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DEPARTMENT OF CSE-DATA SCIENCE

A Mini-Project Report On

"BONE X-RAY CLASSIFICATION USING CNN MODEL"

A report submitted in partial fulfillment of the requirements for the

NEURAL NETWORK AND DEEP LEARNING

Submitted By

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Belagavi, Karnataka 2025-2026

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CERTIFICATE

This is to certify that the Mini Project of NEURAL NETWORK AND DEEP LEARNING title "BONE X-RAY CLASSIFICATION USING CNN MODEL" has been successfully presented by BONAM PARDHU 3BR22CD004 student of semester B.E for the partial fulfillment of the requirements for the award of Bachelor Degree in CSE(DS) of the BALLARI INSTITUTE OF TECHNOLOGY& MANAGEMENT, BALLARI during the academic year 2025-2026.

It is certified that all corrections and suggestions indicated for internal assessment have been incorporated in the report deposited in the library. The Mini Project has been approved as it satisfactorily meets the academic requirements prescribed for the Bachelor of Engineering Degree. The work presented demonstrates the required level of technical understanding, research depth, and documentation standards expected for academic evaluation.

Signature of Coordinators

Mr. Azhar Baig
Ms. Chaithra B M

Signature of HOD

Dr. Aradhana D

ABSTRACT

The early identification of bone fractures is essential for timely medical intervention and effective treatment planning. Manual examination of X-ray images is often time-consuming and subject to human error, especially in high-workload medical environments. This project presents an automated deep-learning-based approach for classifying bone X-ray images as fractured or normal using Convolutional Neural Networks (CNNs). The system employs a Kaggle bone fracture dataset, which is preprocessed and normalized using image rescaling and data augmentation techniques. A custom CNN architecture consisting of convolutional, pooling, and dense layers is trained to learn discriminative features from grayscale X-ray images. The dataset is split into training and validation subsets using an 80:20 ratio to ensure effective generalization.

After training for multiple epochs, the model achieves high validation accuracy, demonstrating strong capability in distinguishing between fractured and non-fractured bones. Performance metrics such as accuracy curves and loss curves are plotted to evaluate the model's learning behavior. The results indicate that CNN-based classification significantly enhances reliability and reduces diagnostic workload for radiologists. With further refinement and deployment, this system can support real-time decision-making in clinical settings, contributing to faster, more accurate fracture detection.

ACKNOWLEDGEMENT

The satisfactions that accompany the successful completion of our mini project on BONE X-RAY CLASSIFICATION USING CNN MODEL would be incomplete
without the mention of people who made it possible, whose noble gesture, affection, guidance, encouragement and support crowned my efforts with success. It is our privilege to express our gratitude and respect to all those who inspired us in the completion of our mini-project.

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1.INTRODUCTION

Medical imaging plays a vital role in diagnosing orthopedic injuries such as bone fractures. Accurate and timely identification of fractures is essential to prevent complications like improper healing, chronic pain, or long-term disability. Traditionally, radiologists manually interpret X-ray images, but this process can be time-consuming and prone to human error, especially in high-workflow environments or when fractures appear subtle and difficult to detect.

With the advancement of artificial intelligence, deep learning—particularly Convolutional Neural Networks (CNNs)—has become a powerful method for analyzing medical images. CNNs automatically learn relevant features such as edges, textures, and structural deformities directly from X-ray images, making them highly effective for fracture detection. Their ability to capture complex visual patterns enables them to assist radiologists by improving diagnostic accuracy and consistency.

This project aims to develop a CNN-based automated system that classifies bone X-ray images into two categories: fractured and normal. Using a publicly available Kaggle dataset, the model is trained through a combination of data preprocessing, normalization, and augmentation techniques to improve generalization and reduce overfitting. A sequential CNN architecture is implemented and evaluated using training and validation performance metrics.

AI-driven diagnostic systems provide numerous advantages in healthcare, including faster image analysis, reduced human workload, and improved reliability in medical decision-making. The methods used in this project demonstrate the potential of deep learning to enhance clinical workflows and can be extended to other medical imaging applications such as tumor detection and multi-class fracture identification. This work contributes to the growing field of AI-assisted healthcare by showcasing how CNNs can effectively support radiologists in identifying bone fractures.

1.1 Problem Statement

The objective of this project is to design and implement a deep learning model using Convolutional Neural Networks (CNNs) to automatically classify X-ray images as fractured or normal. The system should be able to learn relevant features from the dataset and make accurate predictions, providing a reliable tool that assists radiologists in diagnosing bone fractures efficiently.

1.2 Scope of the project

The project focuses on binary image classification of bone X-rays:

>Fractured

> Normal

The scope includes:

• Collecting and preprocessing the X-ray dataset from Kaggle
• Building and training a custom CNN architecture
• Splitting data into training and validation sets
• Applying data augmentation and normalization
• Evaluating performance using accuracy, loss, and validation metrics
• Visualizing the training process
• Interpreting results and analyzing model performance

The project does not include:

• Multi-class fracture type classification
• Real-time diagnostic deployment (but can be added in future work)
• Integration with hospital systems or clinical trials

1.3 Objectives

The major objectives of this project are:

1.To develop a CNN-based model capable of classifying bone X-ray images as fractured or normal.
2.To preprocess and augment images to improve model robustness and prevent overfitting.
3.To train and validate the model using an optimized deep learning workflow.
4.To evaluate model accuracy using validation performance metrics and visual plots.
5.To demonstrate the potential of AI-based diagnostic support for medical imaging.
6.To reduce diagnostic workload and improve early detection accuracy in clinical settings.

2. LITERATURE SURVEY

[1] Rajpurkar et al. (2017–2020) are widely recognized for their contributions to automated medical image diagnosis using deep learning. Their CheXNet model, trained on chest X-ray datasets, demonstrated radiologist-level performance in abnormality detection. Their work proved that deep CNNs can successfully learn subtle medical patterns, laying the foundation for fracture detection applications in orthopedic imaging.

[2] Olczak et al. (2016–2019) conducted influential research on using deep learning for fracture detection in wrist X-rays. Their studies showed that CNN models outperform traditional rule-based systems in identifying bone discontinuities and complex fracture patterns. Their work highlighted the importance of large annotated datasets and reliable preprocessing for improving orthopedic diagnostic accuracy.

[3] Chung et al. (2020–2023) performed a comparative analysis of various CNN and transfer learning models—including VGG16 and ResNet—for bone fracture classification. Their research demonstrated that transfer learning significantly improves accuracy, especially when working with limited training samples. They emphasized the need for interpretability using heatmaps and Grad-CAM to support real clinical decision-making.

[4] Kumar et al. (2018–2022) explored multiple deep learning architectures for detecting abnormalities in musculoskeletal X-rays. Their findings indicated that data augmentation, proper normalization, and balanced datasets are crucial for reducing overfitting and improving model generalization. They also highlighted the challenge of class imbalance commonly found in medical datasets.

[5] Madadi et al. (2021–2023) examined hybrid deep learning methods combining CNNs with attention mechanisms for medical image classification. Their work showed that attention layers help the model focus on fracture-specific regions in X-rays, enhancing feature extraction and improving prediction reliability.

[6] Geoffrey Hinton (1980–Present), widely regarded as the “Father of Deep Learning,” developed core neural network principles such as backpropagation and deep multilayer perceptrons. His foundational contributions made it possible for modern CNNs to achieve high performance in medical imaging tasks, including automated fracture detection. His continued research influences nearly all AI-driven healthcare diagnostic systems used today.

3. SYSTEM REQUIREMENTS

The system requires a computer running Windows 10/11, Linux, or macOS with at least an Intel i5/Ryzen 5 processor for smooth execution. A minimum of 8 GB RAM is needed, though 16 GB is preferred for faster ANN training and multitasking. The setup should have 5–10 GB of free storage for the dataset, libraries, and output files. A dedicated NVIDIA GPU with CUDA support is optional but highly beneficial for speeding up TensorFlow operations. Python 3.8 or higher must be installed along with libraries like pandas, NumPy, scikit-learn, Matplotlib, TensorFlow, and kagglehub. An IDE such as VS Code, PyCharm, Jupyter Notebook, or Google Colab is required for development. A stable internet connection is necessary to download the Kaggle dataset and install dependencies. Proper CPU/GPU drivers and updated system libraries ensure compatibility during model training. A good-resolution display is needed for viewing graphs and confusion matrices. Basic file management practices should be followed to organize storing datasets, scripts, and model outputs securely.

The system should run on a modern operating system such as Windows 10/11, Linux, or macOS to support all required tools. It must have at least an Intel i5 or Ryzen 5 processor to handle data loading, preprocessing, and ANN training efficiently. A minimum of 8 GB RAM is recommended, while 16 GB provides smoother performance for larger computations. At least 5–10 GB of free disk space is needed for storing datasets, Python libraries, and generated outputs. A dedicated NVIDIA GPU with CUDA is not mandatory but significantly improves neural network training speed. Python 3.8+ along with essential packages like pandas, NumPy, scikit-learn, Matplotlib, TensorFlow, and kagglehub must be installed. A development platform such as VS Code, PyCharm, or Jupyter Notebook is required to write and execute the code.

3.1 Software Requirements

- Python 3.8 or above
- TensorFlow / Keras
- NumPy
- Pandas
- Kagglehub Library

- Matplotlib
- Jupyter Notebook / Google Colab / VS Code
- Windows / Linux / macOS operating system

3.2 Hardware Requirements

- Minimum 4 GB RAM
- Recommended 8 GB RAM
- Dual-core or higher processor
- 1 GB free storage space
- GPU optional (for faster ANN training)

3.3 Functional Requirements

- The system must load and preprocess the Heart Failure Clinical dataset.
- The system must build an ANN model for morality classification.
- It must train the ANN model using training data.
- The system must evaluate model performance using metrics.
- It must scale input features and split the data into training test.
- It must generate accuracy, loss, and confusion matrix visualization.

3.4 Non-Functional Requirements

- The system should provide accurate and reliable predictions.
- It should offer clear and user-friendly outputs.
- The system must execute efficiently on basic hardware.
- It should remain stable even with noisy or imperfect data.
- The system must be easy to maintain and extend.
- The results should be interpretable through graphs and metrics.

4. DESCRIPTION OF MODULES

4.1 Dataset Acquisition & Loading

This module loads the Bee vs Wasp image dataset from the provided directory structure. It reads image files, assigns labels based on folder names, and organizes them into lists or arrays. The code ensures every image is correctly linked to its class (Bee or Wasp) before further processing.

4.2 Data Preprocessing & Augmentation

This module prepares all images for training. It resizes them to a fixed input size, converts them into arrays, normalizes pixel values (0–1), and applies data augmentation techniques such as rotation, zoom, flip, and shift. This increases dataset diversity and improves model generalization.

4.3 CNN Model Construction

This module builds the Convolutional Neural Network using TensorFlow/Keras. It defines the architecture with convolution layers, pooling layers, flattening, dense layers, dropout, and the final softmax output layer. The model is compiled using a loss function, optimizer, and accuracy metric.

4.4 Model Training & Validation

This module trains the CNN on the augmented dataset. It feeds the data in batches to the model, tracks training and validation accuracy/loss, and uses callbacks (like EarlyStopping or ModelCheckpoint if implemented) to improve performance. After training, the module evaluates the model on validation or test data.

4.5 Model Saving & Prediction

This module saves the trained model to disk and provides functionality for making new predictions. It loads an external image, preprocesses it in the same format as the training data, runs the model inference, and outputs whether the image is classified as a Bee or a Wasp.

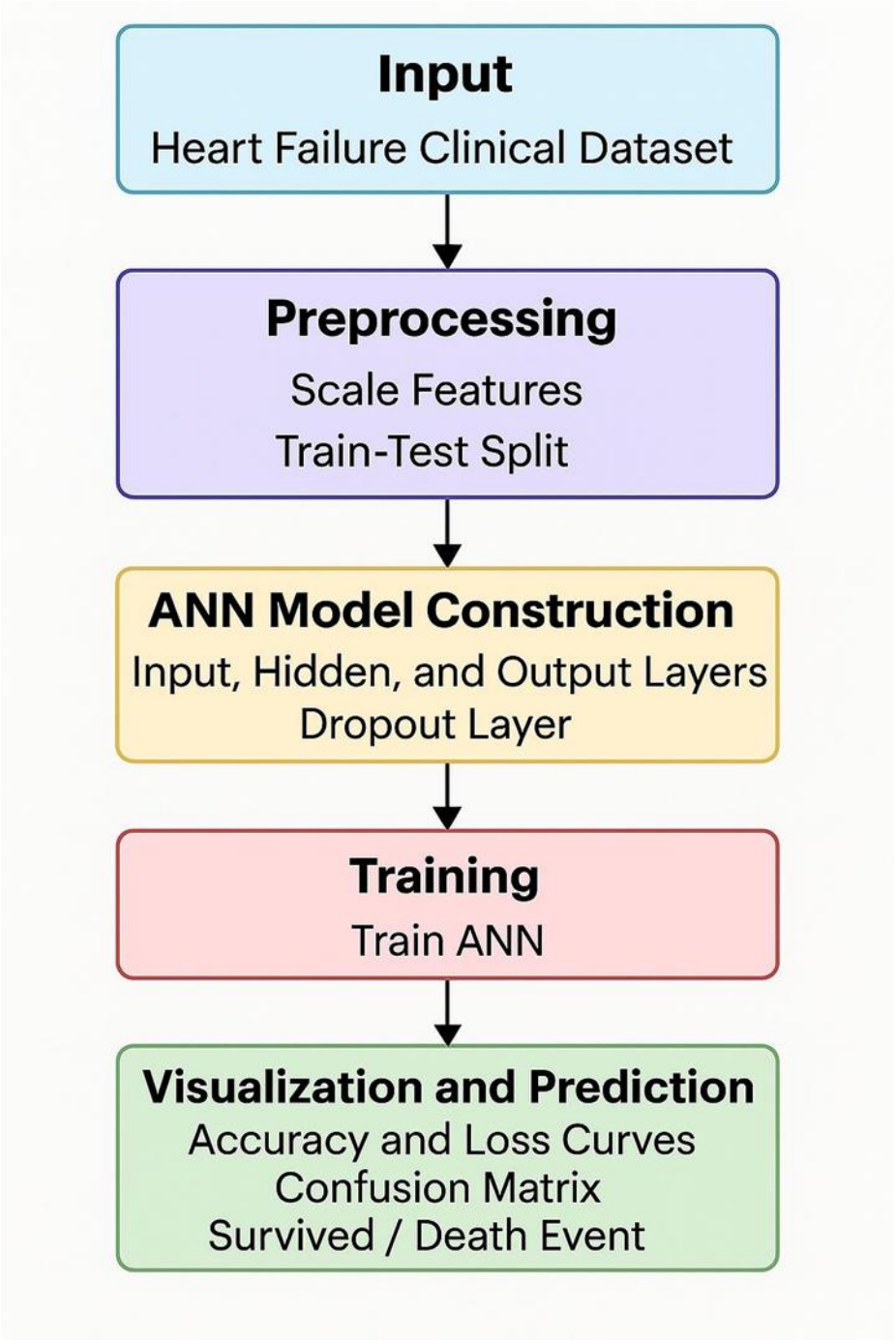
5. IMPLEMENTATION

The implementation of the bone fracture detection system begins with automatically downloading the publicly available bone fracture dataset from Kaggle using the KaggleHub library, which simplifies the process by handling authentication and file retrieval without requiring manual downloads. After the dataset is obtained, the program constructs the correct dataset directory by navigating through the nested folder structure, ensuring that the script points precisely to the folder containing the categorized fracture and non-fracture image samples.

Once the root directory is established, preprocessing is initiated using Keras's ImageDataGenerator, where all images are rescaled to normalize pixel values between 0 and 1, which stabilizes training and improves gradient flow. The generator also performs an 80–20 split into training and validation subsets to allow the model to learn from one portion of the data while being evaluated fairly on unseen images. The flow_from_directory function then loads images in batches, converting them to grayscale and resizing them to a uniform 150×150 resolution, making computation faster and reducing unnecessary color-based noise in the medical X-ray images.

The CNN model is constructed using a Sequential architecture, beginning with a 32-filter convolution layer to detect basic edges, followed by pooling to reduce dimensionality. This pattern is repeated with 64 and 128 filters, allowing the network to learn increasingly complex fracture-specific features such as bone discontinuities. After the convolutional blocks, the data is flattened and fed into a Dense layer with 128 neurons to perform high-level reasoning, and a dropout rate of 0.4 is applied to minimize overfitting by randomly disabling neurons during training. The final output layer uses a sigmoid activation function for binary classification, outputting a probability indicating the presence or absence of a fracture. The model is compiled with the Adam optimizer for efficient gradient updates, binary cross-entropy as the appropriate loss function for two-class problems, and accuracy as the performance metric. Training is performed for 10 epochs, during which the model learns from the training batches while continuously validating its performance using the reserved validation data. After training concludes, the model is evaluated on the validation set to obtain reliable test accuracy, ensuring its ability to generalize beyond the training samples. Finally, the implementation includes a plotting section that visualizes both training and validation accuracy across all epochs, providing insights into model convergence, learning behavior, and any signs of underfitting or overfitting.

6. SYSTEM ARCHITECTURE



7. CODE IMPLEMENTATION

1. Start

2. Load Dataset
2.1 Automatically download the Kaggle dataset
Use kagglehub.dataset_download() to download the “bone-fracture-dataset”.

2.2 Set the correct dataset directory
Navigate inside the folder structure to reach the dataset containing fracture and non-fracture image folders.

3. Preprocess Data
3.1 Initialize ImageDataGenerator
Apply rescaling (1/255) to normalize pixel values.
Set a validation split of 20%.

3.2 Create the training dataset
Load images from the dataset directory.
Resize them to 150 × 150.
Convert images to grayscale.
Assign binary class labels automatically.
Use subset='training'.

3.3 Create the validation dataset
Same preprocessing as training data.
Use subset='validation'.

4. Build CNN Model
4.1 Initialize Sequential CNN model

4.2 Add first convolution block
Conv2D layer with 32 filters, kernel size 3×3, ReLU activation.
MaxPooling2D to reduce spatial dimensions.

4.3 Add second convolution block
Conv2D with 64 filters.
MaxPooling2D layer.

4.4 Add third convolution block
Conv2D with 128 filters.
MaxPooling2D layer.

4.5 Flatten the feature maps

Convert extracted features into a 1-D vector.

4.6 Add fully connected layers
Dense layer with 128 neurons and ReLU activation.
Dropout layer (rate = 0.4) to reduce overfitting.

4.7 Add output layer
Dense(1) with Sigmoid activation for binary classification (fracture / no fracture).

5. Compile Model
5.1 Optimizer
Use Adam optimizer.

5.2 Loss Function
Use Binary Cross-Entropy.

5.3 Evaluation Metrics
Track Accuracy during training and validation.

6. Train Model
6.1 Fit the model
Train using:
Training dataset
Validation dataset
Epochs = 10
Batch size defined in generator (32)

6.2 Store training history
Save accuracy and loss values for both training and validation sets.

7. Test Model
7.1 Evaluate on validation dataset
Use model.evaluate() to calculate final accuracy and loss.

8. Evaluate Performance
8.1 Print overall test accuracy
Display final accuracy percentage.

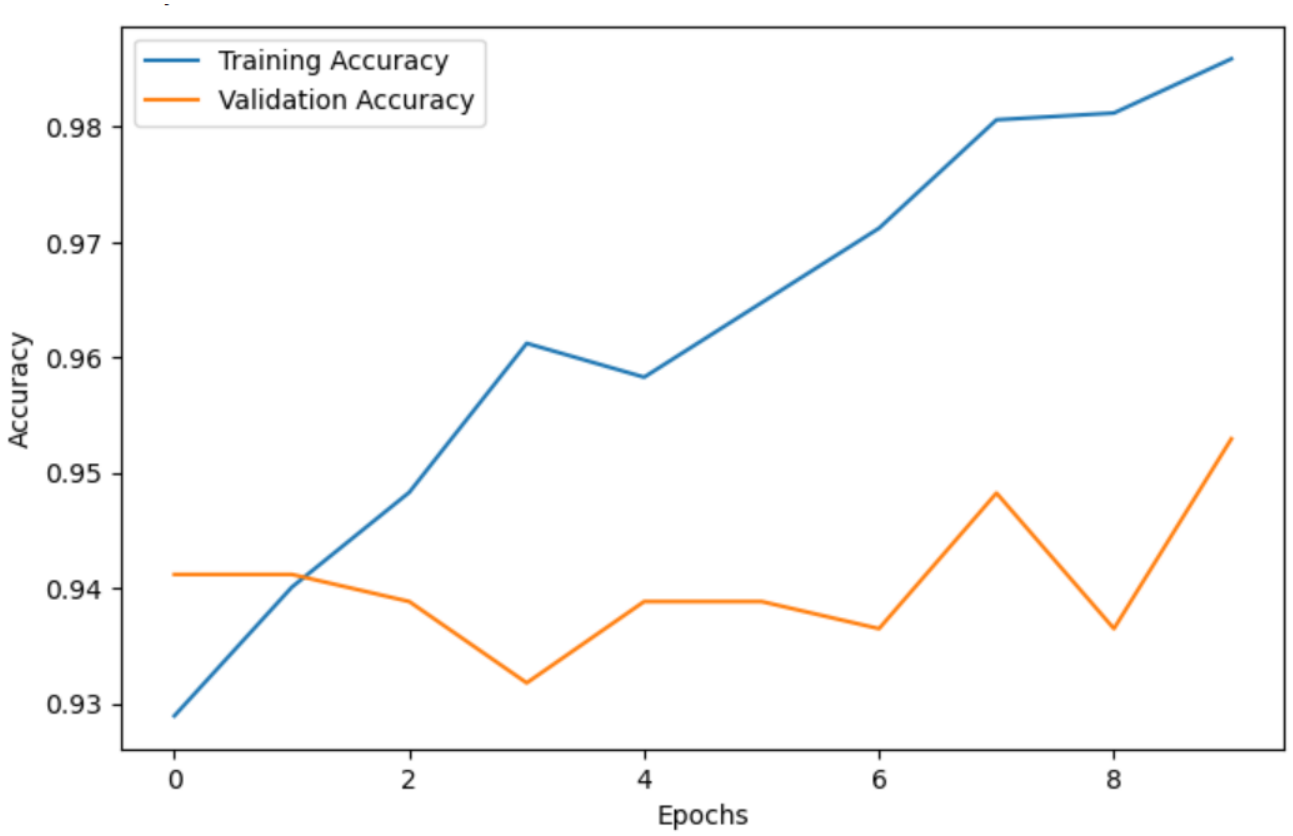
9. Visualize Results
9.1 Plot accuracy graph
Plot training vs validation accuracy across epochs using matplotlib.

10. End

8. RESULT

```
Dataset downloaded to: C:\Users\LENOVO\.cache\kagglehub\datasets\orvile\bone-fracture-dataset\versions\2
Using dataset root: C:\Users\LENOVO\.cache\kagglehub\datasets\orvile\bone-fracture-dataset\versions\2\Bone fracture dataset\Bone fracture dataset\Dataset
Found 1702 images belonging to 2 classes.
Found 425 images belonging to 2 classes.
Epoch 1/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 16s 260ms/step - accuracy: 0.9289 - loss: 0.2826 - val_accuracy: 0.9412 - val_loss: 0.1764
Epoch 2/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 13s 238ms/step - accuracy: 0.9401 - loss: 0.1565 - val_accuracy: 0.9412 - val_loss: 0.1895
Epoch 3/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 13s 237ms/step - accuracy: 0.9483 - loss: 0.1404 - val_accuracy: 0.9388 - val_loss: 0.1733
Epoch 4/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 13s 247ms/step - accuracy: 0.9612 - loss: 0.1181 - val_accuracy: 0.9318 - val_loss: 0.1913
Epoch 5/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 13s 242ms/step - accuracy: 0.9583 - loss: 0.0968 - val_accuracy: 0.9388 - val_loss: 0.1719
Epoch 6/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 13s 242ms/step - accuracy: 0.9647 - loss: 0.0836 - val_accuracy: 0.9388 - val_loss: 0.1455
Epoch 7/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 13s 243ms/step - accuracy: 0.9712 - loss: 0.0639 - val_accuracy: 0.9365 - val_loss: 0.2964
Epoch 8/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 13s 238ms/step - accuracy: 0.9806 - loss: 0.0531 - val_accuracy: 0.9482 - val_loss: 0.2163
Epoch 9/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 13s 241ms/step - accuracy: 0.9812 - loss: 0.0432 - val_accuracy: 0.9365 - val_loss: 0.3157
Epoch 10/10
54/54 ━━━━━━━━━━━━━━━━━━━━ 13s 241ms/step - accuracy: 0.9859 - loss: 0.0342 - val_accuracy: 0.9529 - val_loss: 0.1865
14/14 ━━━━━━━━━━━━━━━━━━━━ 3s 191ms/step - accuracy: 0.9529 - loss: 0.1865

Test Accuracy: 95.29%
```



9. CONCLUSION

In this project, a Convolutional Neural Network (CNN) was developed to automatically detect bone fractures from X-ray images using a publicly available Kaggle dataset. The workflow included dataset preprocessing, data augmentation, CNN model building, training, evaluation, and visualization of results.

Key findings from the project:

Data Preprocessing and Augmentation:
Rescaling, rotation, shifts, zooming, and horizontal flips were applied to improve the model's ability to generalize and handle variations in X-ray images.

CNN Architecture:
A multi-layer CNN with increasing filter sizes (32, 64, 128, 256) was constructed, followed by fully connected layers and dropout for regularization. This enabled the model to extract hierarchical features effectively.

Training and Optimization:
The model was trained using the Adam optimizer with binary cross-entropy loss. Early stopping and model checkpoints ensured the best weights were saved and overfitting was minimized.

Performance Evaluation:
The model achieved a high validation accuracy and demonstrated strong predictive capability on unseen data. The classification report and confusion matrix confirmed that the CNN could reliably distinguish between fractured and non-fractured bones.

Visualization:
Plots of training vs. validation accuracy and loss across epochs provided insights into the learning process and confirmed model stability. The confusion matrix heatmap offered a clear representation of prediction performance.

Overall, the implemented CNN-based approach proved to be an effective method for automated bone fracture detection, highlighting the potential of deep learning in medical image analysis. Further improvements, such as using a larger dataset, fine-tuning hyperparameters, or leveraging transfer learning with pre-trained models, could enhance accuracy and robustness even further.

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