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BONE FRACTURE CLASSIFICATION THROUGH EDGE DETECTION USING DL IN MEDICAL IMAGING

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CONTENTS

INTRODUCTION

In this project, we introduce a unique wide attribute integration approach that combines a deep ConvNet with an enhanced canny edge detection technique to effectively differentiate between fractured and healthy bone images.This hybrid approach leverages canny edge detection for feature extraction to identify the edges of objects in an image, which can serve as crucial features for identifying regions of interest and deep ConvNet for classification, improving the model's capacity to learn more meaningful features related to object boundaries and offering competitive computational times and diagnostic accuracy compared to other CNN models.

LITERATURE SURVEY

The literature survey in this paper focuses on the application of Artificial Intelligence (AI), particularly Deep Learning (DL) and Machine Learning (ML), for automated bone fracture detection in medical images. It highlights the limitations of traditional manual analysis and the potential of AI to improve diagnostic accuracy and efficiency.

- M.R. OGIELA AND T. HACHA] "IMAGE PROCESSING, PATTERN RECOGNITION, AND SEMANTIC UNDERSTANDING TECHNIQUES " IN NATURAL USER INTERFACE IN MEDICAL IMAGE ANALYSIS, SPRINGER"
- •" P.P ACHARJYA, R. DAS & D. GHOSHAL "STUDY AND COMPARISON OF DIFFERENT EDGE DETECTORS FOR IMAGE SEGMENTATION" IJCSI INTERNATIONAL JOURNAL OF COMPUTER SCIENCE ISSUES, VOL. 12, NO. 13.."

EXSITING SYSTEM

Existing systems for automated bone fracture detection utilize Deep Convolutional Networks (DeepConv) as a primary architecture for learning features directly from X-ray images. These DeepConv models, with their multiple layers of convolution, pooling, and activation, aim to automatically identify patterns indicative of fractures.

Both DeepConv and ResNet architectures are employed in existing automated bone fracture detection systems. They take X-ray images as input and, after learning from large labeled datasets, output diagnostic predictions. ResNet's ability to handle greater depth often makes it a preferred choice for achieving state-of-the-art performance in this medical imaging task.

OBJECTIVES

Develop a hybrid Deep ConvNet model integrating canny edge detection for accurate and efficient bone fracture detection and classification.

Objective 1: To collect and preprocess a comprehensive dataset of bone X-ray images.
Objective 2: To develop and train the hybrid deep ConvNet model using canny edge images.
Objective 3: To evaluate the performance of the hybrid Deep ConvNet against existing models.
Objective 4: Optimize the model for real-time application.

DATASET DETAILS

- DATASETSOURCE :MURA(MUSCULOSKELETAL RADIOGRAPGHS)
- TOTAL NO OF IMAGES: 24,600
- CONTAINS BOTH FRACTURED AND NON FRACTURED IMAGES

DATASET SPLIT	TRAIN	TEST	VALID
FRACTURED	11000	1000	1100
NON-FRACTURED	10000	500	800
	87%	8%	5%

SOFTWARE REQUIREMENTS

- OperatingSystem:Windows 10/11,macOS,Linux
- Programming Languages: python
- Development Environment/IDE :Vscode / Googlecollab
- Libraries and Frameworks:NumPy, Pandas,React,TensorFlow,PyTorch.

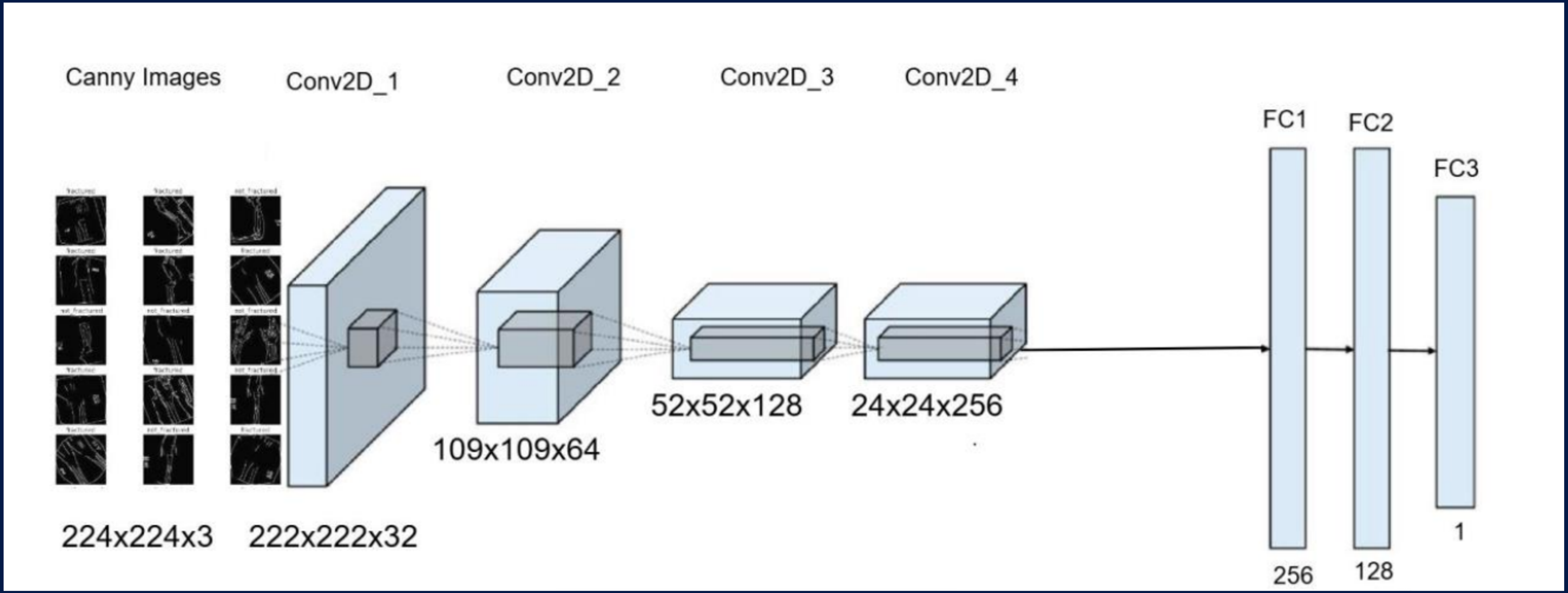
HARDWARE REQUIREMENTS

- High-performance GPU for model training.
- Sufficient storage for large datasets.

PROPOSED SYSTEM

This Deep ConvNet leverages Canny edge detection as a crucial preprocessing step for image analysis. By inputting edge-emphasized images, the model focuses on structural information like boundaries and contours. This approach aims to reduce noise, improve generalization (especially with less data), and enhance the interpretability of the model's predictions by learning from distinct features. The network then progressively extracts and refines these edge-derived features through its convolutional layers, ultimately leading to a classification.

PROPOSED SYSTEM ARCHITECTURE



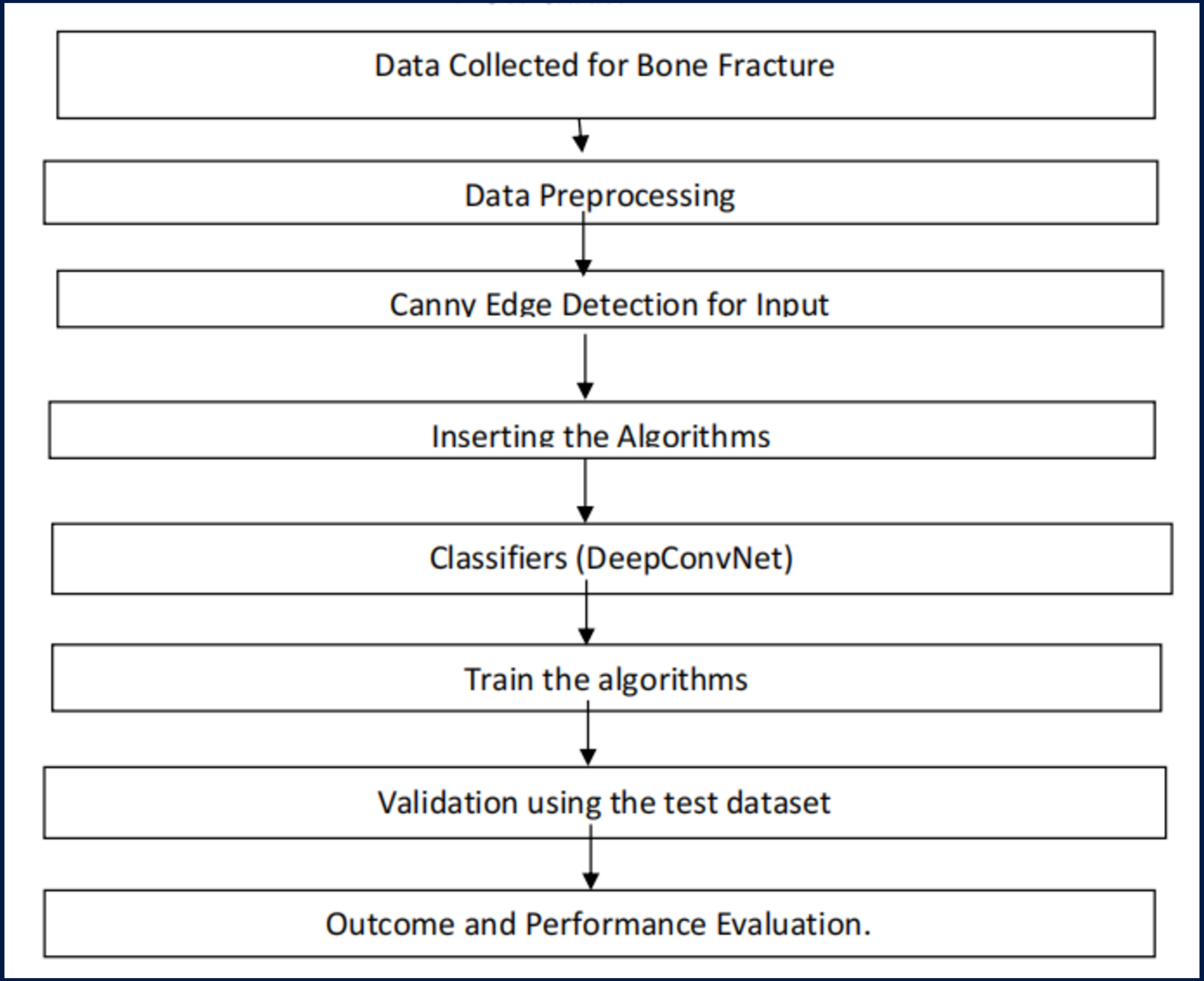
DeepConNet with Canny Edge Detection Architecture

Architecture of DeepConNet with Canny Edge Detection

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 32)	896
batch_normalization (Batch Normalization)	(None, 222, 222, 32)	128
max_pooling2d (MaxPooling2 D)	(None, 111, 111, 32)	0
conv2d_1 (Conv2D)	(None, 109, 109, 64)	18496
batch_normalization_1 (Bat chNormalization)	(None, 109, 109, 64)	256
max_pooling2d_1 (MaxPoolin g2D)	(None, 54, 54, 64)	0
dropout (Dropout)	(None, 54, 54, 64)	0
conv2d_2 (Conv2D)	(None, 52, 52, 128)	73856
batch_normalization_2 (Bat chNormalization)	(None, 52, 52, 128)	512
max_pooling2d_2 (MaxPoolin g2D)	(None, 26, 26, 128)	0
dropout_1 (Dropout)	(None, 26, 26, 128)	0
conv2d_3 (Conv2D)	(None, 24, 24, 256)	295168
batch_normalization_3 (Bat chNormalization)	(None, 24, 24, 256)	1024
max_pooling2d_3 (MaxPoolin g2D)	(None, 12, 12, 256)	0
dropout_2 (Dropout)	(None, 12, 12, 256)	0
global_average_pooling2d (GlobalAveragePooling2D)	(None, 256)	0
dense (Dense)	(None, 256)	65792
dropout_3 (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 128)	32896
dropout_4 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 1)	129

Total params: 489153 (1.87 MB)
Trainable params: 488193 (1.86 MB)
Non-trainable params: 960 (3.75 KB)

PROPOSED MODEL DESIGN



PREPROCESSING TECHNIQUE USED

- Data preprocessing in medical imaging is a critical stage that enhances the standard and usability of the data before it is analysed or used for diagnostic purposes. This process involves several stages, including noise reduction, normalization, segmentation, and canny edge detection, to improve the accuracy of the subsequent analysis.

- Noise reduction techniques, such as filtering, help remove artifacts and irrelevant information from the images. Normalization ensures that the data is consistent and comparable across different images by adjusting pixel values. Segmentation involves dividing the image into regions or structures of interest, to focus on specific areas relevant to diagnosis.

- These functions are used to prepare bone fracture X-ray images before processing them into the deep learning model. By resizing the images and applying canny edge detection, the preprocessing enhances relevant features (like fractures) and standardizes the input size, improving the model's capability to learn and generate accurate classifications.

MODEL TRAINING

- The model is a Deep ConvNet that uses Canny edge detection for pre-processing input images to emphasize structural features.

- The pre-processing involves converting images to grayscale, resizing them to 224x224, applying Canny edge detection, and converting back to RGB.

- The model receives the pre-processed 224x224x3 images.

- The architecture consists of convolutional layers with increasing filters (32, 64, 128) to extract features, batch normalization for training stability, max pooling to reduce dimensions, and dropout to prevent overfitting.

- Feature maps are flattened and passed to dense layers for classification, with dropout used again.

- The final layer uses a sigmoid function for binary classification, and the model is compiled with the binary cross-entropy loss.

PERFORMANCE EVALUATION

MODEL	Type of Bone	Precision	Recall	F1-Score	Accuracy
DeepConvNet Model	Fracture	0.98	0.89	0.93	0.93
	Not Fracture	0.89	0.98	0.93	
ResNet	Fracture	0.97	0.97	0.97	0.96
	Not Fracture	0.96	0.97	0.97	
Proposed Hybrid DeepConvNet Model with Canny Edge	Fracture	1	0.98	0.98	0.98
	Not Fracture	0.96	0.98	0.98	

CONCLUSION

The study proposes a deep learning model using a deep ConvNet with canny edge detection to improve bone fracture detection in X-rays. This approach aims for higher accuracy and efficiency. Results show the method's effectiveness (98% accuracy), highlighting deep learning's potential in medical imaging. Accurate fracture detection can lead to positive outcomes such as preventing severe complications and reducing healthcare costs through timely intervention. The research emphasizes the technology's role in assisting healthcare, early diagnosis and decision making.

THANK YOU