Smart Fracture Detection: A Deep Learning Approach to Bone Imaging Using CNN

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ABSTRACT

Bone fractures tend to be one of the commonest medical conditions that need prompt and accurate diagnosis for the right treatment and healing. The traditional methods for detecting fracture rely a lot on human errors and long manual analyses of X-ray images. Bone fracture detection forms a lot of essential diagnoses in this medical field, taking long time durations. This research proposes a machine learning system based on a deep CNN model to achieve automatic bone fracture identification. This convolutional neural network model will be trained on a large dataset of X-ray images to learn the patterns associated with the fracture. Training, testing, and validation comprise the three sections of the dataset. The efficiency of the suggested approach in detecting with high perfection is demonstrated by its 96.33% accuracy rate. When compared with traditional methods, the use of CNNs significantly decreases the amount of time needed for diagnosis and increases the overall accuracy of fracture identification. The system can precisely detect bone fractures thanks to the suggested model's influence on a deep CNN architecture that extracts characteristics from X-ray pictures. A widely utilized technique in image processing and computer vision, canny edge detection is frequently used in combination with CNNs to detect bone fractures. The dataset consists of medical photos with annotations that have been pre-processed for augmentation and normalization to increase the robustness of the model. By getting the AI based solutions integrated into clinical workflows, this research signifies the great role deep learning can play in the revolution of fracture diagnosis.

Keywords: CNN; X-ray images; Bone fracture; Deep Learning; Medical Image Analysis.

I. INTRODUCTION

The fracture detection, particularly subtle or complex once, poses and challenge in medical diagnostics. The human body contains 206 bones, including a variety of bone kinds. Bone fractures in humans can be caused due to a number of reasons such as accidents, aging, hunger, heredity, and illnesses. The most common method for diagnosing bone fractures is radiographic imaging, particularly X-rays. Nevertheless, the exact interpretation of these images is primarily dependent on the significant experience and expertise of the professionals. With skilled radiologists, still point analysis can be erroneous, particularly in the case of revealing fine fractures under the high pressure, semi-parallel condition. To cope with these difficulties, the idea of automated systems that detect fractures has come into the spotlight. The use of deep learning and artificial intelligence in medical imaging workflows has been established to be an effective method of improving diagnostic efficiency and accuracy. The rise of artificial intelligence and machine learning has introduced a lot of opportunities for the automatic detection of fractures. The recent growth in deep learning has made convolutional neural networks especially promising for the precise analysis of medical images, offering a high level of consistency and accuracy. CNNs perform well when it comes to detecting detailed features like patterns, textures, and discontinuities in images. It is essential to identify fractures since features like patterns, textures, discontinuities are very much the same as those that can be located among fractures. They can point out hardly seen abnormalities, that traditional methods and human experts couldn't, especially for complex or subtle fractures that are hard to be detected easily overlooked. These AI systems can help radiologists by acting as a second check, making sure that fractures are found quickly and accurately. AI supports radiologists by reducing their mental workload and the chance of making mistakes, allowing them to focus on more complex cases and improving patient care. The findings of this research add to the growing evidence that supports using AI in medical imaging and highlight its ability to improve diagnostic practices in healthcare. However, using CNN-based solutions for fracture detection comes with challenges. Their ability to work with different types of imaging and fractures makes them more useful in clinical settings, and their potential for real time analysis is especially important in emergencies or busy situations. Key challenges include making sure there are high-quality, labelled datasets available and dealing with differences in imaging methods and patient groups.

II. LITERATURE REVIEW

For many years, research has been going on to make medical imaging effective in diagnosing bone fractures. Traditional methods, such as manual interpretation of X-ray images, have been widely employed in examining fracture; nevertheless, they have their own limitations of efficiency and accuracy. The analysis of medical images has been significantly affected by deep learning among other things, the most notable of which is the Convolutional Neural Networks (CNNs), which have introduced new ways of using fracture detection that are entirely automated. In this study [2], the research project aims at building on the improved automation of fracture detection from X-ray images using the CNN model. The training was carried out with 9,103 X-ray images split between two classes as "Fractured" and "Not Fractured. The model, in its learning of subtle patterns, achieved an admirable accuracy of 91% and an excellent precision and recall of 89.5% and 87%, respectively. In another study [6], proposes an ensemble model combining MobileNetV2, Vgg16, InceptionV3, and ResNet50 for automated humerus bone fracture detection in X-ray images. Using the MURA-v1.1 dataset with an 80:20 training- validation split, the model achieved high accuracy (92.96%), recall (91.62%), and F1 score (92.14%), outperforming modified deep-learning models. In this study [5], purports a review of the latest techniques aimed at detection anomalies in medical imagery. The study is delved into towards the MURA dataset-the openly available, large dataset of 40,561 X-ray images over 12,173 patients across seven types of bones. Future research scope for further exploration in this discipline has also been discussed in the paper. The findings highlight its potential to improve diagnostic accuracy and efficiency in orthopaedic radiology. This review is based on the research papers in the field, which take a closer look at new technologies and obstacles encountered while integrating CNNs for bone fracture identification.

A. X-ray Imaging for Bone Fracture Detection:

One of the most common and efficient methods for diagnosing bone fractures, especially in both routine and emergency health conditions, is X-ray. It is a technique that allows the generation of non- invasive images of the body through the use of electromagnetic waves. Specifically, by the passage of electromagnetic radiation through the body structure, it is able to form pictures of the internal structure. Bones appear lighter on X-ray images because they absorb the radiation. This essentially means that they are easy to differentiate from the soft tissue that surrounds the bones. Hence the X-rays can be well used to diagnose fractures and also to inspect the bones. In [3], researchers looked at 270 X-ray images. They tried different methods like Naïve Bayes, Decision Tree, Nearest Neighbors, Random Forest, and SVM. In the end, SVM gave the results with a score of 0.92. This is a great step to help doctors make better diagnoses and decisions for their patients. Most of the healthcare facilities including the hospitals, ERs, outpatient clinics and the smaller clinics have the X-ray machines that are available to the general public. X-ray is the frontline diagnostic tool to find the bone fractures in urban as well as rural areas because the machines are commonly found everywhere.

B. Deep Learning in Medical Imaging:

Because of deep learning particularly the use of Convolutional Neural Networks (CNNs), which are smart tools for a computer to automate the image analysis, medical pictures look largely different and meaningful engineering has been achieved. Image analysis based on deep learning, in which a machine automatically decides what the most relevant indicators for a given task are from a related image, is an approach that has gradually replaced the one that predominantly used manual feature extraction and domain expertise. Deep learning models have become quite versatile in the medical application domain since the advent of this technology. They can be used for an infinite number of tasks like cancer cell detection, bone lesions, and some other illnesses recognition and the like. A neural network is a machine learning method, and it is in deep learning that we find different layers stacking up. As a result, the lower layers tend to learn simple features and represent them in the simplest way possible, while the higher layers learn the more abstract features. Unlike traditional machine learning approaches, the big advantage of an AI model is that it can discover which are the most relevant features of the data by itself, without the need for any human feature engineering.

C. Classification using CNN:

A classification layer is used as part of a comprehensive neural network design to determine if a fracture is present or absent in X-ray pictures. In order to provide a prediction, this layer processes the high- level features that were retrieved by the previous convolutional and pooling layers. The neural network's convolutional layers use the Xray pictures to extract hierarchical and spatial properties. Pooling layers may then down sample these features, reducing the spatial dimensions while retaining the most relevant information. These features are represented in a multi-dimensional array or tensor. The multidimensional tensor is flattened into a one-dimensional vector. This step ensures compatibility with fully connected (dense) layers, which require a vector input. Flattening transforms the spatially distributed feature maps into a format suitable for learning global patterns. The flattened feature vector is passed through one or more fully connected (dense) layers. These layers discover intricate connections between the target variable—in this case, whether a fracture is present or not and the retrieved properties. To minimize overfitting, dropout layers are employed between dense layers. In this study [7], describes the automated method of improving the accuracy of bone fracture classification using machine learning. Among the two models

of Multilayer Perceptron (MLP) and Convolutional Neural Network (CNN) being compared, the CNN model achieved an accuracy of 94%, whereas the MLP achieved only 73% on a large dataset. The results demonstrate CNN's ability to detect intricate fracture patterns and form a promising approach for enhancing diagnostic accuracy and patient care in orthopaedic medicine. By randomly deactivating a portion of neurons during training, dropout keeps the network from becoming overly dependent on particular features and promotes the acquisition of more universal patterns. A sigmoid activation function, which produces a probability value between 0 and 1, is used in the last dense layer. The model's confidence that a fracture is visible in the X-ray image is represented by this probability. Because it converts any real- valued integer into a restricted range and makes it easier to interpret as a likelihood, the sigmoid function is perfect for binary classification jobs.

III. METHODOLOGY

The proposed method describes a systematic approach to automatically identify bone fractures from X-ray pictures. The method uses deep learning algorithms, performance evaluation, and picture preprocessing to achieve great efficiency and accuracy in fracture classification. The system's sequential workflow is depicted in Figure 1.
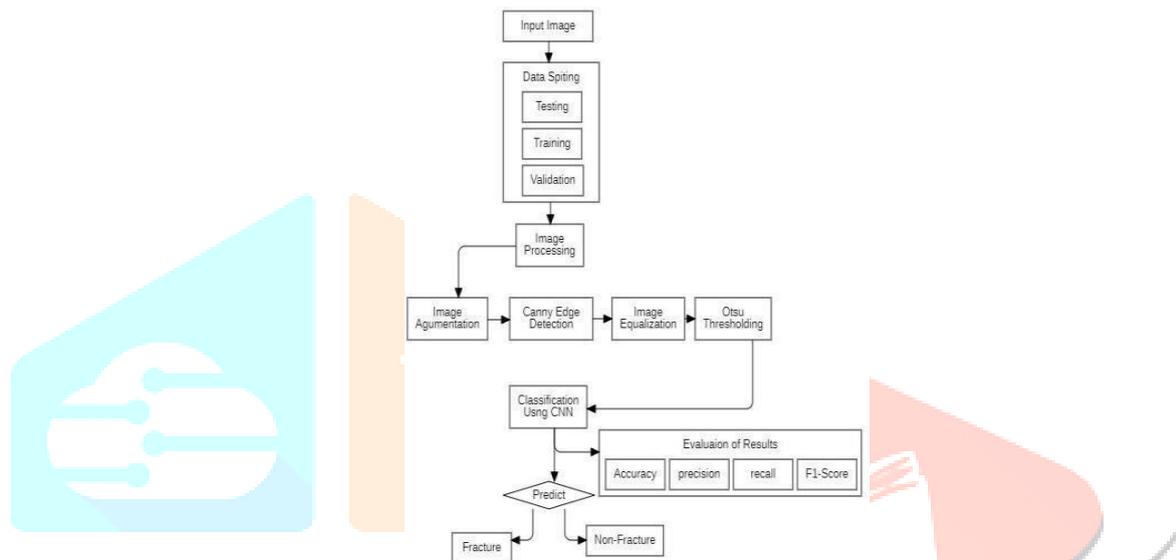

Figure 1: Workflow diagram of the proposed system.

A. Dataset:

To perform research on bone fracture detection using a convolutional neural network, the dataset of X-ray images was collected from Kaggle. The dataset contains 10,580 radiographic images (X-ray) data. This dataset divided fractured and non-fractured X-ray images. There present body regions, including knees, upper limb, lower limb, hips, lumber, etc. The dataset is categorized into train, test, and validation folders, each containing fractured and non-fractured radiographic images. This dataset is divided into three parts. Training, testing, and validation. Training data has 9246 images, the testing data has 506 images, and the validation data has 828 images.

B. Image Augmentation:

There are used image for the data augmentation technique to achieve better performance. In deep learning and computer vision, image augmentation is a technique that applies several alterations to existing images in order to artificially increase the size and variety of a dataset. It boosts the strength and impact of depictions for jobs like dividing spotting things, and sorting pictures. Adding variety creates many versions of current images mimicking a huge dataset. This means tweaking pictures in a dataset to make it bigger and more varied without getting more data. This helps avoid overtraining when teaching good data-capturing systems with lots of power. Changed-up pictures push the system to grasp key traits instead of relying on specific unimportant details. For example, turning or moving pictures makes the model focus on key layouts no matter which way they face. Getting and tagging new data can cost a lot and take ages. Adding variety lets you reuse what you have cutting down the need to gather more info.

Figure 2: Augmentation image result.

C. Canny Edge Detection:

The main aim of this method is to deal with different types of X-ray images either with fractures or without fractures. Canny Edge Detection is a method that has been most embraced by edge detection approach in computer vision and image processing due to its effectiveness and reliability. It is considered as difficult and famous in the field of computer vision and image processing, mainly due to its high ability to recognize boundaries in the available digital images. Among the computer vision and image processing subdomains, Canny Edge Detection is one of the most complex and popular methods. The algorithm is able to detect edges with the highest possible accuracy, and it is looking only at sharp changes in the image intensity while reducing the noise and irrelevant data to a minimum. Canny gives you an allowance for finding true edges and casting out the false ones from the very beginning in its design aspects positive. Of the initial noise reduction step, one is the issue of spurious edges that may emerge due to the random variation of the image. It is especially important in real- world situations where images often have artifacts or background noise. Canny is useful for dealing with complex images having many objects, different contrasts and textures, and hence it is a powerful tool for a wide array of scenarios.
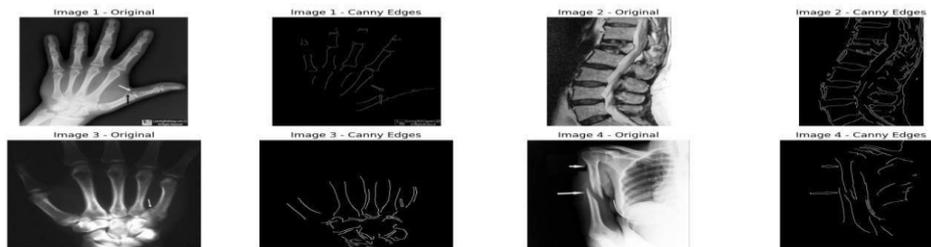

Figure 3: Sample images of canny edge detection results.

D. Image Equalization:

Image equalization is a basic but effective image processing technique aimed at enhancing the contrast of digital images. Histogram equalization is one of the most popular and widely used techniques for image equalization. Its principal application is redistributing the histogram evenly, which could effectively improve the global contrast of an original image as much as possible. With this help, the visibility of interesting details would be improved greatly so that they can be easily perceived by both the human visual system and other computer machine vision algorithms. For this reason, it has been widely applied to numerous scientific and engineering fields, such as computer vision, remote sensing imagery, robotic imaging, and biometric technology. wireless stereovision video evaluation X-ray bag systems microarray imaging biomedical signal enhancement optimal immunohistochemical architecture Jews scoring information. In the medical imaging domain, particularly, histogram equalization enhancement is useful in detecting some subtle abnormalities from low-contrast areas in X-rays.
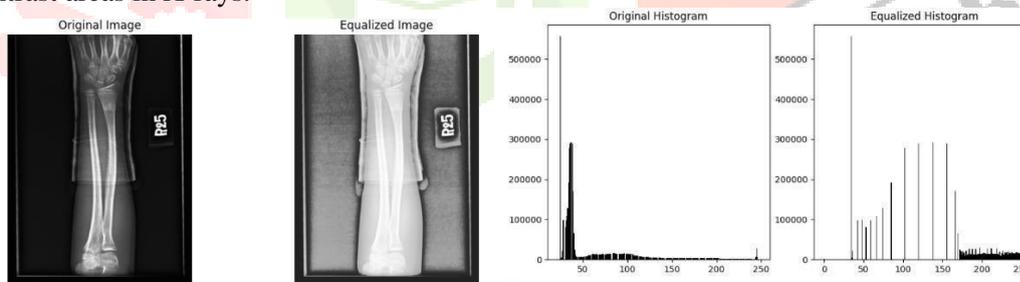

Figure 4: Equalization image and Histogram.

E. Otsu Thresholding:

Otsu's thresholding is an efficient thresholding technique that automatically selects an optimal threshold value through which it is possible to separate the foreground from the background regions in an image. By minimizing intra-class variance or equivalently maximizing inter-class variance, the method achieves effective segmentation for images with bimodal intensity distributions. In medical imaging, for example, X-rays, Otsu's method can be very helpful in revealing certain target structures. Otsu's thresholding is a very important technique for image binarization and serves well the purpose for many applications. Considering its limitations, it is necessary to take into account the image geometry and, at times, combine different methods to obtain reliable results.
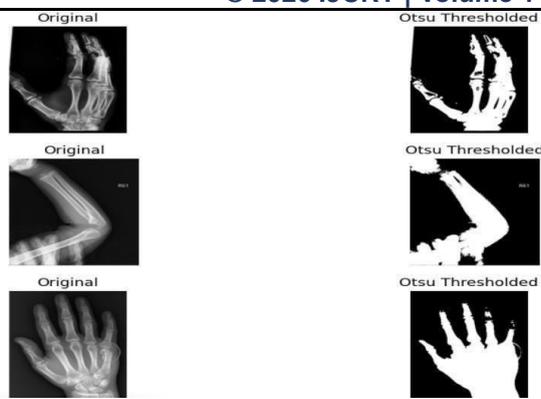
Figure 5: Sample images of Otsu Thresholding.

IV.   RESULTS AND DISCUSSION

The 13 epochs in all were used to train the convolutional neural network (CNN) model. In order to allow the model enough time to find patterns in the data set internally without overtraining on a specific model, these training periods were carefully selected to strike a balance between underfitting and overfitting. This method produced a well-fitting model by offering steady and well-integrated loss functions. After completing the training set, the CNN model achieved an impressive accuracy of 96.33% to distinguish between fractures and non-fractures. This high accuracy highlights the strong ability of the model to it will emphasize the correct classification of images. The visual performance results are presented in Fig. 6 which shows the achieved accuracy, and shows the loss trends in the training process.
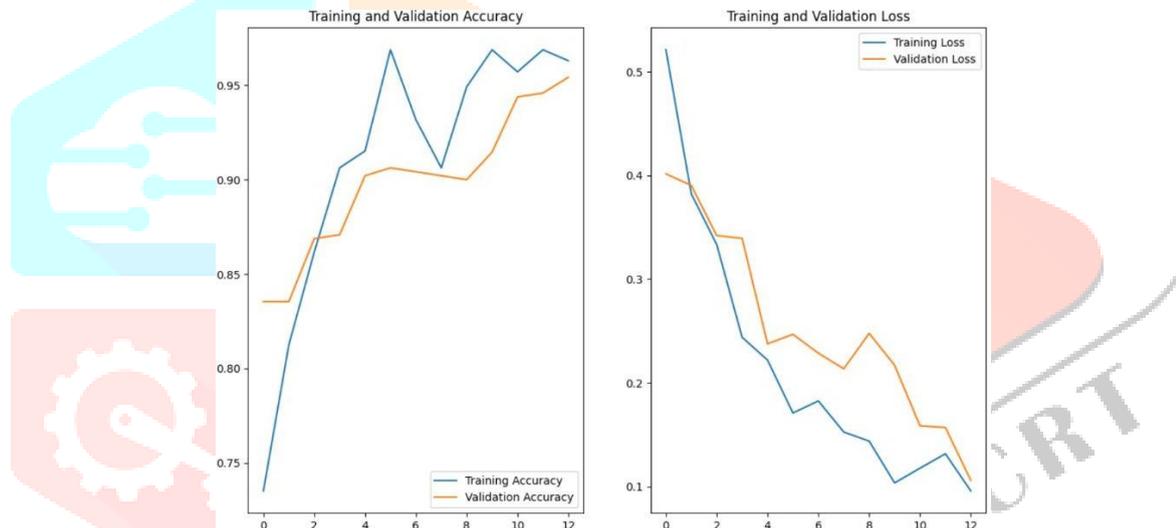

Figure 6: Accuracy and loss curves for both the training and validation processes

The performance metrics of a model for a classification task, specifically in the context of identifying "fractured" and "not fractured" cases. The metrics shown include Precision, Recall, F1-Score, Accuracy, Macro Average, and average weighted. Precision quantifies the proportion of the model's positive predictions that come true. There 93% of fractures and 97% of non-fractures were accurately identified. In medical diagnosis, where misclassifying non-fracture patients as fractures could result in needless therapies or interventions, this high precision is very important. Together, these findings show how well the CNN model detects fractures, making it a reliable instrument for medical imaging analysis Recall indicates in proportion the real positive cases which have been detected correctly by the model. The recall rate was 97% for fractured and 94% for non-fractured. F1-Score the harmonic mean of Precision and Recall, providing a balance between the two. It is particularly useful when the data is uneven because it accounts for both false positives and false negatives. A high F1 score means that the machine learning model has achieved a balanced precision and recall for it. Using these evaluation metrics, the model gets a complete overview of its performance. Every metric focuses on a specific classification aspect, thus, a scenario in which the model is not only accurate but is also effective in its handling positive and negative classifications among various situations is ensured. The F1- Score of fractured 95% and non-fractured 95%. The proposed model result shown in Fig. 7 with better performance.
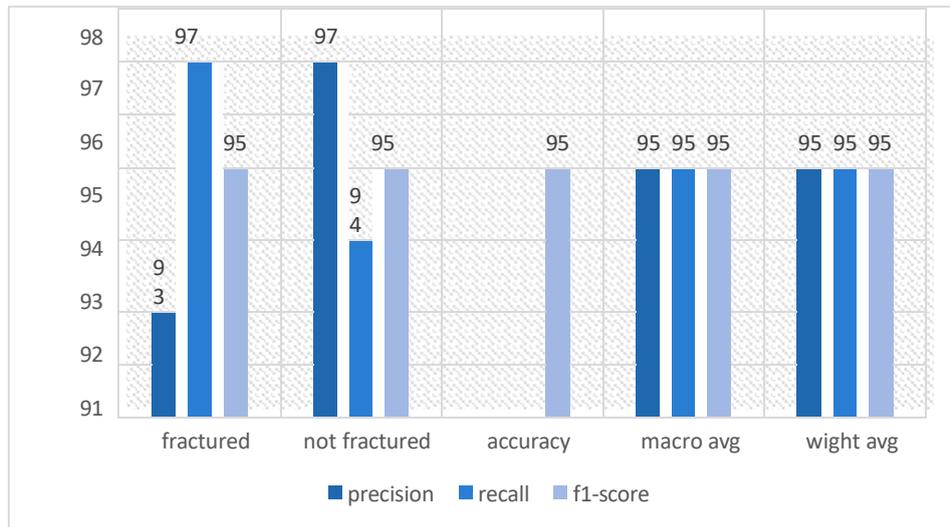
Figure 7: Classification Report.

V.   CONCLUSION AND FUTURE WORK

Patient's optimal care can be a result of exact and quick detection of bone fractures. Conventional diagnostic technology, which stress on human judgment, is utilized to a great extent but is a very long process and too error prone such as chemotherapy, which inevitably leads to the development of resistance to drugs Initially, the study suggests the idea of obtaining more accurate statistics for solving the inaccuracies, like making the diagnosis of fractures by the combination of handcraft data and deep learning-based features. A diverse collection of 10,580 Xray images was used in the study, and it was prepared to resemble what happens in real-time, and the images were chosen specifically to make this work. Therefore, the model could perform well under several clinical circumstances. The preprocessing was characterized by the functionality of the pipeline, which was designed to enhance the resolution of the images by carrying out noise reduction and normalization techniques. An additional advantage was that bone structure usually appears with simple edge detection, developed by the Canny algorithm. This is important in the timely application of treatments. Furthermore, this is the precondition for the broken fibres to be seen completely. Through the existing deep learning, a Convolutional Neural Network (CNN) was initiated, and formerly it was updated to make raw data sets from the images better. The work increased the classification accuracy for the problem of bone fracture by approximatively 96.33%. Several performance indices were utilized in order to ensure the reliability and applicability of the system, for example, precision, recall, F1-score, and support measures. These articles were not only solid evidence of the system's trustworthiness but were also show trials in which the model was always working accurately. By using handcrafted features and deep learning, the study aimed to develop a robust and efficient system for the detection of fractures. would be very helpful for explorations of other types of fractures like hairline fractures, compound fractures, and comminuted fractures in future experiments.

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