Deep Learning Analysis of Bone Fracture Using Images Processing Techniques

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ABSTRACT

Fracture can be defined as a condition of breakage or lack of bone continuity. Computer-based techniques are increasingly being used to identify faults and cracks. An effective system can be identified by two important characteristics: it must be able to detect quickly and accurately, while utilizing modern techniques and utilizing resources efficiently. Bone fractures are caused by an excess external force that exceeds the bone's threshold. A Canny Edge detection method uses automated fracture detection to detect bone fractures, which overcomes the noise issue. Several edge detection techniques are available., including Canny, Log, Prewitt, and Robert. Because these techniques cannot perform multiresolution analysis, they are not useful for detecting minor details during analysis. Additionally, when dealing with noisy images, these techniques cannot work as well as they do with high-quality, high-resolution images because they are not able to differentiate edges from noise. To overcome this this problematic condition, we proposed deep learning based Convolution Neural Network (CNN). We discovered that the suggested strategy offered superior edge identification results at aggregate levels when taking our simulations into account. The suggested approach has been shown to be more resilient than the present edge detectors in terms of extracting the required data, performing the required processing, and handling noise.

Keywords— Fracture, Bone alignment, Deep Learning, Fracture classification.

I. INTRODUCTION

Medical images are an important part of figuring out what's wrong with a person. In diagnostic radiology, the computerized analysis of medical images has been the main focus. It gives tools that will change the way physiology is seen and make diagnosis faster [1]. Multidimensional image analysis and classification techniques are used to get important clinical information to improve the diagnosis and treatment of disease. In 1960, researchers began to look at how computers could be used to analyses medical images in a quantitative way. At that time, everyone thought that computers were so much better than humans that they would completely replace radiologists in finding problems in medical images [2]. Usually, the radiologist makes a diagnosis and gives treatment based on what he or she knows. This sometimes happens because of a mistake made by a person. So, radiologists can use the Computer Aided

Diagnosis (CAD) package on the workstation to make better diagnoses. Before making a final decision, you have to read images through the computerized package and then ask to see what the computer came up with. At the moment, there are two ways to use the CAD system.

In the first method, the computer's results are used as a second opinion [3]. The radiologists then make their own decision and look at the image to see if there are any two abnormalities. This makes it harder to tell if something is wrong and also takes longer to find. In the second method, the computer's results are shown first, and the radiologist makes the final choice. This makes it easier to decide what to do in the end [4]. But if the computer output is wrong in any way, it has a bad effect. The main goal of CAD is to make the detection more sensitive by reducing the bad effects. If the CAD package has a high rate of false positives, it is hard to use. A good CAD package must have a high level of sensitivity and specificity. Even in the majority of wealthy nations, bone fracture is a prevalent issue, hence the number of bone Fractures are rising quickly [5]. Any simple mishap or pressure might result in a bone fracture. So, the effectiveness of any recommended treatment is frequently dependent upon prompt and correct diagnoses [6]. In real life, radiologists and doctors use X-ray scans to determine the exact type of fracture and whether or not a fracture has occurred. It may take a lot of time and effort to manually inspect X-rays for fractures. A radiologist may miss a broken image among healthy ones [7]. In order to inform the doctors, the CAD system can be utilized to help spot suspect cases in X-ray images. Since the only choice up until now has always been to rely only on radiological professionals for such a vital topic, an automatic diagnosis system has always seemed like a good notion. Many fields, including face identification, fingerprint recognition, fracture detection, and segmentation, use image processing and machine learning-based investigations [8]. They are divided into Supervised Learning techniques, such as Machine Learning and Deep Learning algorithms, depending on whether a set with known classes is required for their training. In order to overcome the time consuming and instead of using three algorithms here CNN is implemented Convolutional neural networks use image identification and classification to find items. It is composed of neurons with programmable biases and weights [9]. Each neuron receives a large number of inputs, weights the sum of those inputs, then sends the result through an activation function to produce an output. The primary purposes of CNNs are to classify images, group them based on similarities, and then perform object recognition. To improve acquisition speed, image quality, and cost-effectiveness, DL is applied during image capture and restructuring [10]. Additionally, it has the ability to register, de-noise, and translate images between several modalities. Anomaly detection, segmentation, and other DL methods for medical image processing are also now being developed.

II. LITERATURE SURVEY

Hum Yan Chai et al. [11] came up with a way to use GLCM computer techniques to automatically find femur bone fractures. Based on the GLCM parameter value, this method was able to classify whether or not a bone fracture was present. The line between not having a bone fracture and having one is set at a value of 0.95. At least 86.67 percent of the time, the algorithm that was made is right, which means that it will be a good way to automatically spot bone fractures.

Cephas Paul Edward & Hilda Hepzibah [12] introduce a segmentation technique to modify the representation of an image into fragments. Secondly the edges are identified by scanning the image carefully by analyzing the change of intensity that occurs rapidly. Edge detection method returns a binary image, different edge finding methods like Sobel operative, Prewitt operator, Laplacian of a Gaussian and Canny are applied on X-Ray images. Quality metrics like mean and standard deviation are used to analyze the results.

Mario Mustra et al. [13] illustrate that more than one X-ray image is needed to observe multiple fractures. Multiple fractures often occur in spine, legs and arms. Therefore, software is needed for automatic or semiautomatic image stitching to combine multiple images into one. This work proposes a method for automatic alignment of bone images. The work uses Otsu's method for optimal threshold to calculate the rotation angle.

San Myint et al. [14] describe an automated system to detect the bone fracture. This work compares the presentation of canny edge detector with other edge detectors such as Sobel, Prewitt, and Robert. After the edge detection process from the edge image straight lines and angles are generated using Hough transform. The Hough transform convert every edge point in the edge map to all possible lines. At last the system determines whether a fracture exists or not.

Luis Nascimento & Graca Ruano [15] point out that on determining stress fractures ultrasound imaging represents a cheap and fast alternative. On this concept a 3-stage process for automatic papers of bone breaks on ultrasound images was projected. This approach yields a correct classification of bone fractures in 89% of the 44 analyzed images.

According to Court-Brown CM, Caesar B, the review article provides an overview of the epidemiology of adult fractures, including the incidence and prevalence of different types of fractures. The article also discusses the impact of fractures on patient outcomes and healthcare systems [16].

Marsh JL, Slongo TF, Agel J, et al proves that the article describes the Orthopaedic Trauma Association classification system for fractures and dislocations, which is widely used in clinical practice and research. The classification system provides a standardized approach to describing and categorizing fractures based on several criteria [17].

As Explained by Slobogean GP, Sprague SA, Scott T, McKee MD. This article provides a comprehensive review of the management of fractures in the elderly population, who are at increased risk of fractures due to age-related changes in bone quality and strength. The article discusses the challenges of managing fractures in this population and provides guidance on treatment options [18].

Slongo TF, Schmid T, Wilkins KE mentioned that This study evaluated the outcomes of physeal sparing surgery for epiphyseal plate fractures of the distal humerus in children. The study found that physeal sparing surgery led to good functional outcomes and minimal growth disturbance compared to traditional surgical techniques [19].

Egol KA, Pahk B, Walsh M, Tejwani NC, Davidovitch R, Koval KJ discussed the study evaluated the outcomes of unstable ankle fractures with and without syndesmotic stabilization. The study found that syndesmotic stabilization led to better outcomes in terms of ankle function and pain [20].

Selvikvåg Lundervold, A., & Lundervold,.An overview of deep learning in medical imaging focusing on MRI proposes that The authors provide a detailed discussion of the specific applications of deep learning in MRI, including image reconstruction, noise reduction, and segmentation. They also highlight the potential benefits of using deep learning in MRI, such as improved image quality and reduced scan time. The article also discusses some of the challenges and limitations of using deep learning in medical imaging, such as the need for large datasets and the potential for overfitting. The authors note that while deep learning has shown promise in medical imaging, further research is needed to fully understand its potential and limitations. Overall, the article provides a comprehensive overview of the current state of deep learning in medical imaging, with a specific focus on MRI. It highlights the potential benefits and challenges of using deep learning in this field, and provides insights into future directions for research [21].

A. I. Korda, et al., The study aimed to develop an automatic system that could identify patterns of eye movements associated with different oculomotor behaviors, such as fixations, saccades, and smooth pursuit, using eye-tracking data. The authors proposed a feature extraction method based on a set of temporal and spatial features of eye movements, and used several pattern recognition techniques, such as support vector machines and artificial neural networks, to classify the eye movements. The study used eye-tracking data from 10 participants who performed a series of visual tasks, including reading and watching videos. The results showed that the proposed system could accurately identify oculomotor behavior with an average accuracy of over 90%.

The paper presents several strengths, including the use of multiple pattern recognition techniques and the evaluation of the system on real eye-tracking data. However, the study was limited by its small sample size, and the use of only a few visual tasks to elicit oculomotor behavior. Overall, the paper suggests that pattern recognition techniques can be useful in identifying oculomotor behavior from eye-tracking data. The study may have potential implications for the development of automated systems for the diagnosis and treatment of oculomotor disorders [22].

X. Yu, et al., describes the development of a diagnostic system for osteoporosis using artificial neural networks (ANNs). Osteoporosis is a common bone disease that can lead to an increased risk of fractures, and early diagnosis is important for effective treatment and management. The authors used a dataset of bone mineral density (BMD) measurements from 1,028 patients to train and test the ANN model. The ANN was designed to predict the likelihood of osteoporosis based on various factors, including age, gender, weight, and BMD measurements. The results showed that the ANN model achieved an accuracy rate of 93.62%, which was higher than other traditional diagnostic methods. The authors concluded that ANNs could be a useful tool in the diagnosis of osteoporosis and could potentially improve the accuracy and efficiency of diagnosis [23].

B. R. McCreadie and S. A. Goldstein, developed The article discusses the limitations of using bone mineral density (BMD) as the sole predictor of fracture risk. While BMD is an important factor in determining bone strength, other factors such as bone geometry, microarchitecture, and material properties also play a significant role. The article reviews several studies that suggest that incorporating these additional factors into fracture risk assessment models can improve their accuracy. The authors also discuss the limitations of current methods for measuring BMD and propose that future research should focus on developing better methods for measuring bone quality and strength. They suggest that this could lead to more accurate fracture risk assessments and improved treatments for osteoporosis. Overall, the article highlights the importance of considering multiple factors when assessing fracture risk and encourages further research into developing more comprehensive methods for evaluating bone strength [24].

S. Tassani, et al., A comparison between osteoarthritic and non-pathological bone" by S. Tassani et al., published in Clinical Biomechanics in July 2011, investigates the relationship between bone quantity and trabecular structure in osteoarthritic and non-pathological bone. The study uses high-resolution micro-CT to analyze bone samples from the femoral head of patients with osteoarthritis and healthy individuals. The researchers measure various bone parameters, such as bone volume fraction, trabecular thickness, and trabecular spacing, to evaluate the trabecular structure of the bone. The results show that in both healthy and osteoarthritic bone, bone volume fraction is positively correlated with trabecular thickness and negatively correlated with trabecular spacing. However, the osteoarthritic bone samples showed a lower bone volume fraction and a more disrupted trabecular structure compared to healthy bone samples. The authors conclude that the trabecular structure is dependent on the quantity of bone, and that osteoarthritis is associated with a reduction in bone quantity and a more disrupted trabecular structure. This study provides insight into the changes in bone structure associated with osteoarthritis, which may help in the development of new treatments for this condition [25].

A. M. Parfitt, et al., The article an estimate of the worldwide prevalence, mortality, and disability associated with hip fracture by O. Johnell and J.A. Kanis, published in Osteoporosis International in May 2004, provides an estimation of the prevalence, mortality, and disability associated with hip fracture on a global scale. The authors conducted a review of published data on hip fractures from various countries and regions around the world. They used this data to estimate the number of hip fractures that occurred each year and the associated mortality and disability rates. The authors found that approximately 1.6 million hip fractures occurred worldwide each year in 2000, and they projected that this number would increase to 6.3 million by 2050 due to aging populations. They estimated that the mortality rate associated with hip fractures was around 14%, and the disability rate was 50%. Furthermore, they estimated that the global cost of hip fractures in 2000 was approximately 32 billion US dollars. The authors concluded that hip fractures represent a significant public health concern worldwide, with substantial associated mortality, disability, and economic costs. They emphasized the importance of preventive measures, including screening for osteoporosis and fall prevention programs, in reducing the incidence and impact of hip fractures [26].

D.-G. Kim, et al., A type of bone tissue found in the vertebral bodies called trabecular bone is examined in this study to see how its properties relate to the compressive strength of the vertebral bodies in human subjects. The authors proposed that the compressive strength of the vertebral bodies would be influenced by the distribution of trabecular bone characteristics. The work used finite element analysis to simulate the mechanical behaviour of the bones under compressive loads and micro-CT scans to produce high-resolution pictures of the vertebral bodies. The findings demonstrated that the trabecular bone characteristics within the vertebral bodies varied significantly regionally and that these differences significantly affected the compressive strength of the bones. The scientists came to the conclusion that while determining the risk of vertebral fractures and developing measures to avoid them, regional variations in the trabecular bone characteristics should be taken into account. The study emphasises the significance of comprehending bone tissue's mechanical characteristics and its function in maintaining the body's overall structural integrity [27].

E. Perilli, et al., The article describes the development and use of a physical phantom for the calibration of X-ray microtomography systems. X-ray microtomography is a non-invasive imaging technique that allows for the visualization and measurement of the internal structure of objects, including biological tissues and materials. Calibration is an important step in the use of X-ray microtomography, as it ensures that the images produced are accurate and can be used for quantitative analysis. The physical phantom developed by the authors consists of a set of cylindrical rods with different diameters and densities. The rods are made of materials with known X-ray attenuation coefficients and are arranged in a precise pattern. The phantom is scanned using X-ray micro tomography, and the resulting images are used to calibrate the system. The authors describe the construction of the phantom and the methodology used to calibrate the X-ray micro tomography system. They also provide examples of the use of the phantom in calibrating different systems and in performing quantitative analysis of bone tissue. Overall, the article provides valuable information for researchers and practitioners who use X-ray micro tomography for imaging and analysis. The physical phantom described in the article can be used to ensure the accuracy and reproducibility of X-ray micro tomography measurements, which is important for the development of new imaging techniques and the validation of existing ones [28].

III. FRACTURE TYPES

The skeletal system is a living organ that gives the body its shape, allows motor function and movement, allows breathing, makes cells from marrow, protects vital organs, and plays a key role in maintaining homeostasis. The bones in a person's body are always changing, and this is because the environment is always changing. The average person has 206 bones in their body. Their shapes tell us what they are. It can be divided into long bones, short bones, flat bones, irregular bones, and sesamoid bones based on their shapes. Our skeleton is held together by the long bones, which are longer than they are wide. The femur and the thigh bone are both long bones. Bones that are short are wider than they are long. Short bones are the tarsal in the foot and the carpals in the hand. Shot bones make up the ankle, wrist, etc. The muscles attach to flat bones because they are flat and have a flat surface. Libs is the best example of flat bones. The bones that don't fit into any of the other groups are called irregular bones. Some examples of irregular bones are the vertebrae in our spine and the bones in our faces. The bones that are rooted in the ligament are called sesamoid bones. These bones are found in the elbow and knee, where a ligament crosses over the joint where two bones meet. The sesamoid bones improve how well the joint works. Sesamoid bones are best shown by the patella, or kneecap. The displacement may be in the form of shift, angulation or rotation as shown in Figure 1.

The fifth type of fracture may be based on how much force was used to break the bone. Fractures from high velocity injuries happen when there is a lot of force, like in a car accident. When these bones break, there is a lot of damage to the soft tissues. Fracture ends have lost a lot of blood supply. These breaks are often unstable and take a long time to heal. Fractures that happen because of low velocity are caused by mild trauma, like a fall. Since there isn't much damage to soft tissue, these fractures tend to heal in a predictable way. Lastly, the fractures can be put into groups based on their patterns, which are shown in Figure 2. These patterns are transverse, oblique, spiral, comminuted, and segmental. In a transverse fracture, the line of the break is not along the bone's long axis. This kind of break happens when something hits or bends the bone. Oblique fracture is a type of break where the line of the break is at an angle.

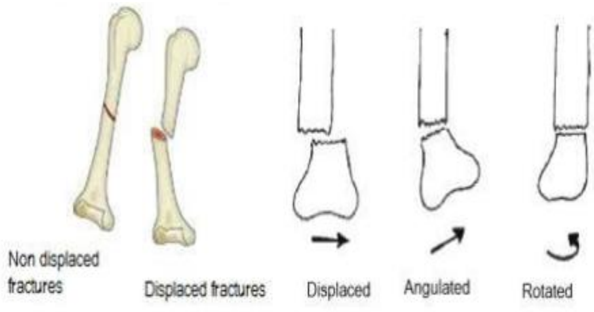

Figure 1 Displacements in fractures

IV. COMPLICATIONS IN FRACTURES

Most fractures can heal without too much trouble with how fractures are treated today. But sometimes fractures cause problems because they are misdiagnosed, which can change how they are treated and how they turn out. Fractures can lead to either short-term or long-term problems.

Acute problems with fractures are usually caused by the initial injury and usually result from the initial trauma. These problems include damage to nerves and blood vessels, soft tissue damage, blood loss, and contamination and infection in the area where the fracture is. Fractures can sometimes cause problems after they have been treated, like not healing properly, getting an infection, or losing the ability to do something. Fracture location and pattern, type of treatment, patient age, nutritional status, smoking status, and alcohol use all play a role in whether or not a fracture will lead to complications.

Delayed or nonunion: A fracture that heals slowly or improperly is referred to as having a delayed union or nonunion. This might happen if the blood supply to the broken bone is insufficient or if the alignment of the bone fragments is off. Surgery, such as bone grafting, or electrical stimulation may be used as a form of treatment for delayed or nonunion.

Malunion: A fracture can become malunioned when it heals improperly, leading to a deformity or functional disability. This may occur if there is a delay in receiving treatment or if the bone fragments are not correctly positioned during the healing process. Surgery to realign the bone pieces may be used to treat malunion.

Infection: If germs enter the body through an open wound or during a fracture healing procedure, infection may result. Infections can manifest as redness, swelling, warmth, and fever. Antibiotics, wound care, or surgery to remove infected tissue are all possible forms of infection treatment.

Deep Vein Thrombosis (DVT): A blood clot forms in a deep vein, commonly in the legs, causing deep vein thrombosis. This can happen as a side effect of a fracture since the injury's accompanying immobilization increases the chance of blood clots developing. Swelling, discomfort, and warmth in the afflicted limb are possible DVT symptoms. Compression stockings and blood-thinning drugs may be used as DVT treatment.

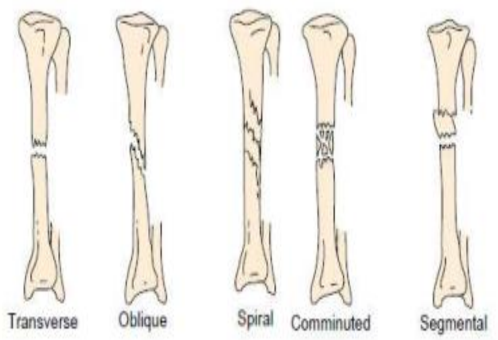

Figure 2 Patterns of fracture

V. EFFECTS OF MISDIAGNOSED FRACTURES

When fractures aren't found right away, it can have big effects on the body. Many fractures that are not properly diagnosed cause damage to the blood vessels, which can lead to bleeding inside the body or from an open wound. If the hip or knee is out of place, it can stop blood from getting to the leg. Because of this, the leg's tissues won't get enough blood and will die. If the tissues die, a piece of the leg has to be cut off. Nerves are stretched, bruised, or crushed when a bone breaks. So, a wrong diagnosis of a fracture can damage nerves. Another major cause of wrong diagnoses is fat embolism. Because sometimes fat comes out of the inside of the bone. This fat could move through the veins, get stuck in the lungs, and stop a blood vessel from working. Because of this, the body doesn't get enough oxygen, which can cause shortness of breath and chest pain. To avoid misdiagnosing fractures, medical image segmentation uses three general methods: manual segmentation, semi-automatic segmentation, and automatic segmentation. They all have good and bad points. Manual segmentation by experts in a given field is the most accurate, but it takes a lot of time. In semi-automatic segmentation, the user must provide a small number of inputs to help the segmentation work correctly. Automatic segmentation doesn't need any help from the user, which makes it much harder to get accurate results. Still, it is the only practical way to deal with a large number of images in a lot of situations. So, the main goal of this research is to make the automatic segmentation more accurate.

VI. DETECTION IN X-RAY IMAGES

Accurate Diagnoses of health problems are very important these days. Computers can help doctors find cracks by flagging suspicious cases for closer checks and drawing the doctor's attention to suspicious cases. Diagnostic X-rays are very important for finding problems in the body, and they don't hurt you in the process. Tian et al. did the first research on finding fractures in X-ray images by figuring out the angle between the neck axis and the shaft axis then reported ways to find femur fractures using X-ray images' Gabor, Markov Random Field, and gradient intensity features. said that multi-level SVMs were trained to classify the samples based on different types of features. The performance of each SVM wasn't very good. So, a simple voting system was suggested to combine the classifiers in order to improve the overall accuracy and sensitivity.

VII.PROBLEM STATEMENT

Accurate Diagnoses of health problems are very important now. Computers can help doctors find cracks by cases for closer examination and drawing the doctor's attention to those cases. So, it can help them get a better and faster diagnosis. Finding cracks in X-ray images with a computer is a hard and challenging problem. Diagnostic X-rays are very important for finding problems in the body, and they don't hurt you in the process. Approximate computing (AC) is a prominent research area in computing paradigm for data analytics and cognitive applications. AC trades off minimal amount of computing accuracy to improve the computational throughput with plateauing resource budgets. In CNN, AC enables various optimization where an inexact solution is sufficient for solving the complex problems.

VIII. PROPOSED WORK

Bone fracture detection using deep learning is an active area of research that has shown promising results. One popular approach is to use Convolutional Neural Networks (CNNs) which are well suited for image processing tasks. Collect a large dataset of X-ray images with both normal and fractured bones. The images can be obtained from publicly available databases or by collaborating with hospitals and clinics. Pre-processing the collected X-ray images to ensure that they are of good quality and suitable for use in training the CNN algorithm. This might involve resizing the images, normalizing pixel values, and augmenting the data to increase the size of the dataset. Develop a CNN algorithm using a popular deep learning framework such as Tensor Flow. Extracting features from the pre-processed images using techniques such as edge detection, and segmentation. The extracted bone's texture properties include the bone's form and orientation. To provide the neural network's inputs, texture features are extracted [11]. Train the CNN algorithm using the pre-processed dataset. The model can be trained using supervised learning techniques, where the images are labeled as normal or fractured. Overall, bone fracture detection using deep learning and CNN algorithms has the potential to improve the correctness and competence of analysis, leading to better patient outcomes. The user inputs the image, it is pre-processed, and then the features are extracted. An extracted image is fed into a neural network, which compares it with pre-trained data and outputs the results.

Convolution Neural Network

CNN is a neural network that works the same way humans do. and is often used to analyze pictures. Using different types of multi-layer perceptron algorithms in CNNs make it so that you don't have to do as much work on the data before you feed it in. CNNs are one of the most common types of neural networks, which are made up of neurons with the same function. weights and biases that can be learned), particularly for data (like images and videos). videos). CNNs work in a way that is a lot like how normal neural networks do. Each neuron gets some inputs, does a dot product, and may or may not do a next. non-linearity. The whole network still shows a single score function that can be different. from the pixels of the original image to the class scores at the other end. Besides that, CNNs also have a loss function (like SVM or Softmax) on the last layer that is fully connected. Still, a The most essential difference among a CNN and other neural networks is that each unit in a CNN layer is a two- or high) dimensional filter that is convolved with the input of that layer instead of a generic matrix multiplication. This is crucial when attempting to extract meaningful patterns from high-dimensional input media like photos and movies.

PROCEDURE

STEP 1. Import the necessary modules and libraries

STEP 2: Load the dataset of X-ray images of bones.

STEP 3: Do preprocessing on the dataset, such as pixel value normalizing and image scaling.

STEP 4: The dataset should be divided into training and testing sets.

STEP 5: Describe the CNN architecture, which could consist of fully connected layers, pooling layers, and convolutional layers.

STEP 6: Using the training set, train the CNN while improving the model using the proper loss function and optimizer.

STEP 7: Use the testing set to evaluate the trained model, calculating metrics like accuracy, precision, and recall.

STEP 8: Keep the practiced model for upcoming use

STEP 9: Predict using a fresh, unviewed bone X-ray image.

STEP 10: Preprocess the image using the training set's transforms.

STEP 11: Determine whether the bone is fractured using the trained model.

STEP 12: Provide an output that includes the forecast and confidence level, which could be a classification or probability output.

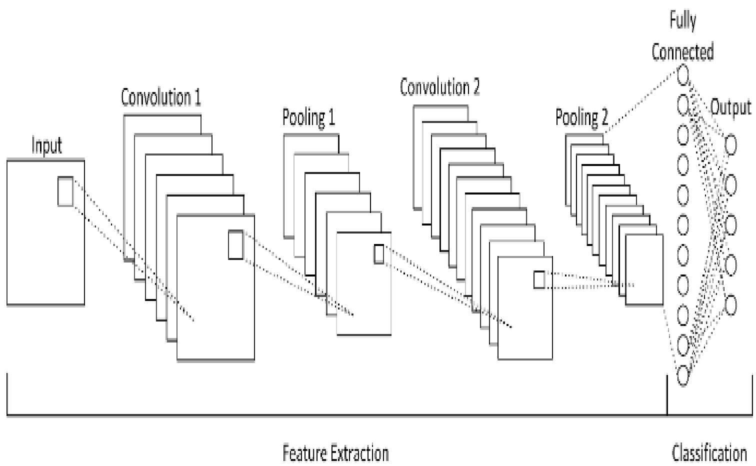

Figure 3 Basic architecture of CNN

IX. METHODOLOGY

A. *Training Process*

1) *Image Pre-Processing*

Pre-processing is an important step in using Convolutional Neural Networks (CNNs) for bone fracture detection in images. Resizing the images to a fixed size is important for reducing the amount of computation required during training. You can resize the images to a standard size, such as 256x256 or 512x512 pixels. The techniques such as smoothing filters or de-noising algorithms to reduce noise in the image and improve the performance of the network. By applying these pre-processing techniques, you can improve the accuracy of your CNN model for bone fracture detection in images.

A. Convolutional Layer

In the proposed study, a network model has been developed. There is convolution, pooling, flattening, and dense layer. To automatically extract the features from the input image and classify them as either cancerous or healthy bone, CNN employs a fully connected layer. The pooling layer and convolution layer (CL) remove features from the image. Each convolution layer and pooling layer uses a size of 3x3 to minimize noise. The dense layer then does classification after that. B.CL: Four convolution layers were used for this project.

three-by-three-filter CL of 16 feature map, CL of 32 feature map, CL of 64 feature map, and CL of 128 feature map

The filter-based convolution layer extracts information.

The convolution layer pulls features from the input image using filters.

B. *Max-Pooling Layer:*

In order to reduce the size of the filter picture, it was used at each convolution layer. The best aspect of the image and the pertinent object were thus the focus of this layer. In the suggested study, at each convolution layer, 2x2 has been used.

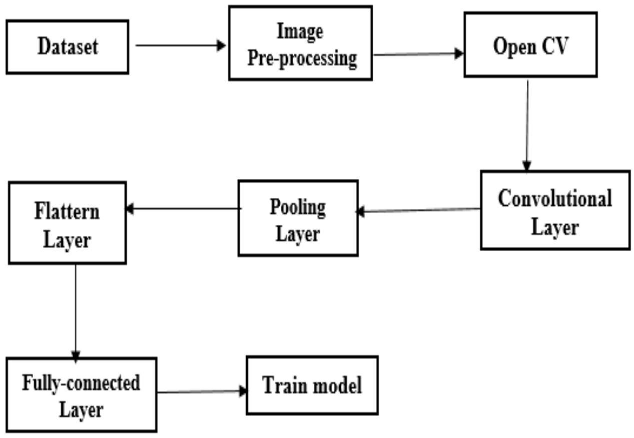

Figure 4 Block diagram for Training Process

C. *Convolution Layer*

Convolution is a mathematical operation that modifies the input images with filter effect. Mathematically, convolution is performed on two functions that outputs to a third function which is essentially a modified version of one of the two input functions.

D. *Flattern Layer:*

The two-dimensional feature vector was condensed in this layer and supplied into the fully linked layer as an array.

E. *Fully Connected Layer*

It is also referred to as the fully dense layer. We added one dense layer because the binary class difficulty was so high. The suggested method predicts both sound and broken bone. The activation function pooling layer is implemented on each layer. Softmax and Adamax, two activation functions, have been used in the dense layer one at a time.

F. *Testing Process*

Bone fracture detection using (CNNs) typically involves the following Testing steps:

Data collection: Collect a dataset of X-ray images with labeled bone fractures. The dataset should contain enough images to provide the CNN with sufficient examples of different types of fractures.

Data pre-processing: Pre-process the images by resizing them to a uniform size, converting them to grayscale or RGB format, and normalizing the pixel values.

Feature extraction: Use a pre-trained CNN to extract features from the X-ray images. This is typically done by removing the last few layers of the CNN and using the output of the remaining layers as a feature vector.

Prediction: CNN can automatically learn and extract complex features from medical images, which can be difficult for traditional machine learning algorithms to identify. This ability to learn complex features is especially useful in bone fracture detection, where fractures can have different shapes, sizes, and orientations. CNN is well-suited for processing large and complex datasets, which is often the case with medical imaging data. This allows CNN to learn from a wide range of images and to identify subtle patterns that may be indicative of a bone fracture. CNN has been shown to achieve high accuracy in bone fracture detection, sometimes outperforming human experts. This is due to its ability to learn from large datasets and to identify subtle patterns that may be difficult for humans to detect. Overall, the use of CNN in bone fracture detection has the potential to improve the accuracy and speed of diagnosis, which can lead to better patient outcomes.

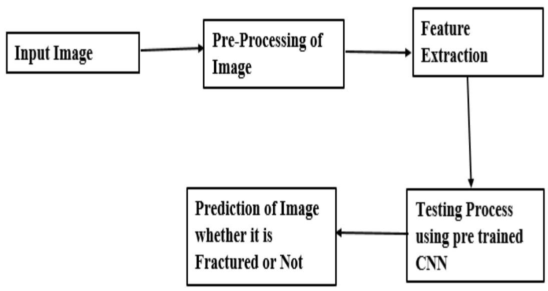

Figure 5 Block diagram for Testing Process

Figure 6 Original Image

Figure 7 Grayscale Image

Figure 8 Binary Image

X. IMPLEMENTATION

Figure 9 represents Bone Fracture Input Screen. The user gives the X-Ray Image as Input and click Submit to get the status, whether the bone is fractured or not.

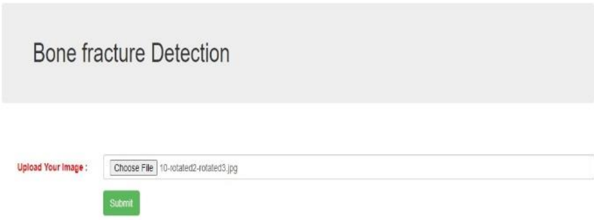

Figure 9: Input Screen

Figure 10 represents that choosing a file and click open for bone fracture prediction. Only the file is selected then it goes to the next level.

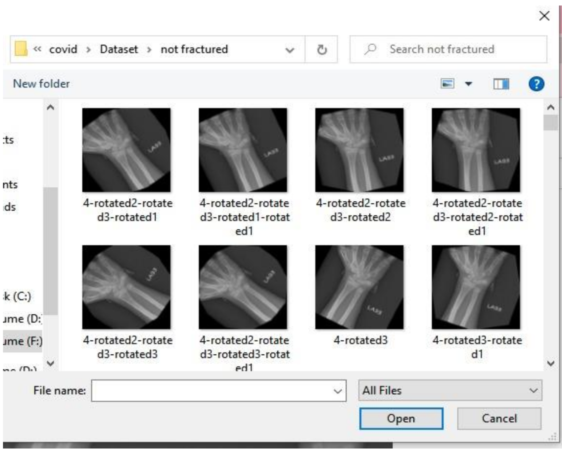

Figure 10: Choose File

The results of bone fracture detection are represented in Figure 11. It shows the model's accuracy and the patient's status, like whether the patient has a bone fracture.

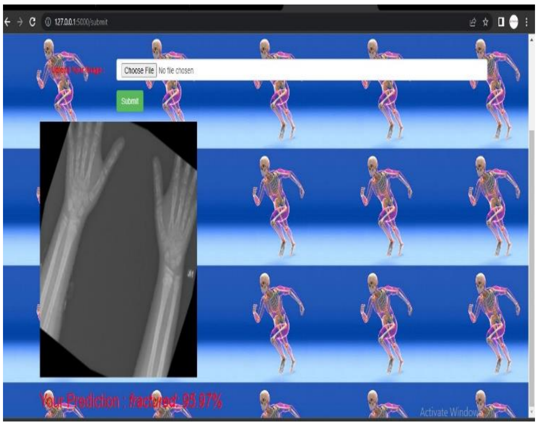

Figure 11: Output Analysis of Proposed Methodology

XI. RESULTS AND DISCUSSIONS

The implementation consequences were tested using numerous X-Ray images. The performance was measured by a computer with a 2.40 GHz Pentium (4) CPU and 512 MB of RAM running Microsoft Windows XP version 2002. This and earlier works were carried out in python with our native dataset. A typical CT scan image consists of 45-75 slices. Also In this study, deep learning algorithms were used to detect bone fracture. X-ray images were captured here for the study. The photographs were first pre-processed. , in the deep learning field and more specifically the statistical classification problem. The rows and columns of the matrix indicate the actual and anticipated instances of each class, respectively (or vice versa).

TP: Patients who were facture as unwell were in fact sick.

FP: Patients who were in fact healthy were mistakenly classified as facture.

TN: Patients that were healthy were accurately classified as such.

FN: Patients who were actually sick were mistakenly classified as healthy.

Table 1: Confusion matrix for Binary forecast

Predicted labels)	Algorithm outputs/labels	
	without facture (Negative/0)	**with facture (Positive/1)**
Patient without-disease (False/0)	TN	FP
Patient with-disease (True/1)	FN	TP

A. Performance Metrics

Our proposed model classification performance by using some metrics, it is discussed in this section.

1. Sensitivity (SE): Bone fracture risk is distinct as the likelihood that a separate would develop the disease and die from it.

$$Sensitivity = \frac{TP}{TP+FN}$$

2. Specificity (SP): In order to avoid developing facture, the chance of certain outcomes is specified as TN.

$$Specificity = \frac{TN}{TN+FP}$$

3. Accuracy (AC): It's based on the likelihood of getting correctly categorized results.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

4. F-score: The F-score is the mean of the replica's sensitivity and specificity, which is used to assess its performance.

$$F-score = 2\cdot\frac{Sensitivity\cdot Specificity}{Sensitivity+Specificity}$$

4.3. Performance Analysis of Proposed CNN for different validation

In this section, the validation of projected method is carried out by changing the percentage of training dataset and testing dataset. Initially, In the experimental analysis of proposed method for 70% of training data and 30% of testing data in terms of numerous metrics.

Table II: comparisons analysis of proposed method with existing machine learning and deep learning modules

Different classifier Models	Sensitivity	Specificity	F-score	Accuracy
Decision Tree	90.56	90.42	91.23	89.63
Support Vector Machine	91.25	89.56	91	90.56
Random forest	93.89	90.28	93.46	91.21
Proposed Method	96.75	94.32	95.09	96.56

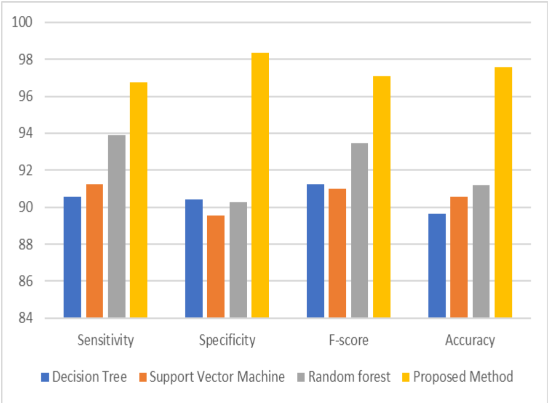

Figure 12: graphical representation of comparisons analysis of projected technique with existing machine learning and deep learning modules

In Table 1, figure 12 and 13 represent that the comparisons analysis of proposed method with existing machine learning modules. In this comparisons analysis we evaluate totally three models as Support Vector Machine, Random Forest and Proposed Method. In this comparisons analysis the proposed model (CNN) reached the better results than other compared model.

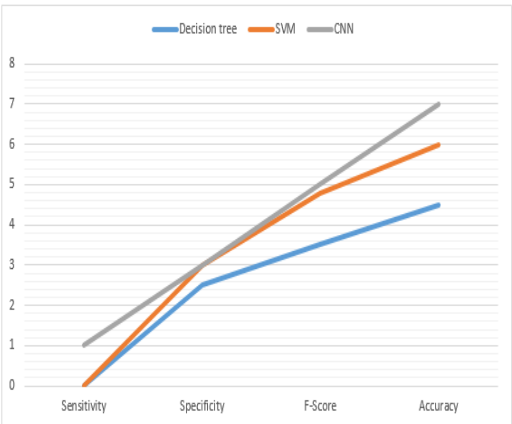

Figure 13: Representation of Results

XII.CONCLUSION

In conclusion Convolutional Neural Networks (CNNs) have been demonstrated to be successful in the identification and categorization of bone fractures in medical imaging. CNN models may learn to recognize and localize fractures with high accuracy by training on huge X-ray datasets, offering invaluable assistance to medical personnel in patient diagnosis and treatment. Using CNNs and other deep learning techniques has the benefit of automating the identification process, which saves time and effort compared to manual analysis. Moreover, CNN models can be trained to distinguish many fracture types, including simple and complex fractures as well as fractures in several bones, enabling more precise and in-depth diagnoses. It is crucial to remember that CNN models are not perfect and are still susceptible to mistakes in fracture detection. A skilled medical professional should always interpret the findings of any automated study and render a final judgement, just as they would with any medical diagnosis. Overall, the use of CNNs to the diagnosis of bone fractures is a promising area of study with the potential to enhance patient outcomes through the provision of precise and effective diagnoses.
CNNs can distinguish between different types of fractures, such as fractures of the wrist, hip, or spine, and can identify bone fractures with excellent accuracy rates. This is especially helpful in clinical settings where prompt and precise fracture diagnosis can guide treatment choices and enhance patient outcomes. But, it's crucial to remember that factors like image quality, variation in fracture forms, and the accessibility of training data can all have an impact on how well CNNs function in detecting bone fractures. Consequently, additional study is required to assess the clinical value of CNNs in real-world settings and to maximize their application for fracture detection and classification.

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