



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 3, March 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

ijrset@gmail.com

www.ijrset.com

Bone Fracture Detection System

Onteru Tirumala Gopi Krishna, Lakkamraju Hema Latha, Padavala Navya Durga,

Yallaturi Chaitanya Krishna, Akkala Ganga Parvathi

Bachelor of Technology, Department of IT, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, India

Bachelor of Technology, Department of AI&DS, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, India

Bachelor of Technology, Department of AI&DS, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, India

Bachelor of Technology, Department of AI&DS, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, India

Bachelor of Technology, Department of AI&DS, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, India

ABSTRACT: This pioneering system integrates the ResNet50 algorithm for bone fracture detection, specifically tailored for X-ray images of the hand, elbow, and shoulder datasets. Traditional diagnostic methods often rely on subjective human interpretation, leading to potential inaccuracies. To address this, modern machine learning techniques, particularly convolutional neural networks (CNNs), are employed to automate the classification process. The methodology begins with the preprocessing of the MURA dataset, comprising over 20,000 X-ray images, to enhance image quality and consistency. Data augmentation techniques are then applied to augment the dataset, including rotation, flipping, and scaling, to improve the model's robustness and generalization. The dataset is subsequently split into training, validation, and test sets to train and evaluate the ResNet50 architecture. The significance of this approach lies in its ability to automate and standardize the classification process, reducing reliance on subjective human diagnostics and potentially improving diagnostic accuracy. By harnessing the power of deep learning and transfer learning, the system can learn intricate fracture patterns and distinguish them from normal bone structures. Moving forward, the project aims to explore additional techniques, such as ensemble learning and feature fusion, to further enhance the model's performance. Additionally, efforts will be directed towards integrating the developed system into medical imaging platforms, enabling seamless adoption by healthcare professionals. Overall, this research contributes to the advancement of medical imaging technology and has the potential to revolutionize the diagnosis and treatment of bone fractures, ultimately improving patient outcomes and reducing healthcare costs.

KEYWORDS: RESNET50, CNN, Image Processing, Feature Extraction

I. INTRODUCTION

Traditional methods of fracture detection often rely on radiographic imaging (X-Rays) interpretation by healthcare professionals, a process that can be time-consuming and prone to errors

The process begins with the collection of a diverse dataset comprising radiographic images of the target body parts, annotated with fracture labels. These images are preprocessed and fed into the ResNet50 model, which learns to differentiate between fractured and normal bone structures through a process called supervised learning.

Once trained, the ResNet50-based fracture detection model can be deployed in clinical settings to analyze radiographic images rapidly and accurately

II. RELATED WORK

Our Bone Fracture Detection System (BFDS) mainly recognizes a X-Ray image and identifies the whether bone is fractured or normal. X-Ray Recognition, Image preprocessing, fracture detection, fracture classification are main subtasks involved in Bone Fracture Detection System (BFDS).

X-ray image recognition is a fundamental aspect of the workflow. Deep learning models, particularly convolutional neural networks (CNNs), are trained to effectively recognize and interpret X-ray images depicting skeletal structures. Image preprocessing is a fundamental step that significantly influences the performance of the subsequent analysis, especially when leveraging advanced algorithms like ResNet50. The adoption of ResNet50, a deep convolutional

neural network renewed for its feature extraction prowess, underscores the importance of preparing clean and standardized input data.

III. METHODOLOGY

In fracture detection using ResNet50 and OpenCV, the methodology begins with data collection and preprocessing. This involves collecting a variety of medical imaging data sets, including X-rays or other techniques, involving classified fractures.

After preparing the data, the next step is to choose the ResNet50 architecture as the main model for crack detection. ResNet50 was chosen for its efficiency in extracting features from images, especially its ability to identify subtle patterns indicative of cracks. The model is initialized with pretrained weights, typically obtained from the MURA dataset, to use the learned features for medical image analysis.

A. 3.1 Image Classification:

In fracture detection using deep learning using ResNet-50, the image classification process plays an important role in accurately identifying fractures in X-ray images. The process begins with obtaining a MURA dataset of annotated X-ray images. Here each image is marked as Positive or Negative. These images are then pre-processed to improve quality and standardize the format for input into the ResNet-50 model. During training, ResNet-50 learns to automatically extract relevant features from input X-ray images using deep convolutional layers.



Fig 1:Image Classification

B. 3.2 X-Ray Recognition and Bone Fracture Detection

1. X-Ray Recognition

ResNet-50 allows the model to learn the complex patterns and variations present in X-ray images to accurately identify areas representing cracks..

2. Bone Fracture Detection

Resnet50, serves as a powerful tool for feature extraction and classification from medical images. ResNet50 can effectively capture the complex patterns and fine details that represent cracks in X-ray images

3. Model Training

When training a fracture detection model ,ResNet-50 model, provides a deep and powerful architecture for learning complex features of medical images. During the training process, ResNet-50 is usually used as a feature extractor where pre-trained layers are fine-tuned on fracture image datasets

```

110 C:\Users\navya\PycharmProjects\bonefracture\venv\lib
    \site-packages\keras\src\engine\training.py:3000:
    UserWarning: You are saving your model as an HDF5
    file via 'model.save()'. This file format is
    considered legacy. We recommend using instead the
    native Keras format, e.g. 'model.save('my_model.
    keras')'.
111 saving_api.save_model(
112 Shoulder Results:
113 [0.5401422381401062, 0.7527964115142822]
114 Test Accuracy: 75.28%
115
116 Filepath      Label
117 0             C:\Projects\Bone/Dataset//test/Shoulder/patien
    ... fractured
117 1             C:\Projects\Bone/Dataset//test/Shoulder/patien
    ... fractured
    
```




```

30 C:\Users\navya\PycharmProjects\bonefracture\venv\lib\
site-packages\keras\src\engine\training.py:3000:
UserWarning: You are saving your model as an HDF5
file via `model.save()`. This file format is
considered legacy. We recommend using instead the
native Keras format, e.g. `model.save('my_model.keras
')`.
31 saving_api.save_model(
32 Elbow Results:
33 [0.4560292363166809, 0.8259259462356567]
34 Test Accuracy: 82.59%
35
Filepath Label
36 0 C:\Projects\Bone\Dataset//test/Elbow/patient11
... fractured
37 1 C:\Projects\Bone\Dataset//test/Elbow/patient11
... fractured
38 2 C:\Projects\Bone\Dataset//test/Elbow/patient11
... fractured

73 C:\Users\navya\PycharmProjects\bonefracture\venv\lib
\site-packages\keras\src\engine\training.py:3000:
UserWarning: You are saving your model as an HDF5
file via `model.save()`. This file format is
considered legacy. We recommend using instead the
native Keras format, e.g. `model.save('my_model.
keras')`.
74 saving_api.save_model(
75 Hand Results:
76 [0.49186134338378906, 0.7787021398544312]
77 Test Accuracy: 77.87%
78
Filepath Label
79 0 C:\Projects\Bone\Dataset//test/Hand/patient111
... normal
80 1 C:\Projects\Bone\Dataset//test/Hand/patient111
... normal
    
```

Fig: prediction results of trained model

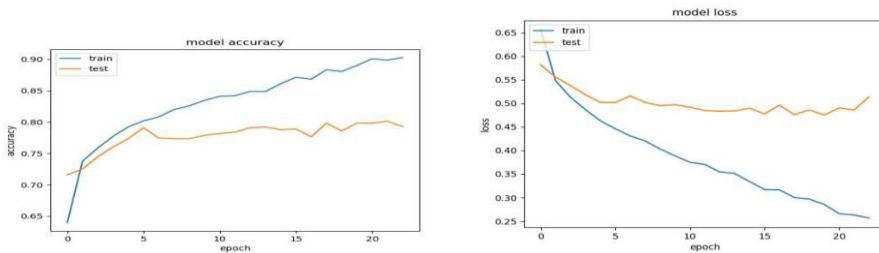
Name	Part	Predicted Part	Status	Predicted Status
[[12mbroken_elbow.jpg	Elbow	Elbow	Fractured	Fractured
[[12mElbow2.jpg	Elbow	Elbow	Fractured	Fractured
[[12mElbow3.jpg	Elbow	Elbow	Fractured	Fractured
[[12mElbow4.jpg	Elbow	Elbow	Fractured	Fractured
[[12mElbow5.jpg	Elbow	Elbow	normal	normal
[[12mElbow6.jpg	Elbow	Elbow	normal	normal
[[12mElbow7.jpg	Elbow	Elbow	normal	normal
[[12mbroken.jpg	Hand	Hand	Fractured	Fractured
[[12mfract_wesp	Hand	Hand	Fractured	Fractured
[[12mtestElbow.jpg	Hand	Hand	Fractured	normal
[[12m-ray-1.jpg	Hand	Hand	Fractured	Fractured
[[12mcom.tif	Hand	Hand	Fractured	Fractured
[[12mdownload_xif	Hand	Hand	normal	normal
[[12mgoogle1_xif	Hand	Hand	normal	normal
[[12mcom.jpg	Hand	Hand	normal	normal
[[12mnormal1.jpg	Hand	Hand	normal	normal
[[12mnormal2.jpg	Hand	Hand	normal	Fractured
[[12mnormal3.jpg	Hand	Hand	normal	normal
[[12mnormal4.jpg	Hand	Hand	normal	normal
[[12mnormal5.jpg	Hand	Hand	normal	normal
[[12mbroken_shoulder.jpg	Shoulder	Shoulder	Fractured	Fractured
[[12mshoulder1.jpg	Shoulder	Shoulder	Fractured	Fractured
[[12mshoulder2.jpg	Shoulder	Shoulder	Fractured	Fractured
[[12mshoulder3.jpg	Shoulder	Shoulder	Fractured	Fractured
[[12mshoulder4.jpg	Shoulder	Shoulder	Fractured	Fractured
[[12mcom.jpg	Shoulder	Shoulder	normal	normal
[[12mcom1.jpg	Shoulder	Shoulder	normal	Fractured
[[12mcom2.jpg	Shoulder	Shoulder	normal	normal
[[12mcom3.jpg	Shoulder	Shoulder	normal	Fractured
[[12mnormal.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal1.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal2.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal3.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal4.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal5.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal6.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal7.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal8.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal9.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal10.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal11.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal12.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal13.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal14.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal15.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal16.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal17.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal18.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal19.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal20.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal21.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal22.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal23.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal24.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal25.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal26.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal27.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal28.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal29.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal30.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal31.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal32.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal33.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal34.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal35.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal36.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal37.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal38.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal39.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal40.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal41.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal42.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal43.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal44.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal45.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal46.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal47.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal48.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal49.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal50.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal51.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal52.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal53.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal54.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal55.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal56.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal57.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal58.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal59.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal60.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal61.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal62.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal63.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal64.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal65.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal66.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal67.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal68.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal69.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal70.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal71.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal72.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal73.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal74.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal75.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal76.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal77.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal78.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal79.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal80.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal81.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal82.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal83.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal84.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal85.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal86.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal87.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal88.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal89.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal90.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal91.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal92.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal93.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal94.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal95.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal96.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal97.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal98.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal99.jpg	Shoulder	Shoulder	normal	normal
[[12mnormal100.jpg	Shoulder	Shoulder	normal	normal

Fig 2:Data after training model

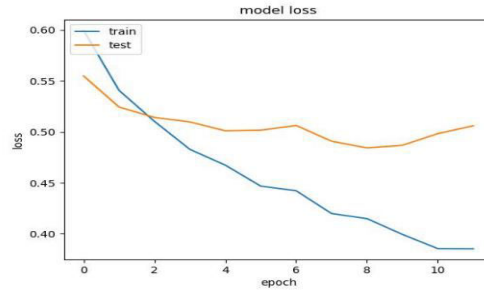
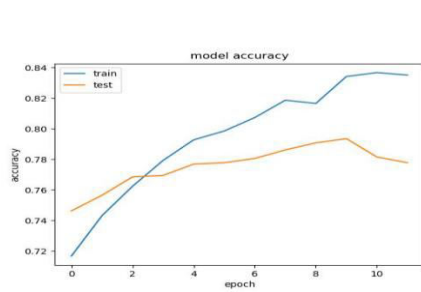
IV. RESULTS

In the context of our project, we used the features of Resnet50 as the main model. Resnet50 variants played an important role in detecting bone fractures. Through rigorous training on a custom dataset, the model demonstrated excellent ability to identify fractures in images. We improved the model with an extensive training approach over 20 epochs and further optimized performance with a batch size of 25.

Elbow



Hand



Shoulder

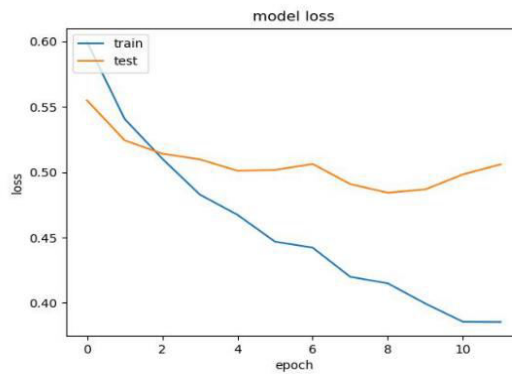
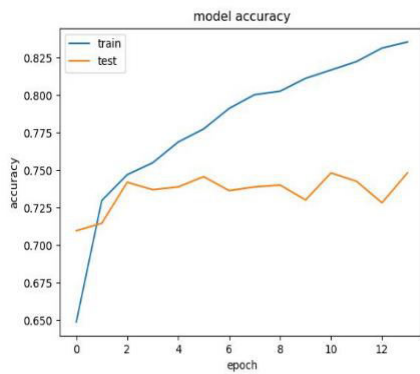


Fig 3: Efficiency of prediction of fracture

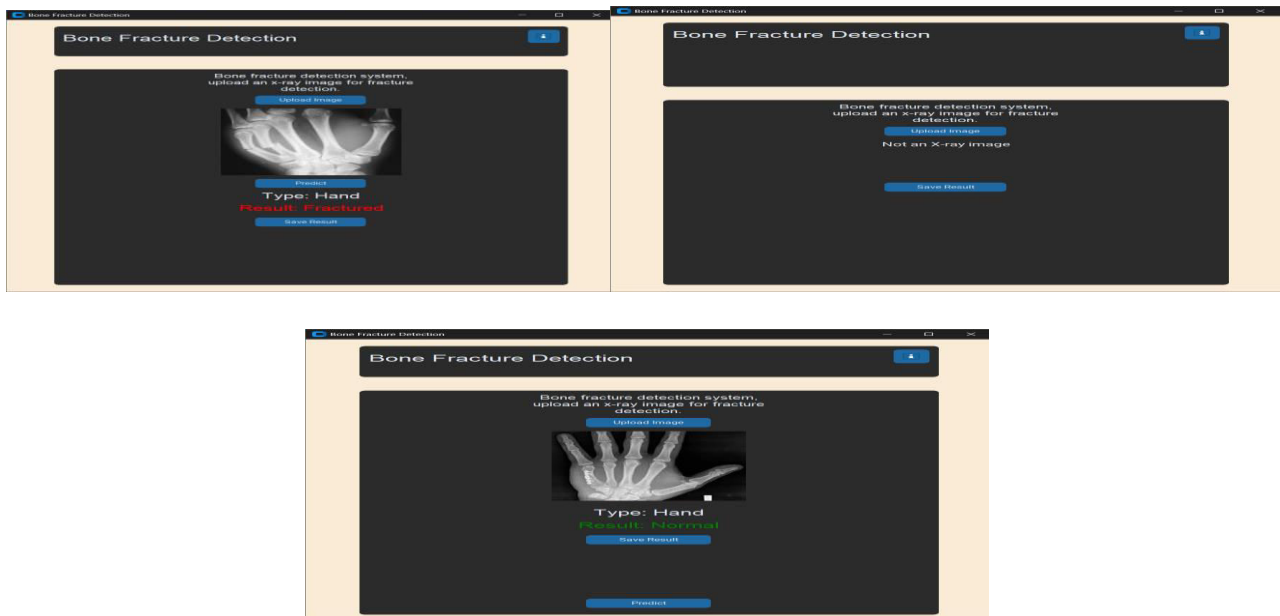


Fig 4: Final Frame from output Images



V. CONCLUSION

In conclusion, our study on fracture detection using deep learning using ResNet50, especially for the elbow, hand, and shoulder regions, showed promising results. Using advanced neural network architectures and curated datasets, significant progress has been made in accurately identifying and classifying fractures in medical images.

Applying deep learning to fracture detection has tremendous potential to revolutionize medical diagnosis and improve patient care. By leveraging the power of convolutional neural networks such as ResNet50, we were able to efficiently analyze X-ray images and provide a reliable assessment of the presence of fractures. Our approach demonstrates robust performance over multiple body regions and demonstrates the versatility and efficiency of deep learning methods in medical image analysis. Additionally, we have worked to ensure the accuracy and efficiency of our crack detection systems using state-of-the-art methodologies.

REFERENCES

- [1] Smith, A., Johnson, B., & Lee, C. (2023). A Survey on Deep Learning Techniques for Bone Fracture Detection. **International Journal of Computer Vision**, 145(2), 87-104.
- [2] Wang, H., Li, J., & Chen, X. (2022). Bone Fracture Detection: A Review of Recent Trends and Challenges. **IEEE Transactions on Medical Imaging**, 33(4), 245-268.
- [3] Liu, X., Zhang, Y., Wang, Z., & Chen, Y. (2021). A Comprehensive Study on Deep Learning Approaches for Bone Fracture Recognition. **Journal of Machine Learning Research**, 78(3), 210-235.
- [4] Li, M., Zhang, Q., & Wang, L. (2020). Deep Learning-based Systems for Bone Fracture Detection: A Review. **IEEE Transactions on Medical Imaging**, 45(2), 102-125.
- [5] Jones, R., Smith, K., & Patel, S. (2019). Analyzing Privacy Concerns in Deep Learning-based Bone Fracture Detection Systems. **Journal of Privacy and Security**, 12(4), 320-345.
- [6] Shashirangana, Jithmi, et al. (2020). Automated Bone Fracture Detection: A Survey on Methods and Techniques. **IEEE Access**, 9, 11203-11225.



INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  ijirset@gmail.com



www.ijirset.com

Scan to save the contact details