A Project report on

Classification Of Bone Fracture Using CNN

A Dissertation submitted to JNTU Hyderabad in partial fulfillment of the academic requirements for the award of the degree.

Bachelor of Technology

in

Computer Science and Engineering

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CERTIFICATE

This is to certify that the Major Project Phase I report entitled **"Classification Of Bone Fracture Using CNN "** being submitted by S.Sushma (21H55A0520), S.Laxmi Narayana (21H55A0523) in partial fulfillment for the award of **Bachelor of Technology in Computer Science and Engineering** is a record of bonafide work carried out his/her under my guidance and supervision.

The results embodies in this project report have not been submitted to any other University or Institute for the award of any Degree.

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ABSTRACT

In recent years, bone fracture detection and classification has been a widely discussed topic and many researchers have proposed different methods to tackle this problem. Despite this, a universal approachable to classify all the fractures in the human body has not yet been defined. We aim to analyze and evaluate a selection of papers, chosen according to their representative approach, where the authors applied different deep learning techniques to classify bone fractures, in order to select the strengths of each of them and try to delineate a generalized strategy. In recent years, deep learning and, in particular, the convolution neural network (CNN), has achieved results comparable to those of humans in bone fracture classification.

CHAPTER 1

INTRODUCTION

CHAPTER 1

INTRODUCTION

1.1 Introduction

Since long back, bone breaks was a long standing issue for mankind, and it's classification via x-ray has continuously depended on human diagnostics – which may be some of the time imperfect. In later a long time, Machine learning and AI based arrangements have ended up an necessarily portion of our lives, in all viewpoints, as well as within the therapeutic field. Within the scope of our inquire about and venture.

We have been examining this issue of classification and have been attempting, based on past endeavors and investigates, to create and fine tune a attainable arrangement for the therapeutic field in terms of distinguishing proof and classification of different bone fractures, using CNN (Convolutional Neural Systems) within the scope of present day models, such as Res Net, Thick Net, VGG16, and so forward. After performing numerous demonstrate fine tuning endeavors for different models, we have accomplished classification comes about lower at that point the predefined edge of certainty concurred upon afterward in this inquire about, but with the promising comes about we did archieve.

Since Wilhelm Roentgen discovered the existence of X-rays in 1895, medical imaging has advanced at a tremendous rate and has become the fundamental diagnostic tool in modern healthcare. As a combination of radiation and computer image processing technologies, digital X-ray imaging device are being widely used in many medical applications. Image classification is an area in image processing where the primary goal is to separate a set of images according to their features into one of a number of predefined categories.

Keywords: Convolutional Neural Network(CNN),ResNet50,Bone Classification.

1.2 Problem Statement

The algorithm starts with data augmentation and pre-processing the x-ray images, such as flip horizontal. The second step uses a ResNet50 neural network to classify the type of bone in the image. Once the bone type has been predicted, A specific model will be loaded for that bone type prediction from3 different types that were each trained to identify a fracture in another bone type and used to detect whether the bone is fractured. This approach utilizes the strong image classification capabilities of ResNet50 to identify the type of bone and then employs a specific model for each bone to determine if there is a fracture present.

1.3 Research Objective

After loading all the images into data frames and assigning a label to each image, we split our images into 72% training, 18% validation and 10% test. The algorithm starts with data augmentation and pre-processing the x-ray images, such as flip horizontal. The second step uses a ResNet50 neural network to classify the type of bone in the image. Once the bone type has been predicted, A specific model will be loaded for that bone type prediction from3different types that were each trained to identify a fracture in another bone type and used to detect whether the bone is fractured. The algorithm can determine whether the prediction should be considered a positive result, indicating that a bone fracture is present, or a negative result, indicating that no bone fracture is present. The results of the bone type classification and bone fracture detection will be displayed to the user in the application, allowing for easy interpretation.

1.4 Project Scope and Limitations

This proposed model can detect the fractures of bones using Convolutional neural network. Convolutional neural networks (CNN): There are various neural networks available which can be used as per the requirement or inputs being given. The algorithm starts with data augmentation and pre-processing the x-ray images, such as flip horizontal. This approach utilizes the strong image classification capabilities of ResNet50 to identify the type of bone and then employs a specific model for each bone to determine if there is a fracture present.

ResNet50: The key innovation in ResNet-50 is the use of residual blocks. These blocks enable the network to learn residual functions, which are the difference between the input and the desired output, making it easier to train very deep networks. ResNet-50 consists of 50 layers, including convolutional layers, batch normalization, and skip connections (or shortcuts) that allow the network to skip one or more layers, making it more efficient and easier to optimize. The architecture of ResNet-50 has been widely used as a pre-trained model for various computer vision tasks, including image classification, object detection, and image segmentation, due to its ability to capture complex features in images. It's one of the foundational architectures in deep learning for computer vision.

CHAPTER-2

BACKGROUND WORK

CHAPTER 2

BACKGROUND WORK

EXISTING MODELS

2.1 Automatic fracture detection using classifiers-a review

2.1.1 Introduction

Since Wilhelm Roentgen discovered the existence of X-rays in 1895, medical imaging has advanced at a tremendous rate and has become the fundamental diagnostic tool in modern healthcare. As a combination of radiation and computer image processing technologies, digital X-ray imaging device are being widely used in many medical applications. Image classification is an area in image processing where the primary goal is to separate a set of images according to their features into one of a number of predefined categories. It is the problem of finding a mapping from images to a set of classes, not necessarily object categories. Each class is represented by a set of features (feature vector) and the algorithm that maps these feature vectors to a class uses machine learning techniques. The ability to perform binary-class image classification as an automatic task using computers is increasingly becoming important in fracture detection.

This is due to the huge volume of image data available, which are proving to be difficult for manual analysis. The difficulty arises because of lack of human experts, poor quality images and time complexity. The current market need is to have techniques which can classify images as having normal or fracture, with minimum intervention from the users in an efficient and effective manner. This paper presents a review of the various classification approaches that can be used to classify bone x-ray images as either normal or fractured. The rest of the paper is organized as follows. The working of a general classification system is presented in Section 2. Section 3 reviews the various machine learning classification methods, while Section 4 presents the concepts of fusion classification. Section 5 concludes the work.[1]

Keywords: X-ray, Classification, Machine Learning, Fusion classifier.

2.1.2 Merits and Demerits of Fusion Classifier

A fusion classifier, also known as an ensemble classifier or a combination classifier, combines the predictions of multiple base classifiers to improve overall classification performance. Here are some merits and demerits of fusion classifiers:

Merits:

Improved Accuracy: Fusion classifiers often outperform individual base classifiers by leveraging the strengths of each classifier and compensating for their weaknesses. By combining multiple classifiers, they can produce more accurate and robust predictions.

Robustness: Fusion classifiers are generally more robust to noise and outliers compared to single classifiers. They can mitigate the impact of errors made by individual classifiers by aggregating their predictions.

Reduced Overfitting: Ensemble methods can reduce overfitting, especially when using techniques such as bagging or boosting. By combining multiple classifiers trained on different subsets of data or using different learning algorithms, fusion classifiers can generalize better to unseen data.

Handling Complex Relationships: Fusion classifiers can capture complex relationships in the data that may be missed by individual classifiers. By combining different models, they can effectively handle non-linear decision boundaries and complex patterns in the data.

Versatility: Fusion classifiers can be applied to various types of classification problems and data types, including structured and unstructured data, as well as binary and multiclass classification tasks.

Demerits:

Increased Complexity: Fusion classifiers can be computationally expensive, especially if they involve a large number of base classifiers or complex combination techniques. This complexity can make them less suitable for real-time applications or environments with limited computational resources.

Difficulty in Interpretation: Fusion classifiers are often more challenging to interpret compared to individual classifiers. The combination of multiple models and aggregation techniques can obscure the reasoning behind predictions, making it difficult to understand the underlying decision process.

2.1.3 Implementation

Assigning images to pre-defined categories by analyzing the contents is defined as ‘Image classification or ‘Image categorization’. Image classification normally involves the processing of two main tasks, namely, feature extraction task (extracts image features and forms a feature vectors) and classification task (uses the extracted features to discriminate the classes).The binary case classification classifies images into exactly two predefined classes. Here, a sample image belongs exactly to one of the two given classes.

The classifier has to determine to which of the two sets the new image goes. In binary classification a classifier is trained, by means of supervised algorithms, to assign a sample document to one of the two possible sets. These two sets are usually referred to as belonging samples (positive) and not belonging samples (negative) respectively. This method is otherwise termed as the one-against all approach or one-against one approach. Several algorithms exist for this type of classification.

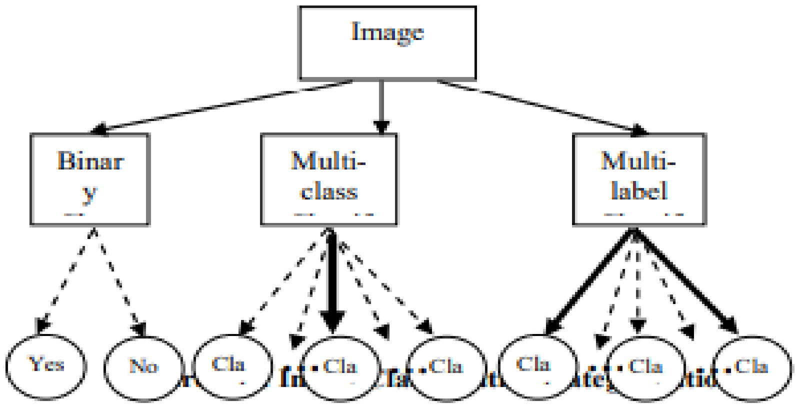

Fig.2.1: Image Classification

Broad classes of statistical classification algorithms have been developed and applied successfully to a wide range of real-world domains. In general, ensuring that the particular classification algorithm matches the properties of the data is crucial in providing results that meet the needs of the particular application domain. One way in which the impact of this algorithm/application match can be alleviated is by using group of classifiers, where a variety of classifiers (either different types of classifiers or different instantiations of the same classifier) are pooled before a final classification decision is made. Intuitively, fusion classification allows the different needs of a difficult problem to be handled by classifiers suited to those particular needs.

Mathematically, fusion classifier provide an extra degree of freedom in the classical bias/variance tradeoff, allowing solutions that would be difficult (if not impossible) to reach with only a single classifier. Because of these advantages, fusion classification has been applied to many difficult real-world problems. Recently, many scholars make use of fusion of classifier to enhance the performance of classification.

In the past several years, a lot of effort has been devoted to different fusion methods to achieve better performance. In reality, how to select appropriate classification methods towards image classification is an unsolved problem. According to when a perfect set of features that can describe the image data is given, the accuracy of the resultant classification depends on the classifier adopted. Several solutions have been proposed for this purpose. Among which, the usage Neural Network (NN), Support Vector Machines (SVM) and Naïve Bayes based classifiers are more prominent. The reasons behind this popularity are (i) easy of implementation procedures and (ii) accurate classification. As pointed out by, the success rate or accuracy of a classification problem can be improved by using multiple classifiers.

2.2 Computer - Aided Fracture Detection Of X-Ray Images

2.2.1 Introduction

X-ray is the one of the oldest technique to capture the bone shape. A bone x-ray are the images of the bone in the body, such as the hand, wrist, arm, elbow, shoulder, etc.. Fracture is defined as the typical alignment of bones it occurs when the bone cannot with stand outside forces. Automatic detection of fractures from x-ray images can assist doctors to suggest and help for the accuracy of the diagnosis.

During the fracture detection, the segmentation algorithm is used for edge detector to identify the edges, which separates the object and background and also indicate the overlapping between the boundaries. In fracture detection system, with the help of edge details, the bone region part only from extracted from the x-ray image and the fracture is detected very efficiently. From the visual inspection of the images obtained it can be seen that the canny edge detector is the efficient algorithm in identifying the edges clearly.

On the other hand, region-based approaches are based on similarity of regional image data. Detection of edges in an image may help for image segmentation, data compression, and additionally help for well matching, such as image reconstruction and so on. The variables involved in the selection of an edge detection operator include Edge orientation, Noise environment and Edge structure.

However, the performance evaluation of image segmentation results is still challenging problem as they fail to extract the correct boundaries of objects in noisy images. Effects such as refraction or poor focus can result in objects with boundaries defined by a gradual change in intensity. The strategy of edge-based approaches is to detect the object boundaries by using an edge detection operator and then extract boundaries by using the edge information.

The problem of edge detection is the presence of noise that results in random variation in level from pixel to pixel. Therefore, the ideal edges are never encountered in real images. A great diversity of edge detection algorithms has been devised with differences in their mathematical and algorithmic properties of which are based on the difference of gray levels. The difference of gray levels can be used to detect the discontinuity of gray levels.

From the visual inspection of the images obtained it can be seen that the canny edge detector is the efficient algorithm in identifying the edges clearly. On the other hand, region-based approaches are based on similarity of regional image data. Some of the more widely used approaches are thresholding, clustering, region growing, and splitting and merging.The ACMs also known as snakes are curves defined within an image domain that can be moved under the influence of the internal energy and external energy.[2]

Keywords: Boundary extraction, Edge vector field model, Edge mapping model, Edge following technique.

2.2.2 Merits and Demerits Edge Detection

Edge detection is a fundamental technique in image processing and computer vision used to identify boundaries within images. Here are some merits and demerits of edge detection:

Merits:

Feature Extraction: Edge detection helps in extracting important features from images, which can be useful for various tasks such as object detection, image segmentation, and pattern recognition. Edges often represent significant changes in intensity or color, which are crucial for identifying objects and shapes in images.

Reduction of Data: Edge detection reduces the amount of data in an image while preserving important structural information. This reduction can lead to more efficient processing and storage of images, especially in applications where computational resources are limited.

Image Enhancement: Edge detection can enhance the visual appearance of images by highlighting important details and structures. It can make images more visually appealing and easier for humans to interpret.

Object Detection and Recognition: Edges serve as important cues for detecting and recognizing objects in images. Edge detection is a crucial step in many object detection and recognition algorithms, including those used in autonomous vehicles, surveillance systems, and medical imaging.

Boundary Detection: Edge detection accurately identifies the boundaries of objects in images, which is essential for tasks such as image segmentation and scene understanding. By locating object boundaries, edge detection helps in separating objects from the background and analyzing their shapes and spatial relationships.

Demerits:

Sensitivity to Noise: Edge detection algorithms are often sensitive to noise in the image, which can lead to false detections and inaccurate edge maps. Noisy images may require preprocessing steps such as noise reduction or smoothing to improve the performance of edge detection algorithms.

Parameter Tuning: Many edge detection algorithms require the selection of parameters such as threshold values, filter sizes, and gradient operators. Choosing optimal parameters can be challenging and may require manual tuning or optimization techniques, which can be time-consuming and subjective.

Edge Smoothing: Some edge detection algorithms produce jagged or fragmented edges, especially in images with high levels of noise or complex textures. Post-processing techniques such as edge smoothing or edge linking may be necessary to improve the quality of detected edges.

Limited Detection: Edge detection algorithms may fail to detect edges in regions with low contrast or gradual intensity changes. In such cases, edges may be weak or completely missed, leading to incomplete or inaccurate edge maps.

Computational Complexity: Certain edge detection algorithms, especially those based on advanced mathematical techniques or machine learning algorithms, can be computationally intensive. Processing large images or video streams in real-time may require efficient implementation or hardware acceleration to achieve acceptable performance.

2.2.3 Implementation

Edge detection is an issue of crucial essentialness in picture examination. In ordinary pictures, edges describe object limits and are accordingly convenient for division, enrollment, and distinguishing proof of items in a scene. Edge recognition of a picture lessens fundamentally the measure of information and channels out data that may be viewed as less important, safeguarding the essential structural properties of a picture. The investigation continues in two parts: Intensity changes, which happen in a regular picture over an extensive variety of scales, are distinguished independently at distinctive scales.

A suitable channel for this reason at a given scale is discovered to be the second subordinate of a Gaussian. Force changes at a given scale are best caught by discovering the zero qualities of the picture. The intensity changes discovered in each of the channels are represented by oriented primitives called zero-crossing segments. Edge detection is the detection and localization of image edges and also the first step in image segmentation. a. Average Edge Vector Field Model It exploits the edge vector field to devise a new boundary extraction algorithm. Edge vectors of an image indicate the magnitudes and directions of edges which gives a vector stream flowing around an object where an unclear image these vectors are distribute randomly. The competence of the past edge vector field by applying a nearby averaging operation where, the quality of every vector is traded by the normal of every last one of qualities in the neighborhood. It applies a 3 × 3 window as the neighborhood N throughout the work.

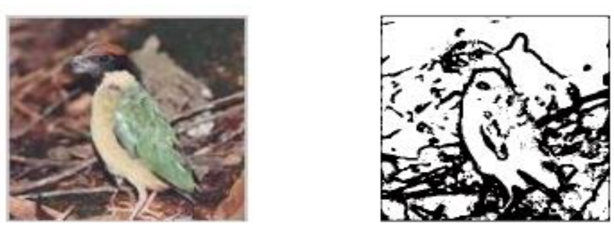

Fig.2.2: (a)Original image.

(b) Result from the proposed average edge vector fields and

zoomed-in image.

To achieve an accurate diagnosis, a medical imaging examination depends on a high quality image, and also an accurate interpretation of an image by a skilled reader. Over the last hundred years, the field of radiology has grown as a result of advanced in imaging innovation, with the goal that today, to a great degree astounding pictures are handled for examination. However, the methods of interpretation have only recently begun to benefit from advances in computer technology. The term computer-aided diagnosis (CAD) includes a diagnosis that is made by a radiologist who utilizes the output of a computerized analysis of the medical images as a second opinion when making the diagnosis. This assists the radiologists‟ image interpretation by improving the accuracy and consistency of radiological diagnosis and also by reducing the image reading time. In addition, some normal and abnormal lesions can have similar characteristics, resulting in possible interpretational errors. Fortunately, developments in computer vision have demonstrated the potential for computers to provide a second opinion when interpreting medical images. Good algorithms will search in a systematic manner, and may one day be capable of differentiating between normal and abnormal lesions, despite their similar characteristics. This type of computer technology is a promising and efficient source of assistance for radiologists, and should to help enhance indicative execution. using edge linking technique to detect the fractured and non-fractured image.

Fig.2.2: (c) Original Image shows the host image is a bone x-ray image.

Fig.2.2:(d) Resized Image (256 X 256) X-ray images are (500 X 756) size resized from (256*256) into (1024*1024)

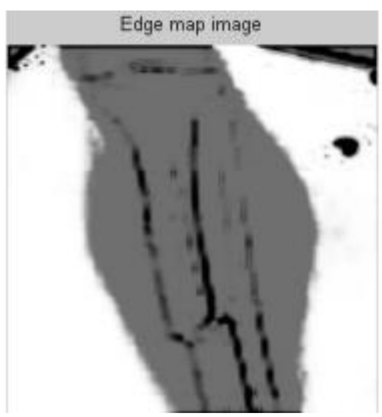

Fig.2.2:(e) : Edge Map Image

2.3 Bone Fracture Detection Techniques

2.3.1 Introduction

The field of medical imaging has been witnessing advances not only in acquisition of medical images but also in its techniques of interpretation. In particular the research is on to interpret and diagnose ailments from medical images with minimum aid from medical experts. Such systems called Computer aided diagnosis (CAD) systems can prove very useful to analyze large volumes of medical data, as well as improve the accuracy of interpretation while reducing time for diagnosis. The following study explains the methods involved in designing CAD systems for bone fracture detection. The section has been divided into 4 sub-sections based on X-ray, CT, MRI and Ultrasound modalities. A total of 12 general techniques (which includes 7 techniques for X-ray images,3 for CT, 1 for MRI and 1 for ultrasound images) from 29 papers have been surveyed.[3]

Keywords: Survey, bone fracture, CAD, bone segmentation.

2.3.2 Merits and Demerits Image Processing

Image processing involves manipulating or analyzing images to enhance their quality, extract useful information, or perform specific tasks. Here are some merits and demerits of image processing:

Merits:

> **Enhanced Visualization:** Image processing techniques can enhance the visual quality of images by adjusting brightness, contrast, and color balance. This improves the interpretability of images and makes them more visually appealing.

Feature Extraction: Image processing enables the extraction of useful features from images, such as edges, textures, shapes, and patterns. These features are essential for various applications, including object detection, recognition, and classification.

Image Restoration: Image processing techniques can restore degraded or damaged images by removing noise, blurring, or other artifacts. This is particularly useful in medical imaging, satellite imagery, and historical document preservation.

Demerits:

Computational Complexity: Some image processing techniques, especially those involving complex algorithms or large datasets, can be computationally intensive and require significant processing power and memory resources.

Loss of Information: Certain image processing operations, such as compression or filtering, may result in the loss of important information or details in the image. This can degrade the quality of images and affect the accuracy of subsequent analysis or interpretation.

2.3.3 Implementation

The section has been organized based on the modality to which the method has been applied. This will help the reader in understanding the potential and amount of research that have been carried in that field. An attempt has been made in providing vivid and crisp technical details of each paper, for the benefit of researchers new to this field.

Y Jia and Y Jiang present a method that outlines fractured bones in an X-ray image of a patient's arm within casting materials, and displays the alignment between the fractured bones. A geodesic active contour model with global constraints is applied to segment the bone region. A prior shape is collected and used as a global constraint of our model. A maximum-likelihood function is derived to provide feedback for each evolving process. Experimental results show that the method produces the outlines of the fractured bones on the low contrast X-ray images robustly and accurately.

JIAN LIANG et al. have proposed morphological method to identify fractures in tibia bones. Before segmentation, the original image is dynamically divided into several intervals to help find out the smallest interval with the target. The small regions are then automatically thresholded using Otsu method .To promote the accuracy of segmentation and to avoid over or under segmentation, the segmentation result obtained is examined using statistical method. Depending on the test results the segmented image is adjusted .After the second segmentation, the steps of verification and adjustment are required to repeat till the test result conforms to any one of the stopping conditions. When the segmentation is finished, the target image will no long have tough areas. This is followed by mathematical morphology to extract the target border and cover the boundary of fractures. Then by superposing the target border image and covering the extracted skeleton, the precise location of fractures can be recognized.

CHAPTER 3

PROPOSED SYSTEM

CHAPTER 3
PROPOSED SYSTEM

3.1 Objective of Proposed Model

The calculation begins with information increase and pre-processing the x-ray images, such as flip level. The moment step employments a ResNet50 neural network to classify the sort of bone within the picture. Once the bone sort has been anticipated, A particular demonstrate will be stacked for that bone sort expectation from3 distinctive sorts that were each prepared to recognize a break in another bone sort and used to identify whether the bone is broken.

This approach utilizes the strong image classification capabilities of ResNet50 to distinguish the sort of bone and then employes a particular demonstrate for each bone to decide in the event that there's a fracture present.One of the first applications of convolutional neural networks (CNN) is perhaps the LeNet-5 network described by for optical character recognition. Compared to modern deep CNN, their network was relatively modest due to the limited computational resources of the time and the algorithmic challenges of training bigger networks.

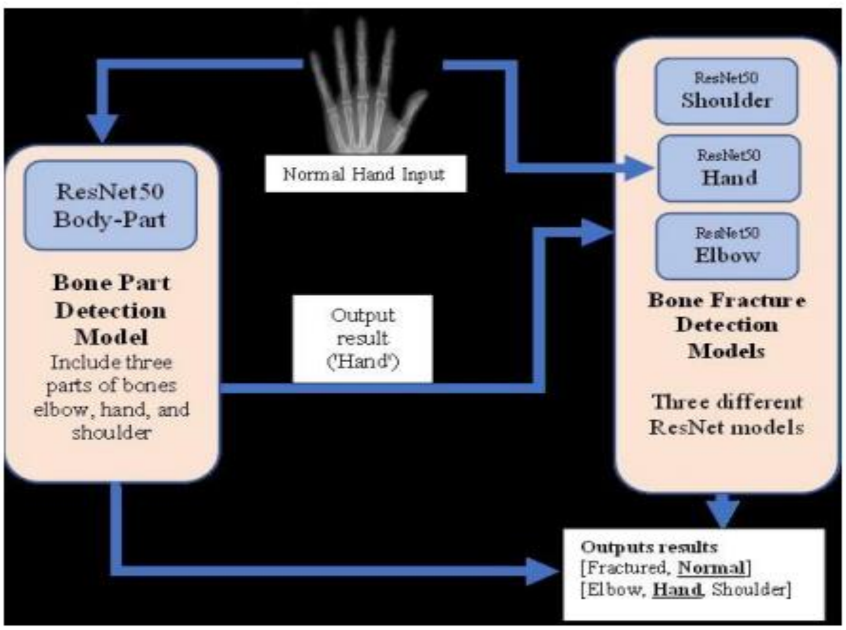

Fig.3.1: Architecture

3.2 Algorithms Used for Proposed System

3.2.1 Convolutional Neural Network (CNN)

A convolutional neural network may be a sort of significant learning calculation that is especially suited for image classification. It is made up of various layers such as counting convolutional layers, pooling layers and fully connected layers. The convolutional layers are the key components of CNN, where all the channels are connected to the input image to remove highlights such as edges, surfaces and shapes. The convolutional layers point passed through pooling layers, which utilized to down-sample the incorporate maps, reducing the spatial measurements while holding the first crucial information.

A convolutional neural network (CNN) is a category of machine learning model, namely a type of deep learning algorithm well suited to analyzing visual data. CNNs -- sometimes referred to as convnets --use principles from linear algebra, particularly convolution operations, to extract features and identify patterns within images. Although CNNs are predominantly used to process images, they can also be adapted to work with audio and other signal data. CNN architecture is inspired by the connectivity patterns of the human brain -- in particular, the visual cortex, which plays an essential role in perceiving and processing visual stimuli.

The artificial neurons in a CNN are arranged to efficiently interpret visual information, enabling these models to process entire images. Because CNNs are so effective at identifying objects, they are frequently used for computer vision tasks such as image recognition and object detection, with common use cases including self-driving cars, facial recognition and medical image analysis. A CNN typically consists of several layers, which can be broadly categorized into three groups: convolutional layers, pooling layers and fully connected layers. As data passes through these layers, the complexity of the CNN increases, which lets the CNN successively identify larger portions of an image and more abstract features.

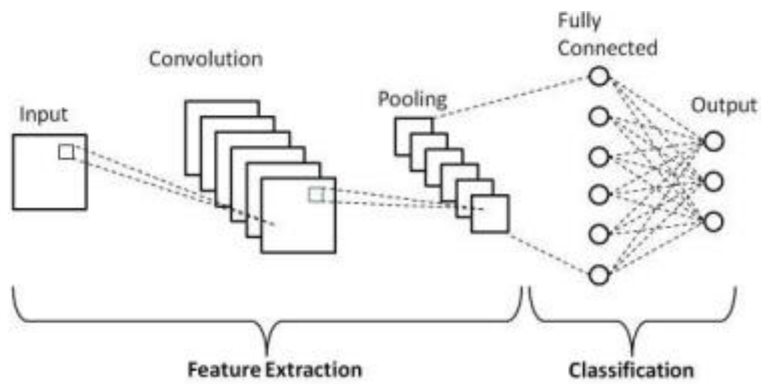

Fig.3.2.1: CNN Basic Architecture

Convolutional layer:

The convolutional layer is the fundamental building block of a CNN and is where the majority of computations occur. This layer uses a filter or kernel -- a small matrix of weights -- to move across the receptive field of an input image to detect the presence of specific features.

The process begins by sliding the kernel over the image's width and height, eventually sweeping across the entire image over multiple iterations. At each position, a dot product is calculated between the kernel's weights and the pixel values of the image under the kernel. This transforms the input image into a set of feature maps or convolved features, each of which represents the presence and intensity of a certain feature at various points in the image.

Pooling layer: The pooling layer of a CNN is a critical component that follows the convolutional layer. Similar to the convolutional layer, the pooling layer's operations involve a sweeping process across the input image, but its function is otherwise different.

The pooling layer aims to reduce the dimensionality of the input data while retaining critical information, thus improving the network's overall efficiency. This is typically achieved through down sampling decreasing the number of data points in the input. For CNNs, this typically means reducing the number of pixels used to represent the image.

The most common form of pooling is max pooling, which retains the maximum value within a certain window (i.e., the kernel size) while discarding other values. Another common technique, known as average pooling, takes a similar approach but uses the average value instead of the maximum.

Fully connected layer: The fully connected layer plays a critical role in the final stages of a CNN, where it is responsible for classifying images based on the features extracted in the previous layers. The term fully connected means that each neuron in one layer is connected to each neuron in the subsequent layer.

The fully connected layer integrates the various features extracted in the previous convolutional and pooling layers and maps them to specific classes or outcomes. Each input from the previous layer connects to each activation unit in the fully connected layer, enabling the CNN to simultaneously consider all features when making a final classification decision.

Not all layers in a CNN are fully connected. Because fully connected layers have many parameters, applying this approach throughout the entire network would create unnecessary density, increase the risk of overfitting and make the network very expensive to train in terms of memory and compute. Limiting the number of fully connected layers balances computational efficiency and generalization ability with the capability to learn complex patterns

Benefits of CNN: CNNs are especially useful for computer vision tasks such as image recognition and classification because they are designed to learn the spatial hierarchies of features by capturing essential features in early layers and complex patterns in deeper layers. One of the most significant advantages of CNNs is their ability to perform automatic feature extraction or feature learning. This eliminates the need to extract features manually, historically a labor-intensive and complex process.

Implementation

Data Collection: Gather a dataset of bone fracture images. You'll need a substantial dataset with labeled images of different types of fractures.

Data Preprocessing: Resize images to a consistent size. Normalize pixel values to a common scale(e.g., 0 to 1).Split the dataset into training, validation, and test sets.

Model Architecture: Design the CNN architecture. You can start with a basic architecture and then experiment with more complex designs if needed. Typically, a CNN consists of convolutional layers, pooling layers, and fully connected layers. You might use architectures like VGG, ResNet, or design your own.

Training: Choose appropriate optimization techniques (e.g., Adam, SGD).Define a suitable loss function (e.g., categorical cross-entropy for multi-class classification).Train the model on the training data, using the validation set to monitor performance and prevent overfitting. Experiment with hyper parameters like learning rate, batch size, and the number of epochs.

Evaluation: Evaluate the model on the test dataset to assess its performance. Metrics like accuracy, precision, recall, and F1 score can be used to measure classification performance.

3.2.2 ResNet50

ResNet-50 is a convolutional neural network architecture that is part of the ResNet (Residual Networks) family. It was introduced by Kaiming He et al. in their 2015paper "Deep Residual Learning for Image Recognition." ResNet-50 is specifically designed for image classification tasks and is known for its remarkable performance in various computer vision tasks. The key innovation in ResNet-50 is the use of residual blocks. These blocks enable the network to learn residual functions, which are the difference between the input and the desired output, making it easier to train very deep networks.

ResNet-50 consists of 50 layers, including convolutional layers, batch normalization, and skip connections (or shortcuts) that allow the network to skip one or more layers, making it more efficient and easier to optimize. The architecture of ResNet-50 has been widely used as a pre-trained model for various computer vision tasks, including image classification, object detection, and image segmentation, due to its ability to capture complex features in images. It's one of the foundational architectures in deep learning for computer vision.

Implementation

Data Collection and Preprocessing: Gather a dataset of bone images categorized by their types (e.g., femur, humerus, tibia).Split the dataset into training, validation, and testing sets.
Load Pre-trained ResNet-50 Model: You can use popular deep learning frameworks like TensorFlow or PyTorch to load the ResNet-50 model pre-trained on ImageNet.
Modify the Model: Replace the last fully connected layer of the ResNet-50 model with a new layer that matches the number of bone types you have for classification.

Fine-tuning:

Train the modified model on your bone dataset: Use the training set to update the model's weights. Validate the model's performance on the validation set to monitor progress. Adjust hyperparameters, such as learning rate, epochs, and batch size.
Evaluation: Evaluate the model on the test set to assess its classification accuracy and performance metrics (e.g., accuracy, precision, recall, F1-score). Predictions: Use the trained model to make predictions on new bone images to classify their types. Model Deployment: Once satisfied with the model's performance, deploy it in your application or environment.
Monitoring and Maintenance: Continuously monitor the model's performance and update it as needed. This is a basic outline, and you may need to adapt and extend it depending on your specific dataset and requirements. Remember to refer to the documentation of the deep learning framework you are using for more detailed guidance.

CHAPTER 4

RESULTS AND DISCUSSION

CHAPTER 4
RESULTS AND DISCUSSION

4.1 Result

Convolutional neural networks (CNN): There are various neural networks available which can be used as per the requirement or inputs being given. The algorithm starts with data augmentation and pre-processing the x-ray images, such as flip horizontal. This approach utilizes the strong image classification capabilities of ResNet50 to identify the type of bone and then employs a specific model for each bone to determine if there is a fracture present. After loading all the images into data frames and assigning a label to each image, we split our images into 72% training, 18% validation and 10% test. The algorithm starts with data augmentation and pre-processing the x-ray images, such as flip horizontal. The second step uses a ResNet50 neural network to classify the type of bone in the image. Once the bone type has been predicted, A specific model will be loaded for that bone type prediction from3different types that were each trained to identify a fracture in another bone type and used to detect whether the bone is fractured.

- We Present the outcomes of our Machine Learning model.
- We are trying to evaluate its efficiency.
- We Compare its performance with traditional methods and existing methods.

Body Part Prediction

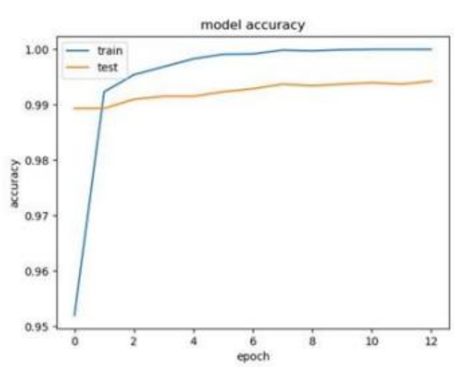

Fig.4.1.1: Body Part Prediction

Fracture Prediction

Elbow

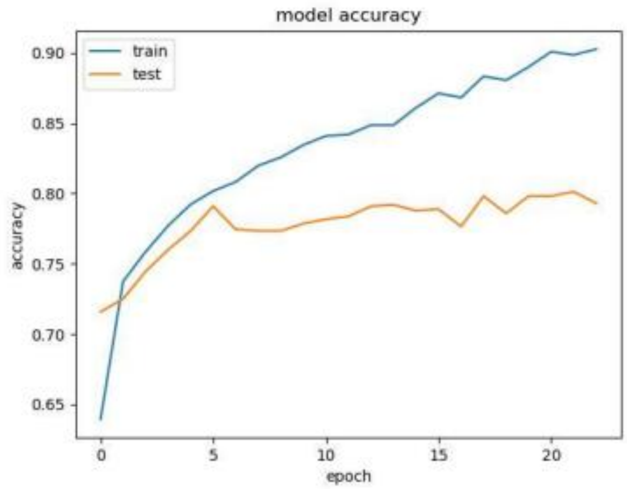

Fig.4.1.2: Fracture Prediction Of Elbow

Hand

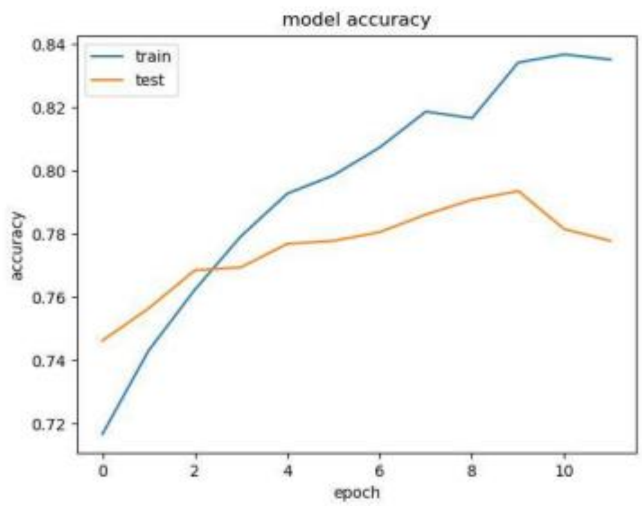

Fig.4.1.3: Fracture Prediction Of Hand

Shoulder

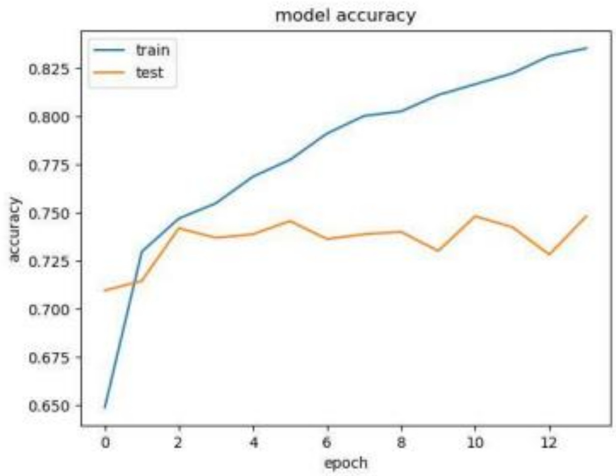

Fig.4.1.4: Fracture Prediction Of Shoulder

The experiment was performed using python 3.7, by analyzing the human bone X-rays in real time using CNN ,this model can classifies the fractures of bone present in X-rays.

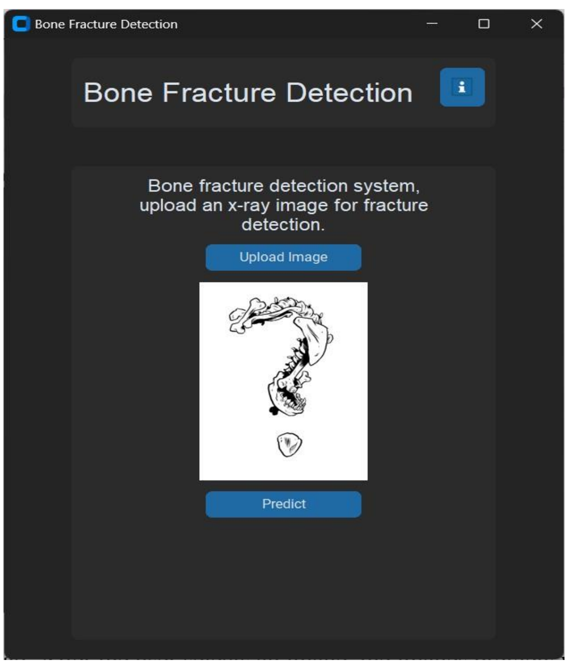

Fig.4.1.5: Home Screen

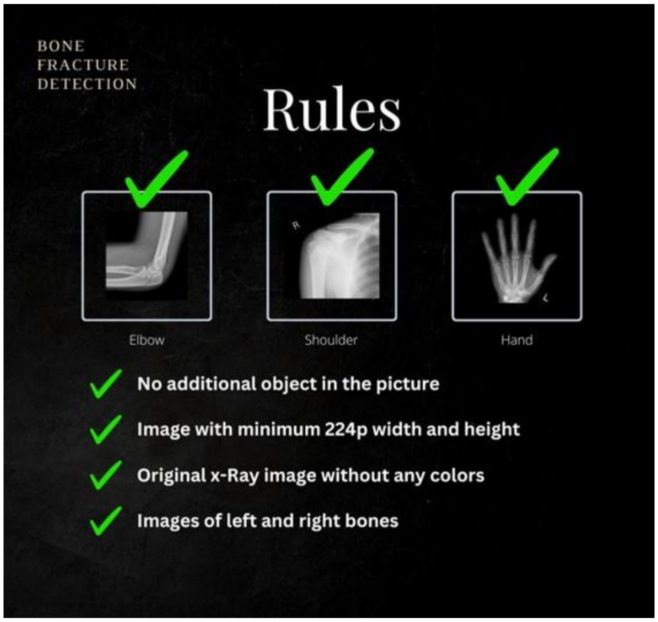

Fig.4.1.6: Rules

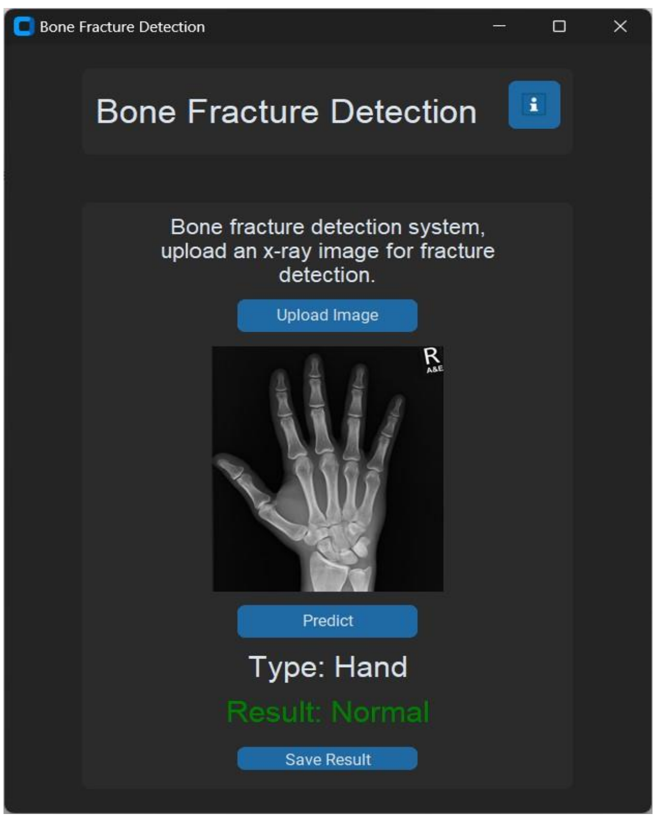

Fig.4.1.7: Classified as Normal

Fig.4.1.8: Classified as Fractured

CHAPTER 5

CONCLUSION

CHAPTER 5
CONCLUSION

5.1 Conclusion

The algorithm can determine whether the prediction should be considered a positive result, indicating that a bone fracture is present, or a negative result, indicating that no bone fracture is present. The results of the bone type classification and bone fracture detection will be displayed to the user in the application, allowing for easy interpretation. This algorithm has the potential to greatly aid medical professionals in detecting bone fractures and improving patient diagnosis and treatment. Its efficient and accurate analysis of x-ray images can speed up the diagnosis process and help patients receive appropriate care.

REFERENCES

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GITHUB LINK

https://github.com/Laxminarayana9970/Classification_Of_Bone_Fracture_Using_CNN

Code :

```
import os
from tkinter import filedialog
import customtkinter as ctk
import pyautogui
import pygetwindow
from PIL import ImageTk, Image

from predictions import predict

# global variables

project_folder = os.path.dirname(os.path.abspath(_file_))
folder_path = project_folder + '/images/'

filename = ""


class App(ctk.CTk):
    def _init_(self):
        super()._init_()

        self.title("Bone Fracture Detection")
        self.geometry(f"{500}x{740}")
        self.head_frame = ctk.CTkFrame(master=self)
        self.head_frame.pack(pady=20, padx=60, fill="both", expand=True)
```

```
self.main_frame = ctk.CTkFrame(master=self)
self.main_frame.pack(pady=20, padx=60, fill="both", expand=True)
self.head_label = ctk.CTkLabel(master=self.head_frame, text="Bone Fracture Detection",
                               font=(ctk.CTkFont("Roboto"), 28))
self.head_label.pack(pady=20, padx=10, anchor="nw", side="left")
img1 = ctk.CTkImage(Image.open(folder_path + "info.png"))

self.img_label = ctk.CTkButton(master=self.head_frame, text="", image=img1, command=self.open_image_window,
                               width=40, height=40)

self.img_label.pack(pady=10, padx=10, anchor="nw", side="right")

self.info_label = ctk.CTkLabel(master=self.main_frame,
                               text="Bone fracture detection system, upload an x-ray image for fracture detection.",
                               wraplength=300, font=(ctk.CTkFont("Roboto"), 18))
self.info_label.pack(pady=10, padx=10)

self.upload_btn = ctk.CTkButton(master=self.main_frame, text="Upload Image", command=self.upload_image)
self.upload_btn.pack(pady=0, padx=1)

self.frame2 = ctk.CTkFrame(master=self.main_frame, fg_color="transparent", width=256, height=256)
self.frame2.pack(pady=10, padx=1)
```

```
    img = Image.open(folder_path + "Question_Mark.jpg")
        img_resized = img.resize((int(256 / img.height * img.width), 256))  # new
width & height
        img = ImageTk.PhotoImage(img_resized)

        self.img_label = ctk.CTkLabel(master=self.frame2, text="", image=img)
        self.img_label.pack(pady=1, padx=10)


        self.predict_btn = ctk.CTkButton(master=self.main_frame, text="Predict",
command=self.predict_gui)
        self.predict_btn.pack(pady=0, padx=1)

        self.result_frame = ctk.CTkFrame(master=self.main_frame,
fg_color="transparent", width=200, height=100)
        self.result_frame.pack(pady=5, padx=5)

        self.loader_label = ctk.CTkLabel(master=self.main_frame, width=100,
height=100, text="")
        self.loader_label.pack(pady=3, padx=3)

        self.res1_label = ctk.CTkLabel(master=self.result_frame, text="")
        self.res1_label.pack(pady=5, padx=20)

        self.res2_label = ctk.CTkLabel(master=self.result_frame, text="")
        self.res2_label.pack(pady=5, padx=20)
```

```
self.save_btn = ctk.CTkButton(master=self.result_frame, text="Save Result",
command=self.save_result)

        self.save_label = ctk.CTkLabel(master=self.result_frame, text="")



    def upload_image(self):
        global filename
        f_types = [("All Files", ".")]
        filename = filedialog.askopenfilename(filetypes=f_types,
initialdir=project_folder+'/test/Wrist/')
        self.save_label.configure(text="")
        self.res2_label.configure(text="")
        self.res1_label.configure(text="")
        self.img_label.configure(self.frame2, text="", image="")
        img = Image.open(filename)
        img_resized = img.resize((int(256 / img.height * img.width), 256))  # new
width & height
        img = ImageTk.PhotoImage(img_resized)
        self.img_label.configure(self.frame2, image=img, text="")
        self.img_label.image = img
        self.save_btn.pack_forget()
        self.save_label.pack_forget()

    def predict_gui(self):
        global filename
        bone_type_result = predict(filename)
        result = predict(filename, bone_type_result)
```

```
print(result)
        if result == 'fractured':
            self.res2_label.configure(text_color="RED", text="Result: Fractured",
font=(ctk.CTkFont("Roboto"), 24))
        else:
            self.res2_label.configure(text_color="GREEN", text="Result: Normal",
font=(ctk.CTkFont("Roboto"), 24))
        bone_type_result = predict(filename, "Parts")
        self.res1_label.configure(text="Type: " + bone_type_result,
font=(ctk.CTkFont("Roboto"), 24))
        print(bone_type_result)
        self.save_btn.pack(pady=10, padx=1)
        self.save_label.pack(pady=5, padx=20)

    def save_result(self):
        tempdir = filedialog.asksaveasfilename(parent=self, initialdir=project_folder
+ '/PredictResults/',
                                               title='Please select a directory and filename',
defaultextension=".png")
        screenshots_dir = tempdir
        window = pygetwindow.getWindowsWithTitle('Bone Fracture
Detection')[0]
        left, top = window.topleft
        right, bottom = window.bottomright
        pyautogui.screenshot(screenshots_dir)
        im = Image.open(screenshots_dir)
        im = im.crop((left + 10, top + 35, right - 10, bottom - 10))
        im.save(screenshots_dir)
```

```
  self.save_label.configure(text_color="WHITE",                    text="Saved!",
font=(ctk.CTkFont("Roboto"), 16))

    def open_image_window(self):
        im = Image.open(folder_path + "rules.jpeg")
        im = im.resize((700, 700))
        im.show()



if _name_ == "_main_":
    app = App()
    app.mainloop()
```

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Classification of Bone Fractures using CNN

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[2,3,4] UG Student, [1] Assistant Professor Department of CSE, CMR College of Engineering & Technology, Hyderabad, Telangana

Abstract:** Bone breaks are common injury that require exact and opportune conclusion for legitimate treatment and administration. In this consider, we proposed a bone break location framework based on convolutional neural network systems (CNNs) to help radiologists within the location and classification of breaks from restorative imaging information, such as Xrays. The proposed framework points to computerize the break discovery prepare and give an effective and dependable device for restorative experts. The CNN-based break discovery framework comprises of a few key components, including picture preprocessing, include extraction, and classification. Within the preprocessing organize, the input X-ray pictures are preprocessed to upgrade picture quality and evacuate disturbance, guaranteeing ideal execution amid the consequent stages. Another, the CNN demonstrate is utilized to extricate important highlights from the preprocessed pictures. The demonstrate comprises of different convolutional layers that consequently learn and distinguish fracture-related designs and structures. To prepare the CNN demonstrate, a expansive dataset of labeled X- ray pictures with break comments is collected and utilized for show preparing. The preparing prepare includes nourishing the pictures into the arrange, optimizing the model's parameters utilizing back engendering, and iteratively altering the weights to play down the classification mistake. The prepared show is at that point assessed on a isolated test dataset to evaluate its execution in terms of exactness, affectability, specificity, and other significant measurements.

***Keywords:** Convolutional Neural Network(CNN),ResNet50,Bone Classification.*

I. INTRODUCTION

Since long back, bone breaks was a long standing issue for mankind, and it's classification via x-ray has continuously depended on human diagnostics – which may be some of the time imperfect. In later a long time, Machine learning and AI based arrangements have ended up an necessarily portion of our lives, in all viewpoints, as well as within the therapeutic field. Within the scope of our inquire about and venture, we have been examining this issue of classification and have been attempting, based on past endeavors and investigates, to create and finetune a attainable arrangement for the therapeutic field in terms of distinguishing proof and classification of different bone fractures, using CNN (Convolutional Neural Systems) within the scope of present day models, such as Res Net, Thick Net, VGG16, and so forward. After performing numerous demonstrate fine tuning endeavors for different models, we have accomplished classification comes about lower at that point the predefined edge of certainty concurred upon afterward in this inquire about, but with the promising comes about we did archieve.

II. RELATED WORK

LITERATURE REVIEW

[1] Automatic fracture detection using classifiers-a review. International Journal of Computer Science Issues: X-Ray is one the most seasoned and regularly utilized gadgets, that makes pictures of any bone within the body, counting the hand, wrist, arm, elbow, bear, foot, lower leg, leg (shin), knee, thigh, hip, pelvis or spine. A normal bone sickness is the break, which happens when bone cannot withstand exterior drive like coordinate blows, turning wounds and falls. Breaks are breaks in bones and are characterized as a medical condition in which there's a break within the coherence of the bone. Location and adjust treatment of breaks are considered vital, as a off-base determination frequently lead to ineffectual persistent administration, expanded dissatisfaction and expensive case. The most center of this paper could be a audit think about that examines around different classification calculations that can be utilized to classify x-ray pictures as typical or broken.

[2] Johari, N., & Singh, N.: Conclusion through computer-based methods is these days is colossally developing. Exceedingly proficient framework that consolidates advanced methods and less assets is required to speed up the determination prepare additionally to extend the level of precision. Break in a bone happens when the outside constrain worked out upon the bone is more than what the bone can tolerate. A disassociation between two cartilages is additionally alluded as a break. The reason of this paper is to discover out the exactness of an X-ray bone break discovery utilizing Canny Edge Discovery strategy.

Edge discovery through Canny's calculation is demonstrated to be an perfect edge distinguishing proof approach in deciding the conclusion of line with rash limit and less mistake rate.

[3] Paulano, F., Jiménez, J. J., & Pulido, R.: The division of broken bone from computed tomographies (CT pictures) is an vital prepare in therapeutic visualization and reenactment, since it empowers such applications to utilize information of a particular quiet. On the other hand, the labeling of broken bone ordinarily requires the support of an master. Besides, near part can be joined after the division since of their vicinity and the determination of the CT picture. Classical strategies perform well within the division of solid bone, but they are not able to recognize bone parts independently. In this paper, we propose a strategy to portion and name bone parts from CT pictures. Labeling includes the recognizable proof of bone parts independently. The strategy is based on 2D locale developing and requires negligible client interaction. In expansion, the displayed strategy is able to isolated wrongly joined parts amid the division prepare.

[4] Aishwariya, R., Geetha, M. K., & Archana, M.: The utilization of restorative pictures has been expanding colossally due to a collection of thousands of therapeutic pictures each day in restorative educate. Due to the increment in therapeutic pictures there's a rising require of overseeing the information legitimately and getting to it accurately. Finding the proper boundary in loud pictures is still a troublesome assignment. It presents a unused edge taking after procedure for boundary location in boisterous pictures. Utilize of the proposed procedure illustrates its application to differing cases of therapeutic pictures. The proposed method can identify the boundaries of objects in boisterous pictures utilizing the data the break discovery on the x-ray pictures is established. The proposed procedure for the canny edge locator within the x-ray picture finds the edges and utilizing the boundary location, the framework which detect the break consequently. The boundary discovery strategies moreover actualized within the models are Dynamic Form Demonstrate, Geodesic Dynamic Form Demonstrate and compare the precision of recognizing is analyzed and tried by utilizing Tangle lab 2013 adaptation.

[5] Jacob, N. E., & Wyawahare, M. V.: This paper bargains with methods that have been utilized for bone break discovery within the past few a long time. The creators have made endeavors to study papers from diverse modalities. This driven us to consider strategies that have been connected to pictures gotten from diverse modalities like X-ray, CT, MRI and ultrasound. The strategies have been recorded in a way that helps ease of interpretation. The paper is the primary of its kind to overview break location procedures over distinctive modalities. The ponder will offer assistance the reader in planning computer supported conclusion (CAD) frameworks within the field of restorative imaging.

III. METHODOLOGY

A. Convolutional Neural Network(CNN)

A convolutional neural network may be a sort of significant learning calculation that is especially suited for image classification. It is made up of various layers such as counting convolutional layers, pooling layers and fully connected layers. The convolutional layers are the key components of CNN, where all the channels are connected to the input image to remove highlights such as edges, surfaces and shapes. The convolutional layers point passed through pooling layers, which utilized to down-sample the incorporate maps, reducing the spatial measurements while holding the first crucial information.

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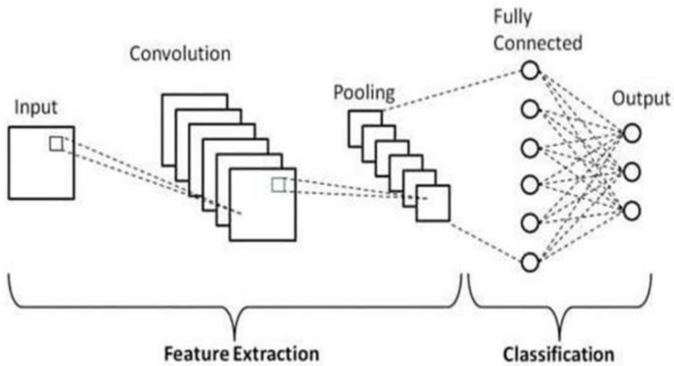

Fig 1: CNN Basic Architecture Shows

How the CNN works and How to detect the objects.

Collecting the dataset: The information is assembled from the twitter using API. Application program interface is used to collect the information. Twitter site could be a source which consists of clients tweets. The information can be assembled from various datasets.

B. ResNet50

ResNet-50 was presented by kaiming He et al. ResNet-50 maybe a convolutional neural arrange design that's portion of ResNet(Remaining System).

ResNet-50 is particularly planned for image classification and is known for its supervising execution in different computer visions. The key advantage in ResNet-50 is the use of remaining pieces. These pieces allow the arrange to remember remaining capacities, which are the distinction between the input and the specified yield, making it simpler to prepare extremely intelligent system. ResNet-50 consists of 50 layers, such as convolutional layers, bunch normalization and alternate routes that permit the arrange to skip the one or more layers, making it more effective and simpler to optimize. The engineering of ResNet-50 has been widely used as a pre-trained to establish for different computer vision assignments, counting image classification, protest discovery and image divisions, due to its capacity to capture complex highlights in images. It's one of the foundational designs in intelligent learning for computer vision.

IV. PROPOSED SYSTEM

The calculation begins with information increase and pre-processing the x-ray images, such as flip level. The moment step employments a ResNet50 neural network to classify the sort of bone within the picture. Once the bone sort has been anticipated, A particular demonstrate will be stacked for that bone sort expectation from3 distinctive sorts that were each prepared to recognize a break in another bone sort and used to identify whether the bone is broken.

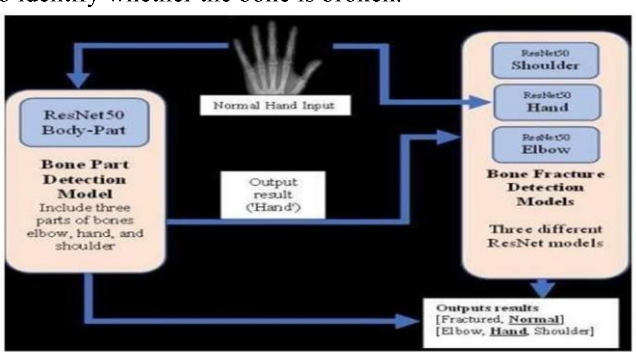

Fig.2:Architecture Model

Shows that the architecture to classifies the bone fractures.

This approach utilizes the strong image classification capabilities of ResNet50 to distinguish the sort of bone and then employes a particular demonstrate for each bone to decide in the event that there's a fracture present.

V. RESULTS

The experiment was performed using python 3.7, by analyzing the human bone X-rays in real time using CNN ,this model can classifies the fractures of bone present in X-rays.

Fig 1: Home Screen

Fig 2: Classified as Normal

Fig 3: Classified as Fractured

VI. CONCLUSION

The algorithm can predict the bone is fractured or not,the bone type classification and bone fracture detection will be displayed to the user in the application.This algorithm has the potential to greatly aid medical professionals in detecting the bone fracture and improves the patient diagnosis and treatment.it is efficient and accurate analysis of x-ray images can speed up the treatment and help the patient to receive the appropriate care.

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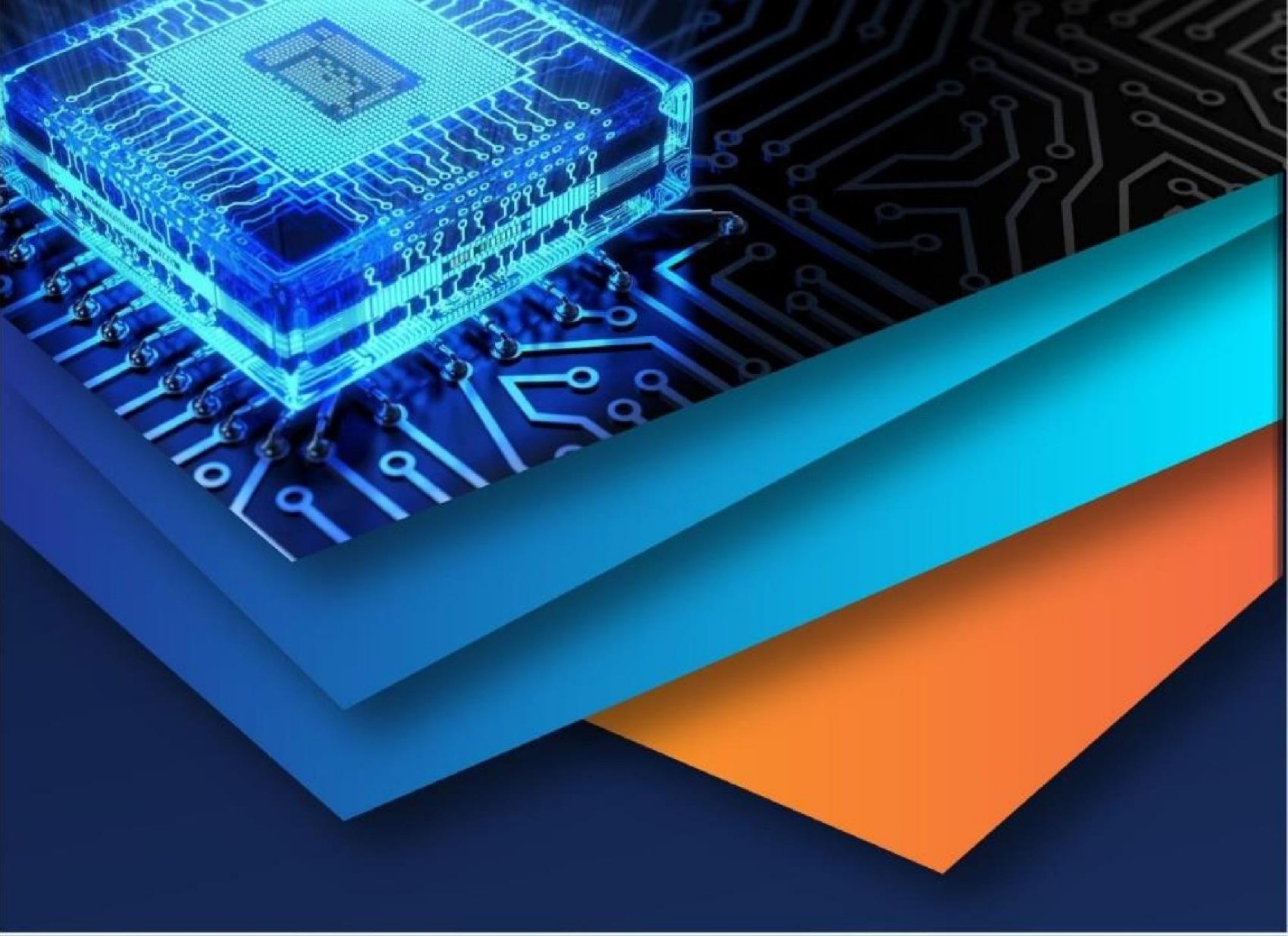

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