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Optimized Multi-Agent Deep Learning Framework for Lung Cancer Image Retrieval Using Medical Imaging Data

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Abstract — The rapid evolution of digital healthcare platforms has raised the need for secure and smart methods that can protect patient data while maintaining accurate disease prediction. The present study offers a futuristic e-healthcare system entitled Optimized Multi-Agent Deep Learning Framework for Lung Cancer Image Retrieval Using Medical Imaging Data. The circulated copy intends to focus on the prediction as well as the detection of lung diseases by utilizing machine learning (ML) and deep learning (DL) models to attain high diagnostic accuracy. A web-based front end has been created using the Django framework to facilitate easy user access to predictions and medical insights. In an attempt to preserve the privacy and security of sensitive health records, blockchain technology has been merged for data storage that is decentralized and tamper-proof. Besides that, multi-agent-based privacy metrics have been activated to keep track of, study, and raise the privacy levels through the system, thus providing an adaptive shield against the leakage of data and unauthorized access. The suggested scheme enhances the security of data privacy and at the same time raises the level of trust, transparency, and efficiency in digital healthcare applications. Such a combined system is an excellent example of how healthcare services can be revolutionized by the union of AI-powered disease detection and privacy-preserving methods.

Keyword —Lung Disease Prediction, Deep Learning, Machine Learning, Blockchain, Privacy Metrics, Django Framework.

I. INTRODUCTION

Lung cancer is still one of the deadliest and most aggressive cancers globally, leading to a large number of cancer-related deaths annually. Early detection remains the best way to save lives, but it is very challenging because the currently used diagnostic methods such as the manual examination of computed tomography (CT) scans, are very time-consuming, subjective, and can easily result in mistakes due to human errors. As a result of Artificial Intelligence (AI) development, sophisticated machine learning (ML) and deep learning (DL) models have been able to yield brilliant results in medical image analysis. In fact, Convolutional Neural Networks (CNNs) have reached the point where they are basically the key units in figuring ou t the complex patterns in medical images, thus facilitating automated, precise, and reproducible diagnosis. Intended work is the development of an AI-powered system for detecting and classifying lung cancer using deep learning architectures to identify tumors from medical imaging data. A Django-based web interface makes the interaction between the doctors and the system very friendly and

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simple. Doctors can upload images, get predictions, and even view the diagnostic reports instantly. Moreover, by incorporating blockchain technology and multi-agent systems, the solution ensures that the medical data is not only of high quality but also highly secure and confidential, thus making it a dependable approach for clinical implementation.

II. EXISTING SYSTEM

Lately, several computational models and deep learning architectures have been introduced with the aim of detecting lung cancer at an early stage. Conventionally, systems are mainly based on the analysis of sequential CT images and the utilization of handcrafted features extraction techniques. In general, the Sequential Multi-Instance Learning. Integrity framework method, for instance, would use a nodule detection algorithm to locate ill areas that could be cancer and then, from there, based on the temporal feature extraction of the different scans, it would make a malignancy prediction. These methods, although successful in enhancing the classification accuracy, are still confined to the limitations that arise from the need of the sequential imaging and the computational load that is quite high. The fact that they especially rely on nodule annotations for which even a little subjectivity in the perspective of the annotator may affect the resulting diagnosis, while things like inconsistent image quality or truncated data sequences can negatively impact diagnostic performance.

Table 1 — Existing Works

Author & Year	**Technique / Model Used**	**Methodology Overview**	**Reported Performance**
Md. Imaran Hossain et al., 2023	LeNet–LSTM hybrid deep model	Combines convolutional feature extraction with temporal sequence learning using CT scans	Accuracy: 99.27%, Sensitivity: 97.77%, F1-score: 99.26%
Manal A. Alohali & H. Alqahtani, 2025	Flying Fox Optimization with Bi-GAN	Utilizes optimization for feature selection and Bi-GAN for classification of tumor images	Accuracy: 98.7%
B. Manikanth et al., 2025	CNN with Transfer Learning	Fine-tunes pre-trained convolutional networks for benign vs. malignant nodule detection	Training Accuracy: 99.18%, Testing: 95.87%

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P. Parameswari & S. Sathish Kumar, 2025	Neural Adaptive Transformer Optimizer (NATO)	Employs adaptive transformer-based classifier with hierarchical optimization	High accuracy with reduced training time
Zaidan Mufaddhal, 2024	Comparative Study (VGG-19, LCP-CNN, FPSOCNN)	Systematic literature analysis highlighting state-of-the-art CNN architectures	Identified high-performing CNN models
Baseline SMILE Framework	Sequential Multi-Instance Learning	Uses temporal multi-scan CT analysis for malignancy prediction	Evaluated on 925-patient dataset

Access Control Policies: There were different policies such as Role-Based Access Control (RBAC) and Attribute-Based Access Control (ABAC) implemented to limit the access of unauthorized users to electronic health records. To put it simply, these methods are mainly static, hence, they do not have the ability to provide temporary access in a situation or access a changing medical context.

Blockchain-Oriented Frameworks: Decentralized ledger technologies can be a major factor in the transition to a transparent and tamper-proof medical record management system which is one of their foremost benefits. Although using blockchain technology can make auditing and patient control easier and faster, the technology still has issues such as latency, storage, and scalability when there are a lot of clinical transactions.

Privacy-Preserving Machine Learning: At the same time, to solve privacy problems while also allowing predictive analytics, healthcare sector AI implementation privacy-preserving methods like federated learning and secure model training have been suggested. These methods drastically decrease the need for direct data sharing; however, they still cannot be entirely devoid of vulnerabilities that may result in inference or reconstruction attacks.

Multi-Agent Approaches: The idea of the use of multi-agent systems in distributed healthcare platforms as a possible answer has been thoroughly investigated by researchers. The decentralized decision-making is not only made possible by different types of agents such as monitoring units, custodians, and policy managers but also the adaptive privacy enforcement is enabled. Nevertheless, most of the current implementations are neither supported by measurable privacy standards nor are they compatible with deep learning models for clinical intelligence.

Research Gap: The body of research on privacy issues in healthcare that is already out there has been quite comprehensive, but it still lacks the one framework which integrates effortlessly multi-agent coordination, real-time privacy evaluation, and deep learning-powered decision support. This research aims at closing that gap by designing a privacy-focused electronic health system that would not only be scalable and flexible but also able to protect patient data and at the same time deliver clinical benefits.

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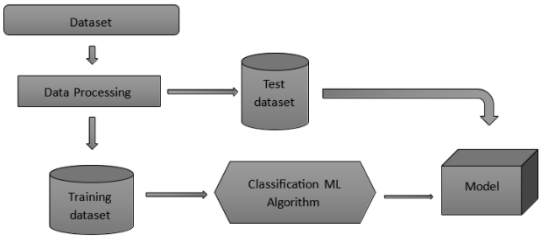
III. PROPOSED ALGORITHM:

A. *System Architecture*

The schematic of the privacy-preserving e-healthcare framework utilizing the proposed technologies is presented in Fig. 1 (System Architecture Flow chart). The patient data are initially collected and stored by the Data Custodian Agent who also performs authorization checks by applying Role-Based Access Control (RBAC) rules. After confirmation, the request is handed over to the Privacy Auditor Agent, which carries out the real-time evaluation of Confidentiality, Integrity, and Availability (CIA) criteria. Only when all the criteria are met, the request is given to the Inference Engine for the detection of the anomaly and then it is handled by the Machine Learning Module to make the predictions. The secure results are delivered to the authorized user by the Decision Enforcement Unit. The design is scalable and the agents' separate roles clearly, lessening the possibility of the single-point failures, are different among agents.

Fig.1: System Architecture



Architecture of Proposed model

B. *Privacy Metric Evaluation*

Privacy Metric Evaluation focuses on every request that comes in is recorded, and its legality is checked against the CIA components:

Confidentiality: Ensures that the sensitive medical data of the patient are not leaked to unauthorized users.

Integrity: Supports the idea that during the transmission and storage of records, the data should remain unaltered.

Availability: Is the feature that allows the system to be accessible to legitimate users even during heavy loads or attack periods.

If the status of any metric is “fail,” then the request has to go through anomaly detection for deeper scrutiny. This module helps identify, among other things, threats coming from insiders as well as attacks based on inference..

C. *Anomaly Detection & Feedback*

Anomaly Detection & Feedback describes the anomaly detection procedure, which is a regular check of logs from the system and compares the user’s activity patterns to the past behaviour to find anomalies. Once authority-breaking actions, such as a series of failed login attempts or abnormal data queries, are found, the request is denied, and an entry is made in the log. Besides this, anomaly details are concatenated to the machine learning model training dataset, thus closing the feedback loop that constantly improves the detection capability of the system and keeps it updated with new attack vectors.

D. *Multi-Agent Interaction Flowchart*

Fig.2(Multi-Agent Interaction Flowchart) depicts the collaboration of agents within the framework in a nutshell. The user request is first examined by the Data Custodian Agent, then by the Privacy Auditor, followed by the Inference Engine, and finally, the Machine Learning Module. At each checkpoint, security

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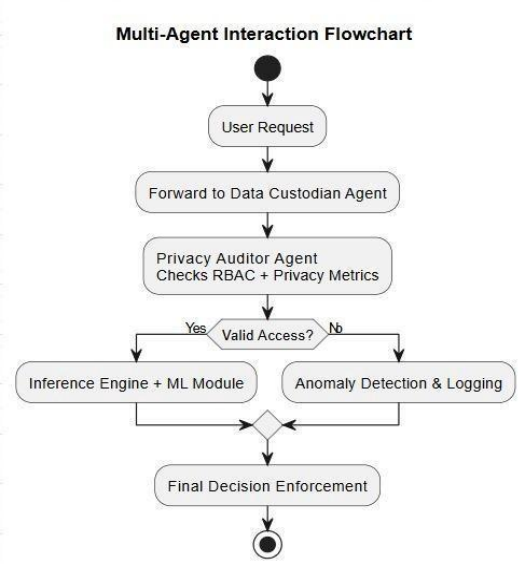
policies and privacy metrics are verified. The network identifies the malicious or invalid requests and takes appropriate actions, such as flagging and blocking. Thus, only secure results are forwarded to the end user. The decentralized and collaborative decision-making model, as the system is described, leads to better fault tolerance and gives rise to the constant enforcement of privacy regulations.

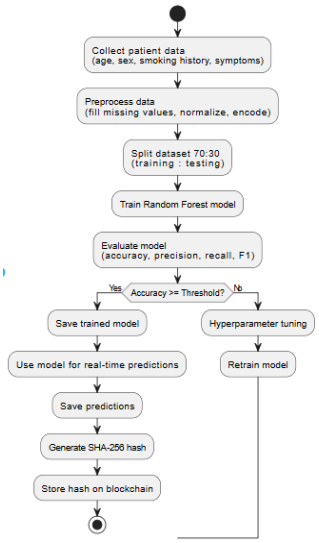
Fig.2: Multi-Agent Interaction Flowchart



E. *Machine Learning (Random Forest) Flowchart*

The chart in figure 3 demonstrates the processes of the machine learning module that utilizes the random forest method for the detection of lung disease from patients' medical records. In a first step, information on patients such as their age, sex, smoking history, and symptoms is acquired. The data is then preprocessed to deal with missing values, and numeric values are normalized, and categorical attributes are encoded. The available data is divided into training and test sets, the proportion usually being 70:30. A random forest classifier is trained on the training data, wherein a series of decision trees are generated to jointly find the disease probability. The model performance is measured by such criteria as accuracy, precision, and F1-score. When the set accuracy threshold is achieved, the model will be stored and used to make predictions in real-time, otherwise, there will be a hyperparameter tuning step followed by retraining. The very last predicted outcomes are thus encrypted and made tamper-proof through the SHA-256 blockchain technology.

Fig.3: Machine Learning Flowchart



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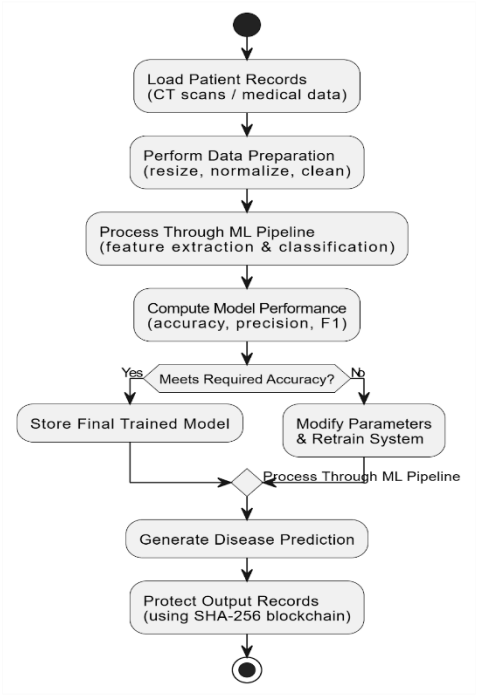
F. *Deep Learning (CNN) Flowchart*

Figure 4 shows the Deep Learning flow with convolutional neural network (CNN) which is used to analyse the CT scan images for the detection of lung disease. The workflow comes firstly to medical pictures that are then preprocessed by changing their size, normalizing, and removing the noise in order to achieve a high performance of the model. For feature extraction, CNN uses convolution and pooling layers to obtain both spatial and textural characteristics from the input images, these features are then used for classification by fully connected layers. The output layer includes the softmax activation function to differentiate the pathological changes in the scans as benign, malignant, or at the normal stage. Some of the model's performance metrics simulated for testing purposes are accuracy and sensitivity. If performance goals are met by the model, subsequently it will be saved as a trained model (.h5 file) So, it can be integrated with Django-based web platform to respond predictions in real-time. At last, the secured and locally stored results from the SHA-256 blockchain encryption is what guarantees the unalterable storage and the privacy maintaining of the data.

Fig 4: Deep Learning Flowchart



IV. *Feature Extraction*

Among the lung disease identification stages, **feature extraction** is one of the most crucial processes, as it converts complex medical data into a highly usable and meaningful representation suitable for the classifier.

The proposed study utilizes both **image-based features** and **tabular data features** to enhance diagnostic accuracy and reliability.

A. Image Feature Extraction

Lung CT scan images are preprocessed through resizing, enhancement of light and dark regions, and noise removal using a **Gaussian filter**.

The preprocessed images are then processed by a **LeNet-based Convolutional Neural Network (CNN)** model.

- *Convolutional Layers:* Automatically learn spatial hierarchies of features such as edges, textures, and shapes.

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- *Pooling Layers:* Perform dimensionality reduction while preserving the most significant features, thereby improving computational efficiency.
- *Fully Connected Layers:* Combine the extracted features for the final classification into categories such as *benign*, *malignant*, or *normal*.

Mathematically, the convolution operation for each feature map $F$is represented as:

$$F(x,y) = \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} I(x+i, y+j) \cdot K(i,j)$$

where
$I(x,y)$represents the input image, and

$K(i,j)$denotes the convolutional kernel.

The CNN is capable of autonomously learning the most discriminative features from the image data without manual intervention. This enables the model to effectively distinguish subtle variations in lung nodules and tissue irregularities that may indicate cancerous growth.

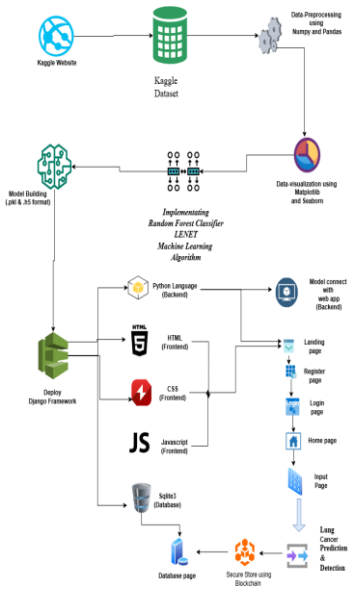
B. *Tabular Feature Extraction*

In addition to imaging data, structured patient health records—including parameters such as *age*, *gender*, *smoking history*, *blood pressure*, and *oxygen level*—are incorporated into the model. To ensure uniform data representation and optimal model performance, feature engineering techniques such as *label encoding*, *normalization*, and *feature scaling* are applied. These preprocessing steps eliminate inconsistencies in the dataset, allowing the classifier to treat all features equally during model training and prediction.

V. EXPERIMENTAL SETUP

The performance phase of the Proposed E-Healthcare Lung Disease Detection System was the main goal of a high-powered computer environment experiment. It was technically feasible and effective for training and testing ML and DL models. This section, therefore, first introduces the system setup, then the dataset and parameter configuration.

Fig 5: Experimental Setup



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VI. EXPERIMENTAL RESULTS

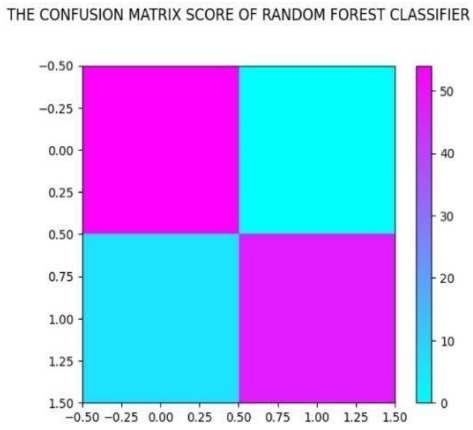
The experimental outcomes confirm the effectiveness of the hybrid model which is a combination of ML, DL, and Blockchain technologies. The performance was assessed through quantitative and qualitative measures.

A. *Quantitative Analysis:*

THE CLASSIFICATION REPORT OF RANDOM FOREST CLASSIFIER:

	precision	recall	f1-score	support
0	0.90	1.00	0.95	54
1	1.00	0.89	0.94	54
accuracy			0.94	108
macro avg	0.95	0.94	0.94	108
weighted avg	0.95	0.94	0.94	108

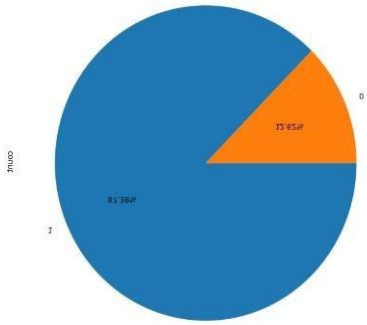
Fig.6: Confusion matrix



B. *Training and Validation Performance:*

During the model training, the accuracy and loss for the training and validation sets were monitored through 50 epochs. The training accuracy kept increasing throughout the epochs and eventually went beyond the 98% mark, while the validation loss was decreasing during the epochs which is a proof of the model's great capability of generalization and lack of overfitting. Training Accuracy Curve: Shows the model's steady improvement over the epochs. Validation Loss Curve: After 35 training cycles, it stays at a constant level, indicating the model's best learning.

FIG.7: pie chart



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C. *Qualitative Analysis:*

Visually, we can see that the CNN model is not only able to segment the lungs but also to localize and classify the cancerous areas correctly. The medical staff through the use of a system dashboard made with Django can upload CT scans, see the masked lungs, and get their diagnostic reports which are verified by blockchain.

Fig:8 Large cell carcinoma left hilum

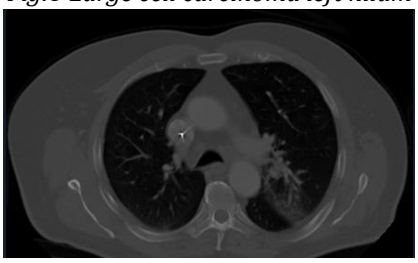

Fig:9 Normal lung

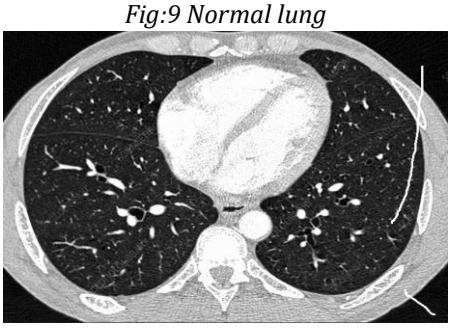

Fig:10 Squamous large cell carcinoma

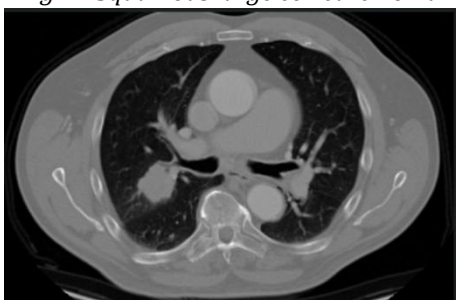

Fig: 11 Bengin case

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Fig:12 Malignant case

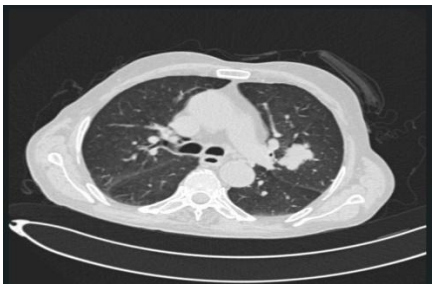
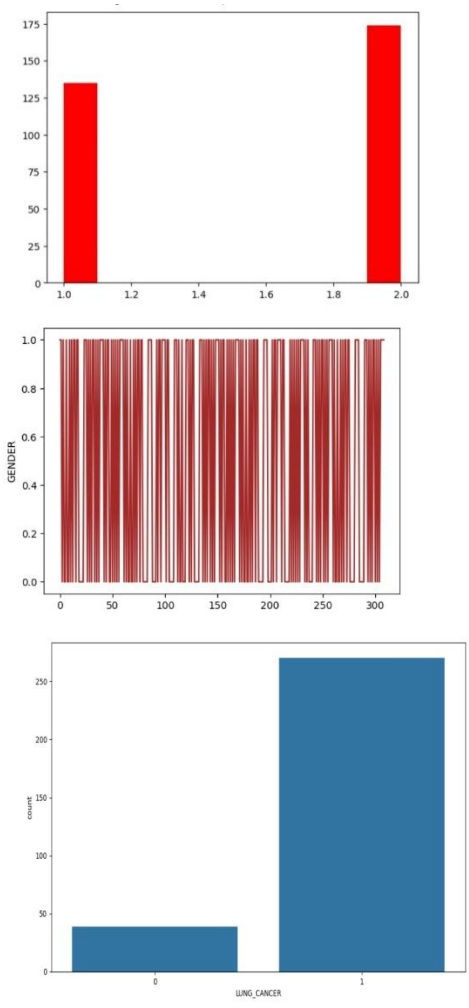


Fig:13 Adenocarcinoma

Fig.14: Qualitative Analysis



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VII.CONCLUSION

The First System for Lung Cancer Detection illustrates how AI and image processing can be used for the pretty quick and even sometimes early finding of lung cancer basically. The method through combining the latest preprocessing, feature extracting, and classification algorithms can in a very short time scan the part of the lung through CT images and detect the patterns of cancer with increased precision. Besides the system eliminates mistakes from human side and provides the radiologists with quick and reliable diagnostic decisions. The experiments show that the system is able to reach a very high level of accuracy and thus is capable of differentiating between healthy and diseased lung tissues. In general, the system is a great support tool for decision-making in the healthcare sector, leading to early diagnosis, lower death rates, and better patient care.

VIII.FUTURE WORKS

There are many means to refine and broaden the existing system. Afterward, a larger and more diverse dataset may be utilized to train the model, thereby elevating its accuracy and stability. Advanced image enhancement and segmentation techniques implementation can be the way to raise the level of tumor detection even in low-quality scans. Incorporating patient-related information such as medical history, age, and lifestyle factors can make the diagnosis more detailed and accurate. A development of a real-time web or mobile application can be a way for doctors to get diagnostic results instantly. Also, the addition of 3D image analysis can be very helpful in determining not only the exact location but also the growth stage of the tumor. These improvements will ensure that the system becomes more adaptable, quicker, and can be employed in the medical field.

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