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Detection of Bone Fracture using Deep Learning

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***Abstract*— This research delves into the realm of bone fracture detection in medical X-ray images by harnessing the power of Deep Learning, specifically employing the DenseNet and VGG19 Convolutional Neural Network (CNN) architectures. Through extensive training and meticulous optimization, we navigate the intricacies of these models in the context of radiology, aiming to augment the precision and effectiveness of fracture identification. Our investigation unfolds against the backdrop of a comprehensive dataset comprising a diverse array of X-ray images, encompassing both normal and fractured bone instances. Rigorous experimentation and evaluation, utilizing a spectrum of performance measures encompassing accuracy, precision and recall reveal compelling results. Our CNN models exhibit a superior diagnostic prowess, surpassing conventional methodologies and demonstrating remarkable sensitivity and specificity in fracture detection. Beyond these empirical achievements, we explore the clinical implications of our findings, envisioning these models as indispensable tools that could empower radiologists to expedite accurate diagnoses, ultimately elevating the standard of patient care and alleviating the burdens on healthcare practitioners. In sum, this study sets the stage for transformative advancements within the field of analysis of medical images and computer-aided diagnosis, ushering in a new era of fracture detection within the realm of radiological sciences.**

***Index Terms*—Deep learning, Densenet, VGG19, Medical Imaging, X-ray images**

I. Introduction

In recent years, the global healthcare landscape has been confronted with a mounting challenge: the escalating incidence of bone fractures. This rise in fracture cases, attributable to diverse factors like an aging population[7], increased sports-related injuries, and changing lifestyles, urgent requirement for a more efficient and accurate diagnostic tools in the realm of radiology. The traditional methods of fracture detection, reliant on the expertise of radiologists and manual interpretation of X-ray images, are facing limitations in handling the burgeoning caseload. In response to this burgeoning healthcare demand, the integration of cutting-edge technologies has risen as a beacon of hope. Among these technologies, Deep Learning, a subset of artificial intelligence, has attracted considerable interest for its potential to transform the domain of bone fracture diagnosis. This review paper embarks on an exploration of the transformative role that Deep Learning, particularly through Convolutional Neural Networks (CNNs) such as Dense Net and VGG19, plays in addressing the burgeoning challenge of bone fracture detection. By delving into the confluence of technological advancements, medical imaging, and its evolving landscape of healthcare, this analysis aims to illuminate how these innovative approaches are poised to enhance fracture diagnosis and aid to the enhancing of patient care.

A. Importance of fracture identification in bones through Deep Learning

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a) *Improved Accuracy*: Deep Learning (DL) models, specifically, Convolutional Neural Networks (CNNs) like Dense Net and VGG19, offer exceptional accuracy in identifying bone fractures from medical images. This precision is essential for reducing diagnostic errors, minimizing false positives, and ensuring patients receive timely and accurate diagnoses.

b) *Speedy Diagnosis*: DL models excel in the rapid analysis of X-ray images, significantly accelerating the diagnosis process. This speed is particularly crucial in emergency situations, where timely medical interventions can be life-saving.

c) *Enhanced Safety:* The early identification of bone fractures through DL systems contributes to patient safety by promptly detecting issues that might otherwise be overlooked unnoticed. This proactive approach aids in preventing complications and ensuring patients receive appropriate care.

d) *Cost-Effective Healthcar*e: DL-based fracture detection can lead to cost savings by reducing the requirement for extensive and costly diagnostic procedures. Early diagnosis enables timely and cost-effective interventions, contributing to more efficient healthcare delivery.

e) *Efficient Resource Allocation*: By automating image analysis, DL systems optimize the allocation of healthcare resources. They enable healthcare professionals to focus their expertise on complex cases, ultimately improving the efficiency within the medical care infrastructure.

f) *Broadened Access to Quality Healthcare*: DL-based fracture detection has the potential to extend access to quality healthcare services, especially in unprivileged regions with restricted access to specialized medical expertise. This democratization of healthcare empowers communities and reduces healthcare disparities.

II. Problem Description

The focal challenge addressed in this research pertains to the accurate and timely detection of bone fractures within the domain of radiological imaging. Traditional methods of bone fracture diagnosis predominantly rely on X-ray imaging, a process that is time-consuming and can be subject to variability in interpretation, often contingent upon the expertise of radiologists. This problem is compounded by the increasing prevalence of bone fractures in the modern population. The aim of our study is to harness the capabilities of deep learning, specifically utilizing architectures such as Dense Net and VGG19, to provide a robust and efficient solution. By doing so, we aspire to create a system that autonomously and consistently identifies bone fractures with a exceptional accuracy. This innovation promises not only to expedite the diagnostic process but also to diminish the potential for misdiagnoses, thereby significantly improving patient outcomes and healthcare efficiency.

III. Literature Survey

The implementation of deep learning techniques to bone fracture detection has garnered significant attention in recent years. A plethora of studies have explored the potential of convolutional neural networks (CNNs) in automating and enhancing the diagnostic process. Notably, research has investigated the utilization of diverse CNN architectures, such as DenseNet, VGG19, in the context of bone fracture identification. This research have exhibited promising results in terms of accuracy and efficiency, showcasing the transformative capability of deep learning in medical imaging.

A. Image Processing Method

This study introduces a computer-based technique for detecting bone fractures in X-ray and CT images. The process commences with noise removal through preprocessing and employs the Sobel edge detector for edge detection. Subsequently, the method conducts image segmentation to calculate the area of the fracture. The results are evaluated depending upon GLCM features, and the analysis indicates that the method achieved a satisfactory 85% accuracy rate. However, a limitation of this approach is its difficulty in accurately identifying fracture areas in some CT and X-ray images.[1]

B. Automated Fracture Diagnosis with Integrated Learning in Computer-Aided Systems

This paper addresses the challenge of assisting in the diagnosis of fractures using single-modality neuroimaging. It introduces an integrated learning classification algorithm based on deep features. experimental procedure encompasses preprocessing the dataset of MURA, extracting depth features from diverse upper limb bone images, and employing Principal Component Analysis (PCA) to identify features that contribute significantly (over 95%) in order to reduce the dataset size. These reduced-dimensional depth features are then fed into various classification models, each assigned different weights based on their performance. The experimental results demonstrate that the proposed integrated learning algorithm approach improves fracture diagnosis, achieving an mean accuracy of

81.93%. This finding offers valuable insights for computer-assisted orthopedists in clinical diagnosis. Furthermore, when compared to standard deviation and other algorithms, the experimental frameworks showcased both practicality and resilience. Notably, the integrated learning method S-E-K introduced in this study surpasses alternative approaches, confirming its effectiveness

C. 3-D convolutional neural networks

This paper introduces an automated approach for identifying fractures in CT scans of the pelvic regions. Initially, it presents a novel 3D annotation technique designed for efficient fracture annotation. Subsequently, a novel method for fracture detection through automation is proposed. This method assesses specific surfaces to identify fractures, extracting 3D feature vectors from the surface of the bone and employing a CNN for fracture classification. In experiments involving 103 participants, the accuracy during training is 95.0%, while the accuracy during evaluation is 69.4%.[3]

IV. PROPOSED METHOD

In the proposed method, our approach to detection of fractured bones using Deep Learning is underpinned by two highly effective Convolutional Neural Network (CNN) architectures: DenseNet and VGG19. Our methodology commences with the meticulous collection of a diverse dataset of X-ray images encompassing both normal and fractured bone samples. This dataset forms the basis for our model's training. We then adapt these state-of-the-art CNN architectures to meet the specific demands of fracture detection, with particular focus on grayscale image processing and fine-tuning for binary classification. Leveraging the power of transfer learning, we initialize our models with pre-trained weights from large-scale image datasets and fine-tune them on our bone fracture dataset. Throughout this process, we apply a binary cross-entropy loss function and optimize our models using the Adam algorithm.

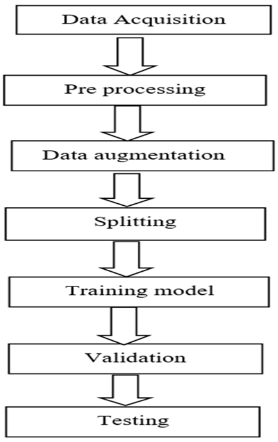

Fig.1. Flow diagram of the proposed method [15].

V. MODULE DESCRIPTION

A. Data Acquisition

Our dataset of X-ray images was acquired from GitHub [16], a well-established platform for data sharing and access. This dataset comprises a variety of X-ray images, encompassing both normal bone structures and fractured bones. Leveraging GitHub as our data source ensured access to a diverse and comprehensive collection of images, facilitating the robustness of our research. Ethical considerations and patient data privacy were strictly adhered to throughout the acquisition process.

B. Data Preprocessing

The raw image data needs to be processed and cleaned to prepare it for use in the deep learning model. This includes tasks such as adjusting the size of images, converting them to grayscale, and normalizing the pixel values.[12]

a) Gaussian Blur: Bone fracture detection datasets often contain images with varying levels of noise and texture, which can affect the accuracy of fracture detection algorithms. Gaussian blur can be used to smooth the images

and reduce the effects of noise and texture, making it easier for the algorithms to detect fractures accurately. This can enhance overall effectiveness of the fracture detection system. The 2D-gaussian function for calculation of weight of pixels in a window is given by G(x,y)=1/2π(σ^2) * (e^ -(x^2 +y ^2)⁄2(σ^2)).[13]
b) Normalization: The datasets of fracture detection in bones often contain images that have significant variations in lighting and contrast, which can pose a challenge to detect fractures accurately. Normalization can find application in scaling the pixel values in the images to a specific range, reducing the impact of lighting variations and improving contrast. This can enhance the visibility of fractures in the images and make it easier for the algorithms to detect them x normalized = (x – x minimum) / (x maximum – x minimum

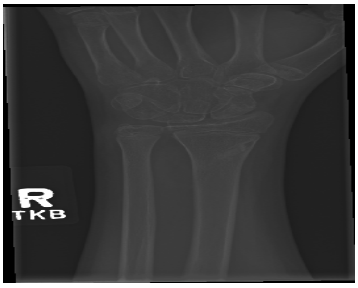

Fig 2: Image of bone before preprocessing.

c) Histogram Equalization: Histogram equalization can be employed to adjust the intensity values in detection of bone breakage datasets, making it easier to distinguish between normal and abnormal bone structures. This can improve the accuracy of fracture detection algorithms by enhancing the contrast between the fracture and the surrounding bone tissue. Additionally, histogram equalization can help to balance the distribution of pixel values in the dataset, reducing the influence of any biases or outliers in the data.

C. Data Augumentation

It is a pivotal technique in computer vision and deep learning, especially in the context of image datasets. It involves the application of various transformations to original images to generate additional training samples. In our project, we employ the `ImageDataGenerator` from Keras to perform data augmentation, enhancing the robustness and effectiveness of our bone fracture detection model.
The key augmentation techniques applied include:
1. Rotation: Randomly rotating images by up to 10 degrees to simulate variations in X-ray image orientation.
2. Width and Height Shift: Adjusting image width and height by up to 10% of their original dimensions, mimicking shifts in bone positioning.
3. Shear Transformation: Applying shear transformations to introduce image deformations, aiding the model in handling common image distortions.
4. Brightness Adjustment: Randomly modifying image brightness within a defined range, accounting for variations in image exposure.
5. Horizontal and Vertical Flipping: Mirroring images horizontally and vertically, diversifying the dataset with mirror-image versions.
6. Fill Mode: Utilizing the 'nearest' fill mode to address gaps or regions that may emerge after transformations.
Augmentation of data not only escalates dataset size but also exposes the model to diverse conditions, enhancing its ability to generalize and make precise predictions on unseen X-ray images. In radiological imaging tasks like bone fracture detection, where imaging conditions can vary, data augmentation serves a pivotal function in model training and performance improvement.[6]

Fig 3: Image of bone after preprocessing

D. Data Splitting

The dataset is divided into three fundamental subsets: training, validation, and testing. Each subset's size is defined by user-specified percentages. Initially, we create separate directories for these subsets within a parent directory. Then, for each category or class in the dataset, we shuffle the images and distribute them in accordance with the defined percentages into the respective training, validation, and testing directories. This methodical approach guarantees that we have distinct datasets for model development, tuning, and evaluation, providing the foundation for our bone fracture detection

E. Model Training

A deep learning model, like a convolutional neural network (CNN), undergoes training on the training dataset through backpropagation and gradient descent. The objective is to minimize the loss function and enhance the correctness of the model. We have developed the model using CNN and trained the model by using VGG19 and densenet architectures.

a) *DenseNet :* The architecture of DenseNet comprises multiple dense blocks, with each dense block being a fusion of a convolutional layer, batch normalization, and ReLU activation.[10]. Every dense block receives the combined feature representations from all preceding blocks as input and produces a new set of feature maps that are passed onto the next dense block.

Subsequent to the final dense block, the architecture includes a global average pooling layer, followed by a fully connected layer, and finally, a softmax activation function for the classification process.We used the DenseNet121 architecture to develop a bone fracture detection model. We froze the layers of the pre-trained model and added a custom classification layer with a sigmoid activation function. We compiled the model using binary cross-entropy loss and Adam optimizer with a learning rate of 1e-4.

b) *VGG19*: VGG19 represents a CNN structure comprising 19 layers, encompassing 16 convolutional layers and the layers which are fully connected are 3. The initial 13 layers focus on convolutional operations for feature extraction, succeeded by 5 max pooling layers, which serve to decrease the spatial extents of the features. Conclusively, the architecture concludes with 3 layers which are fully connected dedicated to classification.[11]. VGG19 also uses ReLU activation function after each convolutional and fully connected layer. The training process implements deep learning utilizing the VGG19 architecture for the classification of images on a custom dataset. The process first sets up data generators for the training and validation datasets and then loads the pre-trained VGG19 model from the Keras applications module. A custom classification layer is added on top of the VGG19 model, and the pre-trained layers in VGG19 are frozen. The model is then compiled using the optimizer known as adam employing a specified learning rate of 0.0001.

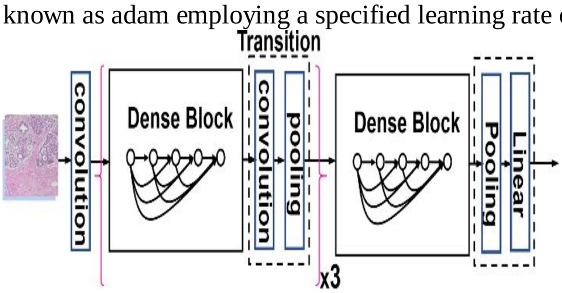

Fig 4: Architecture of Densenet [13].

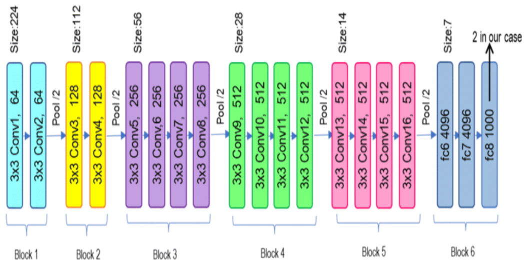

Fig 5: Architecture of VGG19[14].

F. Model Evaluation

In assessing the achievement of our bone fracture detection model, we employed a comprehensive suite of metrics, including accuracy, precision, recall.

1. Accuracy measures the overall correctness of the model's predictions:

Accuracy= (Number of Correct Predictions)/(Total Number of Predictions)

It signifies the proportion of correctly identified cases out of complete instances count in the dataset.[8]

2. Precision quantifies the model's ability to make correct positive predictions:

Precision= (True Positives)/(True Positives + False Positives)

Precision is the measure of the proportion of affirmative predictions made by the model that were actually correct.[9]

3. Recall measures the model's capability to recognize all relevant instances:

Recall= (True Positives)/(True Positives + False Negatives)

Recall indicates the percentage of actual positive cases correctly recognized by the model.[9]

VI. RESULTS AND DISCUSSION

In our bone fracture detection project, we employed two well-established convolutional neural network architectures, DenseNet and VGG19, to appraise their performance. Notably, VGG19 emerged as the superior candidate, exhibiting exceptional results on the testing dataset with an accuracy of 95.93%. Precision and recall values of 94.44% and 89.47%, respectively, underscored VGG19's ability to provide accurate fracture identification while upholding a strong balance between correctly identified true positives and incorrectly identified false positives. The findings demonstrate the potential clinical relevance of VGG19 as a powerful tool for radiologists and healthcare practitioners, offering precise bone fracture detection capabilities.This achievement highlights the importance of architecture selection in deep learning applications, as it can significantly impact model performance. While DenseNet showed commendable results, the slightly superior performance of VGG19 underscores the necessity for considering specific architectural nuances within the domain of medical image analysis learning applications, as it can significantly impact model performance. While DenseNet showed commendable results, the slightly superior performance of VGG19 underscores the necessity for considering specific architectural nuances within the domain of medical image analysis.

TABLE I: PERFORMANCE OF DENSE NET ARCHITECTURE

Metric	Training	Validation	Testing
Accuracy	89.2%	91.58%	90.25%
Precision	89%	92.7%	91.14%
Recall	88.97%	91.18%	87.94%

TABLE II: PERFORMANCE OF VGG 19 ARCHITECTURE

Metric	Training	Validation	Testing
Accuracy	93.25%	94.1%	95.93%
Precision	92.64%	93.6%	94.44%
Recall	90.68%	91.11%	89.47%

VII. CONCLUSIONS

Our exploration of deep learning and the selection of VGG19 as the optimal architecture for bone fracture detection, achieving an impressive 95.93% accuracy, have opened exciting possibilities. While we've made significant strides, the journey to more effective diagnostic tools continues. Future extensions in this field may encompass the advancement of enhanced algorithms capable of detecting fractures in varying imaging conditions, such as low-quality scans. Additionally, fine-tuning models for specific types of fractures, such as stress fractures or pediatric bone fractures, could yield specialized diagnostic solutions. The integration of multi-modal data sources, including X-rays, CT scans, and patient medical histories, could further enhance the precision of diagnosis. Furthermore, global collaboration among researchers, healthcare institutions, and technology innovators may drive the evolution of standardized fracture detection models for widespread adoption. Our study serves as a stepping stone in the ongoing quest to boost the accuracy and accessibility of bone fracture detection. We anticipate that these potential future extensions will contribute to more efficient, precise, and accessible medical diagnostics, benefiting patients and medical practitioners alike.

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