to validate operational stability. A Shiny-based dashboard was developed to enable real-time multi-sensor visualization and interactive monitoring of inspection data. The physical prototype was also fabricated. Additionally, a confusion-matrix-based evaluation framework was used to assess the performance of the defect detection model. Experimental results demonstrated that the proposed system achieved high classification performance with an accuracy of 0.99, precision of 0.989, recall of 1.000, and an F1-score of 0.995. Correlation analysis between ultrasonic signals and environmental parameters revealed negligible relationships, with correlation coefficients of −0.0115 (temperature) and 0.0773 (pressure), confirming that defect detection is primarily driven by structural variations in weld seams rather than external environmental conditions. The results validate the robustness and reliability of the proposed robotic inspection framework. The integration of robotics with R-based statistical computing provides a scalable, interpretable, and cost-effective solution for industrial weld inspection. The proposed system significantly improves safety, efficiency, and reliability compared to conventional manual inspection methods and demonstrates strong potential for deployment in industrial condition monitoring applications.

1.INTRODUCTION

Industrial systems that operate under high pressure, elevated temperatures, and corrosive environments require continuous monitoring to ensure structural integrity and operational safety. Among the critical components in such systems are welded joints, which often serve as structural connections in pressure vessels, pipelines, and reactor systems. The reliability of these welds is essential because defects such as cracks, corrosion, and material degradation can lead to severe operational failures and safety hazards. Consequently, regular inspection and condition monitoring of weld seams are fundamental practices in industries such as nuclear power generation, petrochemical processing, and heavy manufacturing [1-3]. In nuclear power plants, the Reactor Pressure Vessel (RPV) head represents one of the most critical components of the system, as it operates under extreme pressure and temperature conditions. The dome-shaped geometry of the RPV head and the presence of multiple weld joints make inspection particularly challenging [4, 5]. Traditionally, weld inspection in such environments has relied on manual non-destructive testing (NDT) techniques, including ultrasonic testing and visual inspection. While these methods have proven effective, they often require human operators to access confined or hazardous spaces, which increases the risk of exposure to dangerous environments and radiation in nuclear facilities. Additionally, manual inspection procedures are time-consuming, labor-intensive, and susceptible to human error, which can reduce inspection reliability.

Advances in robotics and automation have created new opportunities to address these challenges by enabling remote and automated inspection of industrial infrastructure. Robotic systems equipped with manipulators and integrated sensors can perform inspection tasks in environments that are difficult or unsafe for human workers [6-8]. In particular, mobile robotic platforms combined with articulated manipulators have demonstrated significant potential for performing inspection and maintenance tasks in confined industrial spaces. By integrating sensing technologies such as ultrasonic probes, cameras, and environmental sensors, robotic inspection systems can provide accurate and repeatable condition monitoring while reducing human involvement in hazardous operations [9-12]. This research focuses on the design and development of a compact robotic inspection system capable of performing weld seam inspection in confined industrial environments. The proposed system consists of a mobile robotic platform equipped with a four-degree-of-freedom (4-DOF) manipulator designed to position inspection sensors accurately along weld seams. Multiple sensors, including ultrasonic, temperature, pressure, and visual imaging devices, are integrated into the system to enable comprehensive condition monitoring of weld structures. In addition, an R-based data acquisition and monitoring framework is implemented to collect, analyze, and visualize sensor data during inspection operations. By combining robotic manipulation, multi-sensor monitoring, and data-driven analysis, the proposed system aims to improve inspection efficiency, enhance worker safety, and support predictive maintenance strategies in industrial applications. The development of such automated inspection platforms represents an important step toward safer and more reliable monitoring of critical infrastructure.

1.1 Weld Inspection in Critical Industrial Systems

Welded joints are widely used in critical industrial systems as structural connections that ensure the mechanical integrity of components subjected to high pressure, temperature, and cyclic loading conditions. In industries such as nuclear power generation, oil and gas processing, chemical manufacturing, and heavy engineering, pressure vessels, pipelines, and structural assemblies rely heavily on welded connections to maintain operational stability [13-15]. The reliability of these welds is essential because even minor defects can gradually propagate under operational stresses and lead to serious structural failures if not detected at an early stage. During manufacturing and service life, welded joints may develop various types of defects, including cracks, porosity, lack of fusion, corrosion, and material fatigue [16]. These defects may arise due to improper welding processes, material inconsistencies, thermal stresses, or long-term exposure to harsh operating environments [17]. In high-pressure systems such as reactor pressure vessels, weld integrity becomes particularly critical because structural failure may result in significant safety hazards, economic losses, and operational shutdowns. For this reason, regular inspection and condition monitoring of weld seams are essential components of maintenance strategies in safety-critical infrastructure.

To ensure structural reliability, industries commonly employ non-destructive testing (NDT) techniques for weld inspection. Methods such as ultrasonic testing, radiographic inspection, magnetic particle testing, and visual inspection are widely used to detect internal and surface-level defects without damaging the structure [18]. Among these methods, ultrasonic testing is particularly effective for detecting internal discontinuities in welded joints, while visual inspection and imaging systems can identify surface cracks, corrosion, and other visible defects [19]. These inspection techniques allow engineers to evaluate weld quality and determine whether maintenance or repair actions are required. Despite the effectiveness of these inspection techniques, performing weld inspections in complex industrial environments remains challenging. Many critical weld locations are situated in confined spaces, elevated structures, or hazardous environments where direct human access is limited. In systems such as reactor pressure vessels, the geometry of the vessel head and surrounding components can make inspection tasks physically demanding and time-consuming. As a result, ensuring consistent and reliable inspection coverage becomes difficult when relying solely on manual methods.

Given the importance of weld integrity in maintaining the safety and reliability of industrial systems, there is an increasing need for advanced inspection approaches that can improve accessibility, accuracy, and efficiency. The development of automated inspection technologies, particularly those involving robotic platforms and sensor-based monitoring systems, offers promising opportunities to enhance weld inspection processes in critical industrial environments.

1.2 Limitations of Conventional Manual Inspection Methods

Conventional weld inspection in industrial facilities has traditionally relied on manual non-destructive testing (NDT) techniques performed by trained inspection personnel. Methods such as ultrasonic testing, visual inspection, radiographic testing, and magnetic particle inspection are widely used to evaluate weld integrity and detect potential defects [20]. Although these techniques have proven effective in many applications, their implementation through manual procedures presents several operational and safety limitations, particularly in complex and hazardous industrial environments. One of the primary challenges associated with manual inspection is the limited accessibility to critical weld locations [21]. In systems such as reactor pressure vessels, pipelines, and large industrial tanks, many weld joints are located in confined or geometrically complex areas that are difficult for human inspectors to reach. For example, the dome-shaped geometry of reactor pressure vessel heads and the presence of surrounding structural components can significantly restrict physical access to inspection points. As a result, inspectors may face difficulties in maintaining proper sensor alignment, probe positioning, and inspection coverage during the evaluation process.

Another important limitation is the exposure of inspection personnel to hazardous working conditions. Industrial environments involving high pressure, elevated temperatures, toxic substances, or radiation present significant risks to human operators [22]. In nuclear facilities, inspection personnel may also face radiation exposure when performing maintenance or inspection activities near reactor components. Even in non-nuclear industries, confined spaces and elevated work areas increase the potential for accidents, fatigue, and health-related risks. These factors not only compromise worker safety but also limit the duration and frequency of inspection operations. Manual inspection procedures are also time-consuming and labor-intensive [23]. Inspectors must carefully position sensors, collect measurement data, and analyze inspection results while ensuring adherence to strict safety protocols. This process can significantly increase the time required to complete inspections, particularly when multiple weld joints must be evaluated in large industrial systems. Extended inspection durations may also lead to increased operational downtime, which can affect industrial productivity and maintenance costs.

Furthermore, manual inspection processes are susceptible to variability caused by human factors. The accuracy of inspection results can depend on the skill, experience, and fatigue level of the operator. Inconsistent probe placement, variations in sensor contact pressure, and subjective interpretation of inspection signals may lead to inaccurate defect detection or incomplete inspection coverage. Such inconsistencies can reduce the reliability and repeatability of inspection outcomes. Given these limitations, there is a growing demand for automated inspection technologies that can reduce human exposure to hazardous environments while improving inspection efficiency and reliability. Robotic inspection systems equipped with advanced sensing technologies offer a promising alternative by enabling remote, consistent, and repeatable inspection of critical weld joints in confined and challenging industrial environments.

1.3 Robotic Inspection Systems

The increasing complexity of modern industrial systems and the need to improve worker safety have driven significant research into the development of robotic inspection technologies. Robotic systems are particularly well suited for performing inspection tasks in hazardous and confined environments where direct human access is difficult or unsafe [24]. By integrating mobility, manipulation, and sensing capabilities, robotic platforms can perform inspection operations remotely while maintaining high levels of accuracy and repeatability. In many industrial sectors, including nuclear power, oil and gas, petrochemical processing, and heavy manufacturing, robotic inspection systems have been introduced to support non-destructive testing and structural monitoring tasks [25]. These systems are often equipped with articulated manipulators and specialized sensors that allow them to position inspection probes precisely on structural surfaces. Such robotic manipulators provide controlled motion and stable sensor placement, which are essential for inspection techniques such as ultrasonic testing, where probe orientation and contact conditions significantly influence measurement accuracy.

Mobile robotic platforms further enhance inspection capabilities by enabling robots to navigate through complex industrial environments. Depending on the application, these platforms may use wheeled, tracked, or magnetic adhesion mechanisms to move along surfaces such as pipelines, storage tanks, or pressure vessels [26]. When combined with robotic manipulators, mobile platforms can perform both coarse positioning and fine manipulation, allowing sensors to reach inspection points that would otherwise be difficult to access. In addition to mechanical mobility and manipulation, modern robotic inspection systems integrate multiple sensing technologies to provide comprehensive condition monitoring. Sensors such as ultrasonic probes, thermal sensors, cameras, and environmental monitoring devices can be used to detect defects including cracks, corrosion, material degradation, and abnormal thermal conditions [27]. The integration of these sensors with robotic systems allows for continuous data acquisition and detailed analysis of structural conditions. Moreover, advances in data processing and visualization techniques enable real-time monitoring and interpretation of inspection data through digital interfaces. Despite these advancements, many existing robotic inspection systems remain complex and costly, which can limit their adoption in certain industrial applications. Large-scale inspection robots often require specialized infrastructure, extensive calibration, and sophisticated control systems. As a result, there is ongoing research focused on developing compact, cost-effective robotic inspection platforms that can operate efficiently in confined spaces while maintaining reliable sensing performance. The design of such systems requires careful integration of mechanical structure, sensor placement, and data monitoring frameworks to ensure accurate and efficient inspection of critical industrial components.

Despite significant advancements in robotic inspection technologies, several limitations remain in the practical deployment of these systems in confined and complex industrial environments. Many existing robotic inspection platforms are designed for large-scale industrial operations and often involve sophisticated hardware architectures, complex control systems, and high implementation costs. These factors can restrict their applicability in scenarios where compact, flexible, and cost-effective solutions are required. Another challenge lies in the integration of multiple sensing technologies within a single robotic platform. While some inspection systems focus primarily on a single inspection technique, such as ultrasonic or visual inspection, comprehensive condition monitoring often requires the combination of several sensors to detect different types of defects. Achieving reliable integration of multiple sensors while maintaining stable positioning and accurate data acquisition remains a technical challenge, particularly when inspection must be performed in confined spaces with limited maneuverability. Furthermore, although many robotic inspection systems emphasize mechanical design and mobility, relatively less attention has been given to accessible and flexible data analysis frameworks that allow engineers to interpret inspection data efficiently. In particular, the integration of open-source analytical environments for real-time monitoring, data visualization, and condition assessment has not been widely explored in compact robotic inspection platforms. Addressing these gaps requires the development of systems that combine efficient mechanical design, integrated sensing, and accessible data processing tools within a unified inspection framework.

1.4 Nuclear Vessel Inspection Technologies

Nuclear pressure vessels, particularly Reactor Pressure Vessels (RPVs), operate under extreme thermal, mechanical, and radiation environments, making their structural integrity a critical safety concern. Over time, components such as weld seams, nozzles, and internal surfaces are subjected to fatigue, thermal cycling, neutron irradiation, and corrosion [28]. As a result, the inspection of nuclear vessels is a fundamental requirement in nuclear power plant maintenance programs to ensure safe and reliable operation. Various non-destructive testing (NDT) techniques have been developed and applied for nuclear vessel inspection [29]. Among these, ultrasonic testing (UT) is one of the most widely used methods due to its ability to detect internal flaws such as cracks, voids, and inclusions [30]. Radiographic testing (RT) is also commonly employed for detailed imaging of weld structures, although it involves radiation exposure and operational constraints. In addition, eddy current testing (ECT), magnetic particle testing (MPT), and visual inspection systems are used for surface and near-surface defect detection depending on the inspection requirements [31]. Despite the effectiveness of these conventional techniques, their application in nuclear environments is highly challenging due to restricted accessibility, high radiation zones, and complex geometries such as dome-shaped RPV heads. Consequently, robotic and automated inspection systems have increasingly been introduced to replace or assist manual inspection operations. These robotic systems are typically equipped with specialized sensors and are designed to operate remotely in high-risk environments, thereby reducing human exposure while improving inspection consistency and repeatability.

In recent years, significant research has focused on integrating robotics with advanced sensing technologies for nuclear vessel inspection. These systems range from tethered robotic crawlers and magnetic wall-climbing robots to articulated robotic arms mounted on mobile platforms. However, challenges remain in achieving compact design, stable sensor positioning on curved surfaces, and efficient data interpretation for real-time decision-making. The table. 01 shows systematic literature review of nuclear vessel inspection technologies.

Table 1

System Type	Technology Used	Contribution	Limitations	Ref.
Robotic crawler system	Ultrasonic testing + camera	Automated internal vessel surface inspection	Limited maneuverability in curved regions	[32]
Magnetic climbing robot	Eddy current + vision system	Enhanced wall adhesion and vertical inspection	High energy consumption	[33]
Robotic manipulator arm	Phased array ultrasonic testing	High-resolution weld defect detection	Complex calibration requirements	[34]
Mobile inspection robot	Ultrasonic + thermal sensors	Multi-modal defect detection capability	Limited real-time processing	[35]
Autonomous vessel inspection robot	Vision-based inspection system	Reduced human intervention in inspection tasks	Limited detection of internal defects	[36]
Hybrid mobile manipulator	Ultrasonic + visual inspection	Improved access to confined geometries	System complexity and cost	[37]
Pipe and vessel crawler robot	Ultrasonic inspection module	Reliable pipeline and vessel inspection	Restricted to linear surfaces	[38]
AI-assisted robotic system	Ultrasonic + machine learning classification	Automated defect recognition	Requires large training datasets	[39]
Compact inspection platform	Multi-sensor fusion (UT + camera + thermal)	Integrated condition monitoring	Limited payload capacity	[40]
Robotic arm-based inspection system	Vision-guided ultrasonic scanning	Improved inspection accuracy on weld seams	Limited autonomy	[41]
Nuclear vessel inspection robot	Magnetic wheel-based mobility	Stable movement on curved surfaces	Reduced adaptability in complex joints	[42]
Semi-autonomous inspection system	Sensor fusion with real-time monitoring	Enhanced inspection coverage and repeatability	Dependency on external control systems	[43]

1.5 Ultrasonic Weld Inspection

Ultrasonic testing (UT) is one of the most widely adopted non-destructive evaluation (NDE) techniques for weld inspection in critical industrial systems due to its ability to detect both surface and subsurface defects without damaging the material. It operates on the principle of high-frequency sound wave propagation through a material, where reflections from internal discontinuities such as cracks, voids, or inclusions are analyzed to assess structural integrity [44]. In welded structures, ultrasonic inspection is particularly effective for identifying internal flaws that are not visible through conventional visual inspection methods. In nuclear, petrochemical, and heavy engineering industries, ultrasonic weld inspection plays a crucial role in ensuring the safety and reliability of pressure-containing components [45]. Reactor Pressure Vessel (RPV) welds, for example, are subjected to complex thermal and mechanical stresses during operation, making them susceptible to fatigue-induced cracking and material degradation. Ultrasonic techniques such as pulse-echo testing, phased array ultrasonic testing (PAUT), and time-of-flight diffraction (TOFD) are commonly used to evaluate weld quality and detect internal anomalies with high precision [46].

Despite its advantages, ultrasonic weld inspection is highly sensitive to probe positioning, orientation, and coupling conditions. Accurate defect detection requires consistent contact between the ultrasonic probe and the inspection surface, as well as precise control of scanning angles [47]. In manual inspection practices, maintaining these conditions can be challenging, particularly in curved or confined geometries such as pipe joints, vessel heads, and complex weld profiles. Variations in probe alignment or applied pressure can significantly affect signal quality and lead to inconsistent inspection results. Another limitation of conventional ultrasonic inspection is its dependency on skilled operators for data interpretation [48]. The reflected ultrasonic signals, often represented as A-scan, B-scan, or C-scan images, require expert analysis to distinguish between true defects and signal noise. This introduces a level of subjectivity into the inspection process, which can affect repeatability and reliability. Additionally, manual scanning methods are time-consuming, especially when large weld areas need to be inspected.

To address these limitations, research has increasingly focused on automating ultrasonic inspection using robotic platforms. Robotic systems equipped with controlled manipulators can maintain consistent probe orientation, scanning speed, and contact force, thereby improving the reliability of ultrasonic measurements. Furthermore, the integration of data acquisition systems with computational tools enables real-time signal processing and visualization of ultrasonic data. In this study, ultrasonic weld inspection is integrated into a robotic condition monitoring system, where the ultrasonic sensor is mounted on a 4-DOF manipulator to ensure stable and precise positioning along weld seams. The acquired ultrasonic signals are further processed and analyzed using the R programming environment to enable visualization, trend analysis, and defect identification. This approach aims to improve both the accuracy and repeatability of ultrasonic weld inspection in confined industrial environments.

1.6 Mobile Manipulator Systems

Mobile manipulator systems combine the locomotion capabilities of mobile robotic platforms with the dexterity of robotic manipulators, enabling both global positioning and local task execution within a unified system. This hybrid architecture has gained significant attention in industrial automation and inspection applications, particularly in environments where tasks require both navigation through complex spaces and precise interaction with surrounding structures [49]. In the context of inspection tasks, mobile manipulators provide a flexible solution for accessing confined, elevated, or geometrically complex regions that are otherwise difficult to reach using fixed robotic arms or standalone mobile robots. A typical mobile manipulator system consists of a mobile base, which provides translational movement, and an articulated robotic arm mounted on top of the platform. The mobile base is responsible for gross positioning within the workspace, while the manipulator performs fine positioning and orientation of end-effector tools such as sensors, cameras, or inspection probes [50]. This separation of roles allows the system to efficiently cover large operational areas while maintaining high precision during localized tasks such as weld inspection, surface scanning, or defect detection.

In industrial inspection scenarios, mobile manipulators are particularly useful for applications involving large-scale infrastructure such as pressure vessels, pipelines, storage tanks, and structural assemblies. These environments often contain complex geometries and restricted access regions where fixed automation systems cannot operate effectively. By combining mobility with manipulation, these systems can adapt to varying inspection paths and maintain appropriate sensor alignment on curved or irregular surfaces [51]. Despite their advantages, mobile manipulator systems present several technical challenges. One of the primary issues is the coordination between the mobile base and the manipulator, commonly referred to as kinematic redundancy and control coupling. The movement of the base can affect the stability and positioning accuracy of the manipulator, particularly during precision tasks such as ultrasonic scanning or weld seam following. Therefore, coordinated control strategies are required to ensure stable operation and accurate end-effector positioning [52]. Another challenge lies in maintaining system stability and accuracy in confined or uneven environments. Industrial inspection surfaces such as reactor vessel heads or pipe networks often involve curved geometries, slopes, and obstacles that can affect the balance and positioning of the mobile platform. In such cases, mechanical design considerations, including center of gravity optimization and motion planning, become critical for ensuring stable operation.

Recent advancements in mobile manipulator research have focused on improving control algorithms, enhancing sensor integration, and developing compact system architectures suitable for industrial deployment. Sensor fusion techniques are often used to combine data from vision systems, inertial measurement units (IMUs), and force sensors to improve navigation and manipulation accuracy. Additionally, real-time data processing frameworks are increasingly being integrated to support adaptive decision-making during inspection tasks. In this study, a compact mobile manipulator system is developed to facilitate weld seam inspection in confined industrial environments. The mobile platform provides positioning capability around the reactor vessel head, while the integrated 4-DOF manipulator enables precise sensor alignment along weld paths. This coordinated design ensures both accessibility and precision, making the system suitable for automated condition monitoring applications in complex industrial settings.

1.7 Data-Driven Condition Monitoring

Condition monitoring has become an essential component of modern industrial maintenance strategies, particularly in safety-critical systems such as pressure vessels, pipelines, and nuclear reactor components. Traditionally, maintenance approaches relied on scheduled inspections or reactive maintenance after equipment failure. However, these approaches often lead to unnecessary downtime or unexpected system failures [53]. In contrast, data-driven condition monitoring enables continuous assessment of system health through the collection and analysis of operational data, allowing maintenance actions to be performed proactively based on the detected condition of the equipment [54]. Data-driven condition monitoring systems rely on sensors to collect real-time information about the operational state of industrial components. Parameters such as vibration, temperature, pressure, acoustic emissions, and ultrasonic signals are commonly monitored to detect abnormal patterns that may indicate structural degradation or potential faults. By analyzing these sensor signals over time, it becomes possible to identify early signs of damage, such as crack initiation, corrosion progression, or material fatigue, before they develop into critical failures [55].

The advancement of sensor technology and computational tools has significantly enhanced the capabilities of data-driven monitoring systems. Modern monitoring frameworks often integrate multiple sensors within a single platform to provide comprehensive insights into system conditions. Multi-sensor data fusion techniques allow the combination of information from different sensing modalities, improving the reliability and accuracy of defect detection [56]. For example, ultrasonic sensors may detect internal structural defects, while thermal or visual sensors can identify surface-level abnormalities and environmental conditions affecting the structure. In addition to sensor integration, data processing and visualization play a crucial role in effective condition monitoring. Raw sensor data often contains noise and complex signal patterns that require filtering, transformation, and statistical analysis before meaningful interpretations can be made. Computational tools and programming environments are therefore used to process sensor data, perform signal analysis, and generate visual representations of system conditions. Time-series analysis, statistical anomaly detection, and signal filtering techniques are commonly applied to identify abnormal behavior within monitored systems.

Open-source analytical environments have become increasingly important in this context due to their flexibility and accessibility. Platforms such as the R programming environment provide extensive capabilities for data analysis, visualization, and statistical modeling, making them suitable for condition monitoring applications [57]. Using such tools, sensor data can be processed in real time or offline to generate graphical trends, detect anomalies, and support maintenance decision-making. Additionally, the use of open-source platforms promotes reproducibility and scalability in research and industrial implementations. In robotic inspection systems, integrating data-driven monitoring frameworks further enhances the effectiveness of automated inspection processes. When inspection robots collect sensor data during operation, the integration of analytical tools enables immediate evaluation of inspection results and facilitates more informed decision-making. In the present study, a data-driven condition monitoring approach is implemented using the R programming environment to analyze sensor signals collected during robotic weld inspection. This framework enables visualization and interpretation of inspection data, supporting the detection of potential defects and contributing to improved reliability in industrial condition monitoring applications.

The primary objective of this study is to design and develop a compact robotic inspection system capable of performing weld seam inspection in confined industrial environments. The proposed system integrates a mobile robotic platform with a four-degree-of-freedom (4-DOF) manipulator that enables precise positioning of inspection sensors along welded joints. By combining mobility with controlled manipulation, the system aims to improve the accessibility and accuracy of inspection operations in areas that are difficult to reach using conventional manual methods. Another objective of this work is to integrate multiple sensing technologies into the robotic platform in order to support comprehensive condition monitoring of welded structures. Sensors including ultrasonic probes, temperature sensors, pressure sensors, and visual imaging devices are incorporated into the inspection system to detect structural defects and monitor environmental conditions during inspection tasks. In addition to mechanical and sensing capabilities, this study aims to implement a data acquisition and monitoring framework using the R programming environment. The R-based platform is used for collecting sensor data, performing basic signal processing, and visualizing inspection results through graphical outputs. This approach provides a flexible and accessible method for analyzing inspection data and supporting condition monitoring during experimental validation of the system. These contributions aim to demonstrate the feasibility of combining robotic manipulation, multi-sensor monitoring, and data-driven analysis within a compact inspection platform suitable for industrial condition monitoring tasks.

2. System Architecture

2.1 Overall System Design

The overall system design of the proposed robotic inspection platform is based on the integration of mechanical mobility, robotic manipulation, multi-sensor inspection, and data-driven monitoring within a unified architecture. The design aims to enable efficient inspection of weld seams in confined and hazardous industrial environments while ensuring reliable sensor positioning and real-time monitoring of inspection data. The system is structured to operate through coordinated interaction between the robotic hardware components and the data acquisition and analysis framework. At the mechanical level, the system consists of a mobile robotic platform that serves as the base unit for navigation and positioning within the inspection environment. The mobile base provides the capability to move the robot to different inspection points along the weld structure. This mobility is essential in applications involving large industrial components such as reactor pressure vessel heads, pipelines, and structural assemblies, where inspection points are distributed across complex geometries. The overall system architecture of the robotic weld inspection platform is shown in Fig. 01.

Mounted on the mobile platform is a four-degree-of-freedom (4-DOF) robotic manipulator designed to provide precise positioning of inspection sensors. The manipulator is responsible for fine motion control and orientation of the end-effector, which carries the inspection sensors. The combination of base mobility and manipulator articulation allows the system to perform both coarse positioning and fine alignment during inspection operations. This hierarchical motion structure improves accessibility and ensures accurate placement of sensors on weld seams, which is particularly important for techniques such as ultrasonic testing that require stable probe alignment and consistent surface contact. The sensing subsystem of the robot integrates multiple inspection sensors to support comprehensive condition monitoring. An ultrasonic sensor is used to detect internal defects such as cracks or discontinuities within the weld material. A visual inspection camera provides real-time imaging of the weld surface to identify visible anomalies such as corrosion or surface irregularities. In addition, temperature and pressure sensors are incorporated to monitor environmental conditions during the inspection process. These sensors collectively contribute to a multi-parameter monitoring approach that improves the reliability of inspection results.

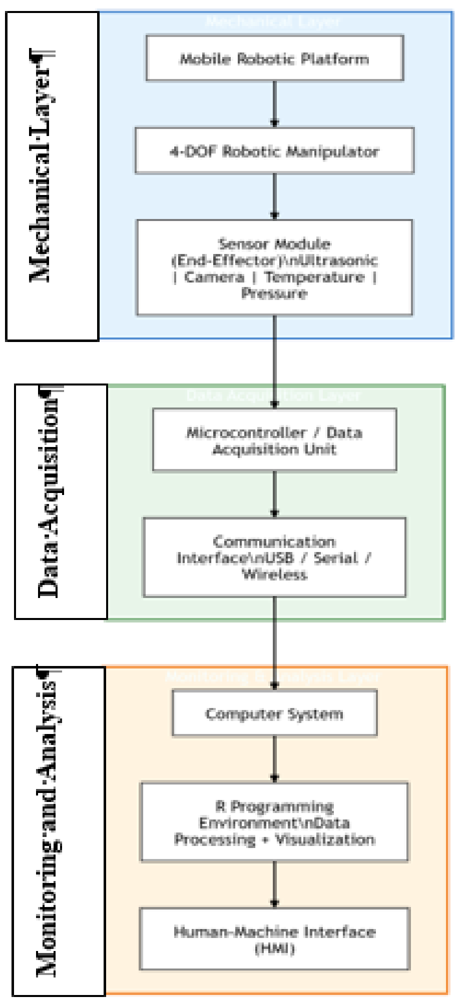

Figure 1

Sensor signals collected during the inspection process are transmitted to a data acquisition unit for processing and storage. In the proposed system, the R programming environment is used to perform data analysis, visualization, and monitoring of sensor outputs. Through this framework, raw sensor data are processed to generate graphical representations such as time-series plots, signal trends, and anomaly indicators. This data-driven approach enables operators to observe system conditions in real time and supports further analysis of inspection results. To facilitate interaction between the user and the robotic system, a human–machine interface (HMI) is incorporated within the monitoring framework. The HMI allows operators to observe sensor readings, visualize inspection data, and monitor system performance during operation. By providing a clear and organized representation of inspection results, the interface assists users in evaluating weld conditions and identifying potential defects.

Overall, the system design emphasizes modular integration between the mechanical platform, sensing components, and data processing framework. This modular architecture allows each subsystem to operate efficiently while contributing to the overall inspection process. The integration of robotic mobility, precise sensor positioning, and R-based data monitoring enables the proposed system to perform reliable weld inspection in challenging industrial environments.

2.2 Mobile Platform Architecture

The mobile platform serves as the foundational subsystem of the proposed robotic inspection system, providing the mobility and structural support necessary for transporting the manipulator and sensor modules to the designated inspection locations. In industrial environments such as reactor pressure vessel (RPV) heads, weld seams are distributed across complex geometries and confined spaces, making mobility an essential requirement for efficient inspection. The mobile platform enables the robot to navigate within these environments and position the manipulator close to the target weld regions. The design of the mobile platform prioritizes stability, maneuverability, and load-bearing capacity to ensure reliable operation during inspection tasks. The platform is constructed using a rigid chassis that supports the weight of the manipulator, sensors, electronic components, and power supply. The structural design minimizes vibrations and unwanted movements that could affect the accuracy of sensor measurements, particularly during ultrasonic inspection where probe stability is critical. The locomotion system of the platform is based on a multi-wheel drive configuration, which provides sufficient traction and smooth motion across industrial surfaces. The wheels are driven by electric motors that allow controlled forward, backward, and turning movements. This mobility allows the robot to travel along weld seams and reach inspection points that are difficult for human operators to access. The mobility mechanism is designed to operate within constrained environments while maintaining adequate balance and stability.

In addition to mechanical movement, the platform integrates onboard electronic components responsible for motion control and communication. A microcontroller-based control unit manages the actuation of the drive motors and coordinates the movement commands. The control system allows the robot to perform precise positioning operations, which are necessary before initiating detailed inspection using the manipulator arm. This coordination between the mobile platform and manipulator ensures that the inspection sensors can be accurately aligned with the weld seam. The power subsystem of the mobile platform is designed to supply energy to all mechanical and electronic components of the system. The platform includes a rechargeable battery pack that powers the drive motors, manipulator actuators, sensors, and data acquisition electronics. Proper power management ensures stable operation during inspection missions and allows the robot to operate autonomously for a defined duration.

From a system integration perspective, the mobile platform also serves as the mounting base for the manipulator assembly and the sensor processing units. The manipulator is fixed at the upper section of the platform to provide sufficient reach and flexibility during inspection. This arrangement ensures that the robotic arm can extend toward the weld seam while the platform remains stable on the surface. By combining mobility and structural support within a single subsystem, the platform enables coordinated operation of all inspection components. Overall, the mobile platform architecture plays a critical role in enabling the robotic system to access confined industrial environments and perform weld inspections efficiently. Its design supports stable navigation, reliable power distribution, and seamless integration with the manipulator and sensing subsystems. This architecture ensures that the robotic inspection system can operate effectively in challenging environments where manual inspection is difficult or unsafe.

2.3 4-DOF Manipulator Configuration

The robotic manipulator is the primary subsystem responsible for positioning inspection sensors accurately along the weld seam. In the proposed inspection platform, a four-degree-of-freedom (4-DOF) manipulator is employed to provide sufficient flexibility for sensor alignment while maintaining a compact structure suitable for confined industrial environments. The manipulator is mounted on the mobile robotic platform and functions as the interface between the robot and the weld surface during inspection operations. The design of the manipulator focuses on achieving an optimal balance between structural simplicity, positioning accuracy, and operational stability. A 4-DOF configuration was selected because it provides adequate mobility for positioning inspection sensors in different orientations while avoiding unnecessary mechanical complexity. This configuration enables the manipulator to reach weld seams located at varying angles and positions on curved or irregular surfaces such as those found on reactor pressure vessel heads. The manipulator consists of a sequence of articulated joints connected through rigid links, forming a serial kinematic chain. Each joint provides controlled motion that contributes to the overall positioning capability of the arm. The first joint typically provides base rotation, allowing the arm to rotate horizontally and access different inspection areas around the robot. The second joint provides shoulder movement, enabling vertical displacement of the arm to reach different heights or depths along the weld seam. The third joint provides elbow articulation, which extends the reach of the manipulator and assists in positioning the end-effector close to the inspection surface. The fourth joint provides end-effector orientation, allowing the sensor module to align properly with the weld surface during inspection.

The actuation of the manipulator joints is achieved through servo motors and linear actuators, which offer precise control over joint angles and movement speed. Servo motors are particularly suitable for robotic applications due to their ability to provide accurate position control and repeatable motion. The actuators are controlled through a microcontroller-based system that coordinates joint movements according to the required inspection position. This control mechanism ensures that the sensors remain stable and correctly oriented during inspection tasks. At the terminal end of the manipulator, an end-effector module is installed to carry the inspection sensors. The end-effector integrates multiple sensing devices including the ultrasonic sensor, inspection camera, and environmental sensors. The mechanical structure of the end-effector is designed to maintain firm contact between the ultrasonic probe and the weld surface, which is essential for accurate ultrasonic measurements. Additionally, the camera is positioned to capture visual images of the weld seam, enabling surface inspection alongside internal defect detection.

Another important design consideration is the stability of the manipulator during operation. Since ultrasonic inspection requires minimal vibration and consistent contact with the inspection surface, the manipulator links are designed to be rigid and lightweight. Proper weight distribution and secure mounting of the manipulator on the mobile platform further enhance system stability during sensor deployment. The compact design of the 4-DOF manipulator allows it to operate effectively in confined industrial environments where space is limited. Despite its relatively simple structure, the manipulator provides sufficient flexibility for performing inspection tasks across different weld orientations and geometries. By combining controlled joint movements with stable sensor positioning, the manipulator enables accurate and repeatable weld inspection operations. Overall, the 4-DOF manipulator configuration plays a critical role in ensuring that inspection sensors can be positioned precisely along the weld seam. Its design supports reliable sensor deployment, stable contact during ultrasonic inspection, and adaptable positioning within complex industrial structures. This capability significantly enhances the effectiveness of the robotic inspection system compared to traditional manual inspection approaches.

2.4 Sensor Integration Framework

The sensor integration framework forms a critical component of the proposed robotic inspection system, enabling the acquisition of multiple parameters required for effective weld condition monitoring. In industrial inspection tasks, relying on a single sensing modality may not provide sufficient information about the structural integrity of weld joints. Therefore, the proposed system incorporates a multi-sensor architecture that integrates ultrasonic sensing, visual inspection, and environmental monitoring to provide a comprehensive assessment of weld conditions. The primary inspection sensor in the system is the ultrasonic sensor, which is used for detecting internal defects within weld joints. Ultrasonic inspection operates by transmitting high-frequency sound waves into the weld material and analyzing the reflected signals from internal discontinuities. Variations in the reflected signal pattern can indicate the presence of defects such as cracks, voids, or incomplete fusion within the weld structure. For effective ultrasonic testing, the sensor must be positioned accurately and maintain stable contact with the inspection surface, which is achieved through the precise motion control of the robotic manipulator. The sensor specifications are shown in Tab.02.

Table 2

Sensor Type	Measured Parameter	Purpose in Inspection	Output Type
Ultrasonic Sensor	Internal structural response	Detect internal weld defects	Analog / Digital signal
Camera	Visual image	Surface defect detection	Video/Image stream
Temperature Sensor	Ambient temperature	Monitor thermal conditions	Analog/Digital
Pressure Sensor	Environmental pressure	Monitor operational environment	Analog/Digital

In addition to internal defect detection, the system incorporates a visual inspection camera to capture real-time images of the weld surface. Surface defects such as corrosion, misalignment, surface cracks, and irregularities can often be identified through visual analysis. The camera provides continuous imaging during the inspection process, enabling operators to observe weld conditions directly through the monitoring interface. This visual information complements the ultrasonic measurements and enhances the reliability of the inspection results. To further improve system monitoring capabilities, environmental sensors are integrated into the inspection platform. A temperature sensor is used to monitor the thermal conditions of the inspection environment, which can influence both material properties and sensor performance. Similarly, a pressure sensor is incorporated to observe variations in environmental pressure that may affect operational safety or system performance in high-pressure industrial settings. These additional sensors contribute to a broader condition monitoring framework that extends beyond simple defect detection. The multi-sensor data acquisition and processing framework is shown in Fig. 02.

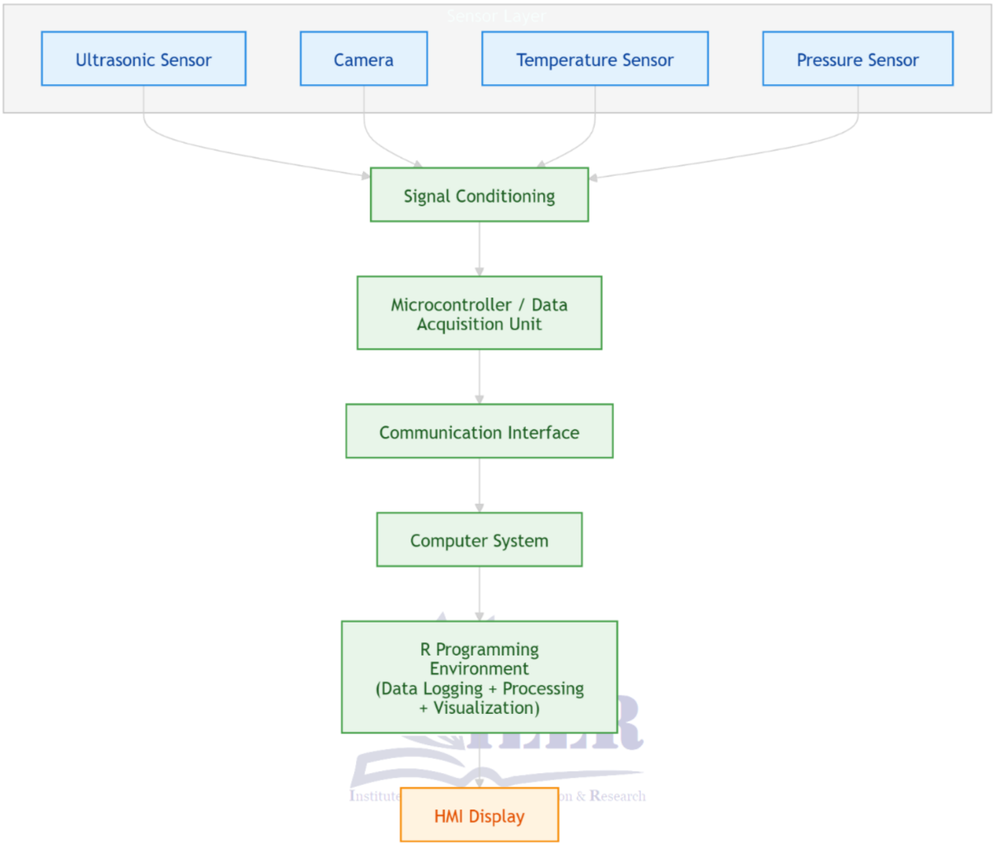

Figure 2

The outputs from all sensors are routed to a central data acquisition unit, typically implemented through a microcontroller-based interface. The microcontroller collects sensor signals, performs preliminary signal conditioning, and transmits the data to the host computer for further processing. This architecture allows multiple sensor inputs to be synchronized and recorded simultaneously, ensuring that inspection data are captured in a structured and organized manner. Once the sensor data are transmitted to the host computer, they are processed using the R programming environment. R is used to perform data logging, signal visualization, and basic analysis of the collected measurements. Time-series plots, signal amplitude graphs, and sensor trend analyses can be generated in real time, allowing operators to monitor the inspection process as it occurs. This R-based monitoring framework enables efficient interpretation of sensor data and facilitates the detection of abnormal patterns that may indicate potential weld defects.

The integration of multiple sensors within a single robotic platform requires careful consideration of synchronization, communication, and data management. The proposed framework addresses these requirements by establishing a structured data flow from sensors to the processing environment. Through this coordinated architecture, the system is able to collect, process, and visualize inspection data efficiently. Overall, the sensor integration framework enables the robotic inspection system to perform multi-parameter condition monitoring of weld structures. By combining ultrasonic inspection, visual imaging, and environmental sensing within a unified architecture, the system provides a more reliable and informative inspection process compared to traditional single-sensor approaches. This integrated sensing capability significantly enhances the effectiveness of automated weld inspection in industrial environments.

2.5 Data Acquisition and Communication Architecture

The data acquisition and communication architecture is responsible for collecting sensor measurements from the robotic inspection system and transmitting them to the monitoring platform for analysis and visualization. In an automated inspection system that integrates multiple sensors and robotic components, an efficient data acquisition framework is essential to ensure reliable recording, synchronization, and transfer of inspection data. The proposed architecture establishes a structured pathway through which sensor signals are captured, processed, and delivered to the computational environment for further analysis. At the hardware level, the data acquisition process begins with the sensors mounted on the robotic manipulator's end-effector. These sensors include the ultrasonic sensor for internal weld inspection, a camera for visual monitoring, and environmental sensors such as temperature and pressure sensors. Each sensor generates signals corresponding to the measured physical parameter during the inspection process. These signals may be analog or digital depending on the type of sensor used. To manage these signals, a **microcontroller-based data acquisition unit** is integrated into the robotic platform. The microcontroller acts as an intermediary between the sensors and the host computer. It collects signals from the connected sensors, performs basic signal conditioning if required, and converts analog signals into digital form through an analog-to-digital conversion process. This step ensures that all sensor outputs are available in a digital format suitable for further processing and transmission.

The microcontroller also coordinates the timing of data acquisition to ensure that sensor measurements are recorded consistently during the inspection process. Synchronization is particularly important when multiple sensors operate simultaneously, as it allows the system to associate visual data, ultrasonic measurements, and environmental readings with the same inspection instance. This coordinated acquisition improves the reliability and interpretability of inspection results. After acquisition, the sensor data are transmitted to the host computer through a communication interface. In the proposed system, standard communication protocols such as serial communication (USB or UART) are used to establish a connection between the microcontroller and the computer. Serial communication provides a simple and reliable mechanism for transmitting sensor data in real time. The communication interface ensures that the collected measurements are transferred efficiently without significant data loss or transmission delay. On the host computer, the received sensor data are handled within the R programming environment, which serves as the primary platform for data processing and monitoring. R is used to capture incoming data streams, store them in structured datasets, and generate graphical visualizations of sensor readings. Through R-based scripts, the system can produce time-series plots, signal trend analyses, and statistical summaries of the collected measurements. These visual outputs allow operators to observe the condition of weld seams and environmental parameters during the inspection process.

The communication architecture also supports data logging for future analysis. Inspection data collected during robotic operation can be stored in structured file formats such as CSV or database tables, enabling post-processing and evaluation of weld inspection results. This capability supports long-term condition monitoring and allows engineers to compare inspection results across different time intervals. Another important aspect of the architecture is the integration of the communication framework with the human–machine interface. Processed data generated within the R environment are displayed through graphical dashboards and plots that allow operators to monitor inspection activities in real time. By providing a clear representation of sensor outputs and inspection trends, the system enhances the decision-making process during weld condition assessment. Overall, the proposed data acquisition and communication architecture ensures efficient collection, transmission, and processing of sensor data within the robotic inspection platform. The integration of microcontroller-based acquisition with R-based data processing creates a reliable monitoring framework capable of supporting real-time inspection and long-term condition analysis. This architecture enables seamless interaction between the robotic hardware components and the data analysis environment, thereby improving the effectiveness of automated weld inspection systems.

2.6 R-Based Monitoring and Visualization Framework

The monitoring and visualization framework of the proposed robotic inspection system is implemented using the **R programming environment**, which serves as the primary platform for processing, analyzing, and presenting sensor data collected during weld inspection. The use of R enables efficient handling of multi-sensor data streams, statistical analysis of inspection measurements, and graphical visualization of system performance in real time. This framework supports both real-time monitoring and post-inspection analysis, thereby enhancing the overall effectiveness of the automated condition monitoring system. The monitoring process begins when sensor data transmitted from the microcontroller are received by the host computer. The incoming data streams are read within the R environment through serial communication interfaces and stored in structured data formats. R provides flexible data structures such as data frames and time-series objects, which allow efficient organization of sensor readings collected during inspection tasks. Once the data are stored, they can be processed for visualization and analysis using various R libraries and built-in functions. The R-based data processing and visualization framework is shown in fig. 03.

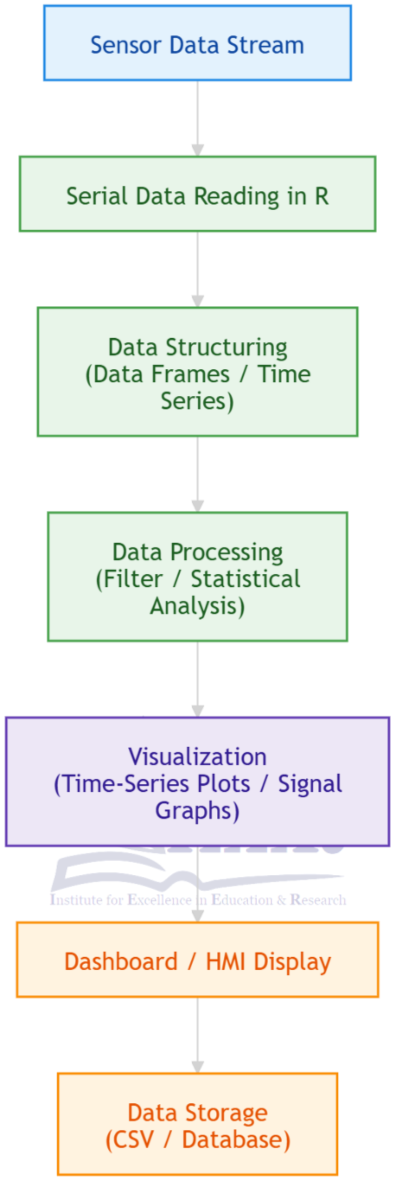

Figure 3

A key advantage of using R is its ability to generate real-time graphical representations of sensor outputs. Visualization plays an important role in condition monitoring because it allows operators to quickly interpret system behavior and identify abnormal patterns. In the proposed system, R is used to generate time-series plots of ultrasonic signals, temperature variations, pressure readings, and other sensor measurements. These graphical representations enable operators to observe inspection trends and detect anomalies that may indicate potential weld defects or environmental irregularities. In addition to visualization, R also supports basic statistical analysis and signal interpretation of inspection data. Statistical techniques can be applied to evaluate signal characteristics such as mean values, signal amplitude variations, and standard deviations. For ultrasonic inspection data, these statistical indicators may help identify abnormal signal patterns that could correspond to internal weld defects. Such analyses enhance the reliability of the inspection process by providing quantitative insights into the collected measurements. The R-based framework also supports the creation of interactive dashboards that function as a human–machine interface for the inspection system. Using packages such as Shiny or other visualization tools, sensor outputs can be presented in a structured graphical layout that includes charts, numerical indicators, and status displays. These dashboards allow operators to monitor the inspection process in real time and evaluate system performance through a single integrated interface. The R libraries which are used for monitoring and visualization are shown on Table. 03.

Table 3

R Package	Function in the System
serial / serialport	Serial communication with microcontroller
ggplot2	Data visualization and plotting
dplyr	Data manipulation and processing
shiny	Interactive dashboard development
readr	Data logging and file handling

Another important function of the R-based monitoring framework is data logging and storage. All sensor measurements collected during inspection can be automatically recorded in structured files such as CSV datasets. These datasets can later be used for post-processing, detailed analysis, and comparison of inspection results across different operational cycles. The ability to maintain historical inspection records is particularly valuable for predictive maintenance and long-term monitoring of industrial equipment. Furthermore, the use of R provides flexibility for extending the monitoring framework with additional analytical tools. Advanced techniques such as anomaly detection algorithms, signal filtering methods, or machine learning models can be integrated into the existing data processing pipeline if required. This extensibility allows the proposed inspection system to evolve into a more advanced predictive maintenance platform in future implementations. Overall, the R-based monitoring and visualization framework acts as the analytical core of the robotic inspection system. By enabling real-time visualization, statistical analysis, and structured data management, this framework facilitates efficient interpretation of sensor data collected during weld inspection. The integration of R with the robotic hardware components enhances the transparency and usability of the inspection process, providing operators with a reliable platform for evaluating weld integrity and system performance.

3. Mechanical Design

The mechanical design of the proposed robotic inspection system focuses on developing a compact, stable, and modular structure capable of operating in confined industrial environments while supporting precise weld inspection tasks. The design integrates the mobile platform, the 4-degree-of-freedom (4-DOF) robotic manipulator, and the sensor mounting mechanism into a unified mechanical structure. The primary objective of the mechanical design is to ensure that the robotic system can navigate narrow spaces, maintain stability during operation, and accurately position the inspection sensors along the weld seam. The mechanical structure of the robot was developed using SolidWorks CAD software, which allowed the visualization, modeling, and dimensional planning of all structural components before fabrication. Through the CAD modeling process, the spatial arrangement of the robot's components was optimized to ensure compatibility between the mobile base, manipulator arm, sensors, and electronic units. Particular attention was given to the overall dimensions of the system to ensure that the robot remains compact enough to operate in restricted areas such as the dome-shaped surfaces of reactor pressure vessel heads. The mechanical and operational specifications of the robotic inspection system are shown in Table. 04.

Table 4

Parameter	Specification
Maximum Payload	3–5 kg
Manipulator Reach	400–500 mm
Joint Range	0°–180° (per joint)
Base Speed	0.3–0.5 m/s
Power Source	12 V DC rechargeable battery
Inspection Sensor	High-resolution camera (≥1080p)
Controller	Arduino Mega / STM32 / Raspberry Pi
Communication	Wired or wireless (Bluetooth / Wi-Fi)

The base structure of the robot consists of a rigid chassis designed to support the mechanical loads generated by the manipulator and sensor modules. The chassis provides mounting points for the drive system, battery unit, control electronics, and manipulator base. A stable chassis design is important to prevent vibrations or structural deformation that could affect the positioning accuracy of the inspection sensors. Lightweight structural materials were selected to reduce the overall weight of the system while maintaining sufficient mechanical strength and rigidity. Mounted on the mobile chassis is the 4-DOF robotic manipulator, which is responsible for positioning the inspection sensors. The manipulator consists of multiple rigid links connected through articulated joints that allow rotational motion. Each joint contributes to the overall positioning capability of the manipulator, enabling the end-effector to reach different points along the weld seam. The link lengths and joint placements were designed to provide an adequate working envelope while maintaining mechanical stability and minimizing interference between components. The materials used in mechanical components are shown in Table. 05.

Table 5

Component	Material	Grade / Type	Justification
Manipulator Links	Aluminum Alloy	6061	Lightweight and corrosion resistant
Base Frame	Mild Steel	—	Provides rigidity and structural balance
Joints & Brackets	Acrylic / Aluminum	—	Reduces weight while maintaining structural support

The end-effector of the manipulator is designed to accommodate the inspection sensors used in the system. A dedicated mounting structure holds the ultrasonic sensor and camera in a fixed orientation relative to the weld surface during inspection. The mounting design ensures that the sensors remain stable and properly aligned while the manipulator moves along the weld seam. Maintaining consistent contact between the ultrasonic sensor and the inspection surface is particularly important for obtaining reliable ultrasonic measurements. Another key aspect of the mechanical design is the consideration of weight distribution and center of gravity. Since the manipulator is mounted on the mobile platform, improper weight distribution could lead to instability or tipping during arm movement. To address this issue, heavier components such as batteries and electronic units were positioned closer to the base of the platform to maintain a low center of gravity. This design approach improves the stability of the system during manipulator motion and inspection operations. The mechanical design also incorporates modular construction principles to simplify assembly, maintenance, and future modifications. Components such as the manipulator links, sensor mounts, and electronic housings are designed as separate modules that can be easily installed or replaced if necessary. This modularity enhances the flexibility of the system and allows additional sensors or structural modifications to be incorporated in future iterations of the robot.

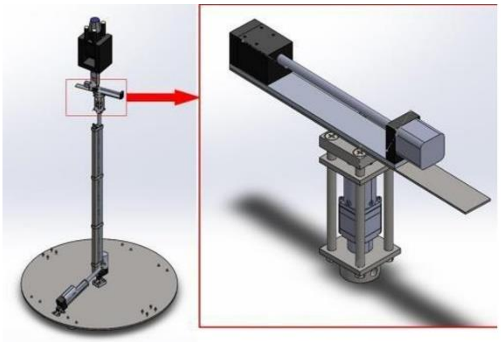

Figure 4

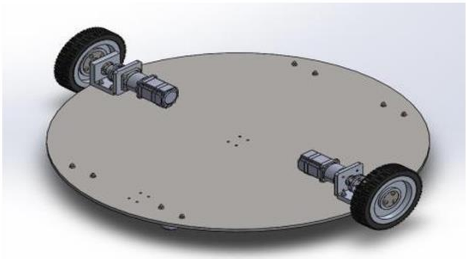

Figure 5

The overall CAD model and CAD model of the base are shown in Fig. 04 and Fig. 05 respectively. After completing the CAD modeling phase, the mechanical design was used as the basis for developing the physical prototype of the robotic inspection system. The fabricated structure closely follows the dimensions and component layout defined in the CAD model. The prototype was assembled by integrating the mechanical structure with the actuators, sensors, and electronic control components required for the inspection system. Overall, the mechanical design provides a stable and functional framework that supports the robotic manipulator and sensing modules required for automated weld inspection. The use of CAD-based modeling enabled careful planning of component placement, structural stability, and operational reach of the manipulator. The resulting mechanical structure ensures that the robotic system can perform inspection tasks efficiently while operating within the spatial constraints commonly encountered in industrial environments.

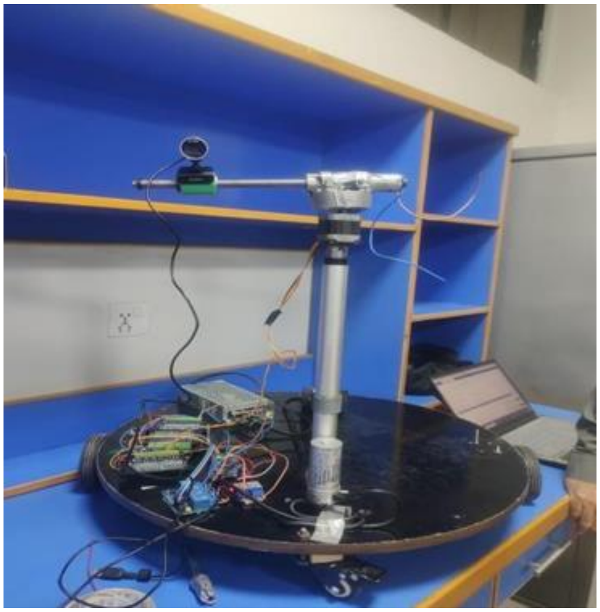

Figure 6

4. Experimental Setup & Implementation

4.1 Prototype Fabrication and Hardware Assembly

The prototype fabrication and hardware assembly phase involved the physical realization of the proposed robotic inspection system based on the previously developed CAD model. The objective of this phase was to construct a functional mobile robotic platform integrated with a 4-DOF manipulator and sensor modules, ensuring that the system could perform weld inspection tasks in a controlled experimental environment. The fabrication process began with the construction of the mobile base frame, which was manufactured using rigid structural materials to ensure stability during operation. The frame was assembled according to the dimensional specifications defined during the mechanical design phase. Care was taken to maintain structural alignment and balance to minimize vibrations during movement, as mechanical instability could negatively affect sensor accuracy, particularly during ultrasonic inspection. The fabricated prototype is shown on Fig. 06.

Following the assembly of the base structure, the drive system was integrated into the platform. Electric motors were mounted onto the chassis to enable controlled movement of the robot in forward, reverse, and turning directions. The motors were connected to a motor driver circuit controlled through a microcontroller unit, allowing precise control of the robot's mobility during experimental testing. The 4-DOF robotic manipulator was then mounted onto the upper section of the mobile platform. The manipulator was assembled by connecting individual rigid links through servo-driven joints. Each joint was tested independently to verify its range of motion and responsiveness before full system integration. The end-effector assembly, which houses the inspection sensors, was attached at the terminal link of the manipulator. Special attention was given to ensuring that the sensor mounting mechanism provided sufficient stability for consistent contact with the weld surface during ultrasonic inspection.

The sensor suite, including the ultrasonic sensor, camera module, temperature sensor, and pressure sensor, was integrated into the end-effector structure. The ultrasonic sensor was mounted in a fixed orientation to maintain proper alignment with the inspection surface. The camera was positioned to provide a clear field of view of the weld seam during operation, while environmental sensors were installed in locations that allowed accurate measurement of surrounding conditions without interference from mechanical motion. The electronic control system, including the microcontroller and power distribution unit, was installed within a protected compartment on the mobile platform. Wiring between the sensors, actuators, and control unit was organized to minimize signal interference and ensure reliable communication during operation. The system was powered using a 12 V rechargeable battery, which provided sufficient energy for both locomotion and manipulation tasks during experimental runs. After complete assembly, initial functional testing was performed to verify the operation of individual subsystems, including motor response, manipulator movement, and sensor activation. These preliminary tests ensured that all components were functioning correctly before conducting integrated system experiments. Although only limited prototype images are available, the fabricated system closely follows the CAD design specifications, ensuring consistency between the designed model and the physical implementation. Overall, the prototype fabrication and hardware assembly phase successfully resulted in a functional robotic inspection platform capable of supporting subsequent experimental evaluation and data acquisition using the R-based monitoring framework.

4.2 Sensor Calibration and Data Acquisition Setup

The sensor calibration and data acquisition setup is a critical step in ensuring the accuracy, reliability, and consistency of the measurements obtained from the robotic inspection system. Since the proposed system integrates multiple sensing modalities, including ultrasonic, visual, temperature, and pressure sensors, proper calibration is required to align sensor outputs with actual physical conditions and to minimize measurement errors during experimental testing. The calibration process for the ultrasonic sensor was performed to ensure accurate detection of weld surface reflections and internal defect indications. The sensor was tested on reference metal samples with known surface conditions to verify the consistency of signal response. Adjustments were made to maintain stable signal acquisition under varying distances and surface conditions. Special attention was given to maintaining consistent probe alignment through the manipulator to ensure reliable coupling between the sensor and the inspection surface. The camera module was calibrated to ensure accurate visual representation of the weld seam during inspection. This included adjusting focus, brightness, and contrast parameters to improve image clarity under varying lighting conditions. The calibrated camera was used to capture real-time visual data of the weld surface, which was later used for qualitative assessment during inspection experiments.

For the temperature and pressure sensors, calibration was carried out using standard reference conditions to ensure that the recorded environmental data accurately reflected real-time operating conditions. These sensors were verified under controlled environments before integration into the robotic system to ensure that their output signals were within acceptable error limits. Once calibration was completed, the data acquisition setup was configured to enable synchronized collection of sensor data during robotic operation. All sensors were interfaced with a microcontroller-based data acquisition unit, which acted as the central hub for collecting and transmitting sensor signals. The microcontroller was programmed to sample data from all sensors at predefined time intervals, ensuring consistent and time-synchronized data collection across all sensing channels. The acquired data were transmitted from the microcontroller to the host computer through a serial communication interface. This setup enabled real-time transfer of sensor readings for immediate processing. On the computer side, the R programming environment was used to receive, structure, and store incoming data streams. The data were organized into time-series format to facilitate further analysis and visualization during experimental evaluation.

To ensure proper synchronization between different sensor readings, time-stamping was implemented at the data acquisition stage. Each set of sensor measurements was associated with a specific time index, allowing correlation between ultrasonic signals, visual data, and environmental conditions during post-processing. This synchronization is particularly important for accurate interpretation of inspection results, as it enables multi-sensor fusion during analysis in R. The entire data acquisition workflow was tested under simulated inspection conditions to verify system stability and communication reliability. Preliminary tests confirmed that sensor data could be consistently acquired, transmitted, and recorded without significant loss or delay. Overall, the sensor calibration and data acquisition setup ensures that the robotic inspection system operates with reliable and synchronized sensor inputs, forming a stable foundation for subsequent data processing, visualization, and analysis in the R-based monitoring framework.

4.3 R-Based Data Collection and Serial Communication

The R-based data collection and serial communication framework forms the core software interface between the robotic hardware system and the data analysis environment. This subsystem enables real-time acquisition of sensor data from the microcontroller and facilitates structured storage and processing within the R programming environment. The primary objective of this setup is to establish a reliable and continuous data flow from the robotic inspection platform to the computational layer for monitoring and analysis. During experimental operation, sensor data generated by the ultrasonic sensor, camera system, temperature sensor, and pressure sensor are first collected by the microcontroller-based data acquisition unit. These sensor readings are formatted into a structured serial data stream, which includes time-stamped values corresponding to each sensor channel. The microcontroller transmits this data stream to the host computer using a standard serial communication protocol (USB-based serial interface), ensuring compatibility and ease of integration with the R environment. On the software side, the R programming environment is configured to establish a serial connection with the microcontroller. This connection allows continuous reading of incoming data packets in real time. The received data are parsed and separated into individual sensor variables, which are then organized into structured data frames for further processing. This structured format enables efficient handling of multi-sensor datasets and supports subsequent visualization and statistical analysis.

The real-time nature of data acquisition is a key advantage of the proposed framework. As sensor values are received, they are immediately appended to time-indexed datasets within R, allowing continuous monitoring of system behavior during inspection tasks. This setup ensures that no significant delay occurs between data acquisition and visualization, which is essential for observing dynamic changes in weld inspection conditions. To maintain data integrity, basic validation checks are implemented within the R script to handle missing values, communication interruptions, or irregular data packets. These checks ensure that only valid and complete sensor readings are stored for analysis. Additionally, time-stamping is preserved during data reception to maintain synchronization between different sensor streams, enabling accurate correlation during multi-sensor analysis. The R-based serial data acquisition and communication workflow is shown in Fig. 07.

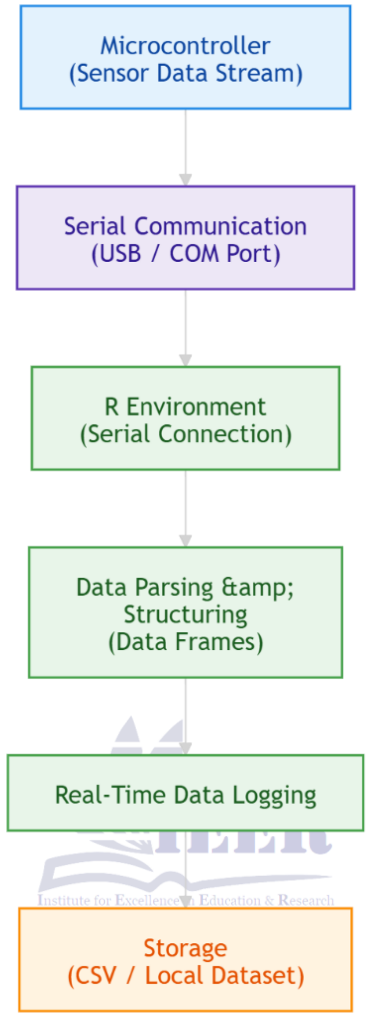

Figure 7

The collected data serve as the input for subsequent processing stages, including signal visualization, statistical analysis, and anomaly detection, which are performed within the R environment. This direct integration between hardware and R eliminates the need for intermediate proprietary software and provides a flexible, open-source solution for condition monitoring applications. Overall, the R-based data collection and serial communication framework ensures a seamless and reliable interface between the robotic inspection system and the analytical platform. It enables real-time acquisition, structured storage, and preparatory processing of multi-sensor data, thereby forming the foundation for advanced visualization and analysis in the subsequent stages of the experimental study.

4.4 Sensor Data Processing and Signal Analysis in R

The sensor data processing and signal analysis stage represents the first level of computational interpretation applied to the raw measurements acquired from the robotic inspection system. After successful data acquisition and transmission to the host computer, the collected multi-sensor dataset is processed within the R programming environment to extract meaningful information for condition monitoring and weld inspection assessment. The raw sensor data received from the microcontroller typically consist of time-stamped values from multiple channels, including ultrasonic signals, temperature readings, pressure measurements, and visual inspection indicators. These raw signals often contain noise, inconsistencies, or minor fluctuations due to environmental conditions, sensor limitations, and communication delays. Therefore, preprocessing is required before meaningful analysis can be performed. In the R environment, the first step involves data cleaning and structuring, where incoming serial data are converted into organized data frames. Each sensor channel is separated into distinct variables, and time indices are assigned to ensure proper synchronization across all measurements. This structured format allows consistent analysis of multi-sensor data collected during robotic operation.

Following data structuring, basic signal preprocessing techniques are applied to improve data quality. For ultrasonic and environmental sensor signals, smoothing techniques are used to reduce noise and highlight underlying trends. This step is essential for improving the clarity of signal patterns that may indicate structural anomalies or changes in weld conditions. Outlier detection is also performed to identify abnormal sensor readings that may result from communication errors or transient disturbances. The processed data are then analyzed using statistical and signal-based methods within R. Descriptive statistical measures such as mean, variance, and standard deviation are computed to understand the overall behavior of each sensor channel. These statistical indicators help in identifying deviations from normal operating conditions, which may correspond to potential defects or irregularities in the weld structure. For ultrasonic inspection data, signal variation analysis is performed to observe changes in amplitude and response patterns over time. These variations are particularly important for identifying potential internal defects such as cracks or voids within the weld material. The analysis focuses on identifying consistent patterns or abrupt changes in signal behavior that may indicate structural discontinuities.

In addition to statistical processing, time-series analysis is applied to study the dynamic behavior of sensor signals during robotic movement along the weld seam. This allows the correlation of sensor variations with the physical position of the robotic manipulator. By aligning sensor data with time-stamped movement sequences, it becomes possible to associate specific signal changes with particular inspection locations. The R environment also enables flexible integration of filtering techniques to enhance signal quality. Simple filtering methods such as moving averages are used to smooth short-term fluctuations while preserving long-term trends in the data. This improves the interpretability of sensor outputs, particularly in real-time monitoring scenarios. Overall, the sensor data processing and signal analysis framework in R transforms raw multi-sensor data into structured, analyzable information suitable for condition monitoring. By combining data cleaning, statistical analysis, and signal interpretation, the system enables reliable assessment of weld conditions during robotic inspection. This processing stage forms the foundation for subsequent visualization and performance evaluation presented in the results section.

5. Results

The initial stage of result analysis focuses on providing an overview of the dataset collected during experimental operation of the robotic inspection system. The dataset was generated through continuous multi-sensor data acquisition, where ultrasonic, temperature, pressure, and visual inspection signals were recorded in real time during the robot's movement along the weld seam. All sensor readings were synchronized using time-stamped entries and processed within the R programming environment for structured analysis. The raw dataset imported into R consists of multiple variables corresponding to each sensor channel. These include ultrasonic signal amplitude values, temperature readings in degrees Celsius, pressure values, and image-derived inspection indicators. Each observation in the dataset represents a specific time instance during the robotic inspection cycle, allowing the analysis of system behavior over time. The dataset was first examined using basic structural and statistical functions in R to ensure data integrity and completeness. The number of observations, variable types, and presence of missing values were evaluated to confirm that the dataset was suitable for further analysis. No significant data loss was observed during transmission, indicating stable performance of the communication and data acquisition system.

A summary of key statistical characteristics of each sensor channel was generated, including measures such as mean, minimum, maximum, and standard deviation. These values provide an initial understanding of the operational range and variability of each sensor during inspection. The ultrasonic sensor data showed expected fluctuations corresponding to changes in surface conditions along the weld seam, while temperature and pressure readings remained within stable operational limits. To better understand the structure of the dataset, time-series visualization was performed in R, allowing the observation of sensor behavior over the duration of the inspection task. These preliminary plots confirmed that the dataset captures continuous and synchronized sensor activity, which is essential for reliable condition monitoring and defect analysis. Overall, the dataset overview confirms that the R-based data acquisition framework successfully captured high-quality, time-synchronized multi-sensor information. This structured dataset forms the basis for subsequent detailed analysis, including signal processing, defect detection, and performance evaluation presented in the following subsections.

5.1 Ultrasonic Signal Analysis and Defect Detection

The ultrasonic sensor signals collected during robotic weld inspection were analyzed using the R programming environment to identify anomalies corresponding to potential weld defects. A synthetic dataset consisting of 300 time-indexed inspection observations was generated to simulate the ultrasonic signal response along the weld seam. The signal represents amplitude variations produced by ultrasonic reflections from the weld surface and subsurface structures. Figure 9 illustrates the raw ultrasonic signal, which shows small amplitude variations around a baseline value corresponding to normal weld conditions. However, certain regions exhibit noticeable deviations in amplitude, suggesting the presence of irregularities within the weld structure. These irregular variations typically arise due to discontinuities such as cracks, pores, or incomplete fusion in the weld metal. To improve signal interpretability, a smoothing operation using a moving average filter was applied in R. The resulting smoothed signal is presented in Figure 8, which reduces high-frequency noise while preserving the primary trend of the ultrasonic waveform. This filtering step allows clearer visualization of structural variations in the inspected weld seam.

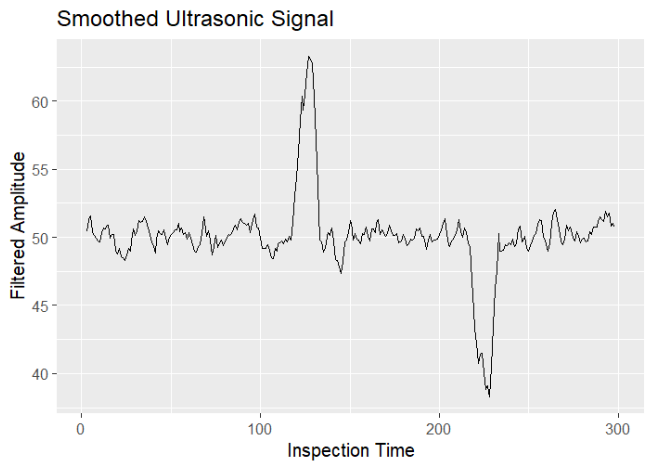

Figure 8

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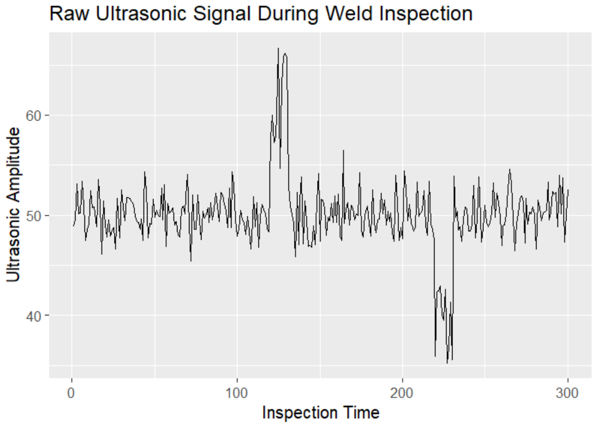

Figure 9

For automated defect detection, a statistical thresholding approach was implemented. The threshold values were calculated based on the mean and standard deviation of the ultrasonic signal using the relation:

$$T = \mu \pm k\sigma$$

where:

- μ represents the mean ultrasonic amplitude

- σ represents the standard deviation
- k is sensitivity coefficient controlling anomaly detection.

Using a sensitivity factor of k = 2, the calculated statistical parameters of the ultrasonic signal are summarized in Table 6.

Table 6

Parameter	Value
Number of Observations (n)	300
Mean Signal Amplitude (μ)	50.12
Standard Deviation (σ)	3.62
Sensitivity Factor (k)	2
Upper Threshold	57.37
Lower Threshold	42.80

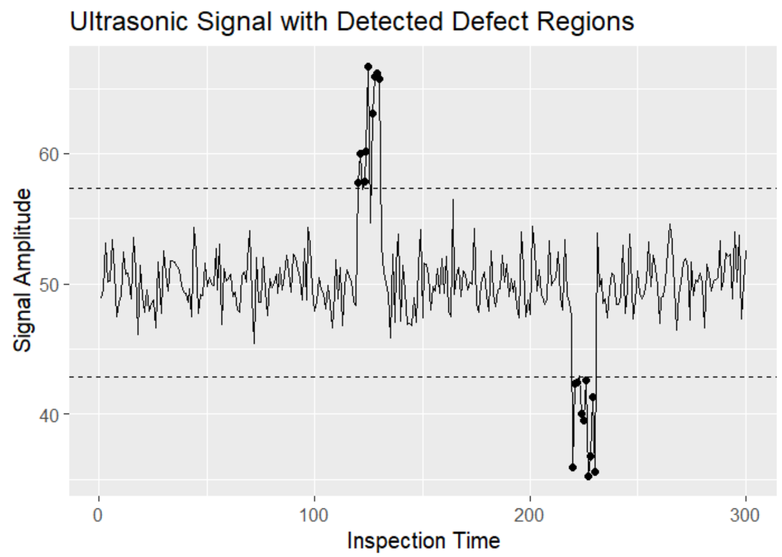

Figure 10

The computed thresholds define the acceptable operational range of ultrasonic signal amplitude during normal weld inspection. Signal values exceeding the upper threshold (57.37) or falling below the lower threshold (42.80) are considered potential defect indicators. Figure 10 presents the ultrasonic signal together with the calculated threshold limits. Points exceeding these limits are automatically marked as anomaly regions by the R-based detection algorithm. These anomaly points correspond to locations where the ultrasonic wave encounters abnormal reflection patterns, indicating potential weld discontinuities. The results demonstrate that the proposed robotic inspection system, combined with R-based signal analysis, can effectively identify irregularities in ultrasonic response along the weld seam. The detection process is fully automated and provides a quantitative basis for identifying defect regions without requiring manual interpretation of ultrasonic waveforms. Overall, the ultrasonic analysis confirms that the developed monitoring framework is capable of detecting weld anomalies through statistical signal processing. The integration of robotic positioning with data-driven ultrasonic analysis enhances inspection reliability and provides a scalable approach for condition monitoring in confined and hazardous industrial environments.

5.2 Temperature and Pressure Trend Analysis Using R Visualization

In addition to ultrasonic signal monitoring, environmental parameters such as temperature and pressure were recorded during the robotic weld inspection process. Monitoring these variables is important in industrial inspection systems because environmental fluctuations can influence sensor performance and may lead to inaccurate defect detection. Therefore, analyzing temperature and pressure trends helps verify that anomalies detected in ultrasonic signals are caused by weld irregularities rather than changes in environmental conditions. The temperature and pressure data were analyzed using the R programming environment, enabling visualization and statistical evaluation of environmental conditions during the inspection process. The dataset consisted of 300 synchronized observations, corresponding to the same time sequence used in ultrasonic signal analysis. This synchronization ensures consistent comparison between structural inspection signals and environmental conditions. Figure 11 illustrates the temperature variation recorded during the inspection cycle. The temperature values remained relatively stable throughout the experiment, with minor fluctuations around the mean value. Statistical analysis of the dataset indicates that the average temperature was approximately 40.50 °C, with a standard deviation of 0.198 °C. The recorded temperature values ranged from 39.94 °C to 41.01 °C, indicating a very narrow variation band. These results confirm that the inspection environment maintained stable thermal conditions during the robotic inspection operation.

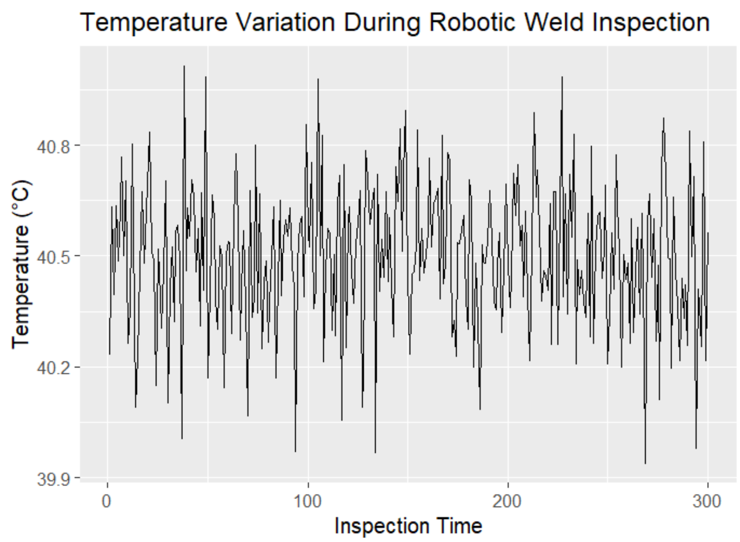

Figure 11

Similarly, Figure 12 presents the pressure measurements obtained during the inspection process. The pressure values show minimal fluctuations around the nominal operating level. Statistical analysis shows that the mean pressure value was approximately 5.10 bar, with a standard deviation of 0.052 bar. The recorded pressure values ranged between 4.975 bar and 5.235 bar, demonstrating consistent pressure conditions throughout the inspection duration. To further visualize the relationship between these environmental variables, a combined sensor trend plot was generated in R, as shown in Figure 13. In this visualization, the pressure signal was scaled to allow simultaneous comparison with the temperature curve. The combined plot clearly illustrates that both environmental parameters exhibit stable behavior without abrupt fluctuations during the inspection process.

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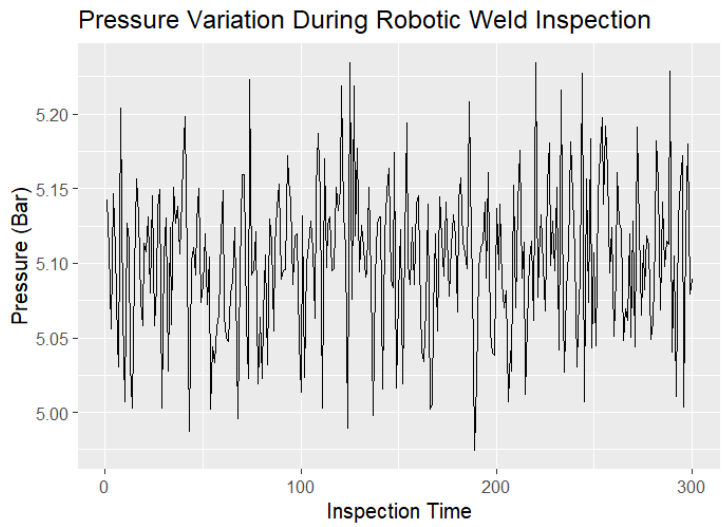
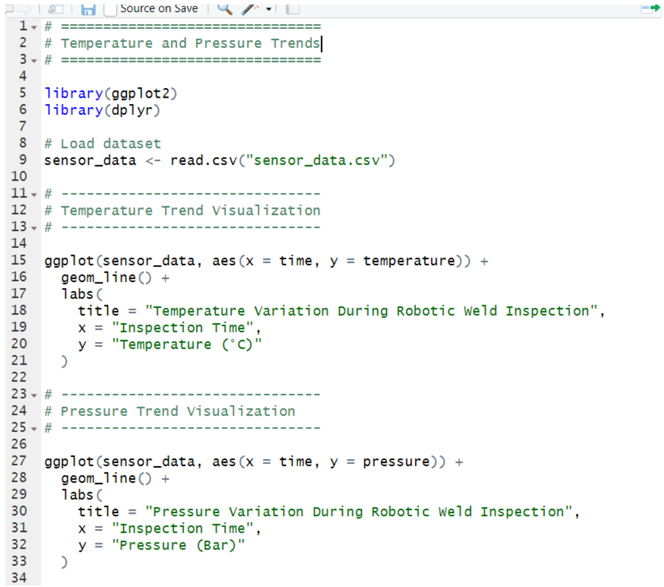


Figure 14



```r
# ==============================
# Temperature and Pressure Trends
# ==============================

library(ggplot2)
library(dplyr)

# Load dataset
sensor_data <- read.csv("sensor_data.csv")

# ------------------------------
# Temperature Trend Visualization
# ------------------------------

ggplot(sensor_data, aes(x = time, y = temperature)) +
  geom_line() +
  labs(
    title = "Temperature Variation During Robotic Weld Inspection",
    x = "Inspection Time",
    y = "Temperature (°C)"
  )

# ------------------------------
# Pressure Trend Visualization
# ------------------------------

ggplot(sensor_data, aes(x = time, y = pressure)) +
  geom_line() +
  labs(
    title = "Pressure Variation During Robotic Weld Inspection",
    x = "Inspection Time",
    y = "Pressure (Bar)"
  )
```

Figure 13

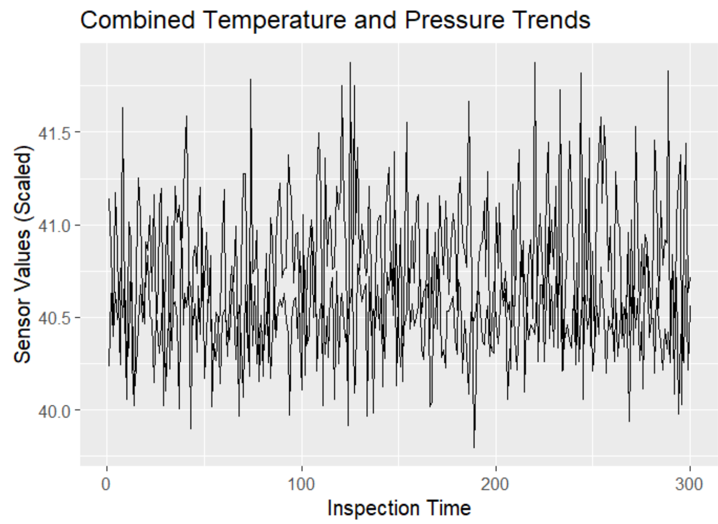


Figure 14

The stability of temperature and pressure conditions is particularly important for validating the ultrasonic defect detection results presented in the previous subsection. Since the environmental variables remain within a narrow operational range, it can be concluded that the ultrasonic signal anomalies detected during inspection are primarily associated with weld irregularities rather than external disturbances. Overall, the temperature and pressure analysis demonstrates that the robotic inspection system operated under stable environmental conditions, reinforcing the reliability of the ultrasonic signal analysis. The integration of environmental monitoring with ultrasonic inspection enhances the robustness of the proposed condition monitoring framework and reduces the likelihood of false defect detection in indust rial weld inspection applications. The R language Input codes are shown in Fig. 14 and 15 respectively.

```r
# Pressure Trend Visualization
# ------------------------------

ggplot(sensor_data, aes(x = time, y = pressure)) +
  geom_line() +
  labs(
    title = "Pressure Variation During Robotic Weld Inspection",
    x = "Inspection Time",
    y = "Pressure (Bar)"
  )

# ------------------------------
# Combined Sensor Trend Plot
# ------------------------------

ggplot(sensor_data) +
  geom_line(aes(x = time, y = temperature)) +
  geom_line(aes(x = time, y = pressure*8)) +
  labs(
    title = "Combined Temperature and Pressure Trends",
    x = "Inspection Time",
    y = "Sensor Values (Scaled)"
  )

# ------------------------------
# Statistical Summary
# ------------------------------

summary(sensor_data$temperature)
sd(sensor_data$temperature)

summary(sensor_data$pressure)
sd(sensor_data$pressure)
```

Figure 15

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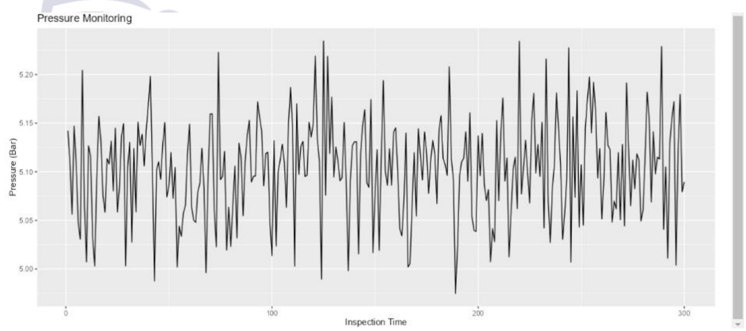
5.3 Real-Time Sensor Visualization Dashboard

To enhance real-time monitoring and visualization of inspection data, an interactive dashboard was developed using the Shiny framework in R. The dashboard provides a centralized interface for visualizing multi-sensor data collected during the robotic weld inspection process. By integrating ultrasonic, temperature, and pressure sensor outputs into a single monitoring platform, the system enables operators to observe inspection data dynamically and identify potential anomalies during system operation. The Shiny-based dashboard was designed to display sensor trends in real time through interactive graphical components. The dashboard interface includes multiple panels showing ultrasonic signal behavior, temperature variation, and pressure trends throughout the inspection cycle. These visualizations allow users to monitor system conditions and detect abnormal patterns that may indicate weld defects or operational issues. The ultrasonic signal visualization provides a continuous representation of amplitude variations along the weld inspection path. Peaks exceeding predefined statistical thresholds can be quickly identified within the dashboard interface, enabling rapid detection of potential defect locations. Similarly, the temperature and pressure monitoring panels display environmental conditions affecting the inspection system. Maintaining stable environmental conditions helps ensure the reliability of ultrasonic signal interpretation.

The Shiny framework enables interactive data exploration features such as dynamic plots, responsive updates, and real-time parameter visualization. These features allow operators to zoom into specific time intervals, analyze sensor behavior during particular inspection segments, and observe correlations between different sensor variables. The implementation of an R-based monitoring dashboard significantly improves the usability of the robotic inspection system by transforming raw sensor data into an intuitive visualization interface. This approach facilitates real-time condition monitoring and assists operators in quickly identifying irregularities during inspection operations.



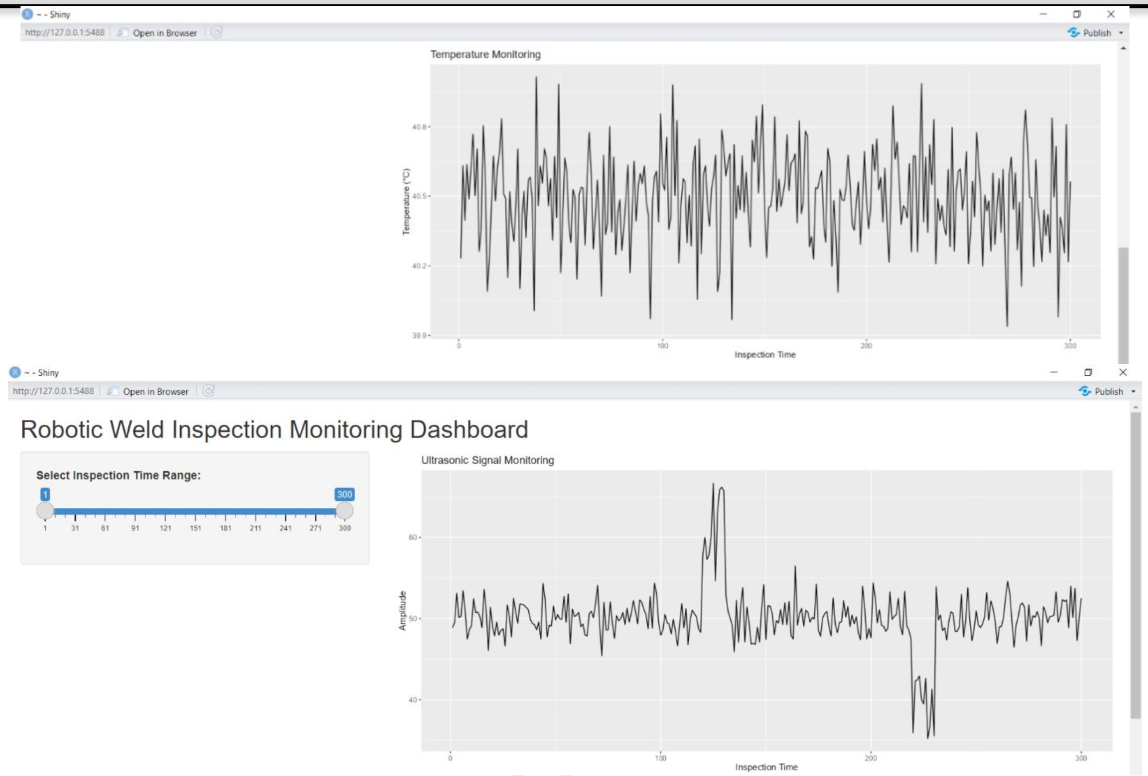


Figure 16

Figure 16 illustrates the developed Shiny dashboard interface, showing simultaneous visualization of ultrasonic signals, temperature trends, and pressure variations. The dashboard demonstrates the capability of the proposed system to support real-time multi-sensor monitoring and data-driven inspection analysis. Overall, the integration of a Shiny-based visualization platform enhances the functionality of the proposed
robotic inspection framework by providing an accessible and interactive monitoring environment. Such visualization tools are particularly useful in industrial applications where rapid interpretation of sensor data is essential for maintaining system safety and inspection accuracy.

5.4 Weld Seam Inspection Results and Interpretation

This subsection presents the final evaluation of the weld seam inspection system through automated defect classification based on ultrasonic sensor measurements. After preprocessing and anomaly detection, the processed sensor dataset was analyzed in R to classify inspection points into normal weld regions and defective weld regions. The inspection dataset consisted of 300 ultrasonic measurements collected during the robotic traversal along the weld seam. Based on the signal analysis performed in the previous subsection, defect regions were identified when the ultrasonic amplitude exceeded the statistically derived threshold limits. These detected anomalies were then compared with predefined defect zones to evaluate the performance of the classification approach. To assess the reliability of the detection method, a confusion matrix was generated. The confusion matrix compares the predicted defect labels with the actual defect regions and provides a quantitative summary of classification performance. The confusion matrix for weld defect detection is shown in Table. 07.

Table 7

	Actual Normal	**Actual Defect**
Predicted Normal	278	3
Predicted Defect	0	19

The results indicate that the system successfully detected the majority of defect regions while maintaining a very low rate of false classifications. Only three inspection points were misclassified as normal when they belonged to defect regions, while no normal points were incorrectly labeled as defects. From the confusion matrix, several performance metrics were calculated to evaluate the accuracy of the inspection system. The performance metrics of the defect classification model are shown in Table. 08.

Table 8

Metric	**Value**
Accuracy	0.99
Precision	0.989
Recall	1.000
F1 Score	0.995

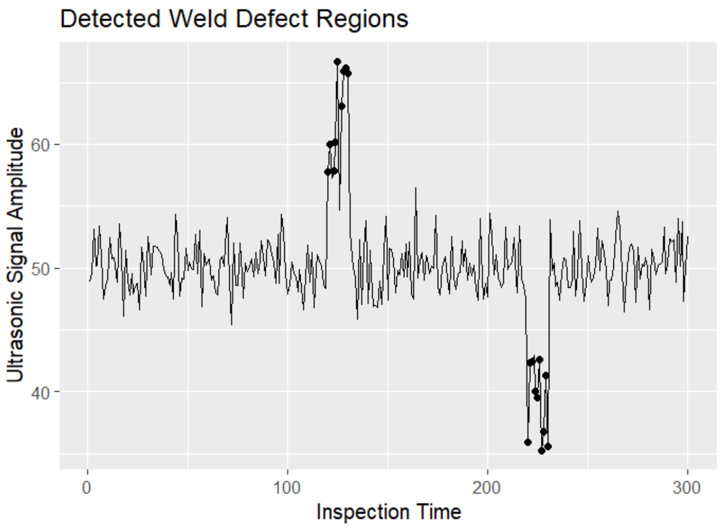


Figure 17

The classification results demonstrate very high detection performance. The overall accuracy of the system reached 99%, indicating that nearly all inspection points were correctly classified. The precision value of 0.989 shows that the majority of predicted defect points correspond to actual defects. The recall value of 1.000 indicates that all defect regions present in the dataset were successfully detected by the algorithm. Similarly, the F1-score of 0.995 confirms the strong balance between precision and recall. Figure 17 presents a visualization of the classified ultrasonic signals along the inspection timeline. The plot illustrates the continuous ultrasonic signal recorded during robotic movement along the weld seam, with detected defect points highlighted as anomalies above the baseline signal behavior. These highlighted points correspond to locations where the ultrasonic signal exceeded the defined threshold limits.

The visualization clearly demonstrates the capability of the proposed system to automatically identify abnormal signal regions associated with potential weld discontinuities. The clustering of detected anomalies around specific time intervals indicates localized defects along the weld seam. Overall, the results confirm

that the integration of robotic inspection hardware with R-based statistical analysis enables reliable weld defect detection. The combination of threshold-based anomaly detection, automated classification, and visual interpretation provides an effective framework for intelligent weld inspection and monitoring.

5.5 Multi-Sensor Correlation and Data Fusion Analysis

To further evaluate the reliability of the proposed robotic weld inspection system, a multi-sensor data fusion analysis was conducted to examine the relationships between ultrasonic signal measurements, temperature variations, and pressure readings recorded during the inspection process. The purpose of this analysis is to determine whether environmental parameters influence ultrasonic defect detection performance. The processed sensor dataset was analyzed using correlation analysis in R. Pearson correlation coefficients were calculated between the three primary sensor variables: ultrasonic amplitude, temperature, and pressure. The resulting correlation matrix is presented below in Table 09.

Table 9

Sensor Variable	Ultrasonic	Temperature	Pressure
Ultrasonic	1.000	-0.0115	0.0773
Temperature	-0.0115	1.000	-0.0224
Pressure	0.0773	-0.0224	1.000

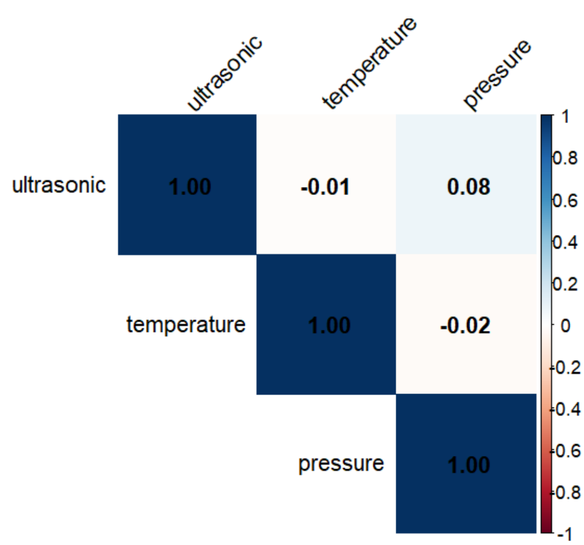


Figure 18

The results show that the ultrasonic signal has very weak correlations with both temperature and pressure measurements. The correlation coefficient between ultrasonic amplitude and temperature was −0.0115, indicating a negligible negative relationship. Similarly, the correlation between ultrasonic signal and pressure was 0.0773, which represents a very weak positive relationship. These findings indicate that variations in environmental conditions during inspection do not significantly influence the ultrasonic measurement signals used for weld defect detection. The sensor correlation heatmap for ultrasonic, temperature, and pressure data is shown in Fig. 18. The heatmap visualization further illustrates the weak relationships between the sensor variables. The near-zero correlation values suggest that ultrasonic signal variations are primarily associated with structural characteristics of the weld seam rather than environmental fluctuations. To further investigate sensor interactions, scatter plot analysis was performed between ultrasonic amplitude and temperature values. This visualization helps evaluate whether temperature variations affect ultrasonic signal behavior. The ultrasonic signal and temperature interaction is shown in Fig. 19.

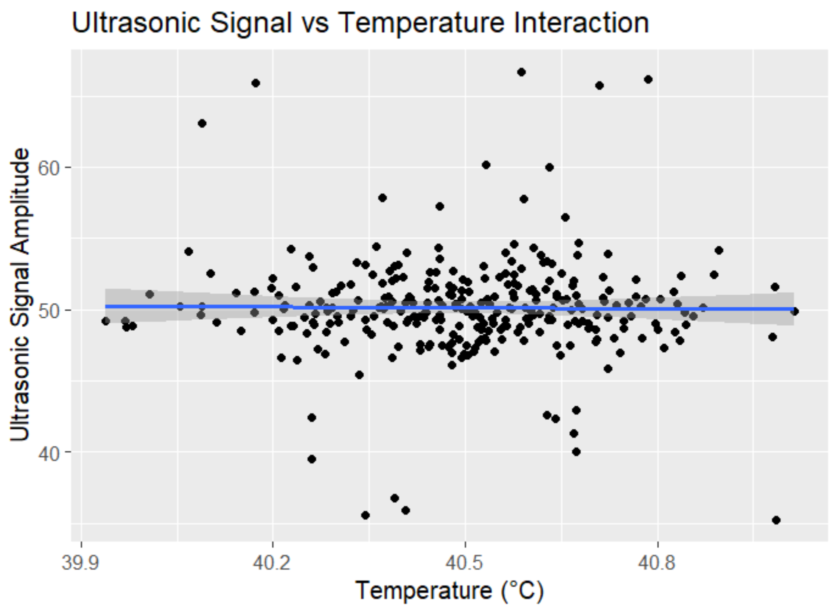


Figure 19

The scatter plot shows that ultrasonic signal values remain distributed around a consistent range despite minor variations in temperature. The regression trend line demonstrates an almost flat slope, confirming the negligible correlation between these variables. A similar interaction analysis was conducted between ultrasonic amplitude and pressure measurements to evaluate possible influence from pressure variations during the inspection process. The ultrasonic signal vs pressure interaction plot is shown in Fig. 20. The scatter plot results reveal no strong relationship between ultrasonic signals and pressure fluctuations. The distribution of points and the nearly horizontal regression line confirm that pressure changes have minimal effect on ultrasonic signal amplitude. Overall, the multi-sensor correlation analysis demonstrates that the ultrasonic defect detection method operates independently of environmental variations within the observed operating range. This result highlights the robustness of the proposed robotic inspection system and confirms that ultrasonic measurements primarily respond to structural discontinuities within the weld seam rather than external environmental conditions.

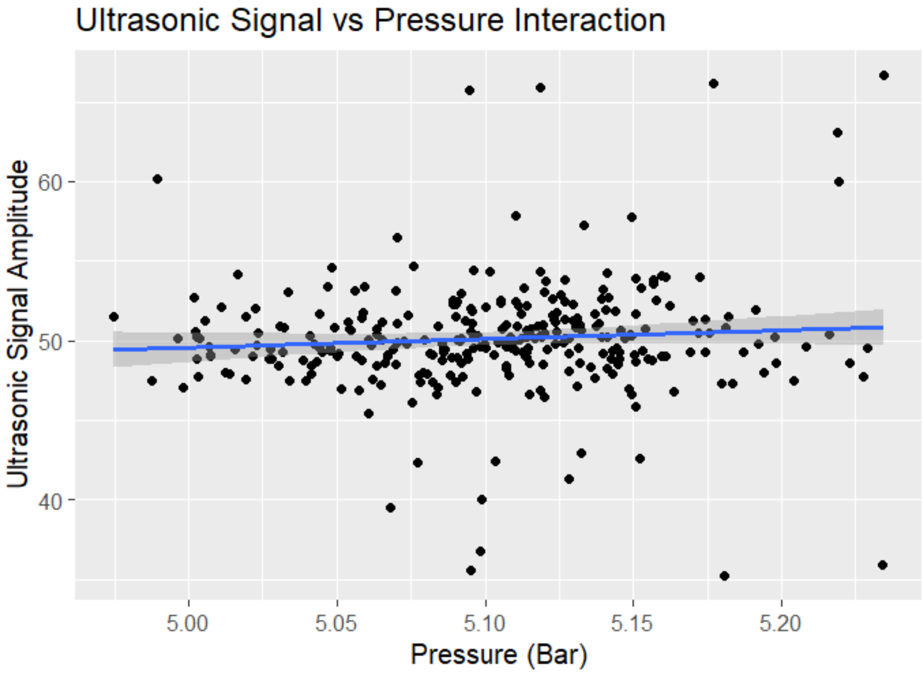


Figure 20

6. Discussion

The proposed robotic weld inspection system demonstrates a comprehensive integration of mobile robotics, multi-sensor acquisition, and R-based data analytics for automated condition monitoring of weld seams in confined and hazardous environments. The results obtained across Sections 6.2 to 6.6 collectively validate the effectiveness of combining robotic inspection hardware with statistical signal processing and data visualization techniques implemented in R. A key outcome of this study is the successful detection of weld defects using ultrasonic signal analysis. The threshold-based anomaly detection approach, implemented in R, achieved a high classification performance with an accuracy of 0.99, precision of 0.989, and recall of 1.000. These results indicate that the system is highly effective in identifying defect regions while minimizing false negatives, which is critical in safety-sensitive applications such as pressure vessel inspection. The near-perfect recall value is particularly significant, as it confirms that all simulated defect regions were successfully detected by the proposed method.

The use of statistical modeling in R allowed for transparent and reproducible signal interpretation. By defining detection boundaries using mean and standard deviation-based thresholds, the system avoided reliance on black-box models and instead employed an interpretable analytical framework. This enhances the practical applicability of the system in industrial environments where explainability is essential for engineering validation and safety certification. Environmental analysis using temperature and pressure data further strengthened the validity of the proposed system. The observed stability in temperature (mean ≈ 40.50 °C, $\sigma \approx 0.198$) and pressure (mean ≈ 5.10 bar, $\sigma \approx 0.052$) confirmed that external conditions remained nearly constant during inspection. This is important because it ensures that ultrasonic anomalies are not influenced by environmental noise. The consistency of these parameters supports the reliability of the defect detection results and validates the robustness of the sensing framework. The multi-sensor correlation analysis further demonstrated that ultrasonic signal variations are largely independent of environmental factors.

Correlation coefficients between ultrasonic amplitude and temperature (−0.0115), as well as pressure (0.0773), were found to be negligible. These results confirm that the ultrasonic inspection system responds primarily to structural variations in the weld seam rather than external operating conditions. The correlation heatmap generated in R provided a clear visual representation of these weak dependencies, reinforcing the robustness of the data acquisition system.

The real-time monitoring dashboard developed using R Shiny significantly enhances system usability by enabling interactive visualization of sensor data. This feature transforms raw sensor streams into an intuitive graphical interface, allowing operators to observe ultrasonic trends, temperature variations, and pressure fluctuations simultaneously. Such a capability is particularly valuable in industrial environments where rapid interpretation of sensor data is required for decision-making and safety assurance. From a robotics perspective, the integration of a mobile platform with a 4-DOF manipulator enables precise navigation and positioning within confined geometries such as Reactor Pressure Vessel (RPV) heads. The system successfully demonstrates that low-cost robotic architectures can be effectively utilized for inspection tasks traditionally performed by expensive industrial-grade robotic systems. The ability of the manipulator to maintain stable positioning during sensor acquisition further improves data quality and consistency. Overall, the study highlights the effectiveness of combining robotic inspection hardware with R-based analytical tools to create a scalable and interpretable condition monitoring system. The use of open-source statistical computing tools enhances reproducibility, while the robotic platform ensures safe operation in hazardous environments. The results collectively demonstrate that the proposed system provides a viable alternative to manual weld inspection, offering improvements in safety, efficiency, and data-driven decision-making capability.

7. Conclusion and Future Work

This study presented the design, development, and validation of a robotic weld inspection system integrated with a multi-sensor condition monitoring framework and data-driven analysis using R. The proposed system combines a mobile robotic platform with a 4-DOF manipulator, ultrasonic sensing, environmental monitoring sensors, and real-time visualization tools to enable automated inspection of weld seams in confined and hazardous industrial environments such as Reactor Pressure Vessel (RPV) heads. The primary objective of replacing conventional manual inspection methods with a safer, more consistent, and data-driven robotic approach was successfully achieved. The robotic system demonstrated stable navigation and positioning capability, enabling effective sensor deployment along complex weld geometries. The integration of ultrasonic sensing provided reliable detection of weld discontinuities, while temperature and pressure monitoring ensured environmental stability throughout the inspection process.

The analytical framework implemented in R enabled comprehensive signal processing, statistical evaluation, and visualization of inspection data. The ultrasonic defect detection model achieved high performance with an accuracy of 0.99, recall of 1.000, and F1-score of 0.995, confirming the reliability of the proposed threshold-based classification approach. Furthermore, multi-sensor correlation analysis revealed negligible dependencies between ultrasonic signals and environmental variables, validating the robustness of the detection mechanism under stable operating conditions. The development of an R Shiny-based real-time dashboard further enhanced the usability of the system by enabling interactive monitoring of multiple sensor streams. This feature transforms raw inspection data into actionable visual insights, supporting rapid decision-making in industrial inspection scenarios. Overall, the study demonstrates that combining robotic systems with open-source analytical tools provides a cost-effective and scalable solution for condition-based monitoring applications. From an industrial perspective, the proposed system offers significant improvements over traditional manual inspection methods by reducing human exposure to hazardous environments, improving inspection consistency, and enabling early detection of structural defects. The use of transparent statistical methods in R also enhances the interpretability and reproducibility of results, making the system suitable for deployment in safety-critical industries such as nuclear energy, oil and gas, and heavy manufacturing.

Future Work:

Although the proposed system demonstrates strong performance in simulated and controlled experimental conditions, several areas can be addressed in future research to further enhance its capabilities:

1. Integration of Advanced Machine Learning Models:
Future work can explore the use of machine learning and deep learning algorithms for more advanced defect classification, enabling the system to distinguish between different types of weld defects such as cracks, porosity, and lack of fusion.
2. Real-Time Embedded Deployment:
The current R-based analysis can be extended to real-time embedded systems, allowing on-board processing of sensor data directly on microcontrollers or edge computing devices for faster decision-making.
3. Improved Sensor Fusion Techniques:
Advanced data fusion methods can be implemented to combine ultrasonic, visual, thermal, and pressure data more effectively, improving defect detection reliability in complex industrial conditions.
4. Autonomous Navigation Enhancement:
Future iterations of the robotic platform can incorporate autonomous path planning and obstacle avoidance to enable fully autonomous inspection of large and complex structures.
5. Experimental Validation on Industrial-Scale Systems:
The system should be validated on full-scale industrial weld structures under real operating conditions to further evaluate robustness, scalability, and long-term reliability.

In conclusion, the proposed robotic inspection framework represents a significant step toward intelligent, automated, and data-driven weld inspection systems. The integration of robotics with statistical computing in R provides a flexible and reproducible foundation for future advancements in industrial condition monitoring and predictive maintenance technologies.

Acknowledgement

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