RESEARCH PAPER

An Explainable Attention-Enhanced Deep Learning Framework for Automated Bone Fracture Detection and Multi-Class Classification in Musculoskeletal Radiographs

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ABSTRACT

In medical diagnosis, detection of bone fractures in respective X-ray images is a primary core task. The order is high accuracy and consistency due to nuanced character of fracture patterns. A close reading of a radiologist is extensive and can lead to diagnostic ambiguity, especially in high-acuity cases. To overcome these obstacles, this paper recommends an increased focus and a deep learning framework for automatic fracture detection and classification. The proposed system uses convolutional neural networks based on ResNet architectures, extended with Convolutional Block Attention Modules (CBAM) to improve feature representation by highlighting significant local and channel information. Performed within the framework, a two-stage pipeline consists of binary classification for fracture identification followed by multi-class classification to separate the specific bone type. The Musculoskeletal Radiographs (MURA) dataset is used for training and evaluation, accounting for multi-regional anatomical data. To enrich image quality and improve feature readability, Contrast Limited Adaptive Histogram Equalization (CLAHE) is used during preprocessing. Besides that, sophisticated training paradigms including data augmentation, Mixup regularization, and adaptive learning rate scheduling are used to improve model generalization and robustness.

Experimental results show that the proposed methodological framework achieves a fracture recognition accuracy of 77%, an improvement of 2.33% over the existing benchmark baseline accuracy of 74.67%. For multi-class classification, the model obtains an accuracy of 96.07%, exceeding the baseline performance of 95.7% by 0.36%. The parent system achieves an accuracy of 86.5%, indicating reliable performance across both detection and classification tasks. Besides that, Grad-CAM is used to generate visual explainability, amplifying clinical insight by highlighting the affected areas in the model's predictions. The proposed framework seamlessly combines preprocessing, attention mechanisms, and deep learning architectures to provide improved performance and interpretability, making it a viable framework for real-world medical imaging applications.

Keywords: Bone Fracture Detection, Deep Learning, Convolutional Neural Networks, ResNet, CBAM, Medical Image Analysis, X-ray Imaging, CLAHE, Grad-CAM, Explainable AI, Multi-Class Classification, Computer-Aided Diagnosis.

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1. INTRODUCTION

In clinical diagnosis and treatment planning, bone fracture detection using X-ray images plays a crucial role. For ensure timely medical intervention, accurately identifying fractures is very important in order to avoid complications. Normally, fracture detection depends on manual examination by radiologists which cam be time consuming and may get complicated when human eye cannot identify properly, especially in cases where fracture is very minor or when fracture has complex patterns. Due to this limitations there is an essential need for an automated system which can be used for decision making by assisting the clinicians. In recent years, deep learning has been a very powerful tool for medical image analysis due to its ability to learn hierarchical feature representations directly from the raw data. Convolutional Neural Networks(CNNs), Specifically shown great performance in image classification and detec- tion Between jobs several architectures, Resist Networks(ResNet) has taken advantage. Good attention to their capability To exercise deep models Addressing efficiently the vanishing gradient problem through residual learning[17]. Regardless their success, Traditional CNN-based approaches may not always be the most focused relevant regions Of medical images, which may be limited. Their effectiveness In fine- grained identification fracture features.

To address this limitation, we propose attention mecha-nism in order to enhance feature learning by enabling the system to focus more on notable regions within the image. The Convolutional Block Attention Module (CBAM) is a lightweight but effective general purpose attention mechanism designed to improve Convolutional Neural Networks (CNN) by focusing more on important features and reducing irrelevant ones. CBAM works by applying channel and spatial attention sequentially to intermediate feature maps by which perfor-mance will be improved in detection and classification tasks integrating seamlessly into existing architectures. In addition, preprocessing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE) are used in order to enhance local contrast by dividing images into small distinct tiles which intend improve the visibility, which is widely used in medical imaging. In this work, we propose an attention-enhanced deep learn-ing framework for automated bone fracture detection and clas-sification. This proposed system follows a two-stage pipeline consisting of binary classification to detect whether fracture is present or not and multi-class classification to identify the specific bone type. The framework Training is provided and evaluated. The Musculoskeletal Radiographs (MURA) dataset [19], which gives a diverse collection of X-ray images across 7 different anatomical regions. In addition, gradient weighted Class Activation Mapping (Grad- CAM) [20] added to give visual explanations, to improve the transparency of the model.

Experimental results Proved it the proposed model sheep improved performance when compared to baseline models, to indicate the effective performance when merged with attention mechanisms and pretreatment techniques. The combination of enhanced feature representation, Effective training strategies, and interpretability do the proposed frame- work suitable to real- world medical imaging applications.

Deep learning approaches I have proven to show significant success. Medical image analysis Work, especially classification and detection problems [28], [29].

A. Key Contributions

The main contributions of this work can be listed as follows:

- Proposing a deep learning-based automatic bone fracture detection and classification system utilizing an attention-based architecture.
- Utilizing the Convolutional Block Attention Module (CBAM) together with ResNet-based models for achiev-ing better performance in bone fractures detection.
- Implementing CLAHE to enhance image quality and increase fracture detectability.
- Utilizing a two-step classification pipeline where a binary classifier determines whether there is a bone fracture or not and a multiclass classifier classifies the bone type.
- Using Grad-CAM for providing interpretable results for enabling better understanding of model predictions in medical contexts.

2. Literature Review

The latest developments in the realm of deep learning have revolutionized the field of medical image analysis, particularly including detection and classification of abnormalities present in the radiographic images. Convolutional Neural Networks (CNNs) have been proved to be the most promising solution due to their ability to automatically learn hierarchical feature representations, therefore reducing the need for manual feature engineering. A number of works What has been discovered? the application where fracture detection X- rays are taken using deep learning methods. Daimler[1] Which offered development. An intelligent system Too automatic detection of bone In breach a similar manner, Katamura[2] Recommended a convolutional neural network Based on ensemble method to ankle fracture detection from x- ray images, to emphasize the productivity of multi- view learning strategies Even with limited training data.

Likewise, Badgeley[3] Investigated deep learning model for hip fracture prediction, Spotlighting the influence on patient- specific and vitality- related variables model performance. To make amends fracture detection accuracy and localization ca- pabilities Further research is focused on. Chung[5] used a framework to proximal humerus fracture detection By using deep learning, confident viable classification performance. Thean[9] Generated automatically fracture detection and localization in wrist radiographs By distributing CNNs, clarifying the capability Of deep learning Clinically recognized models relevant data. Lindsey [13] It turned out to be comprehensive neural networks May increase fracture detection performance beyond manual clinicians efforts, shows the potential AI- Assisted diagnosis. Recent work the challenges affiliated data limitations and model generalization I medical image analysis. Doubles [4] checked the effect of training dataset size, but to emphasize classification performance its influence but model accuracy. Wow 12] Recommended techniques to reduce feature ambiguity I X- ray images, So improvement detection reliability.

Likewise, Wang[16] explored inadequate supervised learning methods, which reduce reliance on fully annotated datasets and enable more scalable training processes.

Besides that application- specific studies, Many deep learning The architecture has been widely adopted. Medical imaging work Residual Networks(ResNet)[17] Facilitation effective training Of deep models through residual learning. Dennis Nate[22] improves feature propagation and reuse Across teams, while VGG networks[23] Still provide a simple effec- tive architecture to image classification.

Later, attention mechanisms such as the Convolutional Block Attention Module(CBAM)[18] is introduced to increase feature representation By enabling models to focus on important spatial and channel information.

Furthermore, interpretation has progress a critical requirement I medical AI systems. Gradient weighting technique Class Activation Mapping(Grad- CAM)[20] allocate visual explanations By highlighting the affected areas model pre- dictions, Thus the increase trust and transparency I clinical applications.

Despite significant advancements, Many challenges remain. Fracture detection from X- ray images. They include low image contrast, Subtle fracture pattern, cross variable anatomical regions, And the need to interpretable models. Current approaches often focus on accuracy, robustness, and explainability across diverse datasets. To address these challenges, It suggests work. A frame- work which integrates image preprocessing. Techniques, Mechanism of attention, and a systematic two- phase classification pipeline. The proposed method is to improve feature representation, improve the model' s focus But relevant regions, and provide. Interpretable outputs, This helps make it more reliable and efficient. Fracture detection system.

3. FUNDAMENTAL CONCEPTS

This section covers the basic ideas behind the proposed deep learning framework. These provide ideas. The theoretical basis to understand how design and implementation the fracture detection and classification system.

A. *Deep Learning in Medical Imaging*

Deep learning is a branch of machine Learning that uses multiple layers. Neural networks Extracting patterns and features from data on data its own. I medical imaging, These models do a great job Analysis the complicated details Found in things favor X- rays, CT scan, and MRIs.

Deep learning models There is no demand for hand- picked features like traditional image processing– they figure out what matters. The raw images. He a huge advantage I medical imaging. Sometimes, tiny differences I the image reveal problems favor breaking, and those details Can slide easily. Older methods. With deep learning, Automated diagnostics can detect these subtle signs More accurate and reliable, and easier to scale. The systems If necessary.

B. *Convolutional Neural Networks (CNN)*

Convolutional Neural Networks, or CNNs, are deep learning models Built to handle. Grid- like data— think images. What does CNNs Standing outside their knack To capture patterns and functions in a visual, thanks to windings. Here' How they are usually formed: You' Get it- tional layers, Aggregate layers and fully connected layers. The convolutional layers Implement scan filters. Image, capturing details such as edges, textures, etc different shapes. Collective teams are in favor of shrinking. The size of those feature maps, something esteem that speeds up Treats and helps. The model recognize Objects Even if they migrate. A bit. Supplied with completely closed layers. The end, to draw everything together to establish the final classification. That's it. A system Which Works really well for tasks appreciate identifying what's in it. A picture. What really sets CNNs Apart from their ability to create these features Step by step, everything from the basics The way to complex shapes. That's why they work so well. Medical image analysis, Where details every level Can monitor more accurate diagnosis.

C. *Residual Networks (ResNet)*

Residual Networks, or ResNet, handle the problem Of deep neural networks Loses accuracy as they attain deeper They Do this by adding skip connections, What two the model focus On learning the difference Among his prophecies and the actual result, Instead of trying to map everything from scratch. Mathematically, a residual block It is represented as:

$$Y = F(x) + x \quad (1)$$

Where x represents the input and F(x) indicates the residual function be taught. This formulation facilitates better gradient flow during backpropagation, Activation the training of deeper networks without performance degradation. I this system, ResNet works. The backbone for both binary and multi- class classification. The main reason? It's best to procure important features from data and remains stable during exercise, even real existence deep setups.

D. *Attention Mechanism and CBAM*

Attention mechanisms Facilitation deep learning Models Zero But the highest important parts of the input. It really means something. Medical imaging, where the fractures Insignificant, they can hardly be seen. Noticeable spots I X- rays. Convolutional Block Attention Module, or CBAM, is a lightweight approach something that increases focus.

Two steps: Which functions should one focus on? First matter most (channel attention), and then by finding exactly where the qualities that I am. The image (spatial attention).

E. *Grad-CAM Explainability*

When you add CBAM to a CNN, A network gets better at highlighting. The relevant regions And tuning out the noise Grad- CAM Let's acquire a observe inside deep learning models and recognize what they notice. It creates heat maps that exhibit parts of an image influence the model' s decision Most of all Here' s Here's how it works: Grad- CAM user the gradients from the target class— go one The model tries to detect- in the last convolutional layer to be built a rough map. This map highlights. The spots I the image that matter most to the prediction. Clinicians Do you want proof? The system not just guessing or focusing. Irrelevant details. With Grad-CAM's visual explanations, they can check the model looking the right areas, to create the whole process feels much more reliable and transparent.

4. DATASET DESCRIPTION

To attain deep learning models to perform well medical images it's not just about fancy algorithms. Honestly, the heart of it the dataset contains– how significant, clean and organized it is. Your data much more important than population think. I this project, I used the Musculoskeletal Radiographs (MURA) dataset [19]. Stand out as one among the largest and most trusted spotting collections musculoskeletal abnormalities I X-ray images.

You're do not deal with a handful of Scan here. The MURA dataset brings together thousands X- rayed from different patients, to cover up seven Main parts of the upper limb: elbow, finger, forearm, hand, humerus, shoulder, and wrist. What is particularly useful is that radiologists the brand each study (Sometimes even more one image per study) as" normal" or “abnormal.” With This kind of guidance, Teaching is manageable a model to admit it a scan shows any signs of a fracture or irregularity— classic binary classification.

But the dataset It doesn't cease there. The way MURA's Structure means you can transfer as you run. A multi- class classification Specify which bone or anatomical region is the problem. This gives a practical advantage- your model won't just flag it. Something' s wrong, Where will it point? The issue It's for doctors this kind Of Detailed production a game-changer: less ambiguity, quicker diagnosis, And finally better care. However, data quality is not the only concern. I medical datasets, you almost Always is an imbalance— way More" normal" cases from" abnormal" ones. If you ignore it, your model Just Learn to engage. It safe And call everything" normal." I dealt with it by choosing carefully an equal count of samples from each group While The building the training Set This is A simple solution He works a long way Courage to create the model reliable, It doesn't matter what kind X- ray It looks. To distribute the data In training and validation Groups also assist to ensure that what the model Learning actually takes position in practice, And we don't just learn it by heart. The samples. Before feeding any X- ray I the model, That's it some cleanup to do Medical images Can Be difficult- sometimes subtle fractures hide inside low contrast or shadows. I used to deal with it. CLAHE(Contrast Limited Adaptive Histogram Equalization) To promote local contrast, To ease the model catch He makes insufficient movements. Each image was resized. 224 of 224 pixels. This is Almost prefer a seizure Your data I a standard uniform, The product is guaranteed to work well. Pre- educated neural networks, As is often expected. This specific size. So normalization the pixel Values stable the ship, To allow the training run Simple without the odd jump in intensity. I'm going to the training pipe myself. Two main stages. First, the model Strain through the images To Generate a decision a fracture Or No- it is your binary classifier in action. When you gather. An abnormal case, The second step in the classification is to identify which bone or area is involved. This two- step strategy Not It just gets it better overall accuracy But It also provides practical results for this. Real- world screening and diagnosis. All things It is understood the MURA dataset is a solid founda- tion For training deep learning systems Identification of violations and abnormal patterns I X- rays. It is diverse, well commented and thoughtfully organized. Paired with the right preprocessing and model architecture, This gives you a significant chance to develop an automated tool that can create a real difference I clinical practice.

5. METHODOLOGY

Here' how the focus session deep learning Framework this serves to label and classify bone fractures. X- Rays. Consider carefully designed, two- part system. First, the framework Tackles image quality, Begins with a straight forward step: to occupy the X- ray image, the speed is then increased. Pre-processing. It helps with cleaning. Any noise or blurry Appreciate it the details really Standing outside.

A. System Overview

The overall architecture of described in the proposed system. Fig. 1. The framework follows a structured pipeline where input X- ray images Processed of multiple stages Interrupt detection and classification.

As shown in Fig. 1, starting with the system. The acquisition of an input image, then through pre- processing to improve it. Image quality. These are processed images. First passed by a binary classification model for damage detection. If a fracture is identity, the image further processing is finished using a multi- class classification model to decide the affected bone type. Finally, Grad- CAM used to give visual explanations of the predictions.

B. Pipeline Description

The proposed framework Works through the following steps:

1) Acquire input: X- ray images Collect and prepare.
2) Before treatment: CLAHE, Resize and normalization are used.
3) Binary Classification: Detect fracture presence.
4) Multi- classification: Identify bone type.
5) Interpreting ability: Generate Grad- CAM heat maps.

C. Image Preprocessing

Medical X- ray images Can Reviews can be tricky– they usually are. Low contrast, And it happens often. A fair bit of noise A mess in the details. That is, remove out the important features And to create those subtle fracture Lines Stands out, we apply a technique Called CLAHE. It is growing. The local contrast I different parts of the image Without improvement The noise is pronounced, but before you drive any of these models, Each image has been resized. 224 of 224 pixels And As usual That way, See deep learning models. A consistent data format Each Interval It helps them learn more effectively.

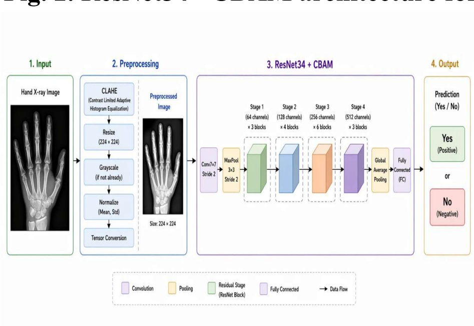
D. Binary Classification Model

The first stage Focusing But fracture detection using a ResNet34- based architecture optimized with CBAM, as shown in Fig. 2. Selected as ResNet34. The backbone to this task because this is Remarkable to dig in complex functions- thanks those residual connections. He gave permission. The network Go intensive without running in the usual problems Value a missing gradient, so it really picks up. The fine I hide the details. Medical images. This is important when it comes to something as subtle as this. Violation detection. Now, CBAM Not Just sit down top of ResNet34; it accelerates. The network's focus. Instead of treating all features Liked CBAM zeroes What It makes a difference most— some spots I a X-ray And specific channels Convey more than others. It helps. The model pay extra attention To This critical details, so those tiny fracture don't go past the lines. The cracks. When all is said and done, the model it spits. A straightforward result: Fracture or fracture. Behind that simple answer, although it is it beautiful?

Sophisticated pipeline working hard Violations The flag to ensure that hardly- there. It's not just about accuracy– it's about making assured nothing unique is missed. Those cases which can easily go unnoticed.

Fig. 1. Proposed focus extends the deep learning framework to the bone. Fracture detection and classification

Fig. 2. ResNet34+ CBAM architecture for binary fracture



detection*Multi-class Classification Model*

The second stage Classifier. Fractured images Uses ResNet18- based architecture integrated with CBAM, As shown in Fig. 3.

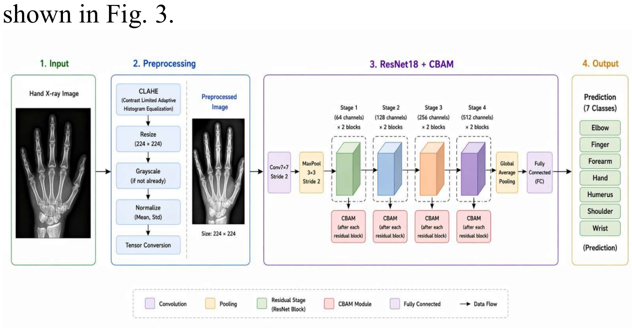


Fig. 3. ResNet18 + CBAM architecture for multi-class bone classification

ResNet18 Fits Bill because not much is needed. Your computer, still, it packs a punch. A punch A punch in terms of accuracy. It’s a solid backbone for image classification Employment, It's exactly what you require when you get it. Seven different categories How to sort the images: Elbow, finger, Forearm, contribution, Humerus, shoulders, and wrist. But the story it doesn't end there.

E. Training Strategy

To improve model performance and generalization:

- Data amplification(rotation, turning, brightness adjustment)
- Mixture supplement for strength
- For Adam W. Optimizer efficient parameter updates
- Planning the pace of learning for stable convergence
- Cross entropy loss with label smoothing

F. Role of CBAM

CBAM steps in to make the model even smarter. This is Value to allocate ResNet18 a pair of glasses and tells you where to investigate. CBAM But zero the parts of each image that matter most By Both local and focused channel features. The channel's attention mechanism selects which features are actually vital– it's the honor filter. The noise to listen the main melody. A local focus then makes sense out of it. The physical regions I the image which are relevant, especially for difficult tasks such as fracture detection. Overall, this combo Improves and creates accuracy. The model more reliable, especially in situations where it is Essential to occupy the smallest details.

G. Model Interpretability by using Grad-CAM

When it comes to figuring out how and why the model made a decision, character- CAM It creates heat maps. That manifest Accurate Parts of an image stir the model’ s prediction. It just isn't. A pretty picture– It is necessary, if you will. Doctors and radiologists What to trust the AI saying. By offering direct insights I the model’ s thought process, Grad- CAM do it the whole system More Evident and straightforward to interpret. That level of clarity I'm essential enough to adopt. Real medical settings, Where decisions are made. Real consequences And believe that everything is.

6. Detailed Technical Analysis

This part I dive the nuts and bolts what kind the proposed framework actually works. It comes in. The details behind the technology, Shows what does it. Fracture detection and classification better.

A. Feature Extraction in CNNs

Convolutional Neural Networks, or CNNs, Extract features from images using a layered approach. But the start, It uses filters to identify networks. Basic stuff— edges, Composition, gradient. He the groundwork, and that is what it allows. The model recognition simple structural patterns I X- ray scans. So when you go deeper the network, Together they form. The basic functions. More complex shapes- value the bones of things contours and larger structures. I the deepest layers, Even CNN appear to understand. Higher- level details: Bone structures, fracture lines, those tiny abnormalities this is very important for fracture diagnosis. This method of stacking feature learning Is huge, especially medical imaging, wherever it may mean small changes. A fracture exist.

Because CNNs ascertain out which features make a difference. Their own, There is no demand for it tedious manual feature engineering. This automatic learning increases efficiency, especially when working. Tricky image analysis the work needed. Precision and attention in detail it allows the model Get it accurate the heart what is important is to create the whole process smarter and more efficient.

B. Effect of CLAHE on Medical Images

Contrast Limited Adaptive Histogram Equalization, or CLAHE, This is a preprocessing trick that really works. The local contrast in pictures, without the noise exit assistance. When you observe medical X- rays, is associated with fractures. The surrounding tissue- Because they are not visible the contrast is very little. So finding them will be harder than you evaluate. Here' how CLAHE helps: It cuts. The whole image Up To me small regions And so it goes histogram equalization But Every single one piece Separate, but instead of bowing the contrast And Everything is meant to grow the grainy noise also CLAHE Restrictions Jump on the contrary a safe level. This means you will obtain better detail Without Drowns everything in noise. The broad advantage here is that small cracks and faint fracture Lines many what would otherwise be invisible- suddenly appears. That extra detail Very crucial for doctors trying to establish a solid diagnosis from an X- ray. And let's express. Deep learning to a second. If you feed a model with a preprocessed image where all those little features ready, the model Locks more about useful information. This improves both how well it detects. A fracture And How accurately can it tell what type of violation has been committed? It's watching So, CLAHE Just Do not decontaminate the image; Establishes the whole detection pipeline to a stronger performance.

C. *Mathematical Insight of CBAM*

The Convolutional Block Attention Module (CBAM) enhances Feature representation by searching attention mechanisms with both channel and spatial dimensions. The module is improved sequentially. Feature maps to emphasize informative regions and pushes irrelevant information.

The channel attention mechanism is defined as:

$$M_c(F) = \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F))) \quad (2)$$

Where F represents the input feature map, andσ means the sigmoid activation function. This procedure identifies the importance of each channel By collecting global spatial information.

The spatial attention mechanism is defined as:

$$M_s(F) = \sigma(f^{7\times7}([AvgPool(F); MaxPool(F)])) \quad (3)$$

Where spatial attention Focuses on identifying the most relevant regions within the feature map. Generated by the attention map these mechanisms multiply by the input features to produce refined feature representations. By combining channel and spatial attention, CBAM activates the model to focus on critical regions I X- ray images, Esteem fracture sites, this improves. Classification accuracy.

D. *Effectiveness of Two-Stage Classification*

The framework Uses two phases classification strategy To increase efficiency while maintaining it the model simpler. I the first step, It runs. A binary classification To absorb about a fracture Does it exist or not? That way, He just has to solution a straightforward question: Is this normal or does it demonstrate up? Signs of a fracture? by narrowing the focus Such the system do it easier Identify violations without confusion unnecessary details. Once this initial filter prisoners anything abnormal, The process shifts gears. Now only flagged images are played. The second stage. Here, the model takes a closer look And running a multi- class classification To find out which bone is affected. I do things two Here's how to avoid confusion. The job with spotting fracture the challenge Bone marking. I the end, This kind of approach helps the model stay Expeditious And organized– locate what's critical. First, Be specific when necessary.

The advantages of this strategy Includes:

- I made it simple. The decision Restrictions The initial stage
- A decrease in computational complexity to multi- class classification
- Improved accuracy by separating classification tasks

It systematically adds. Both efficiency And over- all system performance.

E. *Overfitting and Regularization Techniques*

Deep learning Missing training data for models can be good, especially when they have a lot of it. Parameters and the dataset Not significant Or balanced? This often leads to overfitting- the model begins to rise. Random noise Instead Of the actual patterns We care. To retain things In Czech, delivered to researchers a few regularization I'm moving. The mix during training. One popular approach user dropout layers. By closing randomly some neurons While the model Teacher, apostasy actually compels. The network To develop further robust features, Because no single neuron can be trusted. Its usual neighbors. Observe you too MixUp augmentation too many: this technique Combines images And their labels together, make an instance between a type that inspires. The model Doesn't get too attached any specific detail. Gives the model A wide range of scenarios for training and support push its decision boundaries from several individual samples. There is also weight loss, where the optimizer nudges Model parameters Should be the least achievable. This discour- Age from becoming network redundant complex Conditions will not be normal.

7. Results and Discussion

Here, we are drowning in it a detailed evaluation of the focus increase. The deep learning framework we developed for this. Fracture detection and classification. The main focus is on how well. The models Perform on the validation dataset, and we look mostly at accuracy. Our go- to metric. After running the tests, we take a close look but the numbers How to discern our new approach stack up against the usual baseline models.

By analyzing the results, we obtain a clearer picture exactly how effective the attention mechanisms Is- if they really give. Our framework an advantage when it comes to detecting and classifying breaches. Medical images. This process not only helps us measure improvements, but also better understand Why and where? The new model outperforms older ones.

A. *Performance Comparison*

To consider the effectiveness Of the proposed framework, A comparative analysis is made between baseline ResNet models and better models than CBAM both binary fracture recognition and multi- class bone classification work.

Task	Model	Accuracy (%)
Fracture Recognition	Baseline (ResNet34)	74.67
Fracture Recognition	Proposed (ResNet34 + CBAM)	77
Bone Classification	Baseline (ResNet18)	95.7
Bone Classification	Proposed (ResNet18 + CBAM)	96.07

Table-1 Performance Comparison of Models

Table- 1 Summing up the performance of both baseline And proposed models. It can be observed. The integration of CBAM leads to consistent improvements in both works.

B. *Quantitative Analysis*

The proposed model sheep a fracture recognition ac- curacy Of 77.00%, But improvement the baseline accuracy Of 74.67% of 2.33%. This improvement is significant. Medical imaging contexts, wherever small gains May manage to accuracy better diagnostic outcomes.

To multi- class bone classification, The proposed model achieves an accuracy Of 96.07%, Compared to 95.70% to the baseline model, As a result of that an improvement Of 0.36%. Though the improvement is relatively small, it suggests the baseline model already works well, and the addition of attention mechanisms Provides further refinement.

C. *Interpretation of Results*

The boost in performance actually comes from inclusion. The Convolutional Block Attention Module (CBAM). It helps. The model Turn on zoom the important parts of X- ray images, so it is better to transport those subtle details Case in consideration fracture detection. You know, fractures are often negligible or challenging, so an attention mechanism esteem CBAM do a big difference. There is no binary hierarchy at all. Straightforward here.

Fractures came in all shapes and sizes, And X- ray images the quality can vary widely. The model we deploy stand- up well. These issues— it is quite substantial and seems to be better normalized, even when the images get demanding But when you discern the multi- class classification task, There are things a bit easier. Now, the model must only be told separately different anatomical regions, as is usually the case. Clearer differences— accessible too any model, that's really why the Eco Race jumps so much. This case. Distinct features to make the job simpler.

D. *Model Behavior and Generalization*

The framework Generalization It gets better as the mix goes on. Smart preprocessing, Mechanism of attention, and smarter training strategies. To model CLAHE Really improves the contrast In pictures, This is the model Takes up. Those faint fracture patterns which may otherwise slip by unnoticed. So it is a mixed addition- combined the training data, It makes everything more diverse and helps. The model Development smoother decision boundaries. He a big help When it comes to avoiding overfitting. AdamW optimizer It also comes in performance. Overall, these pieces Work together to create. The model More reliable and robust.

E. *Overall System Performance*

How well do we judge? The system it works by looking. Two main things: How it detects breaches and how it classifies them. Different types of bones. The results are pretty solid- the whole setup is coming. 86.5% accuracy. This is nothing to shrug off, as it shows. The system lasts all the way the entire process.

A big reason to this strong performance comes from the way we are divided the work I two steps. After that, it moves on to the classification of the bone. Keep these tasks separate makes everything so much easier and faster. The accuracy higher. Instead of lumping everything together and risking confusion, this allows for a two- phase approach. Each part of the job become the focus Warrant it, and cease with you better results overall.

F. *Discussion*

The results Really Show how you add attention mechanisms Increases deep learning I model medical image analysis. With CBAM in facility, the model It doesn't waste energy irrelevant parts of the image- It goes zero. Areas that are extremely crucial to doctors. This focus helps the system catch subtle fracture Patterns can cause it to slip past traditional approaches. But top of that, Step appreciate pretreatment CLAHE gain momentum Input quality. It's prefer giving. The model a clearer image to work with, so it captures more. Meaningful features. So there it is Grad- CAM, It moves things forward. Instead of just making predictions, the model Submit now. Visual explanations— actual heat Map shows that it is watching. That kind this openness is incredibly critical in medicine. It helps to trust doctors. The system and understand its reasoning. Overall, this framework Balance accuracy and inter pretability. It does not sacrifice itself one For Second, it is very rare. That combination stand out as a practical choice too automatic fracture detection, I am ready for implementation. The factual world where reliability is essential.

8. LIMITATIONS

Though the proposed focus has increased. Deep learning framework shows improved performance in fracture detection and classification, some limitations must be acknowledged.

- **Dataset Limitations**: The model Works well when it has a lot of data to learn. The MURA dataset is a collection of X- ray images but be it every kind of fracture or every way which the doctor takes X- ray pictures. That can't happen either. Pictures of every type of the patient. That is to say the model can't Act well when it sees new data He hasn't learned that yet.
- The model Only As good as it gets the data learning from this the MURA dataset is vital for the model To understand about X- ray images.

- **Image Quality Variability:** The X-ray images that we use in the system have to be really good. If the X-ray images are not clear or are too blurry it can cause problems. The system looks at the X-ray images to find things but it can get confused if the images are not good enough. Sometimes the images can be too bright or too dark. That can also cause problems. There are things we can do to make the X-ray images better like using a tool called CLAHE. Even, with this tool the X-ray images might still not be perfect and that can affect how well the system works with the X-ray images.
- **Limited clinical validation:** The proposed system was tested with a set of data. To be confident the system Really works. Hospitals and clinics We have to undertake it. Patient information And observe the doctors the results. This will facilitate us to know about the system Positive and works well. The world with the proposed system I am being used real healthcare settings And the proposed system will be checked its reliability and robustness**.**
- **Calculation requirements:** Deep learning models, as an user attention mechanisms Much needed computer power To learn and make predictions. It can happen. A problem When we require to apply these models In places where computersre not very powerful. Deep learning models, like these need Lots of resources.
- **Class asymmetry sensitivity:** Medical datasets It often is a problem. Some fracture types do not have data. How excellent can it be? the model works. It can generate predictions that are not fair if we do nothing about it. The medical datasets and the model performance are really critical. The fracture Species that are underrepresented. The datasets Can cause a lot of trouble.

A. Comparison with Traditional Approaches

The old ways of finding most fractures depend on what the doctor sees. The pictures or implement tools with it old machine learning ways. These methods are widely used. They take it a long time need people Who knows a lot the field and may deviate from one person to the other The new way We're talking about using learning to search automatically. Important things I the X- ray pictures So we don't need to do it manually. That means the model Can find patterns and small changes With whom it is difficult to discern. The old methods. Other ways to use learning look But the whole picture Likewise, what can happen a problem If the important stuff It's just me one part. Our method uses tools such as CBAM To assist the model look But the important parts of the picture And the important things It searches for what it creates it better By finding violations. We also employ Grad- CAM to support us understand how the model do its decisions by showing us pictures what is it looking at? It's better than that. The ways, where we don't really recognize how the decisions is made. So our new way is better than the ways because it is more accurate, automatic and accessible to understand and it fixes something. The problems with the old ways. Deep learning is the new way. An improvement over fracture detection methods and it is better at finding breaches. The deep learning way even more automatic and elementary to understand. Fracture detection methods.

9. Conclusion

This paper is about a way to utilize deep learning to detect and classify bone fractures X- ray images. Uses something called a system. ResNet and the Convolutional Block Attention Module to produce sure it can identify the features I the images. It also uses a technique Called Contrast Limited Adaptive Histogram Equalization to create the images clearer and help to find. Small fractures. The system I activity two steps: First it checks if it is a fracture. It then checks what kind of bone is affected. It does it easier to the system to learn and do better. The results Exhibit it this system really beneficial at finding breaks with an accuracy of 77% and it's good at ranking too. The type of bone Impressed with an accuracy of 96.07%. It is better than the systems tried before. The system is also generally correct with an accuracy of 86.5%.

The system also uses something called Grad- CAM, Which helps us understand how it is formed. Its predictions. This is vital for applications because doctors must be able to trust. The system and understand how it works. The proposed bone fracture detection system by using X- ray images I'm very excellent helping doctors Diagnose fractures accurately and quickly. It uses a combination of techniques to ensure that it works well and is straightforward to use. The bone fracture detection system by using X- ray images is a solution, to medical imaging because it is accurate, efficient and easy to understand. The bone fracture detection system by using X-ray images has a lot of potential to help healthcare professionals do it their jobs better.

A. Future Work

The proposed system some more work needs to be done. We can construct it better by using display data different kinds of fractures and imaging conditions. This will contribute. The system to function well under the circumstances. We should also consider using advanced techniques such as transformer-based models and hybrid deep learning frame- works. The proposed system can work better if we use these techniques. We have to construct. The system Work in hospitals and with real data. This will demonstrate us about the system really works. The world. We also have to construct. The system use resources so it can be used in places where resources are limited. This way the proposed system can be used by humans. The medical field.

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