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FRACTURE VISION: AUTOMATED BONE FRACTURE DETECTION USING X-RAY IMAGES

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Abstract: Bone fractures are common injuries that require early and accurate detection for effective treatment. Traditional fracture identification through manual examination of X-ray images can be time-consuming and may sometimes lead to errors. To overcome these challenges, this paper presents Fracture Vision: Automated Bone Fracture Detection Using X-Ray Images, a deep learning-based system developed using a Convolutional Neural Network (CNN). The proposed system analyzes X-ray images and classifies them into two categories: fractured and normal using a bone fracture binary classification dataset. It provides prediction results along with a confidence percentage and fracture severity classification. The system is implemented as a web-based application using Flask, allowing users to upload X-ray images and obtain results through a user-friendly interface. It also includes patient details management, report generation, and doctor consultation facilities. The proposed system aims to support faster and more accessible preliminary bone fracture detection and assist medical professionals in the diagnostic process.

Keywords: Bone Fracture Detection, Deep Learning, Convolutional Neural Network, X-Ray Images, Medical Image Processing, Image Classification, Flask Web Application.

I. INTRODUCTION

Bone fractures are common injuries that occur when a bone is subjected to excessive force or pressure. They may happen due to accidents, falls, sports injuries, or other physical activities. Early identification of bone fractures is important because proper diagnosis and timely treatment can help prevent further complications. X-ray imaging is one of the most commonly used medical techniques for detecting fractures because it provides clear images of the internal bone structure.

Traditionally, the detection of bone fractures is performed by medical professionals through the manual examination of X-ray images. Although this method is widely used, analyzing a large number of medical images can require considerable time and attention. In some cases, small cracks or less visible fractures may be difficult to identify. Therefore, developing an automated system that can assist in analyzing X-ray images can help improve the efficiency of the initial fracture detection process.

With the advancement of Artificial Intelligence (AI) and Deep Learning, automated medical image analysis has become an important area of research. Deep learning techniques enable computer systems to learn important features directly from images and perform classification tasks. Among these techniques, Convolutional Neural Networks (CNN) are widely used for image recognition and classification because they can automatically extract relevant features such as edges, shapes, patterns, and structural differences from input images.

This project focuses on developing an automated bone fracture detection system using a Convolutional Neural Network. The system is trained using a bone fracture binary classification dataset containing X-ray images of fractured and normal bones. The CNN model learns the patterns from the training images and uses the learned features to classify new X-ray images into two categories: fractured and normal. Image preprocessing techniques are applied to prepare the images before they are given as input to the model.

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The developed system is implemented as a web-based application using the Flask framework. It provides a simple and user-friendly interface through which patients or users can upload their bone X-ray images for analysis. After uploading an image, the trained CNN model processes it and displays the prediction result along with the confidence percentage. The application also includes severity classification to provide additional information about the detected fracture.

In addition to fracture detection, the system provides several supporting features to improve its usability. These include patient details management, doctor and patient login, report generation, report viewing, and doctor consultation facilities. Patients can access their reports and request medical opinions from available doctors through the application. Doctors can view consultation requests and provide their observations to support the patient's further medical evaluation.

The primary aim of this project is to develop an automated and user-friendly bone fracture detection system that uses deep learning to analyze X-ray images. By integrating CNN-based image classification with a Flask web application, the proposed system aims to make the initial fracture screening process faster, more convenient, and accessible. The system is designed to assist medical professionals and users in preliminary fracture identification and is not intended to replace professional medical diagnosis.

Key contributions from the study include:
1. Development of a CNN-based system for automated bone fracture detection using X-ray images.
2. Preprocessing and classification of X-ray images into fractured and normal categories.
3. Prediction of fracture results with confidence percentages and severity classification.
4. Development of a Flask-based web application for uploading X-ray images and viewing detection results.
5. Integration of patient and doctor modules with report generation and doctor consultation facilities.

II. RELATED WORK

There has been significant research interest in the application of Artificial Intelligence and deep learning techniques for automated bone fracture detection using X-ray images. Traditional fracture identification mainly depends on the manual examination of radiographs by medical professionals. However, identifying small or complex fractures can be challenging and time-consuming. To overcome these limitations, researchers have explored various deep learning techniques to improve the accuracy and efficiency of automated fracture detection.

Earlier research by Tanushree Meena and Sudipa Roy [1] introduced a deep supervised learning framework for automatically detecting bone fractures from X-ray images. The proposed approach involved image resizing, normalization, and enhancement followed by CNN-based classification. The system classified X-ray images into fractured and normal categories by learning important visual patterns. The study demonstrated improved diagnostic accuracy and reduced analysis time. However, the performance may decrease when using limited datasets or poor-quality X-ray images.

Amal Alshahrani and Alaa Alsairaf [2] proposed a CNN-based approach for bone fracture classification using X-ray images. Their methodology included image normalization, resizing, and data augmentation to improve image quality and reduce overfitting. The CNN automatically extracted fracture-related features and classified the images into fractured and normal categories. The study demonstrated the effectiveness of CNN techniques for medical image classification. However, the approach requires a sufficiently large labelled dataset and considerable computational resources.

A. Tahir and co-authors [3] proposed an ensemble deep learning model for fracture detection using X-ray images. Their approach combined predictions from multiple neural networks after image preprocessing and data augmentation. The ensemble technique improved accuracy, precision, recall, and F1-score compared with individual models. However, increased computational complexity and longer training time were identified as limitations for practical implementation.

Chen P., Wang L., and Zhao H. [4] developed an object detection approach for identifying fractures in X-ray images. The proposed system focused on detecting the presence of fractures as well as locating their specific regions using bounding boxes. The study demonstrated the usefulness of object detection techniques in identifying fracture locations. However, the system may experience difficulties in detecting very small or overlapping fractures.

Spoorthy Torne and co-authors [5] investigated bone fracture classification using different deep learning architectures, including VGG16, ResNet50, and EfficientNetB0. Their methodology involved image preprocessing, normalization, resizing, data augmentation, and transfer learning. The models were evaluated using accuracy, precision, recall, and F1-

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score. The study demonstrated the effectiveness of deep learning approaches for fracture classification. However, dataset imbalance and computational requirements remain important challenges.

The above-mentioned research works demonstrate the potential of deep learning techniques in automated bone fracture detection. However, challenges remain regarding dataset quality, computational requirements, prediction reliability, and the integration of detection models into user-friendly applications. The proposed system, Fracture Vision, addresses these requirements by developing a CNN-based bone fracture detection system that classifies X-ray images into fractured and normal categories. The system also provides confidence percentages, severity information, and a Flask-based web application with patient management, report generation, and doctor consultation facilities.

Reference	Approach / Technique	Main Focus	Limitation
Meena and Roy [1]	Deep Supervised Learning / CNN	Automated fracture detection	Performance affected by limited datasets
Alshahrani and Alsairaf [2]	CNN	Fracture classification	Requires large labelled datasets
Tahir et al. [3]	Ensemble Deep Learning	Improved fracture prediction	High computational complexity
Chen et al. [4]	Object Detection	Fracture identification and localization	Difficulty detecting small fractures
Torne et al. [5]	Transfer Learning	Bone fracture classification	Computational requirements
Proposed System	CNN	Binary fracture classification, confidence prediction and web-based	application Requires further evaluation using diverse X-ray datasets

III. PROPOSED SYSTEM

The proposed system is an AI-based Bone Fracture Detection System that uses a Convolutional Neural Network (CNN) to analyze bone X-ray images and identify the presence of fractures. The system aims to provide automated fracture classification and assist users in obtaining preliminary detection results through a web-based application.
The system comprises several key stages such as image acquisition, image preprocessing, CNN model training, model evaluation, fracture prediction, severity classification, and result visualization.
The overall workflow can be represented as:
X-Ray Image Upload → Image Preprocessing → CNN Model → Fracture Classification → Confidence Prediction → Severity Classification → Result Display → PDF Report Generation
The system is designed with separate patient and doctor interfaces. Patients can upload X-ray images, view fracture detection results, download reports, and request doctor consultations. Doctors can access consultation requests, examine patient reports, and provide their observations.
The CNN model is integrated with the Flask backend, which processes uploaded images and communicates with the trained model. The frontend provides an interactive interface for patient details, image upload, prediction results, and report management. This separation helps make the application easier to use and maintain.

A. System Architecture

The architectural components of the proposed system include the frontend application, Flask backend server, CNN model, and database and model storage components.The frontend application provides an interface through which patients and doctors can log in and access the system's features. Patients can enter their details, upload X-ray images, view fracture detection results, download PDF reports, and request doctor consultations. Doctors can access patient consultation requests and provide their observations.
The backend server is developed using the Flask framework. It receives requests from the frontend, processes uploaded X-ray images, performs image preprocessing, and passes the processed images to the trained CNN model for prediction. The CNN model analyzes the input X-ray image and classifies it into fractured or normal categories. Based on the model prediction, the system displays the confidence percentage and fracture severity information. A heatmap is also provided to help visualize the important regions of the X-ray image.
The database component stores patient information, doctor details, prediction results, and consultation records. The system also supports PDF report generation, allowing patients to download and maintain their fracture detection reports. The overall architecture integrates deep learning with web application technologies to provide an automated and user-friendly platform for preliminary bone fracture detection.

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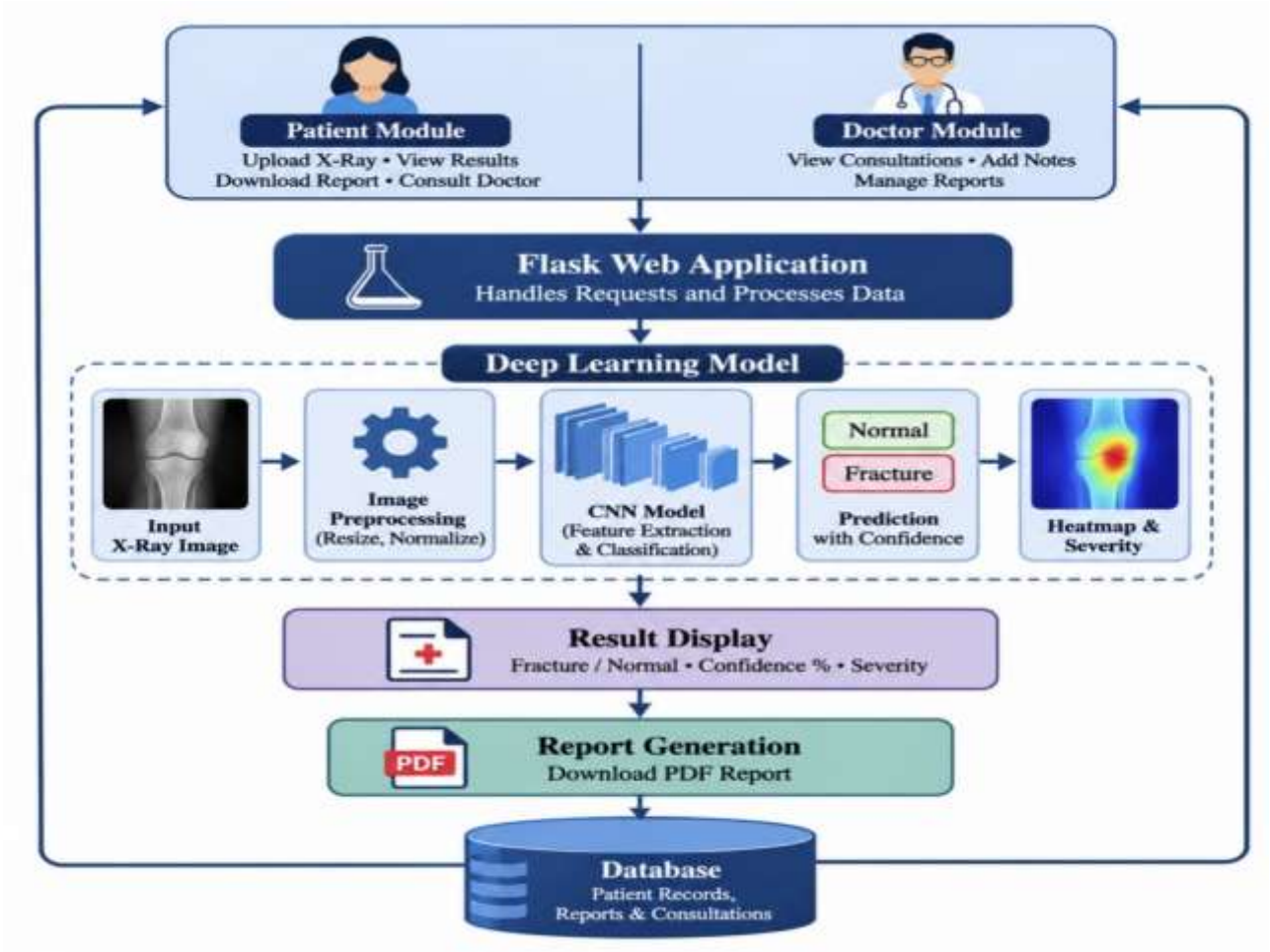


Fig. 1. Architecture of the implemented Fracture Vision: Automated Bone Fracture Detection Using X-Ray Images

IV. METHODOLOGY

A. Dataset

The proposed system uses the Bone Fracture Binary Classification dataset for developing and evaluating the Convolutional Neural Network (CNN) model. The dataset contains X-ray images of normal and fractured bones. These images are used to train and test the model for automated bone fracture identification.

The dataset is organized into three main categories: training, validation, and testing. The training dataset is used to teach the model to identify patterns associated with normal and fractured bones. The validation dataset is used to monitor model performance during training and to identify overfitting. The testing dataset is used to evaluate the performance of the trained model on unseen X-ray images.

The dataset contains the following images:

TABLE II: DATASET USED FOR MODEL DEVELOPMENT AND EVALUATION

Dataset	Normal Images	Fractured Images	Total
Training	4,000	4,000	8,000
Validation	350	350	700
Testing	Included in total	Included in total	500
Total			9,200

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The dataset is used for binary classification, where the two output categories are Normal and Fractured. The training images help the CNN model learn important visual patterns, while the validation and testing images help evaluate its classification performance.

B. Data Preprocessing

Image preprocessing is an important stage in the proposed system because the quality and consistency of input images influence the performance of the CNN model.

The uploaded X-ray images are resized into a fixed dimension of 224 × 224 pixels to maintain uniformity during model training and prediction. Pixel values are normalized by dividing them by 255 so that the image intensity values are converted into a range between 0 and 1.

Data augmentation techniques are applied to the training images to increase the diversity of the dataset and reduce overfitting. These techniques include rotation, zooming, horizontal flipping, and shearing. This helps the model learn different visual variations of bone structures.

The preprocessing pipeline can be represented as:
Raw X-Ray Images → Image Resizing → Normalization → Data Augmentation → Training-Ready Images

The same image resizing and normalization procedures are applied to uploaded X-ray images during prediction to ensure consistency between training and testing.

C. CNN Model Architecture

The proposed system uses a Convolutional Neural Network (CNN) for automated bone fracture detection. CNN is a deep learning technique that is particularly suitable for image classification because it can automatically extract important visual features from input images.

The CNN architecture consists of convolutional layers, activation functions, pooling layers, and fully connected layers. Convolutional layers extract important features such as edges, shapes, textures, and bone patterns from X-ray images. Pooling layers reduce the spatial dimensions of the extracted features and help decrease computational complexity.

The extracted features are passed through fully connected layers to perform classification. The final output layer uses a sigmoid activation function to predict the probability of an input image belonging to the fractured or normal category.
The CNN architecture can be represented as:
Input X-Ray Image → Convolutional Layer → ReLU Activation → Max Pooling → Feature Extraction → Fully Connected Layer → Sigmoid Output → Fracture Classification

The model produces a prediction indicating whether the uploaded X-ray image represents a normal or fractured bone.

D. Model Training

The CNN model is trained using the prepared training dataset. During training, the model learns the visual characteristics of fractured and normal bone images by adjusting its internal weights and parameters.

The training process uses the Adam optimizer to update model weights and binary classification to distinguish between the two categories. The model is trained using a batch size of 32 and images of size 224 × 224 pixels.

The validation dataset is used during training to monitor the model's performance and identify possible overfitting. Data augmentation techniques help improve the model's ability to recognize different image variations.

After completing the training process, the trained model is saved in H5 format and integrated into the Flask web application for performing predictions on newly uploaded X-ray images.

E. Model Evaluation

The performance of the trained CNN model is evaluated using the testing dataset, which contains 500 X-ray images. The evaluation process measures how effectively the model identifies normal and fractured bone images.

The following performance metrics are considered:
1. Accuracy: Measures the overall percentage of correctly classified X-ray images.

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2. Precision: Measures how many images predicted as fractured are actually fractured.
3. Recall: Measures how many actual fractured images are correctly identified.
4. F1-Score: Represents the balance between precision and recall.
5. Confusion Matrix: Represents the correct and incorrect classifications for normal and fractured images.

These evaluation metrics help determine the effectiveness and reliability of the proposed CNN model. Accuracy graphs and confusion matrices are also used to visualize the model's performance.

F. Fracture Prediction and Web Application

The trained CNN model is integrated into a Flask-based web application to provide an interactive platform for bone fracture detection.
Patients can log in, enter their details, upload X-ray images, and obtain fracture detection results. The system processes the uploaded image and passes it to the trained CNN model for classification.

The prediction result displays whether the bone is fractured or normal, along with the confidence percentage and severity information. A heatmap visualization is also provided to highlight important regions of the X-ray image.

The application includes separate patient and doctor modules. Patients can view and download their reports and request consultations from available doctors. Doctors can access consultation requests, examine patient reports, and provide their observations.

The system also supports PDF report generation and stores relevant patient information, prediction results, and consultation records in the database.

The overall prediction workflow is:
Patient Login → Enter Patient Details → Upload X-Ray Image → Image Preprocessing → CNN Prediction → Fracture Result → Confidence and Severity Display → PDF Report Generation

The integration of the CNN model with the Flask web application provides a user-friendly platform for preliminary bone fracture screening and helps simplify the process of X-ray image analysis.

V. DEEP LEARNING MODEL

The proposed Fracture Vision system uses a Convolutional Neural Network (CNN) for automated bone fracture detection and classification using X-ray images. CNN is a deep learning algorithm widely used in image processing and computer vision applications. It automatically extracts important features from images and identifies patterns that help distinguish between normal and fractured bones.

The CNN model is selected because of its ability to learn complex visual features from medical X-ray images without requiring manual feature extraction. The proposed system uses CNN for binary classification of X-ray images into fractured and normal categories.

A. Convolutional Neural Network (CNN)

Convolutional Neural Network is a deep learning model specifically designed for processing image data. It consists of multiple layers that automatically identify and extract important features from input images.

In the proposed system, the CNN model receives preprocessed X-ray images of size 224 × 224 pixels. The convolutional layers extract important visual patterns such as edges, shapes, textures, and bone structures. ReLU activation is used to introduce non-linearity, while pooling layers reduce the spatial dimensions of the extracted features.

The extracted features are passed through fully connected layers to perform the final classification. The output layer uses a sigmoid activation function to determine whether the input X-ray image belongs to the fractured or normal category.

The CNN model follows the following processing sequence:
Input X-Ray Image → Convolutional Layer → ReLU Activation → Max Pooling → Feature Extraction → Fully Connected Layer → Sigmoid Activation → Final Classification

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The trained CNN model is saved in H5 format and integrated into the Flask-based web application. When a patient uploads a new X-ray image, the backend processes the image and passes it to the trained model for prediction.

The system provides the predicted fracture result along with a confidence percentage. It also displays severity information and a heatmap visualization to help identify important regions of the X-ray image.

Advantages of CNN:
1. Automatically extracts important features from X-ray images.
2. Provides effective image classification capabilities.
3. Reduces the need for manual feature extraction.
4. Learns complex patterns associated with fractured and normal bones.
5. Can be integrated into a web-based application for automated prediction.

VI. MODEL TRAINING AND EVALUATION

After completing the image preprocessing stage, the prepared bone fracture dataset is used for training, validation, and testing the Convolutional Neural Network (CNN) model.

The training dataset is used to help the CNN model learn the visual patterns and characteristics associated with normal and fractured bone images. The validation dataset is used to monitor the model's performance during training and to identify possible overfitting. The testing dataset is kept separate and is used to evaluate the performance of the trained model on unseen X-ray images.

The general model training procedure is:
1. Load the Bone Fracture Binary Classification dataset.
2. Resize the X-ray images to 224 × 224 pixels.
3. Normalize the image pixel values between 0 and 1.
4. Apply data augmentation techniques such as rotation, zooming, horizontal flipping, and shearing.
5. Divide the images into training, validation, and testing datasets.
6. Build the Convolutional Neural Network architecture.
7. Train the CNN model using the training images.
8. Validate the model using the validation dataset.
9. Generate predictions using the testing dataset.
10. Calculate evaluation metrics and save the trained model.

The dataset distribution used in the proposed system is:

Dataset	Number of Images
Training	8,000
Validation	700
Testing	500
Total	9,200

The trained CNN model is evaluated using commonly used classification metrics such as accuracy, precision, recall, and F1-score. A confusion matrix is also generated to understand the classification performance of the model for normal and fractured bone images.

Accuracy measures the overall percentage of correctly classified X-ray images.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

Where:
TP represents true positives,
TN represents true negatives,
FP represents false positives, and
FN represents false negatives.

Precision measures how many images predicted as fractured are actually fractured:

$$\text{Precision} = TP / (TP + FP)$$

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Recall measures how many of the actual fractured images are correctly identified by the model:

$$\text{Recall} = TP / (TP + FN)$$

F1-Score combines precision and recall to provide a balanced evaluation:

$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

These evaluation metrics help determine the effectiveness of the CNN model in identifying fractured and normal bone images. Accuracy and loss graphs are used to monitor the training process, while the confusion matrix provides a visual representation of correct and incorrect predictions.

The classification report provides precision, recall, F1-score, and support for both normal and fractured categories, along with macro average and weighted average values.

After successful training, the CNN model is saved in H5 format and integrated into the Flask-based web application. The saved model is used to predict fracture results for newly uploaded X-ray images and display the corresponding confidence percentage and severity information.

VII. SYSTEM IMPLEMENTATION

The proposed Fracture Vision system is implemented as a web-based application consisting of a frontend interface and a backend processing layer. The application integrates a trained Convolutional Neural Network (CNN) model with the Flask framework to provide automated bone fracture detection using X-ray images.

A. Frontend

The frontend is the graphical user interface of the proposed system. It provides separate interfaces for patients, doctors, and administrators to access the system functionalities.

The patient interface allows users to log in, enter their personal details, upload X-ray images, view fracture detection results, download reports, and request doctor consultations.

The doctor interface provides access to patient consultation requests and uploaded reports. Doctors can examine patient information and provide their observations through the consultation module.

The administrator interface allows the management of doctor accounts, patient information, system records, and dashboard statistics.

The main interface provides the following functionalities:

- Patient and doctor authentication.
- Patient details entry.
- X-ray image uploading.
- Fracture detection results.
- Confidence percentage display.
- Fracture severity information.
- Heatmap visualization.
- PDF report generation and downloading.
- Doctor consultation requests.
- Administrative management and dashboard statistics.

The frontend is developed using HTML, CSS, and JavaScript. Different pages are designed to provide a simple and user-friendly experience for patients, doctors, and administrators.

B. Backend

The backend is developed using the Flask framework and acts as the communication layer between the frontend, CNN model, and database.

The backend receives uploaded X-ray images, validates the input, performs the required image preprocessing, and loads the trained CNN model to generate predictions.

The backend also manages patient authentication, doctor authentication, report storage, consultation requests, and PDF report generation. SQLite is used as the database for storing patient details, doctor information, prediction results, and consultation records.



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The general prediction flow is:

X-Ray Image Upload → Flask Backend → Image Validation → Image Preprocessing → CNN Model Prediction → Result Processing → Result Display

This architecture allows the trained CNN model to operate independently of the user interface while providing prediction results through the web application.

C. Prediction Pipeline

When a patient uploads an X-ray image, the backend receives the image and prepares it for prediction using the same preprocessing techniques applied during model training.

The uploaded image is resized to 224 × 224 pixels and normalized by scaling the pixel values between 0 and 1. The processed image is then passed to the trained CNN model.

The CNN model analyzes the image and generates a prediction indicating whether the bone is fractured or normal. The prediction result is processed by the backend to display the corresponding class and confidence percentage.

The system also provides fracture severity information and heatmap visualization as part of the result interface. The prediction details are stored in the database and can be used to generate downloadable PDF reports.

The prediction information is then returned to the frontend, where the patient can view the results. Patients can also send their reports to doctors through the consultation module for further examination.

The prediction pipeline can be represented as:

Patient Login → Patient Details → X-Ray Upload → Image Preprocessing → CNN Classification → Confidence and Severity Display → Heatmap Visualization → Report Generation

D. Database Management

The proposed system uses an SQLite database to manage and maintain application information.

The database stores patient details, doctor login credentials, report information, prediction results, and consultation records. It also maintains the relationship between patients, doctors, and their consultation requests.

The database helps retrieve previously generated reports and supports the administrative functions of the application.

E. Report Generation and Doctor Consultation

The system provides a report generation facility that allows patients to download their fracture detection results in PDF format. The report contains relevant patient details, prediction results, confidence percentage, severity information, and report date.

The doctor consultation module allows patients to select doctors and send consultation requests along with their reports. Doctors can access the submitted requests, examine the reports, and provide their observations.

This feature connects the automated fracture detection process with doctor-based consultation and helps patients obtain further medical guidance.

VIII. RESULTS AND DISCUSSION

The proposed Fracture Vision system was implemented successfully using a Convolutional Neural Network (CNN) for automated bone fracture detection from X-ray images. The trained model was evaluated using test images to determine its ability to distinguish between normal and fractured bones.

The developed web application allows patients to upload X-ray images and obtain prediction results through a user-friendly interface. The system displays the predicted class, confidence percentage, fracture severity information, and heatmap visualization to help users understand the prediction results.

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A. CNN Model Evaluation Results

The performance of the proposed CNN model is evaluated using commonly used classification metrics such as accuracy, precision, recall, and F1-score.
The model performs binary classification by identifying the uploaded X-ray images as either Normal or Fractured.

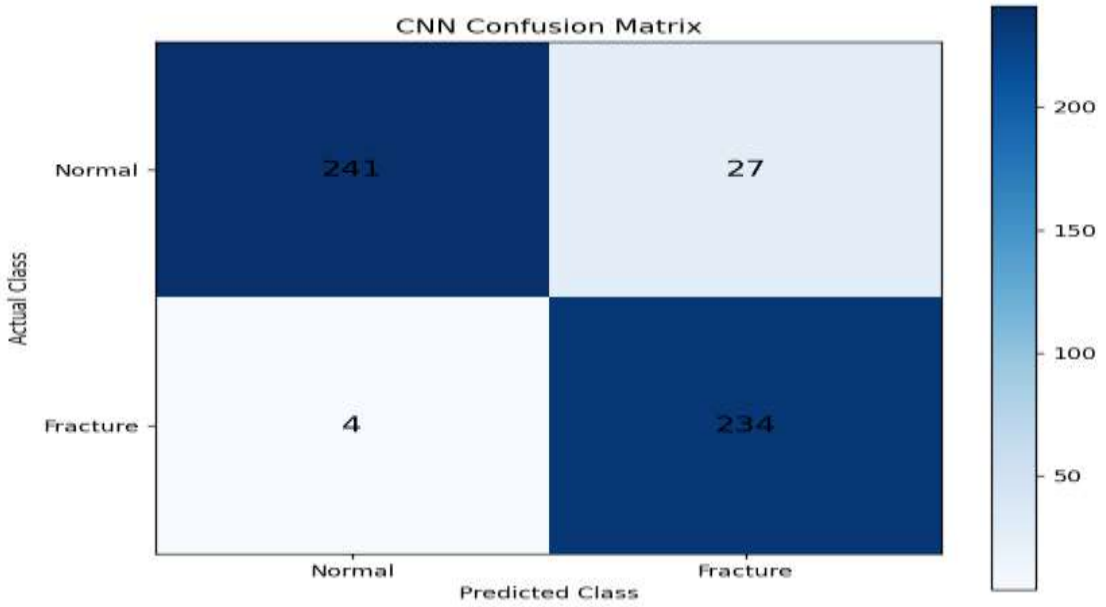


Fig.2.Confusion matrix of the proposed CNN model for bone fracture classification.

The evaluation metrics are used to measure the classification performance of the trained model and determine how accurately it identifies fracture cases.

Table III: Performance Evaluation of the Proposed CNN Model

Evaluation Metric	Obtained Value
Accuracy	93.87%
Precision	98.37%
Recall	89.93%
F1-Score	93.96%

The evaluation results provide an understanding of the model's ability to classify bone X-ray images correctly. Accuracy represents the overall classification performance, while precision and recall measure the reliability of fracture predictions. The F1-score provides a combined measurement of precision and recall.

B. Confusion Matrix Analysis

A confusion matrix is used to evaluate the classification performance of the proposed CNN model. It represents the number of correctly and incorrectly classified X-ray images for both normal and fractured categories.

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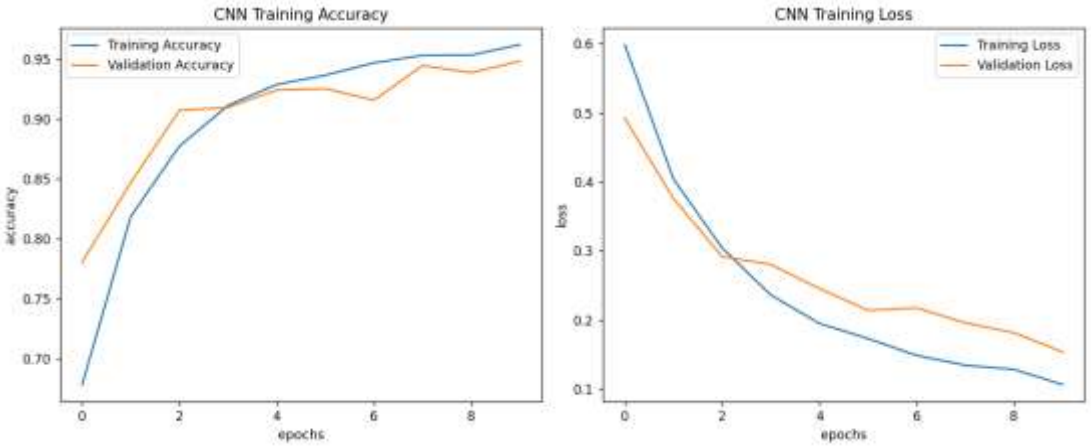


Fig.3.Training and validation accuracy and loss of the CNN model.

The diagonal elements represent correctly classified images, whereas the non-diagonal elements represent incorrectly classified images.
The confusion matrix helps identify whether the model correctly detects fractured bones and distinguishes them from normal bones. It also provides information about false positive and false negative predictions.
A higher number of correctly classified images indicates better classification performance of the proposed CNN model.

C. Fracture Detection Results

The developed Fracture Vision application converts the predictions generated by the CNN model into an understandable format for users.

When an X-ray image is uploaded, the system processes the image and classifies it into one of the following categories:

- Normal Bone
- Fractured Bone

In addition to the classification result, the application displays the confidence percentage associated with the prediction. It also provides heatmap visualization to highlight important image regions considered during the model's prediction.



Fig.4.CNN-based bone fracture prediction with heatmap visualization.

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The system provides fracture severity information to support further understanding of the detected condition. The generated results can also be downloaded as PDF reports for future reference.

D. Web Application Results

The proposed system integrates the trained CNN model with a Flask-based web application. The application provides separate interfaces for patients, doctors, and administrators.
The patient dashboard allows users to upload X-ray images, view detection results, download reports, and request doctor consultations.
The doctor dashboard allows doctors to access consultation requests and review patient reports. The administrator dashboard provides facilities for managing doctors, patients, and system information.



Fig.5.User interface of the proposed Fracture Vision web application.

The integration of the CNN model with the web application makes the fracture detection process accessible through a simple graphical user interface.

IX. DISCUSSION

The implementation demonstrates the integration of deep learning techniques with a web-based bone fracture detection system.

Firstly, the proposed approach uses a Convolutional Neural Network to automatically extract important visual features from X-ray images and classify them into normal and fractured categories. This reduces the need for manual feature extraction during the classification process.

Secondly, the system provides additional information such as prediction confidence, fracture severity, and heatmap visualization. These features help users understand the model's output more effectively.

Another important feature is the integration of the trained CNN model with the Flask framework. Instead of testing the model only as an independent program, the proposed system makes it accessible through a web application where patients can upload images and obtain prediction results.

However, CNN-based fracture detection also has certain limitations. The performance of the model depends on the quality, quantity, and diversity of the training dataset. Poor-quality X-ray images, unusual fracture patterns, and differences in image characteristics may affect prediction performance.

False positive and false negative predictions are also important concerns in medical image classification. Incorrectly identifying a normal bone as fractured or failing to detect an actual fracture may affect the reliability of the system.



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Therefore, the proposed Fracture Vision system is intended to support preliminary fracture identification and should not replace professional medical examination or diagnosis.

Overall, the developed system demonstrates how deep learning and web technologies can be combined to provide an automated and user-friendly approach to bone fracture detection using X-ray images.

X. LIMITATIONS

Although the proposed system provides an automated approach for bone fracture detection using deep learning, there are certain limitations in the current system.

Firstly, the performance of the CNN model depends on the quality and quantity of the training dataset. If the dataset contains unclear, noisy, or incorrectly labelled X-ray images, the model may produce inaccurate predictions.

Secondly, the system is trained using a bone fracture binary classification dataset containing normal and fractured X-ray images. Therefore, its prediction capability is limited to the classes available in the training dataset.

Thirdly, variations in X-ray image quality, bone structure, image orientation, and fracture patterns may affect the accuracy of the prediction.

Fourthly, the confidence percentage and heatmap generated by the system provide model-based prediction information. They should not be considered a replacement for professional medical examination or diagnosis.

Finally, the current system requires users to upload X-ray images manually for fracture detection. The prediction results may also require verification by a qualified medical professional before making treatment decisions.

XI. FUTURE SCOPE

The proposed Fracture Vision system can be improved and extended in several ways to provide more advanced and efficient fracture detection services.

A. Advanced Fracture Classification

The system can be enhanced to identify different types of bone fractures, such as transverse, oblique, spiral, and comminuted fractures, instead of limiting the prediction to normal and fractured categories.

B. Fracture Severity Assessment

Future development can include more detailed fracture severity classification to identify the extent of bone damage and provide additional information to assist doctors during medical evaluation.

C. Improved Deep Learning Model

The CNN model can be further improved by using larger and more diverse X-ray datasets, advanced image preprocessing techniques, and model optimization to improve prediction accuracy and reliability.

D. Integration with Hospitals

The system can be integrated with hospital management systems and electronic medical records to make patient reports and fracture detection results more accessible to authorized doctors.

E. Advanced Doctor Consultation

The consultation module can be enhanced to support online communication between patients and doctors, allowing patients to share X-ray images, download reports, and receive professional medical opinions.

F. Multilingual Voice Assistant

The voice assistant can be further developed to support multiple languages, including English, Kannada, and Hindi, allowing users to interact with the application through voice commands.

G. Mobile Application Development

The proposed system can be extended into a mobile application to provide easier access to bone fracture detection services and patient reports from smartphones.

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XII. CONCLUSION

In this project, an automated bone fracture detection system named Fracture Vision has been developed using deep learning techniques and X-ray image analysis. The proposed system uses a Convolutional Neural Network (CNN) model to classify X-ray images into normal and fractured categories.

The system integrates image preprocessing, CNN model training, prediction, confidence score generation, and heatmap visualization to provide meaningful results to users. The trained model achieved an accuracy of 94.27% on the test dataset containing 506 images, demonstrating its ability to identify normal and fractured bone images.
The developed web-based application provides an interface for patients and doctors to access fracture detection services. It also includes features such as patient details management, report generation, doctor consultation, appointment management, and dashboard facilities.

The heatmap visualization helps users understand the image regions that influence the model prediction. The system also generates classification reports containing precision, recall, and F1-score for evaluating the performance of the CNN model.

Overall, Fracture Vision demonstrates how deep learning and web technologies can be combined to support automated bone fracture detection and simplify the analysis of X-ray images. Although the system has certain limitations, future improvements such as advanced fracture classification, severity assessment, hospital integration, and mobile application development can make it more useful and accessible.

The proposed system is intended to assist medical professionals and should not replace expert medical diagnosis.

REFERENCES

[1] Tanushree Meena and Sudipa Roy, “Bone Fracture Detection Using Deep Supervised Learning from Radiological Images: A Paradigm Shift,” Diagnostics, vol. 12, no. 10, p. 2420, 2022.
[2] Amal Alshahrani and Alaa Alsairafi, “Bone Fracture Classification using Convolutional Neural Networks from X-ray Images,” Engineering, Technology & Applied Science Research, vol. 14, no. 5, pp. 16640–16645, 2024.
[3] A.Tahir, A. Saadia, K. Khan, A. Gul, A. Qahmash, and R.N. Akram, “Enhancing diagnosis: ensemble deep-learning model for fracture detection using X-ray images,” Clinical Radiology, vol. 79, no. 11, pp. e1394–e1402, 2024.
[4] P. Chen, S. Liu, W. Lu, F. Lu, and B. Ding, “WCAY object detection of fractures for X-ray images of multiple sites,” Scientific Reports, vol. 14, Art. no. 26702, 2024.
[5] Spoorthy Torne, D. K. Shetty, K. Makkithaya, P. Hegde, M.Sudhi, P. K. Pullela, T. Tamil Eniyan, R. Kamath, S. Salu, P. Bhat, S. Girisha, and P. S. Priya, “VGG-16, VGG-16 With Random Forest, Resnet50 With SVM, and EfficientNetB0 With XGBoost—Enhancing Bone Fracture Classification in X-Ray Using Deep Learning Models,” IEEE Access, vol. 13, pp. 25568–25577, 2025.
[6] Z. Su, A. Adam, M. F. Nasrudin, M. Ayob, and G.Punganan, “Skeletal Fracture Detection with Deep Learning: A Comprehensive Review,” Diagnostics, vol. 13, no. 20, p. 3245,2023.
[7] S. C. Medaramatla, C. V. Samhitha, S. D. Pande, and S. R. Vinta, “Detection of Hand Bone Fractures in X-Ray Images Using Hybrid YOLO NAS,” IEEE Access, vol. 12, pp. 57661–57673, 2024.
[8] A.Nowroozi, M. A. Salehi, P. Shobeiri, S. Agahi, S. Momtazmanesh, P. Kaviani, and M. K. Kalra, “Artificial intelligence diagnostic accuracy in fracture detection from plain radiographs and comparing it with clinicians: A systematic review and meta-analysis,” Clinical Radiology, vol. 79, no. 8, pp. 579–588, 2024.
[9] S. Ghosh, J. Mallick, M. Chakraborty, and S. Gupta, “Automated Bone Fracture Detection in X-ray Imaging to Improve Orthopaedic Diagnostics in Healthcare,” Procedia Computer Science, vol. 233, pp. 832–840, 2024.
[10] F. Mohammad, S. Al-Ahmadi, and J. Al-Muhtadi, “Block-Deep: A Hybrid Secure Data Storage and Diagnosis Model for Bone Fracture Identification of Athlete From X-Ray and MRI Images,” IEEE Access, vol. 11, pp. 142360–142370, 2023.
[11] R. Hoover, N. Elsayed, Z. ElSayed, and C. Li, “Pre-trained Under Noise: A Framework for Robust Bone Fracture Detection in Medical Imaging,” arXiv preprint arXiv:2507.09731, 2025.
[12] M. Imrankhan, I. Varalakshmi, J. Arthi, P. Pavithra, and J. Reshma, “Deep Learning Model to Detect and Classify Bone Fracture in X-Ray Images,” in 2023 International Conference on System, Computation, Automation and Networking (ICSCAN), Puducherry, India, 2023

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