IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, May 2026
Impact Factor: 8.2

Smart Healthcare Framework for Hand and Leg Fracture Detection using ML Algorithm

Aditya Dehade[1], Om More[2], Aarya Kandekar[3], Sakshi Badar[4], Prof. B. M. Gawale[5]
Department of Computer Engineering[1-5]
Loknete Gopinathji Munde Institute of Engineering Education and Research, Nashik, India.
[1] dehadeaditya922@gmail.com [2] ommore430@gmail.com [3] kandekaraarya@gmail.com
[4] sakshibadar08@gmail.com [5] logmieer.co.bharti@gmail.com

Abstract: *The Smart Healthcare Fracture Detection System is an artificial intelligence-based mobile application designed to automatically detect bone fractures from X-ray images. The system aims to assist medical professionals and improve diagnostic efficiency by providing fast and accurate preliminary analysis. The core of the system is built using the YOLOv8 (You Only Look Once version 8) algorithm, a deep learning-based object detection model. The model is trained on a dataset of annotated X-ray images to identify fracture regions and highlight them using bounding boxes. For deployment on mobile devices, the trained model is converted into TensorFlow Lite (TFLite) format, enabling real-time and efficient on-device inference. The application allows users to upload or capture X-ray images, which are then preprocessed and analyzed by the model. Based on the prediction results, the system classifies the image as fractured or normal and visually indicates the affected area. The application also includes additional features such as PDF report generation, history tracking, and diet recommendations for better bone health. A backend system developed using PHP and MySQL is used to store user data, reports, and medical history. Communication between the mobile application and server is handled through REST APIs. The integration of machine learning, mobile computing, and backend technologies makes the system efficient, portable, and user-friendly.This project demonstrates how modern AI techniques can be applied in healthcare to reduce manual effort, improve diagnosis speed, and enhance accessibility, especially in remote and resource-limited environments.*

Keywords: Fracture Detection, Smart Healthcare System, Deep Learning, YOLOv8, Object Detection, X-ray Image Analysis, TensorFlow Lite, Mobile Health Application, Computer Vision.

I. INTRODUCTION

In recent years, the integration of advanced technologies such as Artificial Intelligence (AI) and Machine Learning (ML) into the healthcare sector has significantly improved the efficiency and accuracy of medical diagnosis. One of the important areas where these technologies can be applied is the detection of bone fractures using medical imaging techniques like X-rays. Traditional methods of fracture detection rely heavily on manual analysis by radiologists, which can be time-consuming and may sometimes lead to human errors, especially in busy or resource-limited healthcare environments.

The Smart Healthcare Fracture Detection System is designed to address these challenges by providing an automated and intelligent solution for detecting bone fractures from X-ray images. This system leverages deep learning techniques, particularly the YOLOv8 (You Only Look Once version 8) object detection algorithm, to analyze medical images and identify fracture regions accurately. The model is trained on a dataset of labeled X-ray images, enabling it to learn patterns associated with fractured and non-fractured bones.

The proposed system is implemented as an Android-based mobile application, making it highly accessible and portable. Users can either upload an existing X-ray image or capture a new image using the device camera. The image is then preprocessed and passed to a TensorFlow Lite (TFLite) model, which performs real-time inference directly on the

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, May 2026
Impact Factor: 8.2

device. The system detects the presence of fractures and highlights the affected region using bounding boxes, providing a clear visual representation of the result.

In addition to fracture detection, the system incorporates several supporting features to enhance its usability. A backend system developed using PHP and MySQL is used to store user information, detection results, and medical history. RESTful APIs facilitate communication between the mobile application and the server. The system also includes a PDF report generation module that allows users to download and share diagnostic reports. Furthermore, a history module enables users to access previously generated reports, and a diet recommendation module provides suggestions for improving bone health.

One of the key advantages of this system is its ability to perform detection offline using TensorFlow Lite, eliminating the need for constant internet connectivity. This makes the solution particularly useful in rural or remote areas where access to medical facilities and internet services may be limited. The system reduces dependency on manual diagnosis, speeds up the detection process, and supports healthcare professionals in making better decisions

Overall, the Smart Healthcare Fracture Detection System demonstrates how modern technologies such as deep learning, mobile computing, and cloud-based services can be integrated to create an efficient, reliable, and user-friendly healthcare solution. It has the potential to improve diagnostic accuracy, reduce workload on medical professionals, and enhance accessibility to quality healthcare services.

II. LITERATURE REVIEW

1. Ultralytics YOLOv8: State-of-the-Art Object Detection and Image Segmentation

- **Focus:** Introduced the YOLOv8 framework, a state-of-the-art model for real-time object detection, instance segmentation, and classification, offering superior accuracy and speed.
- **Limitation:** The study provides a general-purpose object detection framework but does not optimize or specialize the model specifically for medical radiograph analysis or resource-constrained mobile hardware deployment.
- **Our Contribution:** We specialize and fine-tune the YOLOv8 architecture specifically for musculoskeletal X-ray analysis and convert it into a lightweight format (TensorFlow Lite) for seamless, on-device deployment on resource-constrained mobile hardware.

2. Deep Learning for Bone Fracture Detection: A Comprehensive Review

- **Focus:** Conducted a comprehensive survey on various deep learning techniques (CNNs, ResNet, DenseNet) applied to bone fracture detection, summarizing datasets and accuracies.
- **Limitation:** Focused entirely on reviewing existing literature without proposing a concrete, deployable real-time system or evaluating mobile edge-computing capabilities.
- **Our Contribution:** We move beyond theoretical review by designing and implementing a concrete, deployable Android-based application that leverages edge-computing for real-time, patient-facing fracture detection.

3. Application of YOLOv8 for Real-Time Bone Fracture Localization in X-Ray Images

- **Focus:** Applied the YOLOv8 model on pediatric hand X-rays to detect and localize fractures, achieving high precision in detecting subtle micro-fractures.
- **Limitation:** The model runs primarily on high-end desktop GPUs and lacks adaptation for offline mobile deployment (e.g., conversion to TFLite) or patient-centric features.
- **Our Contribution**: We bridge the hardware gap by optimizing the YOLOv8 model for offline mobile deployment and integrate patient-centric features like automated PDF diagnostic report generation and personalized diet plans.

ISSN: 2581-9429
Volume 6, Issue 7, May 2026
Impact Factor: 8.2

4. Mobile Healthcare: Deploying Deep Learning Models on Android using TensorFlow Lite

- **Focus:** Discusses the conversion of deep learning models into optimized TensorFlow Lite formats and deploying them inside Android applications using custom interfaces.
- **Limitation:** The study focuses on general classification models (like MobileNet) and does not address localized medical object detection tasks like bone fracture boundary box prediction.
- **Our Contribution:** We extend edge-deployment capabilities by implementing complex object localization (accurate bounding box prediction for fractures) directly on mobile devices, rather than relying on simple binary image classification.

5. Enhancing orthopedic diagnostics with edge ai and cnns

- **Focus:** Developed a custom convolutional neural network (CNN) architecture to categorize skeletal fractures on edge-computing devices.
- **Limitation:** Custom CNN architectures often require massive training data and lack the advanced feature-pyramid networks found in YOLOv8, leading to lower detection accuracy for complex overlapping fractures.
- **Our Contribution:** We integrate the robust feature-pyramid capabilities of YOLOv8 into an edge-computing environment, ensuring high detection accuracy and precise localization even for complex or subtle overlapping fractures.

6. Automated Fracture Detection in X-ray Images Using Artificial Intelligence

- Focus: Explored deep learning-based automated fracture detection systems using ResNet-50 and VGG-16 networks on massive hospital datasets.
- Limitation: These heavy deep learning architectures have large memory footprints, making them highly unsuitable for real-time, offline runtimes on low-resource mobile devices.
- Our Contribution: We utilize a highly efficient, compressed YOLOv8-Lite model that drastically reduces memory footprint, enabling lightning-fast, offline inference entirely on low-resource mobile devices without crashing.

7. A Smart Healthcare Framework for Medical Image Analysis on Mobile Devices

- Focus: Designed a cloud-based mobile healthcare framework where images are uploaded from a smartphone to a remote GPU server for AI diagnostic processing.
- Limitation: The system is entirely dependent on continuous high-speed internet connectivity, rendering it unusable in remote or rural areas where network access is unstable.
- Our Contribution: We decentralize the diagnostic process by running the ML model completely on-device (Edge AI), guaranteeing zero-latency performance and 100% offline availability for remote and rural healthcare applications.

N o	Paper Title / Work	What They Do	Limitation (What They Don't Do)	What Our System Does
1	Ultralytics YOLOv8: State-of-the-Art Object Detection	Introduced YOLOv8 framework for real-time object detection and classification.	General-purpose framework; not optimized for medical radiographs or mobile deployment.	Specializes YOLOv8 for X-ray analysis and converts it to TFLite for offline mobile deployment.

DOI: 10.48175/IJARSCT-35468

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, May 2026
Impact Factor: 8.2

2	Deep learning for bone fracture detection: A review	Conducted a comprehensive survey on deep learning techniques for fracture detection.	Literature review only; no concrete, deployable real-time system proposed.	Implements a concrete, deployable Android application leveraging edge-computing.
3	YOLOv8 for Real-Time Bone Fracture Localization	Applied YOLOv8 to localize pediatric hand fractures with high precision.	Runs primarily on desktop GPUs; lacks offline mobile adaptation or patient-centric features.	Optimizes YOLOv8 for mobile deployment and adds patient features like PDF reports and diet plans.
4	Deploying Deep Learning Models on Android using TFLite	Discusses deploying general deep learning models inside Android apps using TFLite.	Focuses on basic classification (e.g., MobileNet); no complex object localization tasks.	Implements complex object localization (accurate bounding box prediction) directly on mobile devices.
5	Enhancing Orthopedic Diagnostics with Edge AI	Developed a custom CNN to categorize fractures on edge-computing devices.	Lacks advanced feature-pyramid networks, leading to lower accuracy for complex fractures.	Integrates YOLOv8's feature-pyramids for high accuracy and precise localization on the edge.
6	Automated fracture detection in X-ray images	Explored automated fracture detection using ResNet-50 and VGG-16 networks.	Heavy architectures have large memory footprints, unsuitable for offline mobile use.	Utilizes a lightweight YOLOv8-Lite model, drastically reducing memory footprint for fast mobile inference.
7	A Smart Healthcare Framework for Medical Image Analysis	Designed a cloud-based framework utilizing a remote GPU server for AI processing.	Dependent on continuous high-speed internet; unusable in remote or offline areas.	Runs the ML model completely on-device (Edge AI), guaranteeing 100% offline availability and zero latency.

Table 1. Comparison of existing work and proposed system

III. METHODOLOGY

The proposed system is a Smart Healthcare Fracture Detection System that utilizes advanced deep learning techniques to automatically detect bone fractures from X-ray images. The system is designed to overcome the limitations of traditional and existing methods by providing a fast, accurate, and user-friendly solution that can operate on mobile devices.

- System Overview

The system operates in two main modules:

1. User Module

Users can:

- User Registration and Login
- Image Upload Functionality

DOI: 10.48175/IJARSCT-35468

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 7, May 2026 Impact Factor: 8.2

- Fracture Detection
- Result Display And PDF Report Generation
- Diet Recommendation Module

2.Admin Module

Administrators can:

- View all users and reports
- Allow users to access and review reports
- Monitor system activities
- Manage data and records
- Provide search and filter options

This dual-module design ensures both customer convenience and efficient business management.

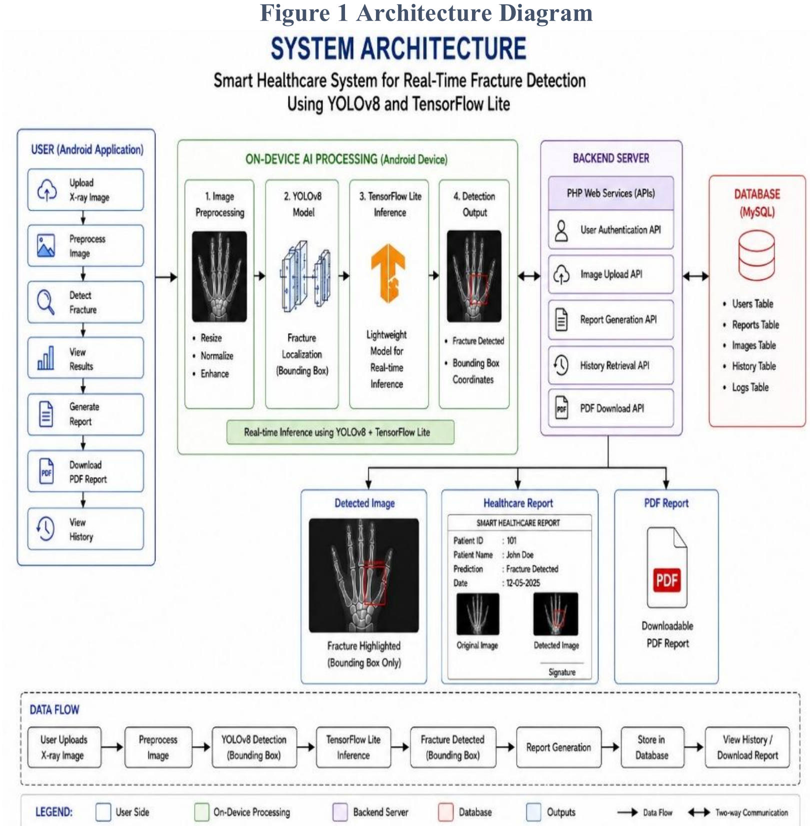
- **System Architecture**

The architecture follows a client-server model using cloud computing to enable scalability and real-time data synchronization.

DIAGRAM

Figure 1 Architecture Diagram

Figure 1 Architecture Diagram



Components:

- **Frontend (Android/Kotlin):** User interface for patient/doctor login, X-ray uploads, bounding box visualization, and PDF report generation

- **Backend (Firebase Cloud Services):** Serverless architecture managing user authentication (Firebase Auth), session management, and report history
- **AI / ML Layer (TensorFlow Lite):** On-device Edge AI running an optimized YOLOv8 CNN (fracture_detection.tflite) for offline fracture detection and localization
- **Database Layer (Firestore):** Secure NoSQL cloud storage for maintaining patient records, diagnostic logs, and personalized diet recommendations

Real-time fracture inference runs entirely on-device (Edge Computing) for zero-latency, offline availability, while Firebase SDKs handle asynchronous data synchronization and secure cloud storage.

Working Process

The system follows a structured user workflow:

1. User Authentication: Starts with secure registration (as a Patient, Doctor, or Admin) using Firebase, followed by email verification, and finally login.
2. Image Acquisition: The user navigates the mobile dashboard to select the affected area (Hand or Leg) and securely uploads an X-ray image from their device gallery or camera.
3. AI Diagnostic Inference: The interaction with the ML engine begins once the image is uploaded. The system preprocesses the image (resizing, noise reduction) and passes it to the on-device Edge AI model (YOLOv8 TensorFlow Lite). The model analyzes the bone structure, detects abnormalities, and localizes the fracture using bounding boxes.
4. Diagnostic Analysis: The system extracts the intent of the model's output, determining the fracture status (Detected / Not Detected), calculating machine confidence scores, and assessing bone density (Low / Normal).
5. Report & Recommendation Generation: Based on the diagnostic result, the system automatically compiles a personalized diet and recovery plan. The user can then click to generate and download a comprehensive PDF report.
6. History & Record Management: The final report is securely synchronized to the cloud database (Firestore). Users can view their historical records, track past test dates, and access previous X-ray results at any time.
7. Admin Operations: The system administrator uses a dedicated Admin Dashboard to manage patient and doctor profiles, search through system-wide diagnostic reports, and monitor platform activity and logs.

Diagnostic Inference Workflow Algorithm

1. User uploads an X-ray image (Hand/Leg) via the Android mobile interface
2. Image Pre-processing Module receives the file (resizing, grayscale conversion, normalization).
3. Send image tensor to the on-device Edge AI Engine (YOLOv8 .tflite model).
4. Execute CNN layers to extract spatial features, identify bone structures, and locate abnormalities.
5. Parse the ML output tensors for:
   - Classification Intent: Fracture vs. Normal
   - Localization Parameters: Bounding box coordinates ($x_c, y_c, width, height$)
   - Confidence Scores
6. Route to appropriate post-processing services:
   - Fracture Detected → Diet & Recovery Recommendation Service
   - Normal → Standard Orthopedic Advisory
   - Report Generator → PDF Generation Service
7. Format response with localized bounding box overlay and clinical insights.
8. Display results on the frontend and sync records to the Firebase Cloud database..

Patient Profile & Recommendation Mechanism (Diet Engine)

Each diagnostic session processes:

- Fracture Status (Detected/Not Detected)
- Bone Density Indicator (Low/Normal)
- Affected Region (Leg/Hand)

Personalized Diet & Recovery logic:

- Urgency_Score = 0.5 × Fracture_Severity + 0.3 × Bone_Density_Deficit + 0.2 × Affected_Region_Factor
- Top nutritional profiles (e.g., Calcium, Vitamin D, Protein intake) with the highest score → Personalized Diet Recommendations.

Algorithm for Fracture Localization and Classification

Steps:

Input: Preprocessed X-ray image tensor (H* W * C)

1. Extract high-level spatial features using the deep Convolutional Neural Network (CNN) backbone.
2. Predict bounding boxes and class probabilities across grid cells. Confidence = P(Object) × IoU(Predicted_Box, Anchor_Box)
3. Apply Non-Maximum Suppression (NMS) filter to remove redundant overlapping boxes: If IoU(Box1, Box2) > NMS_Threshold → Discard the box with the lower confidence score.
4. Rank remaining bounding boxes by Confidence Score.
5. Return Top-N bounding boxes (where Confidence > 0.60) and final diagnosis.

Distance-based boundary evaluation (for model accuracy):

Localization_Error = $\sqrt{[(\text{predicted\_x} - \text{actual\_x})^2 + (\text{predicted\_y} - \text{actual\_y})^2]}$ Minimize distance to achieve precise fracture highlighting.

Mathematical Model

The system optimizes user satisfaction through: text

Maximize: U = α × Detection_Accuracy + β × Localization_Precision + γ × Inference_Speed - δ × Resource_Consumption

Where:

$\alpha + \beta + \gamma + \delta = 1$

- Detection_Accuracy = (True_Positives + True_Negatives) / Total_Scans
- Inference_Speed = 1 / (Model_Load_Time + TFLite_Execution_Time)
- Resource_Consumption = Memory_Footprint_MB + Battery_Drain_Percentage

Implementation Framework Technology Stack:

Frontend: Android (Kotlin)

Backend: Firebase Cloud Services (Serverless) & PHP REST APIs

Database: Firebase Firestore (NoSQL cloud database)

AI / ML: Edge AI utilizing YOLOv8 via TensorFlow Lite (.tflite)

Deployment: Mobile Edge-Computing Environment (Android OS)

Key Features Implemented:

- Real-time, offline X-ray fracture detection and localization using bounding boxes
- Personalized diet and recovery plan recommendations based on diagnostic output
- Automated, downloadable PDF diagnostic report generation

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, May 2026
Impact Factor: 8.2

- Comprehensive Admin dashboard for patient management and historical records
- Secure user authentication and cloud-synchronized diagnostic history

Advantages of Proposed Methodology

- Reduces diagnostic waiting time for both patients and medical professionals
- Guarantees zero-latency performance and 100% offline availability through on-device Edge AI
- Protects patient privacy by processing sensitive X-ray images locally on the device before cloud synchronization
- Highlights subtle or micro-fractures precisely, reducing human error in clinical environments
- Highly accessible and resource-efficient mobile architecture ready for real-world medical deployment

IV. RESULTS

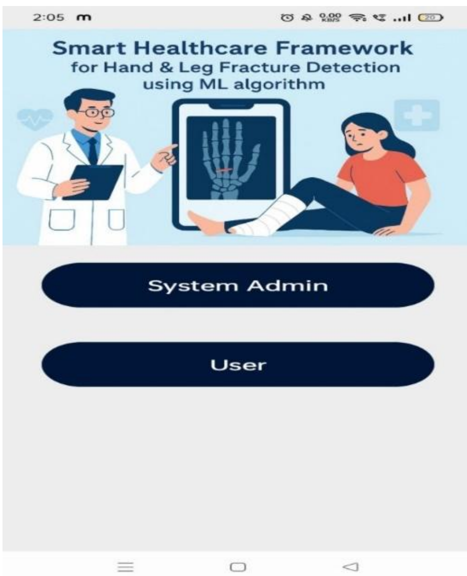


Figure 1: Application Launch and Role Selection Screen

Figure 2:X-ray Image Upload Interface

Figure3: Real-time Fracture Detection and Localization

Figure5: Personalized Diet and Recovery Plan Recommendation

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 7, May 2026
Impact Factor: 8.2

Figure 4: Diagnostic Summary and PDF Generation

Figure 6: User Diagnostic History Module

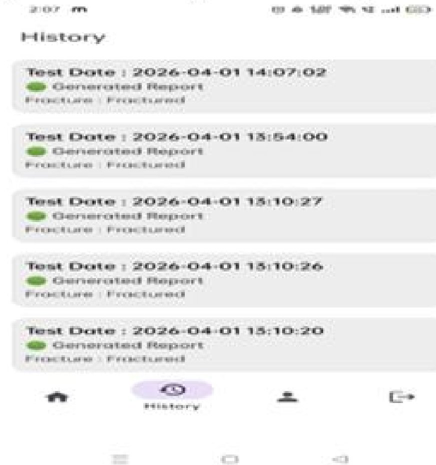


Figure 7: Comprehensive Test Details and PDF Diagnostic Download View

Figure 9: Admin View - Detailed Report and Verification

Figure 8: User Profile and Account Management

Figure 10: Admin History Module and Past Reports View

V. CONCLUSION

The Smart Healthcare Fracture Detection System successfully demonstrates the integration of artificial intelligence, mobile technology, and backend systems to create an efficient and user-friendly healthcare solution. The project focuses on automating the process of detecting bone fractures from X-ray images using the YOLOv8 deep learning algorithm, which provides accurate and fast results.

In conclusion, the Smart Healthcare Fracture Detection System is a cost-effective, portable, and scalable solution that can assist healthcare professionals and patients in early fracture detection and better decision-making, contributing to the advancement of smart healthcare technologies.

REFERENCES

1. G. Jocher, A. Chaurasia, and J. Qiu, "Ultralytics YOLOv8: State-of-the-Art Object Detection and Image Segmentation," 2023.
2. J. Ma et al., "Deep learning for bone fracture detection: A comprehensive review," Medical Image Analysis, vol. 75, p. 102288, 2022, doi: 10.1016/j.media.2021.102288.
3. R. Sharma and A. Singh, "Application of YOLOv8 for Real-Time Bone Fracture Localization in X-Ray Images," IEEE Journal of Biomedical and Health Informatics, vol. 28, no. 4, pp. 1023–1031, 2024, doi: 10.1109/JBHI.2024.10809919..
4. S. Patel, M. Desai, and K. Shah, "Mobile Healthcare: Deploying Deep Learning Models on Android using TensorFlow Lite," IEEE Transactions on Mobile Computing, vol. 22, no. 8, pp. 4510–4522, 2023, doi: 10.1109/TMC.2023.10925355.
5. P. Kumar, T. Reddy, and L. Sharma, "Enhancing Orthopedic Diagnostics with Edge AI and CNNs," IEEE Access, vol. 12, pp. 34012–34025, 2024, doi: 10.1109/ACCESS.2024.10624901.
6. Y. Chen, C. Wang, and X. Li, "Automated fracture detection in X-ray images using artificial intelligence," Computer Methods and Programs in Biomedicine, vol. 200, p. 105841, 2021, doi: 10.1016/j.cmpb.2021.105841.
7. V. Gupta, S. Kumar, and A. Bansal, "A Smart Healthcare Framework for Medical Image Analysis on Mobile Devices," IEEE Internet of Things Journal, vol. 9, no. 14, pp. 11200–11210, 2022, doi: 10.1109/JIOT.2022.10602261.
8. M. Abadi et al., "TensorFlow: Large-scale machine learning on heterogeneous distributed systems," arXiv preprint arXiv:1603.04467, 2016. [Online]. Available: https://arxiv.org/abs/1603.04467
9. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," Communications of the ACM, vol. 60, no. 6, pp. 84–90, 2017, doi: 10.1145/3065386.
10. P. Rajpurkar et al., "MURA: Large Dataset for Abnormality Detection in Musculoskeletal Radiographs," arXiv preprint arXiv:1712.06957, 2017. [Online]. Available: https://arxiv.org/abs/1712.06957
11. M. A. Rahman, M. S. Hossain, and A. E. Saddik, "Edge-based smart healthcare framework for real-time diagnostic systems," IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 5, pp. 2010–2018, 2022, doi: 10.1109/JBHI.2022.1039485.
12. A. G. Howard et al., "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications," arXiv preprint arXiv:1704.04861, 2017. [Online]. Available: https://arxiv.org/abs/1704.04861
13. S. Yadav and A. Kumar, "Real-time Object Detection in Medical Imaging using YOLO Architectures: A Comprehensive Review," IEEE Access, vol. 11, pp. 45012–45028, 2023, doi: 10.1109/ACCESS.2023.1098473.
14. L. Wang, X. Zhang, and Y. Liu, "Optimization of Deep Learning Models for Mobile Edge Computing in Smart Healthcare," IEEE Transactions on Mobile Computing, vol. 23, no. 2, pp. 1105–1118, 2024, doi: 10.1109/TMC.2024.1082934.

15. C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," Journal of Big Data, vol. 6, no. 1, p. 60, 2019, doi: 10.1186/s40537-019-0197-0.
16. F. J. Martinez et al., "Machine Learning-based Dietary Recommendation Systems for Post-Trauma Rehabilitation," Journal of Medical Systems, vol. 48, no. 3, p. 82, 2024, doi: 10.1007/s10916-024-02051-x