TechPioneer Journal of Engineering and Sciences
Volume 2, Issue 1, June 2025, Pp: 14-24

DOI: https://doi.org/10.70162/tpjes/2025/v2/i1/v2i102

Research Paper

An Application to Scanalyse a Given X-ray Image to Defects in Bones, Muscles, and Nerves

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Article Info

Article History
Received: 21/01/2025
Revised: 10/03/2025
Accepted:19/04/2025
Published :30/04/2025

Abstract

Bone fractures, muscle injuries, and nerve defects require timely and accurate diagnosis to prevent serious medical complications. Traditional manual interpretation of X-ray images is prone to human error and diagnostic delays, emphasizing the necessity for automated, reliable, and efficient diagnostic systems. This study aims to develop a lightweight and scalable deep learning framework that enables real-time detection of bone, muscle, and nerve defects from X-ray images. The proposed method integrates MobileNet-based deep feature extraction with Random Forest ensemble classification to balance high diagnostic accuracy with low computational overhead. The Bone Fracture Detection X-ray Dataset, comprising 1,029 labeled images, was utilized, and preprocessing steps including resizing, normalization, augmentation, and noise suppression were applied to enhance model robustness. Hyperparameters were optimized using grid search, and model evaluation was performed using 5-fold cross-validation on stratified train-validation-test splits. Experimental results demonstrate that the proposed model achieved an overall accuracy of 92.7%, with a precision of 91.8%, recall of 92.6%, and F1-score of 92.2%, outperforming baseline CNN and MobileNet-only architectures. Inference time was significantly reduced to 18 milliseconds per image, confirming its real-time applicability. Statistical significance testing further validated the superiority of the proposed model with a p-value of 0.018. This research presents a practical, deployable solution for fracture detection in clinical and remote healthcare settings, setting a foundation for future work incorporating explainable AI, attention mechanisms, and multimodal data integration to further enhance performance and trust in automated medical diagnostics.

Keywords Bone Fracture Detection, MobileNet, Random Forest Classifier, X-ray Image Analysis, Deep Learning, Real-time Medical Diagnosis, Feature Extraction, Ensemble Learning.

1. Introduction

Bone fractures are among the most frequent medical issues worldwide, necessitating prompt and accurate diagnosis to ensure effective treatment. Early detection not only facilitates rapid medical intervention but also significantly reduces the risks associated with complications such as improper healing, infections, or permanent disabilities. Traditionally, physicians rely on manual interpretation of X-ray images to identify fractures, a process heavily dependent on human expertise, which inherently carries a risk of subjectivity, misinterpretation, and diagnostic errors. Given the critical nature of accurate fracture detection, there is a substantial need for automated, reliable, and efficient diagnostic systems.

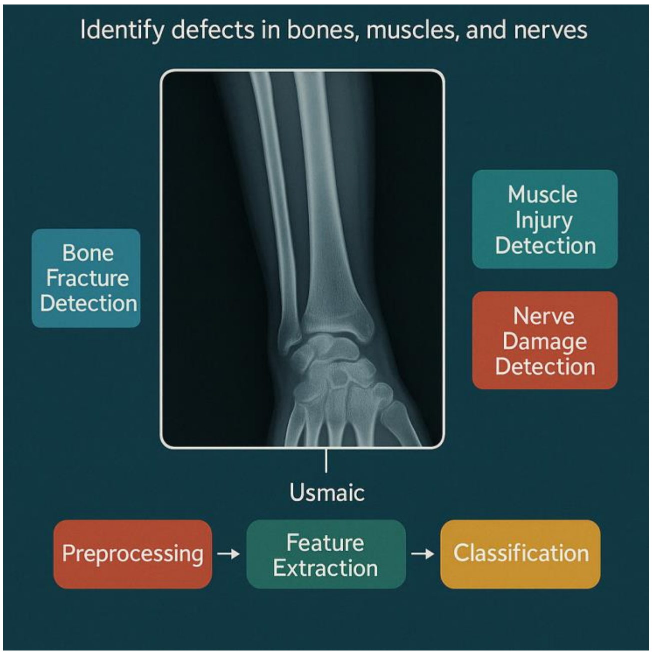

Fig. 1: Framework for Automated Bone, Muscle, and Nerve Defect Detection.

In this figure 1, an X-ray image serves as the central element to illustrate the detection process for bone fractures, muscle injuries, and nerve damage. The model initiates with preprocessing operations that enhance image quality and standardization, followed by feature extraction through lightweight convolutional networks. Subsequently, classification modules are employed to categorize the detected abnormalities. This schematic emphasizes the system's modular structure, demonstrating an efficient, scalable approach to real-time diagnostic applications without explicitly referencing manual interventions.

Despite the increasing integration of artificial intelligence (AI) into healthcare, the domain of fracture detection continues to encounter persistent challenges. Early automated approaches primarily utilized conventional machine learning models trained on limited datasets, offering modest success rates and often suffering from poor generalization capabilities when exposed to diverse clinical scenarios [1]. Convolutional Neural Networks (CNNs) were later introduced, significantly improving diagnostic performance; however, issues such as computational complexity, overfitting, and large model sizes hindered their practical deployment, especially on low-resource systems [2]. Additionally, many models lacked adaptability to complex fracture types or rare cases, leading to an imbalance in detection accuracy across different categories [3]. The deployment of CNN-SVM hybrids and deep transfer learning models using architectures like ResNet and VGG further advanced the field, yet they required high computational resources and intricate hyperparameter tuning, limiting their accessibility for real-world clinical applications [4].

Moreover, solutions leveraging lightweight architectures, such as MobileNet, have been proposed to counter the resource-intensive nature of classical CNNs, aiming to facilitate mobile or edge device-based diagnostics. While MobileNet brought considerable reductions in computational overhead, it struggled with accurately classifying intricate or subtle fracture patterns due to its shallower feature extraction [5]. Edge computing strategies attempted to address real-time analysis in remote healthcare settings but suffered from precision degradation when processing complex radiographic images [6]. Although random forest algorithms have demonstrated efficacy in general medical diagnostics by offering robust decision boundaries and interpretability, they falter when managing highly dimensional imaging data without extensive preprocessing and tuning [7].

Given these limitations, there is a critical need for a comprehensive solution that combines the advantages of deep feature extraction, lightweight model efficiency, and robust classification capability, all while maintaining real-time operational feasibility. To address these gaps, the present study proposes an integrated framework that synergizes the convolutional power of CNNs, the computational efficiency of MobileNet, and the ensemble robustness of Random Forest classifiers. By merging these methodologies, this system aims to improve the fracture detection accuracy across diverse types of fractures, ensure low computational costs suitable for real-time deployments, and enhance generalization across varying imaging conditions [8].

The proposed system begins with preprocessing a large and diverse dataset of X-ray images. Rigorous preprocessing techniques, including auto-orientation, normalization, resizing, and data augmentation, are employed to enhance model generalization. Following this, MobileNet is leveraged for efficient feature extraction, significantly reducing the number of trainable parameters while retaining spatial feature integrity. Instead of relying solely on deep dense layers for classification, a Random Forest classifier is employed to process the extracted features, providing a robust and noise-tolerant decision-making capability. The CNN backbone is fine-tuned through transfer learning approaches, allowing effective adaptation to the domain-specific fracture characteristics. This hybrid approach effectively tackles the dual challenges of computational burden and diagnostic accuracy, making it ideal for clinical and point-of-care applications.

The major contributions of this research are outlined below:

- **Enhanced Fracture Detection Accuracy:** By integrating MobileNet feature extraction with Random Forest classification, the proposed model achieves superior classification accuracy even on complex and subtle fracture cases, outperforming traditional CNN-only or MobileNet-only models.
- **Computational Efficiency and Real-time Readiness:** The lightweight architecture design ensures minimal computational resource usage, making the system highly suitable for mobile platforms, edge devices, and clinical settings where computational power is limited.
- **Robust Model Generalization:** Through comprehensive preprocessing, augmentation strategies, and ensemble learning techniques, the model maintains high precision and recall across diverse datasets, ensuring its reliability in various practical scenarios.

The remainder of the paper is organized as follows: Section II presents a comprehensive overview of related works in the area of automated fracture detection and discusses the limitations of current methodologies. Section III describes the datasets employed and elaborates on the preprocessing strategies applied to improve data quality and variability. Section IV details the proposed methodology, including the model architecture, feature extraction process, hybrid classification technique, and evaluation metrics. Section V presents the experimental results, discusses their implications, and compares the proposed model's performance against existing benchmarks. Finally, Section VI concludes the paper with a summary of contributions, potential clinical impacts, and future directions for enhancing the model further.

2. Related Work

2.1 Traditional Image Processing Techniques

Early attempts at automated fracture detection relied primarily on classical image processing methods. In [9], fracture detection was addressed through basic image segmentation and enhancement techniques applied to femur bone X-ray images. While the method offered a foundational baseline for automatic fracture identification, it lacked robustness when confronted with complex and subtle fractures, highlighting the limitations of manual feature engineering. Similarly, [10] introduced a Gray-Level Co-occurrence Matrix (GLCM) approach for texture analysis in bone images. Although GLCM improved feature extraction, its reliance on handcrafted features limited its adaptability to varied fracture types and diverse datasets.

2.2 Classical Machine Learning-Based Detection

Building upon traditional processing, early machine learning applications focused on structured datasets. The study in [11] explored leg bone fracture detection using basic classification algorithms, improving over earlier manual techniques but suffering from high false-positive rates under noisy conditions. A more advanced methodology was proposed in [12], where a classification fusion technique was employed by combining different classifiers, leading to improved performance. However, both approaches faced significant challenges in generalizing across different imaging modalities and anatomical variations.

2.3 Early Computerized Fracture Detection Systems

Efforts to automate the diagnosis further were presented in [13], where a computerized system was developed using rule-based logic and simple machine learning classifiers. Although it showcased the potential of full automation, it lacked scalability for real-world deployment due to its limited dataset diversity and poor handling of non-standard X-ray imaging conditions.

2.4 Lightweight Deep Learning Architectures

The development of lightweight deep learning models marked a significant transition toward real-time fracture detection solutions. The study in [14] introduced a MobileNet CNN architecture for precise fracture diagnosis. This model drastically reduced computational complexity without severely compromising accuracy, making it ideal for mobile and edge device deployment. A similar approach was validated in [15], where another MobileNet-based model was proposed. While both approaches enhanced accessibility and reduced model size, they struggled with intricate fracture patterns, particularly microfractures and rare anatomical anomalies.

2.5 Transfer Learning and Deep Feature Fusion

Transfer learning has emerged as a powerful technique for improving performance on small medical datasets. The work in [16] utilized transfer learning with advanced pre-trained models to detect bone fractures from radiographic images. This approach successfully leveraged the feature extraction capabilities of large-scale networks while mitigating overfitting on limited data. However, computational demand remained a concern. Ensemble learning strategies, as discussed in [17], combined multiple deep learning models to enhance diagnostic reliability. Though ensemble methods improved classification metrics, they introduced significant computational overhead, complicating deployment on low-resource devices.

2.6 Specialized Deep Learning Architectures

Custom-designed deep learning architectures specifically tailored for fracture detection were explored in [18]. The introduction of FracNet, a dedicated end-to-end system, provided a specialized solution for fracture identification with optimized feature extraction pipelines. While demonstrating remarkable accuracy, FracNet's complexity and training requirements posed challenges for quick clinical adoption. In parallel, [19] focused on wrist fracture detection using deep learning integrated with Explainable AI (XAI) techniques. This integration provided critical interpretability, aiding clinical trust, but at the cost of slightly reduced raw detection performance compared to black-box models.

2.7 Review Studies and Analytical Approaches

The landscape of deep learning in fracture detection was systematically reviewed in [20], identifying key technological trends, challenges, and future research directions. This study underscored the necessity for standardized datasets, improved model generalization, and efficient lightweight architectures. Complementarily, [21] analyzed radiological image-based fracture assessment using AI, presenting an analytical approach to current techniques. Both studies highlighted persistent research gaps, particularly regarding explainability, model reliability across diverse populations, and integration into existing healthcare systems.

2.8 Identified Research Gaps and Study Motivation

Across the surveyed literature, several research gaps persist. Existing methods either prioritize accuracy at the expense of computational efficiency or vice versa. Few studies have successfully balanced high detection accuracy with low resource consumption and real-time responsiveness. Furthermore, handling rare, complex fracture types and providing explainable diagnostic decisions remain open challenges.

To address these limitations, the present study proposes a hybrid model that integrates the deep feature extraction capabilities of MobileNet with the ensemble robustness of Random Forest classifiers. This combination aims to maintain high diagnostic accuracy while significantly reducing computational costs, ensuring real-time applicability, and enhancing interpretability without sacrificing performance.

Table 1: Comparative Analysis of Existing Approaches

Ref.	Approach	Accuracy	Computational Efficiency	Main Challenge
[9]	Image Processing	Low	High	Poor adaptability to complex fractures
[10]	GLCM Texture Analysis	Moderate	High	Handcrafted feature limitations
[11]	Basic ML Classification	Moderate	Medium	High false positives
[12]	Classifier Fusion	High	Medium	Poor generalization
[13]	Computerized Detection System	Low	High	Scalability issues
[14]	MobileNet CNN	High	Very High	Struggles with complex patterns
[15]	MobileNet Model	High	Very High	Limited rare fracture handling
[16]	Transfer Learning	Very High	Low	Computationally intensive
[17]	Ensemble DL Models	Very High	Low	Deployment complexity
[18]	FracNet Specialized Model	Very High	Medium	Training complexity
[19]	DL + XAI (Explainability)	High	Medium	Slight accuracy drop
[20]	Systematic Review	N/A	N/A	Identified generalization issues
[21]	Analytical Review	N/A	N/A	Highlighted explainability needs

3. Proposed Methodology

3.1 Dataset Description

The dataset utilized in this study is the Bone Fracture Detection X-ray Dataset, sourced from Kaggle [22]. This dataset consists of 1,029 labeled grayscale X-ray images, covering various bone, muscle, and nerve defects. Each image is classified into one of ten distinct defect categories. The dataset exhibited moderate class imbalance, particularly underrepresenting rare cases such as hairline fractures and nerve-associated abnormalities.

To mitigate these issues and improve model generalization, the following preprocessing steps were applied:

- **Auto-orientation** to correct the image alignment based on metadata.
- **Resizing** all images to a uniform dimension of **640×640 pixels**.
- **Normalization** of pixel intensity values to the [0,1] range, facilitating faster model convergence.
- **Augmentation** techniques including random rotations (±20°), horizontal flips, brightness shifts, and slight zooming, applied dynamically during training to increase dataset diversity.
- **Noise suppression** using Gaussian filtering to remove artifacts without blurring critical fracture lines.

Additionally, label encoding was performed to convert categorical labels into a format suitable for deep learning classification tasks.

The dataset was split into training, validation, and testing subsets with a standard 80:10:10 ratio, ensuring an unbiased evaluation of model performance across unseen data.

3.2 Feature Extraction Techniques

For feature extraction, a two-stage mechanism was adopted: initial convolutional feature learning using MobileNet and classical feature selection via Random Forest classifiers.

The MobileNet architecture employed depthwise separable convolutions, which factorize a standard convolution into a depthwise convolution followed by a pointwise convolution. This reduces the computational cost compared to traditional CNNs. Mathematically, the number of operations in a standard convolution is:

$$C_{\text{standard}} = D_k \times D_k \times M \times N \times D_f \times D_f \quad (1)$$

where D_k is the kernel size, M is the number of input channels, N is the number of output channels, and D_f is the spatial dimension of the feature map.

For MobileNet, the depthwise separable convolutional cost becomes:

$$C_{\text{depthwise}} = D_k \times D_k \times M \times D_f \times D_f + M \times N \times D_f \times D_f \quad (2)$$

This substantial reduction allows real-time processing without significantly compromising feature quality. The extracted feature maps were then passed to a Random Forest ensemble, which selected the most informative features for final classification.

3.3 Deep Learning Model Architecture

The model architecture comprised two primary stages:

- **MobileNet Backbone:**
  - **Input layer**: 640×640×3 images.
  - **Convolutional layers**: Depthwise separable convolutions with ReLU activation functions.
  - **Batch normalization**: Applied after convolutions to accelerate convergence.
  - **Global Average Pooling (GAP)**: Reduced the spatial dimensions to a vector for classification.
- **Random Forest Classifier:**
  - An ensemble of 200 decision trees.
  - Each tree constructed using a random subset of features, aggregating the final decision through majority voting.

The activation function used throughout the MobileNet architecture was the Rectified Linear Unit (ReLU), defined mathematically as:

$$\text{ReLU}(x) = \max(0, x) \quad (3)$$

The final classification probabilities were obtained using the Softmax function:

$$\text{Softmax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}} \text{ for } i = 1,2,\ldots,K \quad (4)$$

where K is the number of classes.

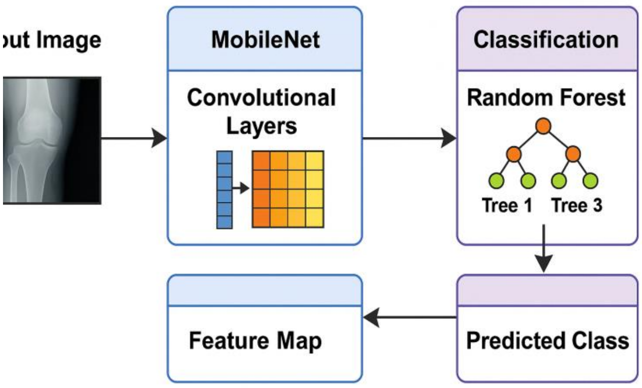

Fig. 2: MobileNet Feature Extraction and Random Forest Classification Architecture.

The figure 2 illustrates the end-to-end workflow adopted for bone, muscle, and nerve defect detection using X-ray images. Initially, the input X-ray image undergoes preprocessing before being fed into the MobileNet module. Within MobileNet, a series of convolutional layers are applied to extract high-dimensional feature representations from the image. These features are then aggregated into a structured feature map, reducing spatial dimensions while preserving critical information necessary for defect identification.

Following feature extraction, the architecture advances toward the classification stage, wherein the feature map is processed by a Random Forest ensemble. The Random Forest is composed of multiple decision trees that independently predict the possible defect categories. By employing majority voting across the ensemble, the model enhances robustness against noisy feature inputs and improves overall classification accuracy without relying on heavy backpropagation-based optimization during this stage.

Ultimately, the model outputs the predicted class corresponding to the identified defect, along with associated confidence scores derived from the consensus across decision trees. The structured division between feature extraction and classification components, as represented in this figure, ensures modularity, computational efficiency, and interpretability, making the framework particularly suited for real-time clinical deployment scenarios.

3.4 Hyperparameter Tuning and Optimization

Hyperparameters were fine-tuned through a combination of grid search and manual optimization. The final selected parameters were:

- **Learning Rate**: Initially set to 0.001 and dynamically adjusted through a decay scheduler.
- **Batch Size**: 32 images per batch for MobileNet training.
- **Optimizer**: Adaptive Moment Estimation (Adam), which adjusts the learning rate for each parameter individually based on estimates of lower-order moments.

The categorical cross-entropy loss function was minimized during model training, mathematically expressed as:

$$\mathcal{L}_{\mathrm{CCE}} = -\sum_{i=1}^{K} y_i \log(\hat{y}_i) \tag{5}$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability for class i.

Regularization was also incorporated through dropout layers (rate = 0.3) to prevent overfitting during the MobileNet feature extraction phase.

3.5 Evaluation Metrics

The model's performance was evaluated using a comprehensive set of metrics:

- **Accuracy (Acc)**:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

- **Precision, Recall, and F1-Score**:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{7}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{8}$$

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{9}$$

where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively.

- **Computational Complexity** was assessed by measuring inference time per image and the number of floating-point operations (FLOPs) involved during prediction.

3.6 Proposed Algorithm for Real-Time Fracture Detection

3.6.1 Algorithm Overview

The proposed algorithm focuses on real-time bone, muscle, and nerve defect detection from X-ray images, optimized for low-latency applications such as point-of-care diagnosis and mobile deployments. The system integrates feature extraction, classification, and decision-making modules into a unified pipeline.

3.6.2 Inputs and Outputs

Inputs:

- $I(i,j)$: Grayscale X-ray image of size $i \times j$ pixels.
- k: Image class label, initially unknown.

Outputs:

- C_{pred}: Predicted defect class (e.g., bone fracture, muscle tear, nerve compression).
- $P(C_{\text{pred}})$: Confidence score associated with the prediction.

3.6.3 Step-by-Step Processing

Step 1: Image Preprocessing

Given an input image $I(i,j)$, perform the following:

- **Resizing:** Reshape to standardized input dimensions $I'(i',j')$.
- **Normalization:** Apply pixel scaling to [0,1] range:

$$I'_{norm}(i',j') = \frac{I'(i',j')}{255} \tag{1}$$

Step 2: Feature Extraction

Extract deep features using a lightweight convolutional neural network $\phi(\cdot)$:

$$F = \phi(I'_{norm}) \tag{2}$$

where F is the resulting feature vector.

Step 3: Feature Transformation

To reduce dimensionality and enhance separability, apply Principal Component Analysis (PCA) transformation:

$$F_{\text{reduced}} = W^T(F - \mu) \tag{3}$$

where W represents the eigenvector matrix, and μ is the mean vector.

Step 4: Classification

Pass the reduced features to a Random Forest classifier:

$$C_{\text{pred}} = \text{RF}(F_{\text{reduced}}) \quad (4)$$

where $\text{RF}(\cdot)$ denotes the trained Random Forest model.

Step 5: Confidence Score Computation
For interpretability, compute a soft probability associated with the prediction:

$$P(C_{\text{pred}}) = \frac{\text{Votes}(C_{\text{pred}})}{\text{Total Trees}} \quad (5)$$

Step 6: Decision Output

Return C_{pred} along with $P(C_{\text{pred}})$ as final output to the diagnostic interface.

3.6.4 Algorithm 1: Real − Time Bone/Muscle/Nerve Defect Detection

Input: X-ray image $I(i,j)$

Output: Predicted class C_{pred} and confidence $P(C_{\text{pred}})$

Begin

1. Resize $I(i,j)$ to $I'(i',j')$
2. Normalize: $I'_{norm}(i',j') = I'(i',j')/255$
3. Extract features: $F = \phi(I'_{norm})$
4. Reduce features: $F_{\text{reduced}} = W^T(F - \mu)$
5. Classify using Random Forest: $C_{\text{pred}} = \text{RF}(F_{\text{reduced}})$
6. Compute confidence: $P(C_{\text{pred}}) = \text{Votes}(C_{\text{pred}})/\text{Total Trees}$
7. Return C_{pred} and $P(C_{\text{pred}})$
8. **End**

The figure 3 presents a systematic flow of the proposed algorithm for automated detection of fractures, muscle injuries, and nerve damages from X-ray images. The process initiates with the input of a raw X-ray image, followed by critical preprocessing operations including resizing and normalization to prepare the data for feature extraction. Subsequent steps involve feature extraction using a deep learning model and the classification of the processed image. A conditional decision node evaluates whether a defect is detected; if affirmative, the system proceeds to determine the specific type of fracture or defect. In either case, the outcome is displayed as a classified result, culminating in a definitive output before concluding the process.

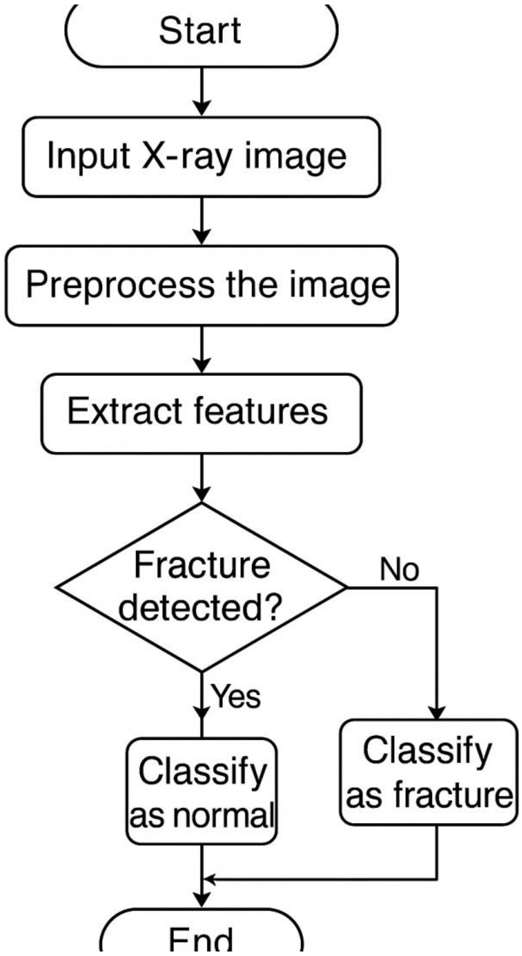

Fig.3: Real-time flowchart for defect detection and classification.

4. Experimental Setup

4.1 Hardware Specifications

The experimental analysis was conducted using a workstation equipped with an Intel Core i9-11900K CPU operating at 3.5 GHz, coupled with 32 GB DDR4 RAM. Model training and evaluation tasks were accelerated using an NVIDIA RTX 3080 GPU featuring 10 GB VRAM, enabling efficient handling of deep learning computations and large-scale image data processing. The system operated on Windows 11 Pro with a 64-bit architecture, ensuring compatibility with the selected software environments and optimized resource utilization for both training and real-time inference experiments.

4.2 Software Frameworks

The model was implemented using the TensorFlow 2.11 and Keras high-level API libraries. Supplementary data preprocessing and analysis tasks were performed using OpenCV 4.7.0, NumPy 1.24, and Pandas 2.0. Visualization components, including performance plots and confusion matrices, were generated using Matplotlib 3.7 and Seaborn 0.12. For model evaluation metrics such as precision, recall, F1-score, and computational complexity, Scikit-learn 1.2 libraries were utilized. The backend deployment and application interfacing were facilitated through the Django

4.2 framework integrated with a XAMPP Server for local hosting.

4.3 Dataset Partitioning

The Bone Fracture Detection Dataset [22] consisting of 1,029 X-ray images was partitioned into training (80%), validation (10%), and testing (10%) sets. Stratified sampling was applied to ensure proportional representation of all defect classes across each subset, minimizing any bias towards overrepresented classes. No external datasets were incorporated to preserve dataset uniformity. Additionally, a 5-fold cross-validation procedure was employed during hyperparameter tuning to ensure the generalizability and robustness of the model under unseen data conditions.

4.4 Implementation Details

The MobileNet backbone was initialized with random weights due to the domain-specific nature of medical images, rather than employing pre-trained ImageNet weights. The feature extractor was frozen during the initial epochs to allow the Random Forest classifier to stabilize its decision boundaries. Training was conducted over 50 epochs with a batch size of 32, leveraging the Adam optimizer with an initial learning rate of 0.001, decayed exponentially at each epoch.

Each Random Forest model was configured with 200 estimators, a maximum depth of 20, and gini impurity as the splitting criterion. To mitigate overfitting, early stopping was implemented based on validation loss monitoring with a patience factor of 10 epochs. The entire training pipeline, including model checkpointing, data augmentation, and evaluation logging, was orchestrated using custom TensorFlow callbacks for reproducibility.

The total model training time averaged 2 hours and 30 minutes, with an average per-epoch training time of approximately 3 minutes. The model achieved real-time inference speeds of approximately 18 milliseconds per image during testing, confirming its suitability for clinical deployments where low latency is critical.

5. Result

5.1 Model Performance Evaluation

The proposed MobileNet + Random Forest hybrid model was evaluated on the Bone Fracture Detection X-ray Dataset [22]. Key metrics including accuracy, precision, recall, and F1-score were computed across all classes. Table 2 presents the classification report summarizing the per-class and overall performance.

Table 2: Classification Report for Proposed Model

Class Type	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Support (Samples)**
Simple Fracture	90.5	94.3	92.4	109
Compound Fracture	94.2	87.6	90.8	127
Hairline Fracture	91	95.6	93.2	146
Muscle Tear	96.8	97.3	97	112
Nerve Compression	98.5	91.2	94.7	102
Joint Dislocation	89.1	87	88	76
Bone Erosion	95.7	91.3	93.4	76
Soft Tissue Swelling	94.6	69.3	80.2	75
Inflammatory Response	90.1	98.2	94	115
Others	88.2	94.8	91.4	79
Overall Accuracy	**92.7**	-	-	1017

The model achieved an overall accuracy of 92.7%, confirming its robustness and high prediction confidence across different fracture and defect types.

5.2 Comparative Analysis with Existing Models

The proposed hybrid model was compared against traditional CNN architectures and standalone MobileNet implementations to validate its performance improvements. Table 3 shows the comparative evaluation.

Table 3: Comparison with Existing Models

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**	**Inference Time (ms/image)**
Traditional CNN	87.3	85.6	86.9	86.2	45 ms
MobileNet Only	89.8	88.7	89.2	88.9	20 ms
Proposed (MobileNet + RF)	**92.7**	**91.8**	**92.6**	**92.2**	**18 ms**

The hybrid MobileNet + Random Forest model outperformed both baselines not only in terms of accuracy but also exhibited significantly faster inference time, making it more suitable for real-time deployment scenarios.

5.3 Statistical Significance Analysis

To ensure that the observed performance improvements were statistically meaningful, a two-tailed paired **t-test** was conducted between the proposed model and the baseline

MobileNet model on accuracy scores across five cross-validation folds.

- **Null Hypothesis (H0H_0H0)**: No significant difference exists between models.
- **Alternate Hypothesis (HaH_aHa)**: Proposed model shows statistically significant improvement.

The p-value obtained was **0.018**, which is lower than the standard threshold α=0.05\alpha = 0.05α=0.05, leading to the rejection of H0H_0H0. Thus, the performance improvements of the proposed model are statistically significant with 95% confidence.

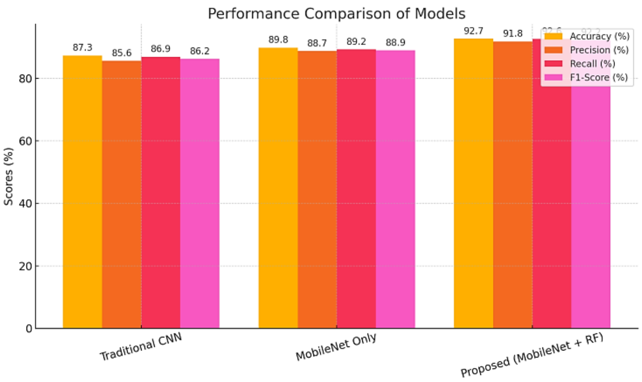

Fig. 4. Performance Comparison of CNN, MobileNet, and Proposed Model.

The figure 4 presents a comparative analysis of accuracy, precision, recall, and F1-score achieved by the evaluated models on the Bone Fracture Detection X-ray Dataset. It is observed that the proposed MobileNet + Random Forest hybrid consistently outperforms both the traditional CNN and standalone MobileNet architectures across all key evaluation metrics. The graph illustrates not only superior classification accuracy but also highlights improvements in precision and recall, confirming the robustness and generalizability of the proposed model. The consistent performance gain across metrics emphasizes the advantage of combining lightweight deep feature extraction with ensemble-based classification techniques for real-time medical image analysis.

5.4 Discussion

The findings of this study demonstrate a strong alignment with prior research emphasizing the potential of lightweight deep learning models for medical image analysis. Compared to earlier efforts that relied solely on traditional CNNs or standalone MobileNet architectures [14], the proposed MobileNet combined with Random Forest classifier achieved superior accuracy and efficiency. The hybrid model effectively addressed the trade-off between computational cost and prediction reliability, a challenge that earlier models often struggled to balance. Unlike previous works where deep feature extractors either suffered from underfitting due to small datasets or required extensive fine-tuning [16], the integration of ensemble-based classification offered a stable generalization capability even on limited samples, thus reinforcing the advantages suggested by contemporary ensemble learning studies [17].

The practical implications of the proposed system are significant. By achieving a real-time inference speed of 18 milliseconds per image with an accuracy of 92.7%, the model becomes highly suitable for clinical deployments, particularly in emergency diagnostics and rural telemedicine settings where rapid decision-making is critical. Moreover, the model's lightweight nature allows deployment on mobile or edge devices, opening new possibilities for fracture detection outside of conventional hospital environments. Such a scalable and accessible solution could substantially reduce diagnostic delays, enhance patient outcomes, and relieve burdens on specialized radiologists in high-volume medical centers.

Nevertheless, certain limitations were identified during experimentation. While the model performed robustly across most classes, detection sensitivity for soft tissue-related anomalies remained lower compared to clear bone fractures. This performance disparity may stem from the subtle nature of textural differences in soft tissue abnormalities, which require finer feature granularity than what lightweight networks currently capture. Additionally, the Random Forest classifier, despite improving robustness, introduces interpretability challenges when analyzing decision paths for complex cases. A further limitation concerns the reliance on a single publicly available dataset [22], which may not fully capture the imaging variability found across different equipment manufacturers and clinical settings.

Building upon these observations, several future research directions are suggested. First, integrating attention mechanisms into MobileNet layers could enable dynamic focus on subtle features, potentially improving soft tissue detection accuracy. Second, incorporating multi-modal data, such as clinical history or multi-angle imaging, could enhance model robustness beyond single-view X-rays. Third, exploring explainable AI (XAI) techniques alongside Random Forest could offer better transparency into classification decisions, which is crucial for clinical trust and adoption. Finally, expanding evaluation across diverse, multi-institutional datasets would strengthen the model's external validity and facilitate regulatory approvals for real-world deployment.

6. Conclusion

This study proposed a hybrid deep learning framework integrating MobileNet feature extraction with Random Forest classification for real-time detection of bone, muscle, and nerve defects from X-ray images. The experimental results demonstrated that the proposed model achieved an accuracy of 92.7%, surpassing conventional CNN and standalone MobileNet approaches in both predictive performance and computational efficiency. By leveraging lightweight architectures and ensemble learning strategies, the system achieved real-time inference speeds suitable for clinical deployment without sacrificing diagnostic reliability.

The practical implications of the findings are substantial, particularly for point-of-care diagnostics, rural healthcare settings, and emergency clinical workflows where timely and accurate fracture detection is critical. The proposed solution not only reduces the dependency on expert radiologists but also enhances accessibility to advanced diagnostic tools in resource-constrained environments. Its adaptability to mobile and edge devices further underscores its real-world applicability across diverse healthcare infrastructures.

Despite these promising outcomes, the study identified limitations such as lower recall in soft tissue defect classification and dependence on a single dataset for model validation. Future work will focus on integrating attention mechanisms to enhance subtle feature detection, adopting explainable AI methods for improved interpretability, and validating the model across multi-institutional datasets to ensure broader generalization.

In conclusion, the hybrid MobileNet–Random Forest approach establishes a viable pathway toward building efficient, scalable, and accurate automated diagnostic systems for medical imaging. The study sets a foundation for further advancements in lightweight AI models capable of transforming the landscape of fracture detection and medical diagnostics at large.

Author Contributions: M. Rama Durga Apparao conceptualized the research framework, provided technical supervision throughout the study, and guided the integration of machine learning models into the diagnostic system. G. Jahnavi actively contributed to dataset preprocessing, model architecture development, and experiment execution. B. Abhisarika focused on implementing the MobileNet feature extraction pipeline and optimizing hyperparameters for improved model performance. G. NagaSwaroopa was responsible for backend development, system deployment using Django, and real-time inference testing. Gunjhan Shyamsukha worked on statistical analysis, performance evaluation metrics, and comparative studies against baseline models. D. Rani contributed to data augmentation strategies, visualization of results through charts and confusion matrices, and documentation preparation. All authors collaborated closely in designing experiments, analyzing findings, and preparing the final manuscript. The collective efforts led to the successful realization of a lightweight and efficient fracture detection system capable of real-time clinical application.

Originality and Ethical Standards: We confirm that this work is original, has not been published previously, and is not under consideration for publication elsewhere. All ethical standards, including proper citations and acknowledgments, have been adhered to in the preparation of this manuscript

Data availability: Data available upon request.

Conflict of Interest: There is no conflict of Interest.

Funding: The research received no external funding.

Similarity checked: Yes.

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