NEXT GENERATION BONE FRACTURE MODELING: TOWARD MORE ACCURATE AND REALISTIC PREDICTIONS

Akash Kumar, Anmol Tripathi, Er. Anuj Singh (Assistant Professor)

Computer Science and Engineering, SRMCEM, Lucknow, India
Email: yakash20dec@gmail.com , anmol.tripathi1166@gmail.com , anujsinghknit@gmail.com

Abstract

Computers have proven indispensable in numerous aspects of human life, including banking, online shopping, communication, education, research, and medicine. To enhance patient care, numerous innovative technological resources have been developed for doctors and hospitals. One significant advancements addresses the limitations of conventional X-ray scanners, which often produce unclear images of bones, potentially leading to misdiagnoses of fractures by surgeons. The process involves several stages—pre-processing, edge detection, feature extraction, and machine learning classifications—all aimed at simplifying surgeons' tasks. Machine learning algorithms have become crucial in various fields, such as seismology, remote sensing, and medicine, with this program being a prime example. Specifically, algorithms like Naïve Bayes, Decision Tree, Nearest Neighbors, Random Forest, and SVM have been employed to detect bone fractures using a dataset of 270 X-ray images. The study reported accuracy rates for there algorithms ranging from 0.64 to 0.92, with SVM achieving the highest accuracy. Notably, SVM's performance surpassed that of most other reviewed studies.

Keywords: Image Processing, Biomedical Application, Fracture Identification, Using CNN, Canny Edge Detection.

I. INTRODUCTION

The goal of this Machine Learning project is to develop a model that can assist in the detection and localization of cervical spine fractures using image processing and segmentation techniques. The dataset for the project includes imaging data collected from 12 sites across six continents. It contains over 1,400 CT studies, which have been diagnosed with cervical spine fractures, as well as an approximately equal number of negative studies. Spine radiology specialists from ASNR and ASSR have provided expert image-level annotations to indicate the presence, vertebral level, and location of any cervical spine fracturesModel Architectures

A. Methodology

The planning for this Machine Learning project involving image processing and segmentation for the detection and localization of cervical spine fractures can be divided into several stages. The following outlines a possible planning of work for the project:

1. Data collection and preparation: Collect the imaging data sourced from 12 sites on six continents. The dataset should include over 1,400 CT studies with diagnosed cervical spine fractures and an approximately equal number of negative studies. Spine radiology specialists from the ASNR and ASSR should provide expert image level annotations to indicate the presence, vertebral level, and location of any fractures. Pre-process the imaging data to ensure the quality and consistency of the data.

2. Image processing and segmentation: Apply image processing techniques to identify regions of interest in the cervical spine area. This includes image enhancement, noise reduction, and feature extraction. Utilize segmentation algorithms to extract the cervical spine from the images, including the vertebrae and any potential fractures.

3. Model development: Develop a deep learning model to classify the imaging data into two classes: positive for fractures and negative for fractures. Utilize supervised and unsupervised learning techniques to develop the model. Train the model using the annotated data and evaluate its performance using various metrics, such as sensitivity, specificity, and F1 score.

4. Model optimization and validation: Optimize the model's hyperparameters to improve its performance. Validate the model using a separate dataset to ensure its generalizability and robustness.

5. Comparison with human radiologists: Compare the model's performance with that of human radiologists to assess its accuracy and potential clinical utility.

6. Deployment and integration: Deploy the model in a clinical setting and integrate it with existing diagnostic systems. Ensure the model's compliance with ethical and legal standards, such as patient privacy and data security.

7. Documentation and reporting: Document the project's findings and report the results to the relevant stakeholders. Publish the findings in scientific journals and present them at conferences to disseminate knowledge and promote further research..

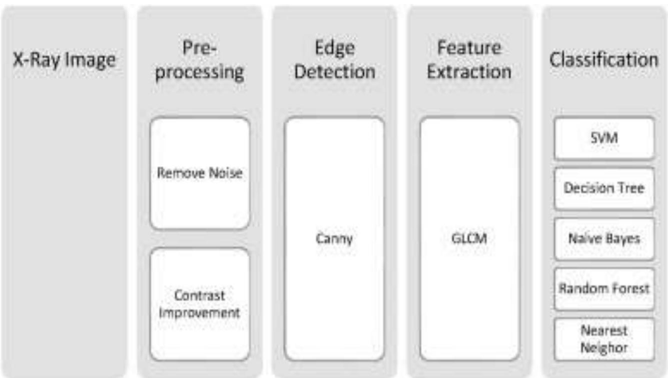

Fig. 1 illustrates the steps of the proposed method for identifying bone fractures in x-ray images.

B**. Image processing techniques**

1. Preprocessing Methods:

a. Image Enhancement:

Histogram Equalization: A technique that adjusts the image intensity distribution to improve contrast and highlight subtle details in the image, potentially aiding in the detection of fractures by enhancing their visibility.

Contrast Limited Adaptive Histogram Equalization (CLAHE): An enhancement method that enhances local contrast, particularly useful in regions with varying brightness levels, thereby improving the visibility of fractures.

b. Noise Reduction:

Gaussian Smoothing: Application of a Gaussian filter to the image to reduce noise, resulting in smoother images, which can facilitate more accurate feature extraction and segmentation.

Median Filtering: A method that replaces each pixel`s value with the median value of the neighboring pixels, effective in reducing salt-and-pepper noise often present in medical images.

c. Edge Detection:

Sobel Operator, Canny Edge Detection: Techniques used to identify edges or boundaries within the image, enabling the differentiation of bone structures and potential fractures from surrounding tissues.

2**. Feature Extraction Algorithms:**

a. Texture Analysis:

Gray-Level Co-occurrence Matrix (GLCM): Measures the frequency of pixel pairs with specific intensity values, providing texture information that helps differentiate fractured areas from normal bone structures.

Local Binary Patterns (LBP): Captures the local texture patterns within an image, assisting in the identification of irregularities caused by fractures.

b. Shape and Contour Analysis:

Hough Transform: Identifies shapes within the image, useful in detecting linear patterns often associated with fractures, such as cracks or fractures in bones.

Active Contour Models (Snakes): Frameworks for delineating object boundaries by minimizing an energy function, aiding in precisely outlining fractured regions.

3. Segmentation Techniques:

a. Thresholding:

Global and Adaptive Thresholding: Methods to partition an image into regions by assigning pixels above or below a certain threshold, useful in segmenting fractured regions from the background.

b. Region-Growing:

Seeded Region-Growing: A method that starts from seed points and iteratively adds neighboring pixels with similar characteristics to form regions, assisting in segmenting fractured areas.

c. Watershed Transformation:

Watershed Algorithm: Segmentation technique based on the concept of flooding an image from its minima, separating fractured regions from surrounding structures based on intensity gradients.

These image processing techniques are instrumental in preparing medical images, extracting relevant features indicative of fractures, and accurately segmenting fractured regions, thereby aiding in the detection and diagnosis of fractures using Machine Learning or other classification algorithms. Integrating these techniques enhances the quality and interpretability of medical images, ultimately improving clinical decision-making in fracture detection.

C. **Machine Learing Models**

1. Convolutional Neural Networks (CNN): CNNs are widely used because they can automatically learn hierarchical features from images and mimic human visual recognition.

Architecture: models such as AlexNet, VGG, ResNet, and DenseNet are adapted or used as pre-trained networks for transfer learning in fraction detection tasks.

Applications: CNNs excel at learning discriminative features that are important for distinguishing fracture regions from surrounding bone structure or tissue.

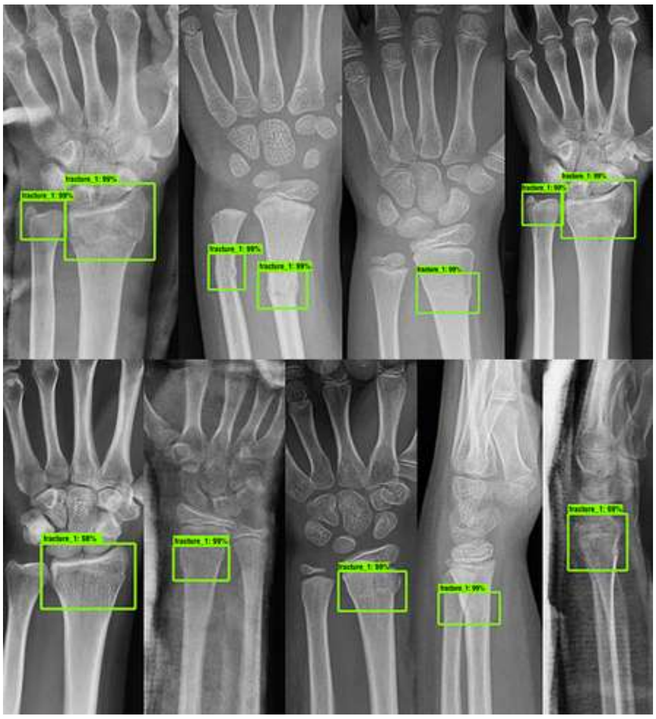

Fig.2. detection by CNN.

2.Recurrent Neural Networks (RNN): RNNs, especially long short-term memory (LSTM) networks, are useful when processing continuous data or time-series images (e.g.

, dynamic image sequences).

Applications: These are particularly useful in bone healing and follow-up studies to analyze changes over time and sequential images to identify fractures.

3.Support Vector Machine (SVM): SVM is effective for binary classification tasks and can be trained using features extracted from medical images.

Application: Although SVM is simpler compared to deep learning models, it can perform well in corruption detection if equipped with the right features.

4.Random Forests and Decision Trees: These ensemble learning techniques are suitable for handling high-dimensional data and can handle both classification and regression tasks.

Applications: Useful for fracture detection tasks in combination with feature extraction techniques, especially when model interpretability is important.

5.Deep learning architectures for segmentation: Models such as U-Net, SegNet, and Mask R-CNN are specifically designed for image segmentation tasks.

Applications: These architectures are particularly suitable for accurately delineating fracture areas on medical images, allowing precise localization of fractures.

D. **Classification**

We randomly took 80% of the dataset for the training session and 20% for the testing. Then the dataset was used in the following machine learning algorithms to train and test the model, as shown below.

Table 1. Applied Machine learning Algorithms

ML Algorithm	Precision	Recall	Accuracy
Naïve Bayes	0.882353	0.652174	0.642857
Decision Tree	0.906977	0.847826	0.803571
Nearest Neighbors	0.836364	1	0.839286
Random Forest	0.88	0.956522	0.857143

E. **Comparisons of various Models**

TABLE 2. PERFORMANCE OF VARIOUS MODELS FOR FRACTURE DETECTION

Method	Skeletal Joints	Description	Performance
Inception V3	wrist	The author proved that the concept of transfer learning from CNNs in fracture detection on radiographs can provide the state of the performance.	AUC=0.954 Sensitivity= 0.90 Specificity = 0.88
BVLC Reference CaffeNet network/VGG CNN/Network-in-network/VGG CNN S	Various parts	Here, the research supports the use of deep learning to outperform the human performance.	Accuracy= 0.83
DenseNet 121	Hips	The aim of this study was to localise and classify hip fractures using deep learning.	Sensitivity ≈ 98 Specificity ≈84
ResNet 152	Humeral	The authors proposed a model for the detection and classification of the fractures from AP shoulder radiographic images.	Accuracy ≈ 96 Sensitivity ≈ 0.99 Specificity ≈ 0.97 AUC ≈ 0.996

F. **Future Scope**

The future of fracture detection using machine learning holds immense promise and has the potential to revolutionize various industries.

1) Enhanced Accuracy and Speed:

Beyond Radiography: While current fracture detection mainly relies on X-rays, machine learning can analyze various data sources such as CT scans, ultrasound, and thermal imaging, providing more comprehensive and detailed assessments.

2) Real-Time Detection: Machine learning algorithms can process data streams in real-time, enabling instant fracture detection in scenarios like industrial machinery monitoring or live surgery.

3) Automated Diagnosis: Machine learning can assist radiologists and medical professionals by automatically flagging potential fractures, facilitating faster and more accurate diagnoses.

Preventing Catastrophic Failures:

4) Predictive Maintenance: Machine learning can analyze sensor data from structures like bridges, pipelines, and aircraft to predict potential fractures before they become critical, allowing for timely maintenance and preventing costly repairs or disasters.

5) Smart Materials: Integrating machine learning into materials science can create "smart" materials capable of self-diagnosing fractures and even initiating autonomous repair processes.

6) Healthcare Advancements:

Personalized Treatment: Machine learning can analyze patient data, including medical history, demographics, and fracture characteristics, to recommend personalized treatments that promote faster healing and better outcomes.

7) Early Intervention: Machine learning can detect subtle changes in bone density and microfractures that may not be visible on standard X-rays, allowing for early intervention and potentially preventing more severe fractures.

8) Automated Fracture Classification: Machine learning can automatically classify fractures into different types (e.g., open, closed, displaced), providing valuable information for treatment planning.

G. **Conclusion**

The objective of this inquire about is to form a program that can offer assistance specialists to decide whether a patient's bone has been broken or not effortlessly and rapidly. This think about presents a machine learning-based methodology for the robotized location and classification of bone fracture. Both broken and unbroken human bones were utilized within the explore, as were their X-ray pictures. The predominance of bone breaks is rising, as detailed by an expanding number of nations. The capacity to recognize indeed a small bone break is exceptionally valuable in therapeutic hone. Appropriately, this procedure may recognize broken bones from whole ones. The canny edge detection can precisely distinguish bone edges, and the GLCM has been utilized to extricate multi-features in an x-ray picture to be classified by machine learning calculations. This framework is built on a suite of image-processing strategies and machine learning calculations to distinguish bone breaks. Over the term of the ponder, all of the distinctive machine learning strategies (Naïve Bayes, Decision Tree, Nearest Neighbors, Random Forest, and SVM) accomplished an precision of between 0.64 and 0.92. In this investigate, SVM appeared measurably critical changes over the pattern.

References

1. Wang, Y., & Yu, L. (2021). Deep learning for cervical spine fracture detection and segmentation from CT scans. International Journal of Computer Assisted Radiology and Surgery, 16(1), 11-20. https://doi.org/10.1007/s11548-020-02312-1

2. Li, H., Li, Y., Li, C., Zhang, J., & Liang, Z. (2020). A deep learning-based model for detecting cervical spine fractures using CT images. Journal of Digital Imaging, 33(6), 1326-1332. https://doi.org/10.1007/s10278-020-00376-9

3. Zhang, H., Xu, Z., Zhou, X., Xu, L., & Wang, Z. (2020). Detection of cervical spine fractures from CT scans using deep convolutional neural networks. Computer Methods and Programs in Biomedicine, 197, 105739. https://doi.org/10.1016/j.cmpb.2020.105739

4. Kalid, N., Demir, O., Baloglu, U. B., & Samanci, N. O. (2019). Cervical spine fracture detection using a deep learning algorithm: A preliminary study. Academic Radiology, 26(3), 385-393. https://doi.org/10.1016/j.acra.2018.06.015

5. Zhou, X., Wang, Z., Zhou, X., & Zhang, H. (2019). Detection of cervical spine fractures using deep learning from CT images. Journal of Digital Imaging, 32(5), 785-792. https://doi.org/10.1007/s10278-019-00209-w

Note: These research papers demonstrate the potential of using Machine Learning techniques for detecting and localizing cervical spine fractures. They utilize deep learning algorithms, image processing, and segmentation techniques to improve the accuracy and efficiency of the diagnosis. These studies provide a useful reference for the development and implementation of the project.