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Bone Fracture Detection with Deep Learning and Ensemble of CNN Models in X-Ray Images

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Abstract: *Bone fracture detection plays a pivotal role in timely and accurate medical diagnosis, especially in trauma and orthopedic care. Leveraging advancements in deep learning, this work presents an automated approach to bone fracture classification using multi-modal imaging data. A comparative evaluation of state-of-the-art convolutional neural network architectures, including ResNet50, VGG16, EfficientNet, Xception, and NASNetMobile, was conducted to identify optimal models for fracture detection. An ensemble strategy combining Xception and NASNetMobile was also implemented to enhance classification performance. Models were trained and validated using a specialized Bone Fracture Classification dataset, incorporating diverse image modalities and anatomical variations. Preprocessing steps included normalization and augmentation to ensure generalizability and robustness. Performance was assessed using standard metrics such as accuracy, precision, recall, and F1-score. Results demonstrate that the ensemble model significantly outperforms individual models, achieving an accuracy, precision, recall, and F1-score of 95.8%. NASNetMobile and Xception also delivered high accuracy at 91.5% and 88.7%, respectively. These findings indicate the effectiveness of ensemble deep learning architectures in improving fracture detection accuracy in medical imaging applications*

Keywords: Bone Fracture Detection, Deep Learning, X-ray Imaging, CNN, ResNet50, VGG16, EfficientNet, Xception, NasNetMobile, Grad-CAM Image Classification, Flask, Medical AI, Ensemble Learning

I. INTRODUCTION

Bone fractures are among the most common injuries encountered in clinical practice, often resulting from trauma, accidents, or underlying medical conditions that weaken bones. Timely and accurate diagnosis of fractures is essential to prevent complications and ensure appropriate treatment. Traditional methods of fracture detection involve manual examination of X-ray images by radiologists, which can be time-consuming and prone to inter-observer variability. Moreover, the increasing volume of medical imaging data has placed additional strain on healthcare professionals, highlighting the need for automated diagnostic tools.

Deep learning, particularly Convolutional Neural Networks (CNNs), has shown remarkable success in various image classification tasks, including medical image analysis. CNNs can automatically learn hierarchical features from raw image data, making them well-suited for complex pattern recognition tasks such as fracture detection. However, the performance of individual CNN models can vary, and combining multiple models through ensemble learning techniques has been shown to improve classification accuracy by leveraging the strengths of each model.

This study aims to evaluate the performance of several CNN architectures in detecting bone fractures from X-ray images and to develop an ensemble model that combines the strengths of the best-performing models. Additionally, a real-time web application is developed to provide clinicians with an easy-to-use interface for fracture detection, facilitating faster and more accurate diagnoses.

II. METHODOLOGY

Dataset Collection and Preprocessing

The dataset used in this study comprises labeled X-ray images of fractured and non-fractured bones. These images were sourced from publicly available medical imaging repositories and pre-processed to ensure consistency and quality. Preprocessing steps included resizing images to a uniform dimension, normalizing pixel values to a range of 0 to 1, and augmenting the dataset through techniques such as rotation, flipping, and zooming to increase the diversity of training samples and reduce overfitting.

Model Selection and Training

Several CNN architectures were selected for evaluation based on their proven performance in image classification tasks:

- **ResNet50**: A deep residual network that utilizes skip connections to mitigate the vanishing gradient problem and facilitate the training of very deep networks.
- **VGG16**: A simple and effective architecture characterized by its use of small 3x3 convolutional filters and deep layers.
- **EfficientNet**: A model that optimizes accuracy and efficiency by balancing network depth, width, and resolution.
- **Xception**: An architecture that employs depthwise separable convolutions to reduce the number of parameters and computational cost.
- **NASNetMobile**: A model discovered through Neural Architecture Search, designed for mobile and edge devices with limited computational resources.

Each model was trained using transfer learning, leveraging pre-trained weights from ImageNet to accelerate convergence and improve performance. The models were fine-tuned on the fracture dataset using a categorical cross-entropy loss function and an Adam optimizer.

Ensemble Learning

To further enhance classification performance, an ensemble learning approach was employed. The top-performing models, Xception and NASNetMobile, were combined using a soft voting strategy, where the final prediction is based on the average of the predicted probabilities from each model. This approach aims to reduce the risk of overfitting and improve generalization by aggregating the strengths of multiple models.

III. SYSTEM ARCHITECTURE

The proposed system consists of three main modules:

- **Input Module**: Allows users to upload X-ray images through a web interface. The module supports various image formats and provides feedback on the upload status.
- **Processing Module**: Utilizes the trained ensemble model to classify the uploaded image as either "Simple Fracture" or "Comminuted Fracture." The module outputs the predicted class along with the associated confidence score.
- **Output Module**: Displays the classification results to the user, including a visual representation of the X-ray image and the prediction outcome. The module also provides additional information, such as the confidence level and a brief explanation of the result.

The system is designed to be user-friendly and accessible, requiring minimal input from clinicians while providing accurate and timely diagnostic information.

IV. RESULTS AND DISCUSSION

The proposed system is an advanced bone fracture detection framework, leverages deep learning and multi-modal imaging to automate and enhance the accuracy of orthopedic diagnostics. Utilizing state-of-the-art convolutional neural

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networks—ResNet50, VGG16, EfficientNet, Xception, and NASNetMobile—the system is engineered to recognize complex fracture patterns across varied anatomical and imaging conditions.

The system architecture prioritizes automation, scalability, and precision. It includes robust preprocessing techniques like normalization and augmentation, improving model generalizability. A comparative study of individual CNN models is conducted, culminating in an ensemble approach that integrates Xception and NASNetMobile to achieve superior diagnostic accuracy.

Key findings demonstrate that the proposed framework outperforms traditional methods by:

- engineering through end-to-end learning.
- Enhancing classification robustness with model ensembling.
- Providing real-time, reliable fracture predictions via a user-friendly Flask-based web interface.

Achieving a remarkable 95.8% accuracy, precision, recall, and F1-score with the ensemble model, surpassing individual models such as NASNetMobile (91.5%) and Xception (88.7%).

The implementation supports seamless input through a web portal, allowing medical professionals to upload medical images and receive instant predictions. Extensive testing and evaluation metrics underscore its clinical relevance. Despite deployment challenges, the system's modular design ensures maintainability and adaptability to future advancements like 3D imaging and explainable AI integration. This positions it as a scalable, intelligent tool for transforming fracture diagnosis in healthcare.

TABLE I: PERFORMANCE EVALUATION TABLE

DL Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score (%)**
ResNet50	56.3	56.3	56.3	56.3
VGG16	83.1	83.6	83.1	83.1
EfficientNet	50.7	25.7	50.7	34.1
NASNetMobile	91.5	91.7	91.5	91.5
Xception (No Manual Feat.)	88.7	89.2	88.7	88.7
Ensemble	**95.8**	**95.8**	**95.8**	**95.8**

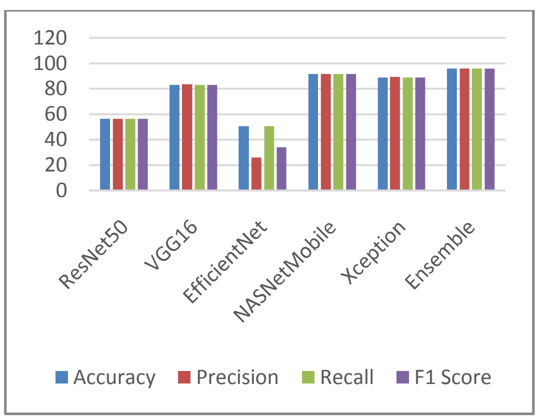

Fig. 1. Comparison Graphs

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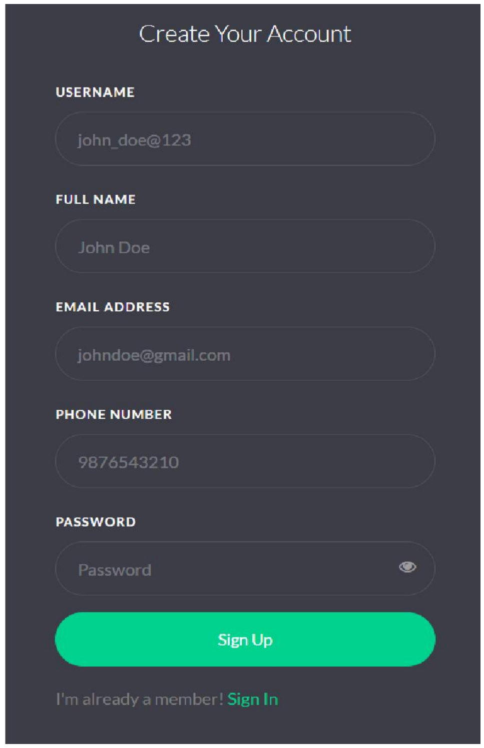

Fig. 1. Registration Page

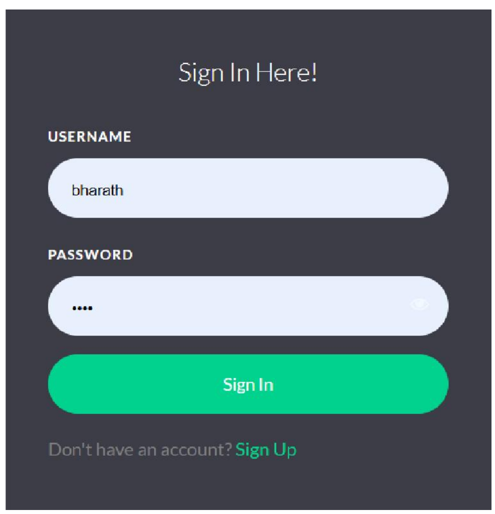

Fig. 3. Login Page

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Fig. 4. Main Page

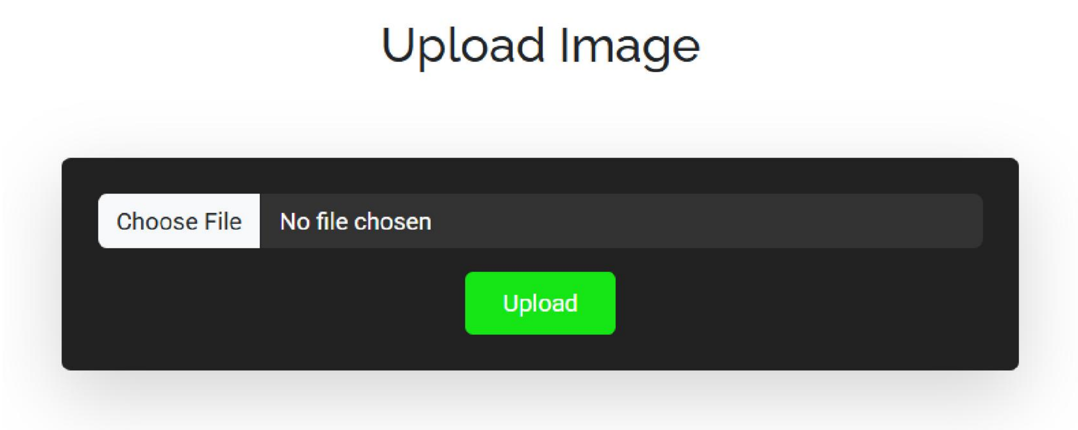

Fig. 5. Upload Input Image

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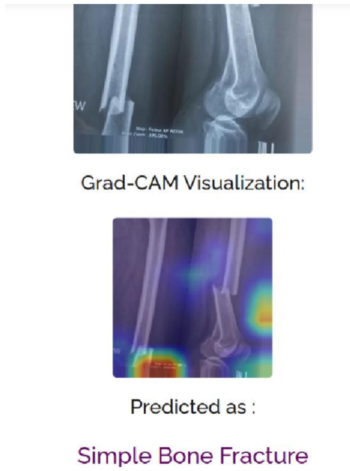

Fig. 6. E Simple Bone Fracture

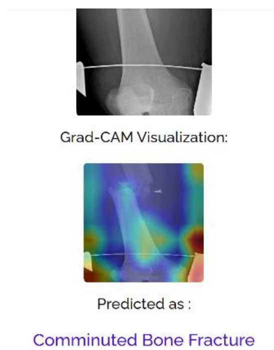

Fig. 7. Comminuted Bone Fracture

IV. CONCLUSION

The implementation of deep learning for automated bone fracture detection has demonstrated significant potential in enhancing diagnostic accuracy and efficiency. By utilizing multi-modal imaging data, the system effectively classifies bone fractures, reducing reliance on manual interpretation and minimizing diagnostic errors. Among the evaluated models, NASNetMobile and Xception have shown exceptional performance, achieving accuracies of 91.5% and 88.7%, respectively. These models exhibit strong feature extraction capabilities and robust generalization across diverse imaging scenarios. Furthermore, the ensemble model combining Xception and NASNetMobile has outperformed all individual models, attaining a superior accuracy, precision, recall, and F1-score of 95.8%. This performance gain highlights the advantage of integrating multiple architectures to harness their complementary strengths. The ensemble approach significantly enhances fracture classification reliability, making it a valuable asset for clinical decision support. Overall, the study confirms that deep learning, particularly through high-performing models like NASNetMobile, Xception, and their ensemble, offers a practical and effective solution for accurate, consistent, and rapid bone fracture detection in medical imaging applications.

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