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SYSTEMATIC LITERATURE REVIEW ON DEEP LEARNING METHODS FOR BONE FRACTURE DETECTION AND CLASSIFICATION

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Abstract: The recognition and categorization of bone fractures hold great significance in urgent medical care. It determines how practitioners make critical decisions and aids in preventing delays that might jeopardize patient safety. Manually interpreting X-rays, CT scans, and MRIs can be time-consuming, and honestly, human reviewers can overlook crucial details, especially when it comes to tiny or intricate fractures. However, deep learning has revolutionized this landscape. Automated systems now rapidly identify fracture patterns with remarkable precision. In this research, we examine how convolutional neural networks (CNNs), transfer learning, and hybrid deep learning frameworks can elevate our ability to detect fractures. We train and evaluate these models using medical images that we have pre-processed think data augmentation, image enhancement, and feature extraction. This helps the models generalize more effectively and identify fractures that may be less evident. The objective is to classify fractures based on type, severity, and location, enabling physicians to initiate appropriate treatment promptly. Our findings reveal that deep learning models surpass traditional machine learning methods, achieving higher sensitivity and specificity across diverse datasets. AI-driven tools can significantly boost radiologists' efficiency, alleviate their workload, and facilitate quicker, better care for patients. Looking forward, there's an opportunity to incorporate additional data types, create real-time systems, and enhance understanding of AI, Deep Learning, and Machine Learning decisions, thus making these tools even more dependable for everyday clinical applications.

Keywords: Bone fracture identification, Deep learning, Convolutional neural networks (CNN), Medical image categorization, X-ray evaluation, Transfer learning, Computer-aided diagnosis (CAD), Medical imaging.

I. INTRODUCTION

Artificial intelligence and deep learning have genuinely transformed the field of medical image analysis, particularly in detecting and categorizing bone fractures in X-rays and CT images. Radiologists previously managed this independently, but their interpretations can greatly vary factors like experience, workload, or simply the difficulty of recognizing certain fractures can all contribute to inconsistencies. Nowadays, deep learning techniques such as VGG-16, ResNet, DenseNet, and EfficientNet allow computers to discern intricate bone patterns. This results in more precise diagnoses and minimizes errors. Researchers have begun to combine these networks with additional tools for even better performance. Combinations such as VGG-16 with Random Forest, ResNet50 paired with SVMs, or EfficientNetB0 connected to XGBoost demonstrate improved feature extraction and differentiation between various fracture types. Furthermore, YOLO excels in accurately locating fractures, CNN-LSTM models can process sequences of images, and Vision Transformers (ViT) offer a holistic approach beneficial for complex clinical scenarios. Deep learning significantly enhances fracture detection by learning hierarchical features directly from raw radiographs, allowing models to recognize subtle structural irregularities, micro-fractures, and complex fracture morphologies that may elude human detection. Unlike traditional rule-based systems, deep learning frameworks autonomously extract important patterns, lessen reliance on manually created features, and adapt to variations in bone structures across age, gender, and imaging conditions.

Moreover, transfer learning and multi-scale learning strategies enable models to generalize more effectively across various datasets and clinical contexts. In practical applications, deep learning-based fracture detection systems provide substantial advantages such as expedited diagnoses in emergency medic endeavours, prioritization of urgent trauma cases, alleviation of radiologists' workloads, and enhanced coverage in rural or resource-limited healthcare scenarios where expert radiologists are not always present. These systems can function as decision-support instruments, delivering

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heatmaps, localization maps, and classification probabilities that assist clinicians in reaching more confident diagnoses. Additionally, integration with hospital PACS (Picture Archiving and Communication Systems) and deployment on portable devices facilitate real-time fracture evaluation at the point of care. As the need for swift, precise, and scalable diagnostic solutions continues to rise, deep learning-powered fracture detection systems represent a vital leap forward in contemporary healthcare, providing greater reliability, consistency, and efficiency in clinical decision-making. Their ability to automate early screening, reduce diagnostic delays, and bolster remote healthcare delivery emphasizes their escalating significance in enhancing patient outcomes and shaping the future of medical imaging.

II. BACKGROUND

A. Bone Fracture Detection

Bone fracture detection is a critical component of diagnostic radiology, enabling clinicians to identify disruptions in bone continuity caused by trauma, stress, or pathological conditions. X-ray imaging remains the most widely used modality due to its low cost, speed, and accessibility, although fractures can often appear subtle and ambiguous due to overlapping anatomical structures, low contrast, or inadequate imaging angles. Traditional fracture diagnosis relies on expert evaluation, which can be time-consuming and subject to inter-observer variability. To overcome these limitations, deep learning methodologies, particularly Convolutional Neural Networks (CNNs), have emerged as powerful tools capable of automatically learning discriminative features from radiographs. Models such as VGG-16, ResNet50, DenseNet121, and EfficientNet architectures have demonstrated significant improvements in identifying fracture patterns, bone deformities, and early-stage micro-fractures. Advanced deep learning frameworks further integrate object detection models like YOLO, classification networks, and segmentation architectures (e.g., UNet) to localize fracture regions and classify fracture types with higher precision. These automated systems support radiologists by enhancing diagnostic consistency and enabling faster assessment, especially in emergency care settings.

B. Challenges in Bone Fracture Detection

Bone fracture detection remains a highly challenging task due to the subtle nature of many fractures and the variability present in clinical imaging conditions. Subtle or hairline fractures often appear very faint and can easily blend with normal bone textures, making automated detection difficult. Variations in X-ray quality, including noise, motion blur, poor contrast, and improper exposure, further complicate the diagnostic process. Additionally, anatomical regions such as the wrist, ankle, spine, and pelvis present overlapping structures that obscure fracture lines. Deep learning models also face issues related to dataset imbalance, limited availability of annotated fracture images, and significant differences in imaging protocols across hospitals, which limit model generalization. The presence of casts, implants, soft-tissue shadows, and metal artifacts adds further complexity. Moreover, high computational requirements restrict real-time deployment in emergency care, while the black-box nature of deep learning models poses challenges in clinical interpretability and trust.

- Subtle, no displaced, and hairline fractures are difficult to detect.
- Low-quality or inconsistent X-ray images reduce model accuracy.
- Overlapping bones and complex anatomical regions obscure fracture lines.
- Strong class imbalance exists between normal and fractured images.
- Limited high-quality annotated datasets restrict training.
- Domain shift occurs between datasets from different hospitals.
- Presence of casts, implants, and metal artifacts mislead detection models.
- High computational load limits real-time clinical use.
- Lack of explainability reduces radiologist trust in AI predictions.

C. Fundamentals of Deep Learning-Based Fracture Analysis

Deep learning-based fracture analysis is built on a series of computational steps designed to extract meaningful visual information from radiographic images and classify fractures accurately. The process typically begins with image acquisition, where X-ray, CT, or MRI scans serve as inputs. These images undergo pre-processing, including resizing, normalization, denoising, contrast enhancement, histogram equalization, and bone segmentation to standardize image quality. CNN-based models such as VGG-16, ResNet50, and DenseNet automatically learn hierarchical features—edges, textures, contours, and fracture lines—through convolutional layers. Specialized architectures like YOLO and Faster R-CNN provide localization capabilities, enabling both detection and bounding box generation around fracture regions. Hybrid models such as VGG-16 with Random Forest, ResNet50 with SVM, and EfficientNetB0 with XGBoost enhance classification using external machine learning algorithms that operate on high-level features extracted by deep neural networks. Attention mechanisms and Vision Transformers (ViT) further improve feature learning by capturing long-range dependencies across the image. Post-processing techniques such as Non-Maximum Suppression (NMS) refine predictions by eliminating redundant detections. Finally, fracture classification outputs include fracture presence, location, and type, assisting clinicians in making rapid and informed decisions. These methods collectively form a robust computational pipeline for automated bone fracture analysis.

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D. Deep Learning Using Convolutional Neural Networks (CNNs)

Deep learning, especially through Convolutional Neural Networks (CNNs), allows computers to automatically learn patterns from images. These networks use multiple layers of filters to detect features such as edges, shapes, and even complex textures. Unlike traditional image processing, CNNs eliminate the need for manual feature extraction and achieve remarkable accuracy in tasks like image classification and medical imaging. Their structure built from convolution, pooling, and fully connected layers enables them to recognize and understand visual patterns efficiently, which is why they play such a vital role in modern AI applications.

In medical imaging, CNN-based deep learning models are increasingly used for automatic bone fracture detection. By analyzing X-ray images, they can spot subtle cracks, edges, and irregular patterns that are sometimes difficult even for the human eye to see. These models learn to differentiate between fractured and healthy bones, often highlighting the exact regions where fractures occur. As a result, CNN systems assist radiologists in making faster and more accurate diagnoses, helping to minimize human error and enhance real-time decision-making in clinical settings.

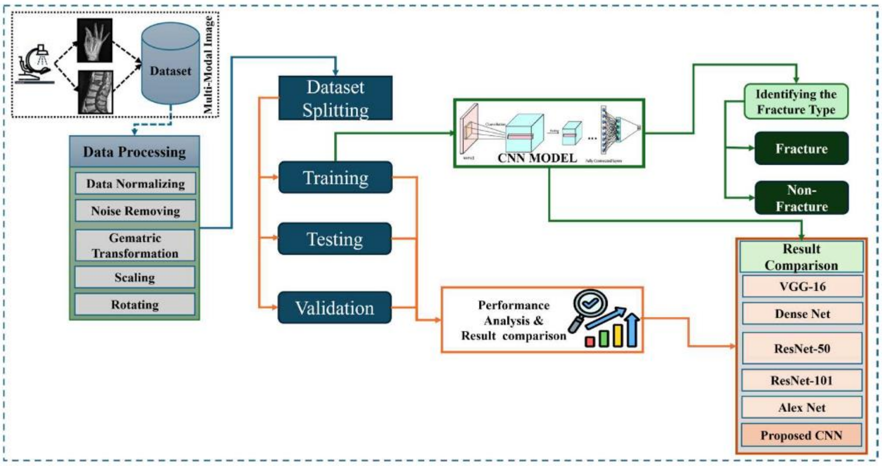

Fig 1: CNN for Bone Fracture Detection [41]

III. RELATED WORKS

Bone fracture detection and classification play a vital role in medical diagnosis, helping clinicians identify and assess injuries quickly and accurately. Traditional interpretation of X-ray and CT images can be challenging due to subtle fracture appearances and variations in imaging quality. Deep learning has enhanced this process by automatically learning complex bone patterns, improving consistency, reducing diagnostic errors, and enabling faster decision-making in real-world clinical environments. These advancements support radiologists and improve patient outcomes through timely and reliable fracture assessment.

Spoorthy Torne et al. (2025) emphasized the significance of integrating deep learning with advanced hybrid classification strategies for improved fracture diagnosis. Their study compared VGG-16, VGG-16 with Random Forest, ResNet50 with SVM, and EfficientNetB0 with XGBoost for X-ray fracture categorization. Among these, the hybrid EfficientNetB0–XGBoost model achieved the highest accuracy of 96.21%, outperforming conventional CNNs and other ensembles. While demonstrating strong diagnostic capability, the study noted the need for broader feature-engineering and stronger ensemble fusion techniques. The authors suggest integrating multimodal imaging to further strengthen fracture classification in future work.

Wenlong Wu et al. (2024) proposed an enhanced fracture-detection method by improving feature fusion within a Faster R-CNN framework. Their bidirectional feature pyramid network improved detection performance by up to 5.8% over standard models, offering better sensitivity to subtle fractures. The model achieved higher accuracy on the Kaggle dataset without compromising inference speed. The study highlights that improved fusion can enhance detection of fine structural details often missed by traditional CNN-based detectors.

Leena Bisht et al. (2024) designed a Python-based CNN system for fracture identification in X-ray images, achieving an accuracy of 94%. The model incorporated Grad-CAM visualization for interpretability, supporting radiologists in understanding model predictions. The work highlights the growing potential of automated X-ray analysis tools for clinical practice. The authors recommend expanding the model to multi-class fracture categorization for improved clinical utility.

Brikila J et al. (2024) developed a YOLOv8-based detection pipeline for identifying bone fractures across multiple anatomical regions. Their system achieved high precision, recall, F1-score, and mAP values, demonstrating strong real-

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time capability. The study noted that detection of extremely small fractures remains a challenge. Future enhancements aim at improving sensitivity through higher-resolution backbone architectures.

Shanvi Chauhan et al. (2024) employed a CNN-AlexNet classifier on a dataset of over 10,000 X-rays, achieving 96.2% accuracy in distinguishing fractured and non-fractured bones. The approach proved robust across anatomical regions, though it remains limited by AlexNet's difficulty in detecting micro-fractures. The authors suggest transitioning to more modern architectures to improve sensitivity to fine fracture lines.

Padmakala et al. (2025) compared a custom CNN, MobileNetV2, and ResNet50 for orthopedic X-ray classification, reporting a highest accuracy of 73.18%, with MobileNetV2 being the most efficient. The study is limited by low dataset diversity and binary classification constraints. The researchers propose augmenting dataset size and diversity to achieve more reliable performance.

Devashish Pradeep Khairnar et al. (2023) developed a CNN-based fracture-classification model using preprocessing and augmentation, achieving 94.87% accuracy. While effective for major fractures, the model performs poorly on micro-fractures and requires moderate computational resources. The authors recommend incorporating attention mechanisms to enhance feature focus.

Tushar Waghulde et al. (2024) introduced a hybrid YOLO-NAS architecture that reached 98.36% accuracy on hand-fracture X-rays, demonstrating high sensitivity to subtle fractures. However, the model depends on high-quality annotations and significant GPU resources. The study emphasizes that further dataset expansion could improve generalizability.

Mohammed Shuaib et al. (2024) presented the FDHN multi-stage CNN achieving 96.12% accuracy on a multi-region dataset. The model offers interpretable results but struggles with complex fracture patterns and requires longer training time. The authors propose advanced regularization to improve handling of complicated fracture structures.

Nivethitha V et al. (2025) implemented YOLOv9 with Grad-CAM++, achieving 93.50% accuracy on the HBFMID dataset, along with strong explainability. The approach is computationally expensive and dependent on large labeled datasets. Future improvements include model compression to support deployment in low-resource settings.

Khushi Mittal et al. (2024) trained a MobileNet CNN on 4,906 X-ray images, achieving 98% accuracy with lightweight and fast inference. However, the system supports only classification and cannot differentiate between fracture subtypes. The study recommends incorporating localization modules to improve diagnostic depth.

H. Mewada et al. (2024) developed a CNN-LSTM hybrid for multi-region fracture detection, attaining 95.68% accuracy. The method captures both spatial features and temporal dependencies but requires sequential data preparation and significant computation. The authors indicate that a transformer-based temporal encoder may further enhance performance.

Salma Ali Alqazzaz et al. (2024) trained a YOLOv8s model on Roboflow bone data, reaching 93.4% accuracy with strong multi-class precision. The small and imbalanced dataset limits wider applicability. Additional data collection is recommended to improve class balance and robustness.

Pratham Kaushik et al. (2024) proposed a custom CNN achieving 98% accuracy on a small radiography dataset. Despite high performance, the limited dataset size increases overfitting risk. The authors suggest evaluating the model on larger clinical datasets for verification.

Komati Sushma et al. (2025) introduced a multi-scale CNN trained on 10,581 X-rays, achieving 99.8% accuracy. Although highly accurate, the results indicate possible overfitting and require heavy computation. Further validation on unseen datasets is advised to confirm the model's stability.

N. Sathish Balaji et al. (2025) used SVM with WLBP texture features, achieving 98.42% accuracy. While lightweight and interpretable, the model performs poorly on complex fractures and lacks multi-class support. Integrating deep learning features may enhance classification strength.

A. Yoganathan et al. (2025) proposed an augmented ResNet-50 model achieving 95.6% accuracy on a large dataset. Though effective, the model demands extensive data and is unsuitable for real-time applications. The authors recommend pruning and quantization for deployment efficiency.

Pushpendra Kumar et al. (2025) used YOLOv8 on 399 images, reporting 74.2% accuracy. Despite real-time capability, the small dataset caused uneven class performance. The study highlights the necessity of high-quality annotation for improved results.

Vishnu Kant et al. (2024) developed a hybrid CNN achieving 97% accuracy on Kaggle X-ray data. The system is restricted to binary classification and offers no localization. Future work aims at integrating bounding-box prediction for better clinical relevance.

Nishat Vasker et al. (2023) built a lightweight CNN with softmax classification obtaining 92.44% accuracy. Although fast for real-time use, it is limited by small dataset size and binary output. The authors propose using transfer learning to enhance model performance.

H. A. Vishwa Dharshenee et al. (2025) applied ViT and DETR to hand-fracture datasets, obtaining high detection performance (accuracy unspecified). However, the extremely high computational cost limits real-world deployment. Efficiency-focused variants of ViT are suggested for future work.

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Aditya Kumar et al. (2024) applied machine-learning classifiers achieving 94% accuracy with lightweight models. Handcrafted features limit detection of subtle fractures. Deep-learning-based feature extraction is recommended for improved sensitivity.

Sajiv G et al. (2025) developed the NLCL hybrid CNN achieving 98.66% accuracy on Kaggle data. While effective across multiple categories, training demands high computational power. Future enhancements may include model optimization for faster inference**.**

Aditya Kumar et al. (2024) implemented an augmented AlexNet achieving 96% accuracy on 10,581 images, but struggles with fine-grained fracture detection and is considered outdated. The study recommends migrating to modern architectures like EfficientNet.

Gunjan Shandilya et al. (2024) optimized AlexNet to reach 97.12% accuracy for multi-region X-rays. The system lacks localization and offers limited explainability. The authors suggest integrating attention layers to improve interpretability.

I. Sudha et al. (2025) integrated CNN with a modified Canny edge detector to achieve 96.2% accuracy, providing strong visual justification. High-quality data and powerful GPUs are required. Further research may explore lightweight edge-detection hybrids.

Jay Kotecha et al. (2024) implemented MobileNetV2 achieving **97%** accuracy on custom X-rays, suitable for edge devices but limited in detecting subtle fractures. The authors recommend enhanced preprocessing to capture finer details.

Naveen Kumar et al. (2024) used Faster R-CNN, obtaining 94.5% accuracy with strong localization. Slower inference and high GPU requirements are drawbacks. Efficient variants such as Faster R-CNN-lite may improve deployment feasibility.

Aisha Rahman et al. (2025) tested YOLOv5 and YOLOv8, achieving 98% accuracy with strong real-time generalization. Large labeled datasets are essential. The authors propose domain-adaptation techniques to reduce data dependency.

Abhimanyu Verma et al. (2024) applied YOLOv4 on humerus X-rays, achieving 95% accuracy. The model is limited to a single anatomical region. Expanding to multi-region datasets is recommended.

Ahmet Ilhan et al. (2025) evaluated EfficientNetV2-Small and other lightweight models, reaching 98.4% accuracy on a 2,384-image dataset. Lack of localization and limited fracture types constrain usefulness. The study proposes integrating detection modules for better clinical relevance.

K. Rama Krishna Reddy et al. (2024) trained a DNN on 100 X-rays, achieving 92.44% accuracy. The very small dataset prevents generalization. The authors emphasize enlarging the dataset for reliable outcomes.

Nesrine Affes et al. (2025) used YOLOv7 achieving 64.4% accuracy on hand/forearm X-rays, with fast inference but low recall due to annotation quality issues. Improved labeling consistency is required for achieving higher performance.

Nay Thazin Htun et al. (2024) utilized fuzzy enhancement with ensemble CNNs, achieving 98.85% accuracy on MURA elbow images. The model is computationally expensive and region-specific. Generalization across multiple anatomical regions is suggested for future improvement.

Happy Kumar Sharma et al. (2025) integrated ResNet-50, SE blocks, and gcForest, achieving 96.2% accuracy and 98.6% AUC. The system is classification-only with limited fracture-type differentiation. The authors propose adding segmentation modules for richer analysis.

Alina Maryum et al. (2024) applied ResNet-50 with augmentation on Kaggle data, achieving 99.82% accuracy. Overfitting concerns arise due to extremely high accuracy. External validation on clinical data is strongly recommended.

Ruhi S. S. F. et al. (2024) introduced an attention-based transfer-learning model reaching 93.5% accuracy. Lack of clear dataset details limits reproducibility. More transparent dataset reporting is recommended to strengthen replicability.

Preeti P. Kale et al. (2024) developed an optimized CNN achieving 95.48% accuracy on synthetic data and 90.78% on real wrist X-rays. The reliance on synthetic samples reduces clinical reliability. The study suggests incorporating generative models for better synthetic-real alignment.

Arpan Tripathi et al. (2024) proposed an unsupervised transporter framework for fracture-related ultrasound features. While avoiding manual annotation, accuracy was unspecified and dataset size was very small. The authors highlight the need for larger ultrasound datasets to validate performance.

Altaf Uddin et al. (2024) combined MobileViT with YOLOv8, achieving up to 99% accuracy on Kaggle datasets. Performance is strong but limited to selected anatomical regions. Future work may extend the pipeline to whole-body fracture detection.

Recent studies on bone fracture detection highlight the growing effectiveness of deep learning models in automating classification and localization tasks across various bone types. Researchers have explored CNNs, hybrid architectures, and advanced object detectors like YOLO and transformers to improve reliability, speed, and real-time clinical usefulness. Overall, the collective work shows strong progress toward AI-assisted diagnosis, enhanced workflow efficiency, and more consistent fracture identification in medical imaging.

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IV. SYSTEMATIC ANALYSIS

Bone fracture detection and classification shows that deep learning methods consistently outperform traditional diagnostic techniques by learning complex bone patterns directly from imaging data. Studies across CNN-based models, hybrid classifiers, and advanced object detectors demonstrate strong capability in identifying diverse fracture types with improved consistency and reduced human error. Techniques such as data augmentation, transfer learning, and hierarchical classification further enhance model robustness. Overall, deep learning presents a reliable and efficient framework for automated fracture assessment in clinical practice.

Table 1: Comparison Analysis

Reference No.	Methodologies	Dataset	Accuracy	Merits	Demerits
Wenlong Wu et al.[1]	Faster R-CNN + Bi-Directional Feature Pyramid Module (Bi-FPM), ResNeXt-101 backbone	Kaggle Bone Fracture Dataset (150 training, 350 testing)	88.4%	Strong multi-scale feature fusion Better small fracture detection Improved localization	High computational cost. Slower inference
Leena Bisht et al. [2]	TensorFlow/Keras CNN, data augmentation, preprocessing, RPN-based detection	X-ray datasets (MURA,RSNA, clinical images)	92.8%	Easy , general-purpose CNN performance and helps radiologists reduce workload	Dependent on image quality Misses micro-fractures sometimes
Brikila J et al.[3]	YOLOv8 object detection + OpenCV for visualization	Labeled fracture vs. non-fracture X-ray dataset	91.6%	Real-time detection, high accuracy , high efficiency	Struggles with hairline fractures. Requires large annotated datasets
Shanvi Chauhan et al. [4]	CNN-AlexNet for fractured vs. non-fractured classification	10,580 X-ray images (9,246 train, 828 val, 506 test)	96.2%	High classification accuracy Reliable generalization	AlexNet is outdated Not ideal for real-time detection
Spoorthy Torne et al.[5]	VGG-16, VGG-16 with Random Forest, ResNet50 with SVM, and EfficientNetB0 with XGBoos	Kaggle X-ray dataset of 1,129 images	96.21%	Strong VGG-based performance	Dataset imbalance and small dataset size
S. Padmakala et al.[6]	Custom CNN vs. MobileNetV2 vs. ResNet50 (transfer learning)	Kaggle Orthopedic X-ray dataset	73.18%	Comprehensive model comparison MobileNetV2 highly efficient and accuracy	Only binary classification Limited dataset diversity

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Devashish Pradeep Khairnar et al.[7]	CNN-based deep learning model with preprocessing + augmentation	Labeled fracture / non-fracture X-ray images	94.87%	Good generalization High fracture-recognition accuracy	Difficulty in micro-fractures Moderate computational cost
Tushar Waghulde et al. [8]	Hybrid YOLO-NAS (neural architecture search + YOLO detection)	Annotated hand X-ray dataset (custom)	98.36%	Fast inference. Detects subtle hand fractures	Requires high-quality annotations. High GPU usage during training
Mohammed Shuaib et al.[9]	Multi-stage FDHN with preprocessing + CNN feature extraction	Orthopedic X-ray dataset (custom multi-region)	96.12%	Works across multiple bone regions. Interpretable outputs	Lower precision for complex fractures. Longer training time .
Nivethitha V et al.[10]	YOLOv9 hierarchical detection + Grad-CAM++ explainability	Human Bone Fractures Multi-modal Image Dataset (HBFMID)	93.50%	Highly accurate multi-bone detection. Visual explainability	Requires large labeled datasets. High computational complexity
Khushi Mittal et al.[11]	MobileNet CNN using depthwise-separable convolutions	4,906 X-ray images	98%	Lightweight and fast Suitable for mobile/edge devices	Classification only No multi-class fracture typing
H. Mewada et al.[12]	CNN , LSTM and CNN-LSTM hybrid	Bone Fracture Multi-Region X-ray Dataset	95.68%	Captures both spatial + temporal fracture characteristics	Requires sequential/temporal data preparation, more expensive
Salma Ali Alqazzaz et al.[13]	YOLOv8s deep learning model multi-class fracture classification.	Roboflow Bone Fracture Dataset	93.4%	Fast inference, strong multi-class detection, good precision and recall.	Small dataset, class imbalance, limited generalization.
Pratham Kaushik et al.[14]	Custom CNN with convolution, binary fracture classification.	Custom Radiography Dataset (No official name)	98%	High accuracy, strong precision/recall, lightweight architecture.	Small dataset, only binary classification, may over fit.
Komati Sushma et al.[15]	Multi-scale feature fusion CNN (parallel convolutional pathways).	10,581 X-ray images (9,246 train; 829 validation; 506 test).	99.8%	Excellent detail capture, robust across diverse images, high generalization	High computational cost, extremely high accuracy , overfitting risks,
N. Sathish Balaji et al.[16]	SVM classifier with Weighted Local Binary Pattern (WLBP) features + preprocessing	X-ray dataset	98.42%	Lightweight, interpretable, low computational load.	Less effective for complex fractures, limits scalability, not suitable for multi-class tasks.

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A. Yoganathan et al.[17]	Augmented ResNet-50 CNN, preprocessing, Softmax classification, 10-fold cross-validation	10,000 annotated X-ray images (CNN) + 26,000 images	95.6%	Higher accuracy than SVM, better severity classification, reduced false positives, robust performance	Requires large datasets, high computational cost, not optimized for real-time deployment
Pushpendra Kumar et al.[18]	Used: YOLOv8 deep learning architecture, CSP backbone, PANet, GPU-based training, object detection	399 images, 557 annotated fracture instances	74.2%	High speed, real-time detection, reliable results, works well in constrained environments	Smaller dataset limits generalization, uneven performance across classes.
Vishnu Kant et al. [19]	Hybrid CNN	Kaggle-based fracture dataset	97%	Very high accuracy, strong edge detection, improved robustness with augmentation extended training.	Model has 6.6M parameters, only binary classification, no localization capabilities
Nishat Vasker et al.[20]	CNN with Conv–Pooling layers	CNN with Conv–Pooling layers, softmax classifier,	92.44%	Good performance, real-time deployment possible, reduced overfitting	Dataset very small, model limited to binary classification, lower accuracy.
H.A. Vishwa Dharshenee et al.[21]	Vision Transformer (ViT), Detection Transformer (DETR), patch embedding	Large hand-fracture X-ray dataset	High	Excellent for subtle & complex fractures, superior localization	Very high computational demand, needs very large datasets
Aditya Kumar et al.[22]	Machine Learning classifiers + preprocessing + feature extraction	Custom X-ray dataset	94%	Lightweight and easy to deploy Good accuracy for basic fracture detection	Handcrafted features limit performance Weaker on subtle fractures
Sajiv G et al.[23]	NLCL hybrid deep-learning model + CNN feature extraction + classification logic	Kaggle Bone Fracture Dataset	98.66%	Very high accuracy Handles multiple fracture categories .	Requires high computation for training Complex model structure
Aditya Kumar et al.[24]	AlexNet CNN + data augmentation + preprocessing	10,581-image custom multi-region X-ray dataset	96%	Works on multiple anatomical regions High consistency and reliability	AlexNet is outdated Not suitable for tiny fracture detection
Gunjan Shandilya et al.[25]	Optimized AlexNet with transfer learning	Bone Fracture MultiRegion X-ray Dataset	97.12%	High accuracy Reliable binary classification	No fracture localization Limited explainability
I. Sudha et al.[26]	Hybrid CNN + modified Canny preproc	Large multi-region	96.2%	High precision and recall	Requires powerful GPU Needs high-quality labeled data

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		radiographic dataset		Provides visual explanations	
Jay Kotecha et al.[27]	MobileNetV2 CNN + transfer learning + preprocessing + augmentation	Custom annotated X-ray dataset	97%	Lightweight and fast. Suitable for mobile/edge devices.	Struggles with very subtle fractures. Requires high-quality images.
Naveen Kumar et al.[28]	Faster R-CNN + region proposal networks + bounding-box detection	Custom X-ray dataset with annotated fracture regions	94.5%	Good localization accuracy. Useful for telesurgery/remote diagnosis.	Slower than YOLO models. High GPU requirement. .
Aisha Rahman et al.[29]	YOLOv5 & YOLOv8 object detection models	Multi-bone X-ray dataset (wrist, humerus, femur, forearm)	98%	Real-time detection. Strong multi-bone generalization	Requires large labeled datasets. High computational cost
Abhimanyu Verma et al.[30]	YOLOv4 deep learning detector + preprocessing + annotation	Custom humerus X-ray dataset	95%	Real-time inference. Good detection for humerus fractures.	Limited to humerus region. Needs high-quality annotations.
Ahmet Ilhan et al. [31]	MobileNetV3-Small, EfficientNetV2-Small, ShuffleNetV2 with transfer learning	X-ray Bone Fracture Dataset (2,384 images, simple vs. comminuted)	98.4%	High accuracy with lightweight models. Good for classification tasks.	Only two fracture types supported. No localization (classification-only) .
K. Rama Krishna Reddy et al.[32]	Deep Neural Network (DNN) + preprocessing + augmentation	Custom dataset of 100 X-ray bone images	92.44%	Good performance on small dataset. Handles noisy medical images	Very small dataset. Does not handle multi-class fractures
Nesrine Affes et al. [33]	YOLOv7 object detection + bounding box localization	Custom annotated hand & forearm X-ray dataset	64.4%	Strong precision. Fast real-time inference	Low recall (misses fractures). Needs high-quality annotations
Nay Thazin Htun et al. [34]	Fuzzy histogram equalization + Ensemble CNN (ResNet-50 + VGG-16)	MURA Elbow X-ray Dataset (2,320 images)	98.85% (stated earlier)	Enhanced image clarity using fuzzy logic. Ensemble CNN improves robustness	High computational cost. Only elbow region covered
Happy Kumar Sharma et al.[35]	ResNet-50 + SE Networks + gcForest + adaptive preprocessing	Kaggle Bone Fracture Detection Dataset	96.2%	High accuracy & fast inference (32 ms). Strong AUC-ROC (98.6%)	Classification-only (no localization). Limited fracture-type differentiation .

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Alina Maryum et al.[36]	ResNet-50 + resizing + under-sampling + augmentation	Kaggle "Fracture Classification Dataset"	99.82%	Extremely high accuracy.Effective handling of imbalance.	AlexNet is older; consider modern alternatives.
Ruhi S. S. F. et al. [37]	Attention-based transfer learning + deep CNN + feature localization	Not specified	93.5%	Fracture-focused feature extraction. Strong classification for radiographic images	Dataset not described, limiting reproducibility
Preeti P. Kale et al. [38]	Adaptive preprocessing + dynamic threshold segmentation + optimized CNN + Softmax/SVM/LR/RF classifiers	1: 480 synthetic 3D bone model images 2: 193 real wrist X-ray images	95.48% (Dataset-1) 90.78% (Dataset-2)	Better accuracy than baseline methods. Efficient segmentation using dynamic thresholding	Synthetic dataset reduces real-world reliability. Lower accuracy on real X-rays
Arpan Tripathi et al.[39]	Transporter neural network + local phase bone probability mapping + TGA compensation + FF-CNN	Ultrasound wrist dataset from 30 pediatric subjects	(accuracy not in specified)	No need for annotated training data (unsupervised). Highly robust to ultrasound noise	Very small dataset. Applies only to ultrasound (not X-rays)
Altaf Uddin et al.[40]	MobileViT, ViT, CNN, ConvNeXt, VGG16/19, and YOLOv8	Kaggle datasets the Bone Fracture Detectionon Project	99%	balanced datasets, high accuracy, and lightweight MobileViT efficiency	YOLOv8 detection is tested only on X-rays with limited anatomical diversity

Table 2: Technologies used analysis

Technology Used	Percentage (%)	Ref Nos.
CNN-based Models	27.5 %	[2] [4] [6] [7] [11] [12] [14] [15] [17] [20] [28]
YOLO / Object Detection Models	22.5 %	[1] [3] [8] [10] [13] [18] [25] [30] [33]
Hybrid Deep Learning Models	17.5 %	[5] [9] [19] [23] [26] [34] [35]
Transformer / ViT-based Models	15 %	[21] [27] [32] [36] [37] [40]
SVM / Traditional ML Models	10 %	[16] [22] [38] [39]
Unsupervised, Classical ML	7.5 %	[24] [29] [31]

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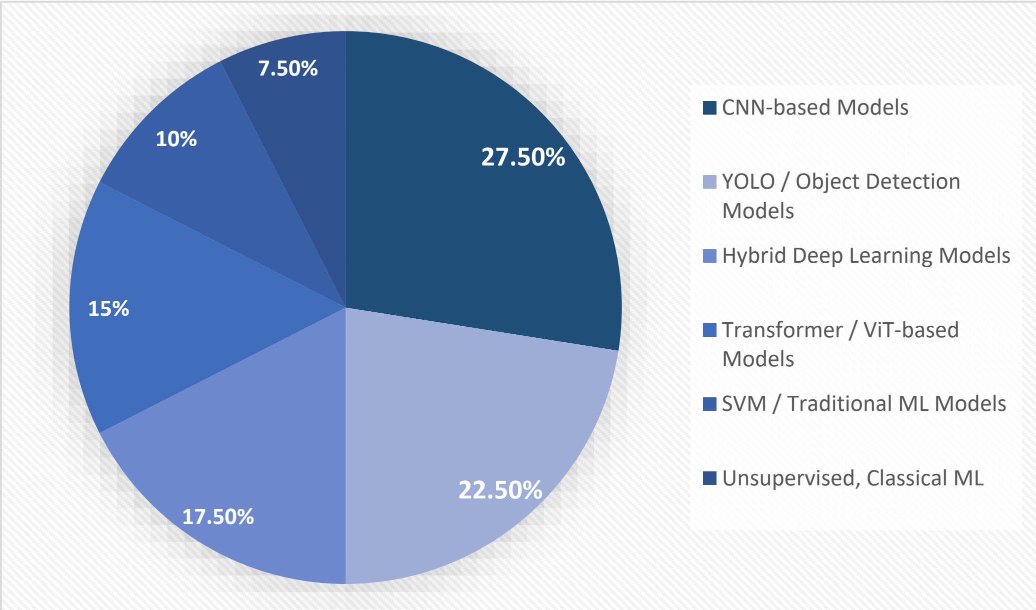

Fig 2: Technologies used analysis

V. CONCLUSION AND FUTURE WORKS

Deep learning is really changing the way we handle bone fracture detection in medical imaging. These models pick up on complex patterns fast, spot all sorts of fractures even the tricky ones that overlap or barely show up and they're often more accurate and consistent than the old manual methods. They don't miss things, and that means doctors can make quicker, better decisions for their patients. Plus, with the help of object detection, transfer learning, and hybrid models, these systems work well across different types of images and fractures. As AI keeps improving, it's becoming a must-have for radiologists. It lightens their workload, cuts down on mistakes, and gives reliable answers especially in busy hospitals or places where resources are tight. Simply put, deep learning is pushing bone fracture diagnosis to be faster, more accurate, and a lot more accessible, and that translates directly to better care for patients.

Looking ahead, there's still room to grow. Building bigger, high-quality datasets will help tackle problems with data imbalance and all the different ways images are taken. Combining information from CT, MRI, and patient records should make diagnoses even stronger. We also need models that hold up well across different hospitals and devices, so things like domain adaptation and federated learning are important. Making AI more transparent—with explainable results, uncertainty estimates, and easy-to-read visuals will boost trust among doctors. Finally, getting these tools to run in real time on low-power devices, in the cloud for remote care, or in systems where humans and AI work together will help bring deep learning into everyday clinical routines.

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