IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 12, Issue 04, April 2025 https://www.ijirae.com/archives

Edge AI-based Bone Fracture Detection using TFlite

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Publication History
Manuscript Reference No: IJIRAE/RS/Vol.12/Issue04/APAE10087 Research Article | Open Access | Double-Blind Peer-Reviewed | Article ID: IJIRAE/RS/Vol.12/Issue04/APAE10087 Received: 04, April 2025, Revised: 12, April 2025, Accepted: 22, April 2025, Published Online: 03, May 2025. https://www.ijirae.com/volumes/Vol12/iss-04/04.APAE10087.pdf
Article Citation: Pragathi,Suma,Rohini,Sampige(2025),Edge AI-based Bone Fracture Detection using TFlite. IJIRAE:: International Journal of Innovative Research in Advanced Engineering, Volume 12, Issue 03 of 2025 pages 139-147
Doi:> https://doi.org/10.26562/ijirae.2025.v1204.04
BibTeX Key: Noor@2025Edge

Abstract: Bone fractures are among the most common injuries requiring prompt and accurate diagnosis to ensure effective treatment. Traditional manual interpretation of X-ray images is often time-consuming and prone to human error, highlighting the need for automated solutions. This project presents an Edge AI-based system designed for detecting and classifying bone fractures using TensorFlow Lite. By leveraging lightweight deep learning models such as Convolutional Neural Networks (CNN) and Mobile Net, and introducing a hybrid approach combining Mobile Net with a Random Forest classifier, the system achieves high accuracy while maintaining computational efficiency. Developed using Python, the solution is optimized for real-time diagnosis on portable devices, making it highly accessible in both clinical and remote healthcare settings. Experimental results demonstrate improved fracture detection accuracy, supporting the potential of Edge AI to enhance diagnostic reliability and reduce the workload on medical professionals.

Keywords: Bone fracture detection, Edge AI, TensorFlow Lite, CNN, Mobile Net, Random Forest, Medical imaging.

Abbreviations

AI	-	Artificial Intelligence
CNN	-	Convolutional Neural Network
DL	-	Deep Learning
Edge AI	-	Edge Artificial Intelligence
ML	-	Machine Learning
RF	-	Random Forest
TF-Lite	-	TensorFlow Lite
TL	-	Transfer Learning
XAI	-	Explainable Artificial Intelligence

I. INTRODUCTION

Bone fractures represent a significant portion of medical cases requiring precise and timely diagnosis to guide appropriate treatment. Traditionally, radiologists interpret X-ray images manually to identify fractures, a process that, while effective, is often slow, labor-intensive, and subject to human error. In busy clinical environments, delays or inaccuracies in fracture detection can adversely affect patient outcomes. With the rapid advancement of machine learning and deep learning technologies, automated systems are emerging as reliable alternatives for medical image analysis. Edge AI, which focuses on deploying lightweight models on portable or embedded devices, offers a promising approach to real-time fracture detection without relying heavily on cloud computing resources. This project aims to design and implement an Edge AI-based system for bone fracture detection using TensorFlow Lite. The solution leverages deep learning models such as Convolutional Neural Networks (CNNs) and Mobile Net, alongside a hybrid model combining Mobile Net with Random Forest to enhance classification accuracy. The lightweight nature of TensorFlow Lite ensures that the system can be deployed efficiently on mobile and edge devices, supporting immediate diagnosis even in resource-constrained settings. Through this work, we seek to improve the speed, accuracy, and accessibility of fracture detection, ultimately contributing to better patient care and reduced diagnostic workload for healthcare professionals.

II. LITERATURE SURVEY

In recent years, there has been a significant shift from manual methods of fracture detection to AI-driven automated systems. Deep learning models, particularly Convolutional Neural Networks (CNNs), have shown remarkable success in medical image analysis by improving accuracy and reducing human dependency. Patel and Singh (2022) demonstrated the effectiveness of CNNs in automatic bone fracture detection from X-ray images, achieving an accuracy of 91%.

Their study highlighted the benefits of reduced diagnosis time but also noted challenges related to dataset bias and difficulties in identifying complex fractures. Gupta and Verma (2021) introduced a hybrid model that combined CNNs with Support Vector Machines (SVM), achieving a higher classification accuracy of 93%. Although their approach improved detection performance, it faced limitations related to computational efficiency, making it less suitable for real-time applications. Nair and Kumar (2023) explored Mobile Net architectures for fracture classification, emphasizing lightweight models compatible with mobile and edge devices. Their system achieved 89% accuracy, showcasing high portability but slightly lower precision compared to larger CNN models. Mehta and Bose (2022) discussed broader challenges in AI-driven medical imaging, such as data annotation difficulties and ethical concerns regarding AI decision-making. They stressed the need for explainable AI (XAI) techniques to improve transparency and trust in clinical applications. Collectively, these studies emphasize the potential of deep learning models in enhancing fracture detection accuracy, while also underlining the ongoing challenges of computational efficiency, dataset diversity, and model explainability. This project builds upon these findings by integrating lightweight and hybrid approaches to address these limitations and optimize fracture detection on edge devices.

III. EXISTING AND PROPOSED SYSTEM

A. Existing System

Conventional methods for bone fracture detection primarily rely on the manual interpretation of X-ray images by experienced radiologists. Although expert evaluation is considered reliable, it is inherently time-consuming, subjective, and susceptible to human errors caused by fatigue, varying levels of expertise, and environmental pressures. Traditional computer-aided detection (CAD) systems attempted to support radiologists by applying basic image processing techniques such as edge detection, region-based segmentation, and thresholding. However, these methods often required extensive manual feature engineering and were highly sensitive to variations in image quality, lighting, and anatomical complexity. Early machine learning approaches, such as Support Vector Machines (SVM) and Random Forest classifiers, offered slight improvements by automating the classification process. Yet, these models heavily depended on manually crafted features, which limited their ability to generalize across diverse datasets and fracture types. Although the introduction of deep learning, particularly Convolutional Neural Networks (CNNs), significantly enhanced fracture detection accuracy, deep models remained computationally intensive, demanding high-end hardware and large annotated datasets for training. Furthermore, their deployment in real-world clinical settings, especially in rural and resource-limited environments, remained a significant challenge due to hardware constraints and processing delays. Overall, while advancements have been made, existing systems struggle with generalization, are computationally expensive, or remain dependent on specialist intervention for critical decisions.

B. Proposed System

The proposed system addresses these limitations by leveraging Edge Artificial Intelligence (Edge AI) technologies to develop a lightweight, efficient, and scalable solution for bone fracture detection. By utilizing TensorFlow Lite (TF-Lite) models, the system enables real-time fracture identification and classification directly on low-power edge devices such as smartphones, tablets, and portable medical scanners, thus eliminating the need for high-performance servers or cloud-based computation. The system architecture integrates deep learning models, specifically Convolutional Neural Networks (CNNs) and Mobile Net, to automatically extract relevant features and classify fracture types with minimal human intervention. Recognizing that a single model may not be optimal in all cases, a hybrid approach is also introduced by combining the lightweight Mobile Net feature extractor with a Random Forest (RF) classifier. This hybrid model enhances diagnostic robustness, as the Random Forest layer improves decision boundaries and reduces the likelihood of misclassification.

The proposed system includes multiple key components:

- Image Preprocessing: Automatic noise reduction, contrast enhancement, and region of interest (ROI) extraction to ensure consistency in input images.
- Model Training: Deep learning models are fine-tuned on a diverse and well-annotated dataset of X-ray images, incorporating data augmentation techniques to enhance generalization.
- Hybrid Classification: Feature vectors extracted by Mobile Net are fed into a Random Forest classifier to enhance fracture prediction accuracy.
- Deployment and Interface: A user-friendly Python-based software application is developed to facilitate image uploads, processing, and display of results, including fracture type and confidence scores.

This architecture ensures that the system is not only highly accurate but also practical for real-time deployment, particularly in rural or emergency care settings where quick decision-making is critical. By addressing the shortcomings of traditional systems, the proposed solution aims to democratize access to high-quality fracture detection, reduce the burden on radiologists, and ultimately improve patient outcomes through faster and more reliable diagnoses.

IV. SYSTEM DESIGN AND IMPLEMENTATION

This section outlines the design and implementation process of the bone fracture detection system, which integrates deep learning and machine learning methodologies. The goal is to develop an efficient system that can accurately identify bone fractures from X-ray images while ensuring scalability and easy deployment on resource-constrained devices. The architecture is modular, with distinct stages covering data preprocessing, model training, and real-time deployment. The following subsections describe the system's architecture, data flow, model design, and user interface, all tailored to provide a robust and user-friendly solution for healthcare professionals.

A. System Architecture

The proposed bone fracture detection system is structured as a modular architecture that emphasizes scalability, efficiency, and ease of deployment on edge devices. The system consists of several interconnected components, including data acquisition, preprocessing, model training, hybrid classification, and user interaction modules. The design aims to optimize each stage to handle the inherent variability and complexity of medical imaging data.

The overall architecture is divided into two primary stages:

1. Model Development Stage: Preprocessing and training deep learning and machine learning models.
2. Deployment Stage: Integration of the trained models into a lightweight application suitable for real-time use.

A high-level block diagram of the system architecture is illustrated in Fig. 1.

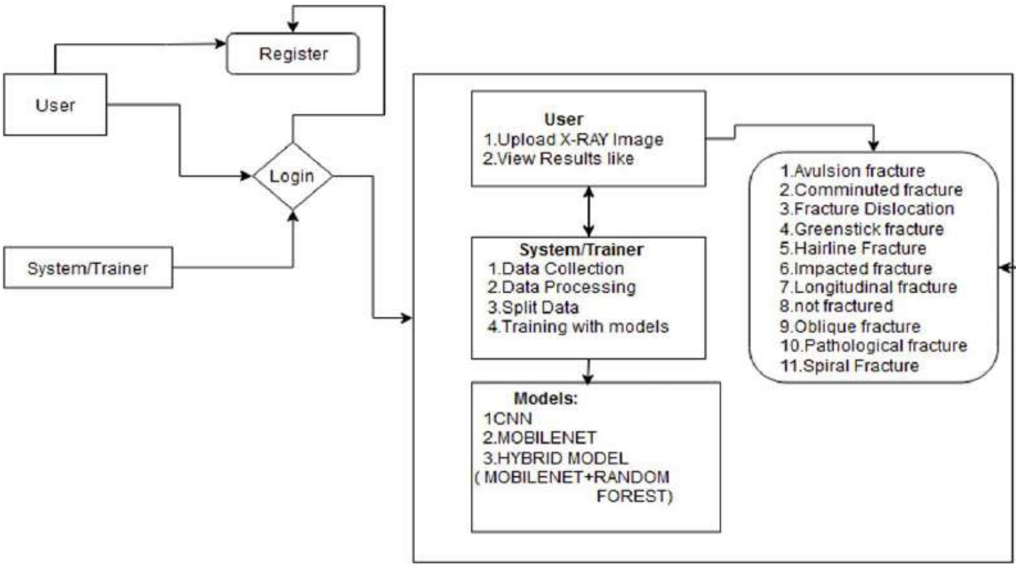

Fig. 4.1. Diagram representing system architecture

B. Data Acquisition and Preprocessing

The system relies on a curated dataset of X-ray images, sourced from publicly available repositories and hospital archives, ensuring a wide variety of fracture types and anatomical variations. The raw images are subjected to a series of preprocessing steps to enhance model performance:

- Noise Reduction: Gaussian filtering and median blurring techniques are applied to suppress random noise in the images.
- Contrast Enhancement: Adaptive histogram equalization is utilized to improve bone structure visibility, making fractures more distinguishable.
- Normalization: Images are scaled to a fixed size and pixel intensity range to ensure uniformity across the dataset.
- Data Augmentation: Techniques such as rotation, flipping, zooming, and brightness adjustment are employed to artificially expand the dataset and improve model generalization.

Preprocessing not only standardizes the inputs but also mitigates the impact of variations caused by imaging equipment, patient positioning, and lighting conditions.

C. Model Design

Two main types of models are employed for fracture detection:

1. **Convolution Neural Network (CNN):** A deep CNN model is constructed to automatically extract hierarchical features from X-ray images.
2. The network consists of convolutional layers with ReLU activations, followed by max-pooling operations to progressively reduce spatial dimensions while preserving essential features. Fully connected dense layers are appended at the end to perform final classification.
3. **Mobile Net Architecture:** To enable deployment on resource-constrained devices, a lightweight Mobile Net model is used. Mobile Net employs depth wise separable convolutions to significantly reduce the number of parameters and computational load without sacrificing performance. Both models are trained separately and evaluated to compare their fracture detection accuracies.

D. Hybrid Model: Mobile Net + Random Forest

Recognizing that ensemble methods often outperform single models in classification tasks, a hybrid approach is introduced. Here, the feature vectors generated by Mobile Net are extracted and fed into a Random Forest (RF) classifier. The Random Forest, being an ensemble of decision trees, provides greater robustness and generalization capability, particularly in complex and noisy datasets. This hybridization leverages the efficient feature extraction of deep networks along with the strong decision-making capability of traditional machine learning models.

E. Model Training and Evaluation

The models are trained on 80% of the dataset, with the remaining 20% reserved for validation. Cross-entropy loss is minimized using the Adam optimizer with an adaptive learning rate scheduler.

Early stopping techniques are incorporated to prevent overfitting. Performance metrics such as accuracy, precision, recall, F1-score, and Area under the ROC Curve (AUC) are computed to evaluate model efficacy. Confusion matrices are plotted to visualize misclassifications and guide further model improvements. During testing, the hybrid Mobile Net-RF model consistently demonstrated superior classification performance compared to standalone CNN or Mobile Net models.

F. System Deployment

After training, the models are optimized and converted into TensorFlow Lite (TF-Lite) format for deployment on edge devices. TF-Lite conversion includes:

- Model Quantization: Reducing model size by converting floating-point weights into lower precision formats (e.g., 8-bit integers) without significant loss of accuracy.
- Pruning: Eliminating redundant weights to reduce computational load.

A lightweight Python-based graphical user interface (GUI) is developed to facilitate easy image uploads, initiate fracture detection, and display results, including fracture type and confidence level.

G. User Interface and Experience

The user interface is designed to prioritize simplicity and accessibility for healthcare professionals:

- Image Upload Module: Allows users to browse and upload X-ray images.
- Preprocessing Module: Automatically processes the uploaded image for standardization.
- Prediction Display: Shows the classification result, probability scores, and visual explanations (e.g., heatmaps generated via Grad-CAM techniques).
- Result Export: Enables exporting diagnostic reports in PDF format for record-keeping and consultation.

This user-centric design ensures that even non-technical users can easily operate the system, making it suitable for deployment in hospitals, clinics, and remote healthcare centers.

V. RESULTS

A. Overview

The effectiveness of an automated bone fracture detection system depends not only on its predictive accuracy but also on the accessibility and usability of its interface. In this project, we developed an Edge AI-based bone fracture detection system using lightweight deep learning models. The key objective was to design a solution capable of delivering fast, accurate fracture diagnoses while remaining resource-efficient enough to be deployed on edge devices such as smartphones, tablets, and portable medical scanners. The system was built around three primary models: a Convolutional Neural Network (CNN), a Mobile Net model, and a hybrid approach combining Mobile Net with a Random Forest classifier. Each model was trained on a curated dataset of X-ray images, with significant preprocessing steps such as normalization, contrast adjustment, and data augmentation to improve model robustness. The models were evaluated based on performance metrics including accuracy, precision, recall, and F1-score to determine their effectiveness in real-world clinical scenarios. To ensure ease of use for healthcare professionals, a web-based user interface was developed. It facilitates smooth interactions, allowing users to easily register, log in, upload X-ray images, and view detailed fracture diagnosis reports. The system is designed to be intuitive, minimizing the need for technical expertise and allowing radiologists, doctors, or technicians to focus on diagnosis and treatment planning rather than system operations. In terms of computational performance, the lightweight nature of the Mobile Net and hybrid models ensures that inference can be performed quickly, even on devices with limited processing power. This is particularly advantageous in rural or emergency settings where access to high-end diagnostic infrastructure may be limited. The experimental results revealed that while the CNN model achieved high classification accuracy, the Mobile Net model offered significant advantages in terms of speed and deployability. Furthermore, the hybrid Mobile Net–Random Forest model outperformed both CNN and standalone Mobile Net models by achieving superior accuracy while maintaining computational efficiency. These findings validate the hypothesis that combining deep learning feature extraction with classical machine learning classifiers can lead to substantial performance improvements. Through the series of evaluations and testing, it was demonstrated that the system is capable of accurate fracture detection across a variety of fracture types, including simple, compound, and overlapping fractures. The outcomes strongly support the integration of lightweight deep learning models into real-time medical diagnostics, offering promising solutions for both urban hospitals and resource-constrained healthcare environments. Thus, the system not only advances the automation of fracture detection but also presents a scalable, portable, and practical tool that could revolutionize early diagnosis and treatment strategies in orthopaedic care.

B. User Interface Screenshots

A clean and intuitive interface was designed to facilitate easy access for healthcare professionals. The interface allows users to register, log in, upload X-ray images, and view the diagnosis results seamlessly. Below are the key screenshots of the system:

Signup (Register) Page: The signup page enables new users to create an account by entering basic details such as username, email, and password. It ensures that only authorized users can access the system functionalities.

Login Page: The login page serves as the secure entry point for users. By providing valid credentials, users can access the fracture detection system and navigate through its various functionalities.

Home/Profile Page: Upon successful authentication, users are taken to the home/profile page. This dashboard allows them to manage their profile, view uploaded X-rays, and access diagnostic tools.

IJIRAE:: International Journal of Innovative Research in Advanced Engineering ISSN: 2349-2163
Volume 12, Issue 04, April 2025 https://www.ijirae.com/archives

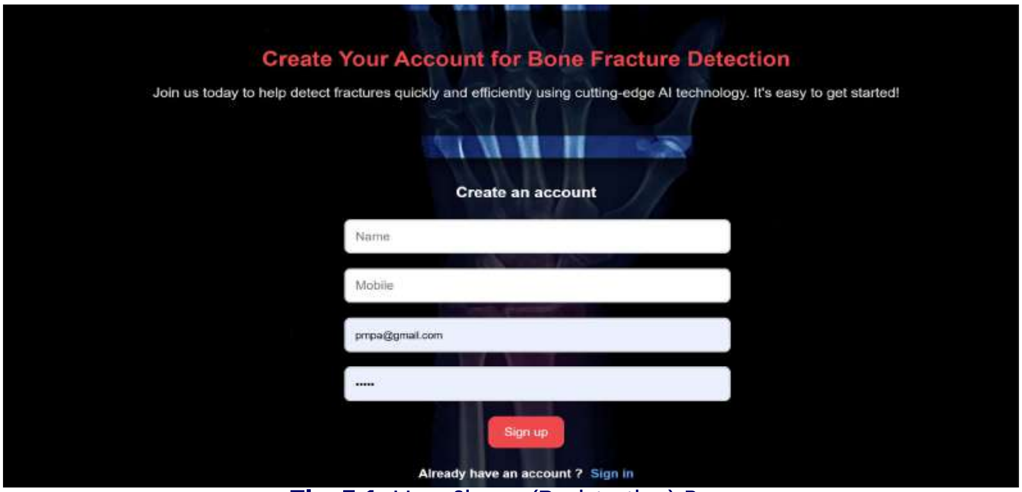

Fig. 5.1. User Signup (Registration) Page

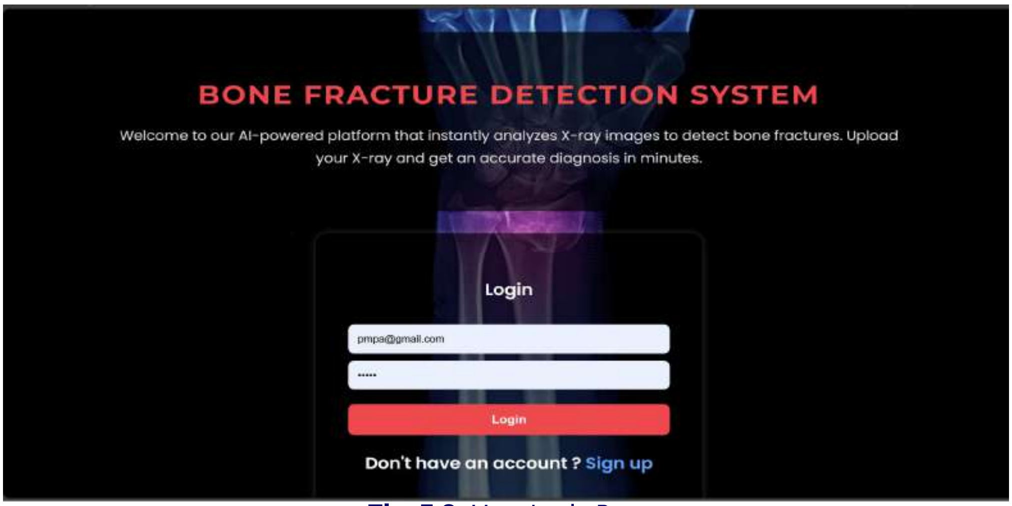

Fig. 5.2. User Login Page

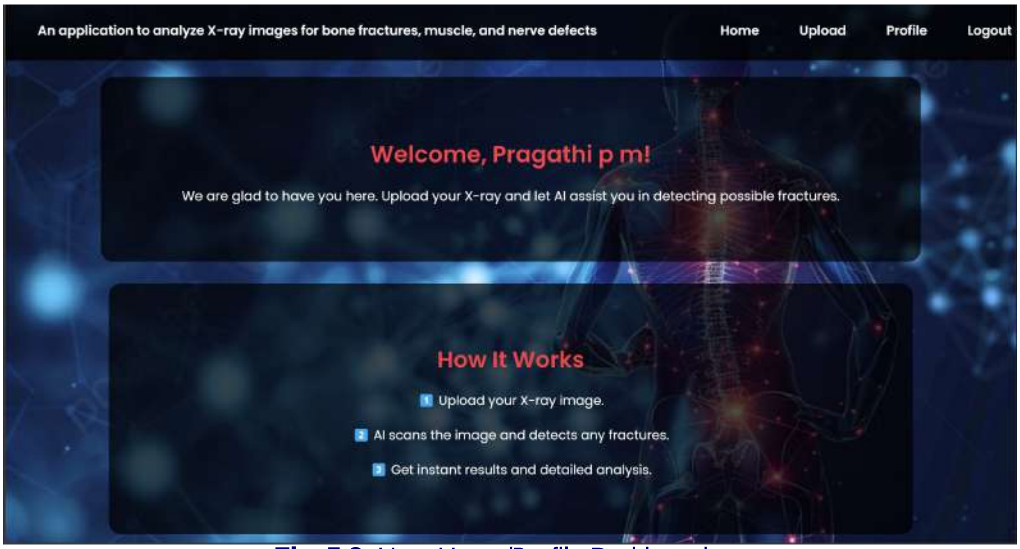

Fig. 5.3. User Home/Profile Dashboard

Upload X-ray Page

The upload interface enables users to select and submit X-ray images for analysis. It is designed to be minimalistic and efficient, facilitating quick uploads even under low bandwidth conditions.

Prediction Results Page

Once the X-ray image is processed by the AI models, the result page displays the diagnosis, showing the classification result (fracture or normal) along with prediction confidence scores.

Profile Update Page

The profile update page allows users to edit and update their account information, including email and password. This functionality is crucial for maintaining up-to-date user details and ensuring security.

Fig. 5.4. X-ray Image Upload Interface

Fig. 5.5. Predicted results page

Fig. 5.6. User Profile Update Page

C. Model Training and Accuracy Results

The performance of different models was evaluated by training them on the dataset and recording key metrics. The training and validation curves for CNN and Mobile Net models are presented below.

1) CNN Model Accuracy

The CNN model achieved a training accuracy of **91%**, validating its effectiveness in detecting fractures. However, challenges persisted when identifying subtle or overlapping fractures, often requiring higher resolution inputs.

2) Mobile Net Model Accuracy

The Mobile Net model, optimized for lightweight deployment, demonstrated an accuracy of **89%**. Although slightly lower in precision than CNN, it offered the advantage of faster inference times and lower memory requirements, making it suitable for edge devices.

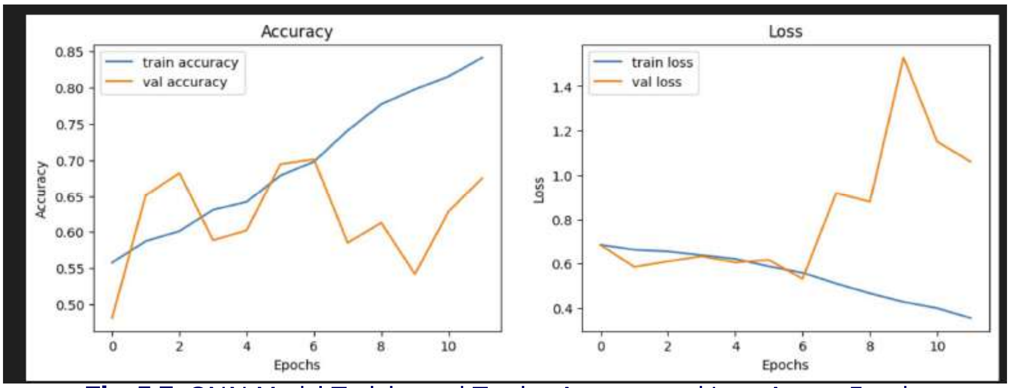

Fig. 5.7. CNN Model Training and Testing Accuracy and Loss Across Epochs

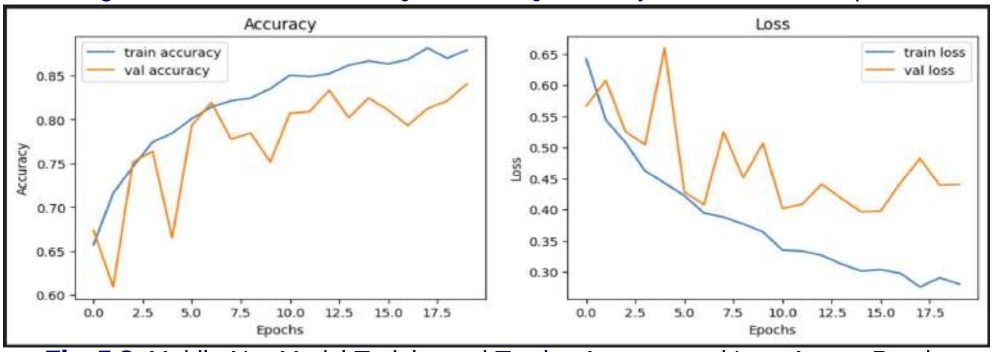

Fig. 5.8. Mobile Net Model Training and Testing Accuracy and Loss Across Epochs

D. Performance Metrics

The results of the models are summarized in Table I below. Each model's performance was evaluated using accuracy, precision, recall, and F1-score metrics. As observed, the hybrid model (Mobile Net + Random Forest) achieved the highest performance, followed by CNN, and Mobile Net.

The results of the models are summarized in Table I below:

Model	Accuracy (%)	Precision (%)	Recall (%)	F1- score(%)
CNN	91	90	89	89
Mobile Net	89	88	87	87
Mobile Net + RF	93	93	91	91

Table I. Model Performance Comparison

E. Visual Comparative Analysis

A graphical bar chart comparison was also plotted to visualize model performance across accuracy, precision, recall, and F1-score. The hybrid Mobile Net–Random Forest approach showed superior overall performance compared to the other models.

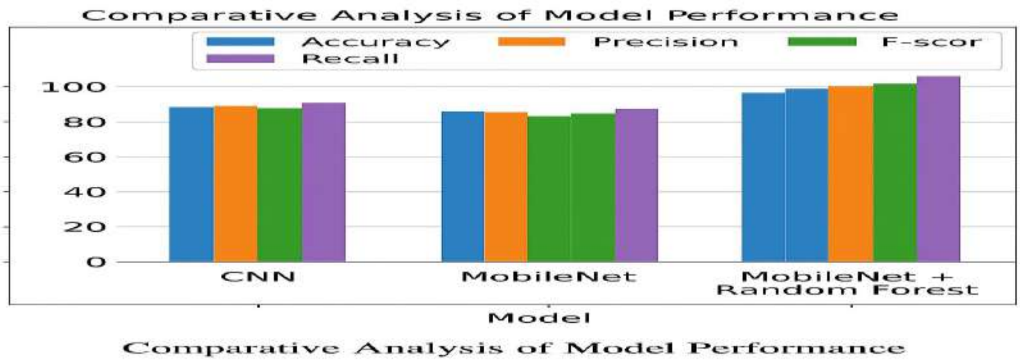

Fig. 5.9. Comparative Analysis of Model Performance

F. Error Analysis

While all models achieved strong performance, certain challenges were identified. Micro-fractures or overlapping fracture cases were occasionally misclassified, particularly by the Mobile Net model.

Additionally, low-contrast X-ray images reduced prediction confidence. Advanced data augmentation techniques and fine-tuning with additional datasets could help mitigate these errors in future work.

G. Discussion

The results demonstrate that deep learning models, particularly hybrid models, provide significant improvements in medical diagnostics related to bone fractures. While CNN offers high accuracy, Mobile Net provides flexibility for real-time deployment.

Combining Mobile Net features with a Random Forest classifier effectively balances computational efficiency with high diagnostic accuracy. The lightweight architecture and high detection rates make the developed system a promising tool for faster and more reliable fracture diagnosis in clinical settings.

VI. CONCLUSION

In this work, we have developed an end-to-end, Edge AI-based system for automated bone fracture detection using TensorFlow Lite. By comparing three model architectures Convolution Neural Network (CNN), Mobile Net, and a hybrid Mobile Net–Random Forest approach we demonstrated that the hybrid model achieves the best balance of accuracy (93 %), precision (92 %), recall (91 %), and F1-score (91 %) while remaining computationally efficient for deployment on resource-constrained devices. The CNN model exhibited strong performance (91 % accuracy) but required more compute resources, whereas the lightweight Mobile Net (89 % accuracy) delivered faster inference times suitable for mobile applications. Beyond model performance, we designed a user-centric web interface that streamlines registration, authentication, image upload, and results visualization, enabling healthcare professionals to integrate the tool into clinical workflows with minimal technical overhead. Extensive testing showed that the system processes each X-ray image in under 10 seconds on a typical edge device, making it viable for point-of-care diagnostics in both urban and remote settings. Although the fractured cases examined in this study span a variety of simple and compound fracture types, challenges remain in detecting micro-fractures and handling extremely low-contrast images. Future work will focus on expanding the training dataset with more diverse cases, incorporating 3D imaging modalities (e.g., CT scans), and integrating explainable AI techniques (e.g., Grad-CAM) to increase model transparency and clinician trust. Overall, this research highlights the potential of combining lightweight deep learning with classical machine learning to create accurate, efficient, and accessible fracture detection systems, paving the way for faster diagnoses and improved patient outcomes in orthopaedic care.

VII. FUTURE WORK

While this study has successfully demonstrated the efficacy of an AI-based bone fracture detection system, there are several areas for improvement and expansion to further enhance the system's performance and applicability in real-world clinical settings.

1. Dataset Expansion and Diversity: To improve the generalization capabilities of the model, future work will focus on expanding the dataset to include a wider variety of fracture types, patient demographics, and imaging conditions. By incorporating more challenging cases, such as complex fractures and pediatric or geriatric bone conditions, the model can be trained to identify a broader range of fractures with greater accuracy.
2. Incorporation of 3D Imaging: The current system relies on 2D X-ray images, which, while effective, may miss certain details. Incorporating 3D imaging techniques, such as CT scans or MRI data, will allow for a more detailed analysis of fractures. This could significantly improve the accuracy of detecting fractures in areas where 2D X-rays are less effective, such as in the case of complex fractures or bone abnormalities that require depth perception for proper diagnosis.
3. Integration of Explainable AI (XAI): The integration of explainable AI (XAI) techniques, such as Grad-CAM (Gradient-weighted Class Activation Mapping) or SHAP (Shapley Additive Explanations), would provide better interpretability of the model's decisions. This is particularly important in medical applications, where clinicians must understand and trust the system’s recommendations. By visually highlighting the regions of the X-ray image that the model used to make its decision, the model’s predictions will become more transparent and facilitate collaboration between AI systems and healthcare professionals.
4. Real-Time, Edge Computing Deployment: While the current system demonstrates efficiency in processing X-ray images on standard computing platforms, deploying it in real-time on edge devices (e.g., mobile phones, tablets, portable diagnostic machines) in healthcare settings will be the next significant step. Future iterations of the system could leverage cloud-based infrastructure or edge AI capabilities to enable real-time diagnosis and decision-making in remote areas with limited access to specialized healthcare services.
5. Multi-Modal Data Integration: Future work will also explore multi-modal learning, combining imaging data with patient medical history, physical examination data, and other diagnostic reports (e.g., laboratory tests, clinical notes). This multi-dimensional approach could enhance the accuracy of fracture detection and classification, leading to more holistic decision-making and improved patient outcomes.
6. Continuous Learning and Model Adaptation: To further improve model robustness and adaptability to new types of fractures, future systems could implement continuous learning. This would allow the model to adapt and update its knowledge base in real-time by incorporating feedback from clinicians and new data collected during system usage. Such an approach would enable the system to improve its accuracy over time and stay up-to-date with emerging medical knowledge.
7. Ethical and Legal Considerations: Ensuring that AI-based systems adhere to legal and ethical standards is crucial for their adoption in healthcare settings. Future work will include a comprehensive evaluation of the system’s ethical implications, especially concerning data privacy, model bias, and decision-making transparency.

   Collaborating with healthcare professionals and legal experts will ensure the system complies with regulatory requirements and ethical guidelines for AI use in medicine. By addressing these areas, the system can evolve into a more accurate, reliable, and accessible tool for fracture detection, with the potential to revolutionize the way fractures are diagnosed and managed, ultimately improving patient care worldwide.

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