

A DENSENET MODEL BASED SYSTEM FOR FRACTURE DETECTION

^{1,*} T. KAVYA, ² T. PRAVALLIKA, ³ V. ALEKHYA, ⁴ S. SAKETH

^{1,2,3,4} B.Tech Students

Dept of Computer Science and Engineering,

Lendi Institute of Engineering & Technology, Vizianagaram, AP, India

18kd1a05f2@lendi.org, 18kd1a05f3@lendi.org, 18kd1a05gs3@lendi.org, 18kd1a05d8@lendi.org

Abstract- The bone is a major component of the human body and bone fractures are common. The doctors use the X-ray image to diagnose the fractured bone. The manual fracture detection technique is time-consuming and also error probability chance is high. It is challenging for doctors to evaluate X-ray images: The first one is X-ray could hide certain particularities of the bone; the second one is a lot of experience is needed to correctly classify different types of fractures and finally, doctors often have to act in emergency situations and may be constrained by fatigue. Therefore, an automated system needs to be developed to diagnose the fractured bone. In the present study, a deep neural network model has been developed to classify fracture and healthy bone. Here we use a Custom Deep Learning model using Deep Neural Networks with intermediate convolutional layers to classify X-ray images of bone fracture from the ones that are not fractured. Transfer Learning is a kind of self-evolving Deep Learning (DL) technique. It is used to achieve high accuracy on classification tasks on images. This project proposes an efficient and swift way to detect the fracture without any misdiagnosis using the Dense Net model.

Keywords - CNN, Dense Net Model, Adam optimizer, X-Ray Detection, MURA dataset, Transfer learning.

1 INTRODUCTION

Bone fracture is a common problem and the number of fractures also increasing day by day very rapidly. A bone fracture may occur due to simple accidents or different types of diseases. Diagnostic medical imaging tools are invaluable. Computed Tomography (CT), Magnetic Resonance Imaging (MRI), and x-rays are examples of such tools which help physicians in detecting different types of abnormalities. A fracture is a condition in which bone continuity is lost, either locally or partially. In general, the state of clinical fractures can be classified into Closed fractures (simple fractures), namely bone fracture fragments that did not penetrate the skin, and open fractures (compound fractures) are fractures that have a relationship with the outside world through a wound in the skin and soft tissues. This fracture can be experienced by a person when traumatized by direct or indirect trauma. Fractures have a profound impact on aspects of the life of patients who experience them. Patients with fractures have a tendency to impair mobilization during

fracture healing. Based on the impact of the effect on the lives of patients with fractures, precise handling is needed. A quick and accurate diagnosis can be crucial to the success of any prescribed treatment. Depending on human experts alone for such a critical matter has caused intolerable errors. Hence, the idea of automating the diagnosis procedure has always been an appealing one.

As with other computer-aided diagnosis systems, the motivations for building this system are:

- (a). reducing human errors (it is well known that the performance of human experts can drop below acceptable levels if they are distracted, stressed, overworked, emotionally unbalanced, etc.).
- (b). reducing the time/effort associated with training and hiring physicians. Eventually, this system can be integrated within the software of the x-ray imaging devices to enable users to produce a quick and highly accurate diagnosis while generating the image.

Another motivation for our work is to help doctors, patients and researchers look for certain cases for research purposes. In modern hospitals, medical images are stored in the standard DICOM (Digital Imaging and Communications in Medicine) format which includes text in the images. Any attempt to retrieve and display these images must go through PACS (Picture Archives and Communication System) hardware. This requires that the name of the patient or identity card number is provided to find any particular image. Thus, searching for some types of cases is usually done manually, which is a very expensive task in terms of time and effort. Providing a tool that can go through a huge database of images and automatically identify the required cases quickly and with high accuracy can save huge amounts of time and effort.

Finally, note that searching through the written reports is not sufficient for this task due to a large number of mistakes in such records. This was observed from personal experience and confirmed by many experienced physicians.

Bones can suffer fractures in spite of their rigidity. Bone fractures can occur due to a simple accident or any other scenario in which high pressure is applied on the bones. There are many types of bone fractures: simple, oblique, compound, comminuted, spiral, greenstick and transverse. In this work, we will consider the problem of detecting fractures in bones without paying attention to the type of fracture. To the best of our knowledge, no prior work have addressed this problem

2 LITERATURE REVIEW

Researchers are engaged on Edge Detection and fracture detection to form a much better and a lot of economical outlines.

D. P. Yadav, Sandeep Rathor [1] In this work, bone fracture detection and classification system using deep learning technique has been developed. The X-ray image of the human fracture bone and the healthy bone were used to perform the experiment. The original 100 images were collected from a different source. The data set was augmented to overcome the overfitting problem in the deep learning on the small data set. Finally, the size of the data set was set to 4000.

Alice Yi Yang, Ling Cheng [2] Proposed two contour-based fracture detection schemes. The development of the contour-based fracture is based on the line-based fracture detection schemes. Existing Computer Aided Diagnosis (CAD) systems commonly employs Convolutional Neural Networks (CNN), although the cost to obtain a high accuracy is the amount of training data required. The purpose of the proposed schemes is to obtain a high classification accuracy with a reduced number of training data through the use of detected contours in X-ray images.

Oishila Bandyopadhyay, Arindam Biswas, Bhabatosh Chanda & Bhargab B. Bhattacharya [3] Proposed a new technique of contour extraction by integrating an entropy-based segmentation approach with adaptive thresholding. The method eliminates the shortcomings of earlier derivative or deformable model-based approaches, and can be fully automated. Experiments with several digital X-ray images reveal encouraging results especially for long-bone X-ray images.

Dzung L. Pham, Chenyang Xu, and Jerry L. Prince [4] Future research in the segmentation of medical images will

strive toward improving the accuracy, precision, and computational speed of segmentation methods, as well as reducing the amount of manual interaction. Accuracy and precision can be improved by incorporating prior information from atlases and by combining discrete and continuous spatial-domain segmentation methods. For increasing computational efficiency, multiscale processing and parallelizable methods such as neural networks are promising approaches.

T. F. Cootes, A. Hill, C. J. Taylor & J. Haslam [5] Described a technique for building compact models of the shape and appearance of flexible objects (such as organs) seen in 2-D images. The models are derived from the statistics of sets of labeled images of examples of the objects. And also described how the method can be simply extended to segment 3-D objects in volume images and to track structures in image sequences.

Seok Won Chung, Seung Seog Han, Ji Whan Lee, Kyung-Soo Oh, Na Ra Kim,

Jong Pil Yoon, Joon Yub Kim, Sung Hoon Moon, Jieun Kwon, Hyo-Jin Lee, Young-Min Noh & Youngjun Kim [6] In this study, they demonstrated the very high performance of deep learning CNN in distinguishing normal shoulders from proximal humerus fractures. They additionally show promising results for classifying fracture type based on plain shoulder AP radiographs, with the deep learning CNN exhibiting superior performance to that of general physicians and general orthopedists.

Maria Amodeo, Vincenzo Abbate, Pasquale Arpaia, Renato Cuocolo, Giovanni Dell'Aversana Orabona, Monica Murero, Marco Parvis, Roberto Prevete, Lorenzo Ugga [7] This study represents a proof of concept for using transfer learning from CNN, pretrained on non-medical images, for maxillofacial fracture detection on CT images.

Findings Out Of Literature Survey

This literature review is written as part of summarized information of existing related work. We reviewed previous work based on different algorithms such as morphology gradient-based image segmentation, algorithms useful for feature extraction of x-ray fracture image, region number, region areas etc. With this review we define the research problem, look for the new ways of analysis and track the support for, "A Dense Net model based system for

Fracture Detection². This review helps to exploring the relationship between design and development, significance of the problem and research outcomes. This chapter not only gives summarized most relevant information but it discussed the steps to conducting qualitative, quantitative and effective research work

3 EXISTING SYSTEM

Proximal humerus fractures are primarily diagnosed using plain radiographs, and the fracture type is determined according to its anatomical location as well as fragmentation and displacement levels. However, since non-orthopedic surgeons or insufficiently experienced orthopedic surgeons are frequently the first doctors to assess fractures, it is not unusual for proximal humerus fractures to be misdiagnosed. In addition, even an experienced orthopedic surgeon can misdiagnose the fracture type due to some factors. Thus, a more efficient and accurate manner of diagnosing and classifying fracture type was developed. They used shoulder radiographs to detect humerus fractures using a CNN model and concluded that the performance of the detection method is affected by the quality of the image.

Disadvantage:

The existing study deals with the shoulder radiographs to detect humerus fractures using a CNN model. But they focused on only a single anatomical region or a single type of fracture and not described about the location of fracture.

4 PROPOSED SYSTEM

Rapidly developing technologies are emerging every day in different fields, especially in the medical environment. However, still some old techniques are quite popular, efficient and effective in this manner. X-Rays are one of these techniques for detection of bone fractures. The bone is a major component of the human body and also fractures became common.

The doctors use the X-ray image to diagnose the fractured bone. The manual fracture detection technique is time consuming and also error probability chance is high. It is challenging for doctors to evaluate X-ray images: firstly, sometimes the size of fractures is not significant and could not be detected easily; secondly, a lot of experience is needed to correctly classify different types of fractures; thirdly,

doctors often have to act in emergency situations and may be constrained by fatigue.

The existing study deals with the shoulder radiographs to detect humerus fractures using a CNN model. But they focused on only a single anatomical region or a single type of fracture. Therefore, an automated system needs to be developed to diagnose the fractured bone. So, our study aims to develop an intelligent classification system that would be capable of detecting all types of bone fractures.

In this, the images of the fractures are processed using different image processing techniques in order to detect their location and a deep neural network model has been developed to classify the fracture and healthy bone. Here we use a Custom Deep Learning model using Deep Neural Networks with intermediate convolutional layers to classify X-ray images of bone fracture from the ones that are not fractured. Transfer Learning is a kind of self-evolving Deep Learning (DL) technique. It is used to achieve high accuracy on classification tasks on images.

Experimentally, the system was tested on different bone fracture images and resulted in an efficient and swift way to detect the fracture without any misdiagnosis using the Dense Net model.

In our project, the accuracy will be measured using precision, recall, f1-score, and confusion matrix.

Precision: The precision is the ratio of correctly predicted positive observations to the total predicted positive observations. And it will be calculated as follows:

$$\text{Precision} = \frac{TP}{TP + FP}$$

Recall: Recall is the ratio of correctly predicted positive observations to all the observations in actual class. And it will be calculated as follows:

$$\text{Recall} = \frac{TP}{TP + FN}$$

True Positives (TP): These are the correctly predicted positive values which means that the value of actual class is yes and the value of predicted class is also yes. E.g. if actual class value indicates that this passenger survived and predicted class tells you the same thing.

True Negatives (TN): These are the correctly predicted negative values which means that the value of actual class is no and value of predicted class is also no. E.g. if actual class

says this passenger did not survive and predicted class tells you the same thing.

False positives and false negatives occur when your actual class contradicts with the predicted class.

False Positives (FP): When actual class is no and the predicted class is yes.

E.g. if actual class says this passenger did not survive but predicted class tells you that this passenger will survive.

False Negatives (FN): When actual class is yes but predicted class is no.

E.g. if actual class value indicates that this passenger survived and predicted class tells you that passenger will die.

F1 score: F1 Score is the weighted average of Precision and Recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F1 is usually more useful than accuracy, especially if you have an uneven class distribution. Accuracy works best if false positives and false negatives have similar cost. If the cost of false positives and false negatives are very different, it's better to look at both Precision and Recall. It can be calculated as follows:

$$F1 \text{ Score} = 2 * (\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision})$$

Confusion Matrix: A confusion matrix is a summary of prediction results on a classification problem. The number of correct and incorrect predictions are summarized with count values and broken down by each class. This is the key to the confusion matrix. The confusion matrix shows the ways in which your classification model is confused when it makes predictions. It gives you insight not only into the errors being made by your classifier but more importantly the types of errors that are being made.

Below is the process for calculating a confusion Matrix -

1. You need a test dataset or a validation dataset with expected outcome values.

2. Make a prediction for each row in your test dataset.

3. From the expected outcomes and predictions count:

- The number of correct predictions for each class.
- The number of incorrect predictions for each class, organized by the class that was predicted.

These numbers are then organized into a table, or a matrix as follows -

- **Expected down the side:** Each row of the matrix corresponds to a predicted class.

- **Predicted across the top:** Each column of the matrix corresponds to an actual class

4.1 System requirement specifications

A system requirements specification (SRS) is a detailed description of a software system to be developed with its functional and non-functional requirements. The System Requirements Specification (SRS) document describes all data, and functional and behavioral requirements of the software under production or development.

It is developed based on Machine Learning algorithms. The software requirement specification document categories: Functional requirements and Non-Functional requirements consistent with all necessary requirements required for project development. A requirement is a statement about what the proposed system does. Requirements can be divided into two majors.

4.1.1 Functional requirements:

Functional requirements may involve calculations, technical details, data manipulation and processing and other specific functionality that define what a system is supposed to accomplish. The Functional Requirements Specification is designed to be read by a general audience. Readers should understand the system, but no particular technical knowledge should be required to understand the document. A functional specification is a formal document used to describe in detail for software developers a product's intended capabilities, appearance, and interactions with users. The purpose of a functional specification is to define the requirements to be implemented by the software solution.

The Functionality of our project is:

- (a). The dataset is given as the input to the system
- (b). It undergoes the preprocessing phase
- (c). In preprocessing phase, noisy data is removed
- (d). Then the problem is identified and notified.

4.1.2 Non-functional requirements:

Non-functional requirements describe the aspects of the system that are not directly related to the functional behavior of the system. Non-functional requirements include a broad variety of requirements that apply to many different aspects of the system, from usability to performance.

- **Efficiency:** We used the machine learning algorithm to get efficient results.

- **Understandability:** Our application is easily understandable by everyone.
- **Accuracy:** Our algorithm gives accurate results that users expect.
- **Usability:** It is very easy to learn and operate the system.
- **Cost and development time:** The cost and development time is very less.

4.2 Feasibility Study

A feasibility study can be considered as a preliminary investigation that helps the management to take a decision about whether the study of the system should be feasible for development or not. The main objective of a feasibility study is to acquire the problem scope instead of solving the problem.

4.3 System Requirements

4.3.1 Software Requirements:

The software requirements are a description of the features and functionalities of the target system. Requirements convey the expectations of users from the software product. The requirements can be obvious or hidden, known or unknown, expected or unexpected from the client's point of view.

- Python Versions: 3.4.x
- Operating System: Windows 8 and above

4.3.2 Hardware Requirements:

The most common set of requirements defined by any operating system or software application is the physical computer resources, also known as hardware. A hardware requirements list is often accompanied by a hardware compatibility list (HCL), especially in case of operating systems. An HCL lists tested, compatible, and sometimes incompatible hardware devices for a particular operating system or application.

- Processors: Intel® Core™ i5 Processors
- Ram: 4GB (or higher)
- Disk Space: 1 TB (or higher)

5 CONCLUSION

A deep Neural Network is a neural network that consists of more than one layer. Each of the layer is used to extract specific features and also helps to make the model focus on relevant part of the image. We used convolution neural network for the feature extraction. It is mostly used for image based data. First the image will be convoluted and

passed to the next layers. model is used for feature extraction from the image, by using deep neural network it takes much time for processing, to produce best and most accurate results. Also the categorical loss will increase layer to layer if we don't drop some features. This cause the model to overfit or underfit. So to resolve this cause we are using Dense Net model. It is a pre-trained model which helps Convolutional Neural networks to retrieve feature extraction from image. For increased accuracy, image classification using CNN is most effective.

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