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DETECTION OF CRACK IN HUMAN BODY USING CONVOLUTIONAL NEURAL NETWORK IN DEEP LEARNING

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Abstract:

Bone fractures are frequent conditions that need accurate and timely diagnosis to ensure successful treatment. The current project showcases a sophisticated technique for bone fracture detection based on Residual Networks (Res Net), a deep learning model widely recognized for delivering outstanding performance on image classification. The main purpose of this work is to construct a strong and precise model able to detect bone fractures in elbows, shoulders, and hands based on X-ray images. We start by collecting a large dataset of medical images with different bone fractures in the given areas. We pre-process the dataset used in model training and testing using data augmentation and pre-processing techniques. We employ the Reset architecture to learn intricate features from such radiographic images such that the model learns to distinguish between fractured and non-fractured bones effectively. In addition to detecting fractures, this project further broadens its scope by providing extensive prevention measures against bone fractures in the target areas. Through the consideration of the clinical significance of the findings, we will be providing useful information that can be used by healthcare workers to improve patient care and prevent injuries.

Keywords — Bone **Fracture Detection, Deep Learning, Convolutional Neural Networks, Residual Networks, Medical Imaging.**

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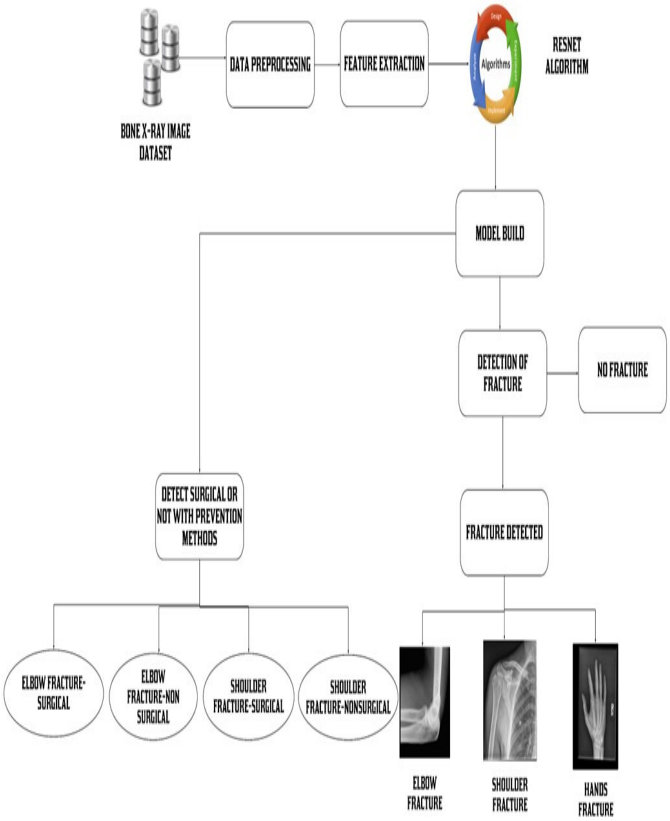
I. INTRODUCTION

Bone fractures need accurate diagnosis to get proper treatment. Conventional diagnosis is done through manual examination, which may take time and is error-prone. The present study proposes a state-of-the-art method of using deep learning, i.e., Res Net, to enhance the accuracy of fracture detection from X-ray images. Using deep learning methods, we are attempting to create an automated, fast, and highly accurate system for bone fracture detection, which would eventually ease the workload of radiologists and eliminate human errors in diagnosis.

SYSTEM ARCHITECTURE

In our system design it is divided into training and testing data and these data are utilized to create a system to identify bone fractures. It detects bone fractures using ResNet algorithm. This module is about gathering and storing data pertinent to the situation from a source. These sources can be X-Ray. The deep learning models are trained on the prepared dataset, and their performance is tested using suitable evaluation metrics, i.e., accuracy. Two models are trained and tested and then those models are integrated to the website.

System Architecture



III. MODULES

A. Data Collection

A good fracture detection model depends on a robust and varied dataset. For the model to be accurate, the dataset must consist of a wide variety of medical images, like X-rays and CT scans, across:

- **Anatomical Diversity**: Various bone structures, including arms, legs, ribs, and the skull.
- **Fracture Variability:** Various types and severities of fractures, like hairline, displaced, and comminuted fractures.
- **Demographic Representation**: Combination of age groups, genders, and ethnicities to develop a more robust and representative model.
- **Imaging Modalities**: Images taken with various imaging modalities and devices to cover differences in contrast and resolution.

B. Image Pre-processing

Raw medical images may be of varying quality, size, and intensity, which make pre-processing necessary to enhance learning efficiency. The following methods are used to standardize and enrich the dataset:
Resizing: Normalizing image sizes to a uniform value helps to maintain uniformity, enabling the CNN model to handle data better.
Normalization: Rescaling pixel intensities (e.g., between 0 and 1) facilitates faster learning and enhances accuracy.
Noise Reduction: Using filters such as Gaussian blur and median filtering eliminates redundant noise that may mislead fracture detection.
Data Augmentation: Methods such as rotation, flipping, and contrast change increase dataset diversity, minimizing over fitting and enhancing the model's generalizability.

C. Image Segmentation

Subtle fractures make segmentation convenient to pinpoint regions of interest. This phase is optional but helpful. To begin with, datasets that comprise medical images of bone fractures appropriate for segmentation should be obtained in such a manner that diversity among fracture types as well as among image qualities are maintained Resizing and normalization pre-processing techniques ensure images are in an appropriate condition for segmentation

Pros Cons:

●Improves accuracy by eliminating unnecessary background details.

●Raises computational complexity and might require additional training data.

D. Feature Extraction

Utilize CNN architecture for automatic feature learning: Design a CNN with convolutional layers that automatically extract relevant features from images. Consider incorporating handcrafted features based on domain knowledge if applicable.

E. Model Training and Testing

Train the CNN model: Divide the pre-processed data (with or without segmentation) into training, validation, and testing sets. Define a loss function appropriate for the classification task.

F. Detection and Classification of fracture

Apply the trained model to new images: The model predicts the presence and location of fractures. Classify the identified fractures based on type and severity (e.g., hairline, displaced).

G. Classify Surgical Fracture or not

Train a separate or extended model: If required, train a separate model (or extend the existing one) to predict whether a fracture requires surgery. This model requires additional data with labels specifying surgical intervention.

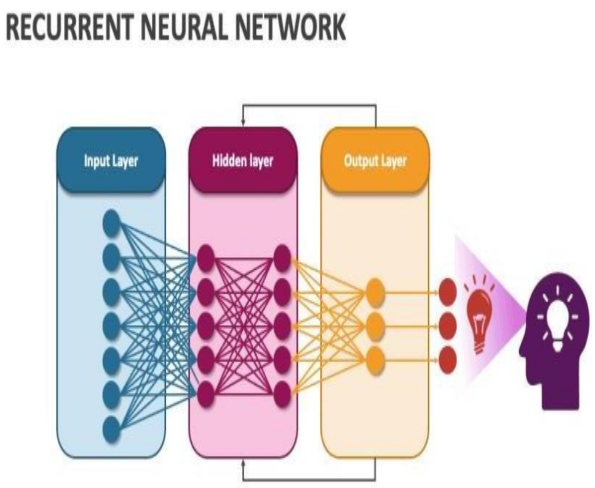
H. Accuracy Evaluation

Assess model performance: Evaluate the final model on the testing set using metrics like accuracy, precision, recall, and F1-score for each classification task. Analyse results to identify strengths and weaknesses of the model. Consider hyper parameter tuning or further architecture adjustments if accuracy requires improvement.

IV. RECURRENT NEURAL NETWORKS

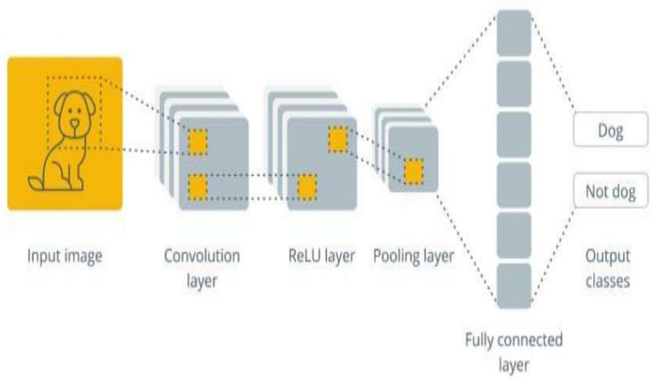
RNN is a multi-layered neural network that is capable of storing data in context nodes, which enables them to learn data sequences and produce different sequences, such as numbers. In simple words, it is an artificial neural network with loops connecting its neurons. Processing input sequences is a good fit for RNN.

- The subsequent step receives its input from the preceding step's output.
- The primary and most significant characteristic of an RNN is its Hidden state, which retains some sequence-related information, since it retains the prior input to the network, the state is also known as the Memory State.
- It does the same job on all inputs or hidden layers to create the output, using the same settings for each input
- Unlike other neural networks, this lowers the parameter complexity, Because of its special capacity to preserve a hidden state, this unit enables the network to recognize sequential relationships by processing and remembering prior inputs.
- The RNN can handle long-term data better with Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) variants.



CONVOLUTIONAL NEURAL NETWORKS

CNNs consist of multiple neurons with a unique algorithm designed to predict outcomes by extracting more complex features from the data in each layer CNNs are well suited for perceptual tasks. Convolutional neural networks outperform other neural networks when it comes to processing inputs such as voice, picture, or audio signals.



They have three main types of layers, which are:
Convolutional layer: The central component of a CNN is the convolutional layer, which is also where most of the computation takes place. It needs a feature map, a filter, and input data as its three necessary components.
Pooling layer: Down sampling, or pooling layers, does dimensionality reduction by lowering the number of parameters in the input. While the pooling process sweeps a filter across the whole input, it differs from the convolutional layer in that the filter is weightless. Rather, the values in the receptive field are subjected to an aggregation function by the kernel, which then fills the output array.
Fully-connected (FC) layer: Each node in the output layer connects directly to a node in the previous layer.
CNN is mostly used when unstructured data (e.g. images) are available and operators have to extract information from them.

DEEP LEARNING

Deep nervous systems allow them to perform many tasks with precision, from object recognition to speech recognition. They can learn on their own, without any prior knowledge explicitly introduced by the organizers.

To capture the idea of deep learning, imagine a family with a baby and parents. The boy always points with his little finger and says the word ‘cat’. As his parents worry about his education, they keep telling him ‘yes, he’s crazy’ or ‘no, he’s not crazy’. The baby stays pointing but is more accurate with the ‘mouse’. The boy deep down didn't know why he could say yesterday or not. Now he has learned how a dog looks at the pet as a whole, focusing on details like the tail or nose, with attention to details like the tail or nose.
The nervous system works in the same way. Each category represents a depth of knowledge, that is, a hierarchy of knowledge. A four-loop neuron will

recognize more complex objects than two layers.

The learning occurs in two phases.

- The first step is to create a mathematical model as output by applying a nonlinear transformation to the input.
- The second phase aims to improve the model using a mathematical technique called derivatives.
- The neural network repeats these two steps hundreds to thousands of times until tolerable accuracy is reached. These two steps are called iterations. Deep learning is now being used in many ways such as driverless cars, mobile phones, Google search engines, fraud detection, TV and more

VII. CONCLUSION

We express our gratitude to Murugappa Polytechnic College for providing resources and support for this study. Special thanks to our project guide, Mr. **Rajendran**, HOD for his guidance throughout the research. Additional appreciation is extended to healthcare professionals and medical imaging specialists who provided valuable insights for dataset preparation and model evaluation

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