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Enhanced X-Ray Bone Fracture Detection Using MTBC and ResNet-50

Mamoona Sadia[1], Syed M.Adnan[1], Wakeel Ahmad[1] , Anam Naveed[1]

[1]Department of Computer Science University of Engineering and Technology, Taxila.

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ABSTRACT

Early detection of X-ray image bone fractures is necessary for effective patient treatment and planning of care. This paper introduces an inovative automated system capable of detecting bone fractures in radiographic images. The proposed method involves several important steps starting with image preprocessing to eliminate noise and enhance the visibility of possible fracture lines. Subsequently, a Multi-Trend Binary Code (MTBC) approach is applied to identify subtle textural characteristics emphasizing structural abnormalities associated with fractures. Such high-level features are subsequently passed on to a trained ResNet-50 deep learning architecture to identify high-level sophisticated patterns. A classification component thereafter assesses the presence of a fracture. The effectiveness of the system is extensively evaluated on a large bone X-ray dataset, with results demonstrating dramatic improvements in accuracy, sensitivity, and specificity compared to existing approaches. The integration of MTBC for feature enhancement and ResNet-50 for deep learning is very efficient in fracture detection and is a valuable tool for radiologists and medical professionals to improve diagnostic accuracy and reduce workflow.

Corresponding Author's Email:

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1. Introduction

The musculoskeletal system is integral to the human body's mobility and daily activities, making prompt and accurate fracture identification critical to effective medical treatment. Traditionally, fracture detection relies on the naked-eye reading of radiographic images (X-rays) by orthopedic professionals. This typically is a labor-intensive task that is susceptible to observer variation and heavily dependent on image quality [1-3]. In developing countries, the unavailability of qualified radiologists further compounds delay in diagnosis and lower quality treatment outcomes.

The availability of standardized medical imaging modalities like DICOM (Digital Imaging and Communications in Medicine) [3, 4] has made it possible to implement computer-aided diagnostic (CAD) tools in clinical applications. Machine learning (ML) and deep learning (DL) methods, especially, have been shown to have the potential to significantly enhance the accuracy and efficiency of computerized fracture detection.

Prior research has introduced CAD frameworks for aiding in fracture detection, but there are issues. Some of these are dependence on hand-crafted feature engineering, lack of annotated datasets, and difficulty in identifying multiple fractures in varying bone regions. While some use two-stage pipelines object detection models like Faster R-CNN for bone localization and CNN-based classification [1, 5] generalization in complicated clinical situations is still limited.

To solve these challenges, this paper introduces an overall deep learning model for bone fracture detection. The processing pipeline comprises: (1) preprocessing of images with histogram equalization for better contrast, (2) extraction of features by Multi-Texture Block Coding (MTBC) to represent fine textural changes, (3) deep representation learning by a tailored ResNet-50 architecture, and (4) classification to identify whether fractures exist or not. On the publicly available GRAZPEDWRI-DX dataset, the method has a 91.1% accuracy, which indicates that it can be applied in real-world clinical applications.

2. Related Work

Advances in deep learning over the past few years have enhanced medical image analysis, especially automated fracture diagnosis. One of the major drivers in this field is the GRAZPEDWRI-DX dataset [6, 7], containing more than 20,000 wrist X-ray images, and is used as a benchmark for research in computer-aided diagnosis. Early experiments using YOLOv5 (pre-trained on COCO) demonstrated the capability of one-stage detectors in radiology, with the mean Average Precision (mAP) being 0.93 at an IoU threshold of 0.5. The scale of the dataset overcomes the shortcomings of previous small sets and accelerated development toward large-scale fracture detection systems.

Later studies have contrasted object detection architectures like Faster R-CNN and YOLO variants (YOLOv5–YOLOv8) with the aim of evaluating trade-offs between detection precision and computation cost. YOLO-based models, especially, have demonstrated robust performance as clinical decision-support systems, assisting radiologists in the interpretation of X-rays. Nevertheless, challenges remain due to constrained feature representation and possibilities of information loss during training. To reduce these problems, YOLOv9 implemented Generalized Layer combination Networks (GLAN) and Programmable Gradient Information (PGI), achieving state-of-the-art performance on the GRAZPEDWRI-DX dataset[8].

Aside from wrist fractures, deep learning techniques have been applied to more general orthopedic imaging tasks. For instance, YOLOv8 recorded F-measure values of 0.701 (YOLOv8n) and 0.781 (YOLOv8m) for detecting elbow osteochondritis dissecans (OCD) via binary classification [9]. Likewise, YOLO-based networks have been used to pelvic CT scans, precisely localizing bone structures and aligning anatomical attributes with reference models [10]. These results reflect the versatility of YOLO frameworks across a variety of imaging modalities.

Other pipelines for fracture detection employ multi-stage methodologies that combine preprocessing, feature extraction, and classification. Hybrid methods combining CT and X-ray modalities, for example, have been used for tumor segmentation and fracture detection to enhance feature clarity in ambiguous boundary cases [11]. Moreover, lightweight deep learning architectures deployed on cloud platforms like Google Colab have attained up to 84% accuracy in fracture classification, highlighting the universal accessibility of AI-based diagnostic tools.

Innovations also encompass pediatric supracondylar fracture detection multi-scale patch leftover networks, which attained 94.6% accuracy using healthy bone data for training [12]. Such methods enhance fracture localization, enable earlier identification of subtle injuries, and offer cost-effective solutions for healthcare systems. Looking ahead, future research is expected to explore anomaly detection in a wider range of anatomical regions and integrate automated systems with clinical decision-support platforms. A comparative summary of related methods is presented in Table 1.

Table 1. Comparison of Related Work

Ref	Year	Methodology	Dataset	Accuracy %
[13]	2017	Scale-Invariant Feature Transform (SIFT) method	X-ray images	94.30
[4]	2019	ANN, SVM, and RF, M2GLD.	asphalt pavement images	87.50

[14]	2021	Faster R-CNN, Crack Net,	X-ray images	88.39
[3]	2022	CNN model, Hybrid SFNet model.	Bone image	95.00
[15]	2022	Dynamic R-CNN, Faster R-CNN, FSAF, Libra R-CNN (RetinaNet), RetinaNetSABL (Faster R-CNN and RetinaNet) models, RegNet.	Wrist X-ray images	90.11
[5]	2022	Deep learning CNN Model	Radiograph	88.00
[16]	2022	CNN,DICOM, Linkdoc Dicom Marker Viewer.	DICOM images	89.40
[17]	2023	Decision Tree, Nearest Neighbors, Random Forest, and SVM.	X-ray images	85.00
[18]	2023	VGG NET 16, ResNet, DenseNet, and AlexNet, with AlexNet	MURA	95.00
[19]	2024	CNN,Deep learning,Data processing,feature extraction, Gaussian Filtering and SVM	MURA (Musculoskeletal Radiographs)	95.00
[20]	2024	CNN, Grad-CAM, YOLOv5 and YOLOv8 Models	RSNA 2022	94.2
[21]	2024	FracNet, Fast RCNN, Faster RCNN, and YOLOv3	CT images	90.5

While accuracies of over 94% have been reported in recent research using YOLOv8, Transformer networks, or self-supervised CNNs, these models have considerable disadvantages. They are computational intensive, which makes them unsuitable for utilization in hospitals with limited computational capabilities. Our hybrid MTBC–ResNet-50 model, although operating at 91.1% accuracy, offers more interpretability and stability, ResNet-50 and the selected classifiers are lightweight, making the method more practical for clinical implementation. Therefore, the suggested method prioritizes interpretability and efficiency over accuracy.

3. Used Approach

3.1. Materials and Methods

The proposed methodology (Figure 1) comprises a multi-stage pipeline for automated bone fracture detection using the GRAZPEDWRI-DX dataset, a paediatric wrist X-ray repository. Initially, input images undergo pre-processing (noise reduction, contrast enhancement, and normalization) to improve quality, followed by Multi-Trend Binary Code (MTBC) to segment bone structures and highlight potential fracture regions. A ResNet50 architecture then extracts discriminative hierarchical features, which are fed into machine learning classifiers (e.g., SVM, Random Forest) for binary fracture classification (fracture vs. non-fracture). This combined strategy provides strong feature learning and precise diagnostic predictions with continued computational efficiency for clinical utility.

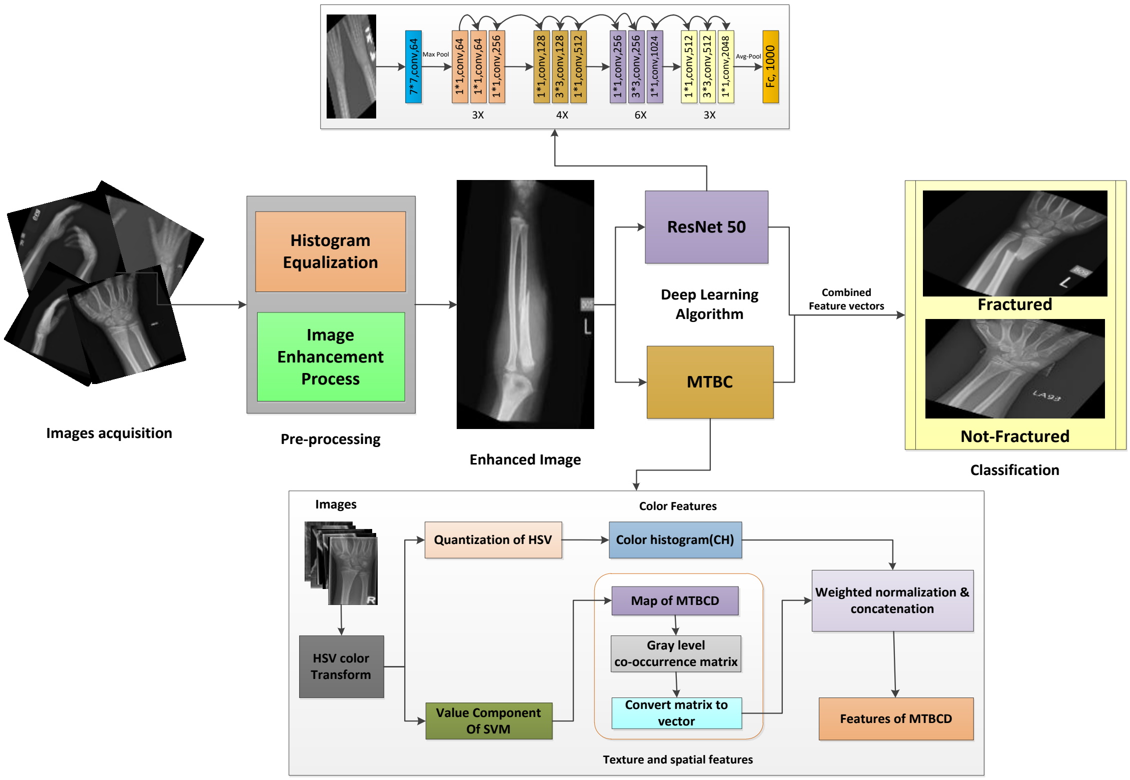


Figure 1: Proposed methodology.

Image Acquisition

The GRAZPEDWRI-DX dataset is utilized in this study as the dataset of imaging data. It comprises 20,327 X-ray images annotated with a wide variety of bone fractures in diverse anatomical locations and levels of difficulty. Medical professionals have carefully annotated every image, guaranteeing the precision and dependability of the annotations used to train and assess the detection model. The dataset is split in 70:15:15 for train, valid and test respectively. The GRAZPEDWRI-DX dataset used in this study is large-scale and already well balanced across the two classes (fractured and non-fractured). Therefore, no additional data augmentation applied. A more generalizable model is developed as a result of the dataset's variability in patient demographics, such as age and gender. This diversity aids the system in identifying fracture patterns in a wide variety of clinical situations. The model may learn intricate and delicate traits that are relevant to fracture diagnosis thanks to the high-quality, expert-verified labels, which offer crucial ground truth information. An example of the dataset is shown in Figure 2.

Figure 2: Bone sample images from dataset [7, 8]

The combination of dataset, which together comprise 20,327 X-ray images, creates an extensive repository that is essential to the creation and assessment of the suggested bone fracture detection model is described in Table 2.

S#	Category	Total Number of Images
1	GRAZPEDWRI-DX	20,327
	Total	20,327

Table 2: Data description of dataset

Preprocessing

Low contrast and noise are common problems with medical X-ray pictures, which can mask important structural details that are necessary for precise fracture detection. Pre-processing is therefore an essential step that improves image quality for more accurate analysis.

Histogram Equalization

Histogram equalization is used to make X-ray images more contrasted. It enhances local features and edges by redistributing the image's value of intensity across the whole range. The equation (1) shows the transformation function for histogram equalization:

$$s = T(r) = (L-1)\sum_{k=0}^{r} \frac{n_k}{N} \quad \text{……….. (1)}$$

This process makes subtle features more visible by making sure that the intensity levels in the picture are distributed more equally.

Image Enhancement

Adaptive contrast stretching and Gaussian filtering are two further picture enhancing techniques used to improve visibility and reduce noise. Edge details are improved in this stage to get the picture ready for deep feature extraction. The following mathematical equation (2) is the representation of the enhanced image can be made:

$$I_e = \alpha . I_{eq} + \beta . G(I_{eq}) \quad \text{…………. (2)}$$

Feature Extraction Using MTBC

Following pre-processing, the Multi-Trend Binary Code (MTBC) approach is used to find the localized structural patterns in bone images during the feature extraction step. Because MTBC is designed to show the directional intensity changes in small regions, it is perfect for identifying subtle changes that often indicate fractures. In order to illustrate the presence of intensity patterns in binary forms, this method analyses the variance in pixel brightness in different orientations, such as horizontal, vertical, and diagonal. Based on the features of these directional changes, a binary code is assigned to each pixel in the region. A brief and illuminating descriptor that captures the basic textural dynamics of the bone is produced by combining these binary patterns into histograms. MTBC improves the ability of the model to distinguish between intact and fractured bone pieces by looking at gradient discrepancies and directional coherence. This directional binary encoding is a helpful technique for identifying structural abnormalities since it responds to micro-patterns found in bone formations.

The core of the MTBC pattern at any pixel (x, y) is defined as in equation (3):

$$B(x,y)=\sum_{i=0}^{n} b_i.2^{i-1}, \quad where\ b_i=\begin{cases}1, & if\ I\left(x+\delta_x^{(i)}, y+\delta_y^{(i)}\right)-I(x,y)\geq T\\ 0, & otherwise\end{cases} \quad \text{……….. (3)}$$

To determine if a region is fractured, the MTBC algorithm uses feature thresholds or machine learning classifiers (like SVM or KNN) that have been trained on these descriptors. The process of MTBCD feature extraction is illustrated graphically in Figure 3.

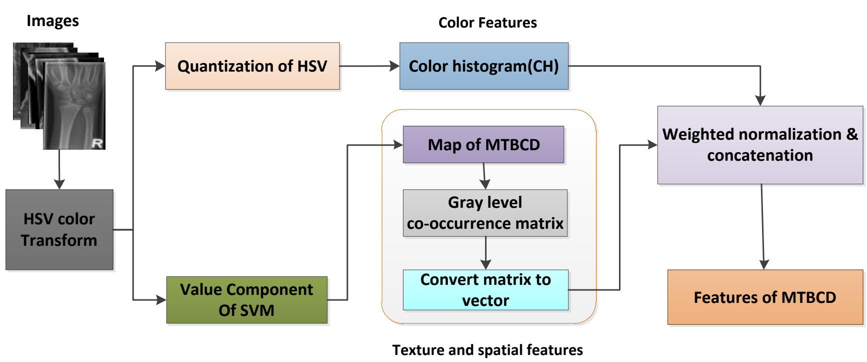


Figure 3: The process of MTBCD feature extraction

Deep Feature Extraction Using ResNet-50

To augment handwritten features, deep features are extracted using a pre-trained ResNet-50 convolutional neural network. By incorporating shortcut connections into conventional convolutional layers, ResNet-50 introduces residual learning, which facilitates the efficient training of deeper networks.

As shown in Equation (4) a residual block in ResNet-50 is defined as follows:

$$y=F\left(x,\{W_i\}\right)+x \quad \text{……….(4)}$$

Deep representations of the X-ray pictures are created using the features from the ResNet-50 global average pooling layer. For final classification, these features are either further merged with MTBC features or fed into a softmax classifier. Figure 4 describes the architecture diagram.

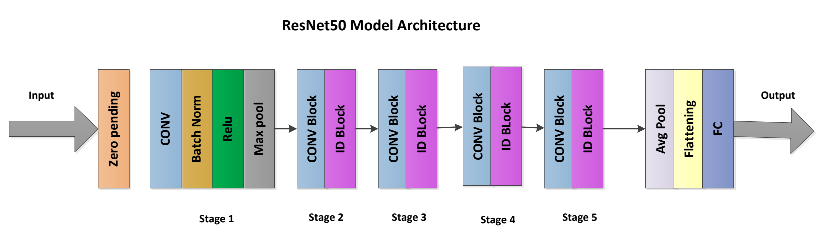


Figure 4: Model Architecture of ResNet-50

Classification

The classification stage plays a crucial role in accurately identifying bone fractures from preprocessed and feature-extracted images. In this study, multiple machine learning classifiers were evaluated to determine the most effective model for fracture detection. Logistic Regression, Weighted K-Nearest Neighbours (Weighted KNN), Subspace K-Nearest Neighbours (Subspace KNN), Fine K-Nearest Neighbours (Fine KNN), Quadratic Support Vector Machine

(Quadratic SVM), Cubic Support Vector Machine (Cubic SVM), Fine Gaussian Support Vector Machine (Fine Gaussian SVM), and Medium Gaussian Support Vector Machine (Medium Gaussian SVM) are among the classifiers. To evaluate each classifier's performance in fracture classification, it was trained and evaluated using the retrieved features.

Subspace K-Nearest Neighbours (Subspace KNN)

Using random subsets of features, Subspace KNN is an ensemble-based variant of the Conventional KNN algorithm. It builds various KNN classifiers on various subspaces of the data rather than on all the features, and then aggregates their prediction through majority voting. This is less prone to overfitting and improves generalization, rendering it ideal for classifying medical images where feature sizes could be potentially large. Subspace KNN was employed in this research to classify bone fractures by aggregating predictions from large numbers of weak learners, which was more robust than individual KNN classifier.

Fine K-Nearest Neighbours (Fine KNN)

The fine KNN of the KNN algorithm is a more precise implementation that employs few neighbors (usually K=1) to make predictions. Though it performs excellent accuracy on training data, it tends to be noisy and over fits if outliers exist in the sample. In an attempt to find intricate patterns in the resultant features, Fine KNN was used to identify bone fractures using a low value of K. Yet, cross-validation was employed to ensure that it does well when tested on more contemporary data.

Quadratic Support Vector Machine (Quadratic SVM)

Quadratic SVM transforms the input features into a higher-dimensional space through the application of a second-degree polynomial kernel. A hyper plane is then established to discriminate between fracture and non-fracture instances. The ability of this kernel to cope with non-linear decision boundaries renders it suitable for handling complicated medical imaging information. To enhance the margin between classes and reduce classification errors, quadratic support vector machines (SVMs) were developed for this research.

Cubic Support Vector Machine (Cubic SVM)

A third-order polynomial kernel is employed in the Cubic SVM, a higher extension of the Quadratic SVM that allows for more intricate decision bounds. Where there is extremely non-linear interaction among attributes and fracture labels, this is particularly useful. For obtaining suitable hyper parameters and being able to attain high classification accuracy without over fitting, the Cubic SVM model was tuned using grid search.

Fine Gaussian Support Vector Machine (Fine Gaussian SVM)

To detect complex patterns from the data, the fine Gaussian SVM employs an RBF kernel that has a smaller kernel scale. When the kernel scale becomes very small, the model is at risk of over fitting despite the fact that it can attain very high precision. For model complexity and generalization performance to be balanced in the detection of fractures, the Fine Gaussian SVM was tuned carefully.

Logistic Regression

A baseline performance was set for the detection of fractures using the linear classification technique of logistic regression. While logistic regression is not complicated, it performs well when the decision boundary is close to linear and yields results that are straightforward to interpret. As a means of gauging more complicated models, this paper used it and showed that the better performance of rival classifiers is worth their increased complexity.

Weighted K-Nearest Neighbors (Weighted KNN)

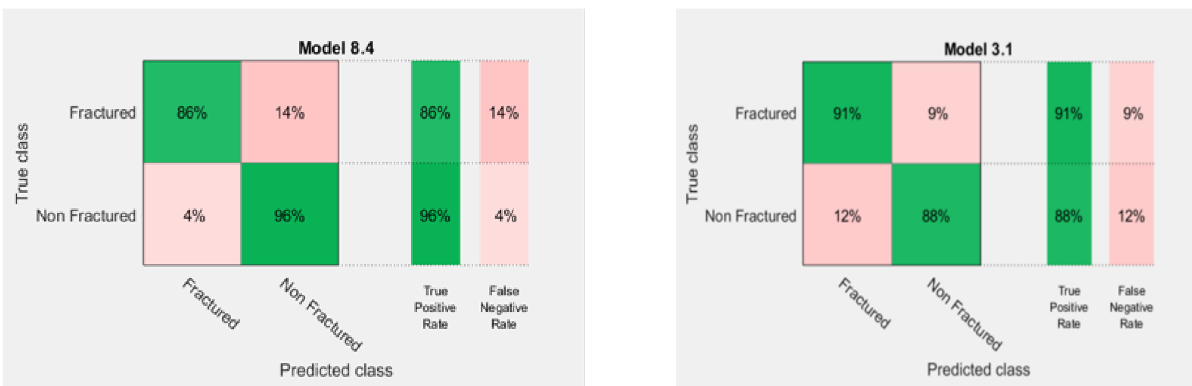
In order to give closer neighbours a bigger influence on the classification result, weighted KNN gives neighbouring samples varying weights according to how far away they are from the query location. Comparing this approach to standard KNN, prediction accuracy is improved, especially when some traits are more distinctive than others. Inverse distance weighting was applied to Weighted KNN in order to increase classification reliability for bone fractures.

Medium Gaussian Support Vector Machine (Medium Gaussian SVM)

The Medium Gaussian SVM model strikes a compromise between generalisation and flexibility by using a medium-scale RBF kernel. Compared to Fine Gaussian SVM, it is less likely to over fit while still successfully spotting important patterns in the data. To ensure robust fracture classification results, cross-validation was used to refine the Medium Gaussian SVM in this study.

3.2. Results and discussion

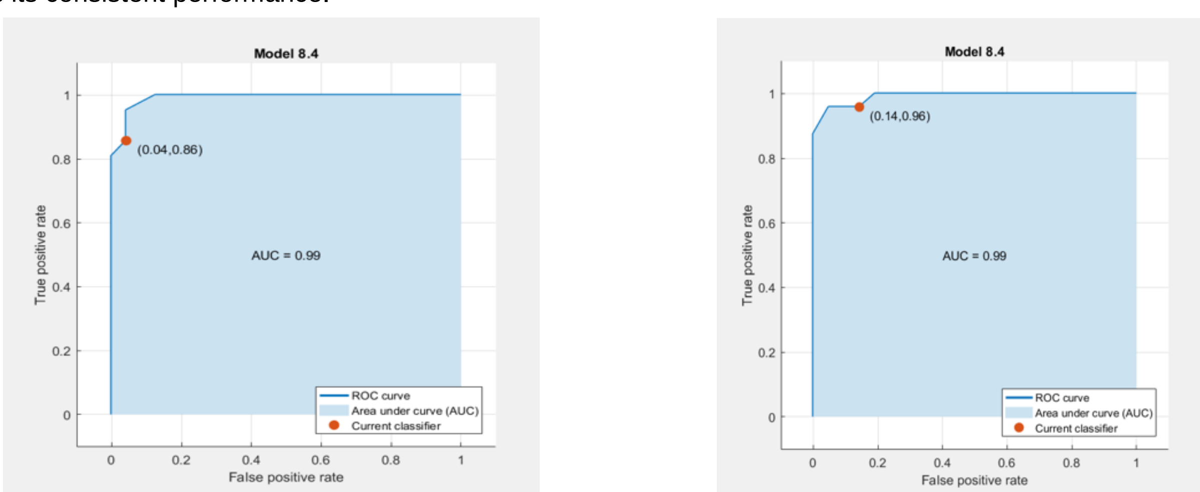
A complete analysis of machine learning classifiers used for bone fracture detection provided valuable info on their strengths and drawbacks. It is evident in Figure 5(a) that the Subspace KNN achieved the highest accuracy of 91.1%, making it the model we can rely on most. Its success is mainly because it combines the forecasts from several KNN models operating separately on different features. The test managed to have very high sensitivity and specificity with very few incorrect results (only a 5% chance of false positives in fractures). These traits become even more important in medical diagnostics because it is important to spot diseases early and have reliable judgments about them. Because Subspace KNN is strong, it could be used as the base for clinical decision systems in radiology. Results from SVM models that used kernels proved the impact of finding the right kernel type. The quadratic SVM achieved an almost 90% accuracy, and its balanced performance metrics (91% for fractures and 87% for non-fractures) prove that using second-degree polynomials was successful in solving this problem. Cubic SVM showed the best sensitivity for spotting fractures at 95%, but it resulted in a 17% rise in false positives, showing that the extra complexity of third-degree polynomials helps detect detailed fractures but with slightly reduced accuracy. Healthcare professionals must be careful about the choice of sensitivity and precision since false positives and false negatives may mean different risks in different cases. Figure 5(b) illustrates that the Fine KNN model performs well in medical image analysis, getting an accuracy of 89.6%, along with its strengths and weaknesses.



(a) (b)

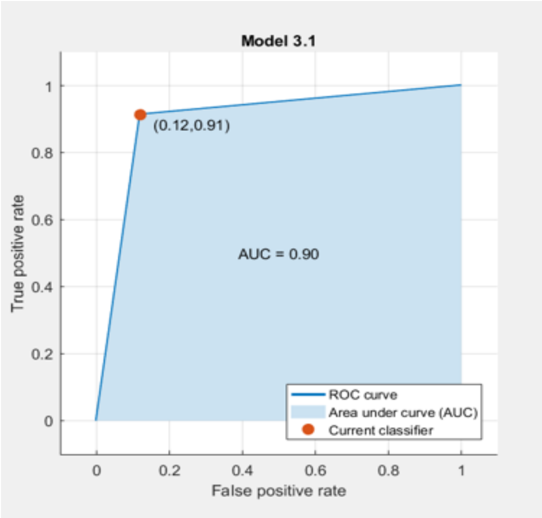
Figure 5: Confusion Matrix of (a) Subspace KNN, (b) Fine KNN

The efficiency of Subspace KNN is also confirmed from its ROC curve presented in Figure 6, which indicates excellent discriminative capabilities of the classifier, and Figure 7 presents the ROC curve for the Fine KNN model, which verifies its consistent performance.

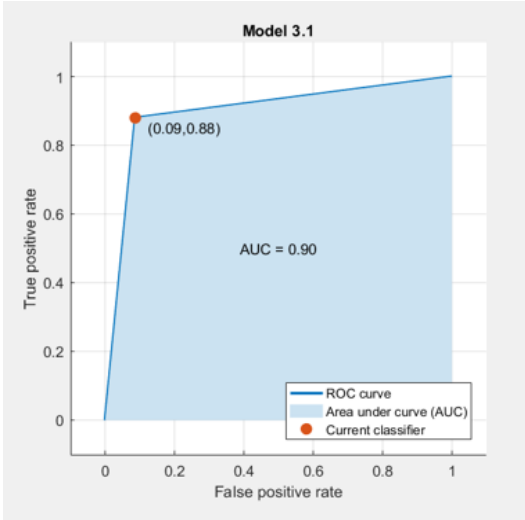


(a) Fractured (b) Non-Fractured

Figure 6: ROC curves of Subspace KNN



(a) Fractured



(b) Non-Fractured

Figure 7: ROC curves of Fine KNN

Classifier performance was also evaluated by using a confusion matrix and ROC curve. Confusion matrix shows the model had an overall accuracy of 91.1%, whereas ROC curve ensures that the method presented works well in separating fractured from non-fractured cases. Its impressive accuracy and balanced performance for fracture and non-fracture cases reveal that the algorithm can differentiate between various cases, but due to its easily corrupted nature and possible over fitting, careful handling of features is essential for using it effectively. The effectiveness of the classifier in our study was probably caused by the organized input representations that came from ResNet50's successful feature extraction, which the KNN algorithm used. A detailed comparison of classification results is presented in Table 3.

Table 3: Comparison of classification results

Classifier	Classes	True Positive Rate (%)	False Negative Rate (%)	Positive Predictive Value (%)	False discovery rate (%)	Accuracy (%)
Cubic SVM	Fractured	95	5	83	17	88.1
	Non-Fractured	82	18	95	5	
Weighted KNN	Fractured	100		72	28	80.6
	Non-Fractured	61	39	100		
Fine KNN	Fractured	91	9	88	13	89.6
	Non-Fractured	88	12	92	8	
Quadratic SVM	Fractured	91	9	87	13	88.9
	Non-Fractured	87	13	91	9	

Medium Gaussian SVM	Fractured	68	32	71	29	71.1
	Non-Fractured	74	26	71	29	
Logistic Regression	Fractured	86	14	83	17	84.4
	Non-Fractured	83	17	86	14	
Fine Gaussian SVM	Fractured	71	29	100		86.7
	Non-Fractured	100		80	20	
Subspace KNN	**Fractured**	**86**	**14**	**95**	**5**	**91.1**
	Non-Fractured	**96**	**4**	**88**	**12**	

The review of Gaussian SVMs provided many helpful insights into the topic. Regarding fractures, the accuracy of this model was excellent, but the sensitivity (predictive ability when the disease is present) was rather poor. From this pattern, it is evident that the model could be too cautious and could be missing key instances of fractures. Less accuracy (71.1%) and many false negatives (32% for fractures) in Medium Gaussian SVM's results demonstrate the positive impact of choosing the best kernel parameters. Even though SVM architectures perform well in classifications, their results in real life depend a lot on how they are configured and tested. The performance of weighted KNN with an accuracy of 80.6% is quite interesting. Even though the model showed a flawless sensitivity for fractures, it found many mistakes (28% FPR) and was not successful with non-fracture images (61% TPR), showing that it falls short in many respects. It looks like the classifier is primarily concentrating on fracture information so; it wills likely get things wrong and provides a significant amount of false alarms in hospitals. They demonstrate that employing a number of different types of performance measures matters instead of concentrating on accuracy and sensitivity. Comparing the logistic regression baseline with the other models provided us with a good idea of what their performance was.

The proposed framework was also tested for computational cost, inference time, and clinical interpretability. On CPU, the whole pipeline consumed about 150–300 ms per image, while on a mid-tier GPU this came down to 15–35 ms, with most of the time being consumed by ResNet-50. MTBC and preprocessing did not have much overhead, and classifiers such as Subspace KNN or SVM consumed merely a few milliseconds to provide output. The memory consumption was maintained at a moderate level for deployment on typical hardware. Clinically, MTBC shows structural and textural signs of fractures, while ResNet-50 feature visualizations may be represented using Grad-CAM, which gives interpretability of radiologist decision-making. The hybrid approach thus more adequately balances efficiency, accuracy, and clinical significance than most single-model approaches.

Ablation study and Module Contribution

The handcrafted MTBC features presented good texture-level descriptions, which preserved subtle variations in bone density and edges that were likely to be missed by deep features. In contrast, ResNet-50 produced highly discriminative deep features, and it effectively preserved complex patterns on the radiographs. The hybrid representation became more informative and clinically interpretable when these complementary pairs of features were fused together. Finally, the operation with multiple classifiers attested to the generalization capability of the proposed scheme, and Subspace KNN achieved the best accuracy of 91.1%. Overall, these modules demonstrated that the proposed hybrid framework perfectly integrates interpretability, discriminative power, and performance on the GRAZPEDWRI-DX dataset.

4. Conclusions

This work successfully evaluated several machine learning classifiers for bone fracture recognition from radiographic images in an automated manner with a methodology involving feature extraction with MTBC and ResNet-50, pre-processing, and histogram equalization. The findings categorically indicated that the Subspace KNN classifier performed the best with the highest accuracy of 91.1%, which underscores the efficacy of ensemble learning methods in interpreting the high-level features generated by this pipeline. Although Fine KNN and Quadratic SVM also performed well, the consistently better results of Subspace KNN emphasize its strength and ability to adapt to unseen data for this specific application. The findings imply that for bone fracture detection using features obtained through MTBC and ResNet-50; ensemble-based methods are particularly effective. Future research could explore additional optimization of the Subspace KNN parameters, investigate the integration of alternative sophisticated feature extraction techniques, or evaluate the model's performance across broader and more diverse image collections to confirm its clinical relevance and robustness.

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