Bone Fractures Classification Using Deep Learning

Submitted By-

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About the Project

- The project focuses on developing a deep learning model to classify the bone X-ray images into two categories fractured and not fractured using Transfer Learning Approach.
- The primary goal is to assist medical professionals by providing a reliable second opinion for detecting bone fractures.
- Leveraging image-based classification techniques, the model learns visual patterns associated with fractures and aims to improve diagnosis efficiency and accuracy.
- The project uses supervised learning on the medical dataset and evaluates performance using standard classification metrics.
- The well known pre-trained EfficientNet model and pre-trained VGG16 model was used in this project for classification task for better results. Where, in the output layer of VGG16 model we used 50% dropout rate.

Dataset Statistics & Samples

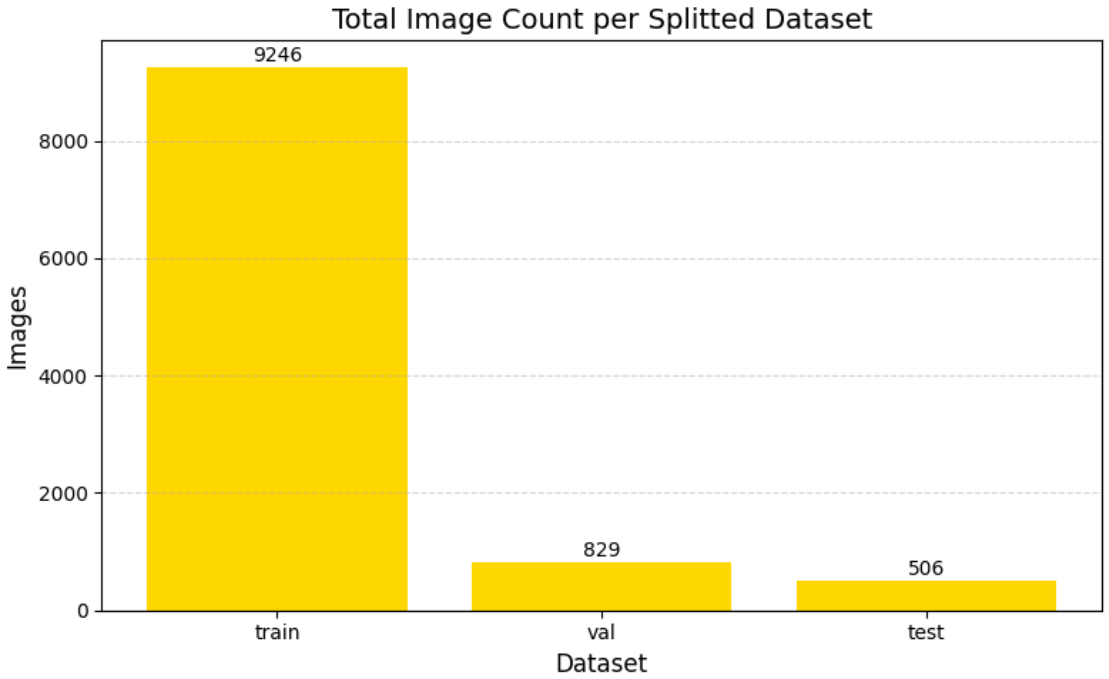

Figure-1: Dataset total samples

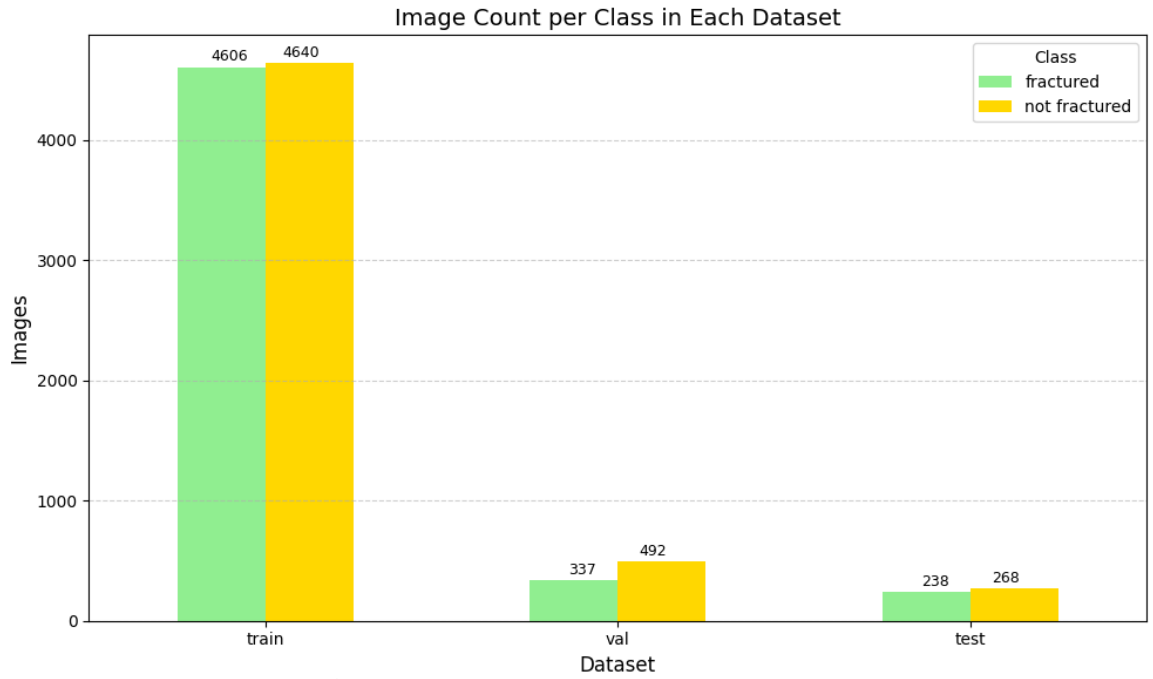

Figure-2: Dataset total samples over class

Figure-3: Dataset Image samples

Model Learning Curve

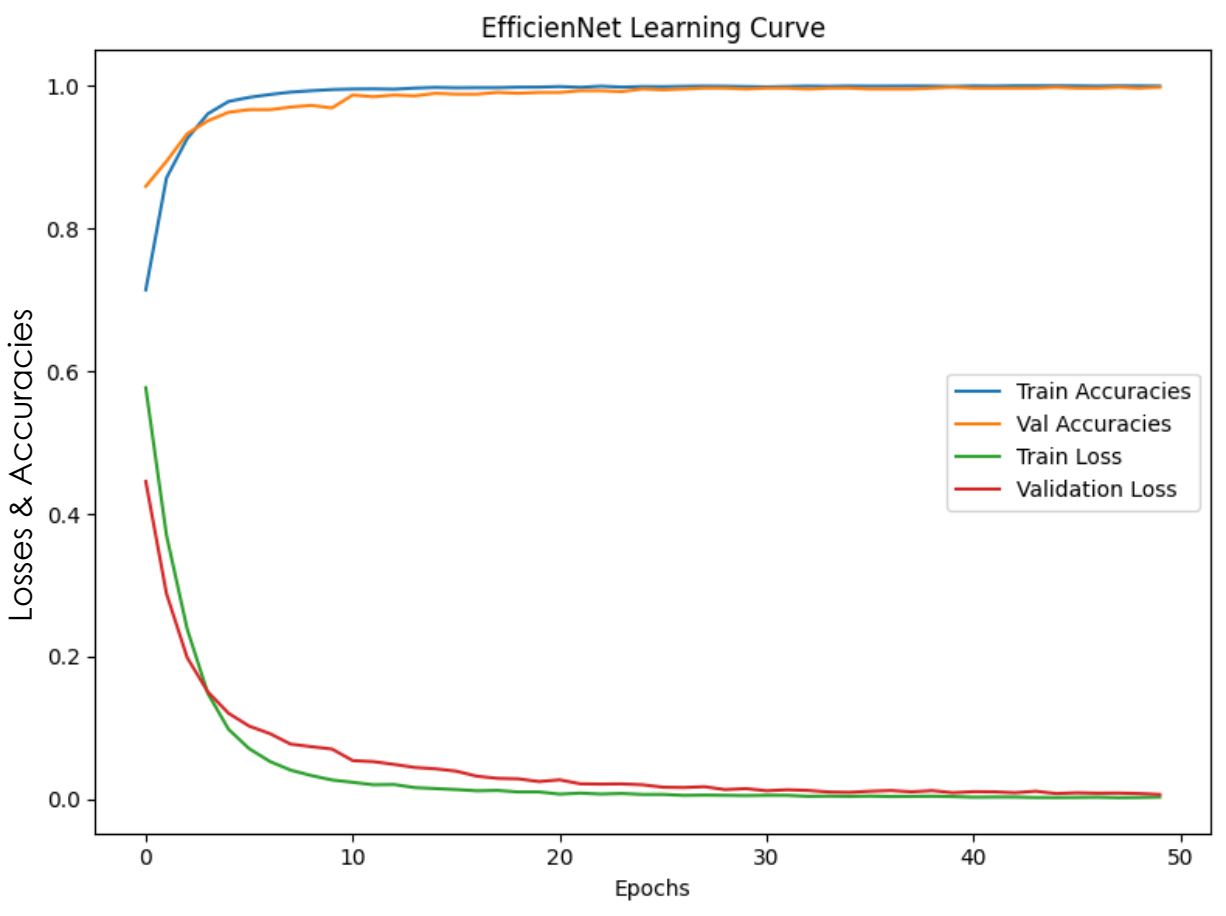

Figure-4: Model Learning Performance Curve Losses & Accuracies over Epoch

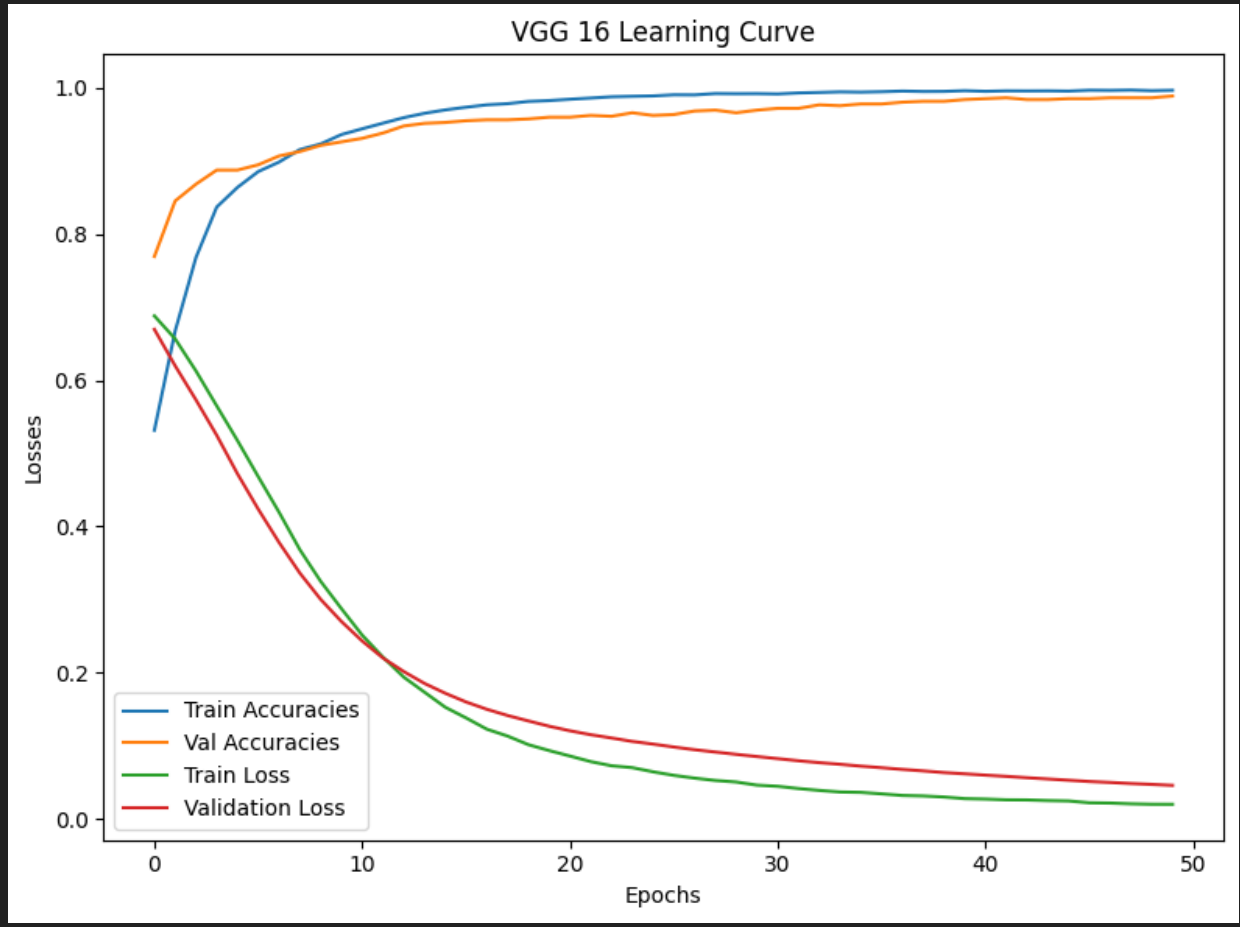

Figure-5: VGG Model Learning Performance Curve Losses & Accuracies over Epoch

Model Status

EfficientNet

- **Model Total Parameters:** 4.01 Million
- **Model Trainable Parameters:** 4.01 Million
- **No of Epoch:** 50
- **Early Stopping:** True
- **Total Training Time:** 57.0m 29s
- **Average Epoch Time:** 01m 20s to 01m 30s
- **Environment**: Kaggle Notebook with P100 GPU

VGG16

- **Model Total Parameters:** 134.27 Million
- **Model Trainable Parameters:** 134.27 Million
- **No of Epoch:** 50
- **Early Stopping:** True
- **Total Training Time:** 1h 32.0m 45s
- **Average Epoch Time:** 03m 20s to 03m 30s
- **Environment**: Kaggle Notebook with P100 GPU

Regularization and Optimization (both model)

- **Loss Function:** Cross Entropy Loss
- **Optimizer:** Stochastic Gradient Descent (SGC)
  - **Learning Rate = 0.001 (0.001 for VGG16)**
  - **Momentum = 0.9**
  - **Weight Decay = 1e-4 (L2 Regularization)**
- **Scheduler: ReduceLROnPlateau**
  - **Mode = min (decreasing validation loss)**
  - **Factor = 0.1 (reduces the learning rate by 10x)**
  - **Patience = 5 (wait patience before reducing the learning rate)**

Model Performance Result

EfficientNet Accuracy Score : 99.21%
VGG16 Accuracy Score : 98.42%

Classification Report:

EfficientNet

	Precision	Recall	F1-score	Support
Fractured	1.00	0.98	0.99	238
Not Fractured	0.99	1.00	0.99	268
Accuracy			0.99	506
Macro Avg	0.99	0.99	0.99	506
	0.99	0.99	0.99	506

VGG16

	Precision	Recall	F1-score	Support
Fractured	0.98	0.98	0.98	238
Not Fractured	0.99	0.98	0.99	268
Accuracy			0.98	506
Macro Avg	0.98	0.98	0.98	506
	0.98	0.98	0.98	506

Model Performance Result (Confusion Matrix)

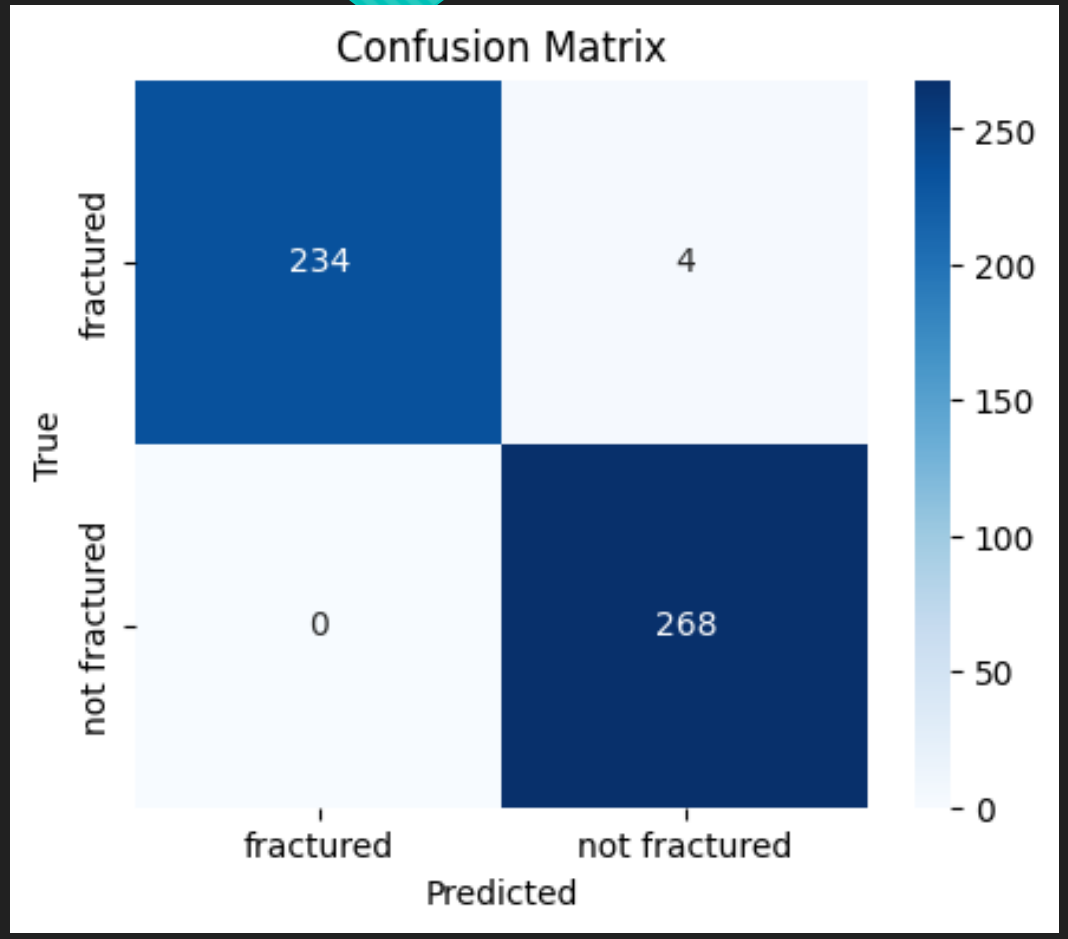

Figure-6: EfficientNet Model Test Performance Confusion Matrix

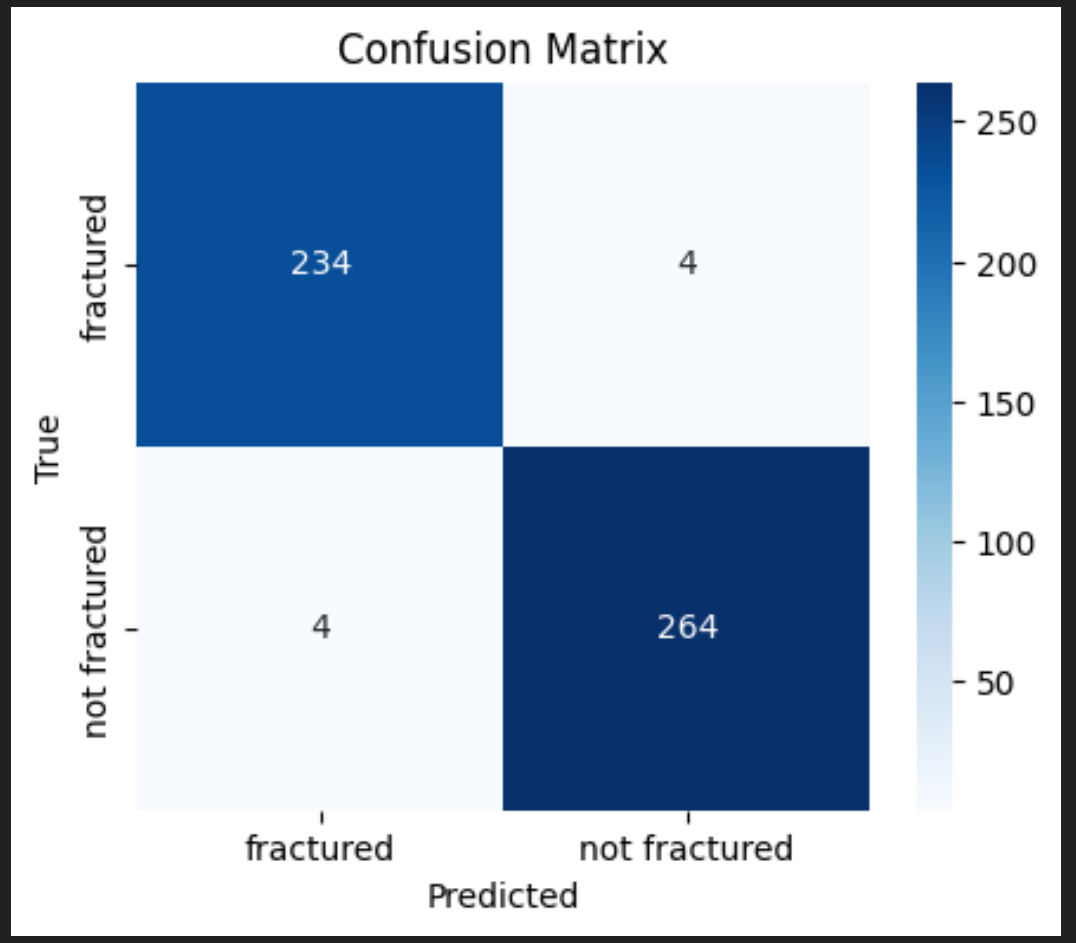

Figure-7: VGG16 Model Test Performance Confusion Matrix

Future Works and Conclusion

Conclusion:

- The EfficientNet Model and VGG16 model was trained using the transfer learning approach to classify bone X-ray images with good accuracy score.
- Both models demonstrates potential as a diagnostic aid in medical imaging. Where the EfficientNet model was trained well for classification Task so it give more better result compare to VGG16.

Future Work:

- Expand the dataset to include different types of fractures and bone regions.
- Incorporate explainable AI (XAI) tools like Grad-CAM to improve model transparency for clinicians.