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BONE FRACTURE DETECTION USING CNN (DEEP LEARNING)

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Abstract: Bone fracture detection using X-ray images is an important task in medical diagnosis, where manual analysis by radiologists can be time-consuming and prone to errors in complex cases. This paper presents a deep learning-based approach for automatic bone fracture classification using hybrid models such as VGG19 with Random Forest, MobileNet with Support Vector Machine (SVM) and Random Forest, and EfficientNet with SVM and XGBoost. The proposed system includes image preprocessing, feature extraction, model training, and performance evaluation using metrics such as accuracy, precision, recall, and F1-score. A simple web interface is also developed for uploading X-ray images and displaying prediction results. Experimental results show that the hybrid deep learning models effectively classify different types of bone fractures with high accuracy. The proposed system can assist healthcare professionals in faster and more reliable fracture diagnosis and demonstrates the potential of artificial intelligence in medical image analysis.

Keywords - Deep Learning, Bone Fracture, X-ray, VGG19, MobileNet, EfficientNet, SVM, Random Forest, Classification.

I. Introduction

The topic of bone fracture classification using deep learning is chosen due to its significant impact on medical diagnostics and the growing potential of artificial intelligence in healthcare. Manual interpretation of X-ray images can be challenging, especially in settings with limited medical expertise or high patient loads. Automating this process using deep learning can assist healthcare professionals in making faster and more accurate decisions. This project offers an opportunity to explore how different deep learning architectures, such as The models used include VGG19 combined with Random Forest, MobileNet with Support Vector Machine (SVM) and Random Forest, EfficientNet with SVM and XGboost, can be leveraged and enhanced with classifiers like SVM and Random Forest. The topic aligns with current trends in AI-driven medical research and provides a valuable learning experience in combining machine learning models with practical applications.

II. RELATED WORK

2.1 Related Work

1. Bone Fracture Classification using Transfer Learning

Shyam Gupta & Dhanisha Sharma (2024)- This study applies transfer learning to classify bone fractures from X-ray images using pre-trained CNN models. The authors use models like VGG19 and ResNet50, fine-tuned on a fracture dataset to reduce training time and improve accuracy. They achieve over 90% accuracy with just a few epochs, demonstrating the efficiency of transfer learning in medical image analysis. The paper emphasizes lightweight models and low resource usage, making it suitable for edge devices and small-scale applications. It supports the idea that deep learning can significantly improve diagnostic tools in healthcare when combined with smart data handling and model reuse.

2. Weakly Supervised Localization and Classification of Proximal Femur Fractures

Jiménez Sánchez et al. (2018)- This paper introduces a method for both localizing and classifying proximal femur fractures using a weakly-supervised CNN approach. Instead of relying on pixel-level annotations, the model learns to detect fractures using only image-level labels. It uses spatial transformers and global average pooling to help the network focus on the fracture regions. The dataset consists of over 1,300 annotated X-rays. The model achieves strong accuracy and outperforms traditional CNNs in fracture classification. The study is important because it reduces the need for detailed medical annotations, which are expensive and time-consuming, while still achieving reliable diagnostic results.

3. Vision Transformer for Femur Fracture Classification

Leonardo Tanzi et al. (2021)- This research explores the use of Vision Transformers (ViT) to classify femur fractures from X-ray images. Unlike CNNs, ViTs process the entire image using attention mechanisms, which helps in capturing long-range dependencies. The model is trained on a large dataset of over 4,000 femur X-rays and achieves an accuracy of ~83%, outperforming conventional CNN-based classifiers. Additionally, the paper reports a 29% improvement in radiologist decision-making when assisted by the ViT model. The study shows the potential of transformer-based architectures in medical imaging and supports the shift from traditional CNNs to more flexible attention-driven deep learning models.

4. Bone Fracture Classification using CNNs from X ray Images

Alshahrani & Alsairafi (2024)- In this study, the authors evaluate convolutional neural networks (CNNs) for classifying bone fractures from X-ray images using the FracAtlas dataset. The experiment compares detection using YOLOv8 and classification using VGG16. Data augmentation and fine-tuning are used to improve model performance. The study focuses on three classes: normal, fractured, and other conditions. After optimization, the models reach high accuracy and F1-scores, demonstrating the effectiveness of deep learning for bone fracture classification. The research highlights the importance of dataset quality, preprocessing, and model tuning. It supports using pre-trained CNNs to simplify implementation in educational or clinical environments.

of five years. The time series monthly data is collected on stock prices for sample firmsand relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

III. PROPOSED WORK

A) Methodology

The methodology for this project involves several key steps to build an effective deep learning-based system for bone fracture classification from X-ray images. The workflow is divided into two main modules: the System Module and the User Module.

In the System Module, the first step is data collection and loading. A publicly available X-ray image dataset is used, containing labeled images of fractured like Avulsion fracture, Comminuted fracture, Fracture Dislocation, Greenstick fracture, Hairline Fracture, Impacted fracture, Longitudinal fracture, Oblique fracture, Pathological fracture, Spiral Fracture. The next step is data preprocessing, which includes resizing, normalization, and data augmentation techniques to improve model generalization and handle class imbalance.

Multiple deep learning models are used for training and evaluation, including The models used include VGG19 combined with Random Forest, MobileNet with Support Vector Machine (SVM) and

Random Forest, EfficientNet with SVM and XGboost. These models are trained on the preprocessed data using supervised learning techniques. For hybrid models, features are extracted from the CNN and passed to machine learning classifiers (SVM or Random Forest) for final prediction. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to compare the performance of all models.

In the User Module, a basic web interface is developed using HTML, CSS, and JavaScript. The user must register and log in to access the classification feature. Once authenticated, users can upload X-ray images, which are sent to the backend model for prediction. The output—indicating whether a fracture is detected or not—is displayed on the frontend.

B) Proposed System

The proposed method uses deep learning models to automatically classify bone fractures in X-ray images. Instead of manually extracting features, convolutional neural networks (CNNs) such as the models used include VGG19 combined with Random Forest, MobileNet with Support Vector Machine (SVM) and Random Forest, EfficientNet with SVM and XGboost, are used to learn features directly from the image data. Some of these models are combined with machine learning classifiers like Support Vector Machine (SVM) and Random Forest to enhance accuracy. The system is trained on labeled X-ray images and evaluated using standard metrics. A simple frontend using HTML, CSS, and JavaScript is developed to show model predictions and support interactive learning.

Advantages of Proposed System

- Automatically learns important features from images.
- Higher accuracy compared to traditional methods.
- Reduces human effort in feature engineering.
- Can handle large and complex datasets effectively.
- Better generalization to new or unseen data.
- Deep models capture more detailed and abstract patterns.
- Hybrid models (e.g., CNN + SVM) improve performance.

C) System Diagram

The proposed system block diagram illustrates the complete workflow of an automated bone fracture detection and classification system using Convolutional Neural Networks (CNNs) and hybrid machine learning classifiers. The process begins with the X-ray image dataset, which contains both fractured and normal bone images collected for model training and testing. These images are then passed through the image preprocessing stage, where operations such as image resizing, normalization, noise reduction, data augmentation, and train–test splitting are performed to improve image quality and enhance model performance. After preprocessing, the images are forwarded to the CNN feature extraction module, where deep learning architectures such as VGG19, MobileNet, and EfficientNet extract important fracture-related features and generate feature maps. The extracted features are then provided to the hybrid classifiers module, which combines CNN-based features with machine learning algorithms including Random Forest (RF), Support Vector Machine (SVM), and XGBoost for improved classification accuracy. The system then performs fracture prediction, where the uploaded X-ray image is classified into specific fracture categories such as Hairline Fracture, Oblique Fracture, Comminuted Fracture, Spiral Fracture, Greenstick Fracture, and Impacted Fracture. To measure the effectiveness of the proposed model, the performance evaluation block computes metrics including accuracy, precision, recall, and F1-score. Finally, the trained model is integrated into a web interface, allowing users to upload X-ray images, view prediction results, and display fracture classification outcomes through an easy-to-use application interface.

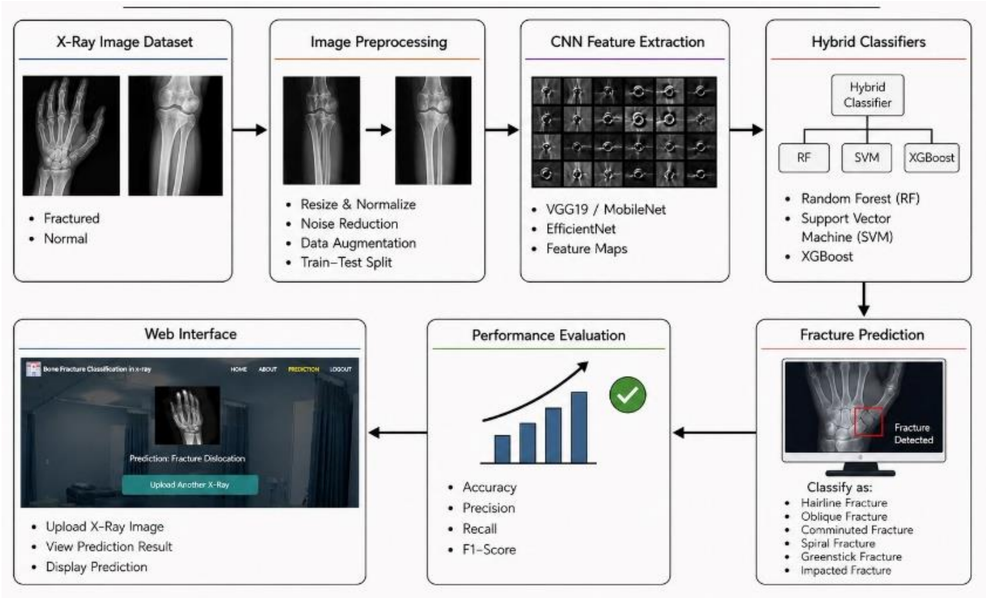

Figure 1: System Block Diagram of Bone Fracture Detection

D) Proposed WorkFlow

The flowchart represents the complete workflow of the proposed bone fracture classification system using X-ray images. The process starts with user registration, where the user creates an account, followed by user login for authentication. If registration or login fails, the system displays the corresponding error message and prompts the user to retry. After successful login, the user uploads an X-ray image, and the system verifies whether the upload is successful; otherwise, an upload error is shown. The uploaded image then undergoes preprocessing techniques such as resizing, normalization, and noise reduction to improve image quality for analysis. The processed image is passed to the classification module, where deep learning and machine learning models analyze the X-ray image to predict the specific type of bone fracture. If any issue occurs during processing or classification, the system displays a processing error message. Upon successful classification, the final fracture prediction result is displayed to the user, and the workflow ends.

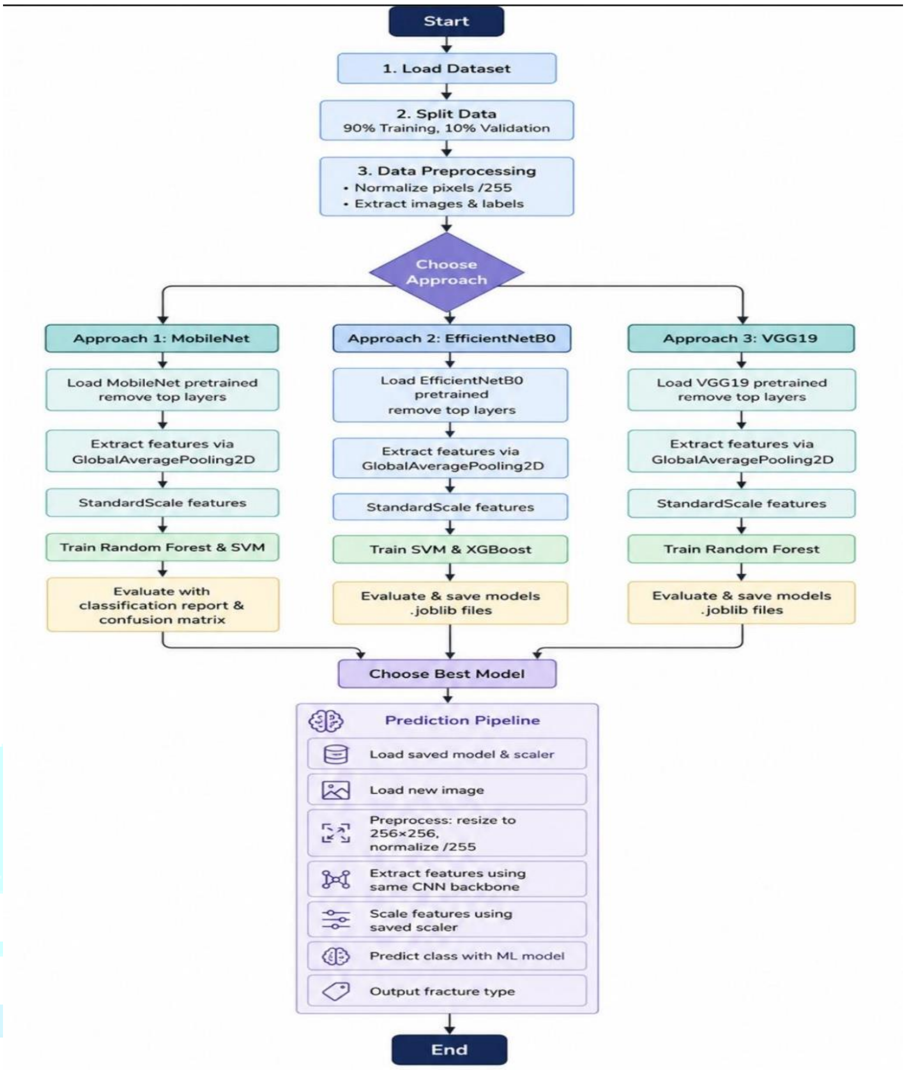

Figure 2: System Workflow

IV. RESULTS

A) MobileNet and SVM

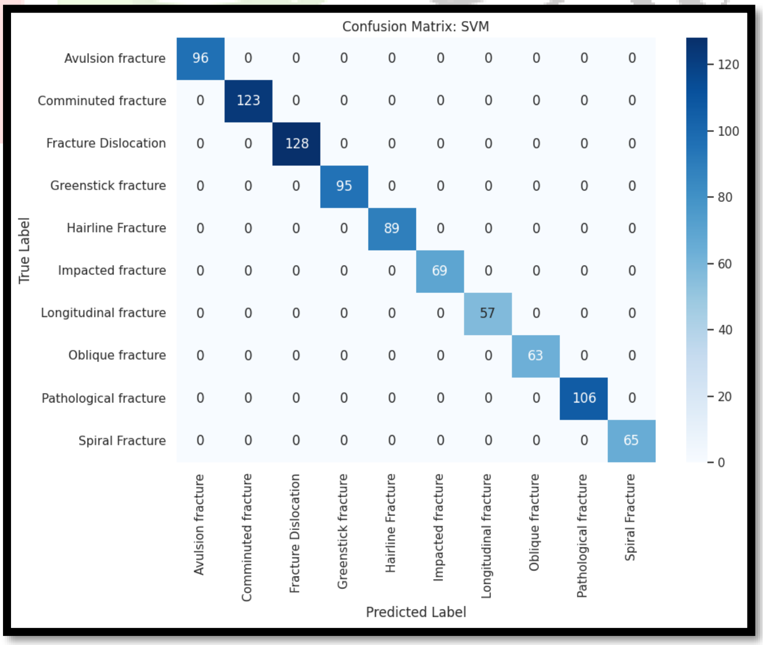

Figure 3: Confusion Matrix of MobileNet and SVM

The confusion matrix shown in Fig. 3 represents the performance of the Support Vector Machine (SVM) classifier in classifying different types of bone fractures from X-ray images. The matrix includes ten fracture categories: Avulsion fracture, Comminuted fracture, Fracture Dislocation, Greenstick fracture, Hairline fracture, Impacted fracture, Longitudinal fracture, Oblique fracture, Pathological fracture, and Spiral fracture. The diagonal elements of the matrix contain the correctly classified samples for each fracture type, while the off-diagonal elements represent misclassifications. In this result, all samples are correctly classified into their respective categories, as indicated by the high values along the diagonal and zero values in all off-diagonal positions. The classifier achieved correct predictions of 96 Avulsion fractures, 123 Comminuted fractures, 128 Fracture Dislocation cases, 95 Greenstick fractures, 89 Hairline fractures, 69 Impacted fractures, 57 Longitudinal fractures, 63 Oblique fractures, 106 Pathological fractures, and 65 Spiral fractures. The absence of misclassification demonstrates the effectiveness of the SVM classifier in accurately distinguishing between multiple fracture types, indicating excellent classification performance and high reliability of the proposed bone fracture detection system.

B) VGG19 and Random Forest

The confusion matrix shown in Fig. 4 illustrates the classification performance of the proposed VGG19 + Random Forest model for multi-class bone fracture detection using X-ray images. The matrix contains ten different fracture categories, namely Avulsion fracture, Comminuted fracture, Fracture Dislocation, Greenstick fracture, Hairline fracture, Impacted fracture, Longitudinal fracture, Oblique fracture, Pathological fracture, and Spiral fracture. In the confusion matrix, the diagonal elements represent correctly classified samples, while the off-diagonal elements indicate misclassified instances. The obtained results show that all fracture samples are accurately classified into their respective categories, with zero misclassifications across all classes. The model correctly identified 96 Avulsion fractures, 123 Comminuted fractures, 128 Fracture Dislocation cases, 95 Greenstick fractures, 89 Hairline fractures, 69 Impacted fractures, 57 Longitudinal fractures, 63 Oblique fractures, 106 Pathological fractures, and 65 Spiral fractures. The strong concentration of values along the diagonal confirms the high effectiveness and robustness of the VGG19 + Random Forest model in distinguishing multiple fracture types. The absence of classification errors demonstrates the capability of the proposed hybrid deep learning approach to achieve highly accurate and reliable fracture type prediction in medical image analysis.

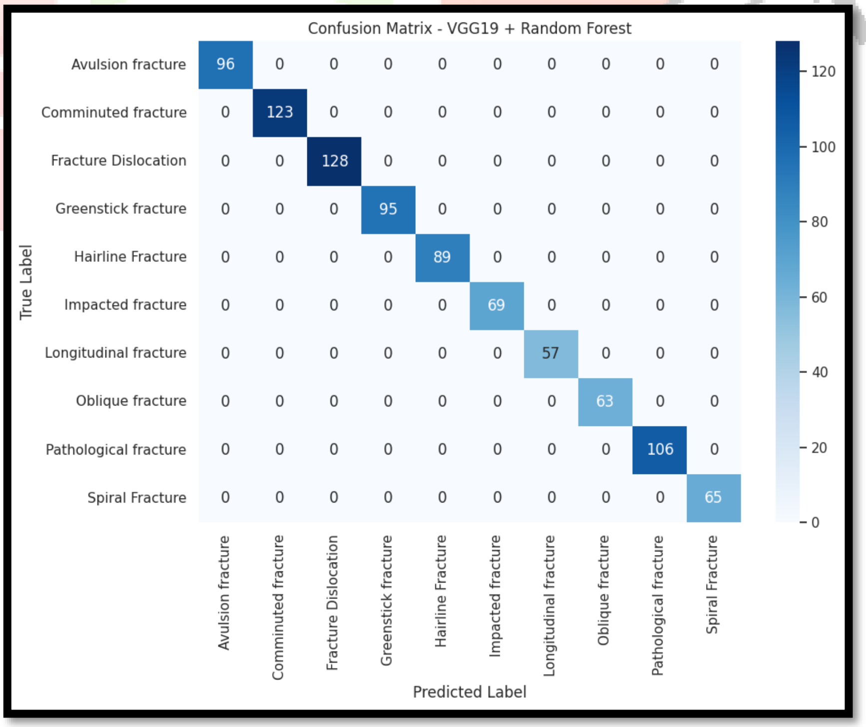

Figure 4: VGG19 and Random Forest

C) EfficientNet and XGBOOST

The confusion matrix presented in Fig. 5 shows the classification performance of the XGBoost classifier for multi-class bone fracture detection using X-ray images. The matrix evaluates the model's ability to correctly identify ten different fracture categories, including Avulsion fracture, Comminuted fracture, Fracture Dislocation, Greenstick fracture, Hairline fracture, Impacted fracture, Longitudinal fracture, Oblique fracture, Pathological fracture, and Spiral fracture. In the confusion matrix, the diagonal elements represent correctly classified samples, whereas the off-diagonal elements indicate incorrect predictions or misclassifications. The obtained results demonstrate that the XGBoost model successfully classified all fracture samples into their respective classes without any misclassification, as all off-diagonal values are zero. The classifier correctly predicted 96 Avulsion fractures, 123 Comminuted fractures, 128 Fracture Dislocation cases, 95 Greenstick fractures, 89 Hairline fractures, 69 Impacted fractures, 57 Longitudinal fractures, 63 Oblique fractures, 106 Pathological fractures, and 65 Spiral fractures. The strong diagonal dominance in the matrix highlights the excellent classification capability of the XGBoost model in distinguishing multiple fracture types from X-ray images. These results indicate that the proposed approach provides highly accurate, robust, and reliable performance for automated bone fracture type prediction in medical image analysis applications.

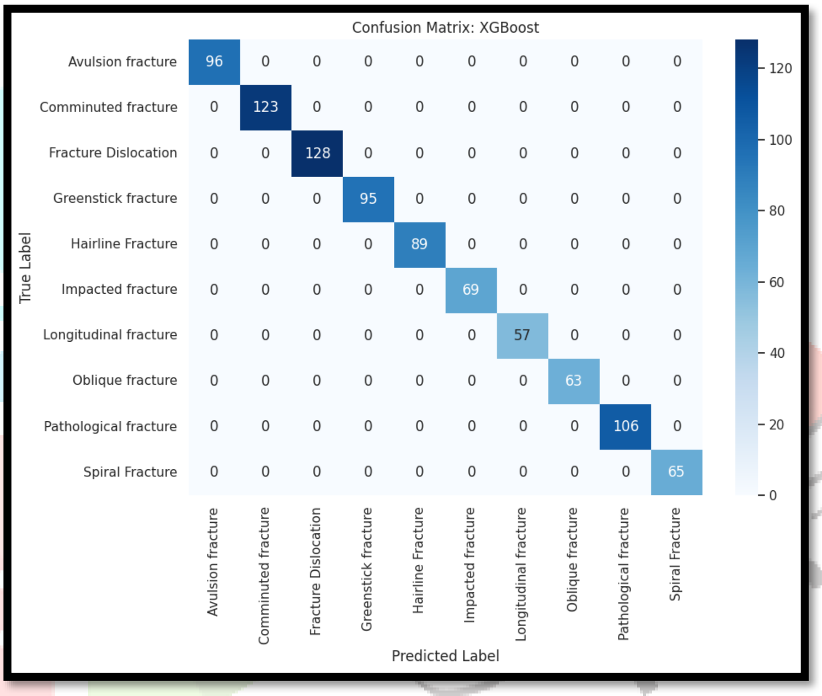

Figure 5: EfficientNet and XGBOOST

D) User Interface

Fig. 6 illustrates the web-based user interface developed for the proposed bone fracture classification system. The interface is designed to provide a simple, interactive, and user-friendly environment for uploading and analyzing X-ray images. The homepage contains navigation options such as Home, About, Prediction, and Logout, enabling users to easily access different sections of the application. The prediction page allows users to upload an X-ray image through a file selection option provided at the center of the interface. Once the image is uploaded, the user can submit it to the system for analysis. After submission, the backend processing module performs image preprocessing, feature extraction, and fracture type classification using the trained deep learning and machine learning models. The system then displays the predicted fracture category to the user. The web interface enhances the usability of the proposed system by enabling fast and efficient fracture analysis through an accessible online platform, making it suitable for practical healthcare and diagnostic support applications.

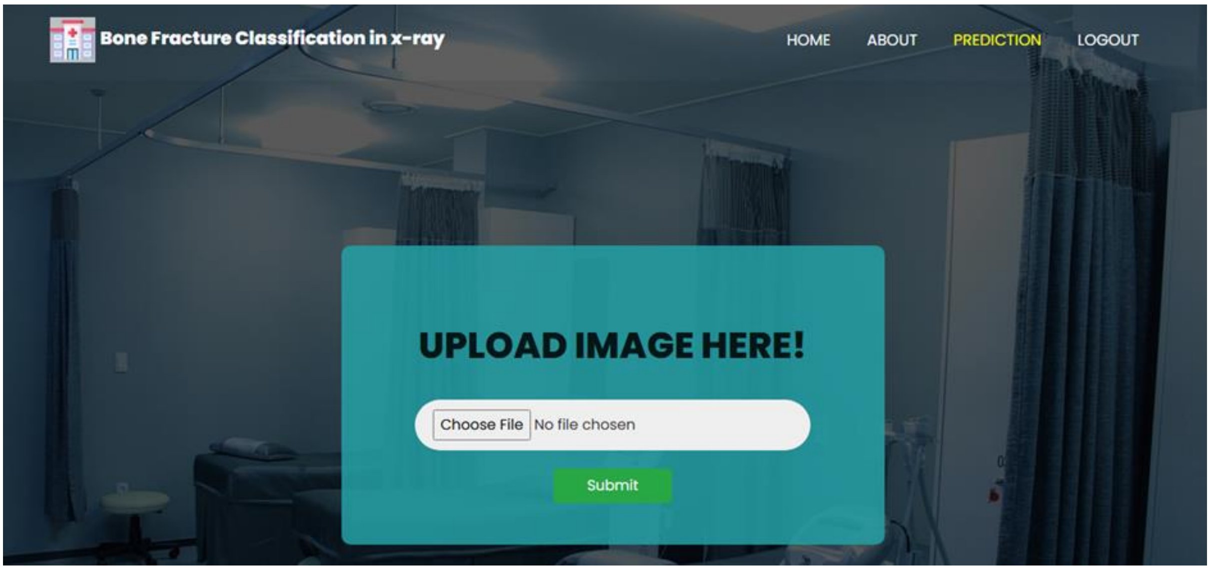

Figure 6: User Interface

V. CONCLUSION AND FUTURE SCOPE

This project demonstrates the effective application of deep learning and machine learning techniques for bone fracture classification using X-ray images. By utilizing hybrid models such as VGG19 with Random Forest, MobileNet with SVM and Random Forest, and EfficientNet with SVM and XGBoost, the system achieves high accuracy and robust fracture type prediction. A simple web-based interface was also developed to support user registration, login, and X-ray image upload for prediction. The study highlights the importance of preprocessing, feature extraction, and model selection in improving medical image classification performance. In the future, the system can be enhanced by using larger and more diverse datasets, advanced preprocessing methods, explainable AI techniques, and deployment as a cloud-based web or mobile application with real-time fracture detection capabilities. Further clinical validation and integration with healthcare systems could help transform the proposed model into a reliable AI-based decision support tool for accurate and early fracture diagnosis.

VI. ACKNOWLEDGEMENT

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