Hybrid SVM–ANN system for automated MRI diagnosis of anterior cruciate ligament injuries

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ABSTRACT

Anterior cruciate ligament (ACL) tears are a frequent cause of knee instability, yet magnetic resonance imaging (MRI) interpretation remains time-consuming and observer-dependent. This paper presents an automated MRI framework for ACL injury screening and severity grading using a hybrid support vector machine–artificial neural network (SVM–ANN) model. A balanced dataset of 600 sagittal knee MRI images from Hospital Taiping (normal, partial tear, complete tear) was standardized via resizing, region-of-interest cropping, contrast enhancement, noise filtering, and segmentation. Morphological and texture features were extracted and reduced using principal component analysis (PCA). The SVM performs the initial screening (injured vs. non-injured) and samples predicted as injured are passed to the artificial neural network (ANN) to classify severity. Using confusion-matrix and receiver operating characteristic (ROC) evaluation, the proposed system achieved 86.2% overall accuracy and 81.7% sensitivity, with the ANN reaching approximately 95% accuracy on injured cases forwarded for grading. A clinician usability survey indicated high acceptance (~95%), supporting the feasibility of deployment as a lightweight decision-support tool. Limitations include reliance on single sagittal slices and single-sequence data; future work will incorporate multi-slice/3D and multi-sequence MRI to improve sensitivity and generalizability.

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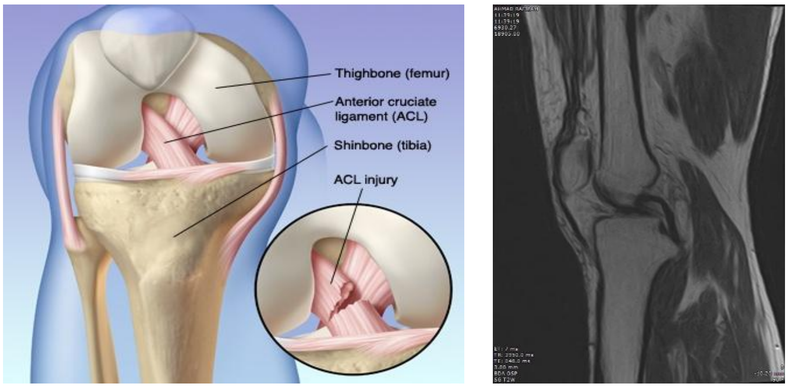
1. INTRODUCTION

Anterior cruciate ligament (ACL) injuries are among the most frequent serious ligament injuries of the knee in sports medicine and are a major cause of functional instability when untreated. Accurate detection and grading are clinically important to guide timely management and to reduce secondary meniscal or chondral damage. Magnetic resonance imaging (MRI) in Figure 1 is widely used to evaluate ACL fiber continuity, signal changes, and associated intra-articular findings [1], [2]. Figure 1(a) is knee anatomy of ACL injury and Figure 1(b) is actual MRI knee. Although MRI provides excellent soft-tissue contrast for evaluating ACL integrity, interpretation still depends on reader expertise and can show inter-observer variability, particularly for partial tears and subtle signal abnormalities. These limitations motivate computer-aided diagnosis systems that can offer objective and reproducible decision support [1], [3], [4].

In many clinical settings, MRI is interpreted by radiology services and then integrated with orthopedic assessment. This multi-step workflow can contribute to delays and variability in grading when case volumes are high or when expertise is limited. Automating parts of the image-based assessment may help standardize grading and shorten the time to a preliminary report, especially in resource-constrained environments [5]. Recent research has demonstrated strong performance for ACL tear detection using multi-sequence radiomics and modern machine learning. For example, Cheng *et al.* [3] used multi-sequence (T1-weighted and PD-weighted) MRI radiomics with an support vector machine (SVM) classifier and reported high area under the curve (AUC), sensitivity, and specificity. Deep learning approaches have also been applied to ACL tear detection and localization on knee MRI [3]. However, many high-performing methods require multi-sequence or multi-slice/3D inputs, intensive feature extraction, and substantial computing resources, which can hinder rapid deployment on lightweight platforms and limit interpretability [6]-[8]. This study targets a complementary niche by proposing a fully automated, computationally efficient pipeline that uses standardized preprocessing, interpretable morphometric features, principal component analysis (PCA) for dimensionality reduction, and a hybrid SVM–artificial neural network (ANN) architecture to i) screen for injury and ii) grade severity. Accordingly, the system is evaluated using confusion matrices, receiver operating characteristic (ROC) analysis, and clinically relevant metrics (accuracy, sensitivity, and specificity). The results section reports both the screening performance (injury vs non-injury) and the grading performance (normal/partial/complete tear) [9]. Clinically, ACL injury assessment typically combines patient history, physical examination (e.g., Lachman, pivot-shift, and anterior drawer tests) and MRI confirmation. Normal ACLs often appear as a continuous low-signal band, whereas partial tears may show waviness, increased signal, or focal fiber disruption; complete tears show discontinuity or non-visualization [1].



(a) (b)

Figure 1. MRI is widely used to (a) knee anatomy of ACL injury and (b) actual MRI knee

Digital image processing has emerged as a critical enabler of automated medical image analysis because it allows systematic enhancement and segmentation of anatomical structures. Basic operations such as resizing, cropping, contrast adjustment, filtering, thresholding and binary inversion are used to standardize input images and prepare for subsequent segmentation and feature extraction [9], [10]. In ACL MRI studies, these methods are applied to isolate the ligament from surrounding bone, cartilage and soft tissues, usually by focusing on a region of interest and then performing morphological operations to sharpen structural boundaries [11], [12]. The work of Mazlan and colleagues describes a comprehensive pipeline that includes resizing to a standard format, cropping to a region determined collectively by medical experts and computational analysis, contrast enhancement to correct dark scans and noise suppression using median or average filters, followed by segmentation using dilation, erosion, boundary tracing and region-propagation techniques. This progression reflects a general consensus in the literature that a robust pre-processing stage is essential for any successful automated ACL diagnosis system.

Beyond preprocessing, segmentation and feature extraction are central to digital interpretation of ACL images. Anatomical studies have reported considerable variation in ACL shape and texture, prompting calls for quantitative analysis of ligament morphology rather than solely visual inspection [13]. Research has shown that parameters such as ligament size, area, orientation angle and elongation correlate with different injury levels, where size often separates intact from severely damaged ligaments, area distinguishes partial from normal injuries, angle reflects complete tears and elongation indicates the degree of stretching or fiber disruption [3], [14], [15]. These insights support the extraction of shape descriptors as core features for machine-learning-based ACL classifiers [16]-[18] as shows in Figure 2.

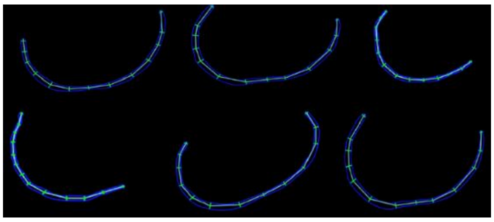


Figure 2. Variation shape of the knee [13]

Machine learning, particularly supervised learning, is now firmly established in the field of medical image analysis [4]. Techniques such as SVM, ANN, logistic regression and decision trees have been extensively used for classification tasks involving tumors, organ segmentation and lesion detection [19]-[21]. In the context of ACL, Mazlan’s early work introduced fuzzy-inference systems using rule-based logic derived from expert knowledge for MRI-based classification, illustrating the feasibility of automating ACL diagnosis [19], [20]. Later studies extended this approach to embrace fully data-driven methods, including SVM-based classification and comparative analyses of embedded systems for ACL MRI diagnosis, which examined the feasibility of implementing ACL diagnostic tools on different hardware platforms [21]. Further work proposed a complete ACL diagnosis system using image processing and SVM, where the authors reported improved performance and provided a stepping stone towards hybrid architectures that integrate more than one classifier [17], [21], [22] as in (1) and (2).

$$\{(x_1,y_1),(x_2,y_2),(x_3,y_3)\ldots,(x_n,y_n)\} \tag{1}$$

$$(w,x)+b=0 \tag{2}$$

The parameter b is scalar, while w is dimensional. The vector w coordinate is perpendicular to separating plane and the offset parameter b is added to increase the margin gap. Removing parameter b, will cause the plane going through the origin (0,0) point and restrict any solution. The parallel planes can be described in (3) and (4) [23].

$$w.x+b=1 \tag{3}$$

$$w.x+b=-1 \tag{4}$$

The condition of training data must be separable, in order for those planes to have no intersect points and maximize their distance. In geometry, determine the distance between those planes represent as $\frac{2}{|w|}$ in minimizing |w|.

2. MATERIAL AND METHOD

The methodology of this study is designed to construct a fully automated diagnostic framework for ACL injuries using MRI and to reflect the steps by which clinicians assess such injuries in practice. The overall workflow extends previous work by Mazlan, who developed an ACL diagnosis system that integrates digital image processing, feature reduction and an ensemble of SVM and ANN classifiers for MRI-based injury diagnosis, and demonstrated its feasibility in a hospital setting as in Figure 3 [18], [22], [24].

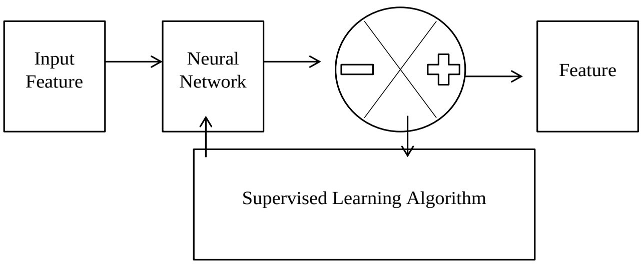


Figure 3. Structure of a supervised learning system

The first stage concerns MRI data acquisition and standardization. All MRI images used in this research were obtained from the radiology department of Hospital Taiping, Malaysia. MRI acquisition details (to address scanner-related variability): all knee MRI examinations were acquired at Hospital Taiping using a consistent clinical knee protocol to minimize intra-dataset variability. The scanner model, field strength: [1.5 T/3 T], and knee coil: [to be specified]. The sagittal images used in this study were exported from the routine protocol. All images were anonymized at export, converted to grayscale, and resized for standardized processing. Slice selection and ground truth labeling: each sample in the dataset corresponds to a 2D sagittal slice image. Reference labels (normal, partial tear, complete tear) were assigned based on the final clinical interpretation of the full MRI examination (multi-slice series) and corresponding radiology/orthopedic assessment, and then mapped to the exported slice used as input to the algorithm. Because the ACL course is oblique relative to the sagittal plane, using a single slice can miss focal fiber disruption; therefore, future work will extend the input from a single slice to multi-slice or 3D volume analysis and/or sagittal reconstructions aligned with the ACL trajectory [3], [14]. The dataset comprises 600 sagittal-plane knee MRI images of grayscale format, each with dimensions of 500×500 pixels.

Among these, 200 represent normal ACL structures, 200 depict partial tears and 200 correspond to complete or complete tears, resulting in a balanced three-class dataset. The images were captured under standardized settings designed to minimize movement artefacts and other sources of noise, such as physiologic motion and magnetic susceptibility effects, so as to ensure a consistent visualization of the knee anatomy. MRI was selected because it offers excellent soft-tissue contrast while using radiofrequency radiation considered safe compared with invasive imaging modalities like arthroscopy [22]. Once collected, the MRI images undergo an image preprocessing pipeline that standardizes resolution, enhances contrast and prepares the images for segmentation and feature extraction. The preprocessing is implemented in MATLAB and begins by resizing each MRI to a uniform size, which facilitates later processing steps and ensures that region-of-interest operations reference consistent coordinates. The system then applies cropping to isolate the ACL region. Through collaborative analysis involving medical experts and inspection of 600 MRI samples, a cropping window located at [30 73 150 190] for resized images of [320 220] was identified as optimal for capturing the ligament area between the femur and tibia. This choice is consistent with prior imaging studies that recommend focusing on anatomically relevant regions to improve efficiency and reduce irrelevant variation in subsequent processing as in (5) [25], [26].

$$(x_{new}, y_{new}) = (x_{old} \times k), (y_{old} \times k) \quad (5)$$

Where by k is the resize gain.

Following cropping, contrast enhancement is applied to redistribute pixel intensities and improve the visibility of ligament structures, especially in scans that initially appear dark or exhibit low contrast. This enhancement increases the effective grayscale dynamic range available for ACL and adjacent tissues, making it easier to distinguish ligament fibers from surrounding structures as illustrate in (6).

$$(x_1, y_1, x_2, y_2) = \left(\frac{x_1}{2}\right), \left(\frac{y_1}{2}\right), \left(\frac{x_2}{2}\right), \left(\frac{y_1}{2}\right) \quad (6)$$

Noise is reduced using median and mean filters to smooth intensity variations and suppress small artefacts while preserving edges, helping standardize image appearance and improve segmentation reliability. Segmentation then isolates the ACL by thresholding grayscale images to binary, followed by morphological refinement: dilation bridges gaps between ligament pixels and erosion removes isolated noise and sharpens boundaries. Boundary tracing extracts a closed ligament contour, and region-based labeling (region propagation) retains the connected ACL object while removing unrelated structures [10], [24]. This fully automated process yields an ACL mask that preserves ligament geometry and location for morphometric analysis, following key stages described by Mazlan [18], [22]. Feature extraction then represents the segmented ACL using quantitative descriptors for machine learning. Guided by orthopedic knowledge and prior studies [3], [13]-[15], features include size, area, orientation angle, elongation, aspect ratio, circularity, centroid, and related region properties (Table 1).

Size and area capture ligament extent and potential fiber loss, angle reflects alignment disruption typical of complete tears, and elongation/aspect ratio/circularity describe shape changes associated with stretching or structural damage. The full set of features can be high-dimensional and may contain redundant or correlated variables, principal component analysis is employed for dimensionality reduction. PCA transforms the original variables into a smaller set of uncorrelated principal components that capture most of the variance in the feature space. In earlier ACL classification work, Mazlan showed that four principal components are sufficient to preserve the discriminative information necessary to distinguish normal, partial and crucial injuries, while simplifying classifier design and mitigating overfitting. Accordingly, this study uses the leading principal components as inputs to the machine-learning models. The machine-learning architecture consists of two levels: an SVM-based screening stage and an ANN-based classification stage. The screening stage addresses the binary question of whether a given MRI scan shows an ACL injury. For this purpose, an SVM is trained on the principal components to separate injured from non-injured cases, leveraging the algorithm's ability to construct optimal separating hyperplanes with maximal margins. Hyperparameters such as the kernel type and regularization factors are tuned empirically using training and validation sets, with performance assessed through confusion matrices and ROC curves. Samples classified as non-injured are labeled as normal and not passed to further processing, whereas samples classified as injured are forwarded to the ANN.

Table 1. Parameter extraction

Feature	Description
X-axis	Elongation pixel in x-axis.
Y-axis	Elongation pixel in y-axis.
Perimeter	Total pixel along ACL boundary.
Area	Triangular area in ACL.
Average pixel	An average pixel of ACL object in image.
Circularity	Circular area in ACL.
Aspect ratio	Ratio vertical pixel line with horizontal pixel line.
Angle	Elongation degree ACL.
Number side	Total pixel ACL object in image.

The ANN, implemented as a feed-forward network trained with the Levenberg–Marquardt algorithm, performs multi-class classification into normal, partial tear and complete tear categories. It accepts the principal components as inputs and produces a three-class output. During training, the network weights are iteratively updated until convergence is achieved based on performance metrics such as mean-squared error and accuracy on training, validation and test sets. Mazlan's thesis reports that, with appropriate configuration, the ANN achieves near-perfect regression values and high class-specific performance indices. These findings inform the network design and training strategy used in the present study as in Figure 4.

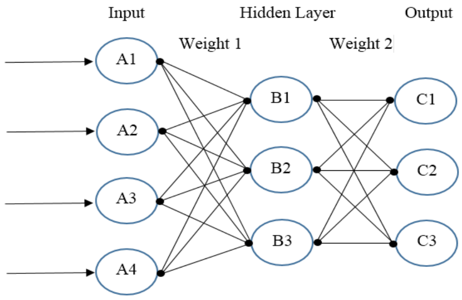
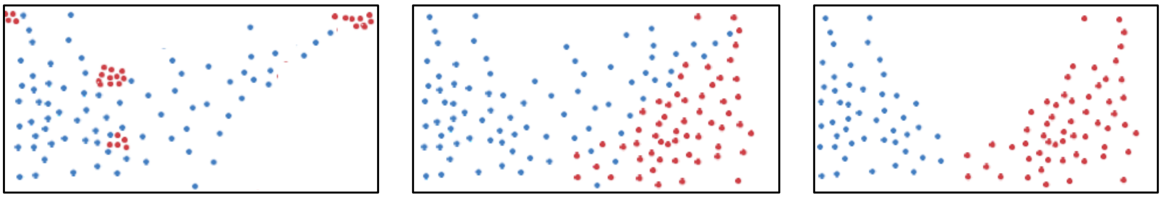


Figure 4. ANN applied for the ACL diagnosis structure

Performance evaluation involves both quantitative and qualitative measures. Quantitatively, the system is evaluated using accuracy, sensitivity, specificity, confusion matrices and ROC curves for the SVM, ANN and the combined hybrid system. Qualitatively, clinical validation is obtained by comparing system outputs against the diagnoses of orthopedic and radiology specialists on selected cases, and by administering an online questionnaire to medical practitioners to gauge usability, usefulness and affordability. The system is ultimately implemented on two platforms: MATLAB, serving as the development and processing environment, and an Android application that delivers a lightweight diagnostic tool for mobile use.

3. RESULTS AND DISCUSSION

The results of this study demonstrate that the proposed SVM–ANN ensemble system can accurately diagnose ACL conditions using MRI and that it aligns closely with clinical expectations. Quantitative performance is summarized using confusion matrices and aggregated metrics for the SVM screening module, the ANN classification module and the integrated hybrid system. The process input obtained data from four features explained in previous chapter. Figure 5(a) does not apply the k-mean technique, while Figure 5(b) applied with $2^{-2}$of (K) and Figure 5(c) with different (K) parameter of 2^{-4}. Red dots mean ACL injury and green dots mean non-ACL injury.



(a) (b) (c)

Figure 5. Data distribution: (a) without the k-mean cluster, (b) 2^{-2} k-mean cluster, and (c) 2^{-4} k-mean cluster

All the clustered parameters based on four features (circularity, aspect ratio, angle and number side) can be easily identified from each group using k-mean cluster which used constant parameter of C=23 with γ=2−4. This figure is the best testing parameter applied on both cluster; higher parameter might produce large margin error, while a low parameter produces less boundary cluster. The approximate coefficient explains the relation between injury data and non-injury data as Table 2 shows the result of screening using SVM with different parameters of gamma. From here, the most suitable value fits for this system is at γ=-4 with an average highest approximate coefficient of 79%.

Table 2. SVM screening with the variable gamma parameter

Phase	Data Scheme	γ=0	γ=-2	γ=-4	γ=-8
Training	70%	40.40%	52.10%	77.40%	61.40%
Testing	20%	47.10%	54.70%	81.20%	72.50%
Validation	10%	38.90%	59.30%	82.50%	68.60%

The ANN applied Levenberg-Marquardt (LM) technique. The LM is a very simple method for approximating a function in classifying ACL injuries LM able to reveal potentially complex relationships for all features in this ACL diagnosis system. It is unable to estimate the output, which result type of ACL injuries. Figure 6 indicates system performance and Figure 7 show the performance without training.

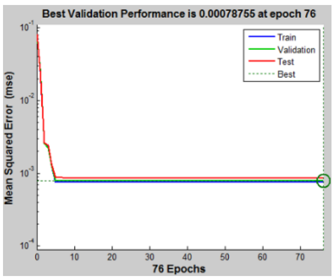


Figure 6. System performance

The training epoch of 76 iterations or epoch has tune weighted from origin value 0.001 to 0.01, whereby lower weight produces smaller data and the impact on graph shows training data pattern of 10^{-3}. Figure 6 plots graph for training state, the gradient a graph shows gradient value decreasing from 0.0007 to 9.681x10^{-6} with 76 epochs. The decreasing is tuned to maximize matching between training data and test data, while Figure 7 shows three graphs which is training, test and overall (all). Training regression plotted at 0.9808, while the validation regression shows at 0.9863 and test regression at 0.9657. From here, the all graph shows most of the data lay on the fit line. The overall performance of training, validation and test shows regression of 0.9785. From here, when all data plotted in a single graph, obviously seen most of the data are not lay on the fit line. Therefore, a further training is required to ensure most of the data lay on the fit line and produced a more accurate system. A confusion matrix method in this research consists of the hybrid combination of SVM and ANN, it is used for a decision support tool that uses a model of decisions and possible consequences including chance event outcomes, resource costs and utility. For the identification of ACL injury, the results are typically presented in terms of the confusion matrix. This matrix shows the dispositions of the set of instances in a matrix form. Suppose an identification system involves only two classes, where each has its associated class labels. There will be four possible outcomes in this case because it is a binary case. Table 3 shows details result on hybrid system.

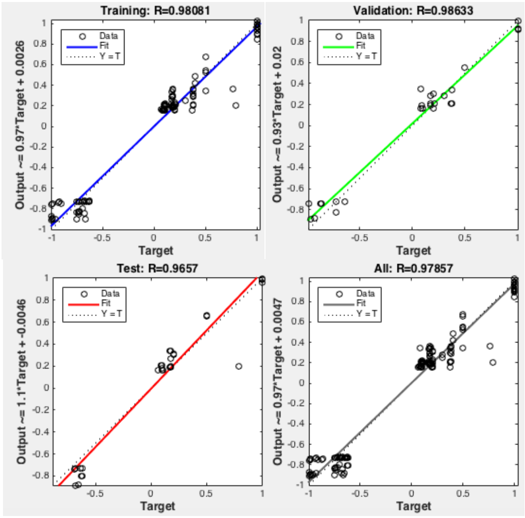


Figure 7. System performance without complete training

Table 3. Details result for hybrid diagnosis system of ACL

Severity	Mild	Moderate	Severe
Accuracy (%)	85.274%	87.731%	87.369%
Error rate (%)	<15%	<14%	<14%
Sensitivity (%)	79.351%	80.924%	82.463%

Table 3 summarizes the hybrid system performance for three severity levels (mild, moderate, and severe), which correspond to increasing degrees of ACL fiber disruption in this dataset. Importantly, clinical treatment decisions (e.g., surgery vs. rehabilitation) depend on additional factors such as knee instability, patient activity demands, and concomitant meniscal or chondral injuries; therefore, the system output should be interpreted as imaging-based severity grading rather than a direct treatment recommendation [2], [14].

Performance comparison and refinement: the hybrid SVM–ANN system attains sensitivity values of approximately 79–82% across severity strata (Table 3), which is lower than several recent multi-sequence radiomics and deep learning approaches. For instance, Cheng *et al.* [3] reported validation sensitivity and specificity of 0.857 and 0.829 (AUC 0.927) using multi-sequence MRI radiomics with an SVM classifier. The performance gap is likely influenced by (i) the use of a single 2D sagittal slice rather than multi-slice/3D inputs, (ii) scanner/protocol variability not fully modeled, and (iii) the use of hand-crafted morphometric features instead of richer texture/radiomics features [12], [25]. Future refinements will prioritize multi-slice aggregation (e.g., slice-wise voting or 3D modeling), protocol harmonization, feature expansion toward radiomics, and comparative benchmarking against lightweight convolutional neural network (CNN) backbones suitable for mobile deployment [5], [14], [26].

4. CONCLUSION

The results show that a structured pipeline standardized preprocessing, interpretable morphometric feature extraction, PCA-based reduction, and hybrid classification can enable automated ACL injury screening and MRI-based severity grading as a decision-support tool (not a replacement for expert reading). A key strength is the two-stage design: the SVM first filters clearly normal cases, reducing ANN workload and allowing the ANN to focus on grading injured scans. This reflects clinical reasoning and, based on confusion matrices and performance comparisons, reduces normal-case misclassification while improving discrimination between partial and complete tears, consistent with Mazlan's findings on hybrid systems.

Clinically motivated choices (region of interest (ROI) definition and morphology-based descriptors linked to ligament continuity/appearance) also improve transparency versus black-box models and support future extension to radiomics or deep features. A preliminary clinician evaluation found the interface and outputs understandable for screening and grading; however, broader multi-disciplinary and prospective assessments especially including more musculoskeletal radiologists are needed to quantify clinical impact. Limitations include reliance on a single sagittal slice (risking missed focal disruption due to the ACL's oblique course), potential scanner/protocol variability, and a modest dataset with hand-crafted features that may underperform multi-sequence radiomics. Real-world deployment will require multi-center prospective validation, protocol harmonization, and threshold calibration; future work will expand data across scanners/sequences, add multi-slice aggregation, and benchmark lightweight deep-learning backbones suitable for edge/mobile use.

Overall, this study presents a fully automated framework integrating preprocessing, PCA-based feature reduction, SVM screening, and ANN grading in a unified architecture. On a balanced dataset of 600 knee MRI images from Hospital Taiping, the system achieved ~86% accuracy and >81% sensitivity, with ROC analysis indicating strong discriminative performance. Expert verification and practitioner survey feedback suggest the outputs align with routine practice and that the tool is usable and potentially cost-effective for deployment.

This work contributes by embedding expert knowledge into an end-to-end platform that combines image processing, machine learning, and confusion-matrix-based evaluation to reduce manual workload, standardize decisions, and support consistent ACL diagnosis. Future work will focus on multi-center expansion, learning features directly from raw images using deep learning, and tighter integration with clinical information technology (IT) systems to improve robustness, accuracy, and adoption in routine orthopedic and sports medicine practice.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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