Bone Break Classification

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Abstract

The bone fracture classification dataset consists of a collection of X-ray images capturing different types of bone breaks. The images cover a range of ten different bone fracture classes. The images in this dataset are not restricted to a specific region of the body. There is also significant variation in the size of the images. For instance, some images are as small as 77x125, whereas others are as large as 640x640. Additionally, the orientation of each image is not standardized. Finally, the images also exhibit varying intensities. Some X-ray images appear to have a very high contrast between the bone and background while others appear more muted.

The intent of this project is to classify each X-ray image into one of these ten bone fracture categories using logistic regression, support-vector machine, and random forest classifiers with the original images and the following engineered features:

- Histogram of Gradients
- Canny Edges
- Contours
- VGG19 Transfer Learning
- Principal Component Analysis

These models with different combinations of these features only achieved a 43% accuracy on the test set at best. It was noted that the training accuracy achieved 100% which indicates poor generalization and overfitting.

Introduction

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Avulsion Fracture

Fracture Dislocation

Comminuted Fracture

Greenstick fracture

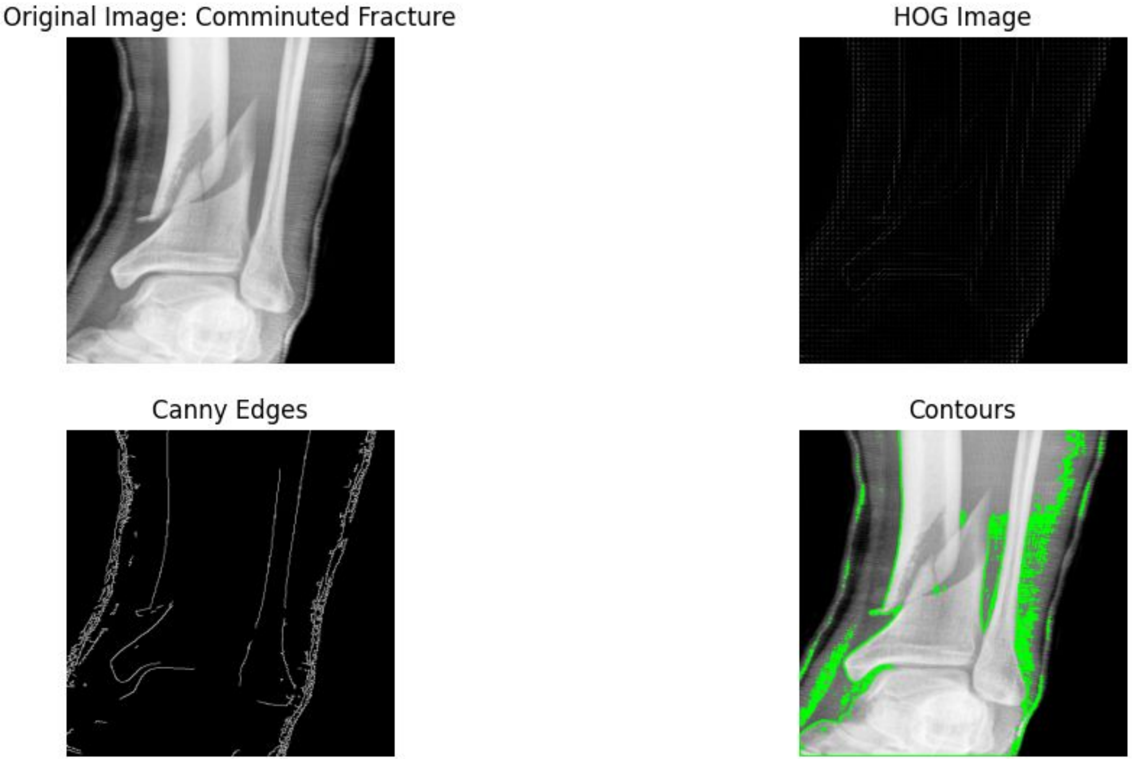
Fractures

Type of Fracture	Description
Avulsion Fracture	characterized by the detachment of a bone fragment due to the pulling force exerted by a tendon or ligament.
Comminuted Fracture	involving the bone being fractured into three or more distinct pieces.
Fracture Dislocation	encompassing both a bone fracture and a concomitant dislocation of the associated joint.
Greenstick fracture	characterized by an incomplete fracture where the bone bends and partially cracks, predominantly observed in pediatric patients.
Hairline Fracture	fine, thin cracks in the bone, often subtle and challenging to detect.
Impacted fracture	occurring when the broken ends of the bone are driven into one another.
Longitudinal fracture	characterized by fracture lines that run parallel to the long axis of the bone.
Oblique fracture	occurring at an angle across the bone, resulting in a diagonal fracture pattern.
Pathological fracture	arising in bones weakened by underlying disease processes.
Spiral fracture	resulting from a rotational force, causing a helical fracture pattern around the bone.

Simple Features

Our top features used are:

1. HOG
2. Canny Edges
3. Contours



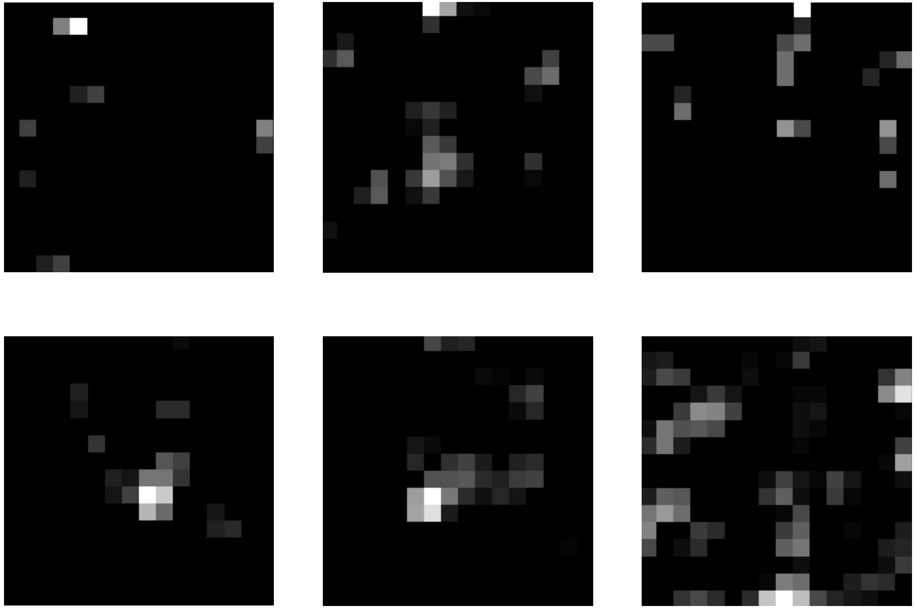
Complex Feature

Complex feature:

1. Tensorflow VGG19 with ImageNet weights

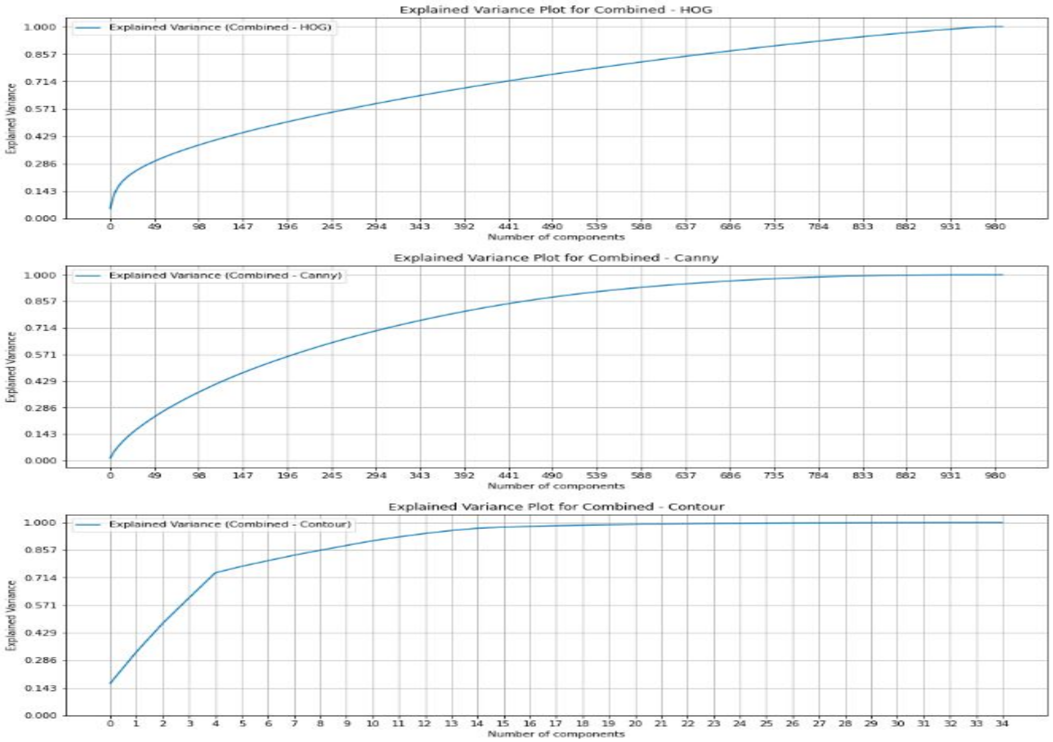
Original Image: Spiral Fracture

VGG19 Features



Dimensionality

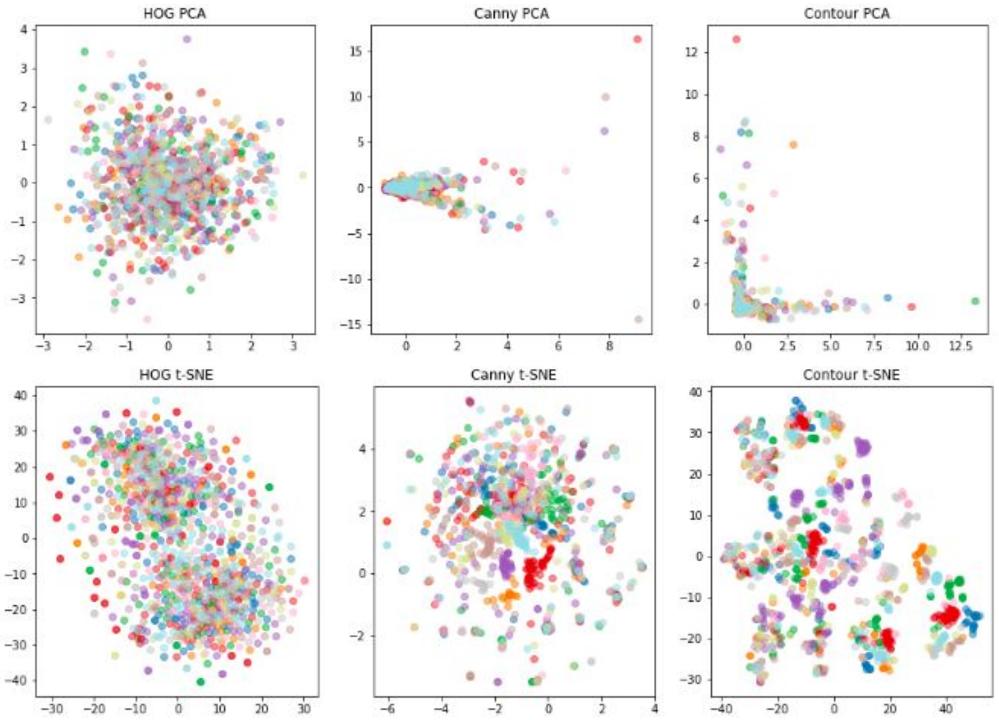
- PCA was ran on all 3 feature vectors
- For Contours and Canny Edges, about half the principal components account for nearly 90% of the variance
- HOG requires more components to capture a higher variance



Dimensionality (PCA and TSNE)

For Canny Edges and Contours, PCA shows that most of the variance is distributed along the first two PC's.

Using t-SNE, we can see some clusters beginning to form



Processing Pipeline

Ingestion

Load

Train / Test sets for all 10 classes

Pre-Processing

Gray-scale

Resize

Histo-gram EQ

Feature Extraction

HOG

Canny Edges

Contours

PCA

VGG19

Model Training

Logistic Reg

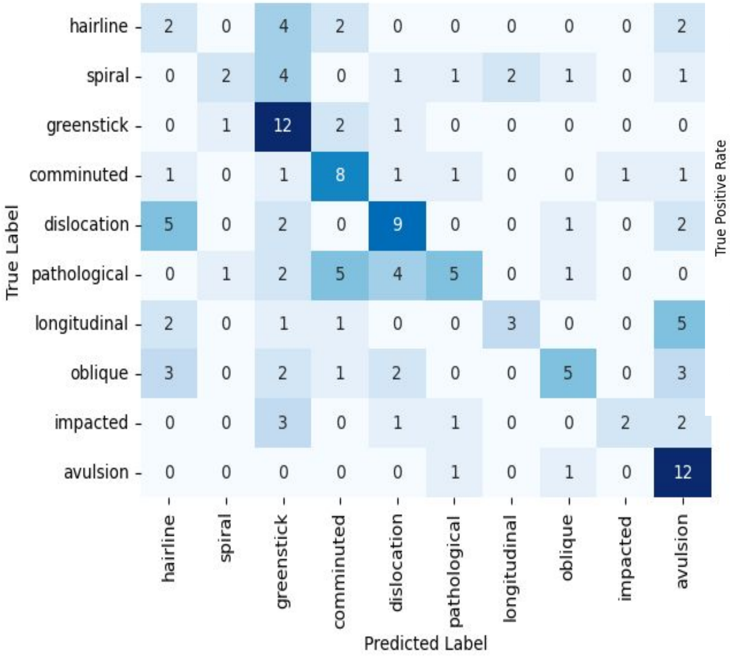
SVM

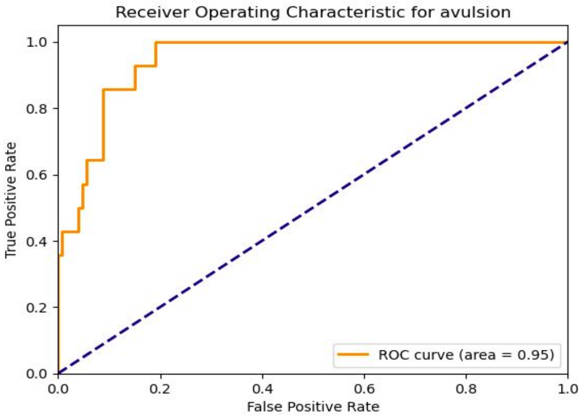
Random Forest

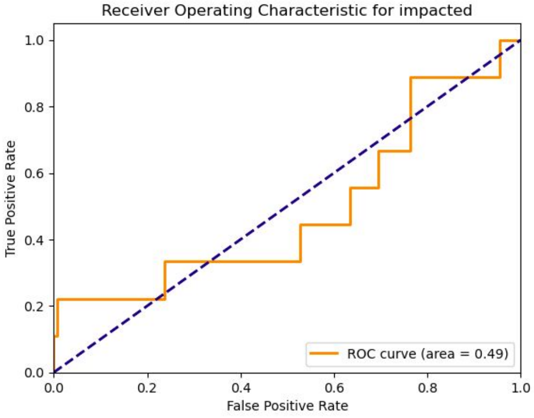
CNN

Baseline image-only model + individual feature models + models with best 2 features

Logistic Regression

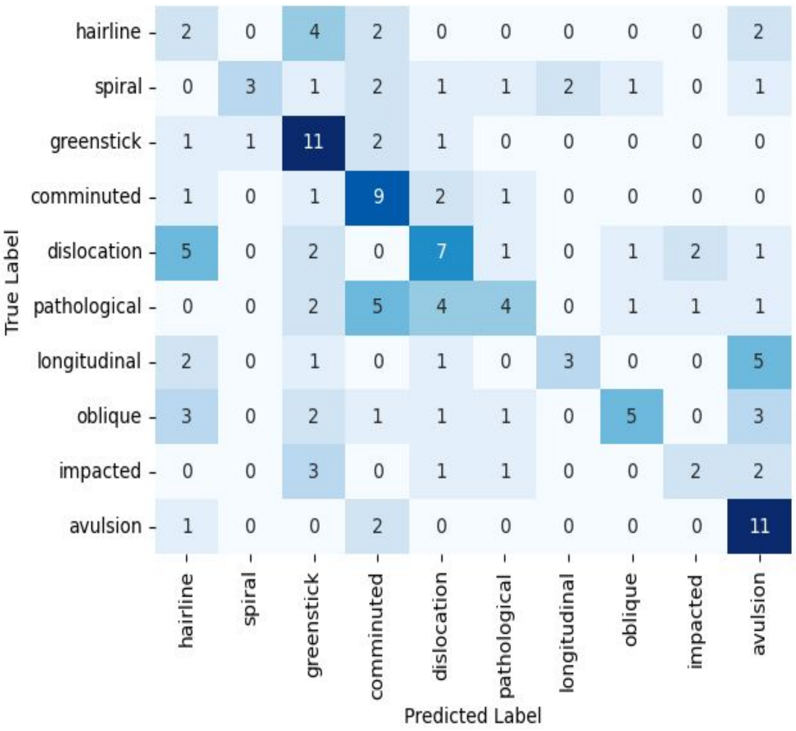


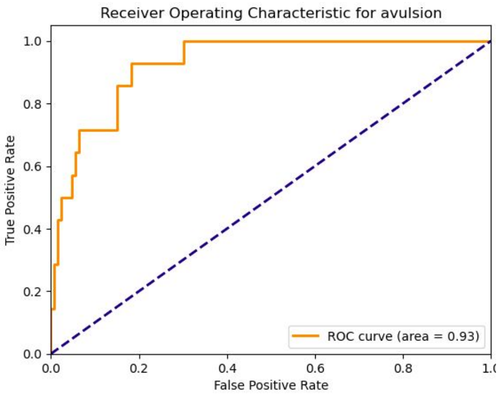


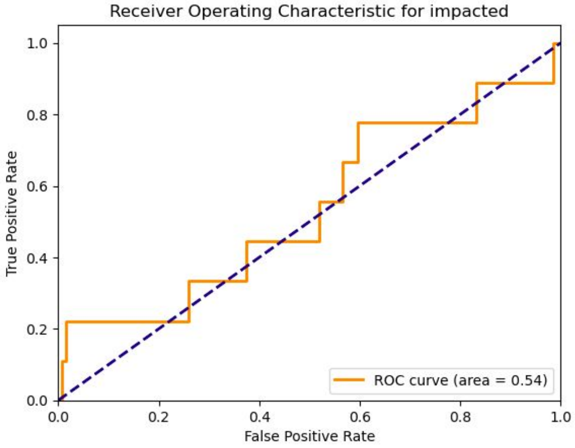


Max_iter: 500
Training time: 773.11 seconds
Inference time: 0.71 seconds
Test Accuracy: 0.4286

Support Vector Machine

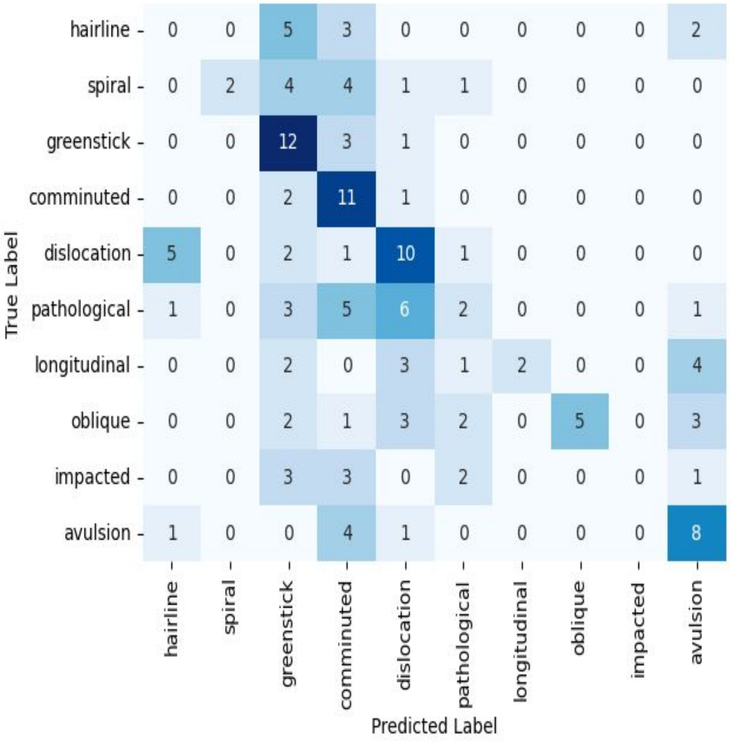


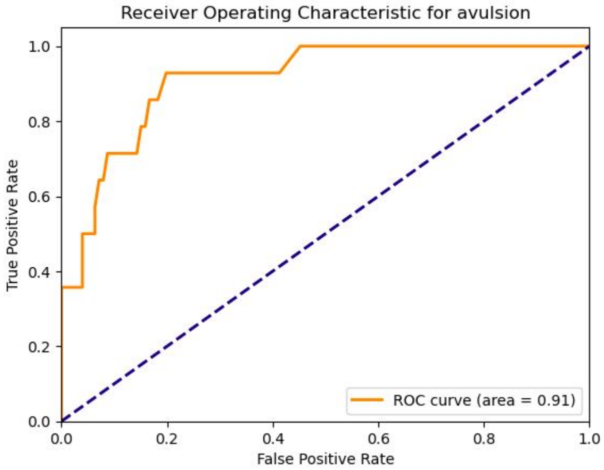


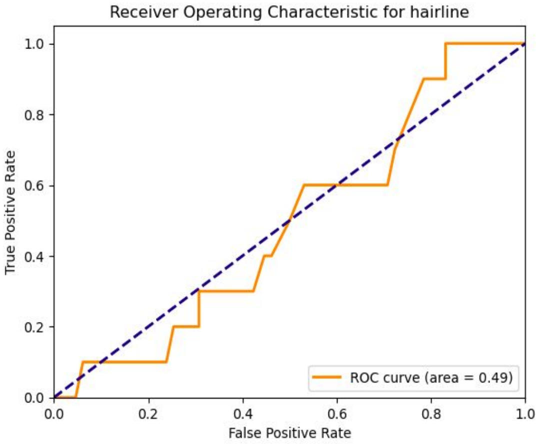


Kernel: linear, C: 100
Training time: 3714.48 seconds
Inference time: 13.50 seconds
Test Accuracy: 0.4071

Random Forest







N_estimators: 10000
Training time: 9149.05 seconds
Inference time: 9.43 seconds
Test Accuracy: 0.3714

Test Results

	Logistic Regression			SVM			Random Forest		
Model	**Accuracy**	**Precision**	**Recall**	**Accuracy**	**Precision**	**Recall**	**Accuracy**	**Precision**	**Recall**
Image	0.2786	0.2562	0.2662	0.3143	0.2785	0.2888	0.3357	0.3267	0.3029
HOG	0.2714	0.2958	0.2539	0.3286	0.3352	0.3073	0.2929	0.3687	0.2704
Canny	0.1786	0.3136	0.1585	0.20	0.2439	0.1793	0.2429	0.3163	0.2077
Contour	0.1643	0.1533	0.1533	0.20	0.2151	0.1846	0.3429	0.4759	0.3047
VGG19	0.4286	0.4742	0.4081	0.4071	0.4563	0.3941	0.3714	0.4685	0.3390
PCA	0.1786	0.1390	0.1695	0.1357	0.2048	0.1453	0.3571	0.3626	0.3248
HOG + VGG19	0.2929	0.3320	0.2734	0.2357	0.2213	0.2214	0.2929	0.3606	0.2615

Conclusion / Next Steps

Improve Model Accuracy:

- Create model to identify fractures
  - *Need medical professions to label fractures*
- Experiment with CNN classifier

Improve Model Generalizability:

- Implement data augmentation techniques
  - *Need additional computing power*