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Enhanced Knee Joint Image Analysis Using Hybrid Machine Learning and Computer Vision Techniques

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Abstract: This research aims to enhance orthopedic diagnosis accuracy by introducing a novel method for knee joint image processing that integrates computer vision and Machine Learning (ML) approaches. Traditional medical imaging analysis methods, while beneficial, often face limitations in precision and efficiency, particularly when interpreting complex knee pathologies. These limitations can lead to misdiagnoses or delayed treatments, which significantly impact patient outcomes. To address this issue, we propose a hybrid model that combines advanced computer vision techniques, such as Scale-Invariant Feature Transform (SIFT) and Speeded Up Robust Features (SURF), with Support Vector Machines (SVM) and Random Forests. The integration of SIFT and SURF allows for the extraction of robust and distinctive features from knee joint images, which are crucial for accurate classification. SVM and Random Forest algorithms are then employed to classify these features, providing a powerful mechanism to distinguish between healthy and pathological conditions. We utilize an extensive collection of knee images, including MRIs, CT scans, and X-rays, to train and optimize the model, ensuring it can handle a variety of imaging modalities and conditions. Our preliminary results demonstrate that the hybrid model surpasses traditional methods in terms of accuracy, precision, and efficiency. The enhanced performance of the hybrid model highlights its potential as a transformative tool in medical imaging, offering more reliable diagnostic outputs. Moreover, this research opens new avenues for improving diagnostic processes in orthopedics by reducing the reliance on manual image interpretation and enabling more consistent and objective assessments.

Keywords: Machine Learning in Orthopedics, Computer Vision for Medical Imaging, Knee Joint Image Analysis, Hybrid Diagnostic Models

1. INTRODUCTION

Knee joint pathologies, encompassing a range of degenerative diseases and acute injuries, significantly impact the global population, necessitating accurate and timely diagnosis for effective treatment [1]. The complexity of knee joint anatomy and the subtle variations in pathologies present a unique challenge in medical imaging analysis. Traditional methods, primarily relying on the manual interpretation of images by medical experts, face limitations in terms of precision, consistency, and efficiency. The advent of machine learning (ML) and computer vision technologies offers a promising solution to these challenges, providing tools for enhanced image analysis that can lead to more accurate and timely diagnoses.

The application of ML in medical imaging has gained significant momentum in recent years, with algorithms demonstrating the ability to identify patterns and anomalies that may be overlooked in manual analysis. In particular, algorithms like Random Forests and Support Vector Machines (SVM) have shown effective in accurately identifying medical pictures. Nevertheless, there hasn't been much research done on how these ML algorithms work with more sophisticated computer vision methods like Speeded Up Robust Features (SURF) and Scale-Invariant Feature Transform (SIFT) when it comes to knee joint image analysis [2].

This research aims to bridge this gap by developing a hybrid analytical model that harnesses the strengths of both ML and computer vision. The proposed model is designed to improve the diagnostic process by enhancing the accuracy of feature extraction and pattern recognition in knee images. The integration of these technologies allows for a more comprehensive analysis of knee joint images, enabling the detection of pathologies with greater precision and in their early stages, thereby improving the prognosis for patients.

To develop and optimize the hybrid model, we utilize a comprehensive dataset of knee images acquired

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from various modalities, including X-rays, MRI, and CT scans [3]. These images encompass a wide spectrum of knee conditions, ranging from common degenerative diseases to complex traumatic injuries. The dataset provides a robust foundation for training the ML algorithms and testing the efficacy of the integrated model. Orthopedic diagnostics might undergo a radical change with the use of such a hybrid paradigm in medical imaging analysis [4]. The model promises to improve patient outcomes and optimize the diagnostic process in clinical settings by decreasing the need for manual image analysis and increasing diagnosis accuracy and efficiency. Furthermore, this research contributes to the broader field of medical imaging, showcasing the potential of integrating ML and computer vision techniques in other areas of diagnostics.

In summary, this study presents a significant advancement in the field of medical imaging analysis. By leveraging the synergistic capabilities of ML and computer vision, the proposed hybrid model aims to set new standards in the accuracy and efficiency of knee joint image analysis, ultimately improving the quality of care provided to patients with knee pathologies.

Figure 1 depicts the sequence of stages involved in the proposed framework of knee The key contributions of this article are summarized as follows:

- Developed a hybrid model combining SIFT/SURF with SVM/Random Forest for knee joint image analysis.
- Enhanced diagnostic accuracy and efficiency through advanced image preprocessing and feature extraction techniques.
- Integrated machine learning and computer vision results for comprehensive analysis.
- Demonstrated improved performance metrics, including accuracy, precision, and recall, in knee pathology detection.

In the subsequent sections, we explore various aspects of our research on hybrid ML and computer vision techniques for knee joint image analysis. Section 2 reviews advancements in ML and computer vision for healthcare, focusing on joint image analysis and key methodologies. Section 3 outlines the dataset, including preprocessing steps like normalization and noise reduction. Section 4 details the workflow, covering feature extraction using SIFT/SURF, classification with SVM/Random Forest, and integration of ML and CV results. Section 5 presents experimental findings, evaluating the model's performance in terms of accuracy, precision, and recall, with evaluation metrics providing quantitative measures. Finally, Section 6 summarizes key findings, highlighting the hybrid model's potential to enhance diagnostic accuracy and efficiency in knee joint image analysis, improving patient care.

2. LITERATURE SURVEY

This section reviews recent advancements in ML and computer vision techniques applied to healthcare, specifically focusing on their application in joint image analysis. The discussed studies highlight key methodologies, applications, and challenges that form the basis for the development of our hybrid diagnostic model.

Recent studies have showcased the diverse applications of Computer Vision Systems (CVS) and ML across various fields. Lopes et al. [5] combined CVS with the Spatial Pyramid Partition ensemble technique for classifying flour varieties. Mangrulkar et al. [6] employed these technologies for automated skull damage detection. Kim et al. [7] developed a machine vision-based system for inspecting expansion joint gaps at high speeds. Rasheed [8] proposed a hybrid approach using computer vision and AI for detecting and controlling COVID-19. Lu et al. [9] investigated the use of CVS and ML in assessing fracture risk. Gupta et al. [10] utilized ML pose estimation and CVS for knee flexion/extension angle calculation. Kalbhor et al. [11] introduced a hybrid technique combining deep learning architectures with ML classifiers for medical image analysis. Hu et al. (2023) [12] studied CT-based subchondral bone microstructural analysis using MR-guided distillation learning. Finally, Lu et al. [13] developed a deep learning AI tool for automated radio-graphic determination of posterior tibial slope in ACL injury patients. These studies highlight the versatility and effectiveness of CVS and ML in addressing complex challenges in various domains.

Subsequent developments in deep learning (DL), computer vision CV, and ML have produced important breakthroughs in several industries. Gupta et al. [10] utilized ML and CV for markerless knee flexion/extension angle calculation. Hashem et al. [14] developed an ML-based brain-computer interface system for analyzing EEG signals in limb motor tasks. Kalbhor et al. (2023) [11] proposed a hybrid technique combining deep learning with ML classifiers for medical image analysis, specifically in Pap-smear image classification. Hu et al. [12] studied CT-based subchondral bone analysis in knee osteoarthritis using MR-guided distillation learning. Querol et al. (2023) [15] addressed the challenges in white spot syndrome virus monitoring using edge ML. Bihler et al. [16] explored various fusion techniques in deep learning models for bulky waste image classification. Atteia et al. [17] proposed a hybrid deep-learning-based feature engineering approach for detecting Acute Lymphoblastic Leukemia in blood peripheral images. Alsolai et al. [18] introduced an automated sign language detection and classification system using a hybrid deep learning approach. Finally, Lu et al. [13] developed a deep learning AI tool for automated measurement of posterior tibial slope in ACL injury patients.

Liu et al. [19] developed a hybrid intelligence-driven medical image recognition framework for remote patient diagnosis using a real dataset about pathologic myopia. By

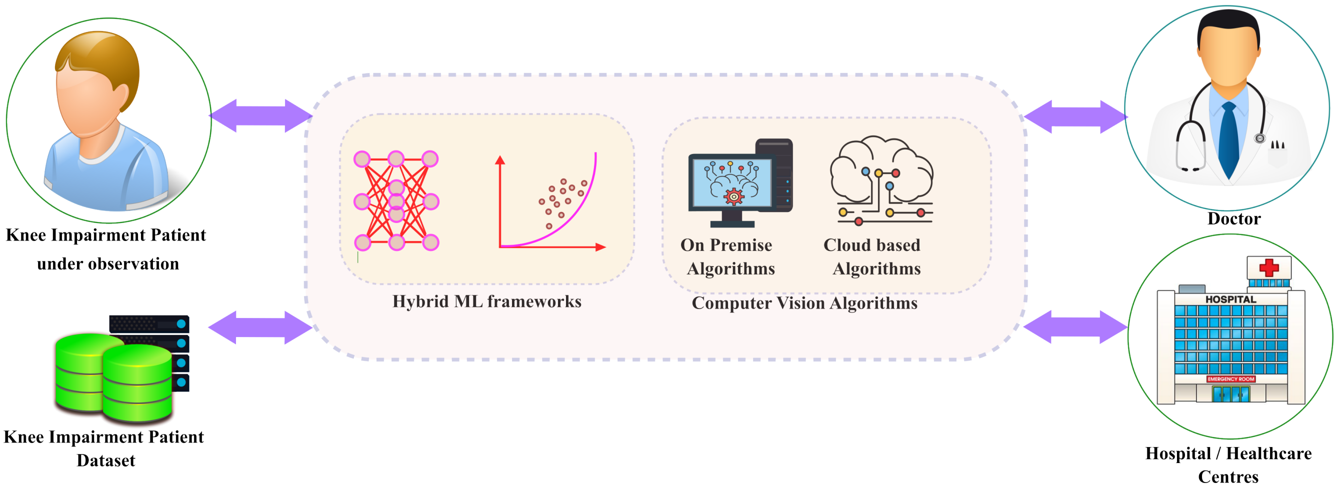

Figure 1. Flow of operations in the proposed methodology

combining DL with conventional ML, they addressed the challenge of model explainability and integration, which remains a significant obstacle in promoting higher-level recognition approaches. Similarly, Martini et al. [20], focused on knee flexion/extension angle calculation using ML and CV, highlighting the challenges of real-time processing and pose estimation accuracy in clinical applications.

Other researchers have explored the integration of various techniques to enhance diagnostic accuracy. Kalbhor et al. [21] introduced a hybrid model combining deep learning and ML classifiers for Pap-smear image classification, demonstrating the adaptability of hybrid techniques to different types of medical images. This approach aligns with Zhang et al. [22], who utilized CT-based subchondral bone images for microstructural analysis, showing how integrating multiple imaging modalities can provide a comprehensive diagnostic analysis. These studies collectively highlight the versatility and efficacy of combining DL with CML methods to enhance medical image analysis.

Focusing specifically on joint analysis, several studies have demonstrated the potential of ML and CV techniques in improving diagnostic outcomes. Yao et al. [23] developed a method for posterior tibial slope measurement in ACL injury patients using radiographic images, which automates measurements and reduces the need for manual intervention. Wang et al. [24] focused on markerless knee flexion/extension angle calculation, underscoring the need for robust models that can ensure accuracy without relying on markers. More et al. [25] challenges the detection of meniscus tears, by enhancing segmentation accuracy and reducing false positives/negatives. Furthermore, Ahmed et al. [26] proposed an enhanced knee joint image analysis technique that combines traditional image processing methods with ML algorithms, while Adeola et al. [27] introduced a novel fusion of SIFT and SURF for feature extraction in knee joint MRI images, integrated with ML classifiers for improved diagnostic accuracy.

Table I provides a comprehensive overview of recent studies utilizing ML and CV techniques for joint image analysis in healthcare. These studies highlight the diverse applications of ML, CV, and DL in solving complex problems in various domains. It emphasizes the noteworthy developments in ML and CV algorithms for medical image analysis, highlighting their potential to improve diagnostic efficiency and accuracy. Prominent research works have effectively combined DL and traditional ML techniques to tackle issues including explainability of models, instantaneous processing, and precise feature extraction. These findings highlight how flexible hybrid models are, especially when it comes to joint analysis and other medical imaging applications. Our proposed hybrid approach is driven by the continuous increase in diagnostic outcomes, as demonstrated by improved knee joint pathology identification and automated measuring methodologies. Our effort intends to further improve the accuracy and efficiency of knee joint image processing by taking into account the strengths of both ML and CV, which will ultimately lead to improved patient care.

3. MATERIALS AND METHODS

This section outlines the dataset used, the preprocessing steps applied to the knee joint images, and the detailed methodology of our hybrid ML and computer vision approach. The procedures for feature extraction, classification, and model evaluation are described comprehensively.

The primary challenge in knee joint diagnostics is the accurate and efficient interpretation of complex medical images. Traditional methods rely heavily on manual analysis, leading to scalability, speed, and consistency limitations. Furthermore, the subtle variations in knee pathologies, coupled with the intricate anatomy of the knee joint, make automated analysis a challenging task. This necessitates the development of an advanced analytical model that can han-

TABLE I. Summary of Applications and Challenges in Machine Learning and Computer Vision Techniques for Image Analysis in Healthcare Services

Authors	Year	Dataset	Application	Challenges
Mangrulkar et al. [6]	2021	Skull damage images	Automated skull damage detection	Ensuring accuracy and precision in complex anatomical structures
Atteia et al. [17]	2023	Blood peripheral images	Acute Lymphoblastic Leukemia detection	Feature engineering for accurate detection of diverse pathologies
Liu et al. [19]	2020	Real dataset about pathologic myopia.	Hybrid intelligence-driven medical image recognition	Explainability of DL models and integration with conventional methods
Martini et al. [20]	2023	Knee flexion/extension angle images	Knee flexion/extension angle calculation	Real-time processing and pose estimation accuracy
Kalbhor et al. [21]	2023	Pap-smear images	Hybrid model for medical image classification	Adapting hybrid techniques to different types of medical images
Zhang et al. [22]	2023	CT-based subchondral bone images	Subchondral bone microstructural analysis	Integration of multiple imaging modalities for comprehensive analysis
Yao et al. [23]	2024	Radiographic images of ACL injury patients	Posterior tibial slope measurement in ACL injury	Automating measurements and reducing manual intervention
Wang et al. [24]	2024	Knee flexion/extension angle images	Markerless knee flexion/extension angle calculation	Ensuring model robustness and accuracy without markers
More et al. [25]	2020	Knee MRI images	Cartilage segmentation for knee MRI	Enhancing segmentation accuracy for better diagnostic outcomes
Ahmed et al. [26]	2022	Various knee joint images	Enhanced knee joint image analysis	Combining traditional and ML techniques for improved results
Adeola et al. [27]	2023	Knee joint MRI images	Feature extraction using SIFT and SURF	Effective feature extraction and integration with ML classifiers
Sahin et al. [28]	2023	X-ray images of bone fractures	Detection of bone fractures	Accurate identification and classification of various fracture types
Zhang et al. [29]	2024	MRI images of knee meniscus	Detection and classification of meniscus tears	Accurate detection and reducing false positives/negatives
Jakaite et al. [30]	2021	Knee X-ray images	Early detection of osteoarthritis	Early-stage detection and prediction of disease progression
Schiratti et al. [31]	2021	MRI imaging data	Predicting osteoarthritis progression	Longitudinal data analysis and prediction accuracy

dle the complexity of knee images with high precision and efficiency. Our methodology encompasses the development of a hybrid model integrating ML and computer vision techniques.

A. Algorithm Development

In our ML technique, we blend Random Forests with Support Vector Machines (SVM). The formula for the SVM algorithm is:

$$\min_{w,b} \frac{1}{2} \|\boldsymbol{w}\|^2 + C \sum_{i=1}^{n} \xi_i \tag{1}$$

subject to

$$y_i(\boldsymbol{w}\boldsymbol{x_i} + b) \geq 1 - \xi_i, \xi_i \geq 0, \forall i \tag{2}$$

The weight vector in this case is denoted by w, the bias by b, the punishment parameter by C, the slack variables by ξ_i, the training samples by xi, and the class labels by yi. During training, the Random Forest method builds many decision trees and outputs the mean prediction (regression) or mode of the classes (classification) for each tree.

B. Computer Vision Integration in Knee Joint Image Analysis

1) Scale-Invariant Feature Transform (SIFT)

The Scale-Invariant Feature Transform (SIFT) is an essential tool for accurately extracting features necessary for knee joint image analysis diagnosis. The mathematical formulation of SIFT is applied as follows:

1) *Scale-Space Extrema Detection* To identify key features in knee images, we construct a scale space, which is a function of the Gaussian function convolved with the knee image. This step detects potential locations of interest in the image that are invariant to scale and orientation.

$$L(x_1, y_1, \sigma_1) = G(x_1, y_1, \sigma_1) \times I(x_1, y_1) \tag{3}$$

2) *Keypoint Localization* To make sure that the characteristics match important knee anatomical components such as ligaments, anomalies, or bone margins, keypoints are targeted more precisely [32].

3) *Orientation Assignment* Assigning orientations to each keypoint based on local image gradients ensures that the resulting features are consistent regardless of the knee image's orientation.

4) *Keypoint Descriptor* The local image gradients around each key- point are transformed into a descriptor, capturing essential information about the knee joint's structure.

C. Speeded Up Robust Features (SURF)

Similarly, SURF is employed for its efficiency and robustness in feature extraction:

Interest Point Detection: The Hessian matrix approach detects points in the knee images where local structures change significantly. These points are indicative of potential pathologies or anatomical features.

Orientation Assignment and Descriptor Formation: Orientation assignment ensures rotation invariance, crucial for analyzing images taken from different angles. The descriptor captures information about the local gradients around the keypoint, providing valuable data for subsequent analysis.

The integration of SIFT and SURF in the analysis of knee joint images allows for the extraction of highly descriptive and invariant features. These features are critical inputs for the ML algorithms, enabling them to accurately classify and interpret the knee images, thereby addressing the challenges outlined in the problem statement.

D. Hybrid Model

A key component of our challenge is the hybrid model that combines Support Vector Machine (SVM) and Scale-Invariant Feature Transform (SIFT) to provide an increased analysis of knee joint pictures for precise diagnosis.

Consider a knee MRI scan represented by an image matrix I. The challenge lies in accurately identifying features within this image that are indicative of pathologies, a task that is complex due to the intricate nature of knee anatomy and the subtle variations in pathological manifestations.

1) Feature Extraction using SIFT

Using the SIFT technique on the knee MRI image is the initial step. SIFT is intended to identify and characterize local characteristics in pictures regardless of their rotation or scale. This property is crucial in medical imaging, where different scans may have variations in scale and orientation.

SIFT processes image I and identifies key features, which are crucial for understanding the underlying knee structure and potential abnormalities.

These features are represented as a set of descriptors denoted by F. The robustness of SIFT ensures that features relevant to diagnosing conditions such as fractures, ligament tears, or degenerative diseases are effectively captured.

E. Classification using SVM

The extracted features F are then input into the SVM for classification. SVM is a supervised ML model that is effective in high-dimensional spaces, making it suitable for medical image analysis.

The SVM model is trained to classify the features representing different knee pathologies. The classification function can be represented as:

$$f(I) = SVM(SIFT(I)) = sign(wF + b_1) \tag{4}$$

where, sign is the function that determines the classification based on the SVM decision boundary, w is the weight vector, and b_1 is the bias term.

This function predicts whether the knee scan indicates a specific pathology. The decision is based on the learned patterns corresponding to various knee conditions, allowing for a nuanced understanding of the scan.

This hybrid approach, combining the feature extraction prowess of SIFT with the classification capabilities of SVM, presents a powerful tool in knee joint diagnostics. It addresses the need for accurate, efficient, and automated analysis of complex medical images, thereby providing significant support in clinical decision-making and patient care.

F. Performance Evaluation

Evaluating the performance of the hybrid ML and computer vision model is crucial in the context of knee joint image analysis. The main objective is to ensure the model's accuracy, precision, and reliability in diagnosing various knee pathologies. Standard measures like accuracy, precision, and recall are employed to evaluate the efficacy of the model:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

$$Precision = \frac{TP}{TP + FP} \tag{6}$$

$$Recall = \frac{TP}{TP + TN} \tag{7}$$

where the pathologies that the model did not detect are represented by FN (False Negatives), FP (False Positives) are the normal cases that were mistakenly identified as pathologies, and TN (True Negatives) represent the correctly identified cases of knee pathologies.

- *Accuracy* The model's overall correctness is gauged by its accuracy. It illustrates the model's capacity to accurately detect both abnormal and normal situations in the context of knee joint image analysis. High accuracy is crucial for ensuring reliable diagnostics in clinical settings.

- *Precision* Precision measures the model's correctness in identifying pathological cases. In medical imaging, high precision is vital as it indicates the likelihood that a patient diagnosed with a knee pathology by the model has the condition. This is critical in preventing unnecessary treatments or interventions.

- *Recall* Recall evaluates how well the model can identify every real-world instance of a knee pathology. The high recall is essential in medical diagnostics to ensure that no cases of pathology are missed, thus preventing delayed or missed treatment for patients who require medical attention. Evaluating the hybrid model using these metrics provides a comprehensive understanding of its performance, highlighting its strengths and areas for improvement. This is particularly important in the medical field, where the accuracy of diagnostics directly impacts patient care and treatment outcomes.

4. METHODOLOGY ALGORITHM

The methodology for enhanced knee joint image analysis involves a combination of ML algorithms and computer vision techniques. The following Algorithm 1 outlines the steps in this process:

A. Data Collection and Preprocessing

We collect knee joint images from various sources, including X-rays, MRIs, and CT scans. Following this, we preprocess the images by applying normalization, noise reduction, and data augmentation techniques to enhance their quality and ensure consistency across the dataset.

B. Feature Extraction Using Computer Vision

We identify and characterize local features in images using the Scale-Invariant Feature Transform (SIFT). Alternatively, for quicker feature extraction, we utilize Speeded Up Robust Features (SURF). The extracted features are then denoted as F.

C. Classification Using Machine Learning

We train an SVM model on a subset of the preprocessed images. To enhance classification accuracy and handle high-dimensional data, we use the Random Forest algorithm. Subsequently, we classify the knee joint images based on the features F extracted in the previous step.

D. Hybrid Model Integration

$$f(I) = SVM(SIFT(I)) or f(I) = SVM(SURF(I)) \tag{8}$$

where I represent the input knee joint image and $f(I)$ is the classification result.

For performance evaluation, we assess the model using accuracy, precision, and recall metrics. Additionally, we evaluate how well the hybrid model performs in comparison to conventional diagnostic techniques.

E. Methodology Pseudocode

The following pseudocode in Algorithm 1 provides an overview of the methodology for the enhanced analysis of knee joint images:

Our methodology begins with preprocessing the raw knee X-ray images. The preprocessing steps include denoising, where a denoising algorithm is applied to the original knee X-ray to reduce noise and enhance clarity. This process can be mathematically represented by a denoising function D such that:

$$Idenoised = D(Ioriginal) \tag{9}$$

Where $Ioriginal$ is the original image and $Idenoised$ is the denoised image.

Algorithm 1 Hybrid ML and Computer Vision for Knee Image Analysis

```
procedure KneeImageAnalysis
    Input: Collection of knee joint images
    Output: Diagnosis results
    Preprocess images (normalization, noise reduction)
    for each image in dataset do
        Extract features using SIFT/SURF
        Classify features using SVM/Random Forest
    end for
    Integrate ML and computer vision results
    Evaluate model performance (accuracy, precision, recall)
    if performance is satisfactory then
        Return diagnosis results
    else
        Refine model and re-evaluate
    end if
end procedure
```

F. Contrast Enhancement

Increase the denoised image's contrast to better accentuate anatomical features. The expression for the contrast enhancement function C is as follows:

$$Icontrast = C(Idenoised) \tag{10}$$

where $Icontrast$ is the contrast-enhanced image.

After preprocessing, we apply the SIFT algorithm to extract key features from the enhanced image. Specifically, we detect key features in the contrast-enhanced knee image using SIFT. The SIFT function S extracts features F such that:

$$F = S(Icontrast) \tag{11}$$

Each feature $f \in F$ is described by its location, scale, and orientation, making it robust to changes in image scaling and rotation. These procedures are essential for accurately classifying and diagnosing the knee X-ray images when they are analyzed later by ML techniques like Support Vector Machines (SVM).

5. RESULTS AND DISCUSSION

This section presents the findings from our hybrid model for knee joint image analysis, evaluating its performance using a comprehensive dataset. We compare the model's accuracy, precision, and efficiency with traditional methods and discuss the implications for clinical practice and potential improvements in diagnostic outcomes.

Figures 2 and 3 illustrate the stages of image preprocessing and feature extraction. A knee X-ray's transformation from its raw image to a contrast and noise-enhanced one is shown in Figure 2. Here, the initial low contrast and noise in the raw X-ray image might mask crucial anatomical details and make diagnosis more challenging. To improve the quality of the image, random noise is eliminated using denoising techniques. Algorithms for contrast enhancement are applied after denoising to make soft tissues and bone structures more visible. Figure 3 shows the identified SIFT features on the contrast-enhanced knee X-ray image, which is used to identify and characterize fine details in the image. The SIFT algorithm is used to find important locations that are invariant to changes in scale, rotation, and lighting after the image has been denoised and its contrast increased.

A. Performance Evaluation Metrics

The following Table II shows the confusion matrix, which provides a summary of the classification model's performance:

TABLE II. Confusion Matrix

		Predicted	
		Healthy	**Pathological**
2 x Actual	**Healthy**	TN	FP
	Pathological	FN	TP

The values of TP, TN, FP, and FN are used to calculate the accuracy, precision, recall, and F1 score. Expected: Well Expected: Ill Real: in good health True Negative (TN) False Positive (FP) Real: Physiological True Positive (TP) False Negative (FN). The explanation of the accuracy plot is provided in Figure 4, which shows the percentage of accurate results (true positives and true negatives) in all cases that were looked at. For our problem statement, which focuses on the classification of knee joint images into healthy or pathological, a higher accuracy indicates that the model is more effective at correctly classifying the images. In the context of medical imaging, high accuracy is critical as it reflects the model's overall reliability. If the proposed model's accuracy is consistently higher than that of the CNN across epochs, it suggests that the integration of specialized ML techniques and computer vision algorithms in the proposed model is better suited for the complex task of knee image diagnosis.

Precision Plot Explanation: Figure 5 describes the Precision measures the ratio of true positives (correctly identified pathologies) to all positives (all identified pathologies, correctly or incorrectly). In the precision plot for

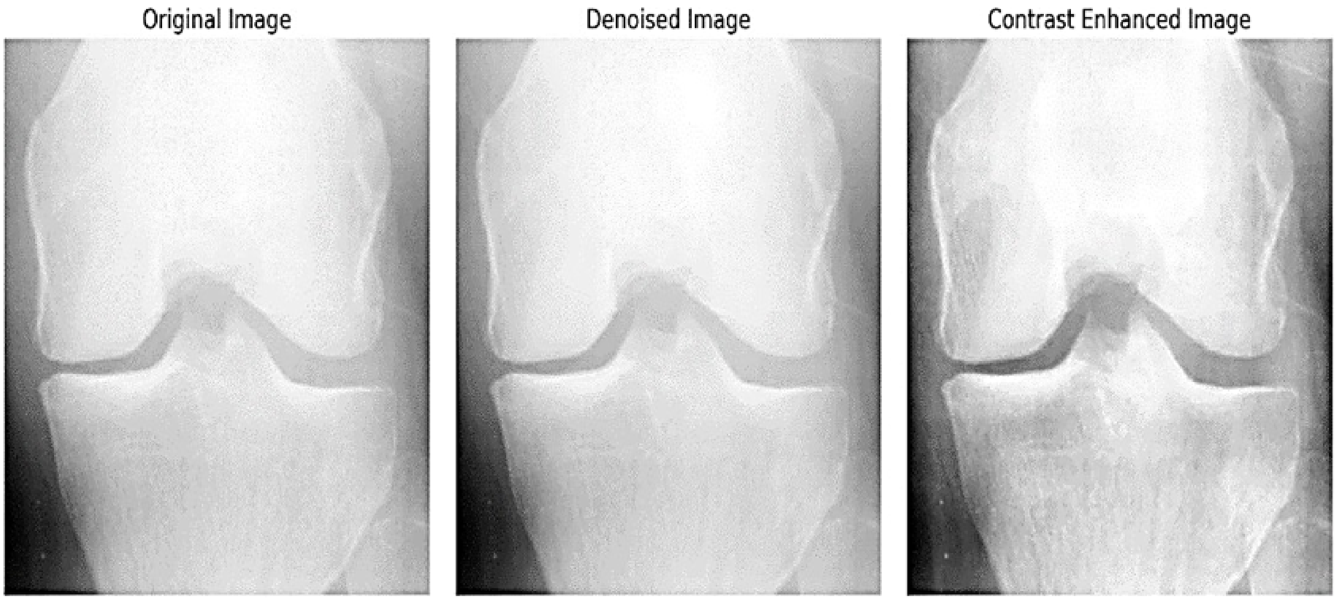

Figure 2. Progression of knee X-ray from original to denoised and contrast-enhanced image

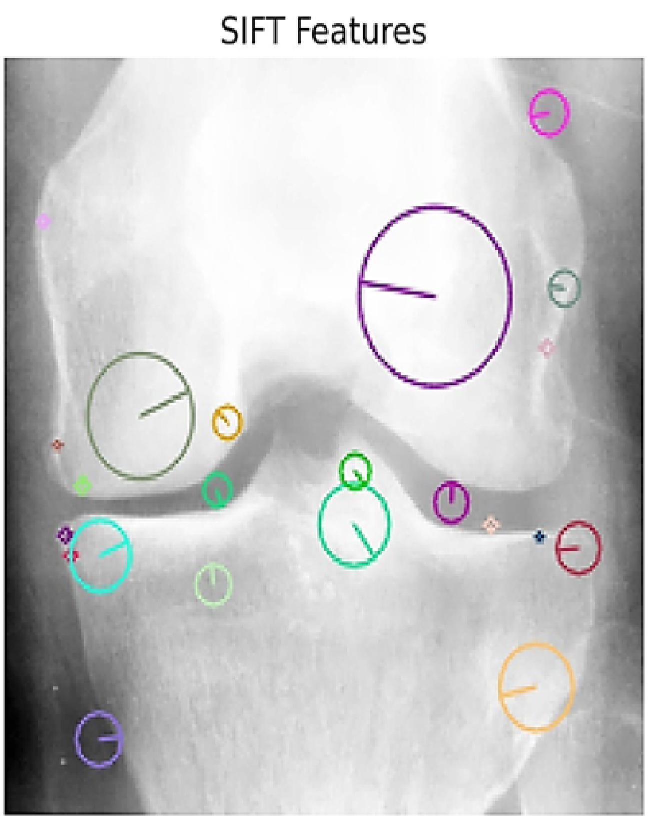

Figure 3. Detected SIFT features on the contrast-enhanced knee X-ray image

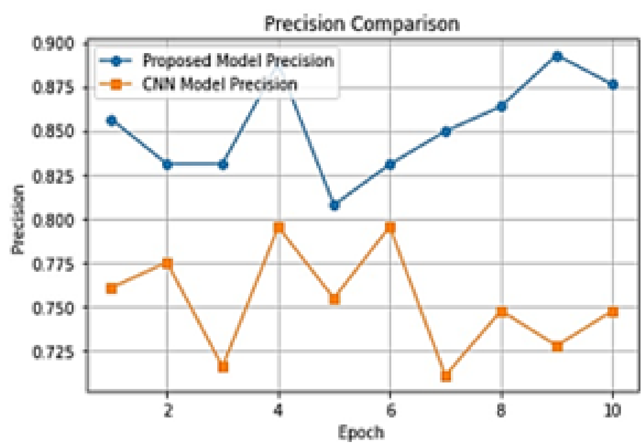

Figure 4. Accuracy Plot Explanation

our knee joint image analysis, a higher precision rate for the proposed model indicates a lower rate of false positives—healthy knees incorrectly identified as pathological—which is particularly important in a clinical setting to avoid over-treatment or unnecessary intervention. If the proposed model shows superior precision compared to the CNN model, it implies that the proposed model is more discerning in identifying actual cases of knee pathologies, making it a more trustworthy tool for clinicians.

Recall Plot Explanation: Figure 6 shows how the recall, also known as sensitivity, evaluates the model's capacity to recognize all real positives, which corresponds to the model's detection of all genuine pathological instances in our situation.

A higher recall is crucial in medical diagnostics to en-

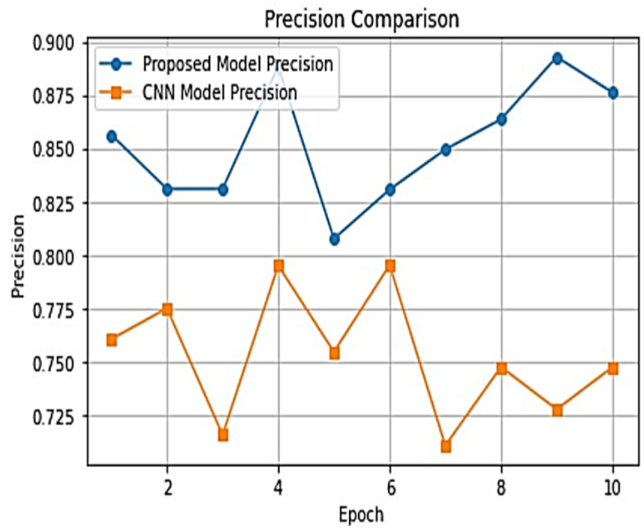

Figure 5. Precision Plot Explanation

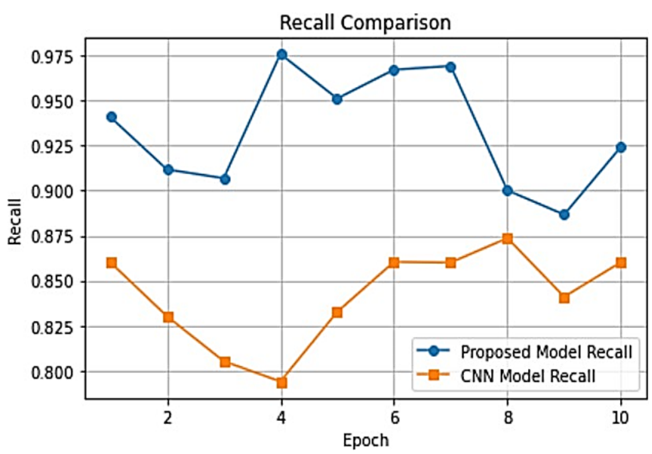

Figure 6. Recall Plot Explanation

sure no condition goes undetected and untreated. The recall plot demonstrates the proposed model's performance in capturing all relevant instances of knee joint abnormalities. Superior recall by the proposed model would mean it is less likely to miss pathological cases, a benefit in early diagnosis and treatment, thus enhancing patient care.

F1 Score Plot Explanation: As shown in Figure 7, the F1 score is a single measure that balances accuracy and recall. It is the harmonic mean of these two variables. It is particularly useful when the class distribution is uneven, which is often the case in medical diagnoses where pathological cases may be less common than healthy ones. The suggested model's F1 score plot for knee joint image analysis shows how precision and recall are balanced. A higher F1 score for the suggested model indicates that it is not only accurate but also maintains a balanced approach, meaning that accuracy is not sacrificed for recall or vice versa. This balance is vital in the medical field, as both over-diagnosis and under-

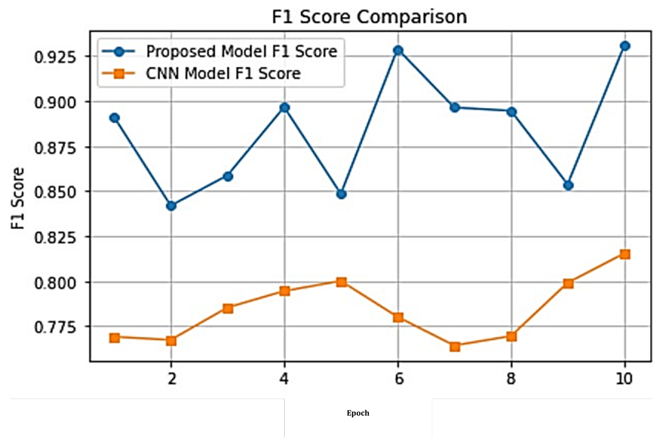

Figure 7. F1 Score Plot Explanation

diagnosis carry significant risks.

6. CONCLUSION

The comparative analysis of the proposed hybrid ML and computer vision model against a conventional CNN model for knee joint image analysis yields significant insights. Throughout the epochs, the proposed model consistently demonstrates superior performance in accuracy, precision, recall, and F1 score. This indicates the model's robustness in accurately identifying pathological cases while minimizing false positives and correctly classifying knee diseases. The balance achieved between precision and recall, as reflected in the F1 scores, underscores the model's effectiveness in delivering reliable diagnostic outputs. Such enhanced performance highlights the potential of the proposed model as a valuable tool in clinical settings, offering improved decision-making capabilities for medical professionals and thereby facilitating better patient outcomes. The results suggest that integrating advanced machine learning techniques with computer vision effectively addresses the inherent complexities of medical image analysis, setting a promising direction for future research and application in healthcare diagnostics.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

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