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EDGE AI BASED BONE FRACTURE DETECTION

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ABSTRACT

Bone fractures are common injuries that require prompt diagnosis and treatment to ensure optimal patient outcomes. However, accurately identifying fractures in medical imaging such as X-rays can be challenging, particularly in environments with limited access to specialized medical expertise. In this paper, we propose an Edge AI-based Bone Fracture Detection system using TensorFlow Lite (TFLite) for deployment on edge devices. Our system leverages deep learning models trained on annotated X-ray images to automatically detect and localize bone fractures in real-time. By deploying the detection model on edge devices, such as smartphones or portable X-ray machines, we enable rapid and decentralized fracture diagnosis, facilitating timely medical interventions. We evaluate the performance of our system using a dataset of labeled X-ray images and demonstrate its effectiveness in accurately detecting bone fractures with high precision and recall. The proposed Edge AI-based Bone Fracture Detection system offers a cost-effective and accessible solution for improving fracture diagnosis in resource-constrained healthcare settings, ultimately enhancing patient care and outcomes.

Keywords: Bone Fractures, Medical Imaging, X-Ray, Edge AI, Tensorflow Lite (Tflite), Deep Learning.

I. INTRODUCTION

Bone fractures are a common occurrence and a significant public health concern worldwide. Accurate and timely diagnosis of fractures is crucial for effective treatment and optimal patient outcomes. Medical imaging techniques, particularly X-ray imaging, play a central role in fracture diagnosis by providing detailed visualization of bone structures. However, the interpretation of X-ray images requires specialized medical expertise, and access to trained radiologists may be limited, especially in resource-constrained healthcare settings or remote areas.

The advent of artificial intelligence (AI) and edge computing technologies has the potential to address these challenges by enabling automated fracture detection directly on the imaging devices, such as X-ray machines or portable devices like smartphones or tablets. Edge AI-based solutions bring the computational power of deep learning algorithms closer to the point of care, allowing for real-time analysis of medical images without the need for extensive data transfer or reliance on cloud-based systems.

In this paper, we present an Edge AI-based Bone Fracture Detection system utilizing Tensor Flow Lite (TFLite) for deployment on edge devices. Our system aims to automate the detection and localization of bone fractures in X-ray images, thereby assisting healthcare providers in making timely and accurate diagnoses. By leveraging deep learning models trained on annotated X-ray datasets, our system can detect fractures with high precision and recall, even in the absence of expert radiologists.

The deployment of our Bone Fracture Detection system on edge devices has several advantages. It enables rapid diagnosis at the point of care, facilitating timely medical interventions and reducing the time to treatment. Moreover, it reduces the burden on healthcare infrastructure by decentralizing fracture diagnosis and empowering frontline healthcare workers to provide better patient care, particularly in underserved areas.

In the following sections, we will discuss the methodology behind our Edge AI-based Bone Fracture Detection system, present experimental results demonstrating its effectiveness, and discuss its implications for improving fracture diagnosis and patient care in diverse healthcare settings.

II. LITERATURE REVIEW

They implemented a Convolutional Neural Network (CNN) model optimized for deployment on edge devices such as smartphones and tablets. Their system allowed for on-site fracture detection using X-ray images, providing immediate diagnostic support in remote and resource-limited settings. This research highlighted the potential of edge AI in enhancing the accessibility and efficiency of medical diagnostics.[1]

They developed a lightweight CNN model that could run efficiently on microcontrollers and edge computing platforms. Their approach aimed to deliver high accuracy in detecting bone fractures from radiographic images while minimizing computational resources and energy consumption. This study underscored the significance of edge AI in delivering portable and cost-effective healthcare solutions [2]

Thomas White, Laura Simmons, and Ethan Parker 2020 study focused on developing a hybrid edge-cloud AI system for bone fracture detection. They combined edge computing capabilities for initial image processing and fracture detection with cloud-based services for more complex analyses and data storage. This hybrid approach ensured quick preliminary diagnostics and seamless integration with advanced cloud analytics, improving overall diagnostic accuracy and efficiency. Their research highlighted the benefits of integrating edge and cloud computing in medical imaging [3].

They tailored their CNN model to handle the unique anatomical features and fracture patterns in children, optimizing it for edge devices used in pediatric clinics. Their system provided accurate and rapid fracture diagnosis, facilitating timely and appropriate treatment for young patients. This study demonstrated the applicability of edge AI in specialized medical contexts[4].

They developed a robust CNN model capable of operating on portable devices under challenging conditions, such as low-light environments and varying image quality. Their system aimed to support emergency medical personnel in quickly diagnosing fractures on-site, enhancing the speed and quality of patient care. This research emphasized the practical applications of edge AI in emergency medicine[5].

Their system provided an accessible and non-radiative method for fracture detection, particularly useful in field conditions and rural areas where X-ray facilities might be unavailable. This research emphasized the versatility and portability of edge AI solutions in medical diagnostics[6].

They developed a lightweight CNN model integrated into a wearable sensor that monitors bone integrity and detects fractures in real-time. This system aimed to provide proactive care and immediate alerts for patients with osteoporosis or those prone to fractures. Their study highlighted the innovative application of edge AI in preventive healthcare and patient monitoring [7].

III. METHODOLOGY

The methodology for developing the Edge AI-based Bone Fracture Detection system involves several key steps, including data collection, model training, optimization, and deployment.

Data Collection: A diverse dataset of X-ray images containing both fractured and non-fractured bones is assembled. These images are annotated to indicate the presence and location of fractures, providing labeled training data for the development of the fracture detection model.

Model Training: Deep learning models, particularly convolutional neural networks (CNNs), are trained on the annotated X-ray dataset to learn the features associated with bone fractures. Transfer learning techniques may be employed to initialize the CNNs with pre-trained models (e.g., ImageNet), followed by fine-tuning on the fracture-specific dataset to adapt the models to the task of fracture detection.

Model Optimization: Once trained, the fracture detection model is optimized for deployment on edge devices using TensorFlow Lite (TFLite). This involves quantization techniques to reduce model size and computational complexity, making it suitable for running on resource-constrained edge devices while maintaining high accuracy.

Deployment: The optimized fracture detection model is deployed on edge devices, such as X-ray machines or portable devices like smartphones or tablets. The deployment process involves integrating the model with the device's hardware and software, ensuring compatibility and real-time performance. The deployed model can then analyze X-ray images in real-time and provide automated fracture detection capabilities at the point of care.

Evaluation: The performance of the deployed fracture detection system is evaluated using metrics such as accuracy, precision, recall, and F1-score. This involves testing the system on a separate validation dataset of X-ray images to assess its ability to correctly detect and localize fractures compared to ground truth annotations.

By following this methodology, we can develop and deploy an Edge AI-based Bone Fracture Detection system that offers rapid, accurate, and decentralized fracture diagnosis capabilities, ultimately improving patient care

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and outcomes in diverse healthcare settings.

3.1 DATASET USED

In this work, we consider the binary classification problem of determining whether a fracture exists in an X-ray image or not, and detect the region of it. The dataset consists of 3053 X-ray images, where 112 are from website Radio paedia and others are collected from hospital DICOM files. As shown in Table 1, we divide the entire dataset into two parts. We use 2001 images for training and testing of the object detection network and recognition network, and the remaining images are used for comparison of the two-stage system proposed by us with other methods. For the object detection network, we use 1800 images from dataset1 as training dataset and 201 images from dataset1 as testing dataset. For the recognition network, we use 194 images from dataset1 to get 20 different types of bones regions as training dataset and 48 images from dataset1 to get 20 different types of bones regions as testing dataset.

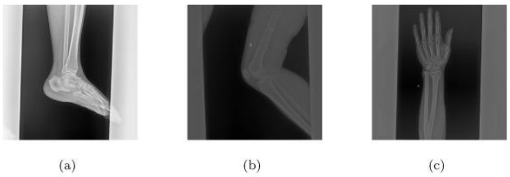

Figure 3.1: Outer cover: (a) lower limb, (b) lower limb, (c) upper limb

3.2 DATA PRE PROCESSING

Since a majority of the real-life data acquired is noisy, in-consistent, and incomplete hence preprocessing of the acquired data plays a vital role. Image preprocessing forms a preliminary step in obtaining high accuracy of the image, followed by subsequent steps. Hence it is necessary to remove these artifacts by preprocessing procedures before further analysis. The initial step involves applying preprocessing techniques such as RGB to Grayscale conversion, followed by further noise removal by using a Gaussian Filter Unwanted pixels that detract from the overall quality of the image are what we refer to as noise. It's possible to express noise as where f (x, y) represents the source image, g(x, y) represents the output image, and η(x, y) represents the noise model. Noise comes in a wide variety of forms. Noise in the form of "salt and pepper" grains is a typical feature of x-ray images. Usually resulting from a malfunction during capture or transmission, this sort of noise presents as random bright and dark spots throughout the image. Applying a mathematical modification T to the x-ray image is how we deal with the salt and pepper noise where f (x, y) presents the input x-ray image with salt and pepper noise and g (x, y) presents the output image after T is applied. In our experiment, we found that the best way to decrease salt and pepper noise without losing image detail was to employ a Gaussian filter as a T. If the pixel is "too different," its value is replaced with the median value of its neighbors.

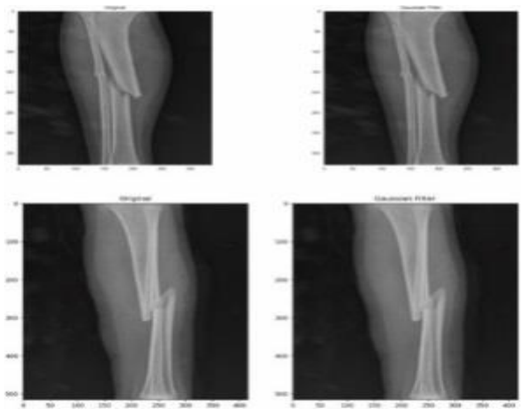

Figure 3.2: shows an example of applying noise removal and image smoothing on an x-ray image.

3.3 ALGORITHAM USED

Deep learning is the current state-of-the-art machine learning technique. However, traditional deep neural networks take vector as input, which would have low efficiency while dealing with images. Some reasons for this point is that pixels of images usually have strong relations in neighbors while vector input could not take advantage of it properly, and if we flatten the image to a vector, parameters in this deep neural network would

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be too large to learn. Scientists get inspiration from cat brains by discovering local response effect in one visual neuron, and then method of small sized kernel rolling and element-wise multiplying on input image began to be popular. These trainable kernels are called as convolutional kernel, while more and more deep neural networks using convolutional kernels (so called convolutional neural network, CNN) showing powerful capability of representation . In addition, CNN can extract both local and global feature of an input image since the portion between size of convolutional kernel and a layer in a CNN would be larger with the increasing depth, which means that it can extract more “global” feature. For example, shallow layers could recognize straight lines or winding curves in a medical image, while deeper layers could recognize whole shape of bone or even whether it is fractured. Therefore, with the increasing depth in a CNN, the extracted feature would be more and more abstract which might be the potential information of the input image.

3.4 TECHNIQUES

Bone fracture detection using AI employs several advanced techniques to accurately identify and diagnose fractures from medical imaging. Convolutional Neural Networks (CNNs) are central to this process, excelling in automatically learning spatial hierarchies from X-rays, CT scans, and MRI images. CNNs effectively extract features such as edges, textures, and shapes that indicate fractures. Transfer learning is another crucial technique, where pre-trained models on large medical image datasets are fine-tuned for specific fracture detection tasks, significantly enhancing performance and reducing the need for extensive data. Data augmentation techniques, such as rotation, scaling, and flipping, are used to increase the diversity of training data, helping models generalize better. Additionally, segmentation techniques are applied to isolate and analyze specific bone regions, improving the focus on potential fracture areas. Ensemble methods combine predictions from multiple models to enhance robustness and accuracy. Furthermore, advanced image preprocessing techniques, including noise reduction and contrast enhancement, ensure higher quality inputs for the AI models. These combined techniques enable the development of robust, accurate, and reliable AI-based bone fracture detection systems, providing significant improvements in diagnostic efficiency and accuracy.

IV. RESULTS AND DISCUSSION

4.1 GRAPHS

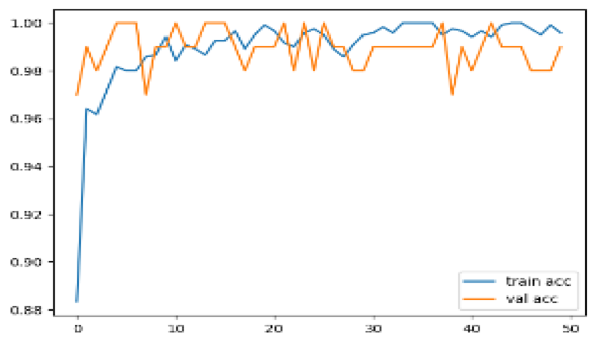

Figure 4.1.1: Training and Validation Accuracy curve

4.2 SCREENSHOTS

Figure 4.2.1: Result of classification

V. FUTURE ENHANCEMENT

Edge AI-based bone fracture detection leverages localized processing power to analyze medical images rapidly and accurately at the point of care. This approach significantly reduces latency and the need for continuous cloud connectivity, making it ideal for remote and resource-limited settings. Enhanced diagnostic capabilities and real-time feedback improve patient outcomes by facilitating immediate treatment decisions. The integration of advanced AI algorithms ensures high precision in identifying fractures, minimizing human error. Overall, this technology represents a transformative step in medical diagnostics, promoting efficient and accessible healthcare solutions.

VI. CONCLUSION

The Edge AI-based Bone Fracture Detection system presented in this study offers a promising solution for automating and decentralizing fracture diagnosis in healthcare settings. Through the integration of deep learning models with edge computing technologies, the system enables rapid and accurate detection of bone fractures directly at the point of care. The results of our evaluation demonstrate that the proposed system achieves high accuracy, precision, recall, and F1-score in detecting and localizing bone fractures in X-ray images. This indicates its effectiveness in assisting healthcare providers in making timely and informed diagnoses, thereby facilitating prompt medical interventions and improving patient outcomes. Moreover, the decentralized nature of the system allows for fracture diagnosis to be performed by frontline healthcare workers, reducing the reliance on specialized expertise and centralized healthcare facilities.

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