DETECTION OF BONE FRACTURE BASED ON XRAY IMAGE USING DEEP LEARNING APPROACH

BY

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This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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DHAKA, BANGLADESH

July 2024

APPROVAL

This Research titled **"Detection Of Bone Fracture Based On X-ray Image Using Deep Learning Approach."** submitted by **Jahid Sizan Sani** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. This Presentation has been held on 13 July 2024.

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DECLARATION

I hereby declare that this research has been done by me under the supervision of **Mr Tanvirul Islam, Lecturer, Department of Computer Science and Engineering** Faculty of Science and Information Technology, Daffodil International University. I also declare that neither this research nor any part of this research has been submitted elsewhere for the award of any degree.

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ACKNOWLEDGEMENT

At First, I would like to express my heartiest thanks and gratefulness to almighty Allah for His divine blessing makes us possible to complete the final year research base project successfully.

I really grateful and wish my profound my indebtedness to **Supervisor Mr Tanvirul Islam, Lecturer, Department of Computer Science and Engineering,** Department of CSE, Faculty of Science and Information Technology, Daffodil International University, Dhaka. His Deep Knowledge & keen interest with supportive instructions helped us in the field of deep learning-based research, finally I completed my work on "**Detection Of Bone Fracture Based On Xray Image Using Deep Learning Approach.**". Their endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts and correcting them at all stage have made it possible to complete this project.

I would like to express my heartiest gratitude to **Mr Tanvirul Islam, Lecturer**, Department of Computer Science and Engineering, Faculty of Science and Information Technology, DIU, for his valuable support and advice to finish my project and also heartiest thanks to other faculty member and the staff of department of CSE, Daffodil International University.

At last, again I want to thank all the good wishers, friends, family, seniors for all the help and inspirations. This research is a result of hard work and all those inspirations and assistance.

Finally, I must acknowledge with due respect the constant support and patients of my parents.

ABSTRACT

A well-established paradigm exists for fracture identification in medical imaging. Computer-assisted diagnostic systems (CAD) are used by many physicians and other health care providers nowadays to help them detect a wide range of ailments more accurately by analyzing medical pictures. An osteoarthritis, pressure, or trauma are the usual causes of fractures in bones. Bone, which supports the entire body, is also a hard material. The bone breakage is therefore thought to be the main issue of the past twelve months. The aim of the study is to determine if both of these bones are both shattered and to identify the kind of injury using an x-ray picture. Deep learning-based algorithms were used in this experiment along with two other class types: Fracture and Normal. In order to predict and recognize X-ray images and categorize bone fractures, five models are used: MobileNetV2, InceptionV3, VGG16, VGG19, and InceptionResNetV2. Lastly, two distinct evaluations of efficiency are used to evaluate the technique's outcomes. The first accuracy set, rating performance for fractures as well as normal situations, employs four potential the results: TP, TN, FP, and FN. With its 94.23% accuracy rate, the InceptionResNetV2 technique makes it possible for my proposed method to autonomously recognize femur and tibia fractures in bones. Ultimately, a web prototype is created by classifying data using the InceptionResNetV2 network to identify fracture.

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CHAPTER 1
Introduction

1.1 Overview

Recent open-ended competitions and clinical research have shown that fracture identification has become one of the most often discussed subjects in the field of medical imaging. To lessen the workload in the medical field and provide doctors more time to attend to the patients who are most important, a system that assists doctors in automatically identifying fractures must be created. Software and technological advancements have made the subject of medical image processing more widely recognized as a valid scientific discipline. It is crucial for improving patient care, making diagnoses, and helping medical professionals decide on the best course of action. A growing number of individuals in today's society suffer from bone fractures, among other diseases. It is crucial to identify and address them as a result. Even in the most industrialized countries, fractures of the bones are a widespread problem that are growing more common very quickly. Bone fractures can occur from straightforward accidents or other circumstances. As such, a timely and precise diagnosis may be necessary for any prescribed treatment to be effective. Actually, X-ray scans are the primary method used by radiologists and other medical experts to determine the precise type of fracture and whether it has occurred. Fracture diagnosis requires a great deal of patience and time when utilizing traditional X-ray methods or human inspection. Research has demonstrated that a fatigued radiologists may overlook a fracture picture amidst normal ones. A computer-vision system that looks for hazardous instances in X-ray photographs can notify doctors. The idea of an automated review technique has long been tempting because depending just on humans to tackle such a large challenge has resulted in unacceptable mistakes. According to San Myint et al., there are four steps involved in identifying fractures in x-ray images: segmentation, preprocessing, classification, and fracture detection. Using a clever edge detector, it also explains how to get the best possible data from a bone picture for segmentation. Using the Hough transformed method, features are extracted for line detection [1].

To quickly and accurately diagnose bone fractures, M. S. Mallikarjunaswamy as well as R. Raman focused on creating an effective image-processing-based approach that can use data from CT and x-ray images. Feature extraction, segmentation, edge detection, and pre-processing were among the image processing techniques used by the researchers. MATLAB 7.8.0 was utilized as a programming tool to divide the bones into cracked and non-fractured categories and evaluate the precision of various techniques. According to their claims, the system could identify fractures in bone with an accuracy rate of 85% with very minor performance constraints.

The fractures pertaining to the femur and tibia can be found using a variety of DL methods. The suggested model includes segmentation feature extraction, classification, first processing, and picture capture. For most of a process sequence, there are several different approaches available with deep learning (DL) and statistical picture analysis. To effectively detect a fractured bone, these procedures must be followed while comparing drawings. First, you need to get damaged JPG, PNG, and Tiff photo files and scan them to start educating the computer. The x-ray pictures that display the broken bone are the first results that the machine displays. Thereafter, the energy density of the original JPG file type was modified further. As mentioned before, the development of an autonomous technological devices technique to detect bone fractures is essential for better medical progress and effective fracture classification. Among the techniques used to classify bone fractures include the prevalence of the Internet of Things, computational imaging, and big data. The benefits of the DL techniques are also shown for this purpose. Because of deep learning technology, the system is able to learn on its own and generate opinions. It is possible to differentiate three different kinds of networks of neurons for deep learning: reinforcement learning, learned learning, and unsupervised learning. Numerous cutting-edge deep learning algorithms have been trained to identify bone fractures by this work; these methods will also do the classification task.

This essay's topics are the tibia and femur. Following image identification, a variety of processing techniques are applied to solve the particular difficulties presented by the authentic bone fracture images in order to achieve a number of goals. The following goals can be accomplished via photo analysis:

- Determining fractures from bone x-ray images.
- Applying the measurements derived from DL models to ascertain the fracture's severity.
- Building a web prototype to determine if an x-ray is broken or not

1.2 Problem Statements

Combining and evaluating all of these authentic data sets seems to be the main task of this endeavor. A range of tools and methods were used to clean up and standard the dataset. In light of the size of the datasets and the fact that they included several layers from various eras, we had to wait a long time to see the final product. More sources of datasets in this field are accessible. Since we didn't conduct the research, I have to put a lot of work into every task, which makes it challenging for me to quickly identify the best responses. Maintaining this enormous amount of information and getting it ready for classification proved to be another challenge when using DL models to categorize the constituent components of the fractures in bones in an online prototype.

1.3 Objectives

Modern times have seen a significant improvement in technology. Innovation can help address any problem. As a result, a lot of research is being done to help the medical industry expand. The worst thing wrong with the healthcare system right now is the bone imaging X-ray. The human body is capable of taking on many different forms. The primary goal of this work was to use deep learning techniques to identify fractures of the tibia and femur. The primary objective entails anticipating the x-ray fracture in order to accurately classify different types of bone fractures. Numerous kinds of fractures in the bones, both typical and abnormal. My objective is to use deep comprehension and image analysis to detect bone fractures in x-ray images. As a result, I became able to establish the following goals:

- To assist patients and the medical field.
- To use deep learning to predict the two types of fracture pictures.
- To compile information that will help predict fractures.

1.4 Motivation

I was drawn to creating products for the medical industry because it is the most crucial aspect of all medical sites. In my opinion and that of the system, the medical field significantly affects every category of illness, including bone fracture. I became a medical professional because of this, treating patients with x-ray-related bone fractures using AL and DL. It took me some time to think of the subject matter that would meet the requirements of the research. Thus, I went to one of my respected professors for guidance. Given the prevalence of fractures in bones damage from x-rays in today's surroundings, it was recommended that I look into a comparable concept. I was ecstatic to decide to focus my research on the medical sector. This is why I chose to write a paper on " Detection Of Bone Fracture Based On Xray Image Using Deep Learning Approach." In addition, I see that society is applying current discoveries to advance the medical sector and that scholars are delving further into the medical domain in an effort to expand upon my own. We were inspired to carry out this type of research-based activity by the following. Since artificial intelligence has connected everything around me, deep learning is crucial.

1.5 Research Question

With a lot of passion and work, this study has been finished. This was a really difficult task for me. Many obstacles stand in the way of creating an accurate, practical, and equitable system. Scholars are interested in knowing the answers to the following important questions so that they can look into this topic more thoroughly and analyze these concepts:

- Have I used raw image data for my deep learning research?
- Have I examined this raw dataset?
- Is it possible to use a deep learning approach to prepare the data beforehand?
- Can patients benefit from this research and these techniques?

1.6 Expected Outcome

Some realities have been included in this portion as they have the most fundamental intended consequence of mine. For the purpose of further research and to predict the actual fate of a bone fracture, a number of techniques for classification are being used to classify the tibia and femur fractures. The objective of this research-based project is to create a thorough, effective approach or strategy that uses a prediction algorithm developed on an unprocessed dataset to identify bone fractures in x-ray photos. As a result, the list of each of the anticipated outcomes that were previously discussed is as follows:

- Based on the analysis of the bone, I will show that the tibia and femur have fractures.
- A deeper comprehension of the procedure for identifying fractured cartilage from x-ray images using DL.
- I want to use out-of-date photo data to compare my results with those of earlier research.
- Depending on the data provided, determining which CNN model with DL is most effective in spotting bone fractures in x-ray pictures.

1.7 Report Organization

The first chapter provided an overview of the study's methodology, including its objectives, sources of inspiration, purpose, and expected outcomes. The overall framework of the inquiry is also described in this section.

The prior achievements in this field are discussed in Chapter 2. The last section of the second chapter continues to show the depth that arises from this subject's limitations. A brief discussion is given of the primary obstacles or restrictions on the research. This chapter addresses the issue, outlines the obstacles that must be overcome to complete the objective, and includes sections on related literature.

The conceptualization of this research endeavor is explained in Chapter 3. More details on the statistical techniques applied to address the investigation's theoretical component may be found in this chapter. This chapter also provides examples of the procedural methods to deep learning technology. The next chapter describes the process for obtaining datasets and the data preparation system. Confusion matrix analysis is also included in the latter portion of this subdivision in order to assess the method and show the accuracy tag of the classifier. To ensure true accuracy while using deep learning approaches, implementation analysis must be included. This section addresses a number of subjects, such as the study topic and tools, workflow, data processing, data collection technique, suggested model, learning approach, and operational needs that have to be fulfilled in order to construct this project. Every DL methodology and classification used in this study has a detailed description supplied for each method.

Chapter 4 presents the experimental results, performance evaluation, and result discussion. A few test photos are included in this section to aid in the project's implementation. An review of the use of methods for deep learning concludes this chapter.

Chapters 5 and 6 included an overview of the study, information on planned activities, and a discussion of the findings. To show whether the undertaking report complies with all standards, this chapter offers a verified example. Effects on the Environment and the Entire Society: The chapter ends by pointing out the inadequacies of my current initiatives, which might influence future employees with comparable goals.

CHAPTER 2
Background

2.1 Overview

This section's primary subjects include the study results, difficulties, relevant literature, and research summary. Under "related Works," I will look at research articles that have been authored by other authors and talk about the relationships between their concepts, correctness, and methodology. I will talk about the articles, methodologies, and reliability of other academic publications that are pertinent to my research in the section focused on comparable works. A synopsis of my relevant work will be included in the section on research descriptions. I explain how I overcome every obstacle I encountered while conducting the investigation and how, even in the most challenging sections, I improved each stratum's dependability. Everything has previously been looked into.

2.2 Related Works

Classifying x-ray images of bone fractures has been a laborious process. Below is a summary of many techniques that have been studied by many researchers for identifying fractures in bones.

An innovative technique for identifying fracture locations in X-rays was presented by Ma and Luo [2]. A recently developed classification network called Break-sensitive artificial neural network (Crack Net) can properly identify and categorize fracture lines. The suggested method could find a broken bone and pinpoint its position in an X-ray picture. Medical personnel can identify a bone fracture with its help. a method for diagnosing fractures using muscle imaging and training. Following 375 comprehensive testing on the Radioed dataset, the suggested procedure outperformed alternative approaches in terms of overall accuracy (88.39%), recall (87.50%), and precision (89.09%).

A research on categorized bone fractures employing deep learning and machine learning was carried out by Karanam et al. [3]. Fractures were assessed, categorized, and recognized using InceptionV3, SVM, random forest modeling, K-nearest neighbor (KNN), and ResNeXt101. Test results were improved by 93.75% using ResNeXt101. The proposed method aids in the diagnosis, classification, and treatment planning of fractures by radiologists and other medical professionals. According to studies, most thinkers are interested in analyzing bone splits; nonetheless, a few researchers have recently developed an interest in classifying bone fractures.

Zhou and colleagues [4] introduced a Faster R-CNN-based method for the automated identification and categorization of rib fractures. This approach succeeded in achieving three objectives: an efficient mechanism, fracture recognition and classification, and model robustness. The more powerful R-CNN outperformed the YOLO V3 algorithm according to the study's measurements for accuracy overall detection speed. This investigation demonstrated impressive success with an accuracy of 91.1% and sensitivity of 86.3%.

A fracture diagnosis and classification method employing X-ray images was described by Hrzˇic´ et al. [5]. Local entropy was employed in this technique to reduce noise in X-ray pictures. A rotating 2D window was used to calculate the local sensitiveness of Entropy for each pixel in the picture. Following the segmentation of the original picture, images were processed using graph theory to improve edge recognition and remove negative bone outlines. Ultimately, the fracture was identified and classified by computing a difference between the recovered and predicted outlines. 91.16% is the rate of discovery and 86.22% is the average accuracy according to the study.

Many line-based fracture detection techniques were established by Yang et al. [6]. These techniques included adaptive progressively variable maximum (ADPO) line-based bone recognition utilizing X-ray pictures, as well as traditional line-based detection. Artificial neural networks, also known as ANNs, are used for fracture classification and property extraction from observable patterns in order to distinguish a broken line from the nonfracture line. The average accuracy of the ADPO-based fracture identification approach was 72.89%, which was better than the conventional line-based fracture detection method.

In a different research, Castro-Gutierrez et al. [7] suggested using SVM for identifying and categorizing of acetabulum fractures in combination with a feature extractor based on the local bipolar pattern (LBP). This method enhances the quality of the images through the preprocessing stage, which facilitates the management of low-resolution images. Overall uniformity, according to the research, is 80%.

Kim and colleagues' study [8] set out to determine the efficacy of pretrained deep learning systems on non-medical pictures for fracture diagnosis and classification. The Lucid version 3 structure's top level was retrained to recognize fractures using wrist radiographs. With an 88% efficiency, the model was effectively trained eight times utilizing 11,112 X-ray pictures. In a different research, D.P. Yadav [9] created a classification system that can identify and group bone fractures. The procedure of developing an artificial neural network for identification and photo augmentation for preparation are the two main stages of the system. The approach proved to have a high categorization rate when evaluated on pictures of bone fractures.

According to Tanzi et al. [10], bone fractures were evaluated using artificial intelligence algorithms. Both the Haar wavelet transform and the scaled inverse frequencies transform (SIFT) were applied in this method. Memory space is preserved by applying Haar wavelet changes; compression, which entails rotation and scaling of characteristic points, is identified using the SIFT technique. The dataset for the study consisted of all 100 X-ray pictures in the collection. After training on thirty X-ray images, the model was evaluated on 70 X-ray images. Area beneath the curve, sensitiveness, specificity, accuracy, and other modern assessment metrics are used when assessing the model. The study asserts an average accuracy of 94.30%.

For the purpose of evaluating rib fractures, Jin et al. [11] created the Frac Net model, a modified 3D U-Net architecture. The components of this architecture are data unpredictable behavior, encoder-decoder, 3D convolution, which is max pooling, and bath-normalization. 420 photos from the Rib Frac data set were used as training data and 120 photographs for testing, in order to train the previously described model. 92.9% was the sensitivity level and 71.5% was the segmented Dice percentage that my approach produced for the test cohort.

To sum up, there is still more study being done on computer-assisted fracture classification and detection. Obtaining an evaluation that's quick, precise, and reasonably priced is still dependent on the qualifications of the radiologist, though. The literature makes it clear that earlier research was inaccurate and unreliable. Furthermore, unlike the suggested method, there isn't a methodical manner to find the fracture fast. In order to utilize a web application to classify bone fractures, I employed five different models—InceptionV3, VGG16, VGG19, MobileNetV2, and InceptionRestNetV2—to forecast and recognize X-ray pictures.

2.3 Research summary

I spent a lot of time researching the many tactics that society offers. A deep learning-based system was recently used to categorize x-ray photographs into five different categories and diagnose bone fractures. I used a variety of methods on my real dataset. In this case, the raw dataset, which I assembled from raw data from multiple hospital sources, served as the main source of information. I'll be able to assess the reliability of the five methods I used as well as study components like the importance of the extra data I provided using the same source. The new dataset is an identical duplicate of the earlier dataset it was joined with. By classifying them into related categories and classes using tags, it is feasible to explain what they represent. Python was the major engine of choice for my feature extraction methods, which used CNN and DL algorithms for web application categorization.

2.4 Challenges

In this research, organizing visual data proved to be too difficult, therefore the primary challenges are not only interpreting what is presented but also acquiring it. We had a difficult time learning about this issue without often attending the hospital to collect data and go through the hospital database. Several methods and technologies were employed to clean and normalize my dataset. With multiple layers and varying epoch scopes, the large datasets took a long time for my computer system to handle. I so had to endure a drawn-out wait to find out the conclusion. The previous datasets on this topic did not accurately reflect my understanding after multiple tests and field research from government agencies, so I had to obtain datasets from actual field hospitals. I had to spend a lot of time figuring out the best ways to finish the assignment swiftly because I had never done research before. Similar to the last example, using DL models for classification led to preprocessing issues with the image data.

CHAPTER 3
Research Methodology

3.1 Overview

The section that follows provides a detailed explanation of the techniques and strategy I employed to classify the many disease categories I examined. The data collection and analysis, together with the suggested model—which is further elucidated by the pertinent computation, graph, table, and explanation—are the primary components. The best accuracy for the study was obtained by splitting and predicting using both my real field dataset and the DL categorization framework. I gave an overview of my statistical assumptions in the chapter's last part. I used two different class types for creating my representations for this experiment. I focused my research on the two main sickness classes—fracture and normal—despite the fact that x-rays can identify additional kinds of bone fractures. Regular x-ray images and bone x-ray images are not the same. In the current study, two different class kinds used all of the participant images to deliver training.

3.2 Requirement Analysis

An area of research that is currently being looked at and explored to clarify ideas for creating models, accomplishing objectives, gathering information, managing, providing instruction, and enhancing performance is called a researched subject. I talk about the instruments and processes I use for measuring. Along with Microsoft software and Python programming, NumPy was utilized in the development of Sk-learn, OpenCV, and other apps. Only testing and training uses are made of the infrastructure at Google Co Lab. Programmers at Google's Colab may write Python-based data mining along with advanced learning algorithms.

Used libraries of all kinds:

- **Matplotlib:** The visualization features of Matplotlib include a collection of techniques called Py-plot graphing. Creating forms is one of its many uses; it helps in plotting borders and identifying lines within a plot, for example.

- **NumPy:** Dealing with matrix in Python is a popular way that may be achieved by utilizing the NumPy package. Covered are matrices, the Fourier transform, and the basics of linear algebra. To make dealing with matrices of various sizes easier in Python, the NumPy package offers resources and tools. Thanks to NumPy, arrays may be built correctly and scientifically. NumPy is a Python package that is used for numerical calculations. "A broad range of varieties Python" is another word that it employs.

- **Sk-learn:** This tool for forecasting data analysis is practical and user-friendly. Open-source software is available for anybody to use and modify to their own specifications. Through expansion, Matplotlib, SciPy, and NumPy were used.

- **Seaborn:** This well-liked data visualization tool is recognized for its history of integrating with matplotlib and for being an easy-to-use tool for creating visually striking and compelling data representations.

- **CV2:** To solve computer vision issues, a set of Python bindings known as OpenCV-Python was developed. It also makes it feasible to identify individuals, possessions, and even handwriting inscriptions by analyzing images and movies.

- **Job-lib:** This more efficient method of avoiding repeating the same computation might save a significant amount of money and time.

- **H5py**: The h5py package offers a Python wrapper for native HDF5 data. Large amounts of quantitative data may be easily handled and stored in HDF5 with the help of NumPy.

- **OS**: Producers can use the range of tools provided through the Python OS aspect to interact with the program that constitutes an aspect of the machine that they are working on.

- **TensorFlow:** This free Python mathematics framework makes the creation of neural networks and self-learning techniques easier and faster.

3.3 Proposed Methodology

There are a number of methods or strategies that may be utilized to figure out how to evaluate the data that was used in this inquiry. The present study used a multi-step technique comprising model selection, creation, data collection, model expansion and improvement, and production.

Step 1: Data Collection: To create my own trustworthy data collection, I collected raw data on statistics from hospitals and analyzed it. There isn't a big, complete dataset available in this region because it is challenging to find the dataset and acquire data for the particular bone fracture using x-ray images of both the tibia and femur.

Step 2: Data preparing: Every type of data was gathered in its unprocessed state from diverse medical sources and managed independently. Numerous data sets may have errors including noise. Technically speaking, I absorb the material first before using the selected data set to move on to the next stage.

Step2: Preprocessing the data: After analyzing each class, the findings were cropped and kept expanding. To make it function, I had to add data and resize. Because I was worried about excessive fitting, I limited the overall amount of increases I made to the largest and most acceptable ones.

Step 4: Selecting Models: Once you've made your choice, use the provided data to train and assess the selected model to increase accuracy. A wide variety of models are used by DL. My equipment was used to try several iterations of the concept before determining which configuration to use for data calculating accuracy.

Step 5: Evaluation of Performance: A discussion of each result is given in this section. After testing and training, these tactics provided us with an insufficient level of reliability for the next two courses. Along with creating an online tool for diagnosing bone fractures using x-ray pictures, they also created a f1 measuring graphic, confusion matrix, recall, and efficiency.

Step 6: Closing Reflections and Upcoming Initiatives: In the part that follows, there is an improvement timeline and summary.

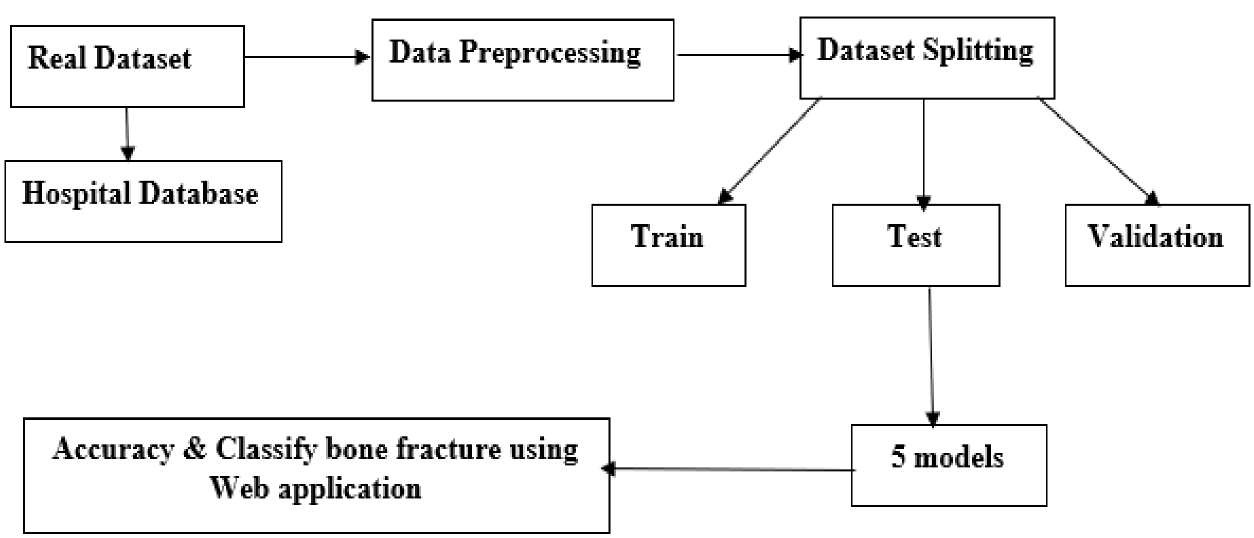

Fig 3.1: The suggested model for the entire study endeavor.

Bone fractures have been classified using the basic concept, as Figure 3.1 illustrates. It is necessary to initially gather raw data from all hospital categories in order to create a dataset. Subsequently, the picture has undergone resizing, tagging, classification, and data augmentation. The machine might then obtain this data after that. I may use this knowledge to train, test, and validate my suggested deep learning algorithms using fresh, real-world datasets. Using x-ray pictures, tibia and broken femurs may be recognized with the smallest precision of DL representations due to the algorithm's accuracy and the web application's precision.

3.4 Data Collection

I've put together a collection of 519 pictures. Real datasets were provided to me by Dhaka Lab Aid, Rangpur Prime Diagnostic Center, Bangladesh Spine and Orthopedic Hospital, and Dhaka itself. The dataset is split into two distinct groups: non-fracture (normal) and fracture, depending on the kind of fracture. The two categories are Normal and Fracture (tibia and femur). There are 305 photos in the fracture class and 214 in the normal class. 20% of the data remains to be categorized as train, and the other fifty per cent is divided into test & validation.

Fig 3.2: Fracture X-ray data.

Fig 3.3: Normal X-ray data.

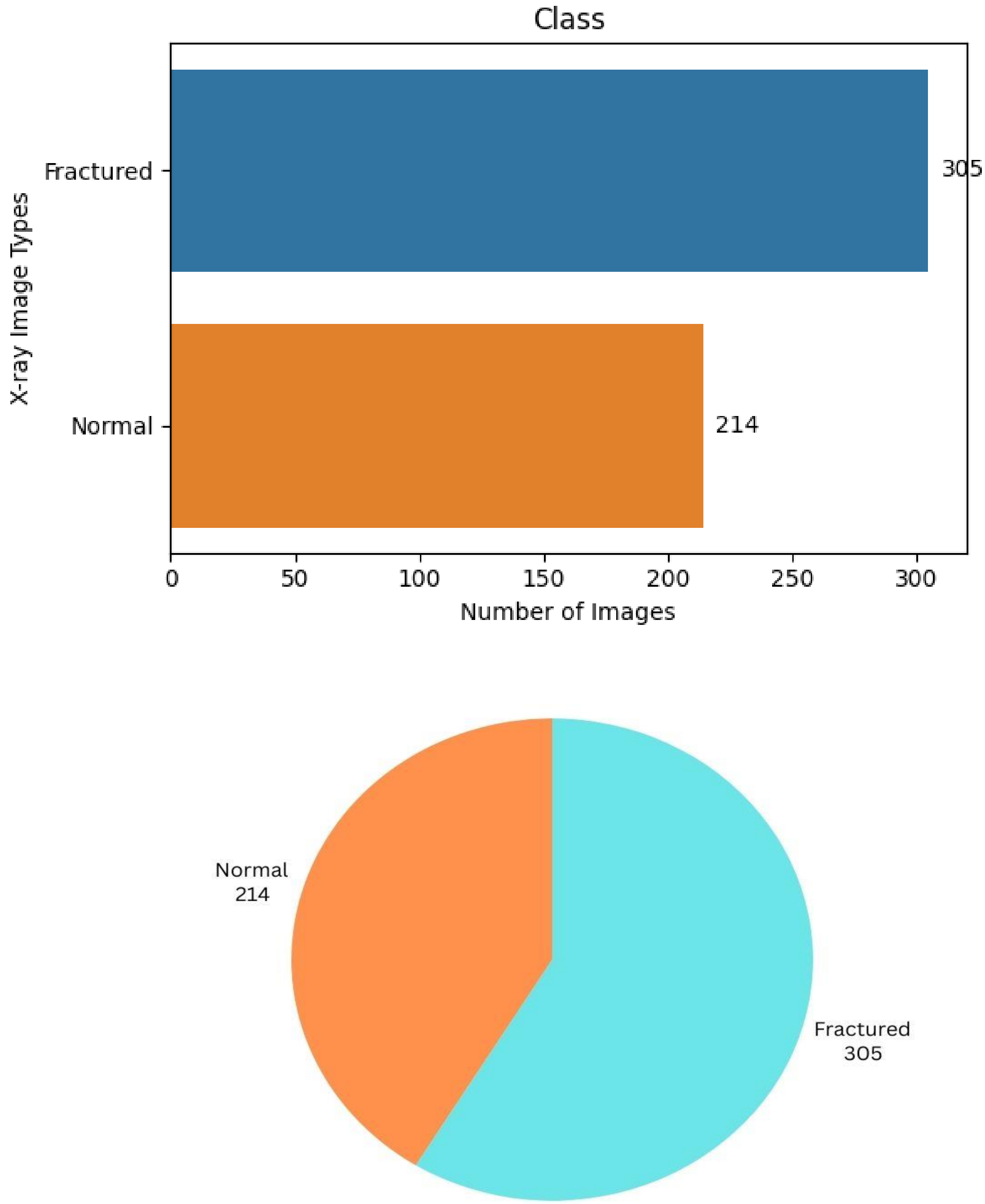

Fig 3.4: Two classes are present in the data.

Table 3.1: Table of Dataset

Classes of Data	Quantity
All Image	519
Fracture	305
Normal	214

Label Maker:

When working with datasets that include a lot of tags spread over several columns or in just one column, methods based on deep learning are commonly applied. These identifiers may take the form of words or integers. Words that identify the subject being learnt are commonly employed in an effort to simplify the material easier for individuals to read. The process of turning tags into a simple numeric format that computers can read is known as encoding. Label coding is one of the processes in this process. DL algorithms have the last say on their decision to use these labels. For uncontrolled training, it is imperative to implement the dataset design stage.

3.5 Statistical Analytics

3.5.1 Data manipulation

The primary component of data is manipulating it. It is important to consider the data processing method used during a data collection. In particular, refined data is useful when interacting with actual data. I'll be visiting hospitals to gather data for my study on typical x-ray images and tibia and femur fractures. After that, the data was combined with information obtained from real medical areas to create a large dataset consisting of two distinct groups. The effectiveness of a dataset change is often determined by the data processing done initially. Results generated with greater expertise will be more accurate. An analytical system has two phases: data replacement and data collecting. Stated differently, it is the main barrier to this type of study-based activity.

- **Data preparation and accumulate:** Every photo in the collection of photographs I utilized was created by combining raw field data that was gathered from medical institutions and had varying widths and heights. My model requires a specific quality for every image; therefore I used an altered script to compress the picture to a constant 224 × 224 pixels. In addition, I have added the suffix "jpg" to every image in my model before processing it. I edited the photos after data augmentation in addition to splitting them and getting them ready for categorization. I used the split version of all the datasets to train the framework because of this.

- Photos with fixed sizes based on codes.
- File types being converted to JPG.
- Remove any inaccurate images.
- Removed images that were useless

```
[ ] print("The classes:\n", np.unique(df['label']))

The classes:
 ['Fractured' 'Normal']
```

Fig 3.5: Two x-ray classes.

Fig 3.6: Bone of X-Ray and label classes: Normal & Fractured.

3.5.2 Data for Training, Testing and Validation

In the popular topic of deep learning, researchers are developing methods for extracting data from documents and producing results based on that information. These algorithms use the incoming data to form an equation, which they then use to interpret or derive conclusions from the data in order to accomplish their goals. These inputs are often separated into many data sets before being utilized in the model-building process. When developing a model, three distinct data sets are usually used: train, genuine, and test. Split the first training dataset in half; the test and validate segments should be 50% and 50%, respectively, and the train segment should be 20% and 80%.

3.5.3 Model of classifying

1. **InceptionResNetV2:** Starting off ResNetV2, a neural network architecture, is the result of combining the following additional deep neural network designs: Inception and ResNet. It is an extension of the Inception architecture with residual relationships, a key feature of ResNet. InceptionResNetV2 was presented by Google researchers as a network belonging to the Inception group. It is well known for exhibiting remarkable capabilities in several artificial intelligence applications, including as classifying pictures and identifying objects. When used to theImageNet massive amounts visual recognition contest (ILSVRC), it demonstrated state-of-the-art performance. Keeping in consciousness that Inception Res Net is a fairly huge and computationally expensive model, its use may be more common in research as well as applications where computing resources are not a major constraint.

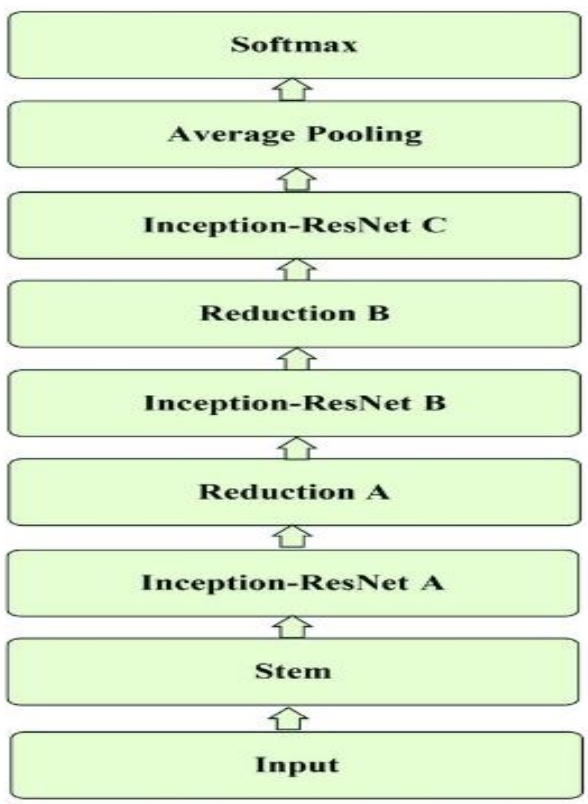

Fig 3.7: The architectural model of InceptionResNetV2. [22]

2. **InceptionV3:** For image identification and classification, CNN InceptionV3's architecture is used. It is a part of the collection of Inception DL concepts that the personnel of the firm came up with to go forward. The InceptionV3 gadget is renowned for its elaborate design and innovative application of the "Starting section," a special feature that improves the system's overall efficacy and accuracy. 48 layers make up the architecture of the InceptionV3 neural network that is deep. Combinations include convolutional layers, fully connected layers, extra classifiers, and levels with optimum pooling. The periodic mixing & multilayered random of the Creativity module (1x1, 3the quantities of x3, which constitute as well as 5x5) allow networks to collect data at multiple degrees of abstraction.

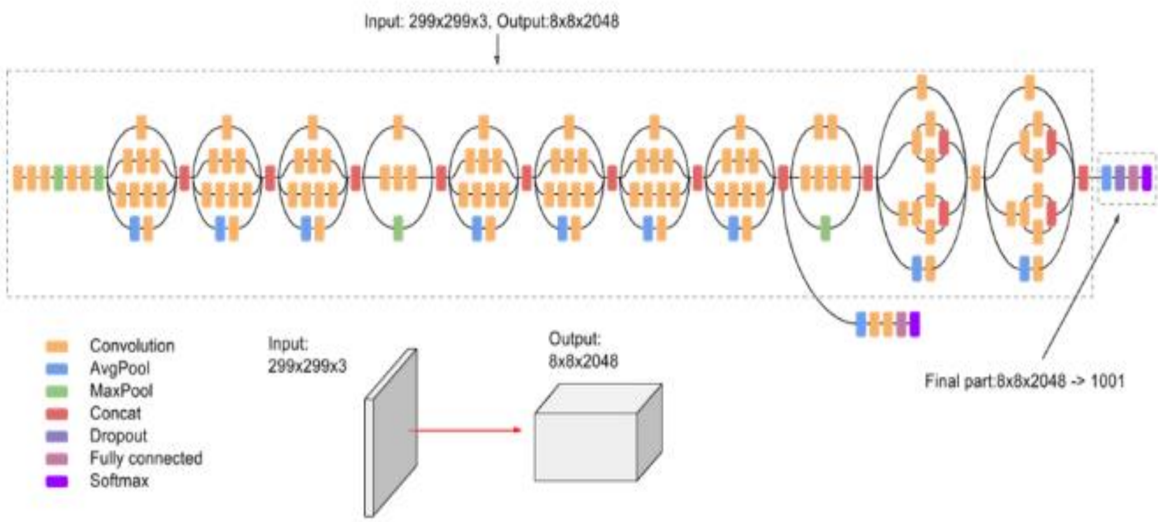

Fig 3.8: The architectural model of Inception V3. [23]

3. **MobileNetV2:** MobileNetV2, a neural network architecture, was developed for resource-constrained portable and device edges. Google researchers developed it to offer a small and powerful model for applications involving computer vision such as object detection and image categorization. MobileNetV2, an improvement over the original Mobile Net, includes new features to boost efficiency. MobileNetV2 makes extensive use of depth-wise distinguishable convolutions in general which are made up of a convolution with depth and a 1x1 pointwise convolution. This separation has a significantly reduced computational cost without compromising expressive capability as compared to ordinary convolutions. All of MobileNetV2's architecture is contained in the first full layer of the convolution with thirty-two filters. There are 19 remaining bottleneck levels that come after it. At the end of the

network, a global mean pooling is typically employed instead of fully connected layers. There are hence fewer parameters, which aids in preventing overfitting.

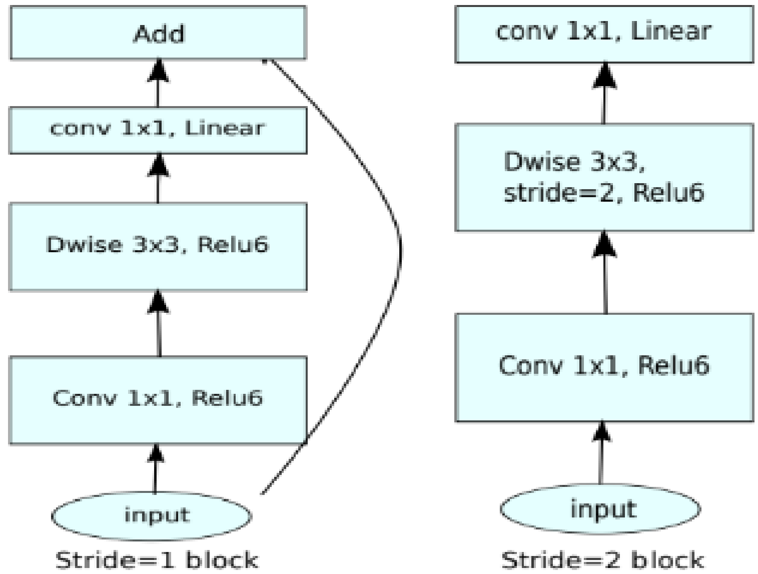

Fig 3.9: The architectural model of Mobile NetV2.[24]

4. **VGG16:** The VGG model—also referred to as VGG Net—is referred to as VGG16. Utilizing sixteen-layer convolutions (CNNs), the algorithm is a neural network. The ImageNet database includes pretrained neural networks that have been trained on over a million photos. Using 1000 different item categories—including a computer mouse, keyboard, pencil, and other animals—the pretrained network is able to categorize photographs. Hence, a vast array of visually rich feature representations have been taught to the network. The network could manage an image source size of 224 × 224. Go to MATLAB's Initially taught Recurrent neuronal network models for more pretrained network options.

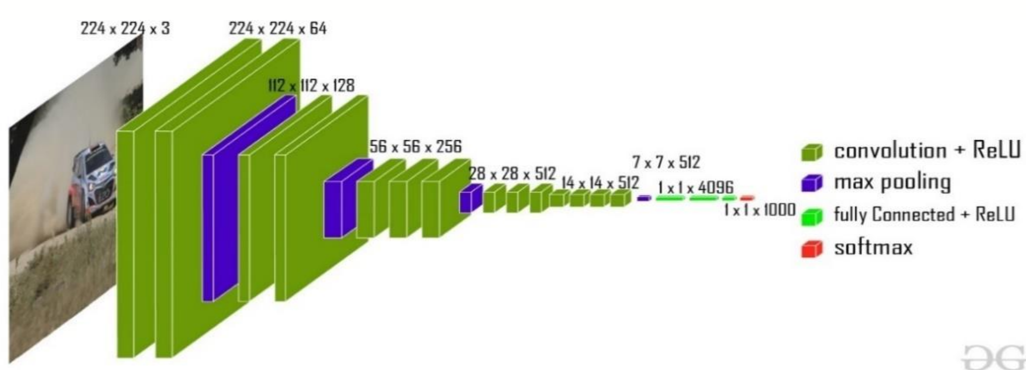

Fig 3.10: The architectural model of VGG16.[25]

The network receives an image with the dimensions (224, 224, 3). Sixty-four channels with the same padding and a 3*3 filter area are included in the first two levels. The stride (2, 2) max pool layer will be followed by an additional layer that has convolution layers with 128 filter measures and filter size (3, 3). Next in sequence is the greatest pooling layer with the highest frequency (2, 2), which is identical to the one that came before it. A set of 256 filters follows two convolutional layers with filtered thicknesses of three and three. A max pool layer comes after two different sets of three separate layers are added using convolution. All 512 filters have the same padding and are of the same size (3, 3).

5. **VGG19:** One SoftMax layer, five Max Pooling layers, three fully connected layers, and nineteen convolutional layers make up the VGG19 model, which is a variation of the VGG model. Given that this network was given an RGB picture with a predetermined dimensions of (224 * 224), the matrix's composition was (224,224, 3). The mean RGB value of each pixel, which was determined throughout the training set, was removed as the single preprocessing step. They were able to fill up the whole picture by using kernels that had a stride approximately one pixel and a size of (3 * 3). The pic's depth depth was preserved by using spatial padding. Attaining maximum pooling included using Speed 2 across 2 * 2.-megapixel panes. After then, the altered uniform unit (ReLu) was used to improve model classification, accelerate computing, and boost non-linearity. The ReLu turned out to be noticeably better than previous models, which relied on sigmoid or tanh functions. A total of 4096-sized layers were created, three of which were fully linked. A final layer known as the soft max functions and an additional layer with an associated channel frequency of 1000 added for a 1000-way categorizing are present.

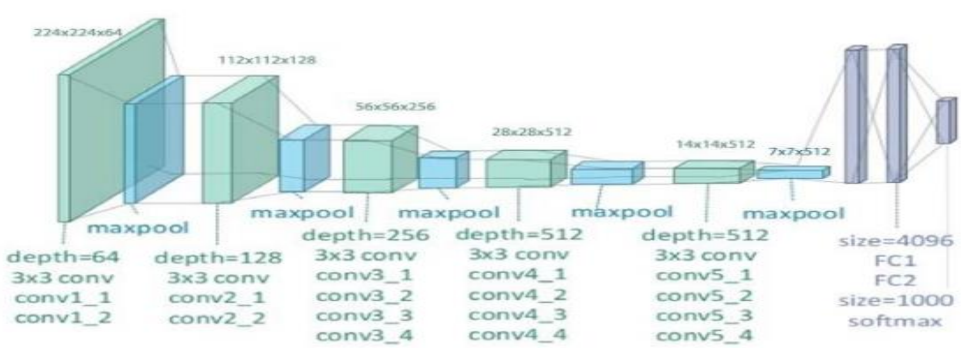

Fig 3.11: The architectural model of VGG19.[26]

3.6 Implementation

The data set must be applied after completing all subsequent processes in order to guarantee accuracy. To make it easier to execute, I separated the work into its most crucial parts. I have to follow these instructions to make sure that my work is completed appropriately.

- Actual collections of datasets.
- Actions taken before processing an image
- Class image prediction.
- The algorithms that are being used.
- X-ray image classification with InceptionResNetV2
- Review the outcomes and correctness.

I have to visit hospitals like Bangladesh Spine and Orthopedic Hospital, Rangpur Prime Diagnostic Center, Dhaka Lab Aid, and others to get x-ray images of the injured and normal tibia and femur bones in order to obtain trustworthy data from a good dataset. I then got to work on the preparation of the data. In this case, I eliminated any extraneous elements from my data, such as noise, incorrect images, incorrectly scaled images, etc. I also use data generators for the longer data train, test, and validity periods.

Before putting the notion into practice, I began experimenting with the coding. I assessed each of the five employed algorithms' accuracy. After the procedure was finished, I evaluated its accuracy. I assessed the accuracy and determined which would be most beneficial for my needs. This has shown to be fairly reliable in identifying bone fractures based on x-ray data. A comprehensive analysis of all relevant mathematical and philosophical ideas and techniques has resulted in the formulation of a set essential prerequisites that are required for any attempt at picture classification. The following results could be required:

1. Hardware and Software Requirements

- Operating Systems: Windows 7 or later;
- Hard Drive: 1 TB or more;
- RAM: 4 GB or less

2. Tool Development

- Environment of python
- PyCharm.
- Google Colab.

CHAPTER 4

Experiment Results and Discussion

4.1 Overview

This section explains how a bone fracture happens using a classification system for x-ray pictures. The processes in the process of producing the model were gathering the images, assessing the information, honing the information, modifying the amount of information, presenting models, and providing advice based on the accuracy of the model. The findings of the study are presented and discussed in this chapter.

4.2 Experimental Result

Using x-rays, several algorithms have forecast the identification of bone fractures. Consequently, I utilized multiple strategies. I evaluated and thought through a number of options before deciding on the best plan of action for the experiment. I tried a number of different approaches to improve the caliber of my work. utilized raw field hospital datasets that were gathered for two courses. The two sets of photographs are the ones with normal bone x-rays and the ones with femur and tibia injury.

I made use of Python libraries, content classification strategies, and pre-existing dictionaries. Considering the deep learning technique looks at the two varieties of fractures in bones such as tibia and femur, the dataset is pertinent. Once more, deep learning has been utilized in this study to employ Python deep learning (DL) models for classification in order to identify the appropriate types of bone fractures from x-raw pictures. developing a web application to analyze x-ray images and determine whether or not something is damaged.

4.3 Descriptive Analysis

The results I got varied according to the classification strategies I used. I have used five different DL algorithms to pinpoint the exact location of the fractured bone using x-ray images. I used 20 epochs and the deep learning techniques InceptionResNetV2, MobileNetV2, InceptionV3, VGG16, and VGG19, which have shown promising results for the accuracy of x-ray bone fracture. The data set used by all the models was the same and included both publicly available data and my own dataset, which I took directly from hospitals after determining which dataset fit the model the best. After finishing the dataset procedure, I used Mat-lab's pre-made libraries to assess the algorithms' correctness. I forecasted x-rays using web prototypes as well.

Table 4.1: Table of Accuracy

Models	**Accuracy Score (AUC)**
InceptionResNetV2	94.23%
MobileNetV2	80.77%
InceptionV3	82.69%
VGG16	90.38%
VGG19	86.54%

The efficacy for many models is shown in the ensuing section. Two open-source programs were used in the procedure: PyCharm and CoLab. There were five models in total: InceptionResNetV2 with 94.23%, MobileNetV2 with 80.77%, InceptionV3 with 82.69%, VGG16 with 90.38% and VGG19 with 86.54% accuracy. With an accuracy of 94.23%, the InceptionResNetV2 models performed the best.

Table 4.2: Classification Report of InceptionResNetV2's.

	Precision	Recall	F1 score	Support
Fractured	1.00	0.90	0.95	29
Normal	0.88	1.00	0.94	23
Accuracy			0.94	52
Macro avg	0.94	0.95	0.94	52
Weighted avg	0.95	0.94	0.94	52

In Table 4.1, show the classification report of InceptionResnetV2. There shows Precision, Recall, F1 score and Support for Fractured and Normal class.

Additionally added Accuracy, Macro avg and Weighted avg.

For Fracture, Precision 1.00, Recall 0.90, F1 score 0.95 and Support 29. On the other side for Normal, Precision 0.88, Recall 1.00, F1 score 0.94 and Support 23

Accuracy of the IneptionResNetv2 model 0.94, Macro avg 0.94 for Precision and 0.95 for Recall and Weighted avg 0.95 for Precision and 0.94 for Recall.

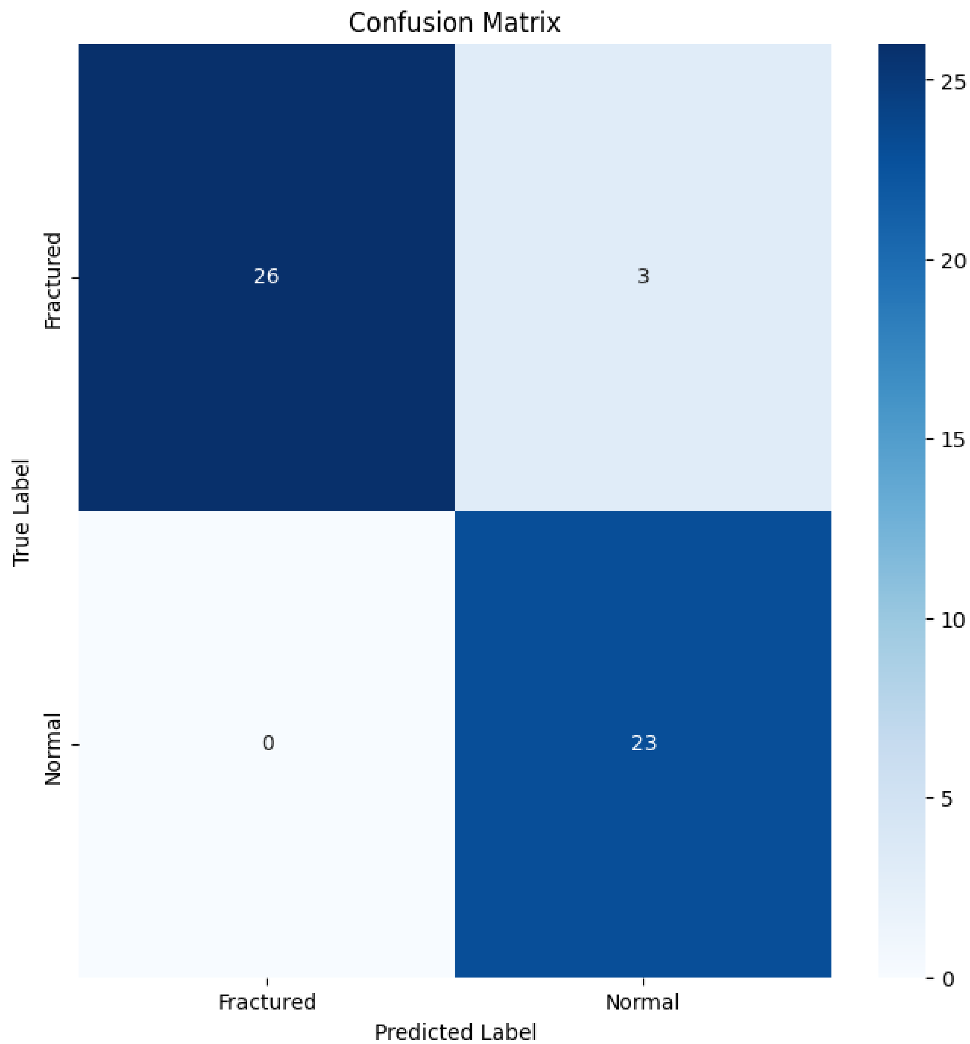

Fig 4.1: Confusion matrix of InceptionResNetV2's.

Just the full categorization result for the InceptionResNetV2 models is shown in order to get the highest accuracy.

Fig. 4.2 below shows the steps involved in using the CNN technique InceptionResNetV2 model to create a viable web-based application and categorize a particular type of x-ray fracture. Figures 4.3, 4.4, and 4.5 show the two formats of an x-ray images—Normal and Fractured—that were correctly predicted by an online application that made use of InceptionResNetV2. Generally speaking, one of the several least supervised techniques for identifying things or prediction is deep learning.

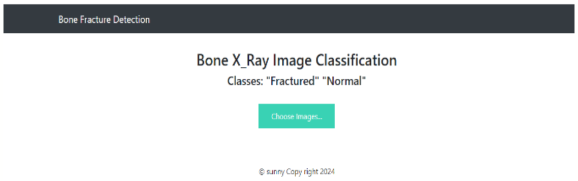

Fig 4.2: Web application prototype for categorizing X-rays

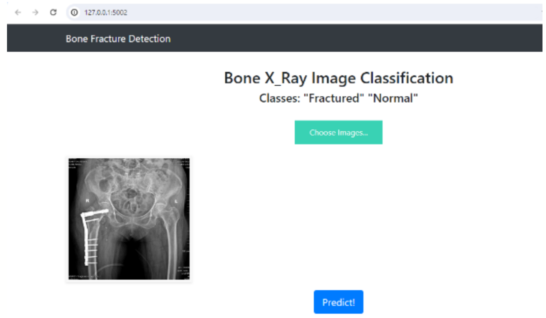

Fig 4.3: A prototype of an online application to choose photographs

Fig 4.4: The fractured x-ray classification of a web application prototype

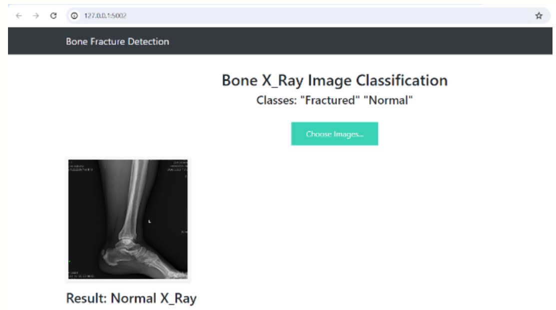

Fig 4.5: The normal x-ray classification of a web application prototype

Figures 4.6 and 4.7 below show the InceptionResNetV2 models' train and validation accuracy as well as loss at an epoch of 20.

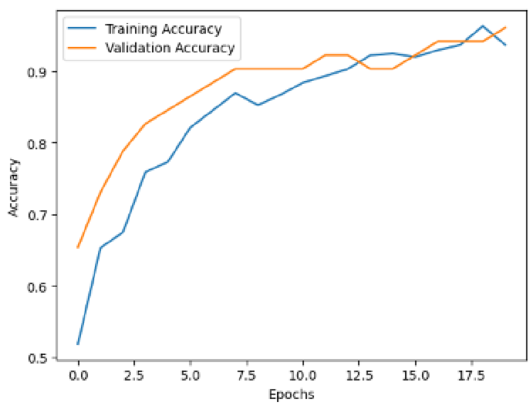

Fig 4.6: Accuracy Curve for Validation and Training of InceptionResNetV2.

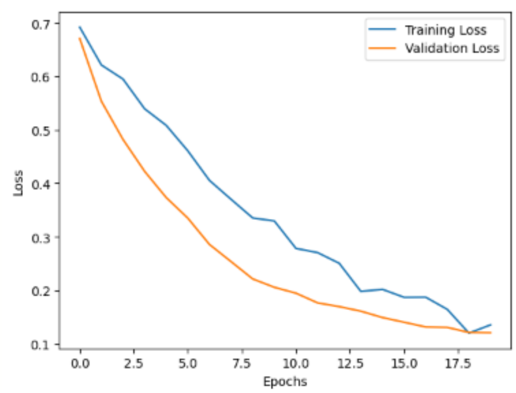

Fig 4.7: Loss Curve for validation and training of InceptionResNetV2.

4.4 Discussion

In this project, I'll forecast bone fracture using DL algorithms and x-ray images. In any field of study, each word should be given a significant amount of weight during the categorization process. I have always looked into the classification of x-rays to determine the cause of bone fractures. The datasets have also been divided into succeeding classes using the dl models. One of the most crucial components of any investigation is the data. The presented data has the potential to significantly alter the study's findings. I reasoned that since this was a combination of real datasets, anyone using one of the two previously accessible datasets would undoubtedly reach a different conclusion. Since I used more data, I might be perceived as being a little more accurate. I used a range of DL method techniques and accuracy ratings to help us achieve my goal. For this project, I employed five distinct algorithms in total. Prior to starting my current project, I needed to gather a few things. Yes, I made my decision and got to work on the algorithm. Next, I determined each algorithm's accuracy like I've already said. I used both of these procedures to get the greatest accuracy of 94.23% for the experiments for the next two categories, which are called InceptionResNetV2 experiments. It is especially noteworthy for the data I supplied since, when it came to the two-bone fracture diagnostics classes utilizing online applications and x-ray images, it performed more accurately than the other models.

Precision: Accuracy, or the degree of precision in which the algorithm generates accurate forecasts, is one metric that is commonly used to assess the efficacy of the model. The entire number of accurate forecasts may be multiplied by the entire amount of true positives to determine efficiency.

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

Recall: Regardless of all pertinent instances, retrieval is the proportion of appropriate cases that were eventually located and recovered. When a method has a high recall rate, it is considered to have produced the most relevant results.

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

F1-Score: The validity of a test is established by taking into account its accuracy and recall. Recall and accuracy complement each other well.

$$\text{F1} = \frac{2 \times precision \times recall}{precision + recall}$$

Accuracy: Reliability is defined as the correlation between an accepted cost and an expected value.

$$\text{accuracy} = \frac{TP+TN}{TP + FN + TN + FP}$$

CHAPTER 5

Impact on Society, Environment and Sustainability

5.1 Impact on Society

Deep learning tactics are utilized to enhance the detection of fractured tibia and femur using x-ray pictures, and deep learning methods are employed for recognizing broken tibia and femur utilizing actual data gathered from numerous hospital sources. Considering the possible ramifications for the neighborhood. These tactics have a number of negative effects on society, such as the following:

- **Strengthen the Medical Sector:** The ability to identify bone fractures from x-ray images is one of the most notable potential benefits of AI and DL techniques, which could advance the field and produce better outcomes. Physicians, patients, and other healthcare workers may all benefit from bone fracture diagnostics by using them to quickly solve problems and expand medical knowledge. In the long run, this might result in more effective medical procedures and better treatment for tibia and femur bones.
- **Economic Benefits:** The application of deep learning-based algorithms for the categorization of tibia and femur bone fractures may prove to be economically advantageous for society. Patients may gain, for instance, if the medical area becomes more well-known. It may be possible to deliver regular status updates without visits from people because to technologies driven by DL. The potential for remote patient monitoring makes this feasible. Early intervention can save costs for patients and health care systems by avoiding the need for more complex and expensive interventions. Better financial outcomes and more efficient medical treatment are possible outcomes as well. Individuals having this kind of issue will become a vital consumer base for the classification of bone fractures.
- **Social benefits:** In addition to possible financial benefits, applying DL methods to x-ray diagnosis of tibia and femur fractures may have positive social effects. Deep learning systems process and evaluate medical images significantly more quickly than human radiologists. This rapidity might result in a speedier diagnosis and treatment plan since fractures require medical attention right away. Human radiologists can interpret images from medicine in various ways from one another. For a variety of medical practitioners, standardizing image analysis with DL algorithms may yield consistent and dependable findings. Deep learning technologies can provide training and knowledge to healthcare workers that can be

advantageous. By giving fewer skilled practitioners greater knowledge and assistance, they may elevate the bar for medical skill as a whole.

Keeping all of this in mind, it's critical to keep in mind that, despite any potential benefits, using in-depth knowledge for medical investigations also raises ethical, legal, and privacy concerns. Safe implementation in the healthcare sector necessitates safeguarding patient confidentiality, data security, and decision-making process transparency for the algorithms.

5.2 Impact on Environment

When employing x-ray data and deep learning algorithms to differentiate between fractures and the tibia and femur, there doesn't appear to be much of an environmental risk. However, there's a potential that developing and putting these strategies into practice could unintentionally worsen environmental deterioration by consuming more resources. The following are some potential environmental damages that these techniques could bring about:

- **Consumption of Energy:** The complexity of the dataset, the available computing power, the physical equipment, and the particular algorithms employed all affect how much energy is required for deep learning (DL) to diagnose x-ray bone fractures. It has to do with the kind of power that is utilized in calculations. Energy from non-renewable sources might have a greater influence on the environment than energy from renewable ones. Energy consumption issues must be considered, even if employing DL to categorize bone fractures may enhance medical results. More efforts are being made to develop environmentally friendly algorithms and technologies in order to reduce the environmental effect of deep learning applications in the medical field.
- **Data archiving:** Large volumes of data should be used for testing and training deep learning systems. Materials and power, two resources that pose a risk to the environment, may need to be used in order to preserve this data. Together with the potential resource-saving techniques to mitigate these impacts, the possible environmental repercussions of knowledge maintenance must be taken into account.
- **Transportation:** If distributed deep learning is able to gather more accurate data and strategies become available to different regions of the world, then using these approaches could result in increased emissions associated to travel. It is imperative to consider the environmental impact of transportation and to make every effort to minimize emissions.

- **Research Data Representations:** The quality & the diversity of the initial training data greatly influences how well deep learning models identify bone fractures. If a great deal of the information being trained comes from a particular social group or demographic, the model might not function as effectively when used with data from other groups. For a structure to be useful across a range of scenarios and patient populations, different training data are necessary.

In conclusion, there are several ways in which the environment affects the use of deep X-ray neural networks for bone fracture detection. A number of other elements are also in play, such as legislative obstacles, public awareness, data presentation, data distribution structure, and environmental concerns. These factors must be carefully considered in order to integrate deep learning technology into a variety of healthcare contexts. Considering the potential unanticipated indirect ecological effects of its production and use, it is essential that the necessary actions be performed and that these ideas be implemented. Using eco-friendly features and calculations to reduce pollution and resource usage are a few examples of these safeguards, as is storing data in a way that conserves resources when possible and, when necessary, minimizing gasses in comparison to public transportation.

5.3 Ethical Aspects

The numerous ethical concerns presented by applying X-ray deep learning to broken bone diagnosis must be addressed in order to ensure a responsible and equitable deployment. The following are some of the most important ethical components:

- **Confidentiality for patients and data protection:** Deep learning algorithms require a large quantity of information about patients to be accessible for training. It is necessary to protect this data's privacy and security. By keeping medical records private and putting strong cybersecurity safeguards in place, data breaches and unauthorized access may be prevented.
- **Algorithm Equality and Bias:** There might be differences in diagnosis accuracy across distinct socioeconomic categories due to algorithmic bias. Maintaining fairness requires identifying and correcting any biases in computational code and training data. In order to detect and rectify bias and advance fair results in healthcare, audits and algorithm monitoring on a regular basis are required.
- **Clinical Evaluation and Trustworthiness**: A thorough clinical validation approach is required to ensure that deep learning simulators are reliable and accurate in real-world healthcare settings. It is important to develop clear guidelines for when healthcare providers should use these models and to educate them about their limitations.

- **Accountabilities**: It's unclear who is giving the final say on decisions derived from DL algorithms. It is crucial to think about who will supervise the approaches' practical and moral application and make sure farmers who suffer from bone fractures having access to the right support systems.
- **Professional Freedom and Cooperation**: DL need to be viewed as a help rather than as taking on the position of a medical expert. It is important to preserve the independence of doctors and nurses in making decisions. Healthcare professionals and AI experts may work together to make sure that innovation enhances clinical expertise rather than detracts from it.

The use of deep learning techniques to X-rays for the diagnosis of fractures poses ethical questions that can be successfully resolved with continued oversight, recurring ethics evaluations, and cooperation between government regulators, healthcare providers, technologists, and ethicists. It usually raises a number of moral questions that require thorough consideration and resolution. Techniques should be created and applied morally and responsibly to maximize their positive effects and minimize their negative ones.

5.4 Sustainability Plan

Creating a sustainable strategy that considers the impact on the environment and resource consumption, along with the long-term feasibility of integrating X-ray deep learning with broken bone diagnostics, is essential. An example of a sustainable plan is as follows:

- **Energy Efficiency**:

  Choice of Hardware: Choose hardware that uses less energy for executing deep learning algorithms. Try to use technology designed for inference activities to reduce the amount of energy used during diagnostic processes.

  Enhancing Cloud Infrastructure: Choose cloud service providers and contracts that put energy efficiency first. Implement resource allocation strategies to minimize idle time and optimize total energy consumption.
- **The effectiveness of algorithms:**

  Model Optimization: The Situation with Maintain the diagnostic precision of deep learning models while continuously enhancing their performance. Among them are techniques for model compression, quantization techniques, and architectural improvements.

  "Real- Processing" refers to the goal of achieving instantaneous processing capabilities in order to minimize the time and resources required for diagnosis and to increase energy efficiency.

  Duty: Clearly defining the roles and responsibilities of all parties engaged in the construction and implementation of DL systems is crucial to ensuring their sustainability. This can mean laying out the specific guidelines for the moral application of the methods as well as the duties of those responsible for seeing to it that they are applied correctly and morally.

By incorporating these components into the implementation and continuous supervision of X-ray DL for fractured bone diagnosis, a sustainable strategy that balances environmental responsibility with technical development may be created. By incorporating sustainability criteria into the usage of DL models for bone fracture diagnosis, it may be possible to improve the healthcare system, reduce the impact on the environment, and raise patient happiness.

CHAPTER 6

Conclusion and Future Research

6.1 Summary of the Study

I've learned a lot about this subject thanks to this investigation. A fractured bone presents a very delicate scenario. This is a major annual contributing cause to the decline in the medical industry. Consequently, I was able to identify two typical fracture scenarios—tibia and femur—by using deep learning and the dataset's x-ray images.

As I've already mentioned, I use a variety of hospital fracture images to get as much real data as I can for my research. By using this data to train my software algorithms on the fracture pattern, I was able to get better at identifying specific types of fractures. Initially, a few issues were resolved. I succeeded in reaching my intended objective. Different DL algorithms yield different results for different users. I go into more depth about this in the following section.

6.2 Conclusion

This study demonstrates how good my methods and findings were. I really think and anticipate that more research in this area will be started when my evaluation is over. I have a ton of ideas to expand on my work thanks to this study. While at work, I made a few blunders. I learned that there were many educational paths I might have taken. We will be able to address any shortcomings or possible problems while carrying out the present project. Furthermore, I offer recommendations for the use of these insights in future research to offer more thorough resolutions to the problems brought up by this investigation. I'm sure that this test will help me understand more about the different aspects of the medical care topic I've decided to study. In my view, it will contribute to the advancement of cutting-edge technological approaches and research that allow us to serve the medical business and allow x-ray pictures to be used for bone fracture diagnosis. By using DL to identify the possibility that both of these types of bones—the tibia and femur—are fractured, I want to offer a novel method for classifying bone fractures based on x-ray images of healthy people. developing a web application for the categorization of x-ray pictures as well. InceptionResNetV2 achieves the highest accuracy of 94.23% among the five models used for analyzing the dataset. To get the highest degree of accuracy, developing a web application that classifies x-ray images using InceptionResNetV2 models.

6.3 Possible impacts

Bone fracture identification in X-ray pictures may be made more accurate with the use of deep learning algorithms. They might be trained to identify complex patterns or microscopic fractures that would be challenging for real radiologists to detect using enormous datasets. Using X-ray deep learning techniques for fracture identification may increase accessibility to healthcare facilities, especially in developing or remote areas where access to trained medical personnel may be limited. Medical personnel might use their resources more wisely if they could precisely identify patients who are more likely to experience a fractured bone. This means focusing specialized therapies on individuals who are most in need of care and allocating medical staff in an efficient manner.

6.4 Future Works

In this medical profession, there are several avenues for future research, especially within the scope of my own studies. I was full of ideas about how to improve my work. As previously stated, I have also discovered a few errors, and these inaccuracies offer opportunities to improve this research. By putting my theories into practice and enhancing prediction outcomes with more opportunities to capture high accuracy, I'll attempt to address this inaccuracy. I intend to correct any mistakes that arise. I have a few more objectives in mind. This prediction may call for more study in this area as it uses x-ray pictures to locate fractures. In order to maximize the benefits for the user, I will include features like the ability to classify different types of bone fractures using the InceptionResNetV2 imitate and other features in the process I use to create the fracture classifying that users can use to identify tibia and femur fractures. I think that working in this kind of career will help me improve medical equipment and increase its important impact on healthcare. I could help with the patients' early fracture diagnosis.

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