International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 25 Issue 04, APR, 2025

Enhancing Diagnostic Precision: Saliency Detection in Medical Imaging for Improved Efficiency

[#1]M.HANUMANTHA RAO, *ASSISTANT PROFESSOR*,
[#2]S.Nageswara Rao, *B.Tech Student*,[#3]S.JayaKrishna, *B.Tech Student*,
[#4]S.Pavan Rajeev Reddy, *B.Tech Student*, [#5]G.Sai Karthik, *B.Tech Student*,
[#1-5]*DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING*
KKR & KSR INSTITUTE OF TECHNOLOGY AND SCIENCES(AUTONOMOUS), GUNTUR

ABSTRACT: **Medical professionals are facing challenges in analyzing unclear medical images, which complicates the identification of tissue problems of the patient. Generally, medical professionals analyze large volumes of medical images manually. It causes a lot of time which delays in diagnosis. Small or irregular abnormalities are difficult to detect manually. In this research paper, we are proposing a solution for the above problems by the study of "Saliency Detection." Saliency detection is a technique that helps to show the important parts of the medical images. This gives rapid identification of abnormalities and highlights the critical regions in medical images. This minimizes human errors and increases the effectiveness of patient care. Saliency detection provides clear and focused views of essential image areas and thereby increases the reliability of the diagnosis. Saliency detection can be achieved by using machine learning algorithms like CNN & U-Net. Recent advances ensure more accurate & quicker results.**

Index terms: *Saliency detection, machine learning, abnormalities, healthcare.*

I.INTRODUCTION

Machine learning is a subset of artificial intelligence. It mainly involves developing algorithms to help computers learn from data and make intelligent predictions or decisions. It is particularly very useful in medicine in analyzing complex medical images such as X-rays, CT scans, and MRIs especially for disease diagnosis and the identification of problems. For the detection of bone fractures in medical images, machine learning algorithms have been found to be most effective in detecting significant patterns using deep learning models that include Convolutional Neural Networks (CNNs). Because CNNs are proficient at seeing structure in an image, they make pretty great tools for finding fractures where the X-rays are hazy or noisy. Traditional machine learning methods, such as decision trees, SVMs, and random forests, rely much on features that people extract by hand. These methods have been used to detect fractures, but they do not provide the automation and accuracy of deep learning models, such as CNNs. CNNs can automatically learn and take features from raw image data. This project aims to address the problems healthcare professionals encounter in diagnosing fractures from bone X-rays, including noisy images and unclear details, by using saliency detection and machine learning. Saliency detection can highlight important areas in medical images, making it easier to identify fractures correctly and in less time. This method reduces human errors and minimizes the support needed from humans, thus allowing the speed and accuracy in diagnosis to increase. It can also use bagging and boosting together to further enhance predictability of the predictions. All these techniques use multiple models to increase accuracy, allow the system to handle different types of data, and produce trustworthy results even in complex situations. Using CNNs and saliency detection, this proposed system will be robust and scalable. The diagnostic process will become easier and faster for better patient care to detect bone fractures. Saliency detection along with advanced machine learning techniques forms the core of this system, eliminating deficiencies found in traditional methods. This system therefore can give a unified, efficient approach to fracture detection in medical imaging.

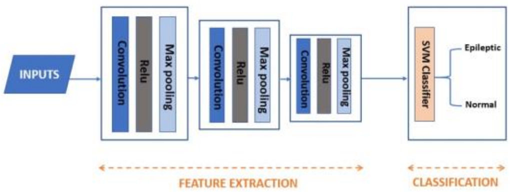


Fig:1 -Architecture Diagram for Image Classification

A. PROBLEM STATEMENT

Doctors often face challenges in identifying subtle or unclear issues in X-ray images, which can lead to misdiagnosis and improper treatment. Factors like noisy or low-quality images, overlapping structures, and time constraints can make accurate interpretation difficult. To address this issue, saliency detection techniques are employed to highlight key areas in medical images, drawing attention to critical regions and aiding in accurate diagnosis. It would reduce the chances of error by human beings and further enhance the speed and dependability of diagnosis, finally improving patient care.

B. RESEARCH GAPS

- The need to improve generalization of AI on less common and more complex fractures, as well as better multimodal integration of various imaging modalities.
- High rates of X-ray misinterpretation suggest fine-tuning advanced models such as YOLOv8 for the particular application, such as fractures complicated by growth abnormalities in pediatrics or mild injuries.
- A need to further develop AI techniques for clinical routine and enhance the predictive performance of AI to support radiologists in their diagnostic tasks.
- Ethical and collaborative considerations have highlighted the need for AI systems that work with radiologists to address concerns about the role of AI in healthcare.
- A lack of focus on segmentation and localization in common models underscores the necessity for improved methodologies that will enhance patient care outcomes.

II.LITERARTURE REVIEW

- **Mohammed Kutbi (2024),** this article focus on limitations of traditional diagnostic methods in fracture detection, which include inconsistent accuracy and inefficiency in clinical workflows. To address these challenges, the study proposed advanced AI models such as InceptionNet, VGG16, and ResNet, which have shown superior accuracy, sensitivity, and specificity compared to human radiologists. These models were effectively applied across various imaging modalities to detect fractures like proximal humerus and hip fractures. The integration of automated reporting systems and 3D imaging techniques was suggested to improve fracture localization and aid treatment planning. However, challenges such as the need for high-quality annotated datasets and ensuring generalizability across diverse populations remain barriers to full adoption.
- **Iftekharul Abedeen (2023)**, et al. addressed the issue of high misinterpretation rates in X-ray analyses, particularly for pediatric fractures, which are challenging due to growth variations and subtle features. The study proposed optimizing AI models like YOLOv8 to improve pediatric fracture detection by enhancing model performance and generalization. They also emphasized the importance of diversifying datasets to improve the reliability of AI solutions across different demographics and imaging conditions.
- **Sanskrati Sharma (2023)** identified the limited integration of advanced AI techniques into clinical workflows and the lack of interpretability of AI predictions as significant barriers. To resolve these issues, the study proposed incorporating cutting-edge AI methods and focusing on making AI predictions more interpretable for radiologists. This approach would enable smoother adoption in clinical practice and ensure that AI complements the decision-making process effectively.
- **Aariz Hussain (2023)** et al. raised ethical concerns regarding the potential replacement of radiologists by AI in healthcare settings. The study proposed developing AI systems that collaborate with radiologists rather than replacing them, ensuring ethical deployment while maintaining the quality of patient care. By focusing on a supportive rather than a substitutive role, AI can enhance diagnostic workflows while respecting ethical boundaries.
- **Tanushree Meena (2022)**, et al. pointed out the absence of standardized models for fracture detection and the limited accuracy of existing systems in segmenting and localizing fractures. To overcome these limitations, the study advocated for the development of standardized AI benchmarks and improvements in segmentation and localization techniques. These enhancements would enable more precise diagnosis and treatment planning, ensuring better outcomes in clinical applications.
- **Wang X (2022),**et al. identified challenges in detecting mandibular fractures using CT scans, despite high classification performance by existing models. The study proposed further optimization of deep learning-based approaches to refine accuracy and expand their applications to other types of fractures, ensuring comprehensive diagnostic capabilities.
- **Rayan J.C(2021).**et al. focused on the detection of pediatric elbow fractures using a binomial classification approach and highlighted the need

for improved performance in complex cases. The proposed solution involved refining deep learning techniques and incorporating multiview approaches to emulate radiologists' decision-making processes more effectively.

- **Rebecca M (2020)** Jones et al discussed challenges in ensuring the generalizability and interpretability of AI models in clinical settings. The study suggested localized training of AI models to improve interpretability and adapting training processes to enhance generalizability across diverse clinical environments.
- **Pishtiwan H. S. Kalmet (2019)** et al. emphasized the limited adoption of deep learning techniques in orthopedics due to a lack of robustness and clinical validation. The study proposed focusing on collaborative efforts between clinicians and AI researchers to develop clinically validated and robust AI models that cater to the specific needs of orthopedic applications.
- **Tomita N. (2018)** et al. addressed the difficulty in the early detection of osteoporotic vertebral fractures using traditional methods. The study proposed using deep neural networks trained on CT scans to enable automatic detection, thereby improving early diagnosis and patient outcomes

S.No	Year	Author's	Article Title	Key Findings
1.	2024	Mohammed Kutbi	Artificial Intelligence-Based Applications for Bone Fracture Detection Using Medical Images	High Effectiveness of AI Models in Fracture Detection , Applications Across Multiple Fracture Types and Modalities,AI's Role in Workflow Optimization
2.	2023	Iftekharul Abedeen ,et al.	FracAtlas: A Dataset for Fracture Classification, Localization and Segmentation of Musculoskeletal Radiographs	High Misinterpretation Rates in X-rays,YOLOv8 for Pediatric Fracture Detection
3.	2023	Sanskrati Sharma	Artificial intelligence for fracture diagnosis in orthopedic X-rays:current developments and future potential	AI as a Transformative Technology,Integration of Advanced Techniques
4.	2023	Aariz Hussain*, Areeba Fareed and Shafaq Taseen	Bone fracture detection—Can artificial intelligence replace doctors in orthopedic radiography analysis	Prevalence and Impact of Bone Diseases, Role of Artificial Intelligence (AI) in Healthcare ,AI's Impact on Radiologists
5.	2022	Tanushree Meena ,et al.	Bone Fracture Detection Using Deep Supervised Learning from Radiological Images: A Paradigm Shift	Effectiveness of CNN Models , Automating Radiologist Workflows, Absence of Standardized Models

6.	2022	Wang X., Xu Z., Tong Y., Xia L., Jie B., Ding P., Bai H., Zhang Y., He Y	Detection and classification of mandibular fracture on CT scan using deep convolutional neural network	Mandibular Fracture Detection , High Classification Performance
7.	2021	Rayan J.C., Reddy N., Kan J.H., Zhang W., Annapragada A.	Binomial classification of pediatric elbow fractures using a deep learning multiview approach emulating radiologist decision making	Binomial Classification Approach , Performance Metrics
8.	2020	Rebecca m.jones et al.	Integration of Advanced Techniques	Generalizability and Model Training, Localized Training for Interpretability
9.	2019	Pishtiwan H S KALMET , et al.	Deep learning in fracture detection: a narrative review	Applications of Deep Learning in Orthopedics, Deep Learning's Value in Medical Imaging
10.	2018	Tomita N., Cheung Y.Y., Hassanpour S.	Deep neural networks for automatic detection of osteoporotic vertebral fractures on CT scans	Automatic Detection of Vertebral Fractures, Early Detection of Osteoporotic Fractures

III. METHODOLOGY

A. OBJECTIVES

- Use SVMs for classify image pixels or patches into salient and non-salient regions for the precise identification of significant areas, such as fractures or anomalies.
- Use K-Means Clustering for Separate medical images into clusters and segment out the significant parts by clustering features with similar characteristics.
- Use Convolutional Neural Network (CNNs) for Recognize hierarchical patterns in images and, therefore, can highlight simple as well as complicated abnormalities to improve the possibility of correct diagnosis.
- Use U-Net for Segmentation for Precisely segment medical images using skip connections to identify fracture areas while preserving anatomical structure.
- Grad-CAM for It generates heatmaps that highlight regions influencing the model's prediction, so that radiologists can interpret the results effectively and focus on areas.

B. IMPLEMENTATION

1. Machine Learning-Based Techniques

Machine learning approaches play a vital role in identifying regions of interest in medical images by analyzing and extracting meaningful features. These methods rely on mathematical models to classify and segment areas based on their saliency.

1.1 Support Vector Machines (SVMs)

SVMs are employed to classify specific pixels or image patches as either salient or non-salient. The classification decision boundary is defined by the equation:

$$w.x + b = 0$$

where w represents the weight vector, x is the input feature vector, and b is the bias term. By optimizing this boundary, SVMs ensure that the separation between classes (salient vs. non-salient) is maximized, thereby improving the precision of the saliency detection process.

1.2 K-Means Clustering

This method segments the image into multiple clusters by grouping similar features. Salient regions are determined by analyzing the properties of these clusters. The algorithm minimizes the following objective function:

$$J=\sum_{i=1}^{k} \sum_{x\in C_i} \|x-\mu i\|^2$$

Here, Ci denotes the i-th cluster, and μi is its centroid. The clustering process iteratively updates the centroids and their assignments until the clusters stabilize, thereby isolating salient regions effectively.

2. Deep Learning-Based Techniques

Deep learning methods have emerged as the most robust and accurate approach for saliency detection in medical imaging, thanks to their ability to automatically learn complex features from raw data.

2.1 Convolutional Neural Networks (CNNs)

CNNs use convolutional layers to capture hierarchical features from medical images. Lower layers identify basic patterns such as edges, while deeper layers capture more abstract details. The convolution operation is defined as:

$$y[i,j]=\sum_m \sum_n x[i+m,j+n]\cdot w[m,n]+b$$

where x is the input I mage, w is the convolution filter, and bb is the bias term. Pooling layers are often included to downsample the feature maps, reducing the computational burden while preserving essential information.

2.2 U-Net for Segmentation

The U-Net architecture is highly effective in segmenting medical images. It consists of two main components:

Encoder: Captures multi-scale features from the input image using a sequence of convolutional and pooling layers.

Decoder: Reconstructs the segmentation map by upsampling the encoded features and combining them with corresponding features from the encoder via skip connections.

Key loss functions used for training U-Net include:

Binary Cross-Entropy Loss:

L=−N1∑i=1N[yilog(y^i)+(1−yi)log(1−y^i)]

Dice Coefficient Loss:

Dice=2|A∩B| / |A|+|B|

These loss functions optimize the overlap between predicted and ground-truth saliency maps.

2.3 Gradient-weighted Class Activation Mapping (Grad-CAM)

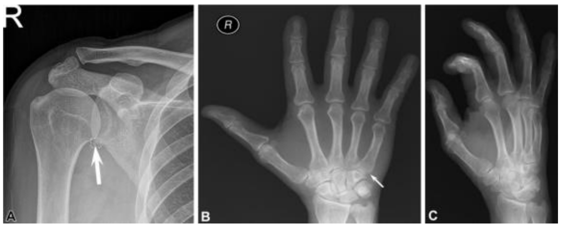
Grad-CAM is utilized to create heatmaps that highlight the areas most influential in a model's predictions. It computes the gradients of the target class score with respect to the feature maps. The Grad-CAM visualization is expressed as:

$$L_c^{Grad\text{-}CAM}=ReLU(\sum_k \alpha_k^c A^k)$$

where α_k^c represents the importance of the k-th feature map A^k for a specific class c. This heatmap provides interpretable insights into the decision-making process of the deep learning model.

IV. RESULTS AND DISCUSSION

According to the research papers for detection of bone fracture using algorithms like Convolutional Neural Networks (CNNs), Deep Learning Ensembles, Machine Learning Algorithms, U-Net , they have got an accuracy of 93%. According to our approach we have additionally used algorithms like Gradient-weighted Class Activation Mapping (Grad-CAM), provides an efficiency around (94-97%) with enhanced adaptability and robustness due to the additional methods employed.



CONCLUSION:

Advanced methodologies like U-Net and Grad-CAM can thus be integrated for the effective application of saliency detection in medical imaging. Using multi-scale feature extraction and reconstruction, U-Net is quite precise in its segmentation of fractures, ensuring it to be a trustworthy tool for localization. Moreover, Grad-CAM enhances the interpretability of critical regions of interest, enabling radiologists to confidently validate AI-driven predictions. These techniques, with optimized datasets and collaborative AI systems, open the way for robust and clinically validated solutions. This approach can potentially enhance diagnostic efficiency and patient outcomes by addressing challenges related to generalization to complex cases and seamless integration into clinical workflow**.**

REFERENCES

[1] **Rui-Yang Ju and Weiming Cai**. "Fracture Detection in Pediatric Wrist Trauma X-rayImages Using YOLOv8 Algorithm". Volume 11, 2023. Page No:1-15.

[2]. **Rebecca M. Jones 1,8, Anuj Sharma1,8, Robert Hotchkiss2, John W. Sperling3, Jackson Hamburger 1, Christian Ledig 1**." Assessment of a deep-learning system for fracture detection in musculoskeletal radiographs". Volume 2020.Page No:1-6. DOI: http://www.nature.com.

[3]. **Sanskrati Sharma***. "Artificial intelligence for fracture diagnosis in orthopedic X-rays:current developments and future potential". Volume 9,2023. PageNo:2-11. DOI:https://doi.org/10.1051/sicotj/2023018.

[4]. **Aariz Hussain*, Areeba Fareed and Shafaq Taseen**." Bone fracture detection—Canartificial intelligence replacedoctors in orthopedic radiography analysis". Volume 8,2023.Page No:1-4 DOI: 10.3389/frai.2023.1223909.

[5]. **Pishtiwan H S KALMET 1*, Sebastian SANDULEANU 2*, Sergey PRIMAKOV 2, Guangyao WU Arthur JOCHEMS 2, Turkey REFAEE 2, Abdalla IBRAHIM 2, Luca v. HULST 1, Philippe LAMBIN2,and Martijn POEZE**."Deep learning in fracture detection: a narrative review". Volume 2020.Page No:212-215.

[6]. **Rui-Yang Ju1 and Weiming Cai2,***." Fracture Detection in Pediatric Wrist Trauma X-rayImages Using YOLOv8 Algorithm". Volume 11,2023. Page No:1-15.

[7]. **Sina Beyraghi 1, Fardin Ghorbani 2, Javad Shabanpour 3, Mir Emad Lajevardi 4,Vahid Nayyeri 5*, Pai-Yen Chen 6 & Omar M. Ramahi** ."Microwave bone fracture diagnosisusing deep neural network". Volume 2023. Page No:1-11. DOI: https://doi.org/10.1038/s41598-023-44131-5.

[8]. **Tanushree Meena and Sudipta Roy**." Bone Fracture Detection Using Deep Supervised Learning fromRadiological Images: A Paradigm Shift". Volume 12,2022 Page No:1-17. DOI: https://doi.org/10.3390/diagnostics12102420.

[9]. **Zhihao Su 1 , Afzan Adam 1,* , Mohammad Faidzul Nasrudin 1 , Masri Ayob 1 and Gauthamen Punganan**." Skeletal Fracture Detection with Deep Learning:A Comprehensive Review". Volume 2023. Page No:1-22. DOI: https://doi.org/10.3390/diagnostics13203245.

[10]. **Iftekharul Abedeen , Md. Ashiqur Rahman, Fatema Zohra Protty**." FracAtlas: A Dataset for FractureClassification ,Localization and Segmentation of MusculoskeletalRadiographs" Volume 2023. Page No.1-8.DOI: https://doi.org/10.1038/s41597-023-02432-4.