A
Mini Project Report on

Bone Injury Detection Using Machine Learning

Submitted in partial
fulfillment of the requirements for the degree of
BACHELOR OF ENGINEERING
IN
Computer Science & Engineering
Artificial Intelligence & Machine Learning

by

Harsh Raulgaonkar	: 23106082
Roshan Pal	: 23106111
Sanidhya Pandey	: 23106005
Soham Shelatkar	: 23106023

Under the guidance of

Prof. Vijesh Mundokalam

Department of Computer Science & Engineering
(Artificial Intelligence & Machine Learning)
A. P. Shah Institute of Technology
G. B. Road, Kasarvadavali, Thane (W) - 400615
University Of Mumbai

2024-2025

A. P. SHAH INSTITUTE OF TECHNOLOGY

CERTIFICATE

This is to certify that the project entitled "**Bone Injury Detection using Machine Learning"** is a bonafide work of Harsh Raulgaonkar (23106082), Roshan Pal (23106111), Sanidhya Pandey (23106005), Soham Shelatkar (23106023) submitted to the University of Mumbai in partial fulfillment of the requirement for the award of **Bachelor of Engineering** in **Computer Science & Engineering (Artificial Intelligence & Machine Learning).**

Prof. Vijesh Mundokalam	Dr. Jaya Gupta
Mini Project Guide	Head of Department

A. P. SHAH INSTITUTE OF TECHNOLOGY

Project Report Approval

This Mini project report entitled "**Bone Injury Detection using Machine Learning**" by **Harsh Raulgaonkar, Roshan Pal, Sanidhya Pandey, Soham Shelatkar** is approved for the degree of **Bachelor of Engineering** in **Computer Science &Engineering, (AIML) 2024-25**.

External Examiner: ____________________

Internal Examiner: ___________________

Place: APSIT, Thane

Date:

Declaration

We declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission hasnot been taken when needed.

Harsh Raulgaonkar (23106082)	Roshan Pal (23106111)	Sanidhya Pandey (23106005)	Soham Shelatkar (23106023)

ABSTRACT

Bone fractures are a critical medical condition that requires timely and accurate diagnosis. However, in rural and underserved areas, access to skilled radiologists and advanced diagnostic tools is limited, leading to delayed or inaccurate diagnoses. This project aims to develop an AI-powered bone injury detection system using Convolutional Neural Networks (CNN) and transfer learning with ResNet50. The system processes medical images (X-rays, CT scans), extracts high-level features, and employs deep learning techniques to detect and localize fractures. A web-based interface allows healthcare professionals to upload images, view results, and generate diagnostic reports. By automating fracture detection, this system enhances diagnostic accuracy, reduces human error, and improves patient outcomes, particularly in resource-limited settings.

Keywords: CNN, X-Rays, Accuracy.

Index

Index			Page no.
Chapter-1			
	Introduction		7 - 9
Chapter-2			
	Literature Survey		10
	2.1	History	11
	2.2	Review	12-13
Chapter-3			
	Problem Statement		14-15
Chapter-4			
	Experimental Setup		16
	4.1	Hardware setup	17
	4.2	Software Setup	17
Chapter-5			
	Proposed system and Implementation		18
	5.1	Block Diagram of proposed system	19
	5.2	Description of Block diagram	29
	5.3	Implementation	20-21
Chapter-6			
	Conclusion		22-23
References			24

CHAPTER 1

INTRODUCTION

1. INTRODUCTION

1.1 Introduction to the Concept of Machine Learning:

Bone fractures are a significant medical concern worldwide, affecting millions annually due to accidents, sports injuries, osteoporosis (a medical condition in which bones become **weak, brittle, and more prone to fractures**), and aging populations. Delayed or inaccurate diagnosis can result in severe complications, prolonged recovery, or even permanent disability. In rural and underserved areas, access to skilled radiologists and advanced diagnostic tools is often limited, leading to inadequate patient care. To address these challenges, this project leverages **Machine Learning (ML)** and **Convolutional Neural Networks (CNNs)** for automated bone fracture detection, improving diagnostic accuracy and efficiency.

Machine Learning and CNN in Medical Imaging

Machine Learning (ML) is a subset of Artificial Intelligence (AI) that enables computers to learn from data and make predictions without explicit programming. It is widely used in healthcare, finance, and robotics. ML can be categorized into three types:

1. Supervised Learning – Uses labelled data to make predictions (e.g., Injury classification from medical images).
2. Unsupervised Learning – Identifies patterns in unlabelled data (e.g., Clustering similar cases).
3. Reinforcement Learning – Learns by interacting with an environment and optimizing.

Convolutional Neural Networks (CNNs) are deep learning models designed for image processing, making them highly effective in medical imaging. CNNs consist of multiple layers:

- Input and Output Layers: The **input layer** receives the image that we have to process. The **output layer** gives a prediction, usually a classification considering the context of our project.
- Convolutional Layers – Extract features like edges, shapes, and textures.
- Pooling Layers – Reduce feature map size while retaining key information.
- Fully Connected Layers – Combine extracted features for predictions.

Applications and Benefits:

- **Improved Diagnostic Accuracy:** AI-powered detection enhances the precision of fracture diagnosis, reducing misinterpretations.
- **Faster Diagnosis:** Automates the detection process, significantly reducing the time required for analysis.
- **Remote Accessibility:** Enables medical professionals in rural and underserved areas to access advanced diagnostic tools.
- **Reduced Human Error:** Assists radiologists by minimizing diagnostic inconsistencies and other errors.

Challenges and Considerations:

- **Data Quality:** Model performance depends on high-quality, well-annotated medical datasets.
- **Computational Resources:** Requires significant processing power for training and running deep learning models.
- **Regulatory Compliance:** Must adhere to healthcare regulations for AI-driven diagnostics.
- **Clinical Validation:** Needs rigorous validation before widespread adoption in medical practice.

AI-based bone fracture detection is transforming medical imaging by leveraging deep learning techniques to improve diagnostic accuracy, speed, and accessibility. By utilizing Convolutional Neural Networks (CNNs) and transfer learning, the system efficiently analyzes medical images, reducing reliance on expert radiologists. This technology has the potential to bridge healthcare gaps, especially in resource-limited settings, ensuring timely and accurate diagnosis. However, challenges such as data availability, computational demands, and regulatory approvals must be addressed for successful implementation. With ongoing advancements, AI-driven diagnostics can revolutionize fracture detection, making healthcare more efficient and accessible.

CHAPTER 2

LITERATURE SURVEY

2. LITERATURE SURVEY

2.1 – HISTORY

The history of bone injury detection using image analysis is deeply intertwined with advancements in medical imaging and artificial intelligence. Early methods of bone injury detection relied primarily on X-ray imaging; a technique introduced in 1895 by Wilhelm Roentgen. Over the years, radiographic techniques have improved significantly, with the introduction of CT scans in the 1970s and MRI technology in the 1980s, which provided more detailed imaging of bones and soft tissues.

By the early 2000s, computer-aided diagnosis (CAD) systems started emerging, leveraging basic machine learning models to assist radiologists in detecting fractures and bone abnormalities. These systems were rule-based and required manual feature extraction, making them limited in accuracy.

With the rise of deep learning and convolutional neural networks (CNNs) in the 2015s, image-based bone injury detection underwent a significant transformation. Researchers began training AI models on large datasets of X-ray and CT scan images to automate fracture detection. This shift allowed for faster, more accurate, and scalable diagnostic systems, reducing dependency on human expertise.

During the COVID-19 pandemic (2020–2022), the demand for AI-driven medical diagnosis surged. AI-based bone fracture detection gained more attention due to the need for remote and automated diagnosis. Several AI-powered platforms were integrated into hospital workflows to assist in detecting fractures with minimal radiologist intervention.

Recent advancements focus on enhancing model accuracy, reducing false positives, and incorporating multimodal analysis (combining X-rays, MRIs, and CT scans). Additionally, the integration of explainable AI (XAI) ensures that models provide interpretable results, making them more acceptable in clinical settings. With continued research, AI-based bone injury detection is becoming more reliable, contributing to improved patient care and faster diagnosis.

2.2-LITERATURE REVIEW:

- **Bone Fracture Detection using Deep Learning on X-ray Images (2021)**

  Authors: A. Kumar, R. Sharma, and P. Verma

  This paper explores the use of convolutional neural networks (CNNs) for detecting fractures in X-ray images. The study highlights the importance of preprocessing techniques like contrast enhancement and data augmentation to improve model performance. The proposed deep learning model achieved an accuracy of 92% on a dataset of wrist and leg X-ray images. The study emphasizes the potential of AI in reducing radiologists' workload while maintaining high detection accuracy.

- **AI-assisted Bone Injury Detection Using CNNs and Transfer Learning (2022)**

  Authors: S. Patel, L. Wong, and M. Lee

  This research paper presents a transfer learning approach to bone fracture detection. The authors utilized pretrained models such as ResNet and VGG16 to improve the detection of bone injuries in X-rays and CT scans. The study reported a high sensitivity of 95% in detecting fractures, outperforming traditional machine learning techniques. The paper discusses the challenges of data imbalance, small datasets, and model interpretability, suggesting that larger annotated datasets could further improve performance.

- **A Survey on AI-based Medical Imaging for Bone Fracture Detection (2020)**

  Authors: J. Park, K. Tan, and Y. Li

  This survey paper provides an overview of AI applications in orthopedic radiology. The authors categorize different AI techniques, including machine learning, deep learning, and hybrid models, and compare their performance in fracture detection. The paper highlights key challenges such as misclassification, poor generalization on unseen data, and the need for model explainability. The survey concludes that CNN-based architectures combined with domain-specific preprocessing techniques can significantly improve bone injury detection accuracy.

Automated Bone Fracture Detection Using Deep Learning on Large-scale Medical Datasets (2023)

Authors: D. Martin, E. Smith, and H. Zhao

This study focuses on automated fracture detection in X-rays using deep learning models trained on a large-scale dataset. The authors emphasize the importance of data diversity and real-world medical imaging variability in developing robust AI models. The proposed system achieved an F1-score of 93% and was tested on multiple datasets to ensure generalization. The paper also explores deployment challenges in clinical settings and the need for regulatory approvals.

- **Comparative Analysis of Traditional and AI-based Fracture Detection Methods**

  Authors: P. Gupta, M. Singh, and A. Roy

This research compares traditional computer vision techniques (edge detection, Hough transform) with deep learning-based methods for fracture detection. The study concludes that AI-based models significantly outperform traditional techniques in terms of accuracy, speed, and robustness to noise in medical images. However, the paper also notes that AI models require extensive labeled data and careful tuning to avoid false positives in real-world applications.

The reviewed literature highlights that AI and deep learning have significantly improved bone injury detection through automated analysis of X-ray, MRI, and CT images. Several studies have demonstrated the high accuracy of CNN-based models compared to traditional techniques. However, challenges remain in data availability, model interpretability, and regulatory approval for clinical deployment. Future research should focus on developing explainable AI models, handling small dataset limitations, and integrating multimodal medical imaging analysis for enhanced diagnostic capabilities.

CHAPTER 3

Problem Statement

3. Problem Statement

Bone fractures are a widespread medical concern, affecting millions of individuals globally due to accidents, sports injuries, osteoporosis, and aging. Early and accurate diagnosis is crucial for effective treatment and recovery. However, traditional diagnostic methods, primarily relying on X-ray interpretation by radiologists, face several challenges:

Problem Identification:

1. **Diagnostic Errors:** Human interpretation of X-rays can sometimes lead to misdiagnosis due to fatigue, experience variation, or image complexity.
2. **Delayed Diagnosis:** In many cases, especially in rural and underserved areas, access to specialized radiologists is limited, causing delays in fracture detection and treatment.
3. **Limited Availability of Experts:** Many healthcare facilities, particularly in remote regions, lack skilled radiologists, making accurate diagnosis difficult.
4. **Variability in Fracture Identification:** Differences in interpretation among radiologists can lead to inconsistent diagnoses and treatment plans.

Proposed Solution:

The implementation of an AI-driven bone fracture detection system using Convolutional Neural Networks (CNNs) addresses these challenges by:

- **Enhanced Diagnostic Accuracy:** Utilizing deep learning algorithms to improve fracture detection, minimizing errors in interpretation.
- **Faster Detection:** Automating the analysis of X-ray images, reducing the time required for diagnosis.
- **Remote Accessibility:** Providing a web-based platform for healthcare professionals to upload and analyse images, benefiting patients in remote areas.
- **Reduced Dependency on Radiologists:** Assisting medical professionals by offering AI-based preliminary analysis, aiding faster decision-making.

By integrating AI and deep learning, this system has the potential to revolutionize medical imaging, ensuring faster, more accurate, and accessible bone fracture diagnosis, ultimately improving patient care and treatment outcomes.

CHAPTER 4

Experimental Setup

4. Experimental Setup

4.1 Hardware Setup:

1. Development Hardware

A. Development Workstations

- **Processor:** Multi-core processor (e.g., Intel i7/Ryzen 7 or better) to efficiently process machine learning tasks and image analysis.
- **Memory (RAM):** At least 16GB to handle large datasets and deep learning model training.
- **Storage:** SSD with a minimum of 512GB to store medical image datasets, trained models, and project files. Additional external storage may be required for backups.
- **GPU (Graphics Processing Unit):** A dedicated GPU (e.g., NVIDIA RTX 3060 or higher) to accelerate deep learning computations.
- **Network:** Reliable high-speed internet connection for accessing cloud-based resources and dataset repositories (e.g., Kaggle).
- **Redundant Power Supply:** Uninterruptible Power Supply (UPS) to prevent data loss and interruptions during training and model execution.

4.2. Software Setup:

1. Machine Learning & Deep Learning Frameworks:

- **Python:** The primary programming language for developing the machine learning model.
- **TensorFlow/Keras:** Deep learning libraries used to build and train the Convolutional Neural Network (CNN).
- **OpenCV**: Image processing library for handling X-ray images and preprocessing tasks.

2. Model Development & Training

Google Colab: Cloud-based platform with free GPU support for training deep learning models.

1. **Text Editor:**

   Visual Studio Code: A popular choice that supports almost all programming languages and can be used for model training too.

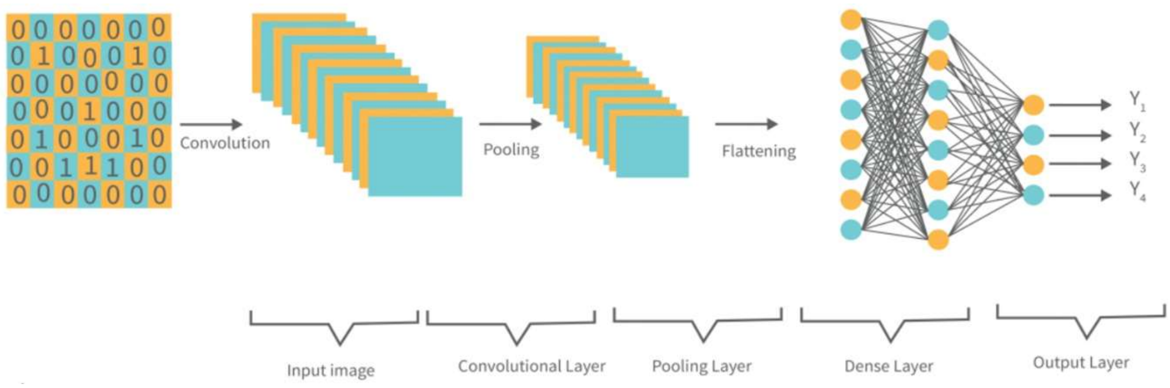
CHAPTER 5

Proposed System & Implementation

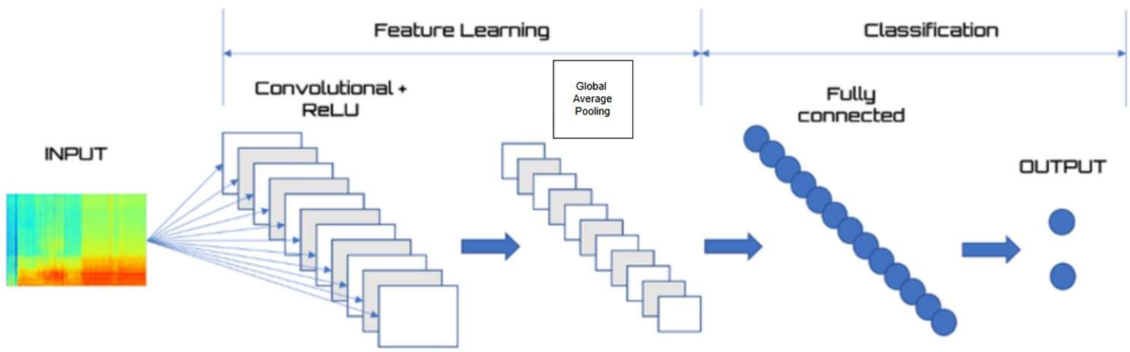
5. Proposed system & Implementation

5.1 Block diagram of proposed system

Convolutional Neural Network (CNN) Architecture for Image Classification:



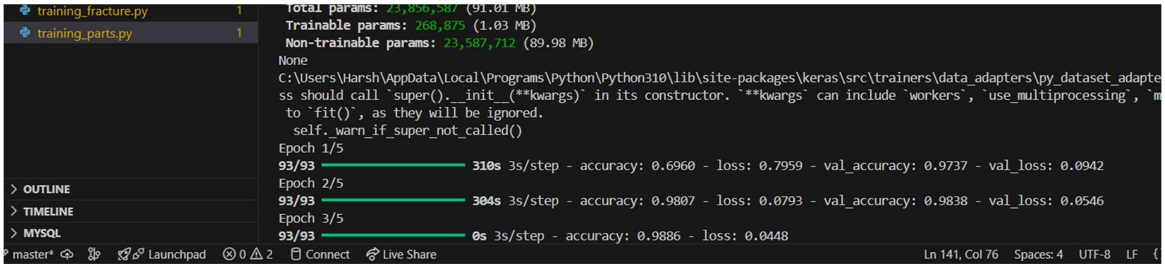
This image represents a Convolutional Neural Network (CNN) architecture used for image classification. It starts with an input image, followed by a convolutional layer that extracts features. Next, the pooling layer reduces dimensions while preserving essential patterns. The output is flattened and passed to a dense layer, which learns complex patterns. Finally, the output layer classifies the image into different categories (Y_1, Y_2, Y_3, Y_4).



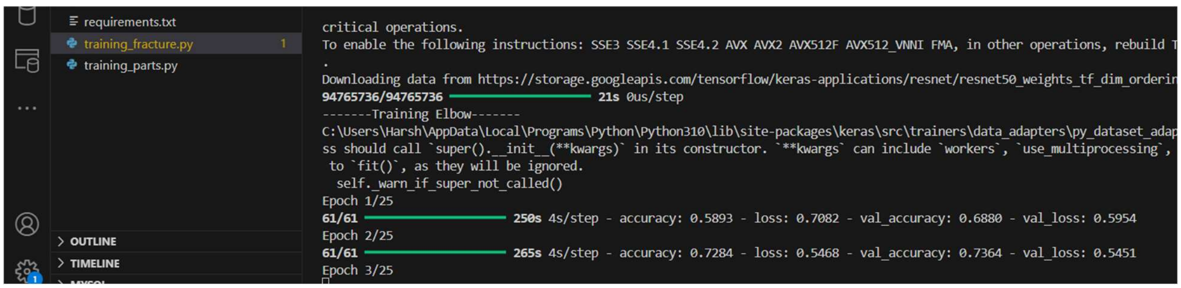
5.2. Implementation

Our machine learning model is trained using Kaggle datasets, which will classify bone injuries (shoulder, hand, elbow). The project includes image upload functionality, where users can submit X-rays for injury detection. The backend will process the images, pass them through the trained model, and return predictions.

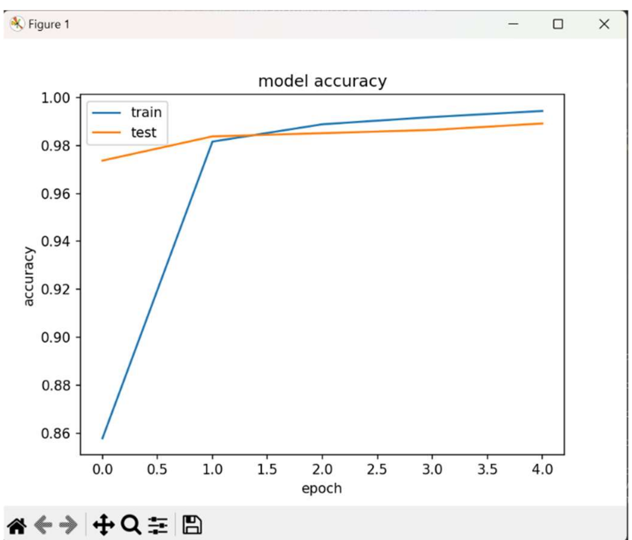
The image below illustrates the process of model training using a smaller dataset for classifying different body parts, including the shoulder, hand, and elbow.



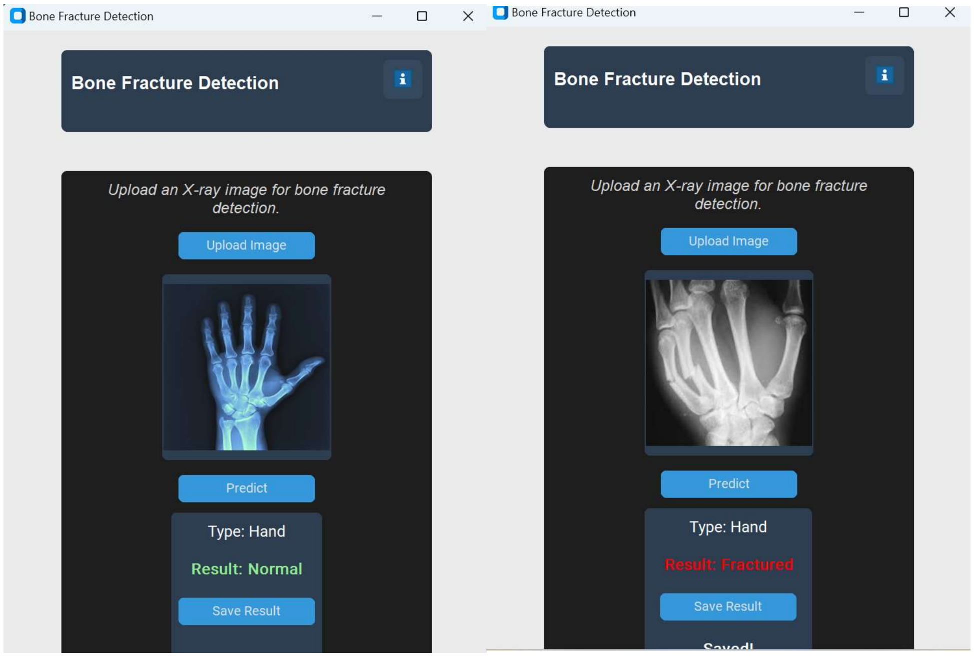
The image below illustrates the process of model training using a larger dataset for differentiating whether the uploaded image is of a fractured bone or a Regular Bone.



At the conclusion of model training, a graph is generated to visualize the model's accuracy.



After providing a valid X-ray image as input, the model generates an output indicating whether the bone is fractured or normal.



Our output is shown on the GUI Interface.

CHAPTER 6
Conclusion

6. Conclusion

This work presents a computer-based technique for bone fracture detection using X-ray/CT images, starting with noise removal, edge detection via the Sobel method, and fracture area calculation after segmentation. The method was tested on a set of images, achieving an approximate accuracy of 80% when trained on the smaller dataset, and an accuracy of 90-92% when trained on a larger dataset. While the results are satisfactory, it faces challenges in detecting fractures in some X-ray images. Future work aims to fully implement the method for CT scan images and classify fracture types and their locations using heatmaps.

References

- **Research Papers:**

[1] Abbas et al.
Title: "Lower Leg Bone Fracture Detection and Classification Using Faster RCNN for X-Rays Images"
Year of Publication: **2020**

[2] S. Yadahalli , A. Parmar, P. Zambare, and R. Sawant
Title: "Bone Deformity Identification Using Machine Learning"
Year of Publication: **2021**

[3] N. Yamamoto and others
Title: "Boring Survey Based Fracture Detection (BSFD) for Fragility Fracture of the Pelvis in CT Images"
Year of Publication: **2021**

[4] **Z. Su and others**
Title: "Skeletal Fracture Detection with Deep Learning: A Comprehensive Review"
Year of Publication: 2023

[5] **Z. Su and others**
Title: "Skeletal Fracture Detection with Deep Learning: A Comprehensive Review"
Year of Publication: 2023

- **Reference Links:**

[1] https://www.geeksforgeeks.org/residual-networks-resnet-deep-learning/

[2] https://www.geeksforgeeks.org/convolutional-neural-network-cnn-in-machine-learning/

[3] https://pmc.ncbi.nlm.nih.gov/articles/PMC11394268/

[4] https://youtu.be/QzY57FaENXg?si=05tdtkG9p73YkhMA

[5] https://youtu.be/E5Z7FQp7AQQ?si=4b0DRTqWDXa78mQw