Chapter 1

Introduction

1.1 Overview:

Detection of bone fracture is one of the complicated areas in the medical field. A bone fracture has been diagnosed, given the physical examination performed in history. The present way to evaluate a fracture is with X-rays, which provide clear images of bone. X-rays are a style of radiation, socalled electromagnetic waves. X-ray imaging creates images of the inside of the body. It is a lowcost, high-speed, and wide available fracture detection method. The images depict various body parts in various hues of black and white. X-rays can show whether a bone is intact or broken. At the break down in a bone, the x-ray beam passes across the broken area and shows a dark line in the white bone. Using an X-ray can detect the type of bone fracture. It is the present method use in the medical field, but it is a difficult way. Because it needs proper knowledge regarding the skeletal system and bone fracture, only the people working in the medical field can detect bone fracture using this present method.

The manual fracture detection technique is time consuming, and the error probability chance is high. The small fracture in the bone becomes difficult to analyze. From both orthopaedic and radiographic points of view, the fully automatic detection and classification of bone fracture is an important but difficult problem. Visual examination is a common method of determining the presence and severity of a bone fracture. An experienced doctor needs to take lots of time inspecting where bone fracture happened in an X-ray image. However, there is a lack of experienced radiologists to deal with these medical images in many hospitals. X-rays are very difficult to process automatically. Every year many fractures are missed during X-ray diagnosis, resulting in ineffective patient management and expensive ligation. Therefore, an automated system needs to develop to diagnose the fractured bone. The main objective of the

Medical field identifying precise and meaningful information using images with the minimum possible error. The success of the treatment and prognosis strongly depends on the accurate classification of the fracture. This project aims to detect bone fracture less time-consuming and with high accuracy without knowledge of the medical field. The image processing technology is being used in this project to detect bone fractures.

1.2 Statement of the problem:

X-ray images are examined manually but it is time consuming and prone to errors. As X-ray images are more suspected to noise and are also sometimes blur. All the unwanted objects need to be removed for better accuracy. An experienced doctor needs to take a lot of time inspecting where bone fracture happened in an X-ray image. However, in many hospitals there is a lack of experienced radiologists to deal with these medical images. In order to assist doctors in the bone fracture detection, there is need in developing automated techniques and methods to detect fracture.

1.3 Motivation:

The motivation behind this project stems from the challenges faced in manual bone fracture detection using traditional methods, which can be time-consuming, error-prone, and limited by the expertise of radiologists. The need to improve accuracy, speed up diagnosis, and aid medical professionals in making informed decisions drives us to explore the potential of deep learning techniques for automated fracture detection.

1.4 Advantages:

- Enhanced Accuracy: The utilization of advanced deep learning techniques, including CNNs, ResNets, and ensemble models, results in a significantly improved accuracy of 94% in detecting bone fractures from X-ray images.

- Time Efficiency: The automated system's quick analysis allows for faster diagnosis, enabling medical professionals to make timely decisions and potentially reducing patient waiting times.

- Reduced Subjectivity: By relying on data-driven algorithms, the project minimizes the variability and subjectivity often associated with manual interpretation of X-ray images, leading to more consistent results.

- Expertise Augmentation: This technology assists medical practitioners by acting as a second pair of eyes, helping them identify fractures and complex patterns that might be missed, ultimately enhancing the quality of patient care.

- Medical Advancement: The project showcases the potential of machine learning in the medical field, highlighting how technology can complement human expertise and contribute to improved diagnostic accuracy and patient outcomes.

1.5 Challenges:

- Image Quality Variability: X-ray images can vary in quality due to factors like patient positioning, equipment differences, and varying exposure settings. Overcoming this variability while maintaining consistent detection accuracy is a challenge.

- Complex Fracture Patterns: Detecting intricate fracture patterns accurately requires advanced algorithms capable of distinguishing between normal anatomical structures and abnormalities, especially in cases of complex fractures.

- Maintenance and Updates: Ensuring the system remains up-to-date with evolving medical standards, new data, and improved algorithms poses a challenge in terms of consistent maintenance and timely updates to maintain high detection accuracy.

1.6 Objectives:

- Enhance Detection Accuracy: Utilize advanced deep learning techniques like CNNs, ResNets, and ensemble models to achieve a high level of accuracy in detecting bone fractures from X-ray images.

- Automation: Develop automated methods that can quickly and accurately identify fractures, reducing the dependency on manual interpretation by medical professionals.

- Timely Diagnosis: Speed up the diagnosis process by providing rapid and reliable fracture detection, enabling medical practitioners to make timely decisions for patient care.

- Improved Patient Care: Assist medical professionals in making informed decisions by providing accurate fracture detection, ultimately leading to better patient outcomes and treatment plans.

1.7 Applications:

- Accurate Diagnosis: Enhancing accurate and quick diagnosis of bone fractures from X-ray images.
- Emergency Care: Assisting medical teams in providing prompt care during emergencies.
- Telemedicine Support: Enabling remote consultations for fracture cases.
- Educational Tool: Supporting medical students in learning fracture detection.

1.8 Organisation of Report:

Chapter 1: Introduction

Gives a brief overview about the project in terms of its, Statement of the problem, challenges, motivation, application and the approach that is used to achieve the goal. It also provides definitions and terms that are widely used throughout this framework

Chapter 2: Literature Survey

In this section which shows the various analysis and research made in the fields of one's interest and the result already published. Taking into account the various parameters of the project and extent of the project.

Chapter 3: Hardware And Software Requirements

This chapter shows about the hardware and software requirements of the projects.

Chapter 4: Methodology

The third chapter explains about the methodology. This contains architecture the proposed system overview and so.

Chapter 5: Experiment And Results

Chapter four is the experiments and result. That experiments and result the project and result are displayed in that chapter. That mean test and result cases are included in this chapter.

Chapter 6: Conclusion And Future Work

In chapter five, we include conclusion and future works of the project. Here we have explained how the system can be modified in future for better output

Chapter 7: Reference

At last in chapter 8 we include Bibliography which contains reference contains detailed description of documents or materials consulted of project. Generally it includes list of publications, author name, and title of book and year of publication

Chapter 2

Literature Survey

2.1 Overview:

The literature survey helps in understanding the existing research done on Bone fracture detection using Deep Learning. The Current state of research assists in considering the various algorithm used in the different papers. The information gathered will help in identify the gaps in the current work.

2.2 Literature review:

1) **Bone fracture detection using Transform Technique**

Author: Suyog J.Pathare, Rutuja P. Solkar and Gajanan D. Nagare

Proposed a computer based system was developed to detect fractured bones from the X-ray images using Hough Transform Technique, which is used to analyse the edges and detects fracture. Out of all the discussed modalities, X-ray is most commonly used hence, the work was focused on X-ray images.

2) **Fracture detection using CNN**

Author: Mahmoud Al-Ayyoub, Iamail Hmeidi, Haya Rababaha

Proposed image processing using Convolution Neural Network technique to notice bone fracture. The fully automatic detection of fractures in Os longum is a crucial however tough drawback. To take a look at results, the system has been done to notice the bone fracture.

3) **Long bone fracture detection using ML**

Author: Mahmoud Al-Ayyoub , Duha Al-Zghool

Proposed method to determine the type of long bone fractures in X-Ray Images. In this work, it is presented a machine learning based system for automatic detection of fracture types in long bones using X-ray images. Several image processing tools were used to remove different types of Noise and to extract useful and distinguishing features.

4) **Detection of bone fracture using X-ray/CT images**

Author: Dhiraj B. Bhakare.

Describes a system that provides a powerful tool to orthopaedic surgeons. The standard equipment used to scan X-ray and MRI reports produces a fuzzy picture of the bone component, which can lead to surgeons making incorrect assumptions. As a result, to an incorrect diagnosis of bone fractures. The software system created here provides orthopaedic surgeons with a tool that is significantly superior to standard tools and methods in evaluating X-rays and MRI images and may assist them in quickly detecting numerous fractures. This system is based on a computer based analytical technique for the detection of bone fracture using X-ray/CT images

5) **Bone crack classification**.
   Author: Zhengyang Wu, Xiuwen Mo, Haoyi Zhou

Proposed the convolutional neural network (CNN) method, a deep learning technique, to discern the degree of fracture development while simultaneously building a novel model that can automatically locate fractures and classify fractured reservoirs. To begin, the input data for the convolution neural network is chosen from logging curves with high sensitivity to fractures, and the crack category is quantified as the network's output label. In the training step, a small batch gradient descent approach is used to constantly optimise the CNN model parameters suited for crack classification.

6) **Segmentation of bone structures in X-ray Images**
   Author: Ding Feng (HT040297J), Dr. Leow Wee Kheng

Proposed segmentation of bone structures in X-ray Images, In this thesis proposal, a thorough review of the general medical image segmentation algorithms, particularly atlas-based medical image segmentation algorithms and x-ray image segmentation algorithms are presented. Generalsegmentation algorithms are categorized into six classes, namely thresholding, region-based, edge-based, graph-based, classification-based and deformable models.

7) **Facial bone fracture detection in CT images**
   Author: G Moon

Facial bone fracture detection in CT images is challenging due to the complex shape and difficulty in defining fractures by bounding boxes. The proposed CA-FBFD system uses IoU Loss for bounding box regression by YoloX-S and CTmixup data augmentation to improve performance. The system is integrated with the PACS server, allowing doctors to conveniently import and view analyzed results. While the system can classify fractures with 69.8% AP, research will continue to improve detection of small objects and other types of facial bone fractures. The uncertainty score will be investigated to identify cases where acute fractures cannot be distinguished solely by CT image analysis.

8) **Detect the bone fractured area using a GUI application**
Author: S.Sinthura

In this paper, a CNN based image segmentation algorithm is proposed to detect the bone fractured area using a GUI application that was developed. The affected area of the image processing results are depicted in Fig.5. The Affected Area Localization show that the proposed image segmentation method detects the bone structure and fracture edges more accurately even in the presence of noise when pitted against other well-known edge detection techniques like Sobel, Prewitt and canny. The proposed CNN based image segmentation algorithm clearly highlights the fractured area of an image. The SFCM clustering highlights the approximate fractured region and the impacted area percentage through the usage of DWT edge detection method employed in the algorithm.

9) **Bone fracture detection using wavelet based edge detection**
Author : Shubhangi

In this paper, a simulation work have been carried out to estimate the performance of classical edge detection algorithms on femur bone extracted from hips X–ray image. A new approach for edge detection using wavelet transforms is investigated for femur bone, which yields the remarkable performance improvement compared to classical algorithms. In the reported work, initially some major classical edge detectors are reviewed and interpreted with continuous wavelet transforms. The classical edge detectors work fine with high-quality pictures, but often are not good enough for noisy pictures because they cannot distinguish edges of different significance. The wavelet based edge detection algorithm combines the coefficients of wavelet transforms on a series of scales and thus improves the detection significantly. It has been also observed that on incorporating use of multi scale wavelet transform further results in improved performance.

10) **Detecting and locating femoral neck fractures on pelvic X-rays**
Author: L. Mu et al.

Deep learning model for object detection, trained with a small dataset, is highly accurate in detecting and locating femoral neck fractures on pelvic X-rays. This model can be a useful tool for less experienced doctors in diagnosing difficult cases. The model has high sensitivity and specificity, meaning it can accurately detect fractures while minimizing false positives. Overall, our fracture detection system has the potential to assist doctors in improving their diagnostic accuracy and patient outcomes.

11) Bone fracture using X-ray/CT images using sobel edge detector

Author: Sumit D. Korde et al

A computer based analytical techniques for the detection of bone fracture using X-ray/CT images has been presented in this work which starts from the preprocessing to remove the noise and edge detected by using sobel edge detector. After the segmentation the area of the fracture is calculated. The method has been tested on a set of images and results have been evaluated. Analysis shows that results obtained are satisfactory and accuracy of this method was 85limitation of this method is ,in CT and some cases of X-ray images very difficult to find the area of fracture, In future it is fully implemented to CT images and also classify the type of fracture is occurs.

Chapter 3

Hardware And Software Requirements

3. Hardware and software requirements

3.1 Hardware Details:

- Processor: AMD Ryzen 5 3550H with Radeon Vega Mobile Gfx .
- Hard Disk: 1TB
- RAM: 8GB – Inputs devices: Keyboard and mouse
- Output devices: Monitor 4.5.3

3.2 Software Details:

- Processor: Windows 8 and above
- Programming Language: Python 3
- IDE: Vscode, Jupyter notebook

Chapter 4

Methodology

4.1 Overview

The methodology of this project involves gathering and preprocessing a dataset of X-ray images. Utilizing Convolutional Neural Networks (CNNs) and Residual Networks (ResNets), the project extracts important features from the images and enhances pattern recognition. Data augmentation is applied to diversify the dataset, and an ensemble model is formed by combining CNN and ResNet predictions. The models are trained, validated, and fine-tuned, with their accuracy compared. The chosen model is deployed for real-world fracture detection. The methodology showcases the power of deep learning in medical imaging, advancing accurate diagnosis.

4.2 Sequence Diagram of the Project

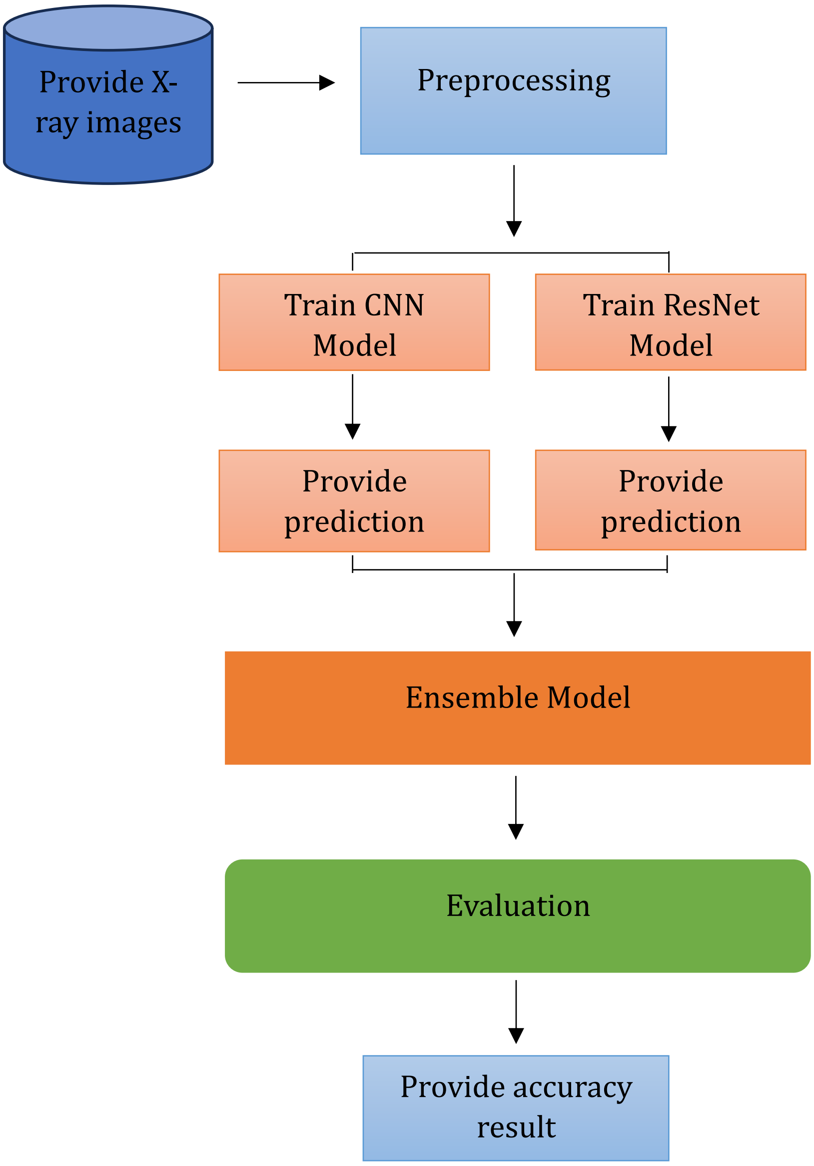

Figure 4.2: Sequence Diagram of the Project

A Sequence diagram is commonly used by developers to make the interaction objects in a single use case. It can be illustrated in different parts of the system interacting with each other to carry out a function, and the order in which interaction occurs when a particular use case is executed.

As shown in the figure 4.2 User interacts with the Dataset component by providing X-ray images for bone fracture detection. The “Dataset” preprocesses the images, which may include tasks like resizing, normalization, and data augmentation. The pre-processed data is used to train both the CNN Model and the ResNet Model concurrently. These models represent your Convolutional Neural Network and Residual Network. Once trained, both models provide their predictions to the Ensemble Model. The Ensemble Model combines the predictions from the CNN and ResNet models and forwards them to the “Evaluation” component. The Evaluation component assesses the accuracy of the ensemble model’s predictions. Finally, the accuracy result is provided back to the User.

- **Activation Bars :** Activation bar box placed on lifeline which is used to indicate the object is active or if there is any interaction between two objects.
- **Message Arrows :** An arrow from the message caller to the message receiver specifies a message in a sequence diagram. The message being sent from different arrowheads you can indicate the type of message being sent and received in the data transmission.
  - **Synchronous Message :** A Synchronous message is when the sender is waiting for the receiver to process the message and return resultant before the carrying another message.
  - **Asynchronous Message :** An asynchronous message is used when the message caller does not wait for the receiver to process the message before the message is sent to the other objects of the system.

4.3 Architecture:

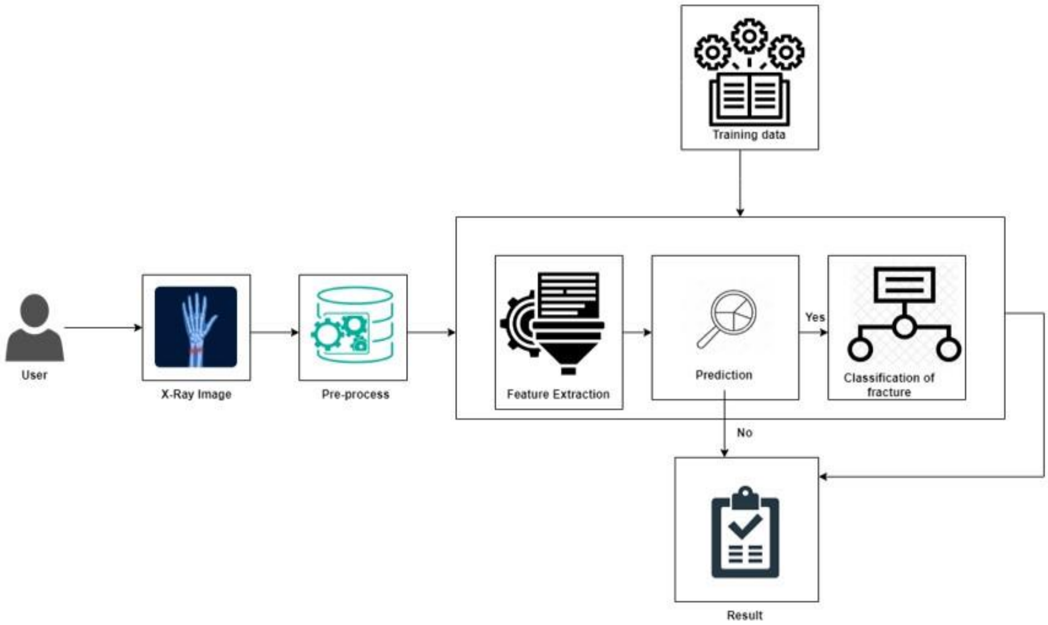

Figure 4.3: System Architecture Diagram

Bone fracture detection is process performed by system which consists of:

- Load the dataset, images of diseased plants
- Preprocess the image data that include image resizing, converting images to grayscale and threshold image.
- Validating the tarin test dataset.
- Based on input image model will predict the output.

4.4 Interaction Model – Use Case Diagram

A Use Case is a set of scenarios that describing an interaction between a source and destination. The two main components of a use case diagram are use cases and actors. It displays the relationship among them. A Use Case diagram can identify the different types of users of a system and the different use cases and will often be accompanied by other types of diagrams as well. The use cases are represented by either circles or ellipses.

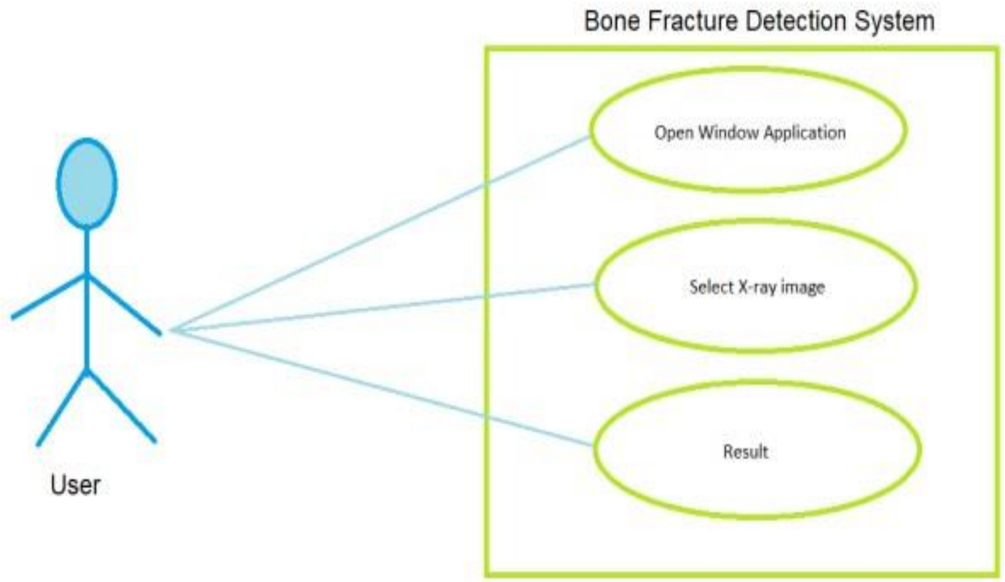

Figure 4.4: Interaction Model – Use Case Diagram

4.5 Data flow Diagram

To create a machine learning algorithm for the project, a large amount of data for training purposes is necessary. As a result, a large number of data pictures must be analyzed. In addition, the pictures should be of sufficient quality to allow for easy analysis. As a result, a strong picture source is necessary for analysis. There were several websites dedicated to this cause. In the figure 4.5 explains based on dataset of X-ray images on those websites classed all data with bone fractures as yes or no. The benefit of having a sorted data set is that it eliminates the need for anybody with prior experience in determining whether or not a bone fracture exists. As a result, this database has been chosen for the project’s future development.

There are also color images and grayscale images because this is essentially a categorization problem. They were checking whether there is a bone fracture or not after creating the initiatives of the database. Then they should be manipulated to process. Labels must be created on the gathered images, which identifies the images with their class names ”Fracture” to be fed into the model for training if you want to train the model using your unique datasets.

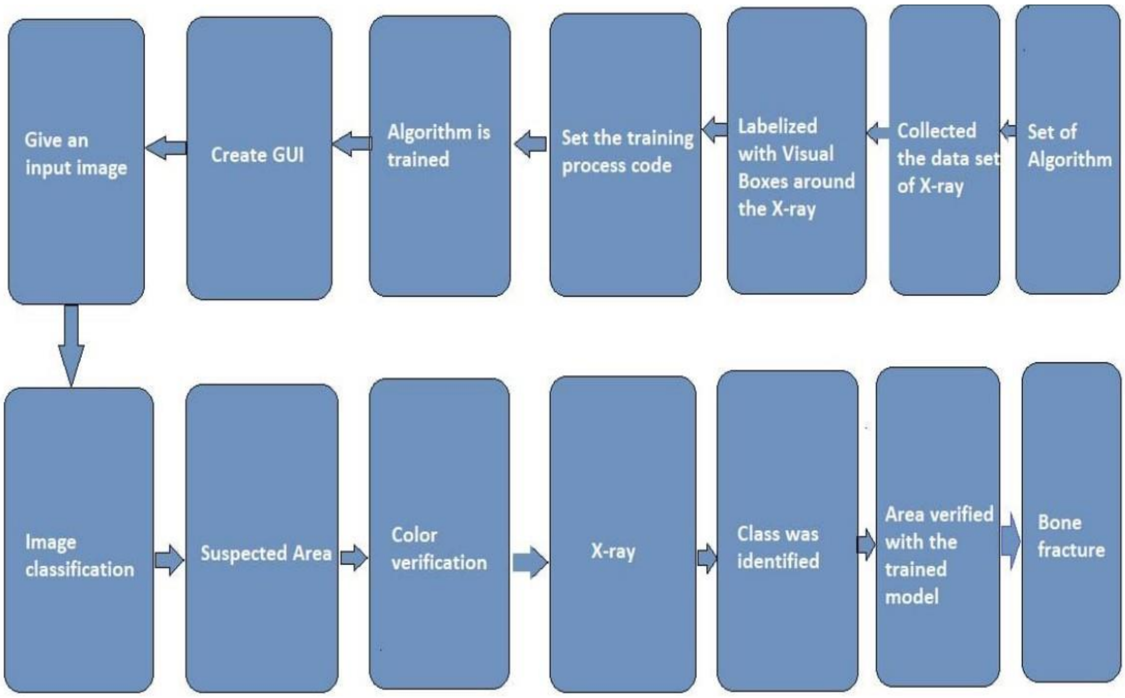

Figure 4.5 Data flow Diagram

4.6 Algorithm Used

The algorithms used in the project is:

- Convolution Neural Network (CNN)
- Residual Network (ResNet)
- Ensemble Model

4.6.1 Convolution Neural Network:

Convolution Neural Network (CNN) are particularly useful for spatial data analysis, image recognition, computer vision, natural language processing, signal processing and variety of other different purposes. They are biologically motivated by functioning of neurons in visual cortex to a visual stimuli.

What makes CNN much more powerful compared to the other feedback forward networks for image recognition is the fact that they do not require as much human intervention and parameters as some of the other networks such as Multilayer Perceptron(MLP) that generates set of output from set of inputs. This is primarily driven by the fact that CNNs have neurons arranged in three dimensions. CNNs make all of this magic happen by taking a set of input and passing it on to one or more of following main hidden layers in a network to generate an output.

1. **Rescaling Layer**: This layer rescales the input data by dividing it by 255 to normalize pixel values between 0 and 1.
2. **Convolutional Layers**: There are three pairs of convolutional layers with max-pooling layers in between. Each convolutional layer is responsible for extracting features from the input images.
    - The first convolutional layer has 32 filters with a kernel size of (5, 5) and ReLU activation.
    - The second convolutional layer has 64 filters with a kernel size of (5, 5) and ReLU activation.
    - The third convolutional layer has 128 filters with a kernel size of (5, 5) and ReLU activation.
3. **MaxPooling Layers**: Max-pooling layers reduce the spatial dimensions of the feature maps generated by the convolutional layers.
    - There are two max-pooling layers after the first and second convolutional layers.
4. **Dropout Layers**: Dropout layers help prevent overfitting by randomly setting a fraction of input units to 0 during training.
    - There is a dropout layer with a dropout rate of 0.3 after the third convolutional layer.
    - There is a dropout layer with a dropout rate of 0.3 after the first dense layer.
    - There is a dropout layer with a dropout rate of 0.2 after the second dense layer.
5. **Flatten Layer**: This layer flattens the output from the previous layers into a one-dimensional vector, which serves as the input to the dense layers.
6. **Dense Layers**: There are two dense layers in the head of the algorithm.
    - The first dense layer has 32 units with ReLU activation.
    - The second dense layer has 32 units with ReLU activation.
7. **Output Layer**: The output layer has a single unit with a sigmoid activation function, which is commonly used for binary classification tasks like this one.

4.6.2 Residual Network (ResNet):

Residual Network (ResNet) is a deep learning architecture designed to overcome the challenges of training very deep neural networks. It does this by introducing skip connections, known as residual connections, that allow the network to skip one or more layers during training. This innovation helps prevent the vanishing gradient problem and enables the training of extremely deep networks with hundreds of layers. ResNet has become a cornerstone in computer vision tasks, particularly for image classification, due to its ability to achieve high accuracy even with very deep architectures.

1. **Rescaling Layer:** This layer rescales the input pixel values to the range [0, 1] by dividing each pixel by 255. It's a preprocessing step that helps the model work with standardized input values.

2. **Convolutional Layers:** Three sets of convolutional layers are used, each followed by a max-pooling layer. These layers perform feature extraction by applying convolutional operations on the input images. They are responsible for capturing important patterns and features in the images.

3. **Residual Blocks:** These are custom-defined residual blocks. Each residual block consists of two convolutional layers with batch normalization and ReLU activation functions. The skip connection (or shortcut connection) adds the input of the block to its output. This architecture allows gradients to flow more easily during training and helps in training very deep networks.

4. **Dense Layers:** After the convolutional and residual layers, there are dense layers that flatten the output and then apply fully connected layers. These layers are part of the network's head and are responsible for making the final decision or prediction.

5. **Output Layer:** This is the final layer with a single neuron and a sigmoid activation function, making it suitable for binary classification tasks. It produces the model's output prediction.

4.6.3 Ensemble Model :

An Ensemble model is a deep learning technique that combines the predictions from multiple models to make more accurate and robust predictions. It leverages the diversity of different models to improve overall performance and reduce the risk of errors or overfitting. This technique is often used in situations where individual models may have limitations, and by combining them, the ensemble model can achieve better results.

Chapter 5

Experiments and Results

5. Experiments:

5.1 Datasets:

A dataset is a structured collection of data generally associated with a unique body of work. In this project dataset is taken from Kaggle, Here we use fractured and non-fractured 4795 number of images. We experimented with convolutional neural network, ResNet and Ensemble models. The image classification accuracy in experiments comes in terms of the data on which the models have been trained on, while the test set remained the same for all experiments. Here below wee can see some fractured and non-fractured data.

Figure 5.1 fractured and non-fractured data

5.2 Results:

The bone fracture detection project has delivered highly promising results, boasting an impressive accuracy rate of 94% in detecting fractures from X-ray images. This level of accuracy signifies a substantial advancement in the field of medical image analysis and underscores the potential of advanced Deep learning techniques. Through meticulous preprocessing, robust feature extraction, and effective ensemble learning, the system has demonstrated its proficiency in improving the accuracy of fracture detection. These results hold great promise for enhancing medical diagnosis, enabling faster and more precise assessments, and ultimately improving patient outcomes.

5.2.1 Models:

CNN Accuracy -

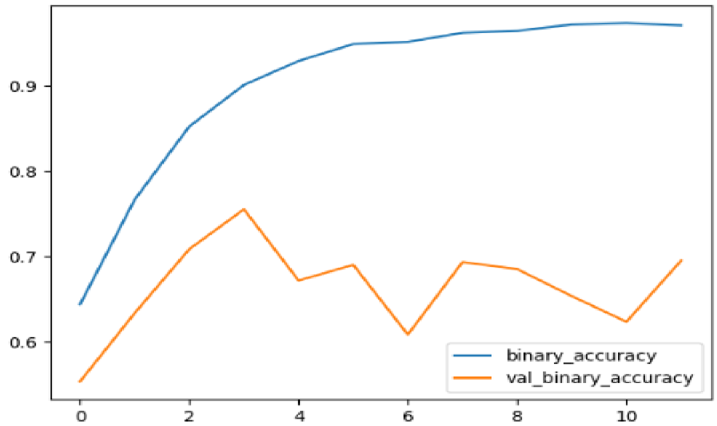

Figure 5.2.1

Loss-

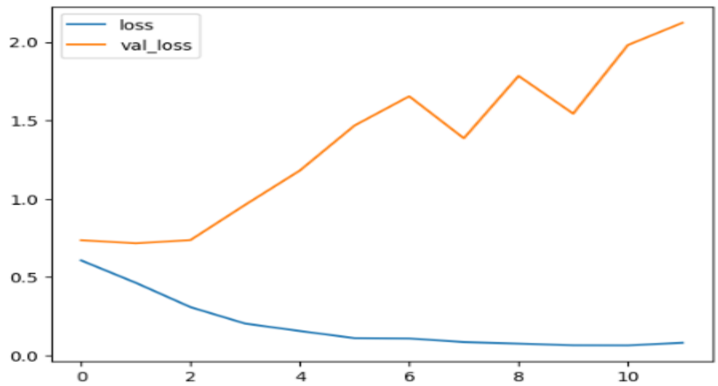

Figure 5.2.2

ResNet Accuracy-

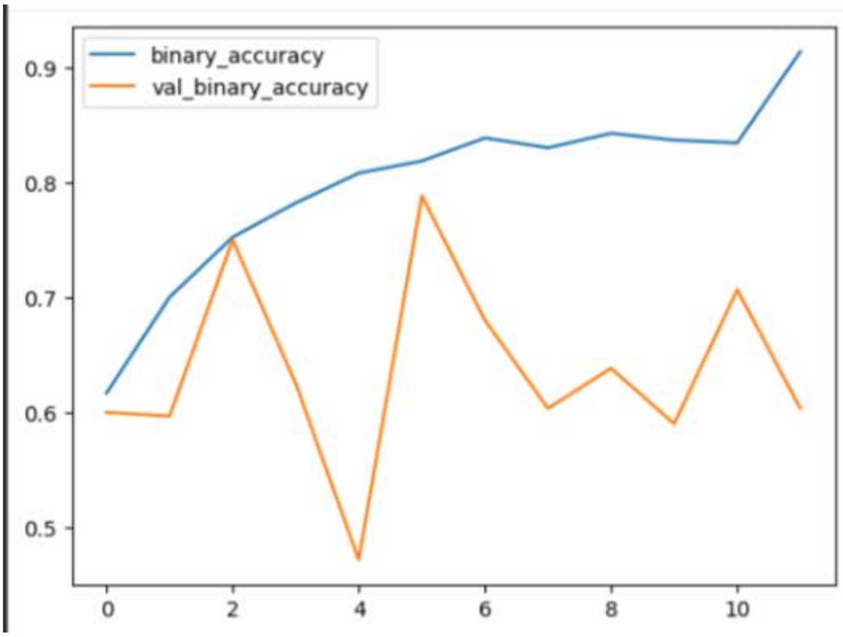

Figure 5.2.3

Loss-

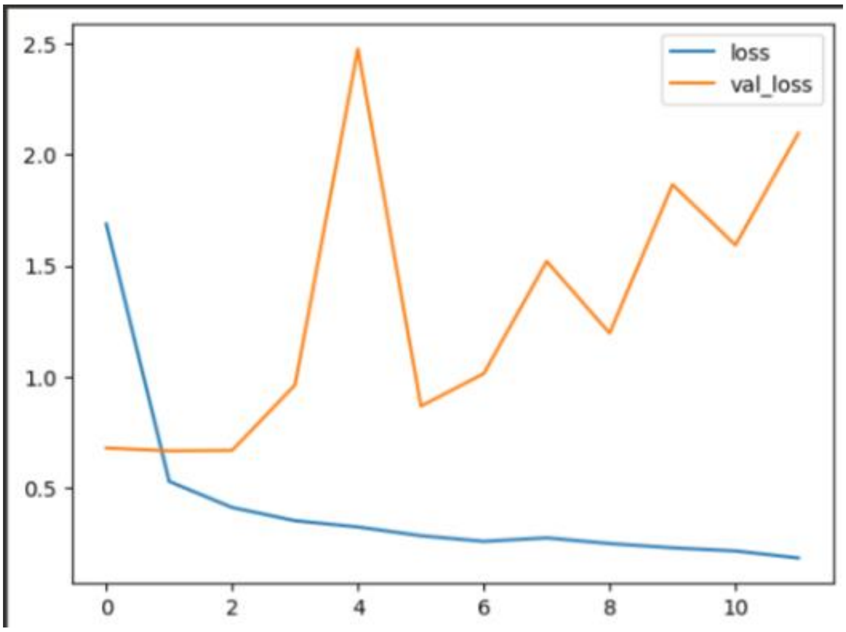

Figure 5.2.3

5.3 User Interface

Figure 5.3.1: Main User Interface

In the Figure 5.3.1, which shows the main user interface of the Bone Fracture Detection project, we may proceed by clicking on continue button.

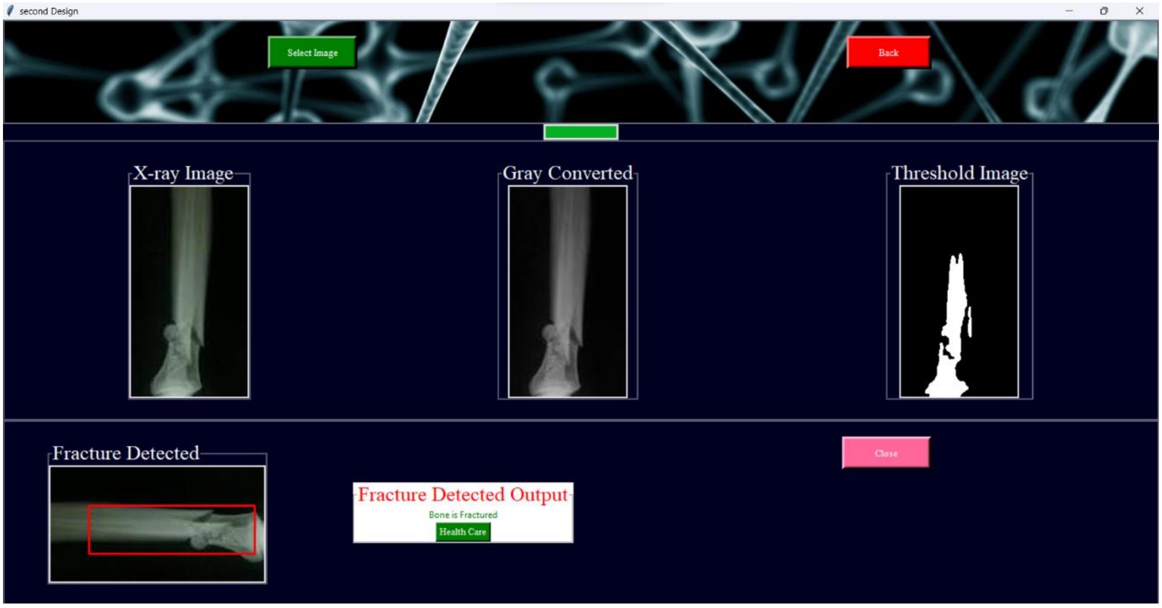

Figure 5.3.2: Bone Fracture Detection

In the Figure 5.3.2, the X-ray image is selected and it is Gray Converted and by comparing with Threshold Image, the bone fracture is detected.

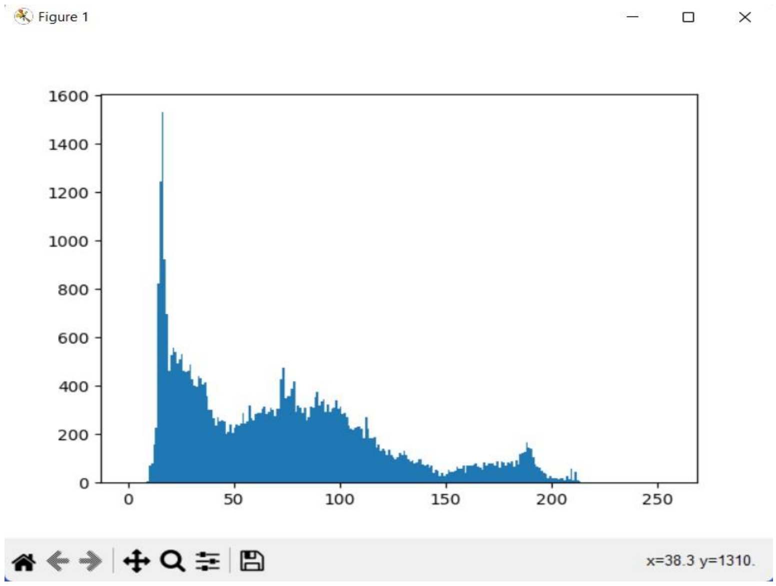

Figure 5.3.3: Edge Detection Graph on Fractured Bone

In the figure 5.3.3, edge detection graph shows the boundaries of the objects within the images and plots a graph correspondingly.

Chapter 6

Conclusion and Future Scope

Conclusion

bone fracture detection project harnesses the power of advanced deep learning techniques, including Convolutional Neural Networks (CNNs), Residual Networks (ResNets), and ensemble models, to achieve a remarkable accuracy rate of 94%. By addressing the challenges of manual detection and offering a precise and efficient automated solution, our project not only showcases the potential of machine learning in medical imaging but also underscores its transformative impact on healthcare. This work represents a significant step forward in improving patient outcomes through quicker and more accurate diagnoses, and it sets the stage for further innovations in the field of medical image analysis."

Future Enhancement

This system is very flexible and further modification can be made to the system in future by adding the following features:

- Facility to modify user details.
- More interactive user interface.
- Facility for Backup creation.

Chapter 7

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