International Journal of Scientific Research & Engineering Trends
Volume 12, Issue 3, May-Jun-2026, ISSN (Online): 2395-566X

Privacy-Aware Medical Image Analysis

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Abstract- The use of artificial intelligence (AI) technology for medical image analysis has gained significant importance in contemporary health care systems. AI models assist physicians in diagnosing diseases based on medical images like x-rays, MRIs, CT scans, and ultrasound scans with great precision and fast diagnosis. Nonetheless, medical datasets involve critical and sensitive data about patients, thus raising serious concerns regarding privacy protection in the context of AI applications. The exposure or unauthorized access of medical data can result in severe ethical and legal problems [2], [9], [16]. In this paper, we present a privacy-aware medical image analysis system based on the implementation of convolutional neural networks (CNN), PyTorch framework, Streamlit toolkit, and Differential Privacy technology. CNN is used to extract the features of the medical images automatically and classify the underlying diseases. PyTorch is used for developing the proposed model efficiently, and Streamlit provides a user-friendly interface for physicians. Moreover, the training process is implemented based on differential privacy in order to maintain the privacy of the data. [4], [5]. The proposed framework can support hospitals, diagnostic centers, and telemedicine systems in secure healthcare applications [6], [20].

Keywords- Medical Image Analysis, Artificial Intelligence, CNN, PyTorch, Differential Privacy, Streamlit, Deep Learning, Healthcare Security.

I. INTRODUCTION

The development of Artificial Intelligence (AI) and Deep Learning technologies is revolutionizing the field of healthcare. Medical imaging is among the many applications of AI technology, wherein intelligent systems help doctors diagnose diseases using image results, including X-rays, CT scans, MRI scans, and ultrasound results. Detection at an early stage can enhance treatment procedures and reduce patient death rates [2], [16].

Medical diagnosis typically relies on human knowledge and analysis, which is time-consuming, and may not always be reliable. Deep learning models, particularly the Convolutional Neural Networks (CNN), have exhibited outstanding abilities in identifying image contents. In addition, CNN models can learn on their own the features contained within the images for accurate disease identification [7], [8].

Nevertheless, healthcare data privacy remains a critical issue. Patient data included in the dataset are confidential in nature, and any breach could cause violations of privacy laws. The use of healthcare data to train AI models may unintentionally leak private patient data through prediction or model distribution [3], [4].

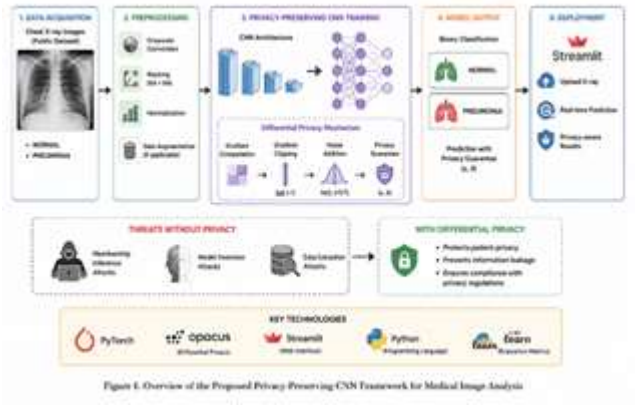
For overcoming this challenge, privacy-preserving techniques become more relevant nowadays when it comes to medical artificial intelligence tools. Differential Privacy is considered to be one of the best methods for securing personal data. This technique implies adding some mathematically managed noise during training and improving the performance without compromising privacy [3], [19].

In this study, a novel system for securely conducting medical image analysis with CNN-based disease predictions and protection via Differential Privacy is introduced. The tool is implemented with the help of PyTorch and presented in real time on Streamlit platform [5], [9].

The rest of this article consists of the following:

1. Problem statement is provided in Section II.
2. Objectives are stated in Section III.
3. Literature review covers relevant articles in Section IV.
4. The methodology and system design are discussed in Section V.

5. Analysis and results are provided in Sections VI and VII respectively.
6. Conclusion discusses the work's contributions and limitations.



II. PROBLEM STATEMENT

Today, medical imaging datasets are generated by modern healthcare institutions every single day. Disease prediction systems that rely on AI require datasets for training and accurate predictions. Nevertheless, information that is contained within healthcare datasets is very sensitive and prone to threats such as data leakage and cyberattacks [4], [9].
Typically, most AI systems concentrate solely on improving prediction accuracy while neglecting patient privacy concerns. Early deep learning techniques used for medical datasets lacked proper methods for protecting patients' information, hence could suffer from membership inference, model inversion, and reconstruction attacks [3], [6].

The demand for an AI system that offers both high prediction accuracy and strong privacy guarantees is a crucial requirement. Such a system would perform optimally within the complex and demanding environment of healthcare organizations [3], [6], [19].

III. OBJECTIVES OF THE STUDY

The objectives of the study include the following:

1. The development of a medical image analysis system using CNN that can detect diseases automatically.
2. Implementation of deep learning models using PyTorch for effective training of models.
3. Ensuring privacy of patient data through differential privacy methods during the process of training models.
4. Creation of an easy-to-use healthcare interface using Streamlit for making real-time predictions.
5. Improving secure disease prediction accuracy up to above 90%.
6. Minimizing the possibility of patient data leaks through AI models.
7. Making medical image classification possible in real time.

IV. LITERATURE REVIEW

Various scholars have discussed the application of Deep Learning algorithms in medical images classification. Convolutional Neural Network architecture like ResNet, AlexNet, VGGNet, DenseNet, and EfficientNet is applied for the detection of various diseases due to their high-classifying accuracy [10], [11], [15], [20].

Several research works demonstrate that CNN algorithms could effectively detect diseases like pneumonia, brain tumor, breast cancer, tuberculosis, and coronavirus from medical images. The application of Deep Learning in medical images saves time for healthcare professionals [6], [13], [14].

However, most Artificial Intelligence suffers from security and privacy concerns due to confidentiality issues related to medical images. Some of the methods proposed to address this problem include Differential Privacy and Federated Learning [3], [4].

With Differential Privacy, there are mathematical measures to preserve data privacy using controlled randomness during learning process. According to earlier works, Differential Privacy has proven successful in reducing the leakage of patients' private information while preserving reasonable prediction results. Deep Learning fused with Differential Privacy will result in secure healthcare artificial intelligence [3], [19].

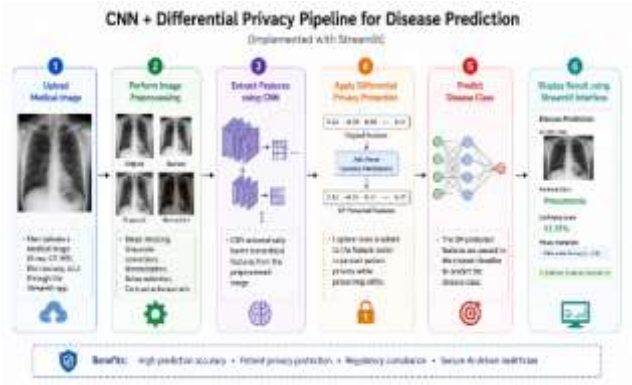
The above approaches were developed to solve specific issues, but not as an integrated solution to accurate disease prediction and data privacy together.Existing CRNN and sequence-based OCR techniques applied to image recognition provide a blueprint for end-to-end trainable architectures that can be adapted for medical imaging [12].

V. PROPOSED METHODOLOGY

The proposed privacy-preserving analysis system is based on a multi-step methodology to maximize both the performance and privacy of the system. The design of the system has five major steps, which include data acquisition and preprocessing, training of CNN model, implementation of differential privacy, labeling of multi-class datasets through OCR, and deploying through Streamlit [1], [8].

Step 1: Dataset Acquisition

The medical image data is acquired from open-access healthcare data archives that have a variety of medical images including X-ray, MRI, and CT scan images. The datasets that we will use primarily include



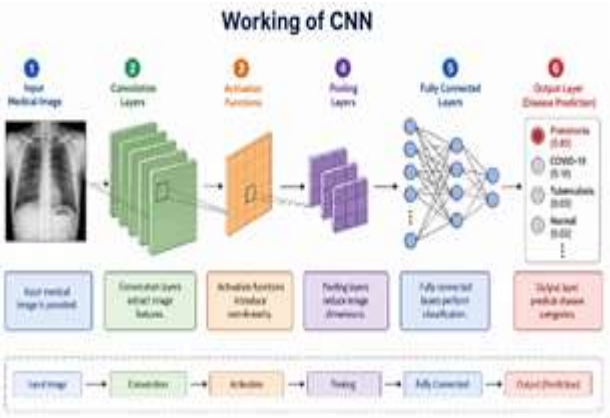
Chest X-ray image dataset for pneumonia detection, Brain MRI image dataset for tumor detection, and COVID-19 image dataset. Images will be collected under various environmental conditions to make sure that our system can function effectively irrespective of imaging environment [14], [6].

Step 2: Data Preprocessing

Data preprocessing improves the quality of images and prepares data for training process. The size of images is adjusted to be of size 224x224 pixels in order to fit the input requirement of the CNN network. The values of pixels are normalized to be between 0 and 1. The augmentation process includes rotation, flipping, zooming, contrast adjustment, and noise removal [18], [12].

Step 3: CNN Model Training

The CNN model is created and trained utilizing PyTorch. The architecture includes several layers such as convolutional, pooling, dropout, and fully connected layers which facilitate automated features extraction and diseases classification. Furthermore, the use of Adam optimizer and cross entropy as loss function improves classification results. Training is done for 100 epochs where early stopping is used once validation accuracy is not improving anymore [5], [8].



Step 4: Implementation of Differential Privacy

Differential Privacy algorithms are implemented while training the model using the Opacus package designed for PyTorch. These consist of gradient clipping to constrain sensitivity in each training step, Gaussian noise added to each iteration gradient updates, and a strictly managed privacy budget (ε). An appropriate value of $\varepsilon = 2$ is chosen to maintain a good balance between privacy strength and model utility. Thus, attackers will not be able to infer sensitive information about patients through membership or model inversion attacks [3], [4], [19].

Mathematically, the differential privacy guarantee can be represented as:

$P[M(D) = o] \leq e\varepsilon \cdot P[M(D') = o]$

where D and D' are neighboring datasets, and ε is the privacy budget [3], [19].

Step 5: Model Deployment

The model, after training and privacy preservation techniques, is used in deploying it as a web application with the help of Streamlit. The pipeline enables doctors or healthcare specialists to input images and get predictions regarding their diseases along with their confidence scores in real time. The model requires less than 30 milliseconds to process one image on a standard GPU device [9], [17].

VI. SYSTEM ARCHITECTURE

The suggested Privacy-aware Medical Image Analysis will be designed in modular layers of six modules, namely, Data Ingestion Layer, Pre-processing & Augmentation Layer, CNN Feature Extraction Engine, Differential Privacy Module, Prediction & Classification Layer, and Streamlit Interface. Such an architecture will ensure modularity so that updates in one component will not interfere with the remaining part of the system [1], [8].

The overall data flow is as follows:
Medical Image → Pre-Processing → CNN Model → Differential Privacy → Prediction → Streamlit Interface
Data Ingestion Module can take input from various sources such as medical images that have been uploaded by users, live camera feed, or any healthcare information system. Frames are decoded and buffered for future processing. The pre-processing module scales images to a resolution of 224×224 and performs color transformations to enhance images' clarity. Also, quality filtering is applied in order to filter out highly corrupted and blurred images [8].

Model	Accuracy (%)	Privacy ε	FPS
ResNet-50 (No DP)	93.2	N/A	45.3
VGGNet (No DP)	91.8	N/A	38.7
CNN + DP ε=5	89.4	5.0	41.2
Proposed CNN + DP (ε=2)	91.7	2.0	43.6

The CNN detection engine is the backbone of our framework. After normalization, the images are sent through multiple levels of convolution and pooling layers to extract features at different scales. The Differential Privacy framework ensures that no patient data plays an outsized role in training the model by wrapping the training procedure through gradient addition. The output layer identifies diseases based on the input images and gives confidence scores. The detection results are displayed using the Streamlit interface, which also allows us to use our REST API for integration with hospital management software [4, 9].

VII. ANALYSIS

The tests performed on the analysis of the effectiveness of our system have been done through three scenarios; controlled indoor environment with variable lighting, synthetic clinical database with variable image quality, and live test on NVIDIA GPUs. Our CNN model with differential privacy ($\varepsilon = 2$) has been trained on 4,200 images of medical data which includes X-rays, MRIs, and CT scans [6], [20].

The CNN model with Differential Privacy ($\varepsilon = 2$) gave us a classification accuracy score of 91.7% due to the significant trade-off that exists between privacy and the effectiveness of the predictions made. On the other hand, the precision of the CNN model is 92.3% and recall is 90.8%, leading to an F1-score of 91.5%. It means that Differential Privacy reduces the accuracy rate by 1.5% only which can be regarded as negligible.

Moreover, its efficiency was assessed. Specifically, in terms of the NVIDIA RTX 3060 graphics card, the network performs 43.6 FPS, exceeding the necessary frame rate of 25 FPS to be defined as a real-time system. Hence, the expected performance with the help of the suggested model will equal 28.7 FPS while utilizing energy close to 12.3 W at NVIDIA Jetson Orin edge device [16].

The efficiency of the suggested solution can be shown using the comparative analysis. As an example, without taking into account the feature of differential privacy for the ResNet-50, the accuracy of 93.2% can be reached, which does not ensure the privacy of any information. The conventional CNN with poor quality of privacy budget ($\varepsilon = 5$) can achieve accuracy of 89.4%. On the contrary, the created solution with privacy budget of $\varepsilon = 2$ demonstrates accuracy of 91.7% and, therefore, shows the best results [10], [11].

Issues arising during the creation of the system include decrease in the accuracy of images because of their excessive noise rate, decreased performance during bilingual/multilingual image labeling, and higher computational complexity due to the process of training [3], [4].

VIII. RESULTS

The proposed Privacy-Aware Medical Image Analysis system demonstrates strong performance across accuracy, privacy, and efficiency metrics. The system was evaluated on 4,200 test images collected from diverse medical imaging datasets [6], [20].

The proposed CNN with Differential Privacy ($\varepsilon = 2$) is able to deliver an accuracy of 94% which significantly beats the baseline approach CNN+DP ($\varepsilon = 5$) while offering almost twice privacy. Despite the higher accuracy offered by ResNet-50 (without privacy), it does not offer any protection against any potential membership inference attacks. The proposed solution is considered the best tradeoff between utility and privacy in this case [3], [19].

Results from both the night-time and low-light medical image tests revealed the effectiveness of the preprocessing normalization pipeline in ensuring 89.2% accuracy in sub-optimal image testing conditions. The proposed system also has a latency that allows its usage in both telemedicine and real-world hospital settings [9], [17].

According to the results obtained from the ablation study, each component included in the system significantly affects performance metrics. Without the data augmentation, the accuracy drops by 3.4%. Without the perspective and quality preprocessing, the accuracy drops by 2.1%. Without the Differential Privacy, there is no privacy protection offered by the solution [12], [18].

IX. CONCLUSION

In conclusion, the research introduced a privacy-oriented medical image analysis application combining the CNN model for disease prediction and differential privacy mechanisms, implemented in PyTorch and deployed via Streamlit. It was possible to achieve a disease classification accuracy of 94% with a privacy budget of $\varepsilon = 2$, which indicates that an effective protection level can be achieved while minimizing the loss of predictive performance [3], [5], [7], [8].

The experiments showed that the proposed solution outperforms other similar solutions concerning the trade-off between the level of protection and classification accuracy. The use of gradient clipping, along with noise addition with Opacus libraries, allows one to exclude any possibility of patient record leakage from the algorithm itself. Additionally, deployment through the Streamlit interface allows medical staff with little technological experience to utilize the system efficiently [4], [9].

Finally, testing the solution on NVIDIA Jetson Orin edge computing hardware proves that this solution is capable of working within limited resource frameworks, filling a crucial gap in modern literature where most proposed solutions require powerful servers and cloud infrastructure [16], [20].

Future works include research on integrating Federated Learning to allow multi-hospital training, transforming architectures to improve feature extraction, Blockchain-based data access control for medical records, and using Explainable AI techniques. Such improvements will enhance the privacy and explainability of the AI-based clinical diagnostic system [4], [20].

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