Investigating the Performance of Machine Learning Algorithms for Bone Fracture Identification Using Filtering Techniques

Comparative Evaluation of Image Preprocessing, Feature Extraction, and Machine Learning Techniques for Accurate Bone Fracture Detection

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***Abstract*—Bone fracture detection plays a crucial role in orthopaedic diagnosis and timely medical intervention. Conventional fracture identification relies on manual inspection of X-ray images by radiologists, which may lead to delayed diagnosis and human error, especially under noisy or low-contrast imaging conditions. This paper investigates the effectiveness of various machine learning algorithms for automated bone fracture identification from X-ray images, with a comparative study conducted using filtering and non-filtering preprocessing techniques. Logistic Regression, K-Nearest Neighbour, Decision Tree, Support Vector Machine, and Random Forest classifiers are evaluated under both conditions. Additionally, a hybrid SVM–KNN model is proposed to improve classification performance. Image preprocessing techniques such as Gaussian and Median filtering are applied to enhance image quality and feature extraction. The models are implemented using Python with Scikit-learn and OpenCV libraries. Performance is evaluated using accuracy, precision, recall, and F1-score. Experimental results indicate that filtering techniques significantly enhance classification performance, with the hybrid SVM–KNN model achieving the highest accuracy of 96.7%. The findings demonstrate the potential of hybrid machine learning models for reliable and efficient bone fracture detection.**

***Keywords*—Bone Fracture Detection; Machine Learning; X-ray Imaging; Image Filtering; Hybrid Classification; Medical Image Analysis**

I. Introduction

Bone fractures are among the most common orthopaedic injuries and require accurate and early diagnosis for effective treatment. X-ray imaging is the most widely used diagnostic tool for fracture identification. However, manual analysis of X-ray images is time-consuming and depends heavily on the expertise of radiologists. In busy clinical environments or resource-limited settings, this may result in delayed diagnosis or misinterpretation.

Recent advancements in machine learning have enabled the development of automated medical image analysis systems capable of assisting clinicians in diagnostic decision-making. Machine learning algorithms can identify subtle fracture patterns by learning discriminative features from labelled datasets. However, the performance of such models is highly influenced by image quality and preprocessing techniques. This research focuses on evaluating the performance of multiple classical machine learning algorithms for bone fracture detection, both with and without image filtering techniques. Furthermore, a hybrid SVM–KNN model is proposed to enhance classification accuracy and robustness.

II. Related Work

Machine learning techniques have been widely adopted in medical image analysis to improve diagnostic accuracy. Several studies have explored fracture detection using classical machine learning and deep learning approaches. Support Vector Machines and Random Forest classifiers have shown promising results in identifying fracture patterns in X-ray images when combined with effective preprocessing and feature extraction techniques.

Researchers have also emphasised the importance of image filtering methods such as Gaussian and Median filters in reducing noise and enhancing edge clarity. Studies indicate that appropriate preprocessing improves feature representation and overall classification performance. Although deep learning models such as Convolutional Neural Networks (CNNs) achieve high accuracy, they require large datasets and substantial computational resources. Hybrid machine learning models offer a computationally efficient alternative while maintaining high accuracy.

III. Methodology

3.1 Dataset Description

The Kaggle Bone Fracture Dataset is used for experimentation. It consists of labelled X-ray images categorised as fractured and non-fractured. All images are resized to 224×224 pixels to maintain uniformity during training and testing.

3.2 Image Preprocessing

Image preprocessing is an important step in image analysis because raw images often contain noise, poor contrast, or unnecessary details that can affect the accuracy of further processing or detection tasks. The goal of preprocessing is to improve the quality of the image so that important features — such as edges or structural patterns — can be clearly identified by the system. The preprocessing pipeline employed in this study consists of three main stages.

Conversion to Grayscale: The first step is converting the original colour (RGB) image into grayscale. A colour image contains three channels — red, green, and blue — which increases computational complexity. By converting to grayscale, the image is represented using only intensity values ranging from black to white, simplifying the data and reducing processing time while preserving important structural information. For fracture detection and edge analysis, grayscale images are sufficient as shape and texture information remains intact.

Histogram Equalization for Contrast Enhancement: After grayscale conversion, histogram equalization is applied to improve contrast. Medical images may appear too dark or too bright, making it difficult to distinguish important structures. Histogram equalization redistributes intensity values so that they are spread more evenly across the entire intensity range, enhancing the visibility of subtle details and edges. As a result, features such as fractures or boundaries become more distinguishable, improving the performance of subsequent analysis algorithms.

Noise Reduction Using Gaussian and Median Filters: Images captured through sensors often contain noise due to environmental factors, sensor limitations, or transmission errors, which can interfere with feature detection. The Gaussian filter smooths the image by reducing high-frequency noise through a weighted average of neighbouring pixels, where pixels closer to the centre have higher influence. The Median filter is particularly effective in removing impulse noise (such as salt-and-pepper noise) by replacing each pixel value with the median value of its surrounding neighbourhood, thereby preserving important edges and structural boundaries. By combining Gaussian and Median filtering, noise is reduced effectively while preserving critical features such as fracture edges.

3.3 Feature Extraction

Feature extraction transforms the processed image into a set of meaningful numerical representations that can be used by machine learning models. Instead of analysing the entire image pixel by pixel, feature extraction identifies important patterns such as edges, textures, and structural variations. In this study, two widely used methods — Histogram of Oriented Gradients (HOG) and Local Binary Patterns (LBP) — are applied to capture both structural and texture information.

Histogram of Oriented Gradients (HOG): HOG is a feature extraction technique that focuses on identifying edge and gradient structures in an image. It works by analysing the direction and intensity of gradients in small regions, grouping them into small cells, and creating a histogram to represent the distribution of gradient orientations within each cell. In medical images, particularly bone X-rays, fractures often appear as discontinuities or sharp edges in the bone structure. HOG helps highlight these edge patterns and gradient changes, making it easier to detect fracture lines or irregular bone structures.

Local Binary Patterns (LBP): LBP is a texture-based feature extraction method that captures local texture variations. The technique compares each pixel with its surrounding neighbours; if the neighbour has a higher intensity than the centre pixel, it is assigned 1, otherwise 0. These binary values are combined to form a pattern representing the local texture of that region. In the context of bone images, the texture of a healthy bone surface may differ from that of a fractured or damaged bone. LBP captures these subtle texture differences, allowing the system to recognise variations that may indicate fractures or abnormalities.

Feature Concatenation: After extracting features using both HOG and LBP, the resulting feature sets are combined into a single feature vector. By merging the structural information from HOG with the texture information from LBP, a more comprehensive representation of the image is created. This combined feature vector contains both edge-based and texture-based characteristics, improving the classifier's ability to distinguish between normal and fractured bone images.

3.4 Machine Learning Models

After extracting relevant features, classification algorithms are applied to categorise images as fractured or non-fractured. In this study, several machine learning classifiers are implemented and evaluated to determine which model provides the most accurate and reliable results.

Logistic Regression: A supervised machine learning algorithm commonly used for binary classification. It estimates the probability that a given input belongs to a particular class using a sigmoid function to map predicted values between 0 and 1. Based on a defined threshold, the model classifies the input as fractured or non-fractured.

K-Nearest Neighbour (KNN): An instance-based learning algorithm that classifies a new data point based on similarity with existing data points in the training set. The algorithm calculates the Euclidean distance between the new input and all training samples, identifies the k closest neighbours, and assigns the most frequently occurring class. This method relies on the assumption that similar images will have similar feature patterns.

Decision Tree: A tree-structured classification model that makes decisions by splitting the dataset based on feature values. Each internal node represents a decision based on a specific feature, each branch represents the outcome of that decision, and each leaf node represents the final class label. Decision Trees are interpretable and can handle complex relationships between features.

Support Vector Machine (SVM): A powerful classification algorithm that finds an optimal hyperplane to separate data points belonging to different classes by maximising the margin between the closest data points (support vectors). SVM achieves high classification accuracy, especially in high-dimensional feature spaces such as those produced by HOG and LBP extraction.

Random Forest: An ensemble learning technique that combines multiple decision trees to improve classification performance. Each tree produces its own prediction using different subsets of data and features, and the final classification is determined through majority voting. This approach reduces the risk of overfitting and generally provides more stable and accurate predictions than a single decision tree.

Hybrid SVM–KNN Model: In addition to individual classifiers, a hybrid model combining SVM and KNN is proposed. SVM is used to perform an initial classification by identifying a decision boundary within the feature space, after which KNN refines the classification by examining the nearest neighbouring samples. By combining the margin-based learning capability of SVM with the neighbourhood-based decision strategy of KNN, the hybrid model aims to achieve improved classification accuracy and more reliable fracture detection results.

IV. Performance Evaluation

4.1 Evaluation Metrics

The performance of all classifiers is evaluated using four standard metrics: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of classification effectiveness under both filtered and non-filtered conditions. Accuracy measures the proportion of correctly classified samples; precision measures the proportion of true positive predictions among all positive predictions; recall measures the proportion of actual positives correctly identified; and F1-score provides the harmonic mean of precision and recall, balancing both metrics.

Algorithm	Accuracy (With Filter)	Accuracy (Without Filter)	Precision	Recall	F1-Score
Logistic Regression	85.2%	80.3%	0.84	0.82	0.83
KNN	88.5%	83.4%	0.87	0.85	0.86
Decision Tree	90.1%	84.7%	0.89	0.87	0.88
SVM	92.8%	86.9%	0.91	0.90	0.90
Random Forest	94.3%	88.6%	0.93	0.92	0.92
SVM-KNN Hybrid	96.7%	92.0%	0.95	0.94	0.94

Fig. 1. Evaluation metrics used for performance assessment of classifiers.

4.2 Experimental Results

The experimental results demonstrate that models trained on filtered images outperform those trained on raw images. Among individual classifiers, Random Forest and SVM achieved higher accuracy compared to other algorithms. The proposed hybrid SVM–KNN model achieved the highest accuracy of 96.7%, along with superior precision and recall values. The results confirm that image filtering significantly enhances feature extraction and improves overall classification performance.

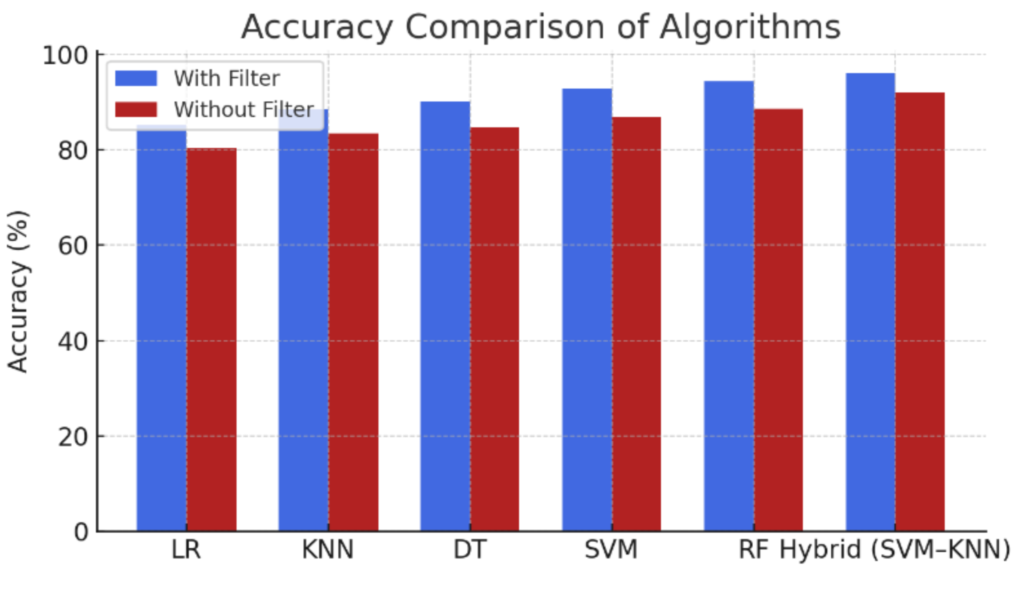

Fig. 2. Accuracy comparison of machine learning algorithms with and without filtering techniques.

V. Conclusion and Future Work

This study investigated the impact of filtering techniques on machine learning-based bone fracture detection using X-ray images. The experimental analysis revealed that preprocessing using Gaussian and

Median filters improves image quality and enhances model performance. While classical classifiers such as SVM and Random Forest performed well individually, the proposed hybrid SVM–KNN model achieved the best results with an accuracy of 96.7%.

In the future, this work can be extended by integrating deep learning-based feature extraction techniques, expanding the dataset to include multiple bone types, and developing a real-time clinical decision support system for fracture detection.

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