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Enhanced Knee Osteoarthritis Classification using a Modified EfficientNetB5 Architecture with Self-Attention Mechanism

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***Abstract*—Knee osteoarthritis, a debilitating and threatening musculoskeletal condition, underscores the critical importance of early detection for timely treatment. Given the seriousness of this health issue, this study explores the use of deep learning as an effective diagnostic tool. The study introduces an innovative method for diagnosing and classifying knee osteoarthritis, achieved through the modification of an EfficientNetB5 architecture and the integration of the Self Attention mechanism, addressing current limitations. The attention mechanism selectively emphasizes crucial features, enabling the model to prioritize and weigh pertinent information in the classification process. To ensure a strong approach, a custom callback is used in training coupled with strategies to solve issues of class imbalance. This approach greatly enhances the diagnosis of musculoskeletal health, meeting the critical need for early intervention with an exceptional 90.86% accuracy with a comparatively smaller dataset. The intentional alteration of the model, along with an emphasis on the Self Attention mechanism, signifies a break from custom and a sincere attempt to improve medical image analysis. The strategy's proven effectiveness not only supports it but also points out areas for improvement, perhaps leading to more accurate diagnostic tools. This technique represents a significant advancement in the treatment of osteoarthritis in the knee, a condition that may have fatal implications.**

***Index Terms*—Knee Osteoarthritis, Self Attention Mechanism, EfficientNetB5, Classification**

I. Introduction

Millions of people worldwide are impacted by knee osteoarthritis, a chronic degenerative joint disease that is becoming increasingly important as a public health concern. The aging population and an increase in cases among younger people as a result of conditions including obesity and joint traumas are contributing to its rising prevalence. Over 364 million people worldwide suffered from knee osteoarthritis in 2019. This crippling ailment severely degrades joint function, causing pain, stiffness, and decreased mobility. With a 7.5% increase since 1990, the age-standardized prevalence indicated that it represented 4.9% of all global causes of disease [1]. Projections for 2050 indicate a troubling 75% surge compared to 2020 [2]. Beyond its profound health impact, knee osteoarthritis imposes substantial economic burdens, exemplified by a study on Dutch workforce absenteeism costs revealed €40 million in annual sick leave due to knee and hip osteoarthritis, with knee osteoarthritis costs approximately double those of hip osteoarthritis [3]. Effective intervention necessitates weight control, lifestyle modifications, and cutting-edge therapies. To address the societal and economic consequences of this widespread musculoskeletal condition, more awareness, early diagnosis, and focused therapies are crucial.

The conventional approach to detecting and treating knee osteoarthritis (KOA) has several shortcomings. Traditional diagnostic methods, which rely on clinical assessment and radiographic imaging, can be time-consuming and insensitive, particularly in places where there is a shortage of medical personnel. This could lead to delays in getting the right diagnosis and treatment. Furthermore, because the condition's symptoms might be modest or confused with aging indicators, people commonly fail to notice it in its early stages. Because of this, people often don't realize they have knee OA until it has progressed to a more severe stage, which makes it more challenging to get the best care and treatment at an early stage. Overcoming this will require research and the application of state-of-the-art diagnostic technologies.

A promising approach to overcoming the shortcomings of traditional knee osteoarthritis (KOA) detection techniques is the combination of deep learning and machine learning. These cutting-edge technologies enable a paradigm change in diagnostics by addressing the sensitivity and time constraints of clinical assessments and conventional imaging. Machine learning models, trained on diverse datasets, excel in identifying subtle patterns indicative of early-stage OA, enabling swifter and more accurate diagnoses [4]. Deep learning, particularly through convolutional neural networks (CNNs), exhibits a superior capability to analyze intricate medical images, surpassing the constraints of conventional radiographic approaches [5], [6]. Healthcare workers may diagnose osteoarthritis (OA)

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early and precisely by utilizing these advancements, which opens the door to prompt interventions and effective management plans. The fusion of deep learning and machine learning is a revolutionary step toward surmounting the limitations of conventional approaches, which will ultimately improve the field of musculoskeletal health diagnostics.

In this study, deep learning techniques were strategically applied for the detection of knee osteoarthritis, aiming to overcome traditional limitations inherent in conventional approaches. The adopted methodology featured a model built upon the EfficientNetB5 architecture, leveraging the power of transfer learning through fine-tuning. This study ensured a strong and fair training environment by carefully addressing the problem of data imbalance, which went beyond architectural issues. This research was further characterized by the addition of a self-attention mechanism, which improved model performance and result interpretability. The research aimed to tackle the common constraint of working with a small dataset. The objective was not only to develop a high-performing model but also to achieve this with limited data. Through the methodical integration of sophisticated deep learning techniques, optimization tactics, and data imbalance mitigation techniques, this work represents a noteworthy advancement in knee OA identification, effectively addressing the drawbacks of traditional diagnostic approaches.

Section II navigates through related works, Section III details the study's research methods, Section IV delves into experimental results, comparing the proposed approach with contemporary research and analyzing the model's performance, Section V acknowledges study limitations, and finally, Section VI concludes the paper.

II. Related Works

Recent studies on the prediction of knee osteoarthritis (KOA) emphasize the importance of utilizing a variety of deep learning strategies. Especially, attention is paid to the fusion of ensemble techniques and deep learning. These efforts demonstrate a commitment to improving diagnostic techniques and treatment approaches in this area by aiming to increase the precision and accuracy of knee OA prognosis.

The study [6] introduces significant contributions to knee osteoarthritis (OA) detection and severity classification, including a fine-tuned CNN for knee segmentation, a self-attention mechanism with a visual transformer for enhanced classification, and evaluation on a large-scale dataset, showcasing improved segmentation efficiency and increased OA severity classification accuracy (69.1%). Notwithstanding these contributions, a noteworthy limitation surfaces in the form of a comparatively lower achieved accuracy.

The study [7] introduces a novel intensity manipulation technique to address pixel intensity variance in knee X-ray images. They use a modified UNet autoencoder as a pre-trained encoder for a ResNet CNN, leveraging manifold learning to overcome dataset collection problems. Further improvements are required for better diagnostic precision, even if the method obtains an accuracy of 78.9%, suggesting effectiveness in improving classification accuracy and overcoming data obstacles.

The study [8] proposes two networks to improve knee osteoarthritis classification from X-rays: one extracts the joint center using VGG, and the other classifies OA grades using ResNet-50. A pre-processing step with frequency domain image filtering enhances accuracy, and a rebalance operation addresses dataset imbalance, significantly boosting accuracy to 81.41% which can be improved.

Cueva et al. [9] utilize a Deep Siamese convolutional neural network and a fine-tuned ResNet-34 in their approach. This model detects lesions in both knees and assigns Kellgren-Lawrence (KL) grades, which evaluate the severity of osteoarthritis. The proposed method achieves an average multi-class accuracy of 61.71%, excelling in KL3 and KL4 classifications but facing challenges in distinguishing KL1 and KL2 classes.

Jain et al. [10] introduces a novel deep convolutional neural network (CNN) for predicting knee osteoarthritis (OA) severity from X-ray images. Utilizing High-Resolution Network (HRNet), attention mechanisms, ordinal loss, and data augmentation techniques, the model achieves a substantial improvement over existing methods, reaching the highest multi-class accuracy of 71.74%.

In their work [11], Wang et al. introduce the Siamese-GAP architecture, extending the classical Siamese network with Global Average Pooling (GAP) modules for multi-level feature capture. GAP-feature vectors are combined by the model, which consists of two CNNs with shared parameters, to produce a feature vector. Grade predictions for KL-0 and KL-2 are made using this vector. With a hybrid loss strategy, the model attains an impressive accuracy of 88.38%, while there is still potential for improvement.

III. Research Methodology

In order to match with the EfficientNetB5 design, the study technique started with scaling photos to 240x240 pixels and converting grayscale to RGB. Synthetic Minority Oversampling Technique (SMOTE) was used to address class imbalance by producing synthetic samples for the minority class to improve model generalization. The dataset was divided into three categories: training (70%), validation (10%), and testing (20%). incorporating a self-attention mechanism into the improved feature extraction of the updated EfficientNetB5. This hybrid architecture helps to effectively detect and classify knee osteoarthritis by combining the pre-trained feature extraction of EfficientNetB5 with additional convolution and dense layers, as well as specific attention techniques. In addition, a customized callback was added to the model training procedure. This custom callback dynamically adjusted the learning rate, monitored metrics, and enabled early stopping, optimizing the model's adaptability and training efficiency. In Figure 1, the workflow of the proposed methodology is illustrated.

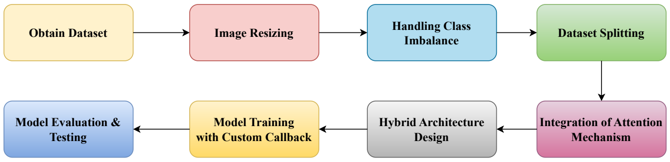

Fig. 1: Workflow of the Proposed Methodology

A. Dataset Description

The research utilized an openly accessible dataset obtained from Mendeley [12] for knee osteoarthritis. The dataset comprises 1650 images distributed across five classes based on Kellgren-Lawrence (KL) grades. KL Grade 0, indicating a normal condition, consists of 514 images. KL Grade 1, categorized as doubtful, comprises 477 images. KL Grade 2, representing a mild condition, includes 232 images. KL Grade 3, indicating moderate severity, is composed of 221 images. Lastly, KL Grade 4, signifying severe osteoarthritis, contains 206 images. Figure 2 displays a selection of sample images extracted from the dataset.

Fig. 2: Sample images from the dataset

B. Dataset Preprocessing

Optimizing the data before preprocessing greatly enhances the performance of the model. The first steps were converting grayscale photographs to RGB format and scaling them to 240x240 pixels. The purpose of this conversion was to align the data with the EfficientNetB5 architecture specifications, guaranteeing best practices for future model training and assessment. In order to address the issue of class imbalance, there were 514 images in the "Normal" class and 206 in the "Severe" class. The Synthetic Minority Over-sampling Technique (SMOTE) addressed class imbalance by generating synthetic samples for the minority class, ensuring balanced representation. This reduced bias toward the majority class, improved training efficiency, and enhanced the model's ability to learn minority class patterns and generalize to new data.

C. Proposed Modified EfficientNetB5 Architecture

In the proposed model, the initial step involves excluding the top layer of the pre-trained EfficientNetB5, preserving its inherent feature extraction capabilities while preparing for subsequent fine-tuning. Following this exclusion, a tailored top layer is introduced to enable fine-tuning and adapt the model for knee osteoarthritis classification. In order to capture complex patterns in knee X-ray pictures and enhance feature representation, this customized top layer combines convolutional and densely linked layers in a strategic manner. A Reshape layer is applied to the representation to align it with the expected structure for succeeding layers after features are extracted using the EfficientNetB5 model. The features are formatted correctly for subsequent processing in the neural network thanks to this reshaping procedure. It makes sure that data moves through the network smoothly, which maximizes the model's capacity to identify pertinent patterns in the incoming data. Figure 3 illustrates the proposed Modified EfficientNetB5 Architecture with Self-Attention Mechanism, providing a visual representation of the model's structure.

Two more convolutional layers are used early on in the suggested model architecture to aid in the extraction of spatial features. 256 filters with a (3,3) kernel size are used in the first convolutional layer, and 128 filters with the same (3,3) kernel size are used in the second convolutional layer. These filters are essential for extracting various spatial features from X-ray pictures of the knee. Selecting various filter sizes improves the model's capability for feature extraction and classification by helping it recognize and understand hierarchical representations of patterns. Each convolutional operation is followed by rectified linear unit (ReLU) activations, which introduce non-linearity and help the model grasp complicated relationships in the input data. The use of different filter sizes is consistent with the objective of attaining a thorough and discriminative feature representation in the classification of knee osteoarthritis.

Batch Normalization strategically follows convolutional and dense layers to stabilize training by normalizing layer outputs. This adjustment ensures a mean of 0 and a standard deviation of 1, addressing internal covariate shift and fostering efficient convergence. After post-convolution, global average pooling reduces dimensions to a single value by averaging each feature map, which condenses spatial information. In order to improve performance, this helps reduce the number of parameters in the neural network architecture, prevent overfitting, and streamline it.

A self-attention mechanism was incorporated before the convolutional layers in the suggested model architecture in order to improve the model's focus on relevant regions in knee X-ray images for the categorization of osteoarthritis. This approach makes it possible for the model to give different input components varied weights, which makes it easier to identify complex patterns and contextual data. Precise localization is essential in the context of medical imaging, particularly for osteoarthritis in the knee. The model performs better in identifying small irregularities because the self-attention process makes sure the model focuses important spatial elements. When it comes to obtaining stronger outcomes and reliable performance in medical picture classification tasks, its inclusion is essential.

The model incorporates three dense layers with 512, 256, and 5 neurons in each layer. The selection of layer sizes accommodates the need to capture hierarchical feature representations, which is in line with the intricacy of classifying knee osteoarthritis. Specifically, the final thick layer has five neurons, which corresponds to the number of classes in the classification task. After every dense layer, a deliberate dropout rate of 0.45 is implemented, serving as a regularization

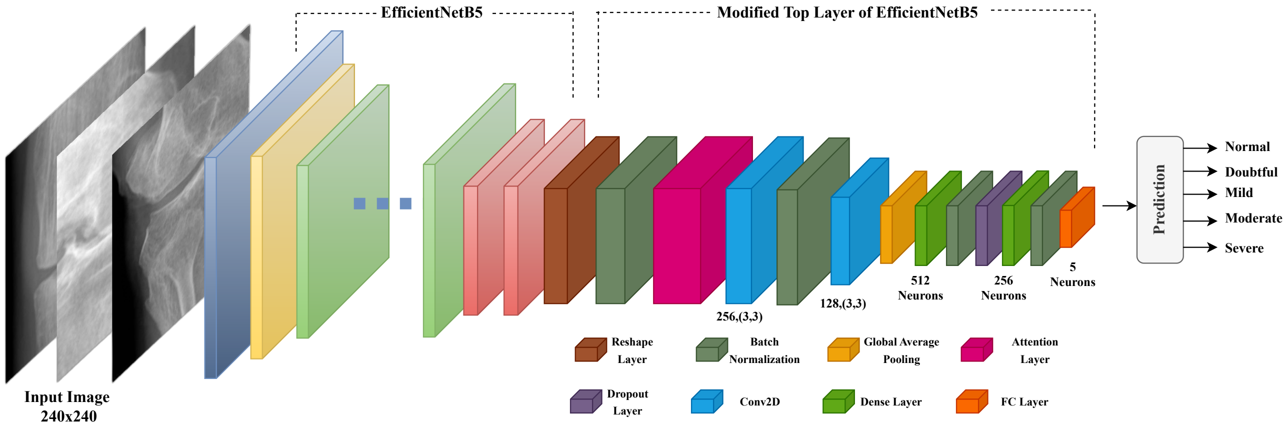

Fig. 3: Architecture of the proposed model

strategy to reduce overfitting. During training, dropout causes a random fraction of neurons to become temporarily inactive, which forces the model to rely on a variety of learning routes. By preventing over-reliance on certain features and improving generalization abilities, this strengthens the classification task's robustness.

D. Self-Attention Mechanism

Figure 4 depicts the self-attention mechanism utilized in the model architecture. This attention layer is a fundamental component that endows the neural network with the ability to selectively attend to different regions of its input. The self-attention mechanism is intricately designed with query W^Q, key W^K, and value W^V weight matrices. As illustrated in the figure, the input tensor X undergoes transformations through these weight matrices, resulting in query ($Q = X \cdot W^Q$), key ($K = X \cdot W^K$), and value ($V = X \cdot W^V$) representations. The attention scores or weights are computed by taking the dot product of the query and key matrices, signifying the significance of each element in the input sequence:

$$\text{Attention Scores} = \text{softmax}(Q \cdot K^T) \tag{1}$$

The subsequent application of a softmax activation ensures proper normalization of these attention scores. The final step involves the weighted sum of values, where the attention scores dictate the emphasis placed on different elements during the aggregation process:

$$\text{Output} = \text{Attention Scores} \cdot V \tag{2}$$

The self-attention process enhances the model's ability to identify subtle correlations, crucial for precise knee osteoarthritis classification. Illustrated in Figure 4, it dynamically allocates attention weights to items in the input sequence, facilitating informed classification decisions.

E. Experimental Setup

The Python-3 Kaggle Notebook experiment utilized a 13GB RAM and 16GB P100 GPU setup. The knee osteoarthritis

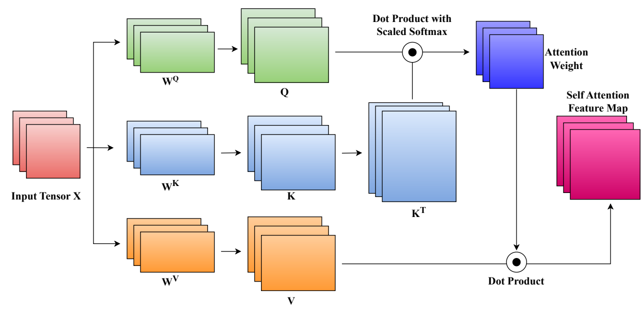

Fig. 4: Self-Attention mechanism

dataset was split into training (70%), testing (20%), and validation (10%) subsets. Softmax activation was used for the last fully connected layer, and ReLU activation handled pattern recognition. To reduce overfitting, dense layers (512 and 256 units) applied L1 activity/bias regularization (0.006 strength) and L2 kernel regularization (0.016 strength), along with a 45% dropout. The Adamax optimizer (learning rate: 0.001) and categorical crossentropy loss supported multi-class classification and parameter updates. Training ran for 100 epochs with a batch size of 16. The custom 'MyCallback' included early stopping (patience: 10 epochs), stop patience (5 epochs), threshold (0.9), a learning rate reduction factor (0.1), checkpoint saving every 10 batches, and user prompts every 10th epoch.

IV. Results and Discussion

A. Performance Analysis

The performance analysis section includes accuracy and loss curves, a confusion matrix, and a comparison of the proposed model with other pretrained models using ROC curves. It concludes with an assessment against models from prior studies.

Fig. 5 depicts the training and validation accuracy of the proposed model while fig. 6 depicts the training and validation loss. The model eventually approaches convergence as training proceeds through repeated epochs with parameter updates

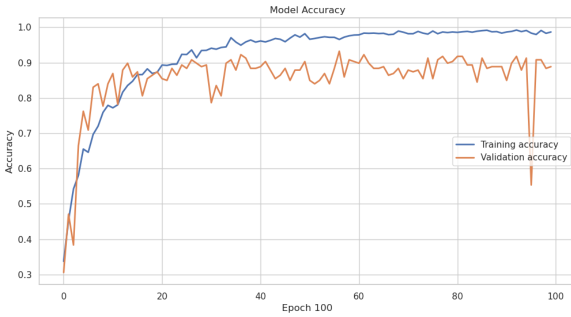

Fig. 5: Accuracy curve for the proposed model

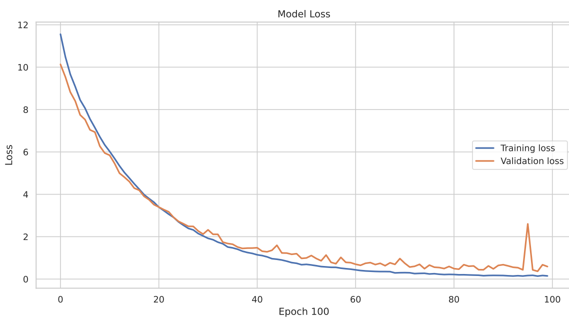

Fig. 6: Loss curve for the proposed model

using backpropagation. Initially, both training and validation accuracies start at low values. A look at the loss curve during this stage shows that the training and validation losses are still very large. The model does not reach optimal gradient weights for any of the trainable parameters until about 40 epochs, at which point convergence is achieved. This implies that the chosen hyperparameters are appropriate, resulting in quick convergence and outstanding performance.

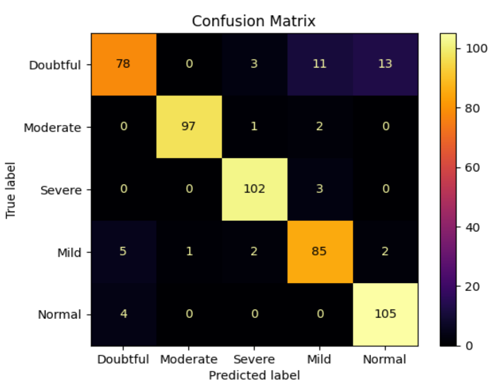

Fig. 7: The confusion matrix for the knee osteoarthritis dataset

The confusion matrix in Fig. 7 illustrates how well the model performs in various classes; almost perfect predictions are seen on the diagonal. The moderate and severe groups exhibit particularly strong performance, demonstrating the model's ability to discriminate between different levels of knee osteoarthritis severity. This result emphasizes the model's competence in producing accurate predictions in a variety of test set scenarios.

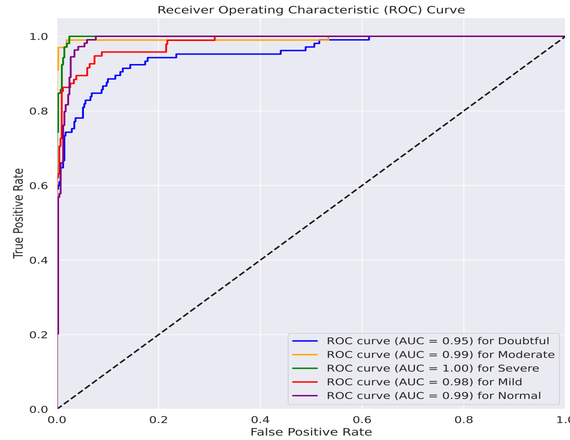

Fig. 8: ROC Curve for the knee osteoarthritis dataset

The effectiveness of the suggested model to distinguish between positive and negative classes was visually evaluated using ROC curves. The model performed exceptionally well, as seen in Fig. 8, where it had a ROC score of 1.00 for the severe class and 0.99 for the normal class. Higher scores were also shown in other classes, demonstrating the model's ability to discriminate between examples in different categories. The self-attention block's proven capacity to accentuate important elements and strengthen their place in the framework served as justification for its inclusion in the model's architecture.

B. *Performance Comparison*

TABLE I: Performance comparison of proposed model with other Tested models

Tested Models	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
DenseNet201	88	88	87	88
InceptionResnetV2	80	80	80	79
Inceptionv3	81	79	81	80
Vgg16	75	77	74	76
Ensemble	89	87	92	90
EfficientNetB5	85	84	85	85
Proposed Model	**91**	**91**	**91**	**91**

A performance comparison between the proposed model and other tested models is shown in Table I, which includes metrics like accuracy, precision, recall, and F1 score. Interestingly, the suggested model performs noticeably better than the other tested models. The suggested model has a remarkable accuracy of 91%, or more specifically 90.86%, indicating its evident superiority in diagnostic skills. This outstanding result highlights the model's efficacy and points to its potential as a top solution in the industry. It is important to note that the values in the table were rounded up to nearest whole number for clarity.

Table II displays a Performance Comparison with Previous Studies, indicating that our model outperforms cutting-edge

TABLE II: Performance Comparison with Prior Studies

Study	Model	Accuracy (%)
[7]	Autoencoder + CNN	78.9
[8]	ResNet-50	81.41
[9]	ResNet-34	61.71
[10]	HRNet	71.74
[11]	Siamese-GAP	88.38
[13]	ResNet + CBAM	74.81
Our Work	**Proposed Model**	**90.86**

methods, even those leveraging intricate models, in terms of accuracy. Remarkably, despite working with a more limited dataset compared to studies presented in the table, such as [7] with 9786 images, [8] with 6380 images and [9] with 9182 image samples, proposed model achieves superior accuracy in classifying knee osteoarthritis.

V. Threats to Validity

By modifying the EfficientNetB5 design and utilizing the Self Attention mechanism, the suggested model in this study was created. In order to evaluate the model's consistency outside of the current dataset, it is imperative to emphasize the necessity of testing it on different sized datasets for knee osteoarthritis (KOA). Significant variations in accuracy and loss were seen during training, especially around the 96th epoch, indicating room for improvement. Though its current use is restricted to X-ray pictures, further iterations will support a wider variety of image formats in order to improve the flexibility and resilience of the model. Furthermore, in subsequent applications, the model can be enhanced with cutting-edge visualization methods such as Grad-CAM. By revealing internal workings and decision-making processes, this integration will promote the model's development and offer insights into how it operates.

VI. Conclusion

This study pioneers a revolutionary method for identifying and categorizing knee osteoarthritis (KOA), even with a modest dataset. An outstanding accuracy of 90.86% is achieved by the customized EfficientNetB5 architecture enhanced with a Self-Attention mechanism. Above state-of-the-art methods, this model not only demonstrates its superiority as a sophisticated diagnostic instrument but also highlights its effectiveness in scenarios with sparse data.

A strong basis is provided by the study approach, which includes crucial components like preparing the dataset, mitigating class imbalances effectively with techniques like SMOTE, and customizing the callback mechanism for optimal model training. The suggested architecture shows its efficacy in improving both feature extraction and classification tasks. It is a synergistic combination of EfficientNetB5 and Self-Attention. Even though the model performs admirably in the diagnosis of knee osteoarthritis (KOA), further research should be done to explore a variety of datasets and possible optimization paths. This ongoing investigation will improve the model's capacity for generalization and increase its flexibility in a range of real-world situations.

This method essentially establishes a new benchmark for musculoskeletal health diagnostics by providing a novel viewpoint for the prompt and precise diagnosis of osteoarthritis in the knee. The research greatly advances the field and takes a crucial step towards transforming our approach to knee osteoarthritis diagnosis by addressing global health challenges linked with this condition.

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