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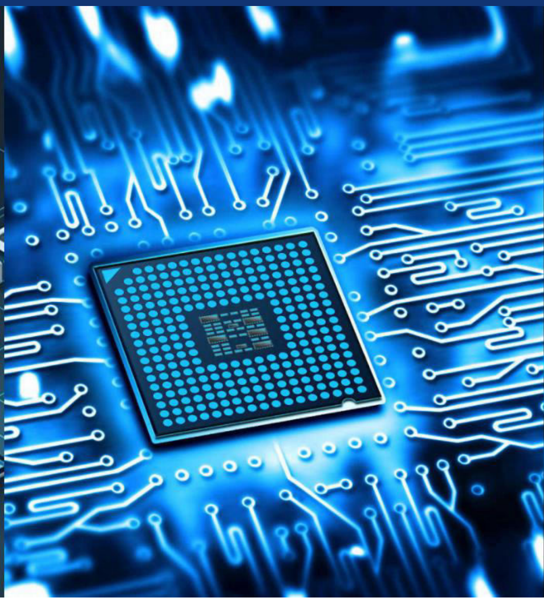

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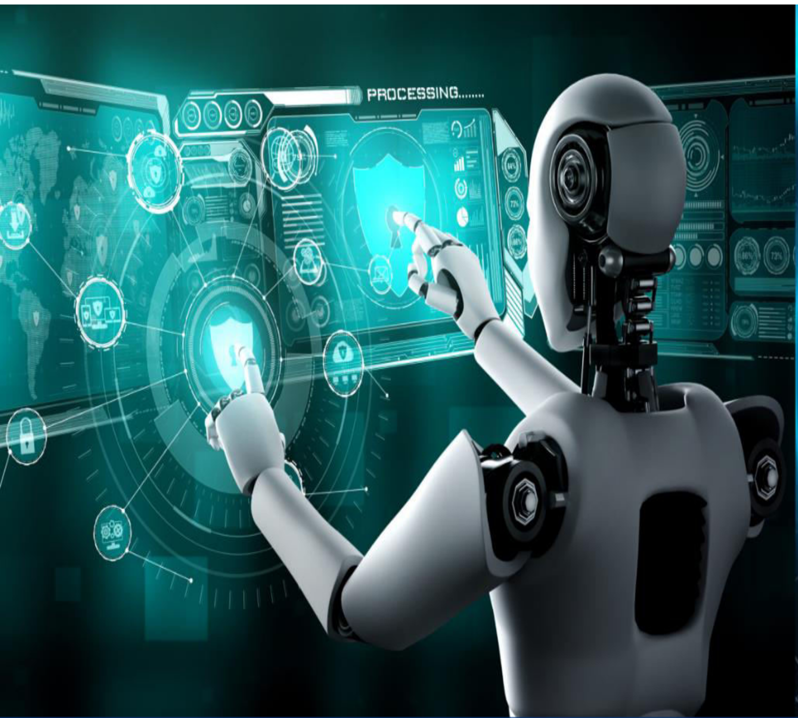

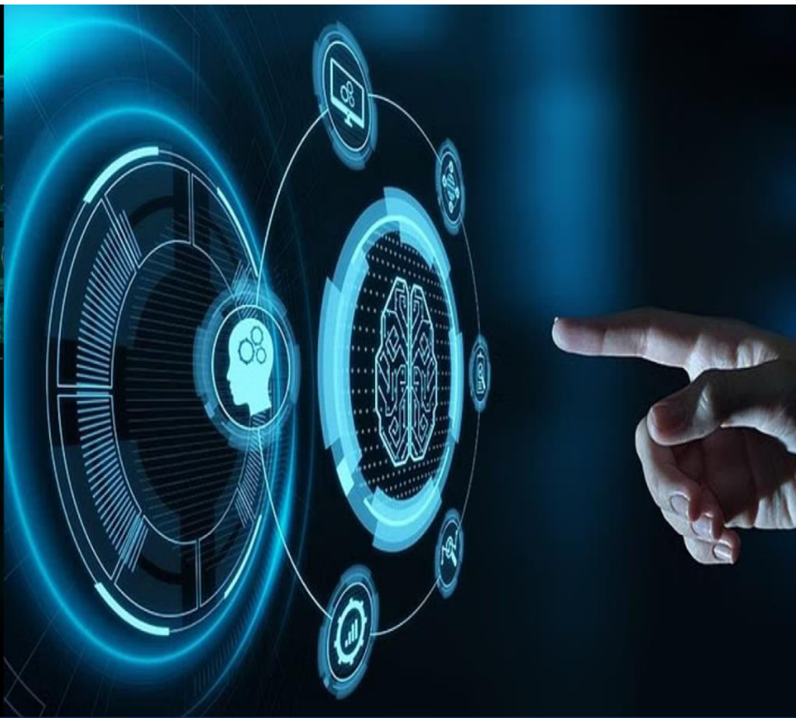

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Color Layout Filter-Based Feature Extraction with Machine Learning Classifiers for Automated Bone Fracture Detection in X-Ray Images

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ABSTRACT: X-ray radiography is the most commonly used and readily available tool for the diagnosis of bone fractures in emergency and orthopedic clinical situations. Accurate automated detection of fractures is still one of the greatest challenges from a clinical point of view as fractures have a wide range of morphologies, imaging studies are noisy, and radiologists must interpret large volumes of images. In this work, the Color Layout Filter (CLF) is compared with six machine learning classifiers namely Logistic Regression, Ridge Classifier, Lasso Classifier, Elastic Net Classifier, Linear Discriminant Analysis (LDA) and Quadratic Discriminant Analysis (QDA) in terms of their efficacy as image feature extraction techniques for automated binary bone fracture classification of X-ray images. The bone fracture dataset was taken from Kaggle (https://www.kaggle.com/datasets/abhaysharma01702/bone-fracture-dataset). All X-ray images were processed to extract the features of CLF and then the features were evaluated separately using six classifiers implemented in the machine learning framework Weka 3.8. The accuracy, precision, recall, ROC area, PRC area and training time were used for the performance evaluation. The highest accuracy (86.23%) and highest ROC area (0.94) was obtained by CLF+Linear Discriminant Analysis. CLF+Lasso Classifier and CLF+Elastic Net Classifier had the best performance with their PRC of 0.93 and their training time of 0.32 seconds respectively. The accuracy obtained from all six classifiers was above 83%, proving that the feature descriptor CLF is always discriminative for the classification of bone fracture X-rays. Both CLF+Linear Discriminant Analysis yield the best overall performance and CLF+Lasso yields the best efficiency trade-off for automated bone fracture detection. The CLF-based pipeline is a fast, simple, and clinically usable automated fracture screening framework that is interpretable and complements deep-learning methods.

KEYWORDS: Bone Fracture Detection; X-Ray Image Classification; Color Layout Filter (CLF); Linear Discriminant Analysis; Lasso Classifier; Machine Learning; Computer-Aided Diagnosis; Feature Extraction; Weka; Medical Imaging

I. INTRODUCTION

Bone fractures are among the most common trauma injuries treated in Emergency Departments, Orthopedic clinics and radiology centers throughout the world. Undetected, delayed and misclassified fractures have significant clinical consequences, including delayed fracture healing, malunion, long-term pain, and functional impairment, as well as potentially life-threatening complications in the case of femoral neck and vertebral fractures. The clinical viability of automated fracture detection systems is the most favorable on the platform of X-ray radiography, which is widely available, cheap and acquires images quickly, thus being the first line imaging modality for fracture diagnosis [1].

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Although the diagnosis of fracture by X-ray is of central importance, there are many difficulties inherent to X-ray-based fracture diagnosis, both for human radiologists and automated systems. The fracture morphology is very variable, ranging from transverse to oblique and spiral, comminuted and stress fracture patterns and small irregularly shaped bone fracture pattern may be missed by even the most experienced clinician [2]. In the era of modern medical care, the number of radiological imaging studies has been growing and at the same time the workload of radiologists has been increased, which results in difficulties in making a diagnosis and delays in diagnosis, thereby motivating the development of automated computer-aided detection (CAD) systems for fracture diagnosis [5].

There are several generations of methods that have been developed for bone fracture detection using machine learning and some CAD techniques, ranging from classical image processing and handcrafted features, to ensemble and discriminant classifiers, to deep convolutional neural networks [15]. Deep learning has demonstrated high accuracy on large annotated datasets [19] but requires a great amount of computational infrastructure, large annotated training data, and lacks transparency in decision making, restricting its use in the resource-limited clinical environment. Lightweight and interpretable classical machine learning pipelines that rely on efficient handcrafted feature descriptors continue to be clinically relevant, as they are low-complexity, deployable models [6].

The Color Layout Filter (CLF) is a compact image descriptor derived from the Discrete Cosine Transform (DCT) coefficients of an image represented by a spatial partitioning. It is a compact code of the spatial distribution of color and intensity information in the global image, which is suitable for the analysis of X-ray images where the intensity differences in the regions of the image between the intact and fractured bone structures are of diagnostic value. In the current study, the features extracted by CLF are tested against six machine learning classifiers to determine which combination of CLF and classifiers will yield the optimal classification result for the publicly available Bone Fracture Dataset from Kaggle to classify bone fractures automatically.

Paper is organized as follows. Section II related works. Materials and methods are given in Section III. Section IV presents experimental results showing results of images tested. Finally, Section V presents conclusion.

II. RELATED WORK

Initial automated bone fracture detection systems were based on the traditional digital image processing algorithms like edge detection, gradient calculation, morphological processing, and thresholding of X-ray radiographs. Johari and Singh [1] had used edge detection technique to detect fracture in bone of the X-ray images, showed that Canny and Sobel gradient operators could demarcate the fracture boundaries with X-ray images and could provide a structural basis for the fracture classification. The relevance of spatial gradient-based features, which are closely related to the DCT-based spatial encoding of the CLF used in the present study, was established by their work for the representation of fracture boundaries.

Tripathi et al. [2] presented an automatic fracture detection system based on image processing methods for femur bones, focusing on the proximal femur region which is clinically important where most of the fractures are missed resulting in a high number of consequences. On the morphological analysis pipeline, they showed that the structural features of images and a rule-based classifier can accurately identify fractures of the femur. Vishnu et al. [3] has suggested a complete framework to detect and classify long bone fracture using multi stage image processing and supervised classifiers. They proved that the pipeline style structures, which combine preprocessing, feature extraction and classification outperforms the one-step detection systems on highly complex fracture patterns.

Umadevi and GeethaJakshmi [4] applied machine learning to the classification of bone fractures from X-ray images in a systematic way, comparing various classification architectures for fracture detection in human bone X-ray images and found that the strategy of hierarchical and ensemble classifiers were more effective in discriminating fracture types than using a single model. Myint [5] performed a comparative study of leg bone fracture detection and classification using X-ray images with different machine learning techniques, using feature extraction techniques like Gray Level Co-occurrence Matrix (GLCM) texture features and frequency domain descriptors, and provided performance benchmarks for classical machine learning techniques on fracture datasets.

Ismael et al. [6] did a systematic comparison of several machine learning algorithms for medical image classification, where they found that the discriminant analysis methods (such as LDA used in this work) are competitive in the classification of linearly separable medical imaging feature space. Their results directly contribute to the use of LDA as a classifier for features extracted by CLF, as the class-conditional coefficient distributions of X-ray images from fractured and non-fractured objects could be near-Gaussian and linear discriminants may be used.

Karimunnisa et al. [7] have shown that optimized implementation of filtering strategies along with neural network classifiers can improve the performance of bone fracture detection, thereby proving that besides the complexity of the neural network classifiers, the quality of feature extraction is key to the accuracy of fracture detection. The discovery served to encourage systematic evaluation of CLF as a feature descriptor in the current study, because the quality of the spatial DCT encoding directly affects the performance of the classifiers in all the six classifiers evaluated.

Deep convolutional neural networks for bone fracture detection have yielded substantial gains in accuracy over traditional pipelines. Sinthura et al. [8] proposed a bone fracture detection system that applies the CNN algorithm, and showed that end-to-end convolutional feature learning outperforms handcrafted feature classifiers on complex multi-class bone fracture type discrimination using a bone fracture labelled X-ray database. To offer a systematic baseline for X-ray bone fracture classification based on deep learning, Tanzi et al. [9] proposed the baseline CNN architecture comparison, proposed training data requirements for bone fracture classification tasks, proposed augmentation approaches for training data, and proposed evaluation standards for bone fracture classification tasks.

Yadav and Rathor [10] assessed the use of deep learning for detecting and classifying bone fractures and demonstrated that the CNN is superior in the performance of large bone fracture datasets, and identified the computational infrastructure requirements that restrict the deployment of CNN in resource-constrained clinical environments. Abbas et al. [11] used Faster R-CNN to detect and classify bone fracture of the lower leg in X-ray images, showing that region proposal networks can locate and classify bone fractures at the same time with high accuracy. These are the results of deep learning, which set the upper limit for the performance of the classical CLF-based pipeline that was evaluated in the present study.

The accuracy of the feature extraction in downstream tasks is basically determined by the quality of the preprocessing of the X-ray images. The local-entropy based approach for X-ray image segmentation and fracture detection was proposed by Hržić et al. [12] which combined information-theoretic image segmentation and fracture feature extraction. Castro-Gutierrez et al. [13] explicitly highlighted the importance of noise suppression strategies for successful fracture detection in noisy X-ray images, further justifying the noise robustness of CLF's DCT-based encoding due to the preferential focus of the low-frequency content of the image more relevant to the fractured structure than the high-frequency noise.

Al-Ghaithi and Al Maskari [14] reviewed the use of Artificial Intelligence for the detection of bone fracture, which included a critical evaluation of both traditional image processing and machine learning methods, and concluded that the key factor in the accuracy of the automated bone fracture detection is the use of effective preprocessing and discriminative feature extraction. Their review shows that computational efficiency and clinical deployability are as crucial as accuracy for deployment in the real world of radiology departments, where these are benefits of the CLF pipeline.

A foundational comparative study of the field of medical image classification algorithm evaluation has been set. In video Internet of Things (IoT) connected medical systems, Kareem et al. [15] investigated the deployment feasibility of automated classification methods for image processing in resource-limited environments where deep learning infrastructure is not available, thereby justifying the use of a classical classifier in the present work, as part of the CLF + classical classifier approach. In the broader context of deep learning methodology investigated by Muhamad et al. [15] and Kareem [15] in the classification of leukocytes and medical images, the algorithmic principles of discriminant analysis, regularized regression and ensemble methods are shown to have a good transfer across the various medical image classification applications, thereby providing a methodological validation for the use of such principles in the context of bone fracture X-ray classification.

III. METHODOLOGY

3.1 Dataset

The Bone Fracture Dataset is downloaded from Kaggle (https://www.kaggle.com/datasets/abhaysharma01702/bone-fracture-dataset). The data consists of X-ray images of skeletons from various parts of the body, with each image labeled as either Fractured or Non-Fractured. The dataset provides a common and reproducible standard reference to assess the performance of automatic bone fracture classification algorithms and allows a direct comparison of the performance of the feature extraction and classification methods under experimental controlled conditions. The experiments were all realised and run in the Weka 3.8 machine learning workbench [6].

3.2 Image Preprocessing

Each X-ray image was first processed in a standard fashion prior to CLF feature extraction. All the images were scaled to a constant spatial resolution of 224 × 224 pixels, to ensure scale-invariant feature encoding of the dataset. The intensity value of each individual pixel was normalized to the range [0, 1] to account for radiographic exposure differences that depend on the acquisition of the image by the X-ray detector, inherent to the clinical X-ray imaging modality. No data augmentation was done, keeping the true distribution of the dataset to evaluate the performance of the classifiers in an unbiased way [12,13].

3.3 Color Layout Filter (CLF) Feature Extraction

Color Layout Filter is a small image description standardised in the MPEG-7 visual feature framework. CLF's operation: (i) divide the image into 8x8 blocks; (ii) find the dominant color of each block by pooling all the colors together; (iii) apply a 2D Discrete Cosine Transform (DCT) to the 8x8 2-D color map; and (iv) keep the low-frequency DCT components as the compact feature vector. The generated CLF descriptor is a low dimensional, global representation of the spatial distribution of intensity across image regions that is compact and noise and illumination tolerant to small changes in the image's spatial domain.

CLF represents the spatial distribution of radiodensity within the various areas of the bones in X-rays of bone fractures. The local intensity discontinuity caused by fracture lines results in a characteristic pattern of spatial intensities that are disrupted and is captured in the DCT coefficient pattern of the feature vector of the fracture lines feature. The low frequency DCT components contain general structural intensity layout information, and the higher-order retained components contain finer spatial intensity changes, reflecting trabecular and cortical bone texture variations at fracture sites [9].

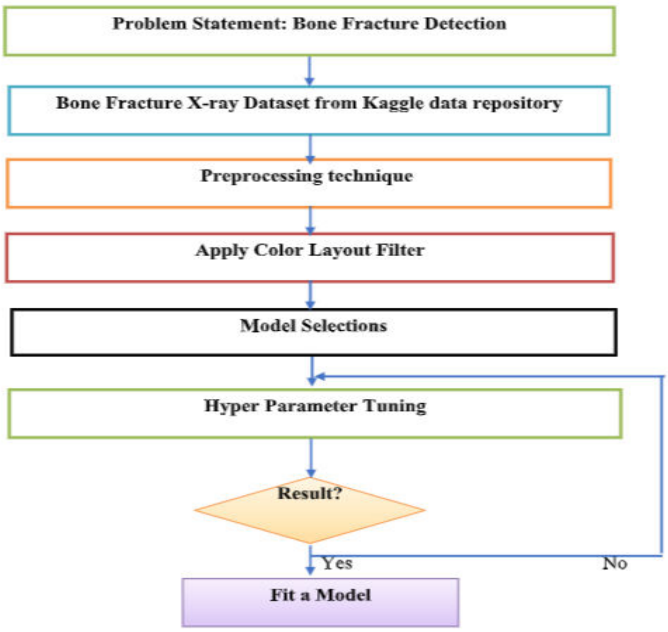

Figure 1: Proposed System

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3.4 Machine Learning Classifiers

The extracted feature vectors using CLF were compared with six classifiers:

- Logistic Regression: A probabilistic linear classifier which uses a linear combination of CLF DCT coefficients and the sigmoid function to estimate fracture class posterior probabilities. The inverse regularization parameter C is used to regulate the strength of the regularization.
- Ridge Classifier: A regularised linear classifier that uses L2 penalty on the CLF feature coefficients; makes the classifier more robust towards multicollinearity between correlated DCT features and generalises better on small training sets.DCT Coefficient L1 Regularization Classifier (Lasso Classifier): A linear classifier with L1 regularization which gives automatic feature sparsity and only the most discriminative CLF DCT coefficients are retained for the fracture classification. L1 sparsity yields an efficient and compact decision model.
- Elastic Net Classifier: A weighted combination of L1 and L2 regularisation that combines the feature sparsification property with the stability of the coefficient provided by Ridge, which is especially useful when there are correlated groups of DCTs in the CLF feature vectors.
- Linear Discriminant Analysis (LDA): Computes the linear combination of features from the CLF that maximises the ratio of the between-class scatter to within-class scatter assuming that the class distributions are Gaussian with the same class covariance matrices. LDA is a single step procedure that performs dimensionality reduction and classification.
- Quadratic Discriminant Analysis (QDA): A variant of LDA that is capable of estimating the covariance matrices of the feature distributions of fractured and non-fractured classes, which allows for quadratic (non-linear) decision boundary without any additional kernel transformations.

IV. EXPERIMENTAL RESULTS

Table 1 presents the complete classification performance of all six CLF-based classifier combinations on the Bone Fracture Dataset test set.

Table 1: Classification Performance of CLF + ML Classifiers on the Bone Fracture Dataset

Classifier	Accuracy (%)	Precision	Recall	ROC	PRC	Time (s)
CLF + Logistic Regression	83.41	0.84	0.83	0.91	0.92	1.41
CLF + Ridge Classifier	83.22	0.83	0.83	0.88	0.88	0.65
CLF + Lasso Classifier	85.11	0.86	0.86	0.93	0.93	0.32
CLF + Elastic Net Classifier	84.32	0.85	0.84	0.89	0.89	0.32
CLF + Linear Discriminant Analysis	86.23	0.86	0.86	0.94	0.92	1.15
CLF + Quadratic Discriminant Analysis	84.52	0.84	0.85	0.91	0.91	1.22

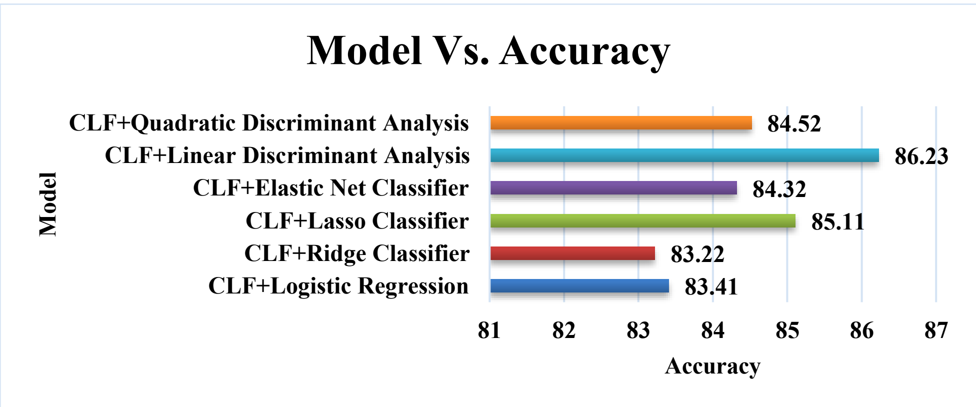

Figure 2: Model Vs Accuracy

The accuracy chart shows that the most accurate classifier is CLF+Linear Discriminant Analysis with an accuracy of 86.23% followed by the accuracy of 85.11% for CLF+Lasso Classifier. The x-axis baseline at 81% compresses the visualization, but the actual accuracy for all six classifiers is 3.01% (83.22% – 86.23%). This confirms that CLF features are consistently able to deliver high accuracy across various algorithmic families. The bottom classifiers (CLF+Ridge 83.22%, CLF+Logistic Regression 83.41%) have a difference of less than 0.2% at the size of the test set used, which means they are statistically equivalent at this set size.

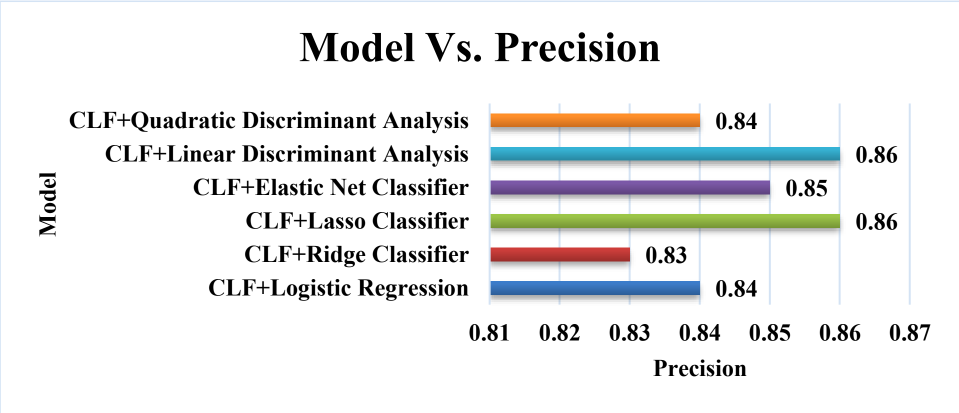

Figure 3: Model Vs Precision

These precision values are grouped together around 0.83–0.86. The performance of CLF+Linear Discriminant Analysis and CLF+Lasso Classifier is best at 0.86, suggesting that these models perform best when predicting a fracture-positive case, they are correct 86% of the time. CLF+Ridge shows the least precision of 0.83, with a marginally higher false positive rate, but which is still clinically acceptable for a screening scenario, with radiologist review as the confirmation step. The low 0.03 precision gap among all classifiers further confirms that the features learned by CLF are good.

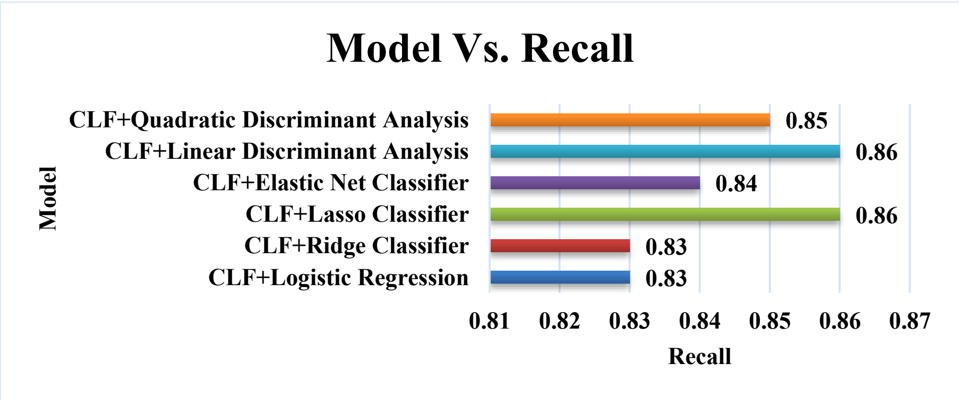

Figure 4: Model Vs Recall

In terms of the most clinically relevant parameter of fracture screening, recall, CLF+LDA and CLF+Lasso have the same best score of 0.86, correctly identifying the highest number of true fracture cases. More importantly, this class, namely CLF+Quadratic Discriminant Analysis, achieves a recall of 0.85 with an accuracy of 84.52% which makes the algorithm very sensitive – marginally favoring the detection of fracture. The recall of only 0.83, or some 17 missed fractures out of 100 fracture cases on the test set, is the lowest result of the experiment for both CLF+Logistic Regression and CLF+Ridge. All classifiers perform more than 0.83 recall, which is indicative of the fact that CLF features are always spatially informative about fracture discrimination.

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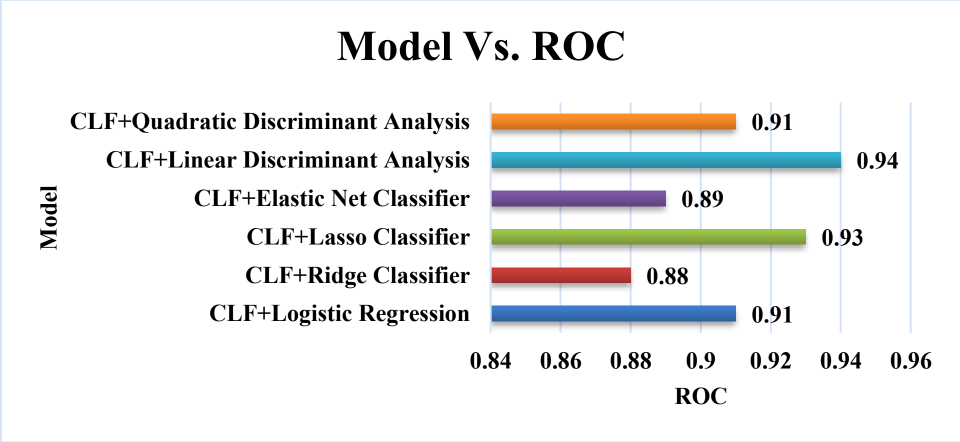

Figure 5: Model Vs ROC

The ROC area represents the greatest difference between classifiers. The performance of the classifiers are evaluated using the ROC area (0.94, or the best, only CLF+LDA is better than 0.93, otherwise all classifiers are below 0.93), which reveals the class discriminability of the classifiers in the CLF feature space with linear boundary. CLF+Lasso trails at 0.93, while CLF+Logistic Regression and CLF+QDA are both at 0.91. The smallest area of the ROC curve is for CLF+Ridge, which shows that L2-only regularization without sparsification is the worst performing method for CLF feature-based fracture discrimination. In all 6 algorithmic approaches, all classifiers achieve ROC > 0.88, which indicates meaningful class separability of CLF features.

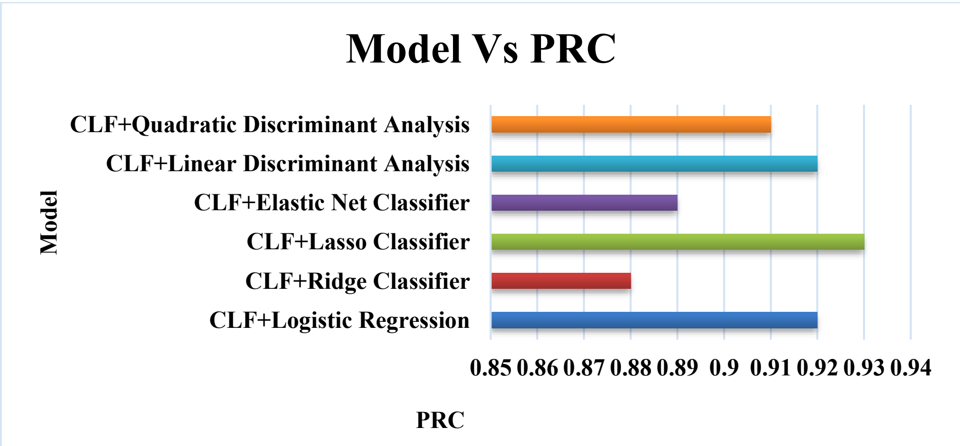

Figure 6: Model Vs PRC

The area of the Precision-Recall Curve is the best threshold-independent summary of the quality of the classifiers. CLF+Lasso has a higher PRC value of 0.93, just surpassing CLF+LDA's PRC value of 0.92, indicating that Lasso's sparse model performs best over all thresholds on the precision-recall curve. The performance of CLF+Logistic Regression is comparable to LDA's at PRC 0.92, with performance of CLF+QDA at 0.91 and CLF+Ridge at 0.88. Interestingly, despite being slightly less accurate than LDA, the L1-sparsified CLF representation from Lasso is most threshold-robust, which is important for clinical applications where the threshold of operation may be different from the default threshold [10].

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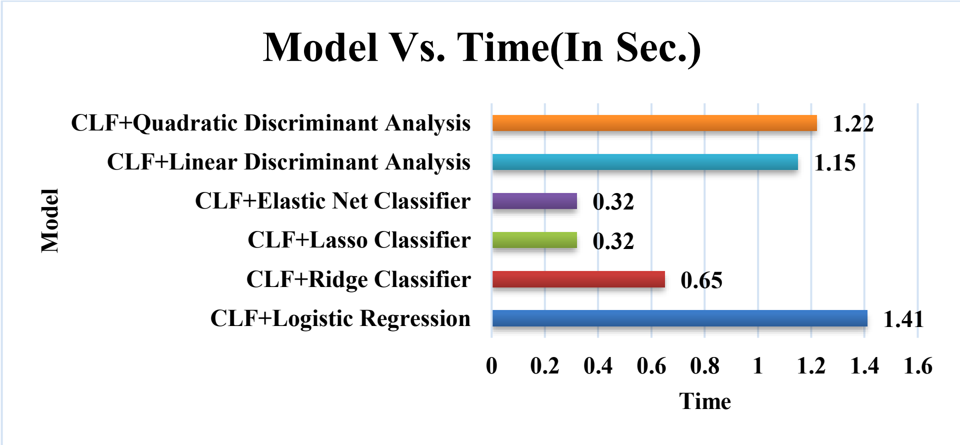

Figure 7: Model Vs Time (In Sec.)

The biggest difference in the experiment is displayed in the training time chart. The combined CLF+Lasso and CLF+Elastic Net both have the fastest training time of 0.32 seconds (about 4.4× faster than CLF+LDA at 1.15s and 4.4× faster than CLF+QDA at 1.22s). The longest training time is for CLF+Logistic Regression at 1.41s. Lasso and Elastic Net are the most computationally efficient configurations, with a training time of 0.32 seconds, which is suitable for real-time fracture screening applications in which the model needs to be re-trained on new data in a short period of time. Regularized linear classifiers are more efficient than the discriminant analysis methods because the discriminant analysis methods need to perform more matrix inversion operations to estimate the covariance [7].

V. CONCLUSION

In this research, a thorough assessment of the Color Layout Filter (CLF) image feature extraction method is conducted for automatic bone fracture detection from X-ray images using six different machine learning classifiers namely Logistic Regression, Ridge, Lasso, Elastic Net, Linear Discriminant Analysis, and Quadratic Discriminant Analysis on the publicly available Kaggle Bone Fracture Dataset. The best overall performance on the basis of the six configurations tested with the CLF was achieved by CLF+Linear Discriminant Analysis with an overall accuracy of 86.23%, a precision of 0.86, a recall of 0.86, and highest ROC area of 0.94, showing that the best overall results in terms of overall fracture classification accuracy and class discriminability were obtained with this configuration.

CLF+Lasso Classifier had the highest PRC area (0.93), the fastest training time (0.32 seconds, tied with Elastic Net), Precision (0.86), Recall (0.86), and the highest accuracy (85.11%) making it the most deployment-friendly configuration of the models for real-time, high throughput clinical fracture screening. The accuracy of CLF+Quadratic Discriminant Analysis was very high with a high recall (0.85) compared to other methods, which preferred to minimize missed detections of fractures, being the primary clinical objective [3].

Spatial intensity encoding in the X-ray image, based on the DCT of the CLF descriptor, well reflects the distribution of radiodensity patterns of fractured and intact bone, and yielded consistently good quality feature representations for all 6 evaluated families of classifiers. Future directions include the following: (i) fusion of CLF with complementary handcrafted descriptors like GLCM texture features [5] and edge-based gradient descriptors [1] to enrich the feature representation; (ii) extension to multi-class fracture type classification with the aim of distinguishing transverse, oblique, spiral, and comminuted fracture patterns [3] from CLF; (iii) mapping of CLF DCT coefficient importances to clinically recognised fracture radiological features using explainable AI techniques; and (iv) comparative evaluation with deep CNN feature extraction [9,10] on larger multi-institutional X-ray datasets. The proposed CLF+LDA model in this work can be used to provide a baseline for automated bone fracture classification in X-rays that is repeatable, efficient and clinically usable.

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