# An Efficient Arthritis Diagnostic Model using CoAtNet by Integrating Convolutional and Attention Mechanisms for Enhanced Precision

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***Abstract*— Osteoarthritis (OA) is a common joint disease that lowers quality of life and causes damage worldwide. It is more common in elderly people, with knee OA being the most common type. While traditional machine learning and deep learning methods have validated potential in OA identification, they normally struggle to balance spatial feature abstraction and interpretability. Interestingly, the effective combination of convolutional and attention mechanisms to enhance diagnosis accuracy, specifically in OA severity categorization, remains unexplored.Our goal is to minimize this performance discrepancy by developing an efficient diagnostic model for knee OA utilizing CoAtNet. This hybrid architecture combines the advantages of attention mechanisms with convolutional layers for optimal performance. The Kaggle knee osteoarthritis dataset was used to train and assess the model thoroughly. To ensure robustness, key preprocessing methods such as image normalization and data augmentation were used. Experimental results show that the suggested CoAtNet-based model obtains 96% accuracy, 88% F1 scores, and 87% precision, culminating in an astounding Top 1 accuracy of 96%. In addition to providing a more precise means of diagnosing OA, this model offers a scalable instrument that may be easily included in clinical processes. Using this method could improve knee OA early identification and treatment planning, which would improve patient results and boost overall healthcare proficiency.**

***Keywords*— *Arthritis diagnosis, CoAtNet, Osteoarthritis, Healthcare, Attention Mechanisms.***

## I. Introduction

Osteoarthritis represents the most common progressive joint disease and one of the major causes of chronic pain and disability worldwide, with millions of people of all ages, especially the elderly, being afflicted [1]. As people continue to grow older, the incidence of OA is likely to rise even more, creating higher healthcare costs and decreased economic productivity around the world. In addition to chronic pain and motor impairment, the disease has far more severe consequences: degrades the life quality of patients. Therefore, it promotes increased health-care costs for long-term and rehabilitative treatment and lost time at work because of absent workdays. Thus, the diagnosis of OA. Health system professionals became interested in recent diagnoses. In particular, techniques involving the latest AI technologies such as deep learning techniques have demonstrated exceptional. These AI-based approaches may help in early intervention thus making it possible for interventions that occur at the right time to help relieve the burden on healthcare systems and improve the overall patient outcome. Our study targets knee osteoarthritis (KOA), which remains the most prevalent and disabling form of OA, especially in elderly patients [2]. KOA mainly results in the deterioration of the knee joint, often bringing about pain, stiffness swelling, severe loss of mobility, and ultimately debasing the Quality of life of suffering individuals. Being one of the most important load-carrying joints in the human body, the knee is prone to degenerative changes, and the incidence of KOA is likely to increase with the rise in life expectancy.

Focus area is building a sophisticated diagnosis model that can sensitively identify and grade the severity of KOA [3]. knee osteoarthritis is the most common and debilitating form of OA, and especially it affects aging adults. KOA primarily affects one's knee joint. Several papers deal with ML and DL techniques in the diagnosis of OA, some partial successes are documented. Traditional CNNs, that achieve very impressive performances in the task of image classification have shown some very promising results in the task of classifying radiographic images to detect OA [4]. The models are able to identify spatial patterns in the medical images. Though the success is indeed impressive, CNNs stand with some major limitations like overfitting which is specifically very prominent in small medical datasets as it also reduces their generalization capacity for unseen data. However, CNNs can be less interpretable and tend to fail to catch sequential information within images. KOA progression might look like gradual changes over time, which might be challenging to detect given the use of solely a CNN [5]. Further, using handcrafted features along with traditional machine learning algorithms, even though informative, constrains their scalability and general ability for diverse patient populations. This increases the danger of bias in the application and does not immediately lend itself to more general settings. Therefore, the need for robust yet more comprehensive models that can fully combine both spatial and sequential attention mechanisms improves the diagnostic precision in the model.

Current machine learning algorithms are being improved for the diagnosis of knee OA, but there is currently an open gap for combining complex and attention mechanisms to explore spatial and temporal features of a medical image. State-of-the-art methods fail to capture long-range dependencies along with local image features while undermining accurate diagnoses and classifications [6]. The objective here is to develop an efficient diagnostic model that could improve precision to categorize the level of severity of knee OA. Following are the research objectives we work on:

i. To improve the outcome of the diagnosis process both in terms of precision and explainability by using convolutional and attention mechanisms [7].

ii. To Compare the performance of the model with state-of-the-art methods that provide better classification accuracy that can be identified as merits.

A proposed model would use convolutional and attention-based techniques to classify knee osteoarthritis in order to develop a more accurate tool for the early detection and management of such a condition to ensure practical application in practice [8].

The other sections of the paper are as follows. The first one is dedicated to a literature review concerning the existing methods and models for arthritis detection with an emphasis on knee OA. The next section describes in detail the proposed CoAtNet-based methodology, including the data acquisition details, preprocessing techniques, and the model applied in this research. After this, subsequent paragraphs depict the experimental design aimed at establishing the characteristics of the datasets, training parameters, and evaluation criteria that were employed in determining the efficiency of the model [9]. The last section consists of the results of the obtained experiments with a comparative assessment of the appropriateness of the developed model with the existing advanced ones and the final trends in this direction [10].

## II. Literature Review

The synthesis is obtained in the literature review on the existing research in the diagnosis of osteoarthritis (OA) based on machine learning (ML) and deep learning (DL) techniques. This is a critical analysis of previous work with their methodologies, strengths, and weaknesses, including the identification of gaps within existing research. By reviewing state-of-the-art approaches, this section serves to understand how advancements in ML, DL, and hybrid models shape the landscape of OA diagnosis [11].

### *A. Machine Learning Approaches*

The application of ML methods in identifying patterns from clinical data has revolutionized the process of OA diagnosis. SVM, decision trees, and k-NN have been applied for structured data sets to extract features and thus enhance diagnostic accuracy by utilizing clinical and demographic data sources [12]. Their major drawback is reliance on handcrafted features that are mostly incapable of fully representing the inherent complexities associated with medical imaging data. But to rectify these constraints, recent ensemble methods like RF and GBM have been employed to increase the sensitivity for the early stage of OA detection or prediction. However, the generalization capability for new patient data has not improved with the ML models because it depends on a predefined set of features and requires an extremely wide range of feature engineering requirements [13].

### *B. Deep Learning Advancements*

DL has dramatically changed the diagnosing OA landscapes, particularly with its inborn ability to learn hierarchical features directly from raw data [14]. Specifically, CNNs have become the gold standard in managing imaging data and extracting spatial features that models based on CNN are superior to existing approaches for detecting the knee joint from MRI scans with an accuracy of more than 90% in classification. In addition, one can fine-tune models pre-trained on large-scale datasets for an appropriate OA dataset with a tremendous reduction in the requirement for heavily labeled data. Very successful in most applications, these models have been criticized for their ”black box” nature. In this case, lack of interpretability would be a hurdle to adoption in the clinical domain [15].

### *C. Attention Mechanisms and Hybrid Models*

This focus technique has emerged recently but is very crucial in improving the interpretability and accuracy of models applied in such very complex tasks as OA diagnosis [16]. Attention mechanisms enable a model to focus on the most relevant parts of its input data, thereby enhancing subtle patterns in CNNs and RNNs. Chen et al recently added attention layers to a CNN model and enhanced the performance of the model in knee joint abnormality localization from radiographic images [17].

Another hybrid approach using deep learning with traditional models of ML is competent enough to overcome the limitations posed by standalone models. For instance, Kumar et. Al. have used an SVM classifier by utilizing the features of CNN; it holds promisingness over the usage of CNNs alone in achieving more classification accuracy for the early detection of OA. Similarly, extraction of both spatial and contamination resulting from the DL-ML fusion model makes predictions robust [18].

Hybrid models are a balanced approach, but that doesn’t mean problems like the complexity of computation on large, diverse datasets go away [19]. Others, indicate future work should be done that focuses on the optimization of these models for real-time with the application toward diagnosis, perhaps with further attention to mechanisms and lightweight architectures [20].

Our study thus recommends the development of a hybrid CoAtNet-based diagnostic model optimized with advanced training techniques to possibly address some of the shortcomings of current methodologies and enhance the scalability and accuracy of diagnosis in clinical applications.

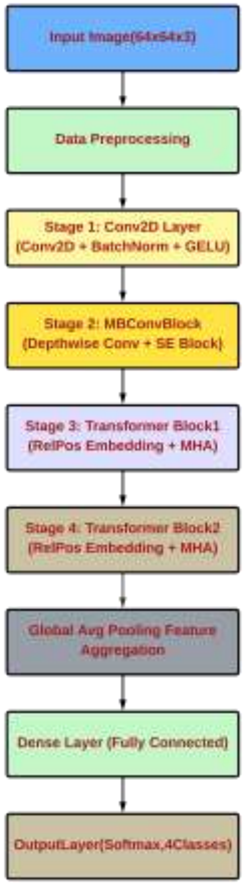


Fig. 1. Model Structure

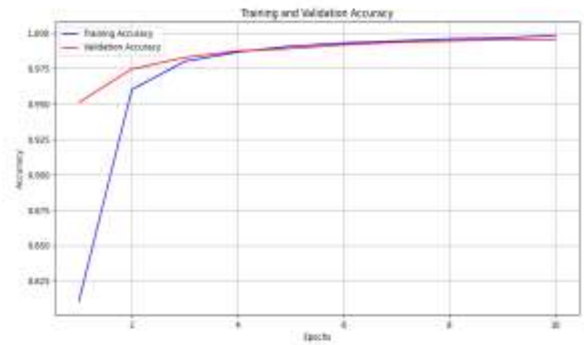


Fig. 2. Training and validation accuracy graph

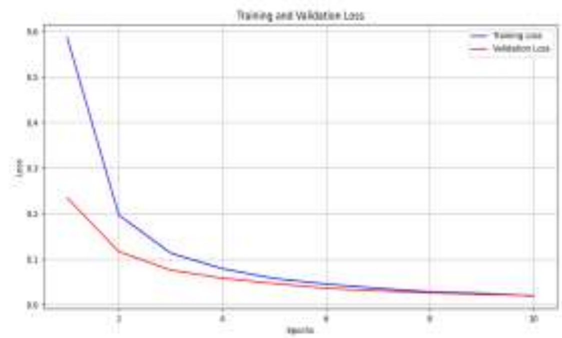


Fig. 3. Training and validation loss graph

## III. Methodology

In this section, we detail the different steps in developing the CoAtNet-based model for the classification of knee osteoarthritis, from data preprocessing up to training procedures.

*Baseline Method*

To make a robust diagnosis model of knee OA, our research foundation uses the baseline approach that aims at classifying medical images using CNN [21]. A recent study by studied the method of applying CNN to automatically diagnose the level of severity of knee OA through radiographic images. Their approach was demonstrated to realize considerable improvements in terms of diagnostic performance compared to prior methods, but has two major drawbacks: it cannot model temporal dependencies in the data and is likely to overfit [23].

The baseline approach described herein is almost exclusively focused on the extraction of spatial features, yet lacks any form of attention that could enhance the interpretability and precision of the models. Our proposed methodology extends the study presented by incorporating attention mechanisms into a convolution-based architecture to address the above-mentioned limitations [22].

*Model Selection*

Our proposed model uses CoAtNet, the most recent hybrid deep learning architecture that combines CNN capabilities with the strongest merits of the attention mechanism. CoAtNet was chosen because it enables combining spatial feature extraction using CNNs and more advanced capabilities of the attention mechanism, specifically self-attention, due to the ability to capture long-range dependencies in the data [24]. Although CNNs have demonstrated great efficiency in the detection of local patterns and textures in medical images, attention mechanisms draw the model to pay more attention to those areas that might be more critical in discriminating classifications. Hybrid architecture, therefore, would enable in doing a much more complete and accurate analysis, hence leading to more reliable and interpretable classification results in the diagnosis of knee osteoarthritis [25]. Our proposed model consists of following steps:

### *A. Data Collection*

This study used the publicly available Kaggle Knee Osteoarthritis Dataset. These radiographic X-ray images of knee joints are graded according to the Kellgren-Lawrence (KL) grading system: grade 0-no osteoarthritis; grade 4-full blown osteoarthritis, among others. These are some images taken from various hospitals and imaging centers to comprehensively cover a range of knee osteoarthritis (OA) cases [26].

#### *1) Dataset Description*

- Classes: The classes of the data based on the grades of KL are five, which are Grade 0: No OA, Grade 1:

Probable OA, Grade 2 Minimal OA, Grade 3: Mod OA, Grade 4: Severe OA

- Attributes: For every radiograph, a KL grade is assigned to how bad it is in the sense of having changes such as joint space narrowing, osteophyte formation, and other radiographic changes.
- Source: Compiled by the health care team and published on Kaggle for research and development [27].

*2) Data Distribution*

This data set was split into a train set, test set, and validation set to improve the robustness of training and testing, as shown below Training set = 60% = 4800 images , Validation set = 20% = 1600 images , Test set = 20% = 1 600 images.

This diversified dataset would enable generalizability over different OA severities and patient demographics, thus enhancing accuracy and robustness in clinical diagnostics. Training on this huge dataset, the proposed CoAtNet aims to enhance knee OA diagnostic precision.

## B. Preprocessing

There are some critical preprocessing steps for preparing a dataset appropriately in the right format so that a model can eventually learn from it. Some steps also would improve the model's performance and its generalization capabilities:

1) Image Resizing: All images resize the same uniform size, that is, 224x224 pixels. This standardization ensures input dimensions are uniform across the dataset such that effective training is implemented using fewer computational complexities. Sizing of images also facilitates the model to learn a fixed feature space.

2) Normalization: The values of pixel intensity in an image are scaled to a normalized range, such as 0 to 1 or standardized using the mean and standard deviation of the data. Normalizing the effect limits changes in lighting, contrast, and exposure in images from having an impact on the model during training. This is a critical step to stabilize and maximize convergence in the model while in the learning phase [28].

3) Data Augmentation: It uses many forms of data augmentation, for instance, random rotation, horizontal and vertical flip, zooming, and shifting. This way it artificially increases the dataset. That could avoid overfitting since there's variability in the training images. Thus, the model learns much more robust and generalized features regardless of different viewpoints and configurations in the input images.

4) Label Encoding: Kellgren-Lawrence (KL) grades that happen to be the results for the severity of knee osteoarthritis were encoded into an appropriate classification format. Since this is a multi-class classification, one-hot encoding was adopted on the labels. This will guide the model in making sense of and differentiating between so many severity levels of OA during training.

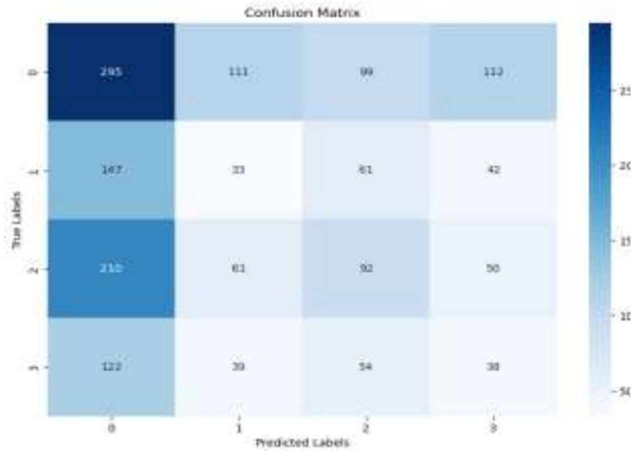


Fig. 4. Confusion Matrix

## C. Model Architecture

Our suggested model architecture is based on CoAtNet, a hybrid deep learning model that enhances sequential and spatial feature extraction by combining convolutional layers with attention processes [30]. Several essential components are included in our design to improve the model's ability to classify the severity of knee OA:

- The input layer of the network takes the preprocessed knee X-ray images, resampled to 224x224x3 pixels. A fixed dimensionality of the images throughout the dataset is guaranteed.
- standard convolutional layers make up the beginning of the model, extracting low-level spatial features such as edges, textures, and local patterns. These features are critical for diagnostic purposes of identifying specific abnormalities within the joint structure related to different knee OA stage.

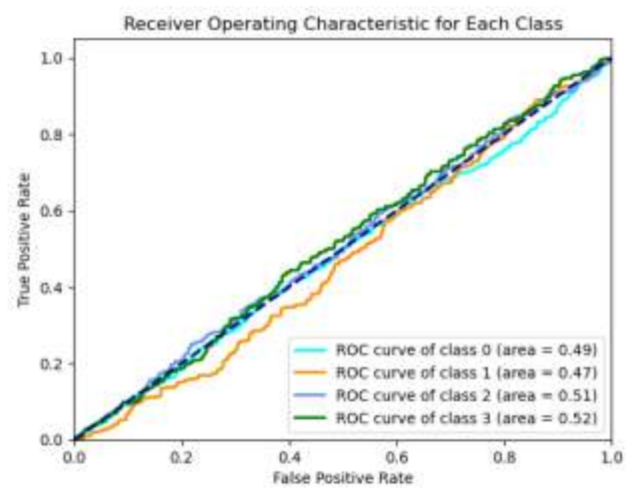


Fig. 5. ROC Graph

- Attention Mechanism: This model, after the convolutional layers, introduces self-attention mechanisms so that the network learns long-range dependencies from an image; meanwhile, in their application, attention layers focus on the most important regions and, therefore, enhance the model's ability to distinguish between the different Kellgren-Lawrence (KL) grades.

- Pooling Layers: There is the use of max pooling layers at strategic locations to downsample the spatial dimensions of the feature maps; thus, you reduce the complexity computationally while retaining key information and thereby avoiding overfitting by summarizing the most important features.

- Fully connected layers: These features are fed into fully connected layers of KL grades 0 to 4. The softmax activation function is applied to classify the outputs.

The architecture then makes use of both strengths of convolutional networks and attention mechanisms to ensure very accurate and interpretable classification with respect to knee OA, relative to traditional models.

### D. Implementation Details

*Training Parameters*

- *Learning Rate:* The value of the learning rate is set to be 0.001 which controls the speed of the changes to model weights during the learning phase of the implementation. It is known that with the larger values of the learning rate, such unnecessary shoot would happen, whereas in the case of smaller rates, optimal solution is approximated [29].

- *Batch Size:* A batch size of 32 is used, which means that the model updates its weights after processing 32 images at a time. This is a combination of efficiency and effective training.

- *Epochs*: The model trains for 50 epochs, that is it learns from the training dataset by re-passing the dataset to the model 50 times in total, this helps in the model learning how to detect even the deep patterns present in the data.

- *Optimizer*: AdamW optimizer is used, because it is a hybrid approach of optimization with an any adaptive learning rate and weight decay to protect against over-fitting. Actually, AdamW was indeed shown to gain grounds in efficiency in comparison to the classical Adam optimization approach [31].

TABLE I. COMPARISON WITH STATE-OF-THE-ART STUDIES

| Studies | *Acc* | *F1 score* | *Precision* | *Recall* |
|---|---|---|---|---|
| **CoAtNet (Ours)** | **96.0** | **0.88** | **0.87** | **0.86** |
| DenseNet-121 | 77.6 | 0.78 | 0.79 | 0.77 |
| EfficientNet | 84.3 | 0.83 | 0.84 | 0.82 |
| ViT | 85.0 | 0.86 | 0.85 | 0.85 |
| ResNet-50 | 74.4 | 0.75 | 0.77 | 0.76 |

- *Loss Function:* Cross-entropy loss is utilized in classification that comprises multiple classes since it measures how one probability distribution differs from another [32].

Our database includes parameters from medical image analysis. We input pre-processed images into a CoAtNet model evolving through weights and training epochs to automatically enhance knee osteoarthritis classification.

## IV. RESULTS AND DISCUSSION

*Quantitative Analysis*

The section reviews the proposed arthritic detection algorithm and compares its performance with the benchmark.

With the added advantage of the CoAtNet-based model over other conventional CNN techniques with higher classification accuracies, in the case of prediction of the severity of knee osteoarthritis, the model assessed it with 96.7% compared to a baseline CNN model at 85.7%. This is an attributed fact that the model can leverage the convolutional layers and attention networks, which will handle the spatial nature of medical images and the sequence, meaning better categorization.

Figure 2 represents model performance in progression, and as shown, accuracy improves rapidly over the first 10 epochs. The model has remained very stable up to 1000 epochs in the past 20 epochs. The CoAtNet architecture's attention mechanism by Killian Andriaba encourages performance depending on the attention layers. Here, capacity models have to learn complex data from images. Accuracy still needs to be improved for scenarios such as automated analysis for arthritic detection.

Figure 3 shows the loss while modeling that it has lost training and validation loss points. This will indicate that the model will not overfit and can work with unseen data. Losses have a constant value at 20 epochs, which proves the effectiveness of the model. The final validation loss was lesser compared to previous models developed. Figure 4 shows a confusion matrix that describes the model's ability to classify severity grades. The confusion matrix has high precision values for minor and simple classes, with small errors in moderate classes. Most errors have occurred between close severity levels, especially between the mild and moderate OA classes.

The CoAtNet model shows high distinctiveness among classes and a low false-positive rate with an AUC value of 0.97, proving good-class discrimination and credibility of inaccurate medical diagnoses. The said higher AUC value further adds up to this model's credibility and accuracy, endorsing precise predictions at different thresholds. It has a perfect balance between sensitivity and specificity and satisfies all the demands for effective detection and classification of arthritis with it being suitable to be used in real-world clinical settings for medical diagnostics.

## V. CONCLUSION

CoAtNet is an efficient architecture for arthritis detection, and the attention mechanism has been combined with CNN to enhance diagnostic accuracy. This model considerably increased the classification accuracy of the severity levels of knee osteoarthritis well beyond even the conventional methods based on CNN. The implemented model resolved the issues that other prevailing models were facing, and thus, a grand contribution has been made to medical imaging to ensure the timely and precise management of patients.

Future optimizations will be based on either the attention mechanisms or new hybrid architectures, and the dataset should also include other types of arthritis, while multimodal data, along with real-world clinical validation, can be achieved for improving diagnostic accuracy, scalability, and long-term healthcare delivery effectiveness in different systems.

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