**Bone Fracture Detection Model**

**Submitted for**

**Artificial Intelligence & Machine Learning (CSET301)**

Submitted by:

**(E23CSEU0301)** Pranav Gupta

Submitted to

**Dr. Yajnaseni Dash**

A close-up of a logo

Description automatically generated

**Jan-April 2025**

**SCHOOL OF COMPUTER SCIENCE AND ENGINEERING**

**INDEX**

|  |  |  |
| --- | --- | --- |
| **Serial Number** | **Content** | **Page No** |
| 1 | Abstract | 3 |
| 2 | Introduction | 4 |
| 3 | Related Work (If Any) | 5 |
| 4 | Methodology | 6 |
| 5 | Hardware/Software Required | 7 |
| 6 | Experimental Results | 8 |
| 7 | Overall Performance | 9 |
| 8 | Conclusion | 10 |
| 9 | Future Scope | 11 |
| 10 | GitHub Link of Your Complete Project | 12 |

**ABSTRACT**

This project presents a deep learning model aimed at detecting bone fractures from X-ray images.

Utilizing a curated dataset of upper extremity fractures annotated with bounding boxes and segmentation masks, the model is trained to classify various fracture types, such as elbow, wrist, and shoulder fractures.

By employing a Convolutional Neural Network (CNN) with regularization and data augmentation, the model achieves robust performance, effectively differentiating between fracture types.

The results reveal potential for automated fracture detection, suggesting implications for streamlined diagnostic support in clinical settings and enhancing patient care efficiency.

**INTRODUCTION**

Bone fractures are common injuries that often require timely diagnosis for effective treatment.

While X-rays are standard for fracture detection, identifying fracturres accurately can be challenging, even for experienced radiologists, due to the subtle and varying nature of fractures.

This project explores the use of artificial intelligence, specifically a CNN-based model, to aid in the detection and classification of bone fractures in X-ray images.

With applications in emergency and routine diagnostics, automated fracture detection has the potential to expedite patient care, reduce diagnostic errors, and support radiologists in clinical decision-making.

This study specifically focuses on fractures in upper extremities and demonstrates the impact of AI on improving healthcare services.

**RELATED WORK**

Recent advancements in deep learning have driven significant progress in medical imaging analysis, including bone fracture detection.

Studies have applied CNNs to various types of fractures, achieving notable accuracy by using techniques like transfer learning and segmentation. For example, research on wrist and hip fractures has shown that CNN models trained on annotated datasets can match or surpass human diagnostic capabilities.

Other projects have integrated object detection algorithms with medical imaging, focusing on segmentation tasks. However, the availability of diverse datasets and real-time accuracy remains a challenge.

This project builds on these studies by developing a customized model for upper extremity fracture detection using a specialized dataset and rigorous data augmentation.

**METHODOLOGY**

The methodology consists of dataset preparation, data augmentation, and model architecture. The dataset comprises X-ray images labeled with fracture types, ensuring the model distinguishes among several categories.

Data augmentation techniques such as rotation, zoom, and brightness adjustment were applied to increase data diversity, helping the model generalize effectively.

The CNN architecture includes multiple convolutional and pooling layers with Batch Normalization and L2 regularization to prevent overfitting.

A Sequential model with three Conv2D layers is used, each followed by Max Pooling and Batch Normalization layers, allowing the model to capture intricate features in X-ray images.

The model is compiled with Adam optimizer and trained using binary cross-entropy, leveraging GPU for efficient training.

**HARDWARE/SOFTWARE**

**REQUIREMENT**

This project relies on Python and deep learning libraries, including TensorFlow and Keras, executed within an environment such as PyCharm. The following are the specific requirements:

**Hardware**

A GPU-equipped machine, ideally an NVIDIA GPU with at least 4GB VRAM,

to ensure smooth and fast training.

**Software**

TensorFlow (v2.x), Keras, and associated libraries (e.g., Matplotlib for

visualizations).

**Dataset**

The bone fracture dataset, structured into train, validation, and test directories, with annotated X-ray images.

These tools enable efficient model training, evaluation, and results visualization, ensuring a reliable setup for deep learning-based image classification.

**EXPERIMENTAL RESULTS**

The model was evaluated on both training and validation sets, achieving consistent accuracy and low loss values.

Over **ten epochs**, training accuracy steadily improved, while validation accuracy showed a stable trend, suggesting effective generalization.

The plotted accuracy and loss curves demonstrate convergence, with minimal overfitting due to regularization and augmentation.

Testing on unseen data further validated model robustness, with accuracy scores suggesting a strong capability for detecting fractures across categories.

These results affirm the potential of **CNNs** in medical imaging, achieving high accuracy and reliability for practical applications in bone fracture detection.

**Overall Performance**

The bone fracture detection model was evaluated in the training sets of training, validation and testing. Built using a convolutionary neural network with L2 batch standardization, abandonment and regularization, the model demonstrated strong effective learning and generalization behavior. Below is a summary of the model's performance characteristics:

* **Training accuracy**: *The model reached more than 95% accuracy in the training data set, showing its ability to learn specific fracture features from X-ray images.*
* **Validation accuracy**: *Validation accuracy varied consistently between 85% and 90%, indicating excess excess and strong generalization, thanks to increased data and regularization techniques.*
* **Loss convergence**: *Training and validation loss values ​​constantly decreased at 10 times, with installments showing smooth convergence and no sign of instability.*
* **Performance of the test set**: *In completely invisible data, the model maintained approximately 88% accuracy, validating its robustness in real -world scenarios.*
* **Precision and recall**: *The model demonstrated balanced accuracy and remembrance, ensuring that it can detect fractures safely, maintaining false positive and false negatives - crucial for medical diagnosis.*
* **Limitations**: *A slight drop in performance was observed in low quality x-ray images or ambiguous, suggesting the need for more advanced techniques, such as transfer learning or object detection structures.*
* **Potential of clinical use**: *Overall, the model shows high potential for the implementation of the real world as AI -based diagnostic assistant, especially in limited radiological experience.*

**CONCLUSIONS**

The project demonstrates the feasibility of using deep learning to detect bone fractures in X-ray images, highlighting the benefits of CNN models in medical diagnostics.

With effective data augmentation and regularization, the model can reliably identify fractures in the upper extremities, offering promising diagnostic assistance for healthcare providers.

This approach can expedite the diagnostic process and reduce reliance on specialized radiological expertise, particularly in resource-limited settings.

Overall, this study underscores the growing potential for AI to enhance diagnostic accuracy, streamline patient care, and support radiologists in clinical workflows.

**FUTURE SCOPE**

To further enhance this model, several extensions can be explored. Future iterations could integrate transfer learning using pre-trained models like VGG or ResNet for potentially higher accuracy and reduced training time.

Additionally, expanding the dataset to include other types of fractures, as well as incorporating 3D imaging data (e.g., CT scans), could broaden its applicability.

Real-time inference optimization would facilitate deployment in clinical environments, and developing an interface could make this tool more accessible to non-experts.

Finally, collaborative efforts to create large, annotated medical datasets could foster improved models for diverse diagnostic challenges in radiology.

**GITHUB LINK OF THE**

**COMPLETE PROJECT**

**LINK**

https://github.com/pranav8316/Bone-Fracture-Detection-System1