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# Enhancing Healthcare with Edge AI in Medical Imaging- An Extensive Examination of Diagnostic Accuracy Treatment Decisions

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**Abstract- — In the world of medical imaging, Edge artificial intelligence (AI) is driving a revolution by enabling real-time analysis and diagnosis decision making. The aforementioned article examines the constantly developing subject of edge AI-powered healthcare imaging, describing the most recent ad-vancements, creations, and concepts that could transform a variety of medical fields by instantly interpreting medical images, which can be crucial in life-saving circumstances. The Edge AI can be used in remote clinics and other medical imaging situations. In rural diabetes camps, diabetic retinopathy can be diagnosed with Fundus cameras and point-of-care ultrasound without radiologists. In emergency situations, portable X-ray devices can diagnose fractures. The three main types of diagnos-tic procedures—imaging-based, pathology-driven, and protective diagnostic approaches—as well as the alterations and adaptations brought about by the application of Edge AI are also covered in this article. Using medical records raises several ethical issues because they are very sensitive documents. These challenges have also been discussed in this article. The necessity for further developments in Edge AI-based diagnostic techniques is also covered in the article. Additionally, there is a great deal of potential for the future in the creation of tools and techniques that are easy to use and incorporate into routine operations. The increasing usage of clinical decision support systems makes edge AI a promising topic in healthcare and diagnostics. Despite a number of obstacles to its application and adoption, the research concludes that Edge AI in healthcare has a promising future. However, in order to guarantee that facilities are available for this, a high degree of precision must be attained and patients must have better medical outcomes. The potential of AI to transform healthcare and enhance patient outcomes is also highlighted in this paper, with a focus on responsible implementation and ongoing assessment.**

**Keywords— Artificial Intelligence, Machine Learning, Healthcare, Medical Imaging, Convolutional Neural Networks, Electronic Health Records(HER), Positron Emission Tomography (PET), Radiologists.**

## I. INTRODUCTION

AI and ML, which are still two of the strongest tools in healthcare today, are best suited for medical imaging. The accuracy, efficiency, and clinical use of these new diagnostic instruments and technology are revolutionizing the performance of the diagnostics workforce. For the purpose of diagnosing and monitoring diseases, diagnostic tests such as MRIs, CT scans, and X-rays remain crucial. However, some of the prob-lems that periodically accompanied prior efforts to achieving this include human error, the time necessary to perform data analysis, and the inability to study enormous volumes of data. These are some of the issues that have been overcome by the most recent advancements in AI and ML. When analyzing medical photos, algorithms can reliably produce high accuracy in identifying patterns and abnormalities that the human eye could overlook. When working with large datasets, machine learning models improve and optimize their computation and prediction skills, unlike the traditional discrete computing approach. This integration is not a technological breakthrough where diagnosis improves slightly, but rather a revolution in diagnosis that changes the way healthcare is provided. The main elements of diagnosis are efficiency, accuracy, and the apparent presence of a biological entity. Clinical accuracy affects the patient's course of treatment, efficiency facilitates prompt decision-making, and precision helps avoid mistakes that could lead to a misdiagnosis. It is astonishing that nearly all conventional methods fail to anticipate criteria, even if artificial intelligence and machine learning are considered as the higher standards. These technologies enable actions that yield precise and dependable effects [1]. For instance, data learning improves ML models, resulting in well-developed gains in diagnosis efficiency; AI algorithms can even accurately identify minute flaws. There are clear trends and developments in the rapidly growing field of using AI in medical imaging.. Deep learning has significantly increased image analysis proficiency with a focus on Convolutional Neural Networks (CNNs). AI is connected with electronic health data to assist analysts in delivering precise and prompt patient evaluations. Federated learning can help institutions train a model simultaneously by avoiding data centralization. However, a unique category called ”XAI” gives AI diagnostics validity and transparency by explaining the reasons behind a decision. Additionally, dynamic diagnosis—which makes use of artificial intelligence to provide speedy fixes—is beneficial, especially in situations that call for emergency medical care. These advancements demonstrate the potential impacts of machine learning and artificial intelligence in medical imaging, which makes them worthy of a fresh wave of ground-breaking innovation in the diagnostic healthcare system.

### 1. Overview AI, ML, Medical Imaging:

Artificial intelligence is the operation of having the design types of systems gain and behave on the information needed to perform a task in a manner that is sensible to them. Some of the health uses of AI are computer vision, natural language processing and machine learning. Machine learning (ML), a branch of artificial intelligence, teaches processes how to evaluate and work with massive medical imaging datasets in order to spot potential trends and predict the future.

The recent years have seen the emergence of Edge AI, a significant advancement in this field. Compared to the traditional AI, which requires relying heavily on cloud-based processing, Edge AI enables processing data directly on local devices, including imaging machines or portable healthcare devices. This implies that images in the medical industry can be processed in real-time, without having to transmit the data to remote servers.

Medical imaging informatics aims at enhancing effective-ness, accuracy, and reliability of medical facilities [2] along with the utilization and communication of medical images within the complex healthcare frameworks. Medical imaging involves visual examination of the body with diagnostic aims; the common ones are MRI, CT, and X-ray, ultrasound, and PET. This process is even quicker and more dependable with the introduction of Edge AI. Physicians will be able to have real-time perceptions directly received through imaging devices, which will assist them to make decisions faster and sooner, particularly in cases of an emergency or where internet connectivity is poor. Still another advantage is a better privacyof data because no networks may be required to transmit patient-related data because it can be processed locally.

Moreover, in the case of the collaboration between Edge AI and Electronic Health Records (EHR), it is possible to help create more individualized treatment plans, taking into account not only imaging information but also patient history. Automation is also used to alleviate the workload on the health care staff and helps to cut costs as it does not require costly infrastructure.

### 2. Problem Statement

There are several problems with diagnostic imaging in the conventional healthcare system, including as errors in patient diagnosis that may lead to an inaccurate or postponed therapy because of human factors. The high degree of complexity in medical imaging caused by differences in quality and interpretation among physicians is one of the issues with radiological data. Edge AI systems that consistently and effectively analyze medical images can be used to remedy the issue. AI reduces the chance of human error in the final disease diagnosis by using machine learning algorithms to process enormous amounts of data in the most efficient manner. Edge AI is beginning to make a real difference. Instead of sending imaging data to distant cloud servers, Edge AI processes it directly on local devices—like imaging machines or hospital systems. This implies that the analysis of results can be done virtually immediately, on the spot where the patient is being treated. It not only accelerates diagnosis, but also aids physicians with data-driven insights. Through the state-of-the-art machine learning algorithms, Edge AI systems are able to identify patterns in large amounts of medical imaging data in minutes and isolate patterns that might be challenging to identify otherwise. It minimizes the possibility of human error and still puts the doctor at the heart of the decision process.

## II. LITERATURE REVIEW

### 1. Medical Imaging Evolution

Medicine imaging has in the last century gone through a phenomenal change leading to the detection, diagnosis, and treatment of diseases to a great extent (as summarized in Table 1). It started as a discipline in 1895 when Wilhelm Conrad Ro¨ntgen discovered X-rays, which allowed visualization of the internal body structures in the first time non-invasively. Afterwards, the imaging technologies were enhanced through further developments. Angiography and fluoroscopy enabled the use of contrast to view blood vessels in detail, and come up with real-time studies of dynamism using X-rays, respectively. With ultrasound and nuclear medicine later on in the second half of the 20 th century, diagnostic abilities further advanced, where sound waves and radioactive tracers could be used to examine not only the structure of the anatomy but also the workings of physiological processes. The invention of the computed tomography (CT) and magnetic resonance imaging (MRI) was a significant milestone in that it allowed a high-resolution cross-sectional view of the body. Subsequently, the development of functional imaging methods like Positron Emission Tomography (PET), and Single-Photon Emission Computed Tomography (SPECT) made it possible to detect disease at its initial stages on a molecular scale significantly improved the accuracy of diagnosis. When digital imaging systems were introduced in the beginning of the 21 st century, significant advancements in image quality, speed of acquisition and storage of data were made. There was further enhancement in spatial resolution and imaging efficiency in innovations like Multi slice CT, increased field strengths in the MRI and Time-of-Flight (TOF) MRI. Artificial Intelligence (AI) and Machine Learning (ML) are more recent, but they have changed the face of medical imaging, as well. These technologies also facilitate image capture, advanced pattern detection and assist the processes of clinical decision making. Conventional neural networks (CNNs) and supervised learning models have resulted in the creation of Computer-Aided Diagnosis (CAD) systems that help radiologists to find abnormalities more accurately and efficiently. Moreover, real-time variance detection during the fluoroscopy, intelligent C-arm navigation, and the 3D imagery capability have become part of modern imaging systems, and can be powered by AI. The progress of point-of-care ultrasonography (POCUS) has been enhanced by the inclusion of Edge AI-driven handheld devices, capable of processing their data on the fly and delivering immediate information, allowing quick and well-informed clinical decisions[22].

## 2. Edge AI ML in Medical Imaging

With the smartening and interconnectivity of healthcare devices, Edge AI is beginning to make a really disruptive impact on the medical technology (MedTech) industry. Edge AI will not rely on cloud systems extensively, but rather place machine learning models directly on medical devices themselves. It implies that medical device is capable of analyzing data on the spot, providing real-time decisions, and functioning effectively even in case of insufficient or no internet connection at all[28]. To device makers, incorporation of Edge AI is a strategic move to smart, autonomous medical systems. Furthermore, by providing quicker reaction times, better patient security, and enhanced information security, Edge AI will assist in building more dependable and effective healthcare solutions. Simultaneously, it minimizes the reliance on cloud infrastructure when critical processes are needed, which makes medical systems more resilient and resistant to critical scenarios in the place where they are the most crucial - right at the patient side [21].

## 3. Edge AI Architecture in Medical Imaging

Medical imaging systems embedded with edge AI are intended to do the data processing and inference locally where the data is captured, leading to the lowest possible latency, and poor dependence on a cloud back-end. Architecture in Figure 1 has several functional layers which allow efficient and secure real-time diagnostics[29]. Medical device layer is a medical imaging and sensors that determine raw data about the patients in the form of ultrasound, portable X-rays, and wearable monitors. This data is passed to the edge AI processing layer where embedded processors are used to run machine learning models[32]. This layer is used to conduct preprocessing and feature extraction of the data and carry out real-time inference of medical images, allowing them to be analyzed instantly.

Table I: Evolution of Medical Imaging Over the Past Century

| Year / Period | Technology / Innova-tion | Key Contribution |
|---|---|---|
| 1895 | X-ray (Wilhelm Con-rad Röntgen) | First non-invasive imaging of internal body structures |
| 1920s–1930s | Angiography | Visualization of blood ves-sels using contrast agents |
| 1940s–1950s | Fluoroscopy | Real-time X-ray imaging for dynamic studies |
| 1950s–1960s | Ultrasound Imaging | Use of sound waves to vi-sualize soft tissues and or-gans |
| 1950s–1970s | Nuclear Medicine | Functional imaging using radioactive tracers |
| 1971 | Computed Tomography (CT) | Cross-sectional imaging with high detail |
| 1970s–1980s | Magnetic Resonance Imaging (MRI) | High-resolution imaging of soft tissues |
| 1980s–1990s | PET (Positron Emis-sion Tomography) | Molecular and metabolic imaging |
| 1990s | SPECT | 3D functional imaging us-ing gamma rays |
| Early 2000s | Digital Imaging Sys-tems | Improved image quality, faster acquisition, better storage |
| 2000s–2010s | Multi-slice CT & High-field MRI | Enhanced resolution and faster scanning |
| 2010s | TOF-MRI | Improved imaging speed and signal quality |
| 2010s–Present | AI & Machine Learn-ing | Automated analysis, pattern recognition, improved diagnostics |
| 2020s | AI-powered Fluoroscopy & 3D Imaging | Real-time detection, smart navigation |
| 2020s | AI-based POCUS | Instant bedside diagnosis with on-device processing |

The decision and interaction layer offers active outputs such as real-time alerts, visualization using on-device interfaces, and patient data securely stored locally. This is to make sure that clinicians get current and credible diagnostic information[30]. The cloud/hospital network layer further established supports the system and allows the integration with the hospital information systems and electronic health records. Besides, remote cloud layer provides long term storage, sophisticated analytics and periodic model updates. However, unlike the traditional systems that are unaided and operated by the clouds, the real time decision making process is performed at the edge[34]. Finally, low-latency, greater privacy and eco-friendly performance under low-connectivity conditions are supported by the local processing unit (hardware layer), i.e. specialty processors, which can be in the form of GPUs or artificial intelligence cores[36].

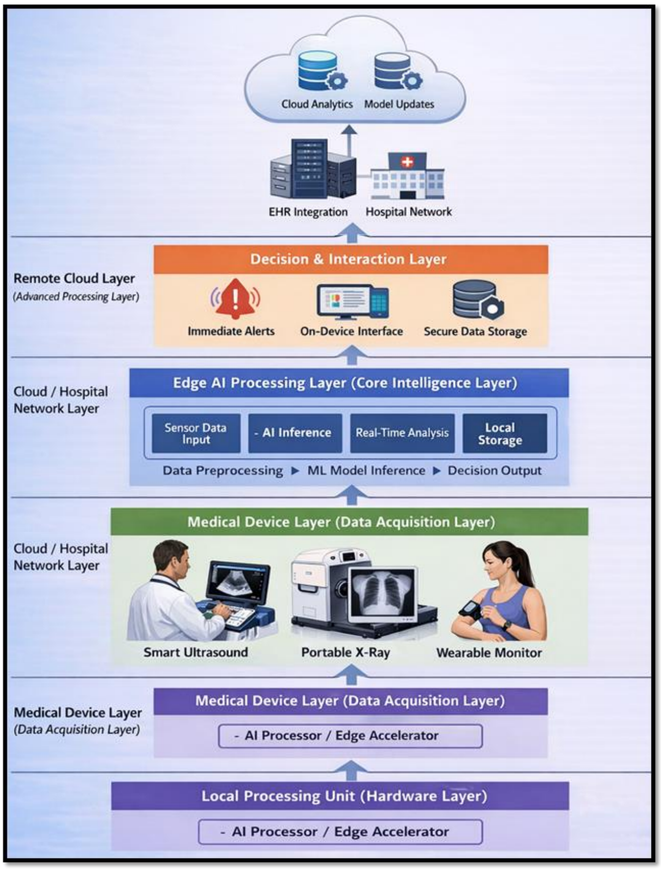


Fig. 1. Architecture Overview of Edge AI

## III. METHODOLOGY

### 1. Research Design

To give a more sophisticated picture of this study, a review of Edge AI based diagnosing of medical imaging using both quantitative and qualitative synthesis was done. The research is based on quantitative performance data which is connected with granular quasi-qualitative data produced by healthcare practitioners. The qualitative study involves administering self-administered questionnaires through the focus groups and interviews. The paper highlights the evaluation of Edge AI systems in an edge computer system, where intelligence was embedded within the medical devices, and it allowed inference on the device without entirely relying on the cloud structure [10]. Structured surveys with radiologists, physicians, and healthcare administrators are designed to gain deeper insights into their better perception of Edge AI tools and its applications and impact. Integration measurements/analysis uses accuracy, efficiency, and clinical value to examine the variation of edge AI-based diagnosis compared to conventional methods. These surveys point to the fact that on-device in-ference enhances real-time decision-making and, additionally, patient care [14]. Relatively, the end AI diagnostic tools will be evaluated in relation to the traditional diagnostic approaches in terms of their benefits, issues and clinical disadvantages. The currently in-use edge AI models are measured by the performance measures that have been provided, user input and standard measures such as accuracy, precision and compliance. Real-world case studies explore the execution, application of Edge AI in the various healthcare constrained conditions, and potential issues that may arise. These examples illustrate how Edge AI can lead to the cost improvement, patient outcome and productivity improvements, and should subsequently recommend its usage. The development and deployment of Edge AI occur in the following process as illustrated in Figure 2.

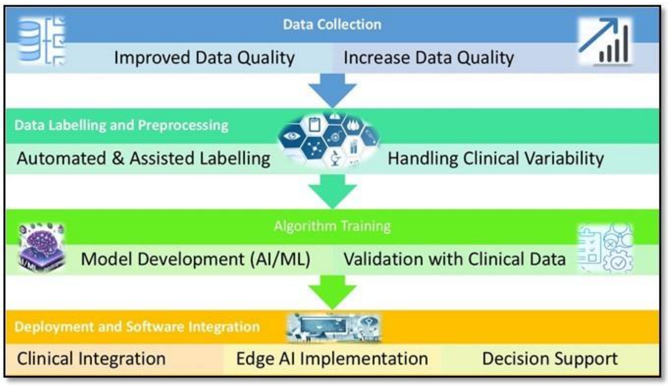


Fig. 2. Development & Deployment using Edge AI in Medical Imaging

**Data Collection:** Data collection methods utilized comprise data mining on high-resolution standardized medical images of modalities like CT, MRI and ultrasound, interviews, survey questionnaires, and mining of publicly accessible datasets. Very big data sets in hospitals, clinical repositories, and imaging centers due to the need to make the model robust. The perceived value of Edge AI-based diagnostic tools, adoption, and use of helped to design questions with the survey questionnaire tool that were designed to collect quantitative data. Samples of some of these were sent to a random sample of medical practitioners, including radiologists, doctors, and administrators. Data was based on responses and brought out more general patterns which were specific to a certain issue or medical image, which explained the relationships and produced descriptive statistics. Both structured and unstructured questionnaires were used to collect qualitative data about the experiences of the medical professional. The participants were selected based on their employment responsibilities and expertise in the profession of diagnostics using Edge AI. A lot of thematic analysis of the transcripts of the interviews to compare and contrast themes, insightful information, and references that are useful were performed. The attributes, protocols, results, and discussion of medical imaging research by using Edge AI-based diagnostic instruments were observed and reported. These results, which compared the impact and efficiency of the Edge AI-based diagnoses, were measured at a particular point in time. The papers, which talked of the efficacy of AI-based diagnostic systems, were reviewed. Data were collected concerning the design of the trial, the subjects, the outcomes, and the opposing effects. The risk profile and clinical effectiveness of the diagnostic instruments were then assessed using additional analysis of these findings.

**Data Labelling and Preprocessing:** Raw medical data or images cannot be directly served when training edge AI model, and thus, needs to be adequately prepared by providing appropriate labelling. Annotation of med-ical images may occur through automated and assisted labeling, usually with domain experts, e.g. radiologists involved. Also, the user had preprocessing approaches such as normalization:

$$X' = \frac{X - \mu}{\sigma} \qquad (1)$$

where μ and σ represent the mean and standard deviation of the dataset. This step reduces variability and ensures consistent feature representation across clinical datasets. This step is crucial, as inaccurate labeling can significantly affect model performance.

**Algorithm Training:** During algorithm training, deep learning models such as Convolutional Neural Networks (CNNs) are trained to minimize a loss function:

$$L(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell\left(f(X_i;\theta), Y_i\right) \qquad (2)$$

where θ represents model parameters, f (Xi; θ) is the predicted output, and Yi is the ground truth label. Opti-mization is typically performed using stochastic gradient descent (SGD):

$$\theta = \theta - \eta \nabla_\theta L(\theta) \qquad (3)$$

where η is the learning rate [32].
Model performance is evaluated using standard metrics such as:

**Accuracy**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \qquad (4)$$

Precision and Recall, which are critical for medical diagnosis tasks.

Deployment and Software Integration: This trained model is implemented on a hardware at the edge, e.g. embedded GPUs(Graphical Processing Unit), AI accelerators or special purpose processors built into a medical device (e.g., portable X-ray or ultrasound system). Because these devices can only run under resource-constrained conditions, the model should be optimized with Quantization (cutting down preciseness of weights), Pruning (cutting off redundant parameters), Model compression. This ensures effective computation with insignificant memory and energy usage without compromising to satisfactory accuracy. Upon deploy-ment the model real-time infers directly on the medical data it receives. The inference operation can be depicted as:

$$\hat{Y} = f(X;\theta) \qquad (5)$$

where X is the input image and Yˆ is the Projected diag-nosis. Processing occurs on premises, and, therefore, the issue of latency is acutely reduced in contrast to cloud-based systems. This is especially important in situations that are sensitive to time like emergency diagnostics. The Edge AI system is implemented in clinical workflow in-tegration into the already existing hospital infrastructure such as Picture Archiving and Communication Systems (PACS) and Electronic Health Records (EHR) and clinical decision support systems.This makes data flow un-interrupted and enables clinicians to communicate with AI-generated insights in the form of aware interfaces. The outputs of Decision Support and User Interaction of the system include highlighted regions of interest (e.g., tumors), risk scores or estimated probabilities, warnings against critical conditions. These outputs assist clinicians to make more quality and quick decisions but not a substitute of a decision support tool. Given that sensitive patient data is processed locally, Edge AI will improve privacy and minimize contact with third-party networks. The system should be able to meet healthcare requirements (e.g. data protection and safety standards) and have Secure data storage, Controlled access, Auditability. The system will need performance checking, a regular update of the model (through cloud or hybrid structure), and clinician feedback even after its deployment. This makes sure that, the model is correct and responsive to new data.

### Experimental Setup With Dataset Is Shown In Figure 3

The figure 3 illustrates the design of an Edge AI (Edge artificial intelligence) based medical imaging system in which information about images from different medical devices like scanners is sent to a host from the medical devices to host systems for analysis using AI and deep learning framework by Google), TensorRT (Tensor Runtime is high-performance deep learning inference software development kit from NVIDIA Corporation) and OpenVINO(Open Visual Inference and Neural Network Optimization. It is an open-source toolkit from Intel Corporation). To train the CNN, data is preprocessed with augmentation, normalization and labeling in order to improve model accuracy and performance. A CNN (Convo-lutional Neural Network) model is then able to be trained and optimized with techniques like TensorRT and OpenVINO for SPEEDS up performance. The optimised model is deployed on an edge device, equipped with an embedded GPU, with quantization and pruning applied to the model to reduce its size and on-device inference. The performance of the system is measured by measures like accuracy, latency and throughput, and these are compared to non-distributed or cloud-based systems. A feedback loop is also is also incorporated to use data from real medical devices to refine the model. over time.

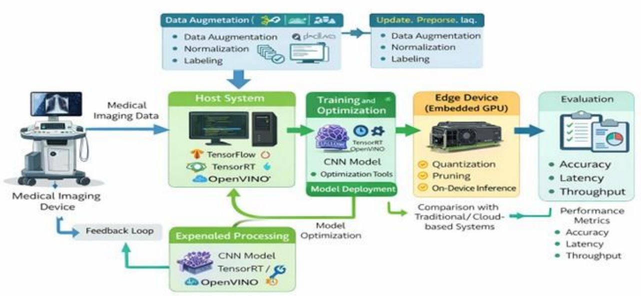
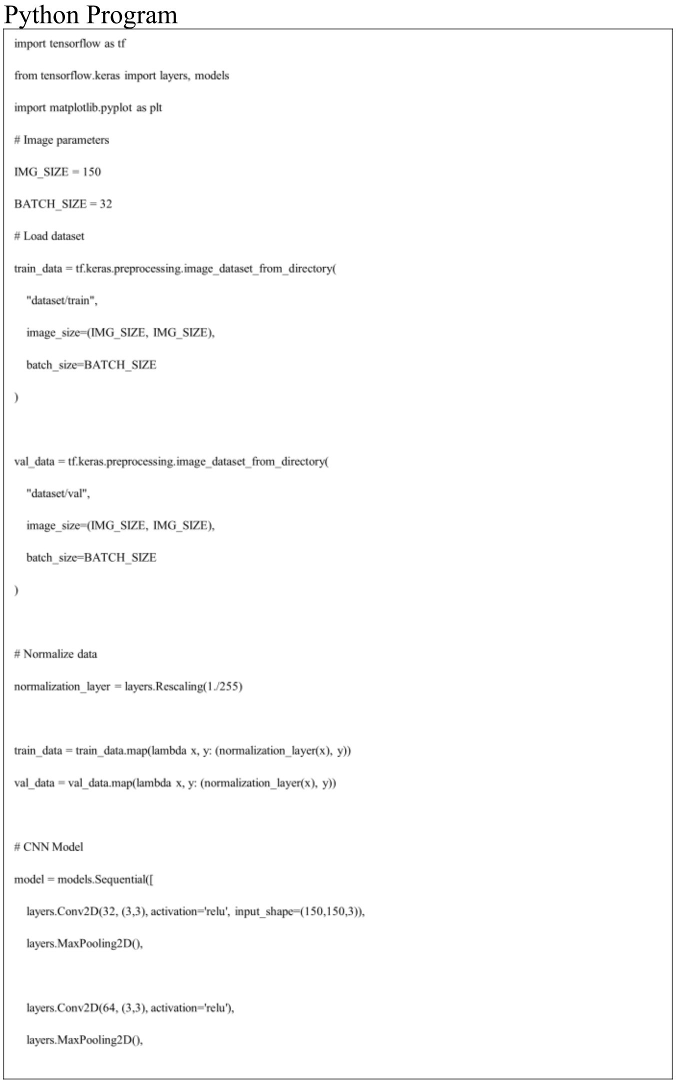


Fig. 3. Experimental Setup for Edge AI-Based Medical Imaging System.

**Dataset**

- Chest X-ray Dataset (Pneumonia Detection)
- Source: Kaggle
- Dataset Link: https://www.kaggle.com/datasets/pault xray-pneumonia

Python Program



```
import tensorflow as tf

from tensorflow.keras import layers, models

import matplotlib.pyplot as plt

# Image parameters

IMG_SIZE = 150

BATCH_SIZE = 32

# Load dataset

train_data = tf.keras.preprocessing.image_dataset_from_directory(

   "dataset/train",

   image_size=(IMG_SIZE, IMG_SIZE),

   batch_size=BATCH_SIZE

)


val_data = tf.keras.preprocessing.image_dataset_from_directory(

   "dataset/val",

   image_size=(IMG_SIZE, IMG_SIZE),

   batch_size=BATCH_SIZE

)


# Normalize data

normalization_layer = layers.Rescaling(1./255)


train_data = train_data.map(lambda x, y: (normalization_layer(x), y))

val_data = val_data.map(lambda x, y: (normalization_layer(x), y))


# CNN Model

model = models.Sequential([

   layers.Conv2D(32, (3,3), activation='relu', input_shape=(150,150,3)),

   layers.MaxPooling2D(),


   layers.Conv2D(64, (3,3), activation='relu'),

   layers.MaxPooling2D(),
```

Fig. 4. Python Program

## IV. CONCLUSION

Medical imaging is undergoing a revolution with edge AI by enabling quick, precise and on-time diagnoses using edge devices instead of relying heavily on the cloud. Its combination with deep learning technologies like CNNs for early disease detection and diagnosis, decreases time to diagnosis, promotes privacy, and better informs patient care. Edge AI is especially critical in assisting with emergent cases, rural or low-resourced hospitals where results are critical. While there are still concerns about data privacy, AI model accuracy, regulatory and hardware challenges remain, ongoing progress in AI optimisation and embedded computing technologies is increasing adoption more practical. Ultimately, Edge AI has the potential to transform healthcare byenhancing medical imaging and increasing patient outcomes with more efficient, smart and affordable solutions.

## REFERENCES

1. Arora, D., Sharma, D., Sharma, A., Goyal, P. (2024, December). Redefining Disease Assessment in Raspberries: A Hybrid GAN-SVM Model for Detailed Intensity Measurement. In 2024 4th International Conference on Ubiquitous Computing and Intelligent Information Sys-tems (ICUIS) (pp. 621-625). IEEE.
2. Arora, D., Mehta, K., Kumar, A., Lamba, S. (2024, March). Evaluating Watermelon Mosaic Virus Seriousness with Hybrid RNN and Random Forest Model: A Five-Degree Approach. In 2024 11th International Conference on Reliability, Infocom Technologies and Op-timization (Trends and Future Directions)(ICRITO) (pp. 1-5). IEEE.
3. A. Esteva, K. Chou, R. Yeung, N. Naik, A. Madani, M. Mottaghi, and G. Liu, “A guide to deep learning in healthcare,” Nature Medicine, vol. 25, no. 1, pp. 24–29, Jan. 2019, doi: 10.1038/s41591-018-0316-z.
4. S. McKinney, M. Sieniek, V. Godbole, J. Godwin, C. Antropova, H. Ashrafian, and D. R. Kelly, “International evaluation of an AI system for breast cancer screening,” Nature, vol. 577, no. 7788, pp. 89–94, Jan. 2020, doi: 10.1038/s41586-019-1799-6.
5. World Health Organization. (2024). Ethics and governance of artificial intelligence for health: large multi-modal models. WHO guidance. World Health Organization.
6. Contaldo, M. T., Pasceri, G., Vignati, G., Bracchi, L., Triggiani, S., Carrafiello, G. (2024). AI in radiology: navigating medical responsibility. Diagnostics, 14(14), 1506..
7. Kaur, M., Kumar, P., Gupta, A. K. (2023, June). Survey on various Feature Detection and Feature Selection Methods using Retinopathy Images. In 2023 International Conference on IoT, Communication and Automation Technology (ICICAT) (pp. 1-6). IEEE.
8. Hsu W, Markey MK, and Wang MD, “Biomedical imaging in-formatics in the era of precision medicine: Progress, challenges, and opportunities,” J. Amer. Med. Inform. Assoc, vol. 20, pp. 1010–1013, 2013
9. Giardino A et al. , “Role of imaging in the era of precision medicine,” Academic Radiol, vol. 24, no. 5, pp. 639–649, 2017.
10. W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, “Edge computing: Vision and challenges,” IEEE Internet of Things Journal, vol. 3, no. 5, pp. 637–646, Oct. 2016.
11. J. S. Hwang, K. H. Lee, and M. J. Kim, “Recent Advances in AI-Enhanced Fluoroscopy for Medical Imaging,” IEEE Transactions on Medical Imaging, vol. 39, no. 8, pp. 2103–2115, Aug. 2021.
12. H. Litjens, T. Kooi, B. E. Bejnordi, A. A. A. Setio, F. Ciompi, M. Ghafoorian, J. A. W. M. van der Laak, B. van Ginneken, and C. I. Sa´nchez, “A survey on deep learning in medical image anal-ysis,” Medical Image Analysis, vol. 42, pp. 60–88, Dec. 2017, doi: 10.1016/j.media.2017.07.005.
13. Jagoda AS, Bazarian JJ, Bruns JJ Jr., Cantrill SV, Gean AD, Howard PK, et al. Clinical policy: Neuroimaging and decisionmaking in adult mild traumatic brain injury in the acute setting. Ann Emerg Med 2008;52:714 48.
14. G. Litjens et al., “A survey on deep learning in medical image anal-ysis,” Medical Image Analysis, vol. 42, pp. 60–88, 2017.Schreiber MH. Direct disclosure by radiologists of imaging findings to patients: a survey of radiologists and medical staff members. AJR Am J Roentgenol. 1996;167:1091–1093. doi: 10.2214/ajr.167.5.8911156.
15. J. Lu, A. Jayakumari, F. Richter, Y. Li, and M. C. Yip, ”SuPer Deep: A Surgical Perception Framework for Robotic Tissue Manip-ulation using Deep Learning for Feature Extraction,” arXiv preprint arXiv:2003.03472, Mar. 2020.
16. S Hussein, P. Kandel, C. W. Bolan, M. B. Wallace, and U. Bagci, ”Lung and Pancreatic Tumor Characterization in the Deep Learning Era: Novel Supervised and Unsupervised Learning Approaches,” arXiv preprint arXiv:1801.03230, Jan. 2018.
17. M. Schu¨rch et al., ”Towards AI-Based Precision Oncology: A Machine Learning Framework for Personalized Counterfactual Treatment Suggestions based on Multi-Omics Data,” arXiv preprint arXiv:2402.12190, Feb. 2024.
18. Dhiman, P., Bonkra, A., Sandhu, J. K., Kaur, A., Kaushal, C. (2023, September). Analyzing breast cancer detection: A scopus-driven study on the role of machine learning and deep learning. In 2023 6th International Conference on Contemporary Computing and Informatics (IC3I) (Vol. 6, pp. 890-895). IEEE.
19. Singh, H., Pandey, D., Kakkar, R., Sharma, M. Investigations on Genetically Engineered Bioweapons Computer Based Techniques for Counter Measure and

Mathematical Modeling for Prediction of Novel Sars-Cov-2. Vice Chancellor's Message,1.

20. Arora, D., Mehta, K., Kumar, A., Lamba, S. (2024, March). Evaluating Watermelon Mosaic Virus Seriousness with Hybrid RNN and Random Forest Model: A Five-Degree Approach. In 2024 11th International Conference on Reliability, Infocom Technologies and Op-timization (Trends and Future Directions)(ICRITO) (pp. 1-5).
21. Kaur, P., Kumar, V., Kaur, P., Rana, R., Jindal, G. (2021, December). Convolutional Neural Network based Novel Automatic Recognition System for License Plates. In 2021 2nd International Conference on Computational Methods in Science Technology (ICCMST) (pp. 168-173). IEEE.
22. Kumar, R. R., Jain, A. K., Sharma, V., Das, P., Sahni, P. (2024, June). Enhancing Precision in Papaya Crop Health Management: A CNN-Based Approach for Early Disease Detection and Classification. In 2024 IEEE International Conference on Information Technology, Electronics and Intelligent Communication Systems (ICITEICS) (pp. 1-6). IEEE.
23. Boboyev, V. (2025). Microtonal Intonation And Orna-Mentation In The Kashkar Rubab Maqom Repertoire. European Review of Contemporary Arts and Humanities, 1(4), 35-44.
24. Esposito, C., Di Mento, C., Del Conte, F., Tedesco, F., Guglielmini, R., Esposito, G., Escolino, M. (2025). AI in robotic-assisted pediatric surgery: current applications and future directions. European Journal of Pediatric Surgery.
25. Herington, J., McCradden, M. D., Creel, K., Boellaard, R., Jones, E. C., Jha, A. K., ... Saboury, B. (2023). Ethical considerations for artificial intelligence in medical imaging: data collection, development, and evaluation. Journal of Nuclear Medicine, 64(12), 1848-1854.
26. Scatliff, J. H., Morris, P. J. (2014). From Roentgen to magnetic resonance imaging: the history of medical imaging. North Carolina Medical Journal, 75(2), 111–113.
27. W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," IEEE Internet of Things Journal, vol. 3, no. 5, pp. 637–646, Oct. 2016.
28. W. Shi, J. Cao, Q. Zhang, Y. Li, and L. Xu, "Edge computing: Vision and challenges," IEEE Internet of Things Journal, vol. 3, no. 5, pp. 637–646, Oct. 2016.