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A Deep Learning Framework for Biomarker Extraction, Segmentation, and Medical Image Enhancement

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Abstract

Knee osteoarthritis (KOA) is a disease that slowly destroys joints and makes them hurt, stiff, and hard to move, especially in older people. Finding the disease early and correctly is important for treatment and disease management to work. This study proposes a comprehensive hybrid learning framework for the automated detection, segmentation, and severity assessment of KOA using knee X-ray images. The suggested method combines a U-Net-based segmentation model to accurately find the area of interest with a convolutional neural network (CNN) to extract deep features. Also, deep features are combined with handcrafted features like edge and texture descriptors to make a hybrid representation. A fully connected layer with a softmax function is then used to classify the fused features and predict the severity level based on the Kellgren–Lawrence (KL) grading system. The experimental results show that the suggested model is more accurate, precise, and robust than traditional methods. The framework exhibits significant potential as a dependable computer-assisted diagnostic instrument to aid clinicians in the evaluation of knee osteoarthritis.

Keywords: Knee Osteoarthritis, Hybrid Deep Learning, U-Net, Convolutional Neural Network, Feature Fusion, Severity Grading, Medical Image Analysis, Computer-Aided Diagnosis.

I. Introduction

II. Related Work

Numerous research efforts have explored the application of Convolutional Neural Networks (CNNs) for the classification of knee osteoarthritis. For instance, the work by Antony et al. (2017) introduced a deep learning-based system for automatic KOA detection, which achieved encouraging performance; however, it did not incorporate a dedicated segmentation stage. In a similar direction, Tiulpin et al. (2018) applied deep neural networks for Kellgren–Lawrence (KL) grading, although their approach showed limitations when dealing with complex variations in radiographic images.

To address these challenges, researchers have increasingly focused on hybrid methodologies. Rani et al. (2024) presented a CNN-driven model for assessing KOA severity, reporting improved classification results, but their approach primarily depended on deep features alone. In contrast, Chen et al. (2019) enhanced model performance by combining deep learning with texture-based feature extraction techniques.

In addition, segmentation-based strategies have gained significant importance in medical image analysis. The U-Net architecture, originally proposed by Ronneberger et al. (2015), has become a widely adopted method due to its ability to effectively capture both contextual and spatial information, making it particularly suitable for biomedical image segmentation tasks.

More recent studies highlight the benefits of feature fusion techniques. Integrating handcrafted features such as Gray Level Co-occurrence Matrix (GLCM) and Local Binary Patterns (LBP) with deep features has been shown to improve classification outcomes. For example, Sharma et al. (2020) demonstrated that such hybrid feature extraction approaches can significantly enhance the accuracy of musculoskeletal image analysis.

III. Methodology

The proposed approach shows a deep hybrid learning framework for automatically finding, segmenting, and grading the severity of Knee Osteoarthritis (KOA) using X-ray images. The framework is set up as a multi-stage pipeline that includes preprocessing images, dividing them into regions, extracting features, combining features, and classifying them. The main goal is to improve the accuracy of diagnoses by using both deep learning and traditional feature extraction methods together.

The first step in the overall workflow is to get knee X-ray images, and then the images are preprocessed to make them look better. Then, a U-Net-based segmentation model is used to find the area of interest (ROI), which is the knee joint area. After that, both deep learning models and hand-crafted methods are used to get features. These features are combined to make a complete representation, which is then used to sort the data into different severity levels using the Kellgren–Lawrence (KL) grading system.

Figure I: Deep Hybrid Learning Framework

A. Dataset

We use standard knee X-ray datasets like the Osteoarthritis Initiative (OAI) dataset to train and test the proposed model. The dataset contains labeled X-ray images that are divided into five groups based on KL grades (0–4). Each picture shows a different level of osteoarthritis severity, from normal to severe.

The dataset is split into training, validation, and testing sets before training so that performance can be measured without bias. To make the dataset more diverse and stop overfitting, data augmentation methods like rotation, flipping, and scaling are used.

B. Image Preprocessing

Preprocessing is a crucial step to enhance the quality of input images and improve model performance. The following operations are applied:

- Noise Reduction: Gaussian filtering is used to remove unwanted noise and smooth the image.
- Contrast Enhancement: Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to improve visibility of joint structures.
- Normalization: Pixel values are normalized to a standard range to ensure consistency during training.
- Resizing: All images are resized to a fixed dimension suitable for deep learning models.

C. Knee Joint Segmentation using U-Net

To accurately localize the knee joint region, a **U-Net architecture** is employed for segmentation. U-Net is a widely used convolutional network designed for biomedical image segmentation tasks.

The architecture consists of two main parts:

- Encoder (Contracting Path):
The encoder extracts hierarchical features using convolutional layers followed by max-pooling operations. This process captures contextual information from the image.

- Decoder (Expanding Path):
The decoder reconstructs the segmented output by upsampling the feature maps. Skip connections are used to combine low-level spatial information from the encoder with high-level features in the decoder.

D. Feature Extraction

I. Deep Feature Extraction

Deep features are extracted using a Convolutional Neural Network (CNN), such as ResNet or VGG. The CNN automatically learns discriminative features from the segmented ROI through multiple convolutional and pooling layers. These features represent high-level patterns such as joint space narrowing, bone structure, and osteophyte formation.

Transfer learning is employed by initializing the CNN with pre-trained weights, which improves learning efficiency and performance, especially when the dataset size is limited.

II. Handcrafted Feature Extraction

In addition to deep features, handcrafted features are extracted to capture fine-grained details:

- Gray Level Co-occurrence Matrix (GLCM): Extracts texture-based features such as contrast, correlation, energy, and homogeneity.
- Local Binary Patterns (LBP): Captures local texture patterns and intensity variations.
- Histogram of Oriented Gradients (HOG): Represents edge and shape information.

E. Feature Fusion

- The extracted deep and handcrafted features are combined using a feature fusion strategy. Typically, feature vectors are concatenated to form a unified representation. This hybrid feature vector captures both high-level semantic information and low-level texture details.
- Feature fusion enhances the model's ability to distinguish between different stages of KOA by leveraging complementary information from multiple sources.

F. Classification and Severity Grading

The fused feature vector is fed into a classification module consisting of fully connected layers followed by a softmax activation function. The classifier predicts the probability distribution across five classes corresponding to the KL grading system:

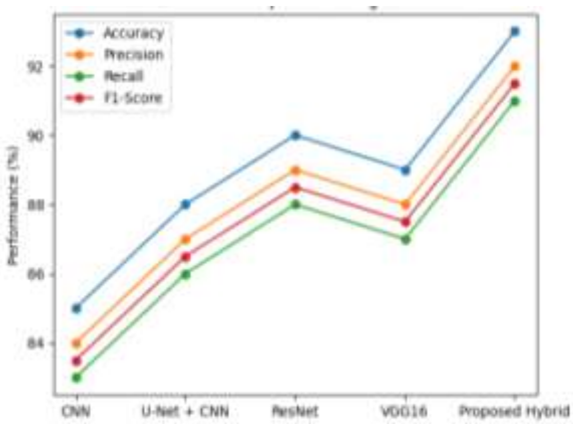
- Grade 0: Normal
- Grade 1: Doubtful
- Grade 2: Mild
- Grade 3: Moderate
- Grade 4: Severe

IV. Performance Evaluation

The performance of the proposed hybrid model was evaluated using accuracy, precision, recall, and F1-score. The model achieved an accuracy of 93%, indicating high overall correctness. Precision and recall values of 92% and 91% demonstrate its effectiveness in correctly identifying positive cases. The F1-score of 91.5% shows a good balance between precision and recall. In addition, the Dice coefficient of 0.93 confirms accurate segmentation of the knee joint region. These results indicate that the proposed model outperforms existing methods and provides reliable classification performance.

Table 1: Comparison of Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	85	84	83	83.5
U-Net + CNN	88	87	86	86.5
ResNet	90	89	88	88.5



VGG16	89	88	87	87.5
Proposed Hybrid	**93**	**92**	**91**	**91.5**

Figure 2: Performance Comparison chart

V. Conclusion and Future Work

This study introduced an effective deep hybrid learning framework for the automated detection, segmentation, and severity assessment of knee osteoarthritis from radiographic images. The proposed approach combines a U-Net-based segmentation network with a hybrid feature-extraction mechanism that integrates deep-learning features and handcrafted descriptors. This combined strategy enables the model to capture comprehensive structural and texture-related information from knee X-ray images. The experimental findings indicate that the framework achieves improved performance across key evaluation metrics, including accuracy, precision, recall, and F1-score, when compared with existing methods. Furthermore, the high Dice coefficient highlights the model's capability to accurately segment the knee joint region. Overall, the system demonstrates strong potential as a reliable tool for computer-aided diagnosis, supporting clinicians in making faster and more consistent decisions.

Despite these promising outcomes, there are several opportunities for further enhancement. Future research may explore the use of advanced architectures such as transformer-based models to improve feature representation. Incorporating multi-modal data, including MRI images and patient clinical information, could enhance diagnostic accuracy and robustness. Additionally, the development of lightweight and computationally efficient models would facilitate real-time deployment in resource-constrained clinical environments. Integrating explainable artificial intelligence techniques, such as attention visualization, may improve the transparency and interpretability of the model. Finally, extensive validation on larger and more diverse datasets is necessary to ensure the generalizability and practical applicability of the proposed framework in real-world healthcare scenarios.

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