DEEP LEARNING

STREAMLINING THE BONE FRACTURE DETECTION USING X- RAY IMAGING AND SEAMLESS PACS DATA EXCHANGE

GROUP ID : A3

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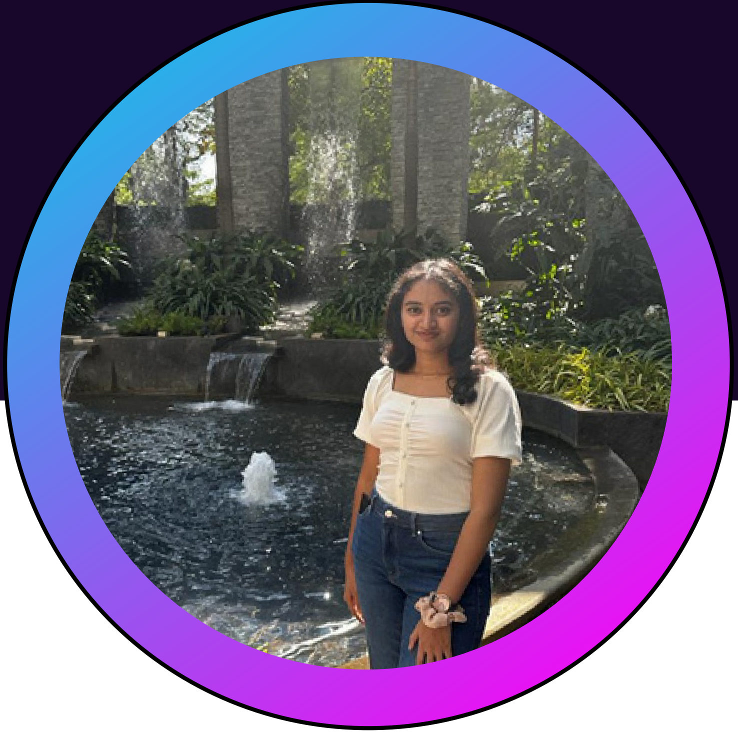

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INTRODUCTION

In the medical field, accurate and timely detection of fractures plays an important role in patient care. This project focuses on developing a disaster recovery system using X-ray imaging. Using advanced image processing and deep learning techniques, the system is designed to detect cracks with high efficiency and effectiveness. In addition, the project connects data through the Picture Archiving and Communication System (PACS), allowing doctors to collaborate and access patient information. The integration of bone detection and PACS data sharing should improve the accuracy of diagnosis, make medical operations more efficient and ultimately improve patient outcomes.

MOTIVATION

- Automated detection and classification of Bone fracture in X-Ray images.
- Enhanced accuracy in fracture detection.
- Seamless PACS data exchange that will enable healthcare professionals to collaborate more effectively, leading to better-informed treatment decisions.

PROBLEM STATEMENT

STREAMLINING THE BONE FRACTURE DETECTION USING X- RAY IMAGING AND SEAMLESS PACS DATA EXCHANGE

To decrease the work of Radialogist by implementing D.L for detecting Bone Fractures from X-Ray. Detecting bone fracture with high accuracy and adding a new feature of sharing the data present in PACS in the format of DICOM as we'll be creating a sharing tool/ button through which the data can be shared in the form of Google Drive, PACS to PACS, etc.This integrated system aims to enhance fracture diagnosis accuracy and streamline cross-institutional medical collaboration.

OBJECTIVES

- It is faster, cheaper, enjoy wider availability and is easier to use.
- Saving time for patients to lower the workload of doctors by screening out the easy case.
- To cut back human errors as a result of doctors in hospitals manually examine an outsized variety of X-ray pictures for fracture.
- DICOM Report Sharing: Implement a secure mechanism to share DICOM-based patient reports among authorized medical professionals and institutions, enabling efficient collaboration and second opinions.
- In long run it will reduce the work of the orthopedics.

LITERATURE SURVEY

Sr. no	Survey	Title	Year	Idea	Techniques	Results	Drawbacks
1	IJRASET	Classification and Detection of Bone fracture using Machine Learning	2022	To identify the fractured bone, the doctor takes x-ray or MRI (Magnetic Resonance Imaging) images	RF (Random Forest), CNN(Convolutional Neural Network), ANN (Artificial Neural Network)	Bone break discovery and order framework utilizing deep learning method has been created	Precision of the model can be additionally improved by determination of other profound learning model
2	RSNA	Convolutional Neural Networks for Automated Fracture Detection and Localization on Wrist Radiographs	2019	To demonstrate the feasibility and performance of an object detection convolutional neural network (CNN) for fracture detection and localization on wrist radiographs.	Computer Applications-Detection/ Diagnosis, Convolutional Neural Network (CNN), Technology Assessment	Deep learning object detection network was able to detect and localize radius and ulna fractures on wrist radiographs with high sensitivity at a per-fracture 96.3%	Does not have access to clinical information and old radiographs that a radiologist can use
3	IEEE	Bone Fracture Detection and Classification using Deep Learning Approach	2020	Deep neural network model has been developed to classify the fracture and healthy bone	Bone fracture, Deep Learning, Fracture detection, Fracture classification	The accuracy of the model is 84.7%	The accuracy of the model can be further improved by selection of other deep learning model
4	IEEE	An automated fracture detection from pelvic CT images with 3-D convolutional neural networks	2020	Automated bone fracture detection from 3-D CT images	CT images, deep learning, automated fracture detection	It extracts the 3-D feature vector for the bonny surface, and detects fractures with means of classification problem with CNN	Shape to improve the detection accuracy and the possibility of applying the proposed method to detect fractures from other body parts.

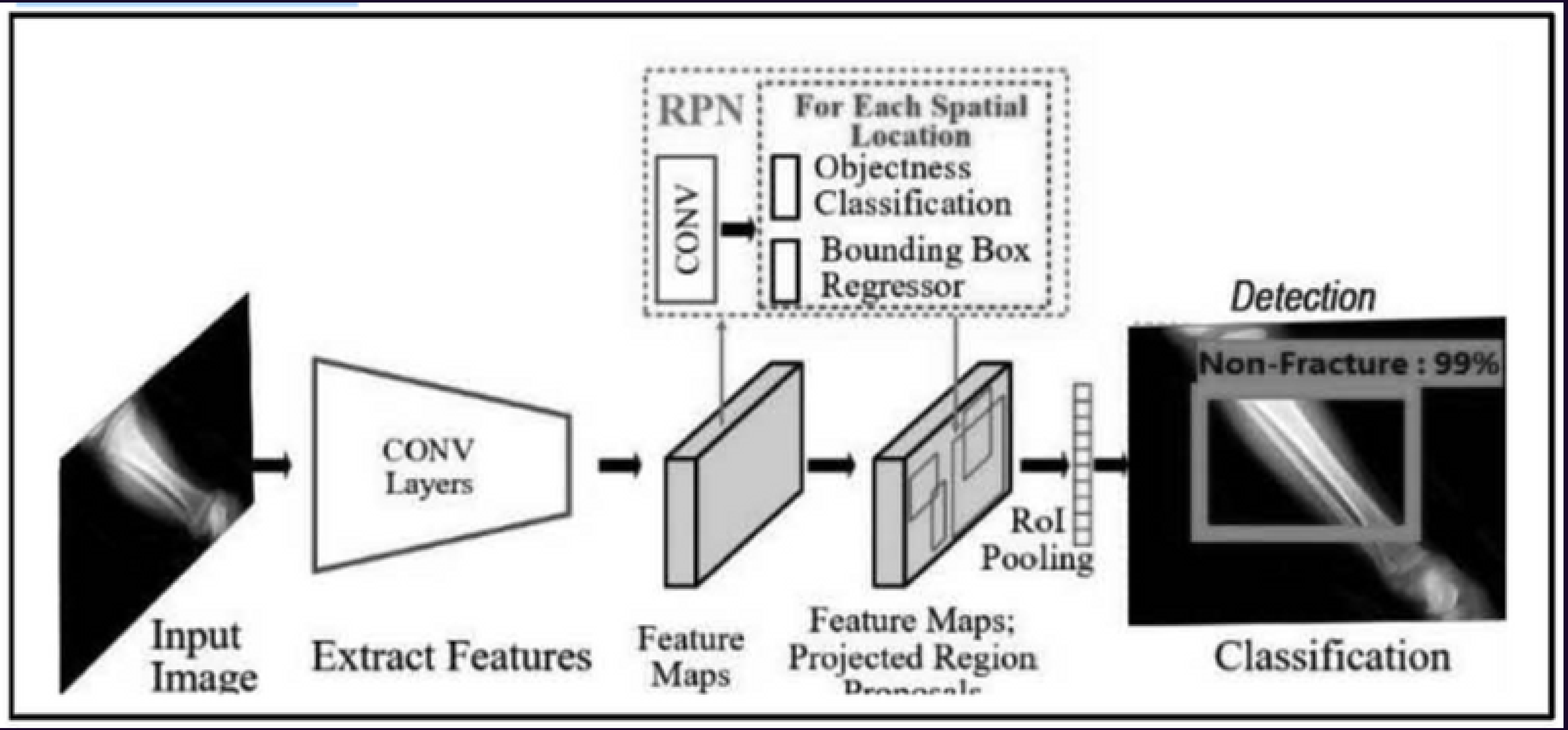
LITERATURE SURVEY

5	ELSEVIER	Detection of bone fracture based on machine learning techniques	2023	To create a program that can help doctors to determine whether a patient's leg bone has been broken or not easily and quickly	Machine learningImage processing, classification	Different machine learning methods achieved an accuracy of between 0.64 and 0.92	Improving accuracy
6	IEEE	Integrating a PACS Network to a Statewide Telemedicine System: A Case Study of the Santa Catarina State Integrated Telemedicine and Telehealth System	2017	A case study for the integration of a PACS network to a statewide telemedicine infrastructure	PACS	The obtained results attest the alignment of the design to the needs of the healthcare units, indicating robustness to support the connection of new units.	Eliminate de direct database access currently performed and to decouple the interface engine from the HIS.
7	IEEE	Enhanced Computer Aided Bone Fracture Detection Employing X-Ray Images by Harris corner detection	2020	Harris corner based detection algorithm is proposed to extract features from the image and the extracted features from this algorithm can identify edges, fractures and corners present in the image	Gaussian filtering, Canny edge Fracture detection, Harris corner detection.	Capability of pre-processing and identifying the fracture and non-fracture bone x-ray images for effective dissemination	Accuracy can be improved
8	International Journal of Healthcare Management	A systematic approach to diagnosis and categorization of bone fractures in X-Ray imagery	2022	To construct an image processing system, including information from X-ray and Computer Tomography (CT) scans, classifying bone fractures rapidly and precisely	CNN, SVM, DNN, SIFT, KNN, RF	Bone fracture detection and classification with accuracy rate of 93%	Improving accuracy
9	International Journal of Dentistry	Automatic Segmentation of Periapical Radiograph Using Color Histogram and Machine Learning for Osteoporosis Detection	2023	Automatic trabecular bone segmentation method for detecting osteoporosis using a color histogram and machine learning (ML)	Decision tree, naive Bayes, and multilayer perceptron	Achieves accuracy, specificity, and sensitivity of 90.48%, 90.90%, and 90.00%, respectively.	Larger samples can be conducted so that the findings can be generalized to large populations

Summary of Research Papers

Study	Type of Image	Feature Extraction Model	Dataset	Accuracy
Kitamura et al.[16]	X-ray	DenseNet-121	14,374 images	95%
Ma et al.[18]	X-ray	CrackNet	1052 images	90.14%
Wang et al.[19]	X-ray	ParallelNet	3842 images	87.8%
Abbas et al.[20]	X-ray	Faster R-CNN	50 images	97%
Beyaz et al.[21]	X-ray	Deep CNN	2106 images	83%
Jones et al.[22]	X-ray	Deep CNN	715,343 images	97.4%
Hardalaç et al.[24]	X-ray	Ensembles deep CNN	569 images	86.39%
Pranata et al.[25]	CT Scan	ResNet + VGG16 + SURF	1931 images	98%
Mutasa et al.[26]	X-ray	GAN + DRS	9063 images	96%

Existing System Architecture



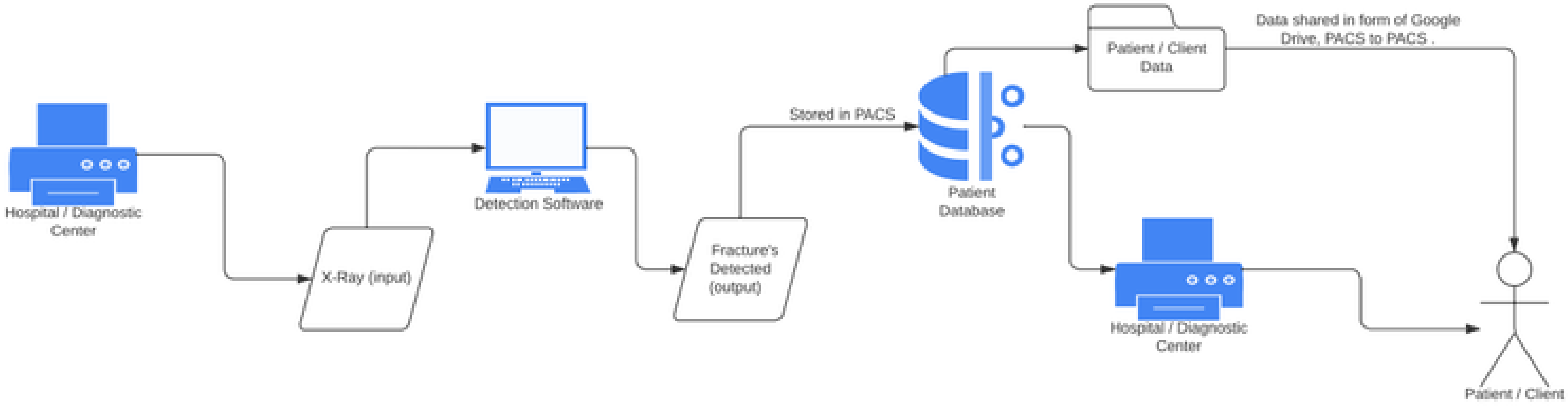
Methodology Utilized:

A system for automated detection and classification of lower leg bone fractures was developed using the Faster R-CNN model with VGG-16 as the base network for feature extraction and classification. The dataset, comprising bone fracture images from 50 patients at BVH Bahawlpur Victoria Hospital, was labeled and normalized. The model consisted of three key components: the Feature Network for generating image features, the Region Proposal Network (RPN) for creating bounding boxes around potential fracture regions, and the Detection Network for final classification and bounding box refinement. Transfer learning was employed to train the model until a low loss rate was achieved.

The RPN produced candidate bounding boxes, which were filtered using Non-Maximum Suppression (NMS). During training, labels were assigned based on Intersection over Union (IOU) with ground truth boxes. The system was evaluated based on detection and classification performance, including Mean Average Precision (mAP). Finally, the model detected fractures, created bounding boxes, and classified the input image as fractured or non-fractured through a series of processing steps involving convolutional layers and feature extraction.

This existing model implements automatic bone fracture detection of lower leg bone by using transfer learning model. The Faster-RCNN deep learning model is selected for detecting the fracture region and classifying them into two classes namely fracture and non-fracture. A deep convolutional network architecture called VGG-16 was used as a base network to implement the Faster-RCNN model (overall accuracy=94%).

Proposed System Architecture



Proposed Methodology

The developed program will receive X-ray input from the hospital or diagnostic facility. The output for the same will be generated after the fractures are found and boxed, representing the fractures visible in the X-ray. The information will be kept in the PACS as DICOM files. The hospital or diagnostic facility will have access to the recorded data so they can send it on to the radiologist for a precise, error-free report. Patients may request direct access to the PACS data maintained at the organizational level if they want more information regarding the fracture found. The patient can receive the information directly via Google Drive.

Overcomes of Proposed System over Existing System

This existing model implements automatic bone fracture detection of lower leg bone by using transfer learning model. The Faster-RCNN deep learning model is selected for detecting the fracture region and classifying them into two classes namely fracture and non-fracture. A deep convolutional network architecture called VGG-16 was used as a base network to implement the Faster-RCNN model (overall accuracy=94%).

In our proposed system we are trying to implement this model for detecting the bone fracture of the whole body i.e. we are implementing for analysis of different bone fracture types. We're also aiming to improving the accuracy further by using combinations of different algorithms. Also, we are providing data sharing feature via pacs.

Methodology

Input: X-Ray Images.

Output: Detection of fractures with high accuracy.

Step 1:

Image Pre-processing in image process- ing we’re using normalisation to normalize pixel values to a specific range (e.g., 0 to 1):

Step 2:

Algorithms - we are going to do the comparison based on the following algorithms:

Convolutional Neural Networks (CNNs): CNNs are the most commonly used deep learning architecture for image-related tasks. They are well-suited for feature extraction from X-ray images.

Transfer Learning: Utilize pre-trained CNN models such as ResNet, VGG and fine-tune them on your bone fracture dataset. Transfer learning can help when you have limited data.

ResNet: ResNets are known for their ability to handle deep neural networks effectively while mitigating the vanishing gradient problem.

SVM: The goal of an SVM is to find a hyperplane that separates data points of different classes while maximizing the margin between them.

K-Nearest Neighbors (KNN): KNN works by assigning a class label to a new data point based on the majority class among its k nearest neighbors in the feature space.

Step 3:

Data Sharing via PACS: DICOM Message Format, DICOM messages follow a specific format with tags (data elements) and values. Network Transfer (TCP/IP), use net- work protocols for secure and efficient data transfer.

Step 4:

Evaluation Metrics -

Accuracy: Measure the ratio of correctly predicted features.

Precision: Measure the ratio of true positive predictions to the total number of positive predictions

Recall (Sensitivity): Measure the ratio of true positive predic- tions to the total number of actual positive cases.

F1-Score: The harmonic mean of precision and recall.

Applications

- **Emergency Medicine** : Rapid fracture detection in emergency departments allows for quick diagnosis and treatment planning, reducing patient wait times and improving outcomes for trauma patients.
- **Orthopedics** : Orthopedic surgeons use streamlined fracture detection to plan surgeries, select appropriate treatment options, and monitor post-surgical healing progress.
- **Radiology Departments** : Radiologists benefit from automation in fracture detection, which enhances workflow efficiency, reduces interpretation time, and ensures accurate reporting.

Applications

- **Remote and Rural Healthcare** : Extending fracture detection capabilities to remote and underserved areas helps bridge the healthcare gap and provides access to specialized services in regions with limited resources.

- **Second opinion** : When the first radiologist encounters a challenging case or subtle fracture, seeking a second opinion can provide additional insights and potentially resolve uncertainties in the diagnosis. This can happen through data sharing via PACS.

Conclusion

The project not only aims to detect bone fractures using X- ray images but also focuses on integrating data sharing through Picture Archiving and Communication Systems (PACS). This system utilizes advanced imaging techniques and deep learning algorithms. Its purpose is to accurately detect bone fractures on X-ray images, thereby aiding in the diagnosis of pain. The system combines state-of-the-art technology with powerful machine learning capabilities, enabling it to efficiently identify and analyze fractures. This innovative approach enhances the diagnostic process and contributes.

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THANK YOU!