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Automated Bone Fracture Detection Using Convolutional Neural Network

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Automated Bone Fracture Detection Using Convolutional Neural Network

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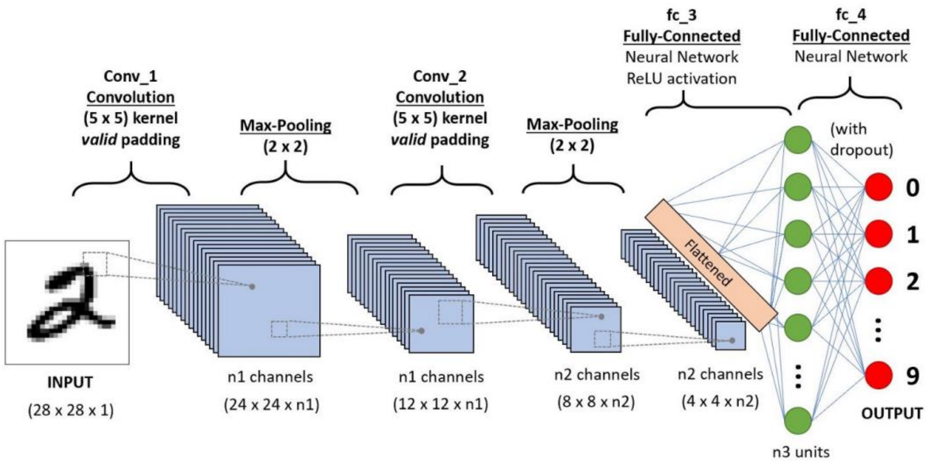
Abstract. Bones are an important part of the human body. Humans are prone to bone fractures, which can occur as a result of tremendous pressure being applied to the bone, or as a result of a simple accident. As a result, in the medical field, an accurate diagnosis of a bone fracture is crucial. In this work, bone fractures are examined using X-ray/CT scans. The purpose of this research is to develop an image processing based system that can classify bone fractures rapidly and accurately using data from x-ray and CT images. In many diagnostic and therapeutic applications, automatic fault detection in MRI and CT images is critical. Tumor segmentation and classification are difficult due to the large amount of data in MR images and the fuzzy boundaries. This project proposed an automatic bone fracture detection system that improves accuracy and yield while cutting down on diagnosis time. The aim is to classify into two categories: normal, fractured. The amount of data in MR and CT pictures is too great for human interpretation and analysis. Bone fracture segmentation in Magnetic Resonance Imaging (MRI) has appeared as an emerging subject study in the realm of medical imaging systems in recent years. The potential to accurately recognise the size and location of a bone fracture is critical in the diagnosis of a fracture. Pre-processing of MR images, feature extraction, and classification are the four stages of the diagnosis procedure. The features are extracted using wavelet transformation after the image has been preprocessed (DWT). Automated fracture identification is essential in a computer-aided telemedicine system. Human arbitrary bones frequently fracture as a consequence of accidental traumas like slipping.Computer-aided diagnosis (CAD) relieves doctors' workload while also detecting fractures. A new classification network sensitive to fracture lines is described, called Crack-Sensitive Convolutional Neural Network (CrackNet). Faster Region with Convolutional Neural Network (Faster R-CNN) is used to identify 20 various types of bone areas in X-ray pictures, and CrackNet is used to assess incase each bone area is broken. The classification accuracy for 100 training and test sets is 99.5%.

1.Introduction

Clinical epidemics may involve fractures or other musculoskeletal harm. In the majority of cases, an X-ray examination is the first and most important step in the interpretation of medical images for patients with fractures, and fractures can be identified with certainty. Despite the fact that X-ray radiography only offers a limited amount of information because of constrained projection views and clinic observations, it nonetheless offers essential triage evidence. The radiological report needs to be precise and immediate in order to provide patients with the right therapy. Due to the swift progress of artificial intelligence, inverstigators have started exploring the use of deep learning and AI to upgrade the efficiency and precision of X-ray fracture diagnosis .The goal of this work was to suggest a method for mitigating feature uncertainty in bone fracture diagnosis on radiographs of diverse body areas[2]. There were 1000 radiography studies in all with hand, wrist, elbow, shoulder, pelvis, knee, ankle, and foot images were grouped into numerous body part types. Radiologists annotated instance segmentation. Processing was done using the FAMO model, and the architecture served as the standard[3]. On each fracture, an average precision analysis was accomplished. For each image and case, area under the receiver operating characteristic curve ,sensitivity and specificity were computed. The AP was improved to 77.4 percent using FAMO as a preprocessor. In another research work by Baskara saikiran et al, with the help of the data the project has collected, different algorithms may successfully distinguish between scan that are fragmented and those that are not as they investigate bone fractures utilising the convolutional Neural Network. The models accuracy ranges from 70% to 87%.The model has looked at about 221 images from the training and test data set. The model accuracy is 87.32% and performed flawlessly because the region based convolution Neural Network technique was being used.

2. CNN Architecture

The CNN is constructed by three different kinds of layers: fullyconnected (FC), pooling, and convolutional layers. The result of stacking these layers is a CNN architecture.



'Figure 1'CNN Architecture with 5x5 kernel

2.1 CNN Architecture and Dataset:

The three layers of the CNN architecture are explained in section 2.1 .The normal and cracked xray images of nearly 100 bones are gathered from kaggle as shown in Figure 2 and 3and the same is shown in the sections below following CNN layers.

2.1.1 Convolutional Layer:

The initial layer that separates the various features from the input images is this layer. Here, a filter of a certain size AxA is convolutioned mathematically with the input image. The convolutional layer is the fundamental component of a convolutional neural network. K learnable filters, or kernels, are used to create the parameters of the convolutional layer. Each kernel has a width and height and is almost always square. By swiping the filter across the input image, the dot product connecting the filter and the parts of the input image is measured with respect to the filter's size. The end outcome is the Feature map, which gives attributes about the region.

2.1.2 Pooling Layer:

A Convolutional Layer is accompanied by a Pooling Layer. Two methods for lowering the size of an input volume are pooling layers and convolution layers with a stride greater than 1. In CNN architectures, pooling layers are commonly included between sequential convolutional layers as shown.

INPUT → CONV → RELU → POOL → CONV → RELU → POOL → FC.

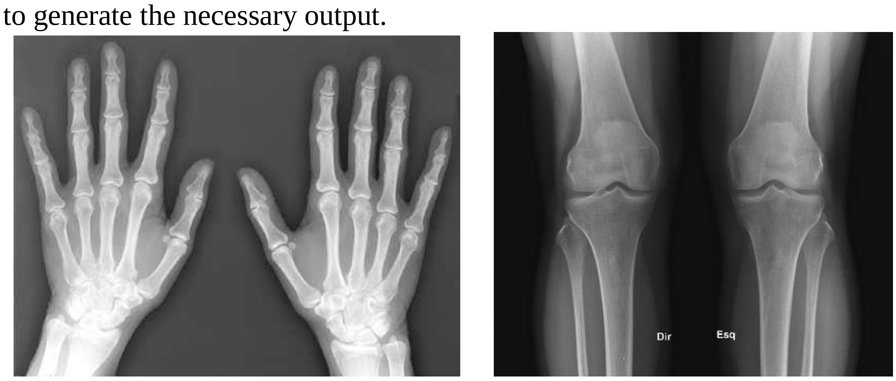
This layer's primary goal is to scale down the convolved feature map in order to save computational expenses. Depending on the method being employed, there are many different types of pooling procedures.In Max Pooling, the feature map's biggest chunk is used using average pooling, the components in an image segment of specific size are averaged out.The cumulative sum of elements in predefined segment is calculated using sum pooling.In Max Pooling, the feature map's biggest chunk is used.Using average pooling, the components in an image segment of a specific size are averaged out.The cumulative sum of elements in the predefined segment is calculated using sum pooling. Usually, the Convolutional Layer and the Data Layer are connected via the Pooling Layer.

2.1.3 Fully Connected Layer:

Weights and biases are incorporated in the Fully Connected layer (FC), which associates the neurons linking layers. As is usual for feedforward neural networks, neurons in completely linked layers are bridged to all activations in the preceding layer. A CNN Architecture frequently positions before the last few levels, the output layer. The input image from the earlier layers is used at this stage and given to the FC layer after being flattened. Several more FC layers are used to convey the flattened vector where the standard functional mathematical procedures are performed and the classification procedure starts.

3. Datasets

Online databases like kaggle are where the input image datasets are gathered. The information that located comprises of XRay photographs of normal and fractured bones. The images are of high quality, allowing for detection and consideration of more precise values during feature extraction. The input dataset set has an overall image count of 100. Out of the available,the images are categorised as Cracked = 100, Normal bone = 100. These distinct folder are then first mounted in the code, utilised for training the model, and finally tested. As a result,these data sets will be used to generate the necessary output.



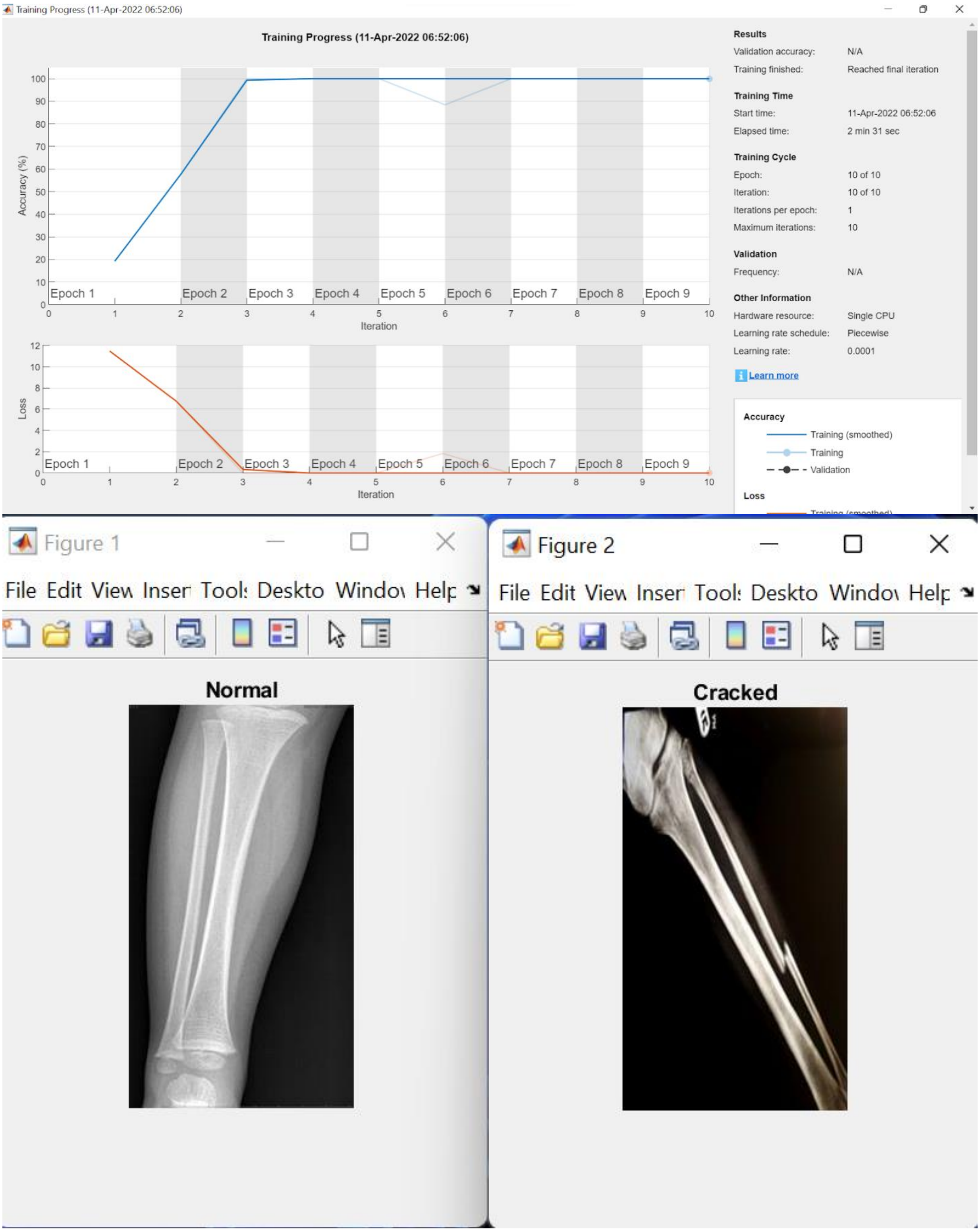
'Figure 2' Palm and knee healthy images

'Figure 3' Foot ankle fractured image

4.Experimental Results

The DICOM format of input image can be resized and converted to JPEG format, but because of its larger size, segmentation will take longer and the image quality will suffer.Consequently, the size should be changed to 256*256. The bone (MRI) scans used in investigation were obtained from hospitalsthat provide diagnostic services. Preprocessing is a technique used toboost an image's quality. Each image has a small amount of salt & pepper noise and blur. Using a Median filter, the noise and blurriness are removed.The median filter is a sliding window spatial filter that changes the midpointvalue of window to the median of every pixels.As one sort of smoothing techniq ueit reduces noiseand maintains the edges of animage by changing the median of all the values through the centre value. It raises an image'squality. There is no loss of contrast,no shifting of boundaries, and no creation of irrational values near borders. CT and MRI images of bone were both used to detect fractures. Thefracture is separated from images of the lung and bone using bothtechniques. The image canbe extensively segmented and ultimately obtained in segment.The categorization is typically used to determine if an image is normal or aberrant.Theclassifier compares the given image within the database if the fracture is identified whilecomparing the each pixel, it displays the message box the fracture is affected, after NN training.

NN is one type of classifier, the features and values of the fracture affected image and non fracture image are already placed in database, the intensity is also having in fracture affected image. A key step in recognising applications and classifications is feature extraction. In this effort, texturebased feature extraction is being done,typically many time.The local region's concept of texture is used to measure and determine the grey scale invariant texture. It is a productive texture operator that classifies picture pixels using a threshold procedure from each pixel's surrounding area and then expresses them as binary numbers.Based on the texture and contrast of an image, the fracture portion is derived from the bone images in this. Preprocessing, segmentation, classification , feature extraction, and statistical values for the input fracture image (MRI/CT) are found. Validation is done at the stage of the fracture in relation to the fracture portion. Using PSO and CSO approaches, the statistical values are calculated for both bone images. Calculated MSE and PSNR values show that the MSE is greater than the PSNR. Sensitivity, specificity, accuracy, and processing time make up the other criteria.Figure4 shown gives normal and cracked image .Also provides accuracy of 99.5% and loss of 0.001 %.10 epochs each with 10 iterations are performed with a learning rate of 0.0001



‘Figure 4’ Normal and cracked image

5.Conclusion

The main purpose of the project is to detect the bone affected areas using image processing technologies with the better algorithm in neural network families with the best technologies of segmentation, feature extraction, pre-processing and clustering. 100 training and test images are utilised to classify bone fracture using CNN. The accuracy of classification obtained is 99.5% and loss of 0.001 % .The work provides increased accuracy than 87.32% of FAMO model .The theme of the project is detection of the affected area using identification with the accuracy percentage . For the next generation it will be used as technologies with the accuracy based on clinical suggestions.

6. References

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