BONE DEFORMITY IDENTIFICATION USING DEEP LEARNING

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ABSTRACT

The success of machine learning algorithms in medical imaging has increased the need for artificially trained models to make them work in the medical field more quickly and efficiently. This paper gives a technique to identify bone fracture using machine learning algorithms, by which workload for orthopedics can be reduced. The significant use of machine learning in this era of big medical data would help gather information from the available x-ray images rather than spending hours in the radiology departments. This paper presents imaging technologies used to identify bone fracture in the human body and give quick results once the x-ray has been taken.

***K*eywords** medical field, orthopaedics, machine learning, xray, bone fracture, image pixels, image soothing, edge detection, ridge regression, pickle library, image reshaping.

1.1 INTRODUCTION

One of the conditions that medical services treat the most frequently is bone injuries. Injuries or illness like fractures can result in bone defects, a dangerous condition. In cruel cases, injuries causes eternal damage or yet death of a patient. The most popular technique for identifying spinal injuries is to take an X-ray imaging of the relevant organ. It can be challenging to analyze an X-ray, particularly in treatment centers when patients are sometimes in tremendous pain and fractures are sometimes not obvious to medical professionals. Orthopedic photography is a branch of radiology that uses, among other things, X-rays, ultrasound imaging (CT), and neuroimaging. A most common method for detecting fractures is a musculoskeletal X-ray image. Incorrect diagnosis can lead to the more unnecessary diagnostic trials, which extends the treatment time and cause bone distortion, which can effect in patient disability in the worst-case scenario. As a result, early diagnosis of abnormalities in a radiographic scan can reduce discomfort duration and protect patients from harmful repercussions. The most prevalent conditions affecting people worldwide are those involving the musculoskeletal system. Both of the immediate specialists who are involved in the urgent care in which any patient with a severe damage is hospitalized once they arrive at the hospital and the physicians who are in charge of categorizing the orthopedic pictures are included in this procedure. Any injury could be precise and reliably detected by healthcare personnel with the help of image-classification software, which would be important in emergency rooms where a second opinion is highly prized. Many of the studies on bone irregularity detection have been published in the recent years but still, most people only examine one form of bone which is impractical in a therapeutic situation. Among most popular methods to discover abnormalities with bones &

other organs in human body is via use of X-ray photographs (also known as radiographs). The result is shadow like picture. The quality of pictures produced by CT & MRI scans is superior than those produced by x-rays, but x-rays are less expensive, more widely available, & simpler to use [4]. The goal of this study is detecting distinct bone cracks into medical X-ray images in order to aid clinicians in diagnosing fractures and administering the appropriate treatment.

1.2 PROBLEM STATEMENT

Bone fracture and deformity detection is a widely discussed topic. The multiple bone fractures often might go unnoticed by the human eye and thus, complete and efficient treatment would become difficult. So, with the aim to develop an intelligent classification system that would be capable of detecting and highlighting bone fractures. This can be achieved by making a Computer-Aided Diagnosis (CAD) system to detect the bone fracture that helps the radiologists or the orthopedics by interpreting the input medical images, mostly x-ray images, in a short period. The need for open datasets, the enormous variability in bone silhouette, and the variety of lesion kinds, all provide support to this approach. As a result, it is physically hard to construct a trustworthy Computational model for skeletal defects. Deep learning, although, has only just lately been applied to this problem.

1.3 OBJECTIVES

- The main objective is to implement a system which detects nine bones instead of only one bone
- As in the previous study. A two-stage design is proposed to examine the impact of bone form variants on the precision of anomaly identification. One classification model is used in the first phase to identify the kind of bone, and the accurate model is used in second phase to detect abnormalities.
- Every classification had received training to detect irregularities in a special variety of bones**.** Another important concept used in the procedure of detection is edge detection which involves automatic identification of the boundaries present between objects.
- This segregation of boundaries benefits in breaking up the image into separately examinable areas. Also, ridge regression gives better performance against data which does not have a pattern similar to the data used for training the model due to the diversity present in the images of the dataset.
- Thus, a ridge regression model coupled with edge detection gives us the desired outcome.

1.4 SCOPE

As we know, bones are one of the most integral parts of the body, and treating them when fractured is even more crucial, and implementing such techniques would reduce the workload in the orthopedic department and give accurate information and results. The future works possible for this project include the deployment of the model in the Xray/CT scan machines itself so that whenever the bone area is scanned the results will be obtained to the patient in a few seconds. In addition to this technology, it is also possible to determine the type of fracture along with its degree. The categorization of clinical representations is a frequently understudied topic of research that requires solutions of recurrent neural networks and issues with Content Based Image Retrieval (CBIR) technologies. The model can effectively and simply assist clinicians in gathering patient data and making treatment recommendations decisions.

1.5 LIMITATIONS

- Limited training data
- Interpretable results
- Class imbalance
- Variability in bone deformities
- Limited generalization

1.6 METHODOLOGY

In this project we are using a Two stage Hybrid Classification method(Xception Network /SVM Algorithm)

SVM (Support Vector Machine):

SVM is a popular supervised learning approach for problems involving regression and classification tasks. It is used to classify data into different classes. SVM trains on a set of label data.
SVM is an algorithm which has lately gained popularity into field of machine learning and pattern recognition. Margin maximisation idea serves as their foundation. SVM undertake structural risk reduction, which increases the classifier's complexity with the goal of getting great generalisation performance. SVM classifies data in a higher dimensional space by creating a hyperplane that optimally divides the data into two groups. For really large datasets, standard numeric algorithms for QP have become unworkable. SVM performseffectively in high-dimensional spaces and produces great texture classification results.

Xception Network:

Xception network is used for classification and detection. Xception is a deep convolution neural network that involves depth wise separable convolutions.
As opposed to the Inception model's inception modules, depth-wise separated computational complexity are used instead of Xception modules.There are those who believe that the Xception is CNN's interpretation of the Inception modules. Between both regular anddepth-wise separable convolutions, it serves like an intermediary step between them. A deep-wise separable convolution is therefore analogous to an inception module with several towers.

LITRATURE SURVEY

2.1 RESEARCH-PAPER-01

Author: B. E. Bejnordi et al.

Title: ''Diagnostic assessment of deep learning algorithms for detection of lymph node metastases in women with breast cancer''

Year: 2017

Proposed work:

Literally the entire pathology images are processed using deep learning algorithms, which could improve the precision and effectiveness of diagnosis. Using flesh slices stained using immunohistochemistry to detect tumors into female lymphatic system carrying breast cancer, computerized learning algorithms are compared to pathologists' diagnoses in a diagnostic setting. The challenge (CAMELYON16) was launched so that researchers may create advanced algorithms for spotting lesion tumours. A learning set of data of whole-slide images across 2 centres inside the Dutch with (n = 110) but without (n = 160) local tumours validated through immunehistochemical marking were made available to participants to assess their ability to construct algorithms. In a 129 whole-slide image independent test set, algorithm performance was assessed (49 with and 80 without metastases)

2.2 RESEARCH-PAPER-02

Author: S. K. Mahendran and S. S. Baboo

Title: ''Automatic fracture detection using classifiers—A review'' Year: 2020

Proposed work:

In this paper Mahendran proposed a computer-aided diagnostics method to find injuries in the long tibia bones of the legs. The raw input x-ray images are subjected to Simultaneous Automatic Contrast adjustment, Edge Enhancement and Noise Removal (SACEN) algorithms for preprocessing. Moreover, textural features are then extracted using Gray Level Co-occurrence Matrix (GLCM). The extracted features are then fed into BPNN, SVM and Naïve Bayes classifiers. Finally, accuracy of 90% is achieved on a dataset of 1000 x-ray images by applying majority voting on the classifier's outputs.

2.4 RESEARCH-PAPER-04

Author: C. M. A. K. Z. Basha, T. M. Padmaja, and G. N. Balaji

Title: ''Automatic X-ray image classification system,'' in Smart Computing and Informatics.

Year: 2017

Proposed work:

The study suggested a method with 5 image processing phases, including denoising with high boost filter, enhancing with an adaptive histogram equalization, extracting statistical features and classifying utilizing an ANN. SVM, probabilistic neural network & back-propagation neural network are used to categorize X-ray pictures into head, neck, skull and foot/palm categories respectively. For classification the probabilistic neural network, and classifiers can be used. With an overall categorization accuracy of 92.3%, this system may be utilized for accurately categorize X-ray pictures in clinical settings.

CHAPTER 3

SYSTEM ANALYSIS AND DESIGN

3.1 SYSTEM ANALYSIS

3.1.1. INTRODUCTION

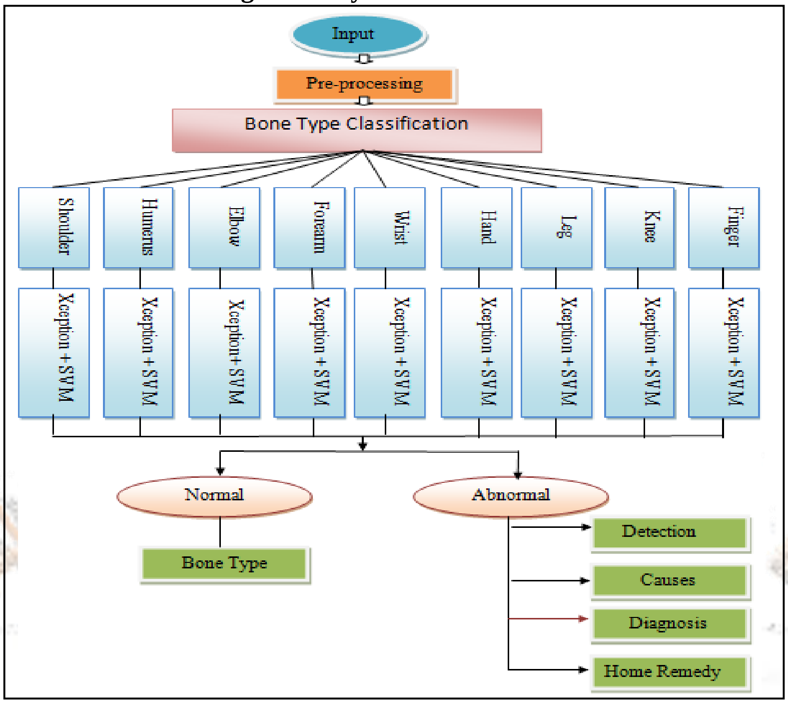
Bone fracture is quite a familiar problem in humans which is caused by falls, accidents, disease as pathological fractures, injury to the overlying skin, hairline fracture, etc. To identify the fracture x-rays and CT scans are used but these cannot always detect the exact location of the fracture. Hence the involvement of machine learning and artificial intelligence would have a great impact on the outcomes and the fracture can be accurately diagnosed. X-Ray imaging technique is often used by orthopedic doctors for fracture detection. Using machine learning tools, we can inventively extract information about the human body conveniently and economically. It is possible because of both hardware and software advancements and the development of existing technology. We know that a single method cannot be applied to all parts of the body, but experimenting with new technology that would be capable of identifying the fractures in our body using one method. Artificial intelligence (AI) and machine learning (ML) techniques are revolutionizing several industrial and research fields so it can be applied to the medical sector as well. This system is an AI and Machine Learning based analysis system. It is applicable to all age groups of men, women and children. It provides a summarized and evaluated results of any detected deformity or fracture based on the x-ray images. Implementation of an image processing based efficient system to accurately detect the fractures in the whole human body is the aim of this project.

3.1.2. SYSTEM ARCHITECTURE

The improved images are fed in first stage, which classifies them into one of nine categories. The categorized bones are then fed into the second stage, which specifies whether the healthy or fractures.

The Xception CNN model is used in both the stages. Moreover, the final layer is replacedwith an SVM layer in the second stage to improve the results. The results shows that the SVM layer is superior. So, the final layer is replaced with an SVM layer in the secondstage to improve the results.

Fig 3.1.2 : System Architecture



3.1.3 EXISTING SYSTEM

In order to attain the best performance and the fewest calculations, the GNG network is combined with the eight original models. Two stages of classification are performed using the features that were derived from GNG. An X-ray of a bone is first divided into one of seven categories, after which it is submitted, in accordance with classification, to each of (7)classifiers developed to handle anomalies in bones. As a result, there are eight models used in the classification step i.e (7)for anomaly detection and onefor classification. The MURA database, the biggest freely released collection of x-ray scans of fractures, has been used in research. The best total accuracy and precision were found to be 95.86 percent and 99.63 percent for the firststage, and 92.50 percent and 92.12 percent for the secondstage.

Disadvantages:

- Accuracy and performance should be increased.
- Initial treatment details are not present.
- Computation and processing time is more.

3.1.4 PROPOSED SYSTEM

A two stage categorization approach is presented for discovering anomalies into the bones. Identifying the kind of bone is the initial stage in the process. The photos from first stage which were properly categorised are then put into second step, which detects the bone abnormality. If the bone is normal, than the type of bone must be determined . If abnormal, it determines the reason of the abnormality, the sickness or disorder. The system then advises how to identify and cure the problem, as well as what home treatments or remedies should beused. For the two stages, the Xception CNN model is utilised in feature extraction and classifying. Moreover, final layer is replaced with an SVM layer in the second stage to improve the results. Furthermore, the proposed method is tested using two different approaches i.e single-view approach, in which only one x-ray picture is fed in two-phase classification method & multi-view approach, in which multiple images are fed in 2 phase classification method for each study, and then a majority voting technique is used to reach a final decision

Advantages:

- The outcomes outperform the most recent pre-trained systems.
- The suggested method considerably reduces processing and response time.
- Easy diagnosis.
- Execution is fairly simple3.2 SYSTEM DESIGN

3.2.1 DATA FLOW DIAGRAM

A data flow diagram (DFD) shows data impacts a system, as well as where it is recorded. It is a schematic representation of how data travels within a structure. Any work process canbe clearly demonstrated using data flow diagrams. Data flow diagram is a significant approach, and has gained popularity.

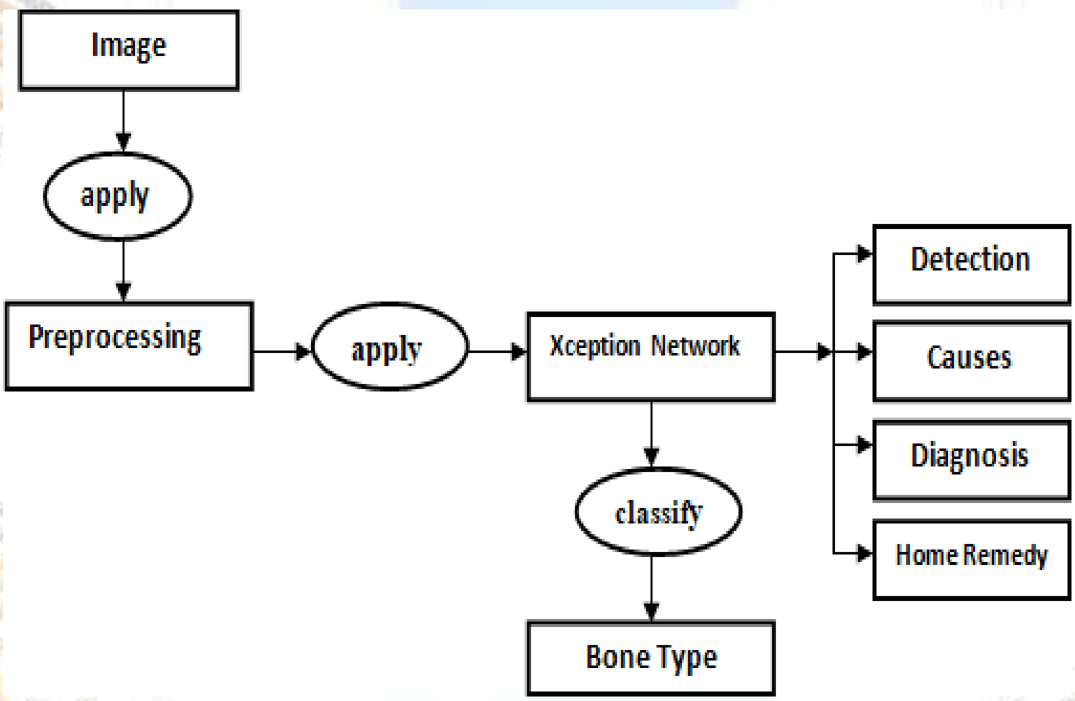


Fig 3.2.1: DFD Diagram

3.2.2 SEQUENCE DIAGRAM

Sequence Diagrams are communication diagrams that explains how the processes are accomplished. A Sequence diagram displays object interactions ordered in time sequence and shows how the objects interact in the circumstance of a collaboration. UML Sequence diagrams are the time-focused and graphically time is represented on vertical axis of the diagram to express the order of the interaction. Sequence diagram consists of a sequence of communication within the system that are communicated among other different process.

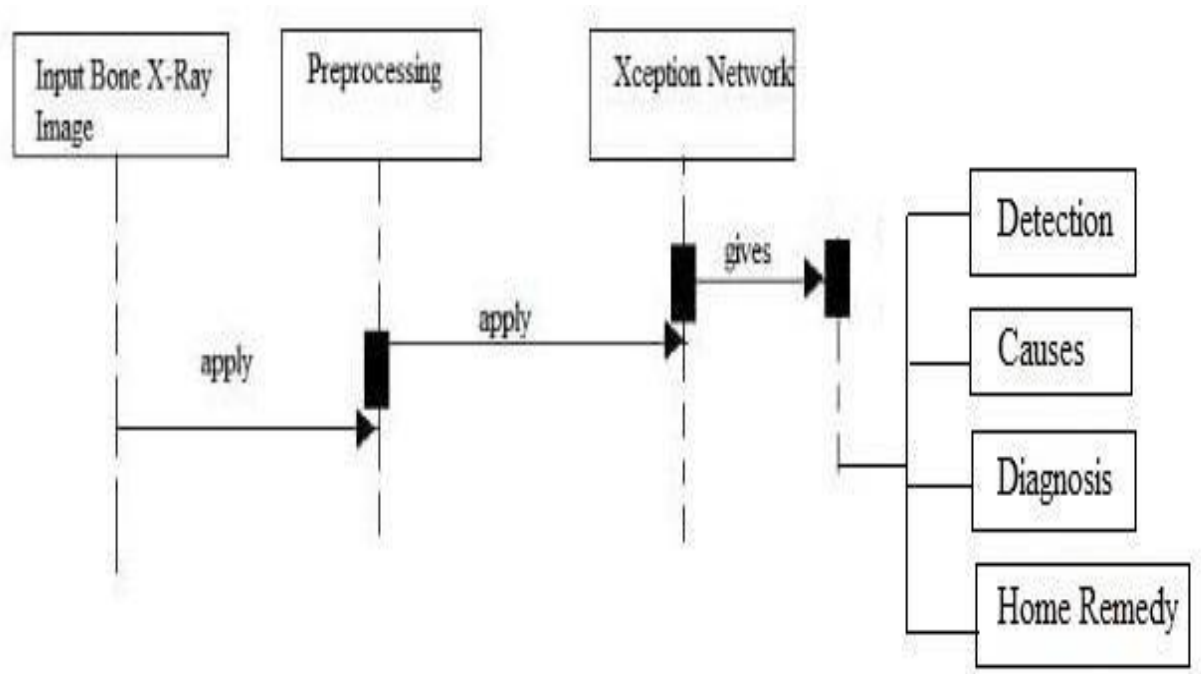


Fig 3.2.2: Sequence Diagram

3.2.3 FLOW CHART A flow sheet can be presentation of steps graphically. It is entirely originated from the engineering science as a tool for presenting algorithms and even program logic however it has extended for the use of other tool for different forms of process. Different flow illustration shapes have absolutely different standard meaning.

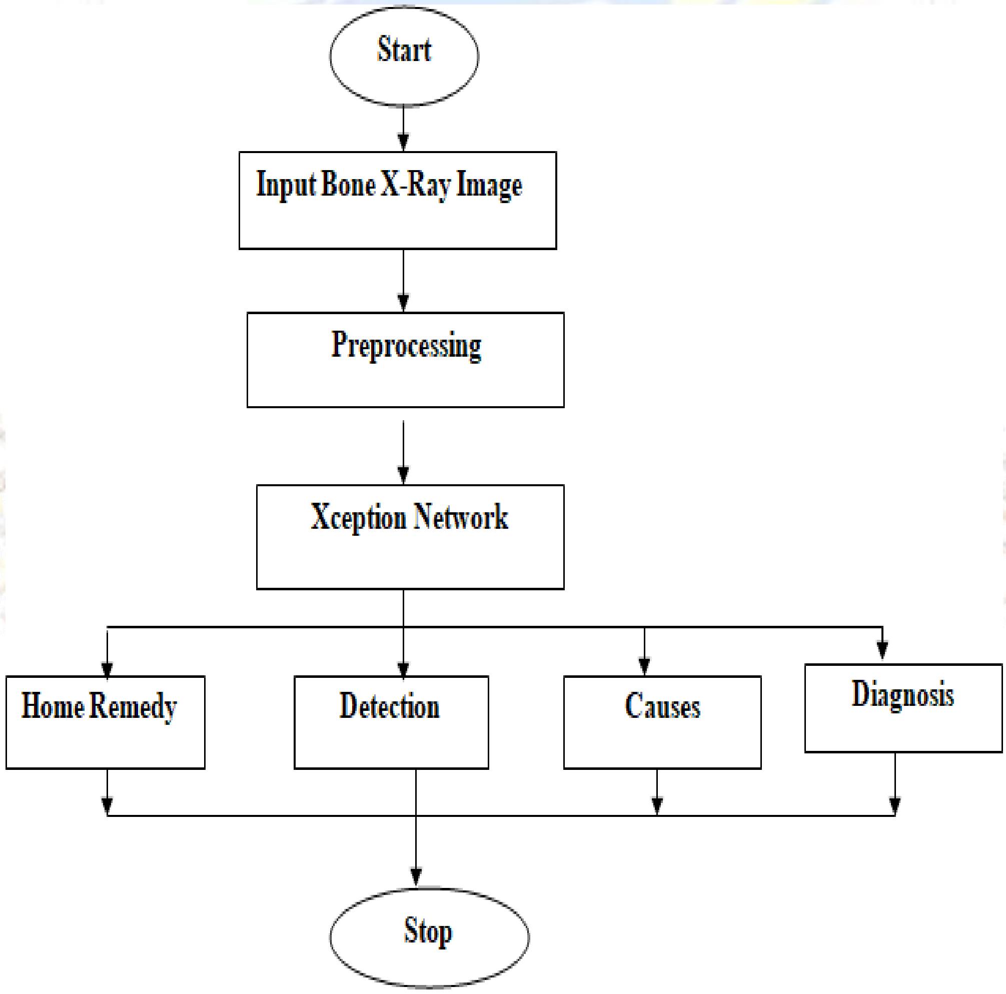


Fig 3.3.3: Flow Chart

3.2.4 USE CASE DIAGRAM

The primary goal of system modelling is to record dynamic activity. Dynamic behaviour is more significant than static behaviour when modelling a system because only static behaviour is insufficient. One of the 5diagrams availablein the UML to represent the dynamic nature is the use case diagram. The use casediagram should interact with some internal or external sources because it is dynamic in nature.q

Both these domestic and foreign entities are referred to by actors. Use case diagrams show actors, used scenarios, and their connections. The diagram is used to model the structure or module of the application. A specific system capability is wrapped in a single usecase diagram. As a result, many employ to model the complete system.

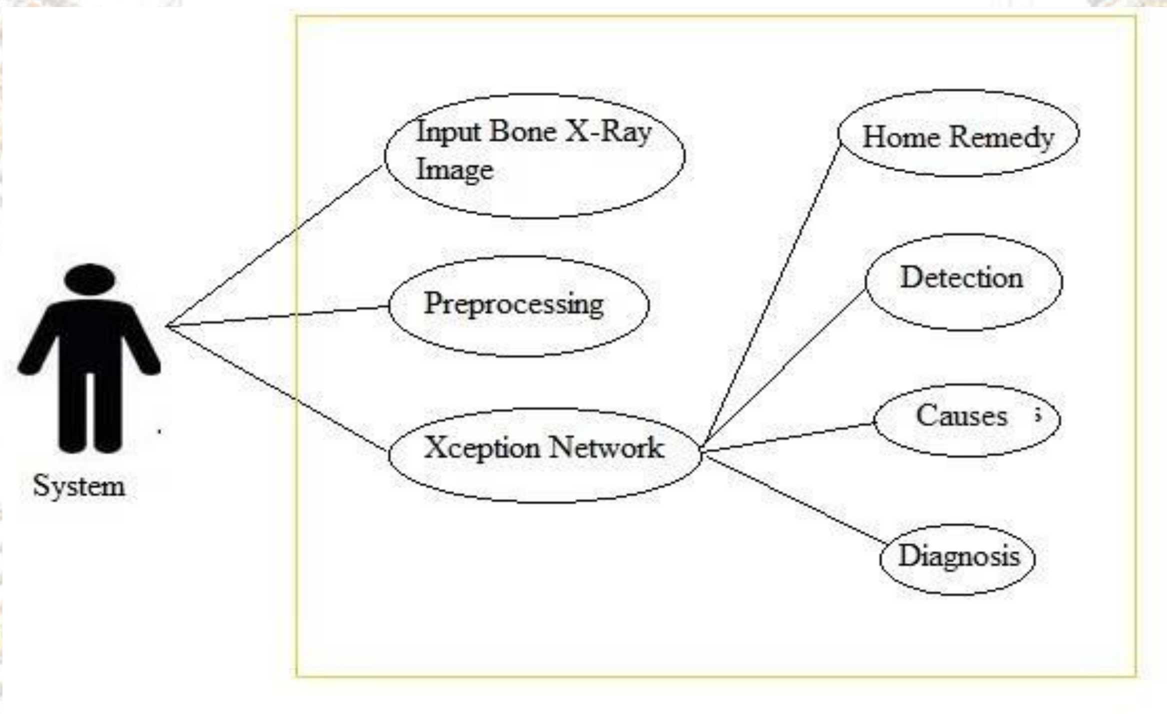


Fig 3.3.4: Use-Case CHAPTER 4

IMPLEMENTATION

4.1 INTRODUCTION

The process having a system staff inspects, operate new equipment, train users, install the new software is known as implementation. Depending on the size of the organisation employing the programme and the dangers involved in doing so. To compare the outcomes, they occasionally run both the old and new systems simultaneously. Developers work to make sure that the system is trouble-free during initial use, regardless of the implementation technique used. The system is assessed to determine its strengths and weaknesses.

4.2 SYSTEM ARCHITECTURE

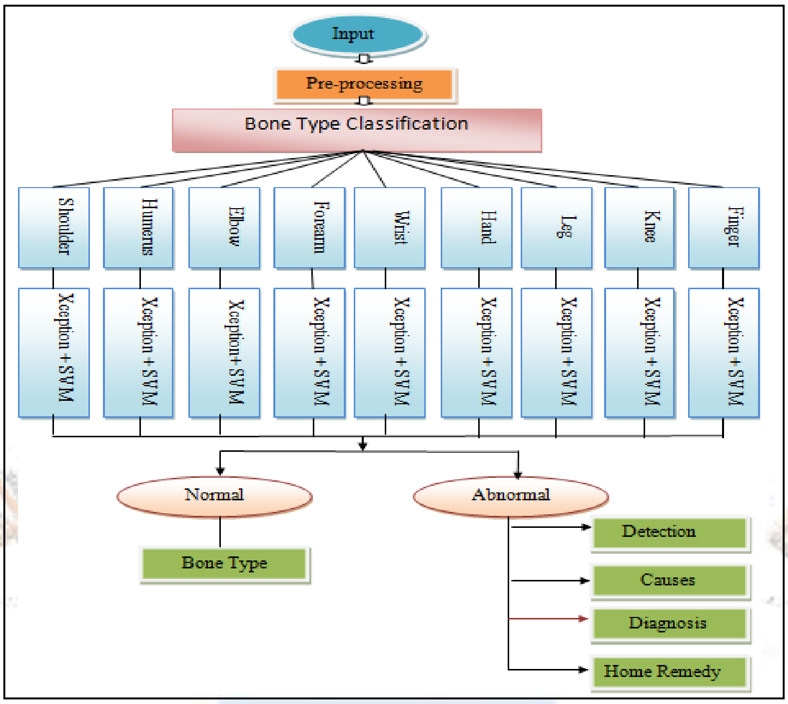


Fig 4.2 : System Architecture diagram

The improved images are fed in first stage, which classifies them into one of nine categories. The categorized bones are then fed into the second stage, which specifies whether the healthy or fractures.

The Xception CNN model is used in both the stages. Moreover, the final layer is replacedwith an SVM layer in the second stage to improve the results. The results shows that the SVM layer is superior. So, the final layer is replaced with an SVM layer in the secondstage to improve the results.

4.3 MODULES

1. Dataset
2. Image Pre-processing
3. Feature Extraction & classification

MODULES DESCRITPTION

4.3.1. Dataset

Mura database is biggest openly accessible database on x-ray bone abnormalities. The training and the testing datasets are included and plays an important role. It includes 40,561 photos from 14,863 studies, each of which is classified as normal or pathological. There are 9,045 studies that are normal and 5,818 studies that are aberrant. The MURA dataset covers avariety of bone abnormalities, including cracks, degenerating joint disorders, also different aberrations, like subluxations & lesions.4.3.2. Image Pre-processing

The main goal is to improve raw x-ray images. To raise importance of bones into photographs, variance amongst bone & background should be maximised. As a result, adaptive histogram equalisation is used in this study to transform the image's intensity to a uniform intensity. The projected framework initiates by removal of noise by x-ray images.

Noise Removal: The unwanted pixels that degrade the image's quality are known as noise. When a camera or transmission fails to record or transmit an image, dark & bright dotslook as salt & pepper noise. Applying a mathematical modification T to x-ray picture eliminates it. $g(x,y)=T[f(x,y)]$ Denoising is performed using the methods such as the averaging filter, median filter and wiener filter method.

4.3.3.Feature Extraction and Classification

An 2-phase categorization is used in the proposed method. For the two steps, the Xception pre-trained model is used. The important features are extracted from the input photos using an unsupervised Xception network. In the classification step, the first stage is tosort the bones into one of nine main categories. The correctly identified images from stage 1 are then transmitted into the second stage, which detects the bone abnormalities. The Xception CNN model is used in both stages. Moreover, the final layer is replaced with an SVM layer into 2nd phase to improve outcomes.

Xception Model

As opposed to the Inception model's inception modules, depth-wise separated computational complexity are used instead of Xception modules.There are those who believe that the Xception is CNN's interpretation of the Inception modules. Between both regular anddepth-wise separable convolutions, it serves like an intermediary step between them. A deep-wise separable convolution is therefore analogous to an inception module with several towers.

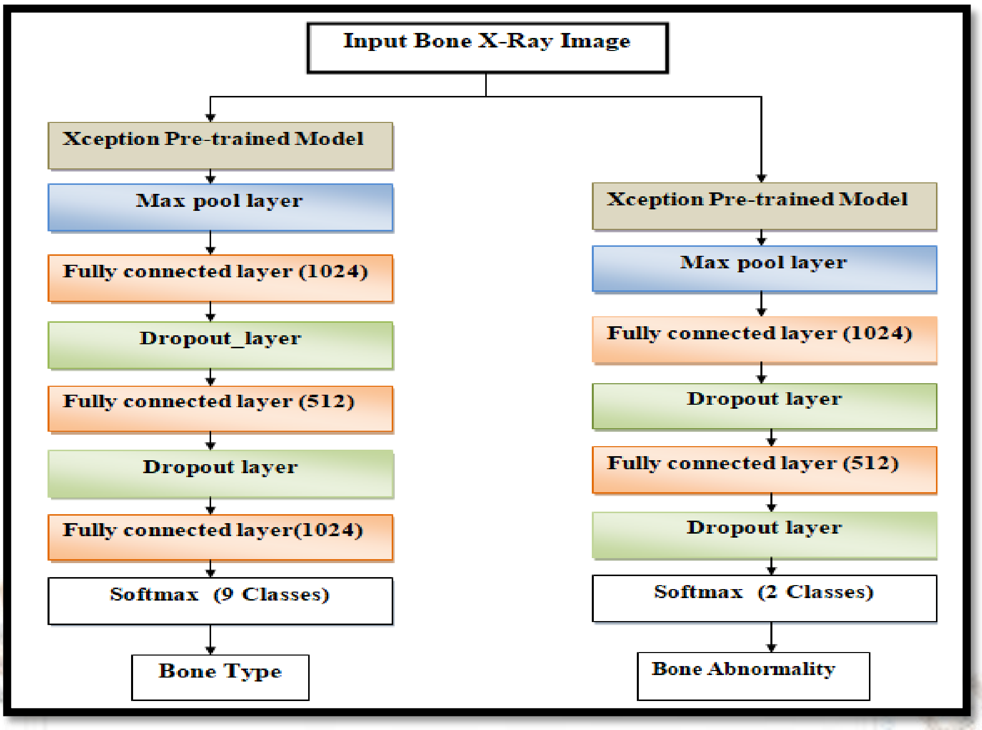


Figure 4.3.3: Xception Model

4.4: ALGORITHM EXPLAINATION

Support Vector Machine(SVM):

SVM is an algorithm which has lately gained popularity into field of machine learning and pattern recognition. Margin maximisation idea' serves as their foundation. SVMundertake structural risk reduction, which increases the classifier's complexity with the goal of getting great generalisation performance. SVM classifies data in a higher dimensional space by creating a hyperplane that optimally divides the data into two groups. For really large datasets, standard numeric algorithms for QP have become unworkable. SVM performseffectively in high-dimensional spaces and produces great texture classification results.Xception Algorithm:

A model is designed using the Xception Algorithm. In comparison to other algorithms examined, an Xception method has greater rate of precision & a quicker training time.

Python Pseudo Code for Xception

img_path='elephant.jpg' img=image.load_image(img_path,target_size=(299,299))

x=image.img_to_array(img)

x=np.expand_dims(x, axis=0) x=preprocess_input(x) print('i/p imageshape:',x.shape)

preds=model.predict(x) print(np.argmax(preds))

print('Predicted:',decode_predictions(preds,1))

INTERPRETATION OF RESULTS

5.1 SNAPSHOTS

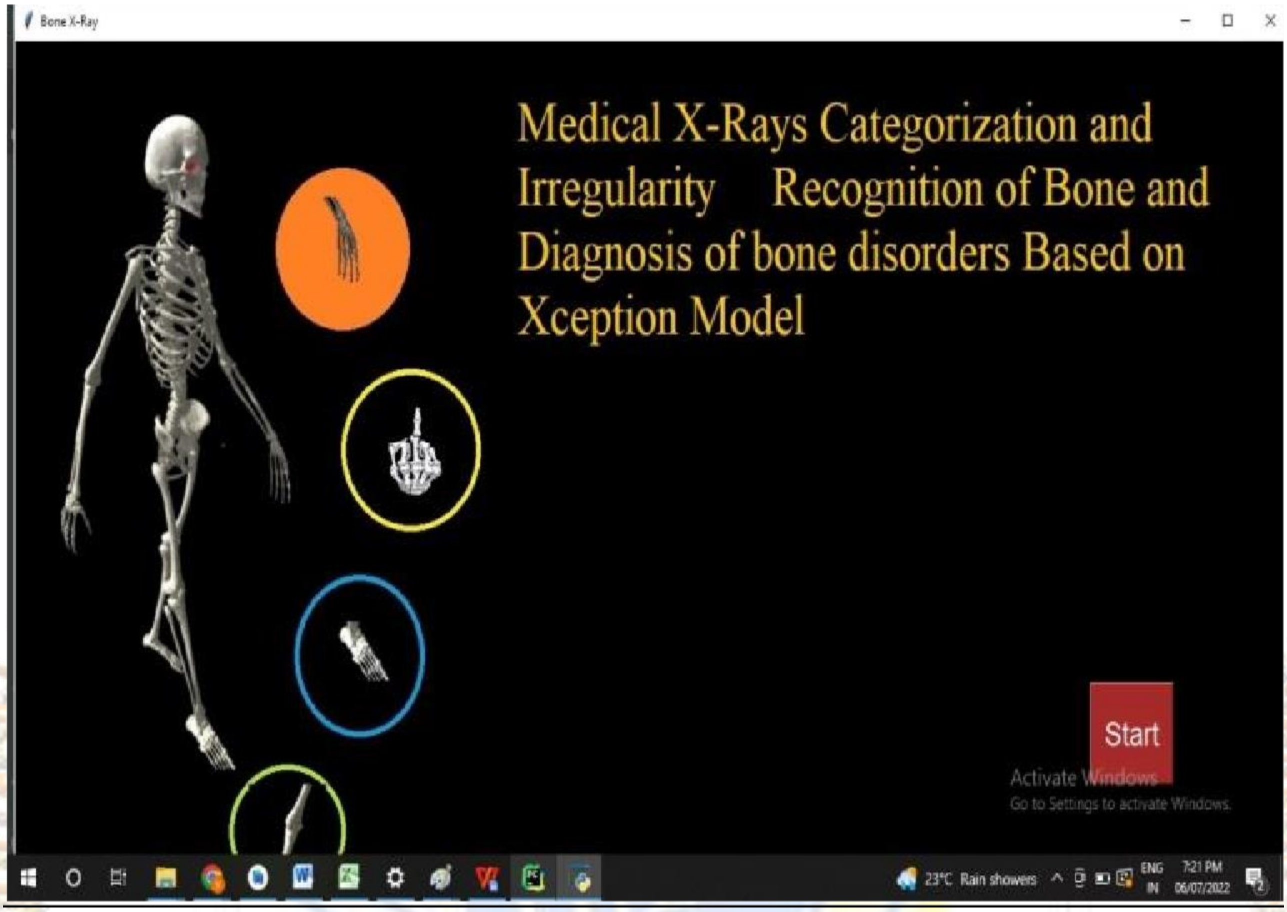


Fig5.1: Main Page

This is the main page of the project the user gets after running the project, here we have to enter the images to be classified.

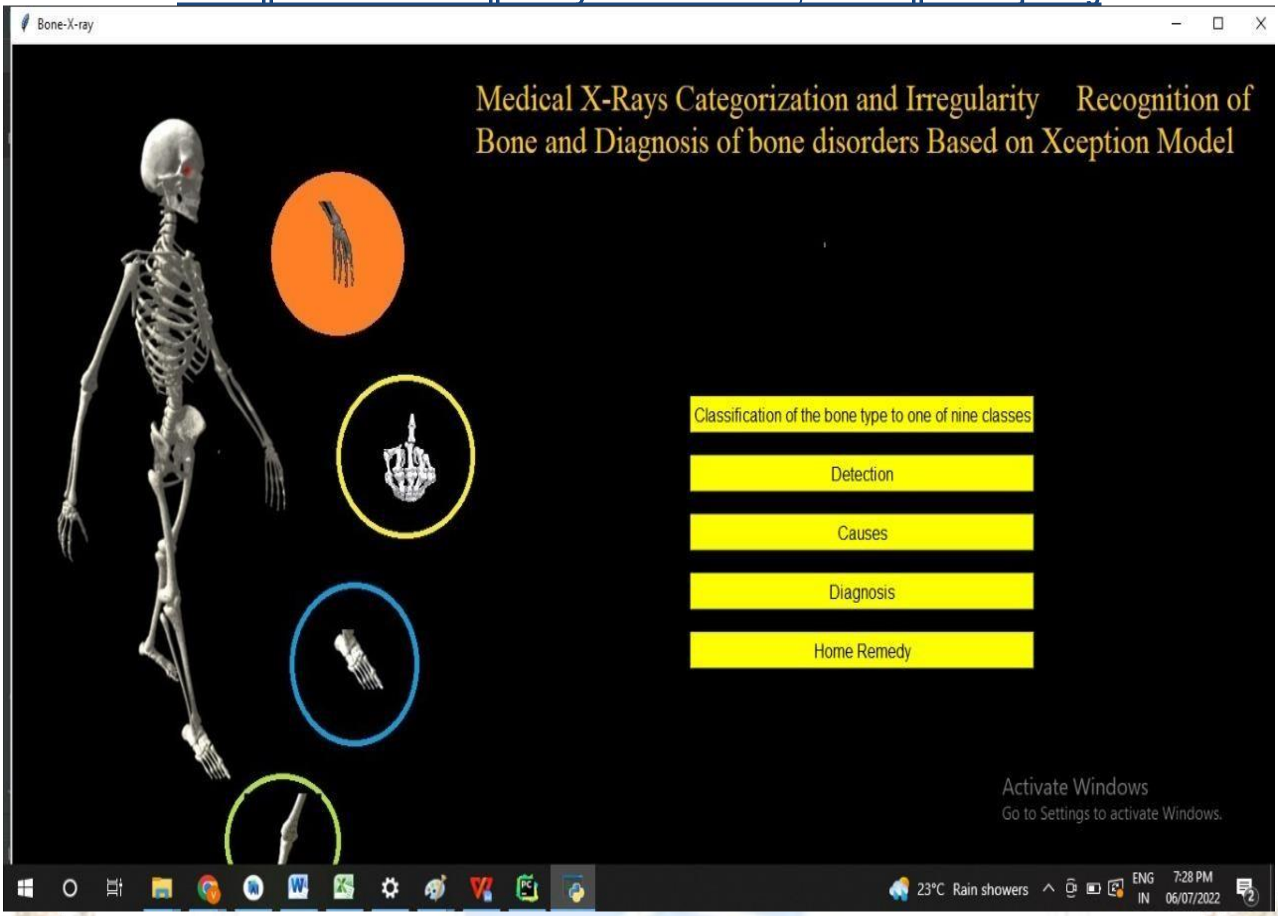


FIG. 5.2: Menu

This is the second page of the project where the user gets such output where he can see the results of the given image and he can select the desired option.

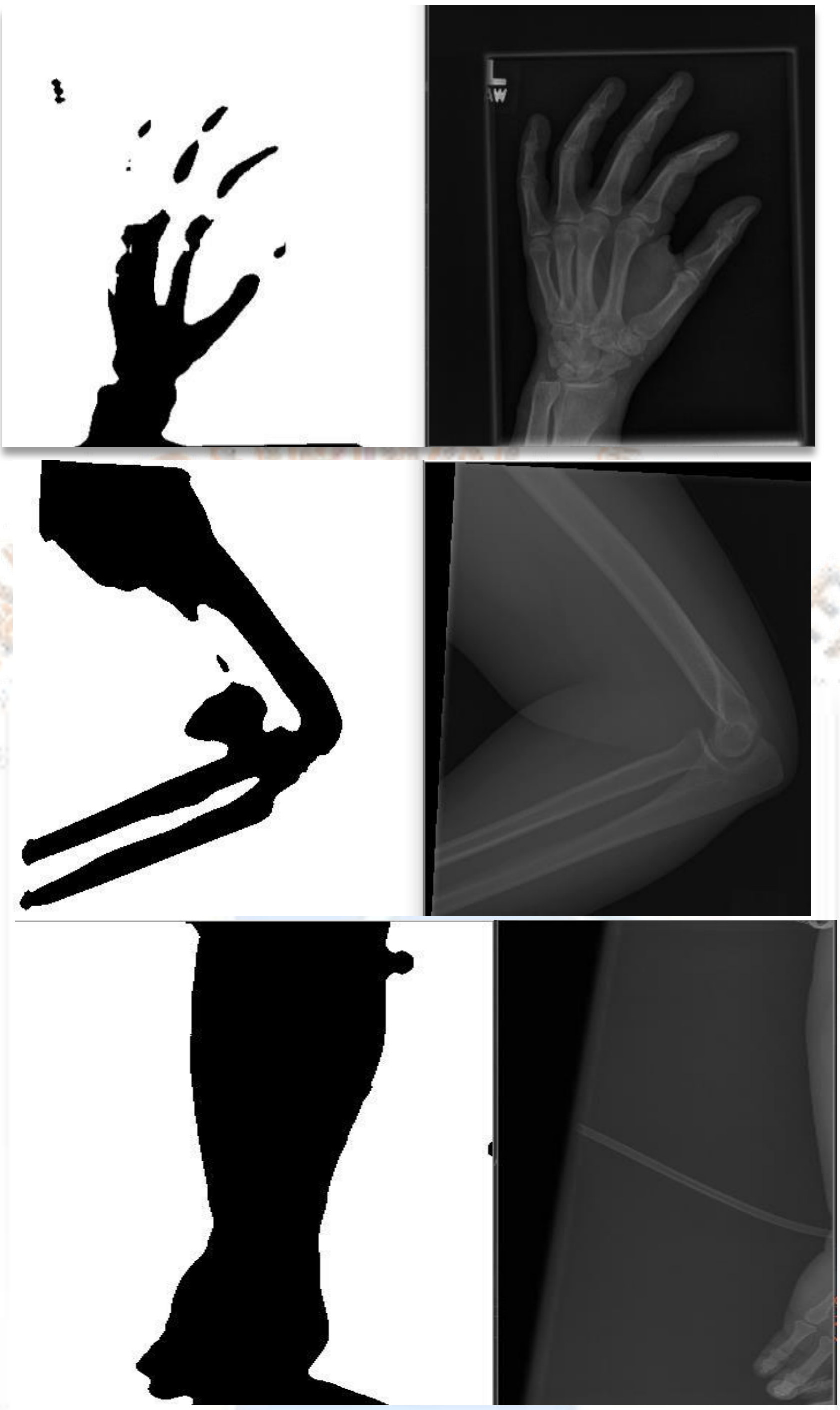


FIG. 5.3: Image pre-processing

In this, the given image is processed through the image preprocessing to reduce the noise and enhance the image to get accurate results.

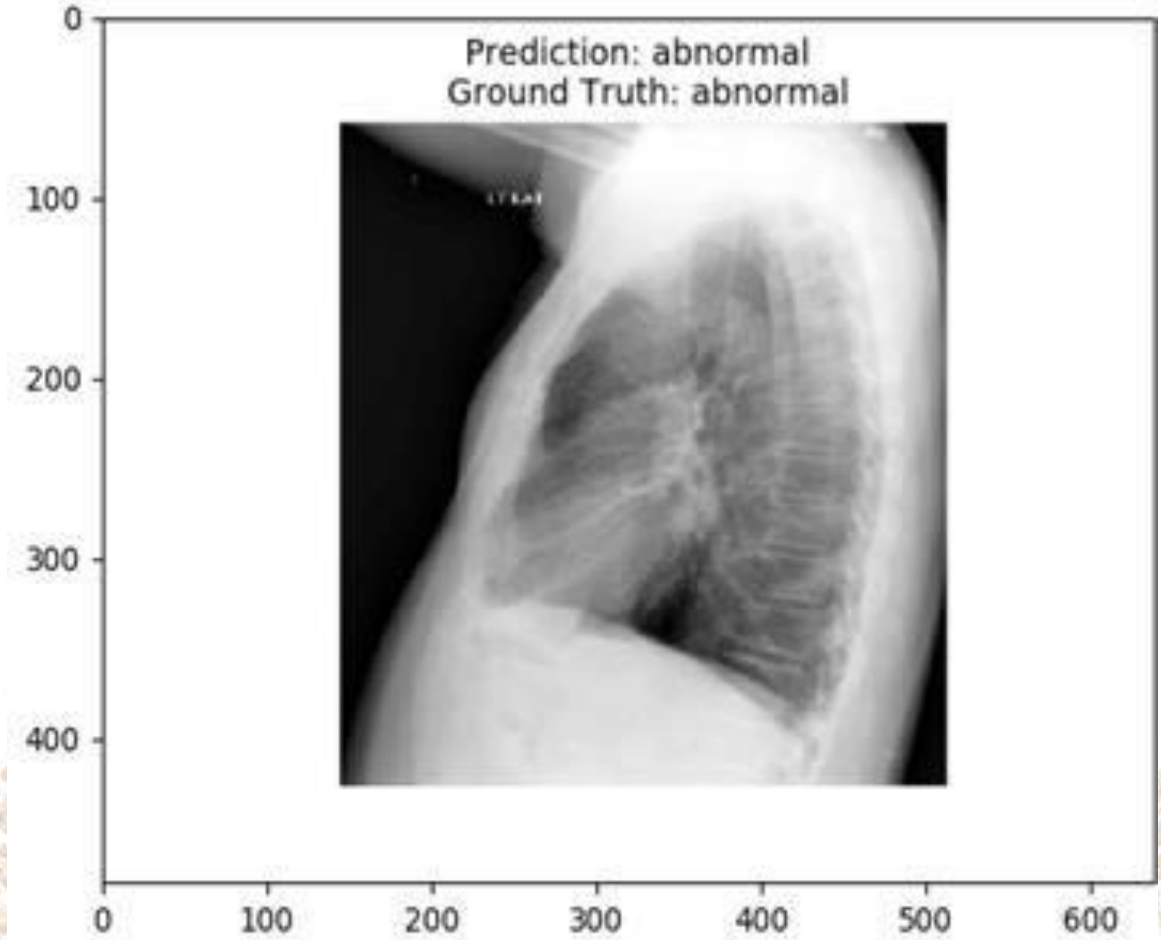


FIG. 5.4: Abnormal bone Classification

The above is the result of image after enhancing it.

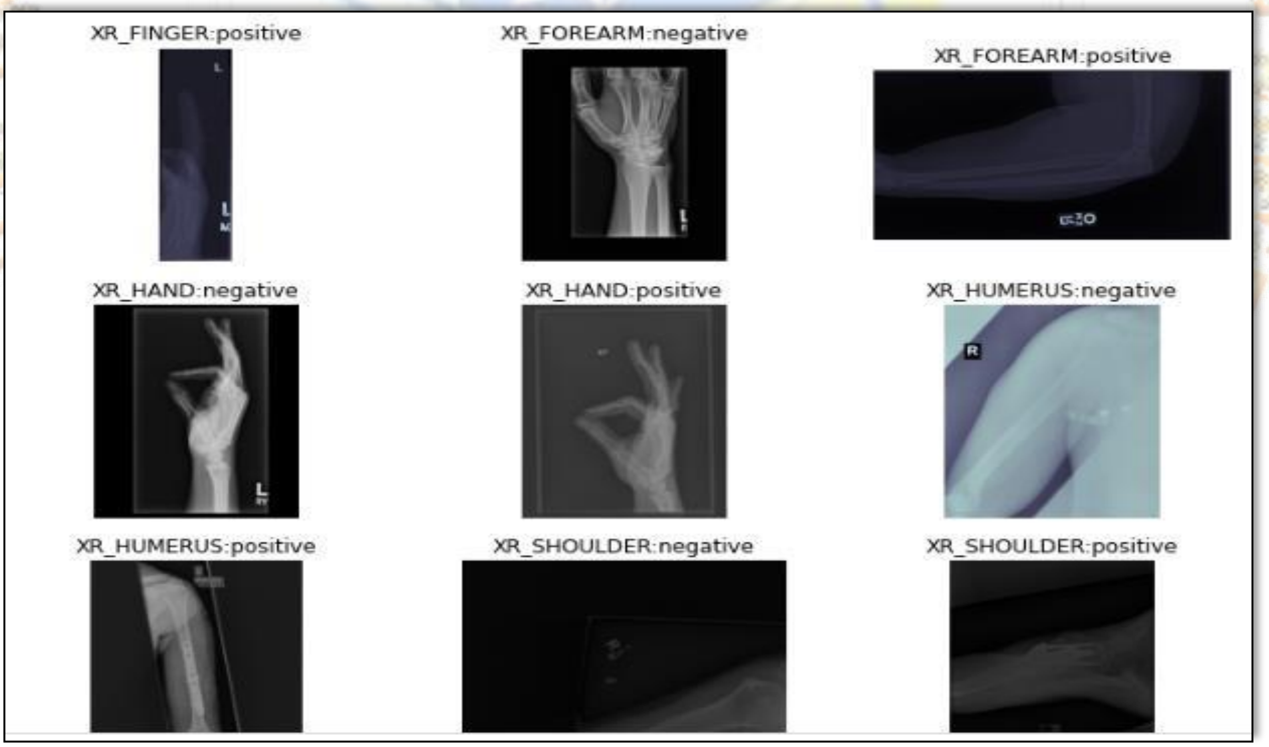


FIG. 5.5: Different Bone X-ray classification from the Dataset.

The above images classifies into two types Negative and Positive

The positive images show that there is no abnormality in the bone.

The negative images shows the abnormality in it.

CONCLUSION

As a final step, it offers a two-stage hybrid method for mutually categorization and irregularity identification of upper extremity top bones. In both training and testing, the MURA dataset is utilized extensively. In order to solve task with fewest possible computations, this research leverages a mix of supervised and unsupervised networks. Unsupervised Xception is used to extract the most essential characteristics from the input images. Ten distinct classification models are used to classify data obtained in a two-stage hybrid categorization phase. Stage one has a single model for classifying bones, whereas stage two includes nine models for detecting bone abnormalities, one for each kind of bone. The bone X-rays from the first stage are sent to 1 of 9 classes for abnormality identification in the second phase, depending on the kind of abnormality they show.The following are some of the benefits of the proposed methods i.e projected technique focuses upon 2 concerns such as the bone type categorization and irregularity recognition, the proposed method considers the upper extremity bones, which include nine different bones rather than only one bone as in the literature and projected technique is scalable due to the two-stage classification approach.

In the near future, we hope to have a database with more bone types (for example, back bones) to take advantage of the suggested architecture's scalability, and testing the planned method on different datasets, explore all the bone abnormalities kinds and building a real time mobile application that can detect the different types of fractures.

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