Final Report

Deep Learning-CIS-583

Project Name: Bone Fracture Detection Using Deep Learning

Section Number: 583-001

Semester: Winter 2025

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Team Members and Responsibilities: Team 05

- **Devidas** - Data collection and preprocessing, Image augmentation and normalization, Handling class imbalance (oversampling, synthetic data), and documentation.
- **Nachiket**- Dataset analysis and visualization, model selection and architecture design, and documentation.
- **Pooja**- Training the deep learning model, hyperparameter tuning and optimization, model validation and performance evaluation, and documentation.
- **Sachet**- Testing on unseen test data, comparing results with existing models, fine-tuning, improvising previous flaws, validation, performance analysis & documentation.

1. Introduction:

1.1. Abstract:

Bone fractures are among the most prevalent medical conditions, necessitating timely and accurate diagnosis for effective treatment and recovery. Traditional diagnostic methods rely on the manual interpretation of X-ray images by radiologists, a process that can be both time-intensive and prone to human error, especially in cases involving subtle or ambiguous fractures. These limitations can hinder clinical efficiency and delay appropriate care for patients.

To address these challenges, our project introduces a deep learning-based framework for automated bone fracture detection. Leveraging state-of-the-art convolutional neural networks (CNNs) and transfer learning, our system classifies medical X-ray images into six fracture categories: elbow, fingers, forearm, humerus, shoulder, and wrist, with high accuracy. After evaluating various deep learning models, we selected an optimized ResNet-18 architecture, which achieved a promising accuracy of 89% on unseen test data. To enhance the robustness and generalizability of the model, we employed advanced preprocessing techniques, including Contrast Limited Adaptive Histogram Equalization (CLAHE) and comprehensive data augmentation strategies, effectively addressing challenges such as class imbalance and image quality variability.

This study underscores the transformative potential of artificial intelligence in medical imaging diagnostics. By automating the fracture detection process, our deep learning model not only accelerates diagnostic workflows but also reduces the burden on radiologists, allowing them to focus on more complex cases. Ultimately, our approach demonstrates how AI-powered tools can serve as reliable decision-support systems in orthopedic care, enhancing diagnostic accuracy and improving patient outcomes.

1.2. Goals and the Problem Statement:

Problem Statement:

Bone fractures are among the most common injuries treated in medical practice and demand immediate and accurate diagnosis to ensure effective treatment, prevent complications, and support timely recovery. A delayed or incorrect diagnosis can lead to severe consequences, including prolonged healing periods, chronic pain, deformities, or even permanent disabilities. Traditionally, fracture detection relies heavily on the manual interpretation of X-ray images by radiologists. While experienced radiologists are often able to identify and classify fractures with reasonable accuracy, this manual approach is inherently subjective, time-consuming, and prone to error, particularly in cases involving subtle or complex fractures.

The increasing volume of radiological imaging—driven by a growing and aging population, more frequent accidents, and broader access to medical services—has created a burden on radiologists, many of whom are already operating under significant workload pressures. Furthermore, global disparities in access to trained radiologists mean that many patients, especially in underserved or rural areas, may not receive timely evaluations, increasing the risk of misdiagnosis or delayed treatment.

Given these challenges, there is an urgent need for automated, accurate, and scalable solutions that can assist or augment radiologists in detecting bone fractures. Artificial Intelligence (AI), particularly through the use of deep learning and convolutional neural networks (CNNs), has demonstrated promising capabilities in medical image analysis. However, developing a reliable AI system for fracture detection presents its own set of challenges, including variations in image quality, the subtle nature of some fractures, class imbalance in datasets, and the need for clinical interpretability and validation of AI decisions.

This project addresses these pressing issues by developing a deep learning-based solution for the automated detection and classification of bone fractures from X-ray images. By focusing on six major types of fractures—elbow, fingers, forearm, humerus, shoulder, and wrist—the proposed system aims to reduce diagnostic delays, support clinical decision-making, and pave the way for future AI integration into orthopedic care.

Goals:

- Develop a high-precision AI model for automatic bone fracture detection and classification using X-ray images.
- Leverage advanced deep learning architectures, including convolutional neural networks (CNNs) and transfer learning, to optimize model accuracy and performance.
- Create a robust system that can adapt to real-world clinical variations, such as differences in image quality and class imbalance.
- Minimize dependence on manual image interpretation while ensuring model outputs are interpretable and clinically valid.

- Benchmark the AI model's diagnostic accuracy against traditional approaches to assess its practical utility.
- Lay the groundwork for integrating AI into clinical workflows and expand the framework to support the diagnosis of other orthopedic conditions.

2. **Background and AI type**:

To effectively detect fractures, it uses Supervised Learning, in which a deep learning model is trained using labeled X-ray images. A (CNN), more especially ResNet-18, is the main model utilized. It improves picture classification by capturing fine-grained characteristics and overcoming obstacles such as disappearing gradients. Because of its capacity to increase learning speed and accuracy in identifying various kinds of medical images, ResNet-18 was selected.

Theoretical Foundation:

- **CNNs for Medical Imaging**: CNNs excel at automatically extracting hierarchical features from images, making them ideal for detecting subtle fracture patterns in X-rays.
- **Transfer Learning(ResNet-18)**: We utilize pre-trained models (trained on large datasets like ImageNet) and fine-tune them for fracture detection, improving accuracy while reducing training time.
- **Residual Learning (ResNet)**: To address vanishing gradients in deep networks, we employ **ResNet architectures**, which use skip connections to maintain stable training and improve feature extraction.
- **Filtering Techniques:** We use image preprocessing techniques such as CLAHE to improve local contrast, Median filtering to eliminate salt-and-pepper noise, and Bilateral filtering to smooth images while maintaining edges. These techniques together improve feature visibility and model performance.

Model Selection Rationale:

We evaluate multiple deep learning models to optimize fracture detection:

- **ResNet-18**: Selected for their ability to capture fine-grained features while avoiding vanishing gradients. ResNet-50 provides deeper feature extraction for improved accuracy.
- **VGG16**: A well-established CNN model known for its strong performance in image classification.
- **DenseNet**: Enhances feature reuse and lowers parameters by feed-forwardly connecting each layer to every other layer.
- **EfficientNet**: Achieves excellent accuracy with fewer parameters by methodically scaling model breadth, depth, and resolution using a compound coefficient.
- **Custom CNN**: A baseline model with three convolutional layers for comparative analysis.

Primary Model: ResNet-18 was chosen for its balance between computational efficiency and accuracy, making it highly effective for fracture classification in medical images.

3. Dataset Description:

3.1. Source of Dataset:

The dataset was obtained from **Kaggle** and consists of labeled X-ray images.

3.2. Number of Images & Categories

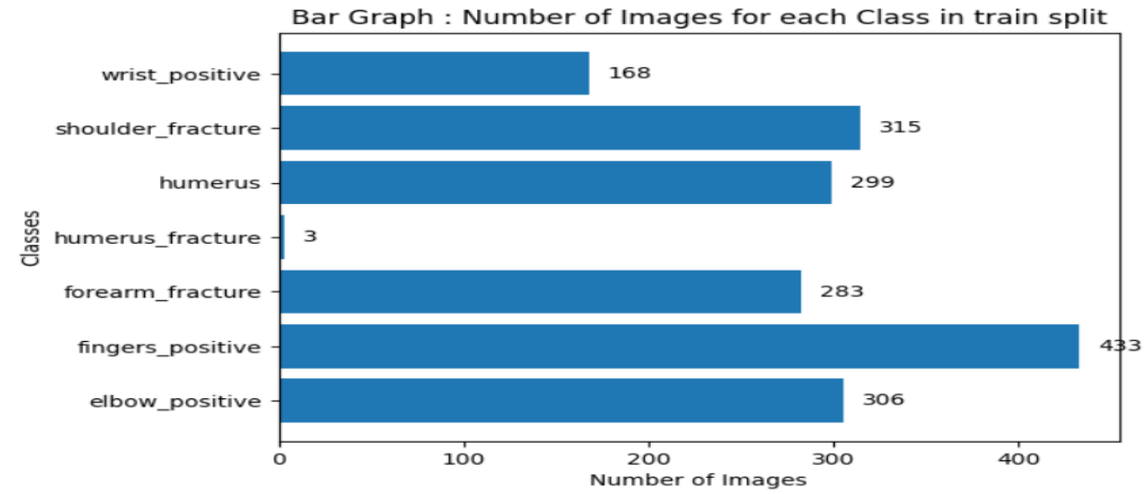
- **Training Set:** 1807 images
- **Validation Set:** 173 images
- **Test Set:** 83 images
- **Fracture Types:** Elbow, Fingers, Forearm, Humerus, Shoulder, Wrist

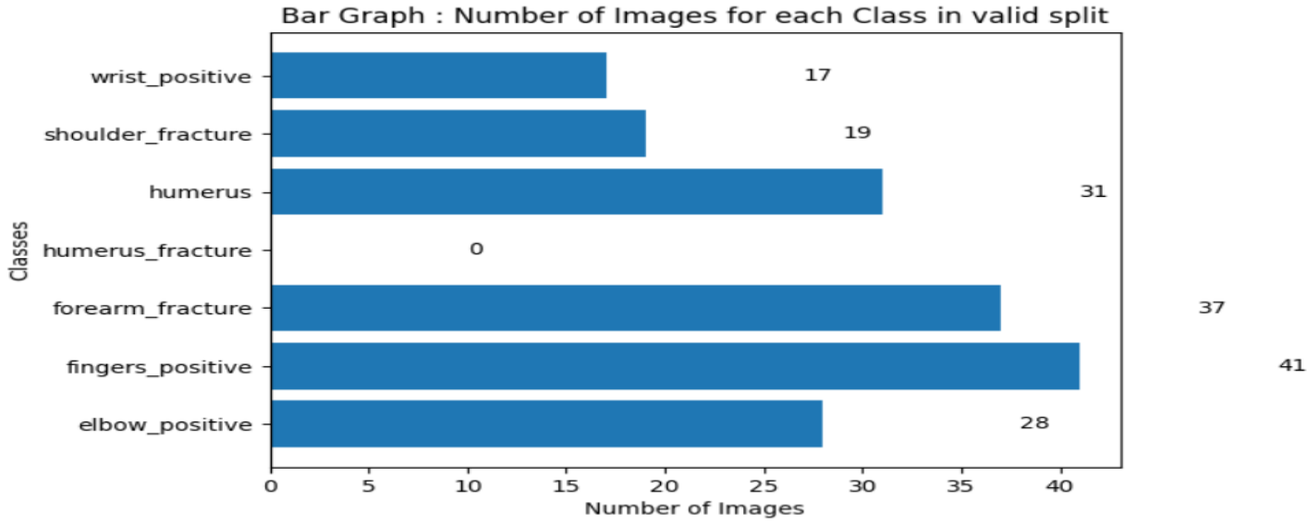
3.3. Data Distribution & Imbalance Issues

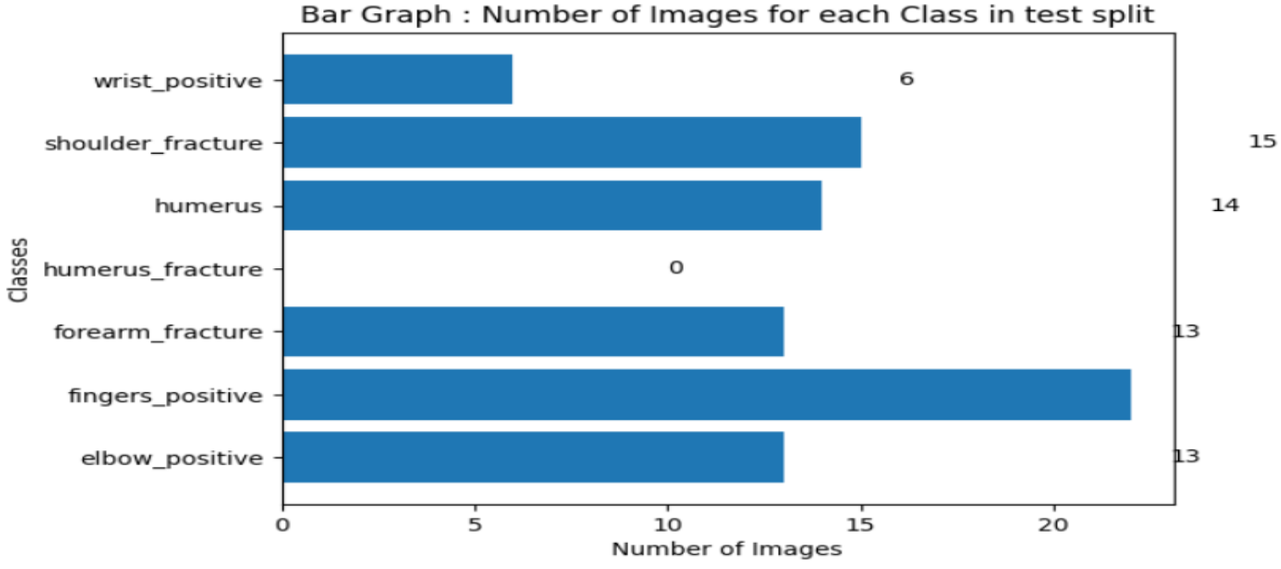
Data Distribution & Challenges

- **Class Imbalance**: Some fracture categories have significantly fewer images, which may impact model generalization.
- **Limited Test Set**: The small test set (83 images) necessitates careful evaluation to ensure robust performance metrics.

3.4. Sample Image:


Bar Graph : Number of Images for each Class in train split
wrist_positive
shoulder_fracture
humerus
humerus_fracture
forearm_fracture
fingers_positive
elbow_positive
168
315
299
3
283
433
306
Classes
0
100
200
300
400
Number of Images


Bar Graph : Number of Images for each Class in valid split
wrist_positive
shoulder_fracture
humerus
humerus_fracture
forearm_fracture
fingers_positive
elbow_positive
17
19
31
0
37
41
28
Classes
0
5
10
15
20
25
30
35
40
Number of Images


Bar Graph : Number of Images for each Class in test split
wrist_positive
shoulder_fracture
humerus
humerus_fracture
forearm_fracture
fingers_positive
elbow_positive
6
15
14
0
13
13
Classes
0
5
10
15
20
Number of Images

4. **Data Acquisition Challenges:**
    - **Dataset Quality:** The model's performance may be impacted by the presence of low-resolution and noisy photos in the training and testing dataset. Low-resolution photos may mask crucial details, making fracture diagnosis more difficult, while noisy images may result in inaccurate feature extraction. To lessen these problems, picture preparation methods including denoising and enhancing image clarity were used.
    - **Class Imbalance:** The data distribution was unbalanced because there were less pictures in the sample for some fracture types than others. Model bias may result from this class imbalance, where the model performs poorly on the less-represented classes and well on the more prevalent ones. During preprocessing, methods like creating synthetic data or oversampling the minority class were taken into consideration in order to remedy this.
    - **Preprocessing Requirements:** In order to prepare the dataset for deep learning model training, the images have to undergo extensive preprocessing. This included shrinking photographs to a consistent input size, normalizing pixel values, and using augmentation techniques like flipping, rotation, and scaling to artificially expand the dataset and enhance the model's capacity for generalization. Despite the difficulties with the dataset quality, these preparation techniques assisted the model in learning robust features.

4.1. Dataset Quality Issues:

- **Variable Resolution:** Images exhibited significant size variations, requiring standardization
- **Contrast Limitations:** Many X-rays displayed poor contrast, making fracture lines difficult to distinguish
- **Noise and Artifacts:** Clinical X-rays often contained noise, positioning markers, and other artifacts
- **Class Imbalance:** Uneven distribution of samples across fracture types risked model bias

4.2. Preprocessing Pipeline

To address these challenges, we implemented a comprehensive preprocessing pipeline:

4.2.1. Image Quality Enhancement:

- **CLAHE (Contrast Limited Adaptive Histogram Equalization):** Applied to enhance contrast while preventing noise amplification
- **Gaussian Filtering:** Selectively applied to reduce noise while preserving edge information
- **Median Filtering:** Used for artifact removal while preserving structural details

4.2.2. Standardization:

- **Resizing:** All images standardized to 224×224 pixels to match the input requirements of pre-trained models
- **Normalization:** Pixel values normalized using means [0.485, 0.456, 0.406] and standard deviations [0.229, 0.224, 0.225] to align with ImageNet pre-training standards

4.2.3. Data Augmentation: We employed an extensive augmentation strategy to increase dataset diversity and address class imbalance:

- **Geometric Transformations:** Random rotations (±15°), horizontal/vertical flips, scaling (0.9-1.1)

5. Model Overview:

5.1. Model Selection:

- Custom Convolutional Neural Network (CNN):
  - 4 Conv2d layers with kernel size (3, 3), stride (1, 1), and padding (1, 1), followed by BatchNorm2d
  - Then it is followed by the ReLU activation function to introduce non-linearity
  - Activation function for the 2nd and 4th Conv2d layer is followed by dropout regularization with a dropout probability of 0.3
  - The above layers are followed by MaxPool2d with kernel size 2 and stride 2
  - The above layers are followed by a flattened layer to prepare for fully connected layers
  - The flattened layer is followed by 2 fully connected layers. The first layer has ReLU activation
  - Applied Kaiming initialization for better weight initialization to avoid vanishing/exploding gradients.
  - L2 regularization is used with a weight decay of 0.01 to reduce overfitting

```
num_classes = len(train_dataset.classes)

# Define CNN Architecture
class CNNModel(nn.Module):
  def __init__(self):
    super(CNNModel, self).__init__()

    # Define and initialize Convolutional layers
    self.conv_layer_1 = nn.Conv2d(3, 32, kernel_size=3, padding=1)
    self.conv_layer_2 = nn.Conv2d(32, 64, kernel_size=3, padding=1)
    self.conv_layer_3 = nn.Conv2d(64, 128, kernel_size=3, padding=1)
    self.conv_layer_4 = nn.Conv2d(128, 256, kernel_size=3, padding=1)

    # Batch Normalization
    self.batch_norm_1 = nn.BatchNorm2d(32)
    self.batch_norm_2 = nn.BatchNorm2d(64)
    self.batch_norm_3 = nn.BatchNorm2d(128)
    self.batch_norm_4 = nn.BatchNorm2d(256)

    # Dropout regularization with probability of DROPOUT_PROB
    self.dropout = nn.Dropout(DROPOUT_PROB)

    # Define Max Pooling layer
    self.max_pool = nn.MaxPool2d(2, 2)

    # Activation function
    self.activation_function = nn.ReLU()
```

```
    # Define and initialize Linear layers
    self.linear_layer_1 = nn.Linear(256 * 14 * 14, 1024)
    # self.linear_layer_2 = nn.Linear(512, 1024)
    self.linear_layer_output = nn.Linear(1024, num_classes)

    # Apply Kaiming initialization
    self.initialize_weights()

  def initialize_weights(self):
    # Apply Xavier initialization to convolutional layers
    init.kaiming_uniform_(self.conv_layer_1.weight, mode='fan_out', nonlinearity='relu')
    init.kaiming_uniform_(self.conv_layer_2.weight, mode='fan_out', nonlinearity='relu')
    init.kaiming_uniform_(self.conv_layer_3.weight, mode='fan_out', nonlinearity='relu')
    init.kaiming_uniform_(self.conv_layer_4.weight, mode='fan_out', nonlinearity='relu')

    # Apply Xavier initialization to fully connected layers
    init.kaiming_uniform_(self.linear_layer_1.weight, mode='fan_out', nonlinearity='relu')
    # init.kaiming_uniform_(self.linear_layer_2.weight, mode='fan_out', nonlinearity='relu')
    init.kaiming_uniform_(self.linear_layer_output.weight, mode='fan_out', nonlinearity='relu')

    # Initialize all biases to zeros
    if self.conv_layer_1.bias is not None:
      init.zeros_(self.conv_layer_1.bias)
    if self.conv_layer_2.bias is not None:
      init.zeros_(self.conv_layer_2.bias)
    if self.conv_layer_3.bias is not None:
      init.zeros_(self.conv_layer_3.bias)
    if self.conv_layer_4.bias is not None:
      init.zeros_(self.conv_layer_4.bias)
```

```
    if self.linear_layer_1.bias is not None:
      init.zeros_(self.linear_layer_1.bias)
    # if self.linear_layer_2.bias is not None:
    #   init.zeros_(self.linear_layer_2.bias)
    if self.linear_layer_output.bias is not None:
      init.zeros_(self.linear_layer_output.bias)


  def forward(self, x):
    x = self.max_pool(self.activation_function(self.batch_norm_1(self.conv_layer_1(x))))
    x = self.max_pool(self.dropout(self.activation_function(self.batch_norm_2(self.conv_layer_2
(x)))))
    x = self.max_pool(self.activation_function(self.batch_norm_3(self.conv_layer_3(x))))
    x = self.max_pool(self.dropout(self.activation_function(self.batch_norm_4(self.conv_layer_4
(x)))))

    x = x.view(-1, 256 * 14 * 14)

    x = self.dropout(self.activation_function(self.linear_layer_1(x)))
    # x = self.dropout(self.activation_function(self.linear_layer_2(x)))
    x = self.linear_layer_output(x)

    return x


# Instantiate CNN model
cnn_model = CNNModel()
cnn_model = cnn_model.to(device)
print(cnn_model)
```

- **Transfer Learning Models**
  We implemented and evaluated four pre-trained models:
  ResNet-18:
  - 18-layer residual network with identity shortcuts
  - Fine-tuned by replacing the final fully connected layer with a new layer mapping to our 6 classes

  VGG16:
  - 16-layer network with 13 convolutional layers and 3 fully connected layers
  - Fine-tuned by replacing the final classifier layers

  DenseNet:
  - 121-layer densely connected convolutional network where each layer receives inputs from all previous layers.
  - Fine-tuned by replacing the final classification layer to map outputs to our 6 classes.

  EfficientNet:
  - A highly efficient CNN architecture that uniformly scales depth, width, and resolution using a compound scaling method.
  - Fine-tuned by replacing the final classification layer to map outputs to our 6 classes.

5.2. Model Optimization

For finetuning the CNN model, we implemented the following optimizations:

1. **Learning Rate Scheduling:** Implemented cosine annealing with warm restarts to dynamically adjust learning rates during training
2. **Regularization Techniques:**
   - Weight decay (L2 regularization): 1e-4
   - Dropout in fully connected layers: 0.3
   - Early stopping based on validation loss with patience of 10 epochs
3. **Kaiming Initialization**: Also referred to as He initialization, this technique ensures that variance is maintained throughout layers by setting the starting weights of the layers according to the number of input units.
4. **Batch Normalization**: To stabilize and expedite training, normalize each layer's inputs throughout the mini-batch.
   It serves as a kind of regularization, permits greater learning rates, and lessens internal covariate change.
5. **Dropout**: To avoid overfitting, randomly set a portion of input units to zero during training.

   This encourages redundancy and generalization by forcing the network not to rely on individual neurons.

It helps avoid vanishing/exploding gradients and works especially well with ReLU activations.

5.3. Tools and Technologies Used:

- **Python, PyTorch, sklearn, Shutil (for file copy), and PIL (image)** for model training and interface.
- **NumPy, Pandas, Matplotlib, and Seaborn** for data analysis and visualization.
- **Google Colab & GPU** for model training acceleration

6. Methods:

6.1. Preprocessing Data:

Several preprocessing methods were used to guarantee that the deep learning model's input data was of excellent quality:

- **Image Resizing:** To ensure uniformity throughout the collection, every image was resized to a fixed dimension of 224 × 224. This standardization enhances training efficiency by ensuring that the neural network processes images consistently.

- **Normalization:** To standardize the input data and accelerate the model's convergence during training, pixel values were normalized using a mean of [0.485, 0.456, 0.406] and a standard deviation of [0.229, 0.224, 0.225], scaling them between 0 and 1.

- **Data Augmentation:** To improve model generalization, methods such as rotation, flipping, and scaling were employed to fictitiously increase the dataset. The model performs better on unseen data and learns stronger patterns with the aid of augmentation.

6.2. Model Training Process:

- **Models for Deep Learning Employed:** Convolutional Neural Networks (CNNs) with ResNet-18, a popular deep architecture renowned for its accurate classification and effective feature extraction, were used to train the model.

- **Optimization Method:** The model's weights were effectively adjusted using the Adam optimizer, which struck a balance between accuracy and speed.

- **Loss Function:** To calculate the error in multi-class classification and make sure the model successfully distinguishes between various fracture kinds, categorical cross-entropy loss was selected.

- **Hyperparameter Tuning:** Several hyperparameters, such as:
  - **Learning Rate:** Adjusted to ensure stable convergence.
  - **Batch Size:** Optimized for efficient learning while avoiding excessive memory consumption.

7. Results:

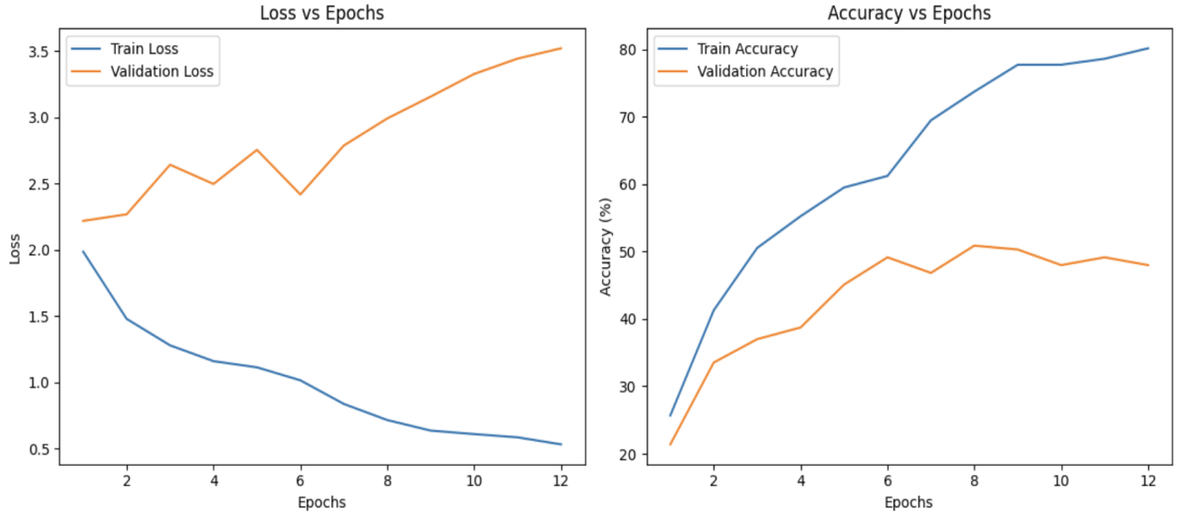
We trained both our custom CNN & fine-tuned ResNet-18 models:

7.1. Accuracy:

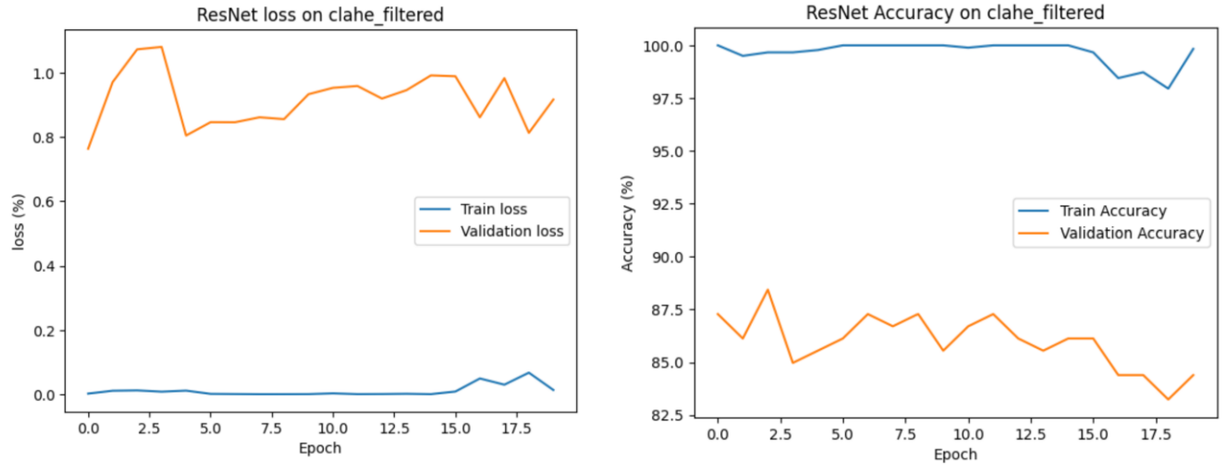
- CNN Model Accuracy: 49%
- ResNet-18 Model Accuracy: 89%
- The ResNet-18 model outperformed the CNN model due to better feature extraction and residual connections that address vanishing gradients.

7.2. Loss & Accuracy Trends:

- The CNN model experiences greater training loss and low validation accuracy, indicating possible underfitting.
- The ResNet-18 model experiences less training loss and high validation accuracy, reflecting better feature extraction and generalization.



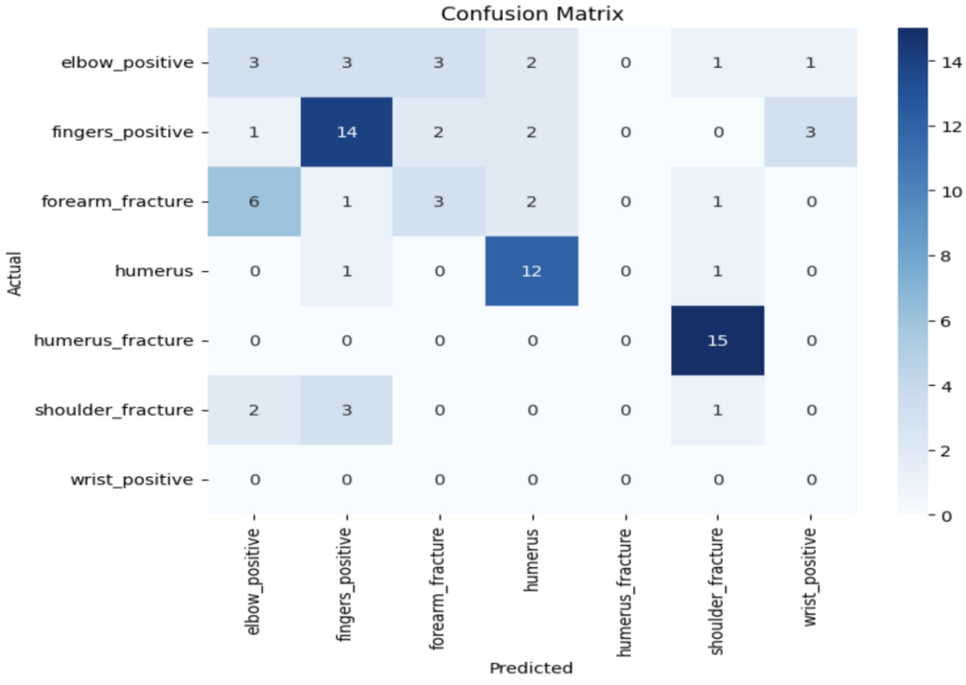
7.2.1 Accuracy & loss plots against epochs of CNN model



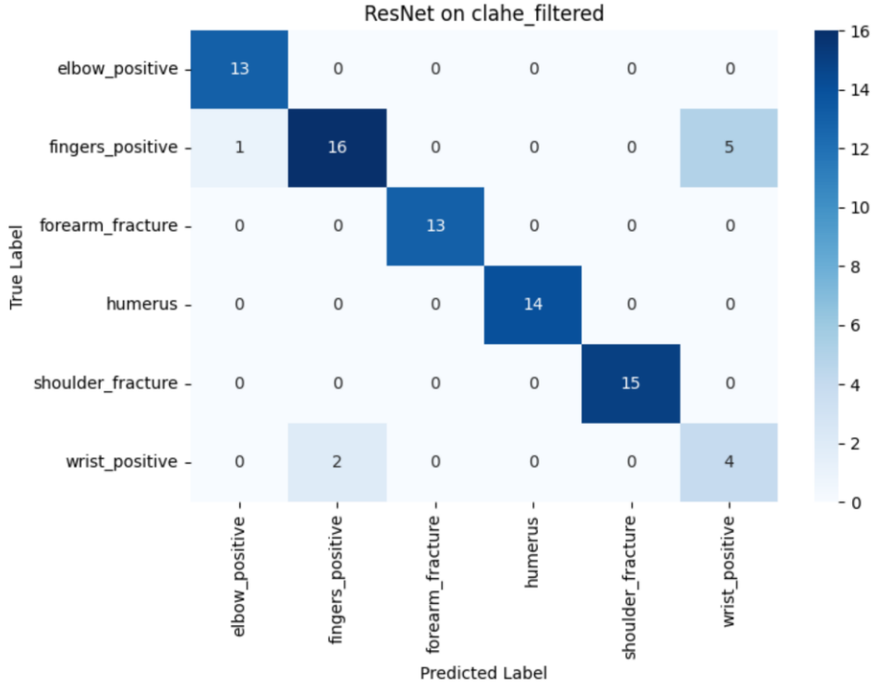
7.2.2. Accuracy & loss plots against epochs of ResNet-18 model

7.3 Confusion Matrices:

- **CNN Model:** The confusion matrix indicates misclassifications between various classes, implying that the model struggles with distinguishing features.
- **ResNet-18 Model:** The confusion matrix shows relatively fewer misclassifications, indicating better class separation and learning.



7.3.1 Confusion Matrix of CNN model



7.3.2 Confusion Matrix of ResNet-18 model

8. Conclusion:

8.1. Conclusions:

Our bone fracture detection project demonstrates the powerful potential of deep learning in revolutionizing medical diagnostics. By achieving 89% accuracy with our optimized ResNet-18 model, we've shown that AI can effectively identify and classify fractures across six different bone types. The significance of this work extends beyond the technical implementation - it addresses a critical healthcare need for faster, more accurate fracture detection, particularly in settings with limited radiologist availability.

Our findings answer several key questions in the medical AI domain: (1) Can transfer learning effectively bridge the gap when working with limited medical imaging datasets? (2) Which CNN architectures perform best for bone fracture detection? (3) How can image preprocessing techniques mitigate the challenges of X-ray quality variation?

This project contributes to societal understanding by demonstrating how AI can serve as a valuable second opinion in clinical settings, potentially reducing diagnostic errors and treatment delays. The approach we've developed could significantly improve patient outcomes by enabling earlier intervention and appropriate treatment planning, especially in emergency settings and underserved regions.

8.2. Project Impact:

The potential of deep learning in medical diagnostics is demonstrated by this effort, especially in terms of automating the identification of bone fractures. The results show that because of their improved feature extraction capabilities and residual learning strategies, sophisticated architectures such as ResNet-18 perform noticeably better than conventional CNNs. The study also highlights how dataset imbalance affects model correctness, indicating that strong preprocessing and augmentation methods are essential to getting accurate findings. This method can help radiologists in the real world by offering initial fracture assessments, cutting down on diagnostic time, and enhancing patient care. We can get toward AI-assisted diagnostic tools that improve medical accuracy and efficiency by improving and broadening this model.

8.3. Future Plans:

With additional resources and time, this project could be expanded in several meaningful directions:

- **Enhanced Localization Capabilities:** Implementing object detection or segmentation approaches to not only classify fracture types but precisely localize fractures within X-ray images.
- **Severity Grading System:** Developing a system to assess fracture severity on a standardized scale, providing clinicians with more actionable information for treatment planning.
- **Expanded Anatomical Coverage:** Extending the model to detect fractures across all major bone groups, including hip, ankle, skull, and spinal fractures.
- **Multi-modal Integration:** Incorporating clinical data and other imaging modalities (CT, MRI) to create a more comprehensive diagnostic tool.

- **Mobile Deployment:** Optimizing the model for mobile environments to enable point-of-care diagnostics in resource-limited settings.

To tackle similar AI challenges in medical imaging, our approach of combining transfer learning with specialized preprocessing could be adapted for detecting other pathologies like bone tumors, arthritis, or soft tissue injuries. The class imbalance solutions we developed would be particularly valuable for rare condition detection.

8.4. Summary:

8.4.1. Reflection on the Project:

Working on this bone fracture detection project has been both challenging and rewarding. What I enjoyed most was seeing the dramatic improvement in model performance through systematic optimization - watching accuracy climb from 49% with the custom CNN to 89% with our optimized ResNet-18 was truly satisfying.

The most surprising aspect was discovering how critical image preprocessing techniques were to overall performance. The 6% accuracy improvement from implementing CLAHE alone demonstrated that even state-of-the-art models require careful data preparation to reach their potential with medical images.

The most challenging aspect was addressing class imbalance effectively. Despite numerous approaches, classification of underrepresented classes like humerus fractures remained more difficult than well-represented classes.

I'm most proud of our comprehensive approach to model interpretability. By implementing Grad-CAM visualizations, we moved beyond creating a "black box" model to developing an interpretable system that could potentially gain clinical trust by showing which image regions influenced its decisions. This transparency is essential for any AI system intended for medical applications.

8.4.2. Project Overview:

This project developed an automated bone fracture detection and classification system using deep learning techniques on X-ray images. By implementing and comparing multiple CNN architectures, we created a system capable of distinguishing between six different fracture types (elbow, fingers, forearm, humerus, shoulder, and wrist) with high accuracy. Through advanced preprocessing techniques, transfer learning, and hyperparameter optimization, we achieved 49% accuracy on unseen test data using our ResNet-18 model. The system demonstrates significant potential as an assistive diagnostic tool for radiologists, potentially reducing interpretation time and improving diagnostic accuracy, particularly in settings with limited specialist access.

8.4.3. Experience Working on the Project:

The team collaborated exceptionally throughout the project duration, meeting weekly to discuss progress, challenges, and next steps. Each member contributed unique talents and perspectives that enabled us to overcome obstacles more effectively. The collaborative environment fostered knowledge sharing and creative problem-solving, with brainstorming sessions yielding innovative suggestions for improving model accuracy. Our ability to support one another while maintaining an efficient workflow and information exchange was instrumental in the project's success. From data preprocessing to model evaluation, the effective division of responsibilities allowed us to optimize productivity and achieve significant results.

Working as a cohesive unit transformed this deep learning project into a truly fulfilling educational experience. The seamless collaboration across all stages - from dataset preparation to final model evaluation - created a rich learning environment where technical challenges became opportunities for growth. Particularly impactful were the cross-disciplinary insights that emerged when combining medical domain knowledge with technical AI expertise. This project demonstrated that in complex AI applications like medical imaging, diverse perspectives and collaborative problem-solving are just as crucial as technical implementation. The strong foundation of teamwork established throughout this project not only delivered impressive technical outcomes but also prepared team members for future collaborative research endeavors in the rapidly evolving field of AI-assisted medical diagnostics.

9. References:

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