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Three-Arm Robotic Diagnostic Coordination Using Artificial Neural Network-Based Decision Support

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Abstract **The growing demand for smart healthcare systems and increasing burden on healthcare professionals have necessitated the need for autonomous diagnostic technologies that can facilitate real-time clinical decision-making. Current robotic diagnostic systems are often limited to discrete tasks, including sensing, monitoring, and diagnostic support. This results in limited coordination, transparency, and decision-making capabilities. The aim of the proposed method is to design a three-arm diagnostic robot with Artificial Neural Network (ANN) intelligence to improve healthcare support. The proposed framework includes dedicated robotic arms for sensing, visualization, and diagnostic tool manipulation, along with a coordinated communication architecture. A decision-support module based on an ANN gathers diagnostic information from the different subsystems of a robot and offers intelligent diagnostic evaluations. A seven-axis coordination approach is implemented to improve the synchronous performance of robotic components and to reduce the operational liabilities during diagnostic operations. The proposed framework was evaluated with four scenarios, and the performance was assessed in terms of transparency, coordination efficiency, association error, diagnostic accuracy, sensing latency, and communication delay. The experimental results showed that the proposed system achieved a diagnosis accuracy of 93% versus 71% for the baseline method. Moreover, the framework achieved 93% of transparency rate, 85% of coordination efficiency, 12% of reduction of association error, a 40 ms sensing latency, and a 15 ms communication delay. Statistical analysis reported consistent performance with deviation values of 1.2%, 1.7%, and 1.3% for arm coordination, visualization, and diagnostic tool management, respectively. The results confirm that the combination of ANN-based decision support and synchronized multi-arm robotic work can significantly improve the diagnostic efficiency and the operational reliability. The proposed architecture provides a strong foundation for future intelligent healthcare systems and enables the development of autonomous robotic diagnostics for advanced medical applications.**

Keywords **Artificial Intelligence (AI); Medical robots; Diagnosis; Neural networks**.

I. Introduction

Modern healthcare systems are under significant strain due to the growing demand for efficient healthcare services and the increasing prevalence of chronic diseases and aging populations [1]. Medical workers often need to monitor different physiological parameters, perform repeated diagnostic tests, and provide constant supervision of patients. These increases workload and reduces work efficiency [2],[3],[4]. The need for remote healthcare services and real-time medical assistance has emphasized the need for intelligent technologies that can allow autonomous diagnostic procedures. Robotic healthcare systems are viable options for improving diagnostic accuracy, reducing human interaction, and enhancing patient care [5],[6]. The combination of artificial intelligence and medical robotics allows autonomous decision-making, continuous monitoring, and advanced diagnostic assistance. Thus, robotic diagnostic systems are an important research area in future

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healthcare environments [7],[8],[9]. Even with significant advancements in healthcare technology, diagnostic procedures are still heavily reliant on manual involvement, continuous patient monitoring, and the teamwork of various clinical resources [10],[11]. The increased complexity of healthcare management, higher patient-to-clinician ratios, and extended diagnostic delays necessitated the development of intelligent robotic devices for autonomous diagnostic processes. Therefore, the evolution of synchronized robotic systems with artificial intelligence has become a prominent research field for next-generation healthcare applications. In the proposed method, the three-arm robot can automatically provide assistance to hospital wards; therefore, it is possible to continuously monitor the current physiological conditions there. Due to this type of automatic procedure, it is possible to reduce the manual working functionalities of the clinician. Further, the designed robot can perform diagnostic activities that include various inspections based on the input image set as indicated in Fig. 1. hence as compared to a conventional robotic model, the three-arm robot can use two arms for sensing and imaging, whereas the other arm can be used for diagnostic operations.

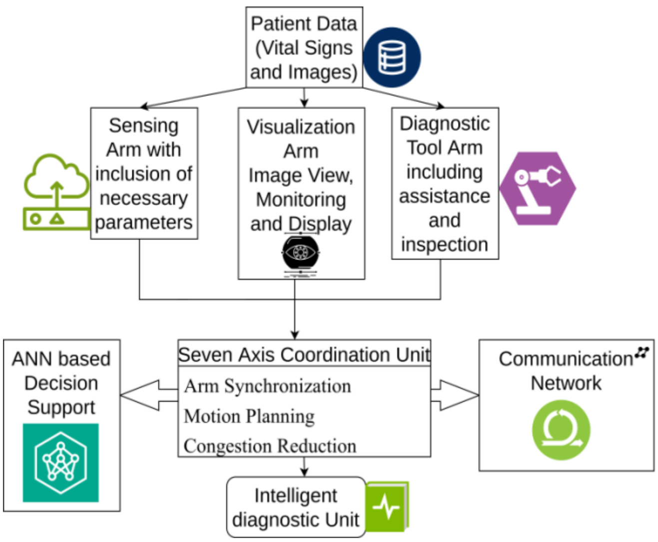

Fig. 1. Block diagram of a diagnosis robot for medical applications.

As a result of the division of arm responsibilities, it is possible to reduce changes across modules, thereby completely guaranteeing transparency in diagnostic operations. Therefore, the three-arm robot provides a practical solution for both autonomous and intelligent diagnosis even in real time environment

A. Background and Related Works

Information on existing works is needed in order to analyze the effects of robots in health care, where an accurate design process is implemented. In most of the existing works, a two-arm robot is introduced in various fields, but related to heath health care diagnostics, only a few researchers examined the design but did not implement it in real-time applications. However, a knowledge-sharing process is provided, thus leading to a successful way for the development of robotic systems. In [1] an augmentation method is used with computed tomography, where real-time analysis is carried out with an individual by implementing high-density mass. The augmentation method provides a clear view of the entire segment of the body, thereby, it is much simple to find the path of failures, and this is processed by robotic implementation. However, image augmentations can only provide an ideal path setup, which in turn provides direct reflections across various boundaries. Instead of using the augmentation process, an alternate method with loading conditions can be provided, thereby before segmentation, control every tissue can be checked, and it can be prevented to have low effect [2]. If high loading conditions are observed, then the continuum robot is introduced to optimize every path in a dynamic way, therefore the diagnosis rate is increased. But an open loop architecture is established for a robotic system, thereby even at high weight conditions, the control process remains at ineffective state. Conversely, an enhanced recovery process after diagnostics is checked with robotic operations in order to approve speedy retrieval of patients [3]. For performing recovery actions, a random trial is performed by examining current body conditions and the difference in proactive state is observed, where if the maximum difference is provided, then the entire control can be provided with trajectory robotic paths.

Though control establishments are made, it is essential to introduce a step-by-step approach in which implementation costs become much higher and the removal period is also maximized. Subsequently, a scanning process is introduced to provide invasive surgeries to patients by using a reconstruction and tracking process [4] where the obtained information is identified using individual operative assessment. For the above-mentioned process, 100% control is established, but both location and identification measurements of tools are not processed under proper utilization. In order to identify the correct location of diseases, the robotic sensing arms must be appropriately established using reality procedures, enabling automatic surgery with improved outcomes. Even after minor surgical treatment, a continuous monitoring process must be provided by a designed robot in such a way to avoid complications in certain flows; therefore, an extended monitoring units are added in order to re-operate the entire system [5]. The process of continuous monitoring reduces major complication risks as entire procedures are carried out

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with fully automated units. At the same time, unclear proportions with respect to monitoring units are provided to experts, making it much more difficult to establish a decision based on optimization. To establish proper design of robots to perform diagnosis a shot-term effective model is incorporated using mathematical representations; thereafter, every standard unit can be established for operating robotic arms [6]. This type of short-term model can provide a definitive standard for every robotic operation, and if any prevention needs to occur, then the connected units with two arms must be replaced by standard operative techniques. At the same time disadvantage of introducing a definitive standard is that flexibility can never be ensured; therefore, the robots must operate under different scaling factors.

Furthermore, the control strategies in robotic diagnosis are provided by using accurate positioning systems where a needle-based surgeries are carried out, and to ensure the safety of individuals, the robot functions according to the commands that are provided in the neural system [7]. As it is well known that the robots must react according to the changing situations, if commands are pre-loaded, then time-based decisions can never be made, thereby only the same functionalities are operated. In every diagnosis process, it is not possible to move patients from one place to another; therefore, the robots can never be fixed at any position [8]. Hence, to provide variable movements a dynamic approach is created with mathematical representations, and this robot is termed as robowalk which is operated on an augmented approach. In the design of mobile robots, the physical dimensions are checked at all coordinate axes, and a desirable force is applied to prevent user fall conditions. Nevertheless, the robotic surgeon can operate with the desired force, as some external commotion force will always be applied by using a low actuated technique. In many circumstances, multiple robots are considered for diagnosis at various places; therefore, interaction between designed robots is needed, and the examination of robots will be processed by using facial expressions [9]. Hence, only image processing techniques are highly helpful to robotic monitoring, and even the robotic operation becomes simple at the diagnosis stage, only if direction metaphors are provided [10]. But in recent times the operation of robots can be directly monitored and controlled due to the presence of two arms as cameras are attached. Table 1 provides a comparison between the existing and proposed approaches in terms of main contributions.

Table 1. Existing vs. Proposed.

Ref.	Methods/ Algorithms	App. Robot type	Sense model	Dataset/ Support
[11],[12], [13],[14]	Descriptor symbol for medical robots	Medical support	Point sensor	Practical signal dataset
[15],[16], [17],[18]	Division control of assisted robots	Surgical support	Image sensor	Medical image dataset
[19],[20], [21],[22]	Inertial parameter for surgical control	Surgical control	Motion sensor	Motion sensor measure
[23],[24], [25]	Security extents using range model	Medical monitor	Multi-sensor route	Clinical records sensor dataset
[26],[27], [28],[29]	Seven axis unit for deep surgical systems	Multi arm surgical	Image sensor	Multi modal analysis dataset
[30],[31], [32],[33], [34]	Robotic sensory arm operation using AI	Quick analytic robot	Point sensor	Multi modal analysis dataset
Proposed	Fully automatic robot for diagnosis using AI algorithm	Distinct analysis	Image sensor	Multi-limit diagnosis with ANN

B. Research Gap and Motivation

It is observed that most of the existing methods, in addition to the approaches listed in Table 1, focus on robots designed for medical applications with the capability of solving multiple problems where artificial intelligence-assisted medical robots are developed for sensing, diagnosis, and assistance. Although significant progress has been made in medical robotics, existing research is largely limited to discrete functions such as physiological sensing, robotic monitoring, image-guided diagnosis, or surgical aid. Most reported solutions rely on single-arm or task-specific robotic architectures and lack a unified framework that can simultaneously performing patient sensing, continuous monitoring, diagnostic tool management, and intelligent diagnostic decision

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support. Furthermore, although artificial intelligence has been extensively used in diagnostic prediction, its combination with coordinated multi-arm robotic systems for autonomous healthcare diagnostics has not been sufficiently studied. Thus, there continue to be challenges in achieving transparent diagnostics, effective multi-arm coordination, reduced motion congestion, and autonomous decision-making in an integrated robotic platform. In order to overcome the above-mentioned limitations, a three-arm artificial intelligence-assisted robotic system for diagnosis is developed, integrating major functionalities such as sensing, visualization, and tool management; hence, an coordinated architecture is observed.

C. Major Contributions

The innovation of this work lies in the integration of a synchronized three-arm robotic structure and an artificial neural network-based diagnostic decision support system. The proposed framework integrates physiological sensing, patient monitoring, diagnostic tool management, transparent communication, and intelligent decision-making in a single platform, unlike existing robotic diagnostic systems designed for specific healthcare functions. A seven-axis coordinated control method is applied to improve the robot interaction and reduce the operation congestion. The integrated architecture enables autonomous diagnostic support but also enhances transparency, coordination efficiency, and diagnostic accuracy. In addition to providing solutions for all increasing demands that are identified as major research gaps in robotic systems, the proposed approach is created with mathematical representations by combining artificial neural networks and decision-making algorithms.

II. Proposed System Model

Due to the increasing requirement of fully automated robotic systems that are used for medical diagnosis, it is essential to design a robot using analytical representations that provides actual movement in order to pick up various gears and to operate the human system without any interventions. Further, the fully automated robots must identify operating parts of humans; therefore, a control mechanism is needed in such cases hence the complete design of robots is made in such a way using master slave combination. The above-mentioned combination indicates that a computer-aided diagnosis is present by establishing dynamic movements, and the entire control is operated by a humanoid. Since an individual operator is present to monitor the entire environment during diagnosis, it is essential to increase transparency during the necessary time periods in order to control the number of errors. Hence, the robotic transparency conditions are formulated using Eq. (1) as follows.

$$trans_i = max \sum_{i=1}^{n} d_f(r,i) \times \begin{bmatrix} fg_1 & \cdots & fg_i \\ \vdots & \ddots & \vdots \\ fg_i & \cdots & fg_n \end{bmatrix} \quad (1)$$

where, $d_f(r,i)$ indicates the dynamic force of robots at initial conditions and $fg_1+..+fg_i$ denotes robotic energy expansion matrix. The overall spatial transformation that improves the transparency of three-arm robot can be established using the potential kinematic relationship as indicated in Eq. (2).

$$trans_{total} = [trans_1 trans_2 trans_3] \quad (2)$$

where, $trans_1 trans_2 trans_3$ indicates the transformation matrix of all three robotic arms. In order to process appropriate operating points, the robots must be positioned properly, thereby complete delay in diagnosis can be reduced. Further, the operating frame must be located at a proper distance to increase the speed of operation, thereby necessary signal flows are acquired as indicated in Eq. (3).

$$position_i = max \sum_{i=1}^{n} \underset{SF_i}{\rightarrow} \times \begin{bmatrix} \omega_1 & \cdots & \omega_i \\ \vdots & \ddots & \vdots \\ \omega_i & \cdots & \omega_n \end{bmatrix} \quad (3)$$

where, $\underset{SF_i}{\rightarrow}$ denotes signal flow vectors and $\omega_1+..+\omega_i+..\omega_n$ indicates toughness matrix values. Since the robotic arms are connected with appropriate distance measurements, it is necessary to provide coordination among the three arms for sensing, visualization and tool management as indicated in Eq. (4).

$$RC = \frac{1}{N} \sum_{i=1}^{n} RC_i \quad (4)$$

where, RC_i represents three-arm coordination. The designed robot must establish a connection with all coordinates, thereby targeting a point in four directions, thus continuous images are taken and saved using the visual system. Hence, this type of visual system identifies the posture of humans and diagnosis is made appropriately, which indicates that real time navigations are present.

$$CU_i = max \sum_{i=1}^{n} \varphi_{in} \times t_p(i) \quad (5)$$

where, φ_{in} denotes robotic target pretense and $t_p(i)$ indicates target coordination units. For diagnosis, the robotic measurement coordination point must be adjusted in such a way to provide an appropriate association between connected components, such as the arm and other measuring materials. Hence, a nominal measurement point must be established in this case using a robotic link as indicated in Eq. (6).

$$RA_i = min \sum_{i=1}^{n} a_t(i) - n_t(i) \quad (6)$$

where, $a_t(i)$ indicates the number of actual connected components and $n_t(i)$ denotes the average number of connected components. Once the coordination points are connected, the robotic movement must be checked with respect to the device, orientation, and transformations. Hence, if all three possibilities remain

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unchanged, it is possible to track the surgical points as indicated in Eq. (7).

$$RM_i = min \sum_{i=1}^{n} \delta_d(i) + rp_i + rt_i \quad (7)$$

where, $\delta_d(i)$ represents the total number of devices and rp_i, rt_i denotes relative position and transformation matrix. Eq. (7) describes that during surgery, the robotic movements are limited; therefore, the relative position of robots must be changed only if transformations are needed, reducing thereby device connections. Since the surgery is processed using automated medical devices, it is essential to check the accuracy of each robot by establishing the relationship between robots. The robotic movements are limited; therefore, the relative position of robots must be changed only if transformations are needed, thereby reducing device connections and patient space by using the gyratory matrix as indicated in Eq. (8).

$$accuracy_i = max \sum_{i=1}^{n} weight_i + (\theta_i \times time_i) \quad (8)$$

where, $weight_i$ denotes corresponding weight, θ_i indicates the number of robot rotations and $time_i$ describes total operating time. In robotic diagnosis, most of the error occurs due to a change in relative position that is caused by external forces, where, depending on the body conditions and portions, appropriate force must be provided. Hence, the error measurement for every robotic movement must be represented as indicated in Eq. (9).

$$Error_i = min \sum_{i=1}^{n} (rf_i - if_i) \times 100 \quad (9)$$

where, rf_i, if_i denotes reference and initial forces, respectively. All parametric relationships for the robotic system are established using min-max functions. If the design model is satisfied, it is possible to provide proper diagnosis to all patients, and a monitoring system can be built at the control center. Hence, the relationship with objective functions is indicated in Eqs. (10) and (11).

$$obj_1 = min \sum_{i=1}^{n} RA_i, RM_i, Error_i \quad (10)$$

$$obj_2 = max \sum_{i=1}^{n} trans_i, position_i, CU_i, accuracy_i \quad (11)$$

The multi-objective functions in Eqs. (10) and (11) are combined with AI algorithms since automatic diagnosis needs to be carried out using robotic arms. Further, each diagnostic data will be stored in the central server where high-error conditions are monitored, and the robotic changes will be made accordingly.

III. Artificial Intelligence Algorithm

Since the process of diagnosis in health care operations is made in an autonomous ways the artificial intelligence algorithm must be integrated with robotic design in order to increase the prediction accuracy. The artificial intelligence algorithm is used to train the robots and to incorporate inputs for a better understanding of unknown data that is related to diagnostics. Further, the processes of vision control, object identification, etc., during diagnosis are handled by the artificial intelligence algorithm. Moreover, the robots can sense and interact with the environment only if artificial intelligence is combined using programming representations, hence robotic movements are appropriately classified. In addition, the proposed method employs a robust artificial intelligence algorithm, in which each task is performed by the designed robot in its own way. Even though there is no human intervention in this type of robot a monitoring output is provided, thereby enabling advisory units to be formed by experts, and if any irregularities are found, then the training process (visual) can be changed immediately. The artificial intelligence technique is integrated into both the mechanical and camera arms of the robots; therefore, only the instructed commands are performed by the robots [35],[36],[37],[38],[39],[40]. Furthermore, the advantages of artificial intelligence algorithms include zero risk procedure, thus achieving greater responsibility in the diagnosis process, and even the availability of robots with strong artificial intelligence is made in a continuous way by combining all digital interventions. In the proposed model, two types of artificial intelligence algorithms, such as an artificial neural network for training the robots and a decision-making algorithm for performing cognitive actions, are implemented. During diagnosis, the robots must be scaled properly using a transfer function to maintain the robots' ability in reach appropriate data, which can never be changed. The diagnosis process will provide accurate outcomes only if actual data is maintained at a proper, consistent rate as indicated in Eq. (12).are

$$scaling_i = \sum_{i=1}^{n} \frac{\max_s d_i}{actual_i} \times 100 \quad (12)$$

where, $actual_i$ denotes actual data and d_i indicates scaled data. The robotic arms are connected using a central controller, which provides a bias operating point to prevent additional weights by using various tools during diagnosis. Hence, each connected unit can be represented using propagation functions as indicated in Eq. (13).

$$CU_i = \sum_{i=1}^{n} (\rho_{in} + b_{in})\,(wt_1 + .. + wt_i) \quad (13)$$

where, ρ_{in},b_{in} denotes propagation and bias inputs and $wt_1 + .. + wt_i$ indicates the weight of tools. For an artificial neural network-based decision framework, the hidden layer within the neurons must be activated; therefore, the output state will be used for disease classification and diagnostic predictions as indicated in Eq.s (14) and (15).

$$hidden_i = f\{wt_1 + .. + wt_i + bias_i\} \quad (14)$$

$$output_i = f\{hidden_i + bias_i\} \quad (15)$$

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where, $bias_i$ and $hidden_i$ denotes bias and a hidden layer. The artificial neural network with robotic units must be optimized for dimensionality; hence, the predicted output can be matched to the required input conditions. However, the dimensionality denotes that robotic networks are fully connected at necessary points, as indicated by accuracy factors.

$$optimize_i = \sum_{i=1}^{n} Dimension_t(i) \times hl_i \quad (16)$$

where, $Dimension_t(i)$ denotes total dimensions and hl_i indicates the number of hidden layers. Eq. (16) describes that if the number of hidden layers, which are denoted as extended arms, is increased, then dimensionalities will be increased, which needs proper optimization to be followed at the necessary points. Each decision on the diagnostic process is considered with respect to various activities of robots, where events and necessary counter measures are observed. Hence, the decision-making process consists of activity measures as indicated in Eq. (17).

$$activity_i = \sum_{i=1}^{n} (\alpha_1 + .. + \alpha_i) \times ctm_t(i) \quad (17)$$

where, $\alpha_1 + .. + \alpha_i$ denotes the total number of events and $ctm_t(i)$ indicates the number of countermeasures. During the process of diagnosis, every robotic action is performed in an automatic way, but before a decision is made, entire cognitive actions are analyzed with respect to expert dependency, thereby a node arm is added in addition to the other two arms. Hence, the dependency factors are formulated using Eq. (18) as follows.

$$DY_i = \sum_{i=1}^{n} \frac{DY_{max}}{DY_{avg}} \times 100 \quad (18)$$

where, DY_{max}, DY_{avg} indicates maximum and average dependencies. To establish complete balance in connected arm units where information is transmitted to end users (experts), balancing conditions are established by using gradient functions where the next movement can be observed. Hence, the gradient functions for balancing robotic activities are indicated in Eq. (19) as follows.

$$balance_i = \sum_{i=1}^{n} GF_i \times DF_i \quad (19)$$

where, GF_i denotes gradient functions and DF_i indicates decision factors with respect to gradient functions. As the system remains completely balanced, it is necessary to measure the overall diagnostic score by considering the derived inputs as indicated in Eq. (20).

$$score_i = \sum_{i=1}^{n} dp_w dp_{norm} \quad (20)$$

A. Algorithm: ANN-based intelligent decision support

Algorithm 1: ANN based intelligent decision support

Begin PROCEDURE ANN
Given Input and Output Features
Physiological sensor data P
Monitoring parameters M; Medical image features I
D: Diagnostic classification
For *i*=1:*n* **do**
1. Acquire physiological signals and attributes of medical images.
2. Collect data and normalize it.
3. Input the extracted features to the ANN input layer.
4. Propagate forward through the buried neurons.
5. Predict the diagnostic category expected.
6. Compute difference between forecasted and actual output.
7. Use backpropagation to update the network weights.
8. Train until convergence criteria is satisfied.

end

9. If the diagnostic confidence ≥ threshold, generate an informed diagnostic decision D.

else

10. Further sensing and feature extraction.
11. Reassess the ANN classification.

end

12. Diagnostic Decision D

end
end PROCEDURE

where, $dp_w dp_{norm}$ denotes the diagnostic parameter, total, and normalized weights. In the case of deviations in the necessary diagnostic parameters, the error measurement values must be processed as indicated in Eq. (21).

$$error_i = \frac{1}{N} \sum_{i=1}^{n} (actual_o - predicted_o) \quad (21)$$

where, $actual_o$, $predicted_o$ denotes actual and predicted output values. Hence, the overall accuracy of three arm robotic system that is used for diagnosis can be measured using Eq. (22) as follows,

$$accuracy_i = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \quad (22)$$

where, TP, TN, FP, FN denotes true, false positive, and negative values. The primary functionality of an artificial neural network integrated for intelligent decision making is to receive complete diagnostic features and measurements observed in both sensing and monitoring states. Hence, the training possibilities must be observed after receiving all types of measurements,

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as indicated in Table 2, and the pseudo code for intelligent decision making is also specified.

Table 2. Training Parameters

Parameter	Value
ANN type	Feed forward neural network
Input features	8
Number of hidden layers	2
Output class	4
Learning rate	0.001
Number of epochs	100
Number of samples	1000 simulation occurrence
Data set source	Simulation generated
Number of batches	32
Training and testing split	70% and 30% respectively
Activation and loss function	ReLU and cross entropy
Output activation	Softmax
Optimizer	Adam
Validation	5 fold cross validation
Class definition	Normal/Abnormal diagnosis
Performance evaluation	Accuracy, precision and error (Statistical analysis)

IV. Results

In this section, the outcomes of designed robots for diagnosis in medical applications are achieved by connecting a virtual communication link where a patient's disease pattern is identified, and images are taken at the initial state. During the simulation process, various operational parameters such as diagnostic images and physiological measurements are provided as input, and intelligent decisions are made using an artificial neural network. The implementation was processed in a MATLAB simulation environment with sensing, visualization, communication, artificial neural network-based decision support, and robotic coordination modules. Four scenarios, such are tested to evaluate the effectiveness of the proposed ANN-based three-arm diagnostic robot. The experimental study showed a significant improvement in all the performance measures considered. Fig. 2. shows the transparency level of the proposed system, which was achieved at 93%. This means that the sensing, visualization, and diagnostic modules were effectively sharing information. Similarly, the coordination efficiency in Fig. 3. reached 85%, which also proves the effectiveness of the seven-axis coordinated control mechanism in resolving the operational conflicts among the robotic arms. The association error decreased to 12% as shown in Fig. 4., which indicates better synchronization and communication between the interconnected robotic components. The diagnostic accuracy of the proposed framework was 93% while the baseline method was 71%, which shows a significant increase in the diagnostic performance as shown in Fig. 5. The system demonstrated real-time operational capabilities with a sensing lag of 40 ms and a communication delay of 15 ms. Statistical analysis showed low deviation values of 1.2%, 1.7%, and 1.3% for arm coordination, visualization, and diagnostic tool management, respectively, indicating stable and reliable performance. Taken together, the results verify the effectiveness of the proposed framework in enhancing transparency, coordination efficiency, diagnostic accuracy, and real-time responsiveness for intelligent healthcare applications.

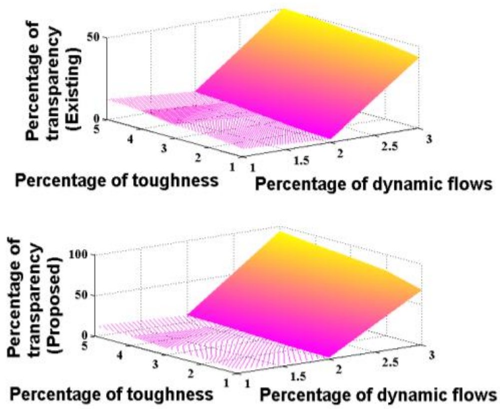

Fig. 2. Transparency in robotic signal flows with durability.

A. Discussions

Scenario 1: Position variations with transparency

To objectively evaluate the transparency of the suggested robotic framework, a transparency metric is proposed, which is based on the effective exchange of information between the sensing, visualization, and diagnostic tool management modules. The transparency percentage was calculated as the ratio of successful coordinated communication events to total communication events. Fig. 2 shows the simulation results for position variations and transparencies. From Fig. 2. it is obvious that the proposed three-arm diagnostic robot exhibits excellent performance by means of the combination of coordinated robotic operation and ANN-based intelligent decision support. The high transparency of 93% achieved is primarily attributed to the specialized communication architecture, which ensures a continuous flow of information between the modules for sensing, visualization, and diagnostic tool handling. Enhanced

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transparency enables the effective transfer of diagnostic data across subsystems and improves operational visibility and decision confidence. The transparency analysis showed that the proposed ANN-based three-arm diagnostic robot achieved a maximum transparency level of 93%, whereas the reference approach [2],[3],[8],[9],[15] reached only 71%. This 22 A percentage point improvement is a result of the suggested communication and coordination paradigm that enables more efficient information transmission between sensing, monitoring, and diagnostic modules.

Scenario 2: Target coordination units

With the establishment of a two-phase robotic arm, it is much easier to combine the coordination units using center point representations. Whereas for three-phase robotic arms it is essential to establish coordination

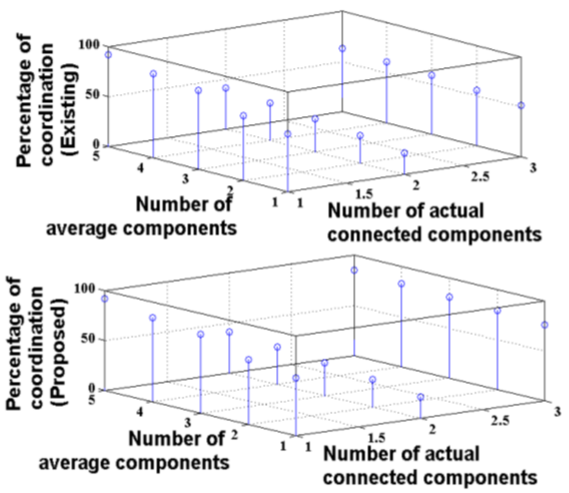

Fig. 3. Comparative analysis of coordination points for all connected components in the third arm.

units by deciding the number of associations between the number of connected and average components. Hence, in this scenario, the target coordination units are observed by instructing the designed robot about tool weights, and the processing state in this type of representation will be equivalent to real time navigations. Fig. 3. illustrates the comparison of coordination units for proposed and existing approaches [9]. From Fig. 3., it is observed that target coordination units are maximized in the case of the projected model as compared to the existing approach. The proposed seven-axis control approach can realize a direct 85% coordination efficiency. Unlike traditional robotic healthcare systems, where sensing and monitoring are carried out separately, the proposed architecture enables collaborative operation of multiple robotic arms. These coordinated capabilities reduce task conflicts, improve the workflow continuity, and increase diagnostic execution speed. According to the coordination evaluation, the suggested system achieved a coordination efficiency of 85%. The improvement is mainly due to the seven-axis control system and the coordinated operation of the sensing, visualization, and diagnostic tool handling arms. Better coordination reduces operational disputes and increases the robot's ability to perform several diagnostic tasks simultaneously.

Scenario 3: Number of associated components

The relative position is the displacement between linked robotic components, and the transformation matrix is the spatial transformation necessary to coordinate the movements of multiple robotic arms. In the proposed paradigm, these metrics are used to quantify operational association and communication consistency. Hence, in this scenario, the associated components in robotic arms are examined according to the defined weight functions. Fig. 4. provides the comparison in terms of association between proposed and existing approaches. From Fig. 4. it is obvious that due to changing weights, the associated components are minimized to a certain level in the case of the proposed method as compared to the existing approach. The association error decreases to 12%, attributable to the ANN-based feature fusion procedure. The system integrates physiological measures, monitoring data and diagnostic signs into a single decision-support framework, reducing inconsistencies between sensing and diagnostic outputs. Thus, the reliability of healthcare assessment has improved significantly. The association error

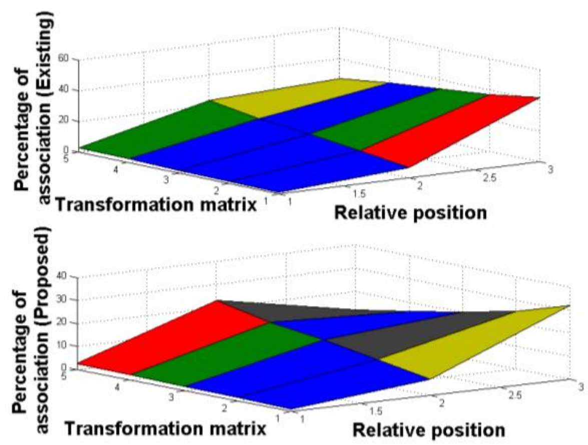

Fig. 4. Arm transformation in accordance with relative position identification.

analysis showed a reduction to 12%, suggesting improved synchronization and communication between the robotic subsystems. The decreased association error indicates that the proposed coordination approach effectively reduces operational mismatches

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and communication inconsistencies, thereby improving overall system reliability.

Scenario 4: Maximization of accuracy

The efficiency of the proposed ANN-based diagnostic framework was assessed by calculating the diagnostic accuracy as the ratio of correctly classified diagnostic cases to the total number of examined cases. The ANN model was trained and validated using simulation-generated physiological parameters and diagnostic image characteristics describing four diagnostic scenarios. From Fig. 5., it is observed that the accuracy of diagnostic robots is increased in the projected model as compared to the existing approach. The 93% diagnostic accuracy indicates that the ANN-based categorization well captures the intricate correlations among patient data. ANN's nonlinear learning enables more accurate diagnostic pattern recognition than traditional rule-based or single-parameter methods. The coordinated interaction of the three robotic arms further enhances the diagnostic performance with more information for the decision-making process. The

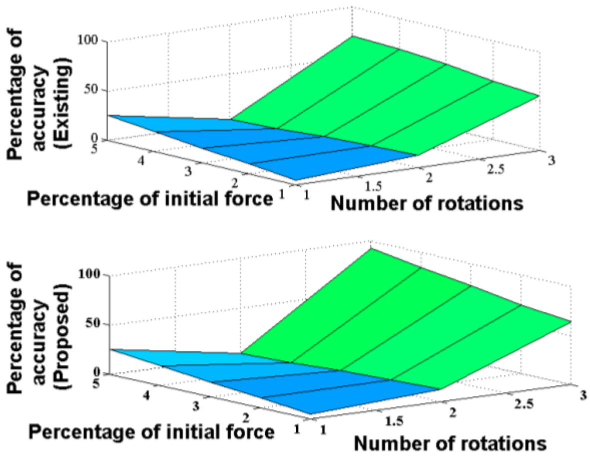

Fig. 5. Accuracy of robotic diagnosis at minimized error rates.

diagnostic accuracy of the comparative approach was 71%, while the diagnostic framework based on ANN was 93%. The 22% improvement is due to the combination of intelligent feature analysis, ANN-based decision support, and coordinated multi-arm robotic operation. The results validate the effectiveness of the proposed architecture for independent diagnostic support in medical applications.

To observe the efficiency of the proposed three-arm robotic system, relevant existing methods [2],[3],[8],[9],[15] are selected to cover various constraints such as sensing, visualization and tool management. The results indicate that the proposed ANN-based three-arm diagnostic robot greatly enhances autonomous healthcare diagnosis. Results achieved for transparency are 93%, coordination

Table 3. Statistical Analysis.

Parameters	Mean	Standard deviation	Confidence interval
Arm coordination	95.6	1.2	94.4-96.2
Visualization	96.3	1.7	94.6-96.7
Tool management	92.4	1.3	91.8-95.8
Sensing time period	40ms	2.1ms	37.2-42ms
Delay	15ms	1.4ms	13.2-16.87ms

efficiency is 85%, association error is 12%, and diagnostic accuracy is 93%. This indicates that the integration of sensing, visualization, diagnostic tool management, and ANN-based decision support can greatly improve the diagnostic performance of the robot. The results show that multi-arm robotic systems working in coordination can provide reliable and transparent diagnostic assistance for healthcare applications. The noted improvements are mainly attributed to the proposed communication architecture, seven-axis coordination mechanism and ANN-based intelligent decision-making framework. The specialized management systems for sensing, visualization and diagnostics reduce operational congestion and improve information flow, while the ANN model provides efficient diagnostic classification by intelligently processing features. Unlike previous robotic diagnostic approaches [2],[3],[8],[9],[15] that are based on separate functionalities such as sensing, monitoring or visualization, the proposed framework offers a unified architecture for collaborative robotic work and autonomous diagnostic support. This resulted in increased transparency, improved coordination efficiency, and improved diagnostic accuracy.

The confidence interval is calculated by considering both mean and standard error deviations, where the proposed three-arm robotic system can able to achieve

Table 4. Key differences and similarities.

Parameters	Existing [2,3]	Existing [8,9]	Proposed
Diagnostic accuracy	71%	71%	93%
Transparency	Moderate	Low	High
Association error	Varying	Varying	Reduced to 12%
Communication framework	Predictable data transfer		Clear frame network
Coordination	Limited		Seven axis matching

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improved consistency in all scenarios, as indicated in Table 3. Further, the proposed system can achieve stable diagnostic operation as deviated values are relatively lower, therefore, the robustness characteristics are also reduced by achieving confidence rates at early iteration periods. Moreover, due to the integration of an artificial neural network in diagnostic operations, intelligent decisions are made, which further improve the performance metrics in the case of the proposed approach; hence, it is possible to provide better classification from all sensor inputs to achieve consistency and reliability. In the real-time performance evaluation, an average sensing time of 40 ms and a communication latency of 15 ms were shown. These numbers indicate that the proposed framework can process physiological data and provide diagnostic conclusions within reasonable real-time operational bounds. Table 4 summarizes the main similarities and differences between existing robotic diagnostic systems and the proposed framework. Existing approaches [2],[3],[8],[9] concentrate on individual functions, e.g., sensing, visualization, or robotic assistance, with only a low grade of coordination between subsystems. The proposed ANN-based three-arm diagnostic robot combines sensing, visualization, diagnostic tool management and intelligent decision support in a unified architecture. This integrated approach enhances the transparency (93%), efficiency of coordination (85%) and diagnostic accuracy (93%) and reduces association error to 12%. The sensing latency of 40 ms and transmission delay of 15 ms show the capability of the proposed framework to enable near real-time healthcare applications. The results of the comparisons show that the proposed system can give a more comprehensive and efficient solution for autonomous medical diagnosis than the previously reported methods.

V. Conclusions

This investigation suggested a three-arm diagnostic robot based on ANN for autonomous healthcare applications to improve diagnostic transparency, robotic coordination, intelligent decision support, and real-time healthcare assistance. A diagnostic decision-making module based on an ANN and a coordinated seven-axis control architecture is used to integrate the specialized sensing, visualization, and diagnostic tool-handling arms in the proposed framework. The experimental evaluation showed promising results in different evaluation categories. The proposed method has achieved 93% f diagnostic accuracy, 93% transparency, 85% coordination efficiency, and a 12% reduction in association error. Moreover, the framework demonstrated real-time operations with 15ms communication latency and 40sms average sensing latency. The results show that the use of ANN-based intelligence and coordinated multi-arm robotic operation can greatly improve the autonomous healthcare diagnosis. The proposed three-arm diagnostic robot with ANN shows promising results. However, there are some limitations to be noted. The work is validated only by simulation and does not involve clinical testing or hardware implementation. In addition, real-world healthcare settings may present challenges such as diagnostic ambiguity, cybersecurity vulnerabilities, and discrepancies that could impact the system's effectiveness. Despite these limitations, the framework is capable of improving hospital efficiency through automated sensing, monitoring and diagnostic assistance, and enhancing patient safety by synchronizing robotic operations. In future work, we plan to clinically validate the method, implement it on hardware, enhance its security and evaluate it extensively in a healthcare setting. Hence, in future, the proposed system can be developed with real-time robotic implementation where clinical validations can be made in a large scale by including long-term reliability and security measures.

Declarations

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Data Availability

The data used in this study were generated through simulation within the MATLAB environment for the evaluation of the proposed ANN-based three-arm diagnostic robot. The simulation data supporting the findings of this study are available from the corresponding author upon reasonable request.

Author Contribution

Hariprasath Manoharan: Conceptualization, methodology, software, simulation, formal analysis, investigation, writing original draft preparation.
T. S. Murugesh: Software support, simulation analysis, validation, writing-review, and editing.
Abirami Manoharan: Methodology, validation, writing-review and editing, supervision.
R. Durga: Formal analysis, validation, data interpretation, writing-review, and editing.
M. Senthil Kumar: Supervision, project administration, critical review, and final approval of the manuscript.

Ethical Approval

This study did not involve human participants, clinical trials, direct patient testing, or the collection of personally

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identifiable patient information. The proposed diagnostic robot was evaluated exclusively through simulation-based implementation and expert technical assessment. The expert assessment was limited to the evaluation of the developed framework and did not involve the collection of personal data or clinical intervention. Therefore, formal ethical approval was not required.

Consent for Publication Participants.
Not applicable, as this study did not involve human participants or identifiable personal data.

Competing Interests
The authors declare no competing interests.

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