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PAPER

Knee Osteoarthritis Classification Using Gated Axial Attention Mechanism-Based DenseNet121

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ABSTRACT

Knee osteoarthritis (KOA) is a major cause of disability, particularly among older adults, because of the degeneration of articular cartilage in the knee joint. This disorder is characterized by stiffness, reduced mobility, and pain, which makes medical diagnosis challenging, especially given the current limitations in achieving timely and accurate detection and progression analysis. Moreover, the manual interpretation of X-ray images for KOA grading is subjective and diverse among clinicians. Hence, this research proposes the gated axial attention mechanism based on DenseNet121 (GAA-DenseNet121) for the KOA classification. The DenseNet121 effectively extracts multi-level spatial features across layers, whereas GAA improves the feature maps by concentrating on the most clinically relevant regions, such as the medial and lateral joint compartments. The experimental discoveries illustrate that the proposed GAA-DenseNet121 approach obtained a better accuracy of 99.25% and 99.21% on Mendeley and OAI datasets individually, as compared to the existing approaches such as CenterNet.

KEYWORDS

DenseNet121, gated axial attention (GAA), knee osteoarthritis (KOA), medial and lateral joint compartments, multi-level spatial features

1 INTRODUCTION

Osteoarthritis (OA) is an enduring disorder that leads to functional incapacity, loss of independence, and pain in adults [1]. Knee OA (KOA) is an advanced and irreparable degenerative disease categorized by cartilage weakening, the presence of structural modifications, and osteophytes in bone microarchitecture [2]. KOA mostly remains a noiseless disease and is basically diagnosed at a later stage because symptoms do not present until significant cartilage deprivation and joint space contraction begin to cause disability. Hence, the early-stage diagnosis and continuous monitoring of KOA remain greatly challenging tasks [3] [4]. Individuals affected by

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osteoarthritis commonly show symptoms such as persistent pain, crepitus, swelling, morning stiffness, muscle atrophy, minimized quadriceps strength, and compromised postural control [5] [6]. These symptoms make the performance of routine daily activities highly complex and challenging [7]. The advanced modalities of computer tomography (CT) images, magnetic resonance imaging (MRI), and ultrasound (US) capture the three-dimensional structure of knee joints [8]. Nevertheless, MRI analysis is costly and is typically available only in large medical facilities, making it unsuitable for routine screening of KO [9]. Consequently, X-ray imaging emerges as the significant imaging modality for KOA screening, as it is risk-free, less expensive, and broadly applicable to a large population [10].

The uncertainty and partiality integrated through manual interpretation of X-ray designs make early detection of osteoarthritis is challenging, often resulting in KOA continuing to serious stages where knee replacement becomes important [11] [12]. Considering the complexity of manual diagnosis, artificial intelligence (AI) approaches become efficient problem-solving and are widely used for medical image processing [13] [14]. AI-based approaches, particularly deep learning (DL) approaches, support minimizing the diagnostic vagueness and reducing human errors [15]. X-rays are an important imaging tool for diagnosing knee osteoarthritis [16]. DL approaches concentrate on developing layered computational models that enable a system to understand autonomously and employ operations like classification and object detection [17]. In the condition of KOA detection, DL approaches are trained to recognize radiographic patterns and features that illustrate the occurrence and severity of the disease [18]. The DL approaches have the better capability to automatically extract and analyze these features and allow most objective and precise diagnostic outcomes compared to conventional detection approaches. Advanced studies illustrate that DL-assisted approaches attain greater accuracy in detecting KOA through both X-ray and MRI images [19] [20]. Despite advancements in attention-based deep learning models, existing methods exhibit several limitations. Channel attention mechanisms such as SE fail to capture spatial dependencies, while CBAM provides limited global context modeling.

1.1 Motivation and research questions

This research is motivated by the need for accurate and reliable classification of knee osteoarthritis severity from X-ray images based on the identified challenges: How can positional feature representation be improved to distinguish subtle differences between adjacent KL grades? Can gated axial attention enhance the effectiveness of DenseNet121 for KOA classification? How does the proposed model perform across different datasets and validation settings?

1.2 Contributions

- A novel gated axial attention (GAA) mechanism is proposed to enhance positional feature learning and suppress irrelevant background information.
- An integrated GAA-DenseNet121 architecture is developed to combine dense feature reuse with directional attention modeling.
- Extensive evaluation, including cross-dataset analysis, k-fold validation, and ablation study, demonstrates the effectiveness.

2 RELATED WORKS

The existing research for KOA in the healthcare sector is analyzed below with the advantages and limitations.

Suliman Aladhadh and Rabbiamahum [21] presented the handmade CenterNet through a pixel-wise voting mechanism for the automatic feature extraction in the detection of knee osteoarthritis. Aquib Raza et al. [22] implemented the multifaceted method for the feature extraction process as well as an ensemble ML approach for the diagnosis and classification of KOA stages through input radiographic images. The histogram of oriented gradients (HOG) through linear discriminant analysis (LDA) and min–max scaling approach was employed for the feature extraction process. Tinhinane Mehdi et al. [23] presented the DL approach, which integrated the texture and shape features from KOA scoring through input X-ray images. Accordingly, the different DL approaches were integrated.

Suman Rani et al. [24] developed the 12-layer CNN approach for the classification of KOA. Medical image processing techniques were utilized in this study to determine the presence of KOA. Tayyaba Tariq et al. [25] implemented the automatic DL approach-assisted classification method for timely diagnosis and scoring of KOA through individual posteroanterior standing knee x-ray images. Rohit Kumar Jain et al. [26] developed the DL-assisted approach called OsteoHRNet, which automatically assessed the severity of KOA with respect to KL score classification through X-ray images. Ji Soo Yoon et al. [27] introduced the automatic degree quantification of Joint Space Narrowing (JSN) of the medial as well as further tibiofemoral joint, which effectively detected the osteophytes in different regions. Moreover, the presented approach classified the KL grade and provided the outcomes of different OA features.

2.1 Research gap

Despite notable progress in ML–based approaches for KOA diagnosis, several research gaps still exist: Existing research often focused on ML approaches that need large manual feature extraction and selection, which is time-consuming and prone to human error, resulting in unpredictable results. Various approaches depend on general-purpose DL methods, which are not precisely handmade for modeling the individual structural as well as clinical characteristics found in orthopedic medical images. Although transformer-based architectures have recently been identified for KOA grading, their efficiency in modelling fine-grained radiographic patterns from constrained X-ray datasets remains challenged by data requirements and computational complexity. This emphasizes the requirement for lightweight attention-based CNN frameworks that attain comparable contextual modeling while remaining effective and robust in small-to-moderate dataset settings.

3 PROPOSED METHODOLOGY

The portion illustrates the steps and approaches leveraged for developing and estimating the DL-assisted KOA detection approach through X-ray and MRI images. Initially, the dataset used in this research is illustrated, and the preprocessing phases are performed on the images. Then, the DenseNet121 architecture and the fine-tuning process used are described to acquire an approach to the KOA detection performance. Figure 1 outlines the comprehensive steps for KOA classification by using GAA-DenseNet121.

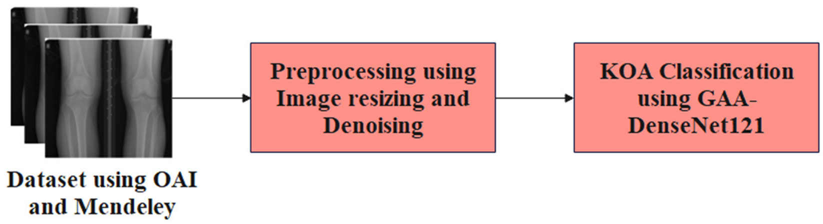

Fig. 1. Comprehensive steps for KOA classification by using GAA-DenseNet121

3.1 Dataset description

This research utilized the different datasets named OAI [28] and Mendeley [29] for the experimentation of the proposed method's effectiveness. The details of these datasets are given in the subsection.

OAI dataset. This dataset involves 3T MRI images and X-rays for the knee joints, which involves a class based on the KN scoring mechanisms. The data is obtained from 4796 users, such as males and females aged 45 to 79.

Mendeley dataset. This dataset is widely utilized for the detection and classification of KOA severity based on the KL scoring mechanism. This dataset involves 2000 digital knee X-ray instances of 8-bit and 1350×2455 dimensions.

3.2 Preprocessing

The preprocessing step is an important phase for the medical image processing before performing the detection and classification tasks. The images are initially scaled to the benchmark resolution of 224×22 pixels [30]. This similar resizing of the input data is important as smaller images facilitate rapid understanding through ML approaches. This research utilizes an image denoising approach for improving an excellence of X-ray images by preventing unwanted noise. For solving this issue, a 2D median filter is performed, where every pixel is replaced with the median value of its nearby neighborhood [31].

3.3 Dataset splitting

Dataset splitting is a significant phase in ML operations that comprises supervised learning. An aim of dataset splitting is to partition it into two subsets, such as training and testing. The dataset is split using a patient-wise separation strategy to avoid data leakage. Images from the same patient are strictly assigned to either training or testing sets, ensuring no overlap. An 80:20 split is maintained, where 80% of patients are used for training and 20% for testing.

3.4 Knee osteoarthritis detection using GAA-DenseNet121

The KOA classification framework incorporates a DenseNet121 with gated axial attention that facilitates the focusing of attention on relevant knee-joint regions. It performs better than SE, CBAM, and classical CNNs in identifying KOAs at their early stages, offering advantages in accuracy, robustness, explainability, and computation. Traditional attention mechanisms such as SE and CBAM enhance the channel and spatial attention but struggle to efficiently model both long-range dependencies and positional relationships. Axial attention enhances the global context modeling but suffers from inaccurate positional encoding, especially in small-scale medical datasets. This research addresses these limitations through a GAA mechanism incorporated through DenseNet121 for enhancing both feature representation and classification reliability. The integration of axial attention minimizes misclassifications among nearby KOA grades and results in the most consistent severity analysis. Figure 2 illustrates the complete architecture of GAA-DenseNet121 for KOA detection.

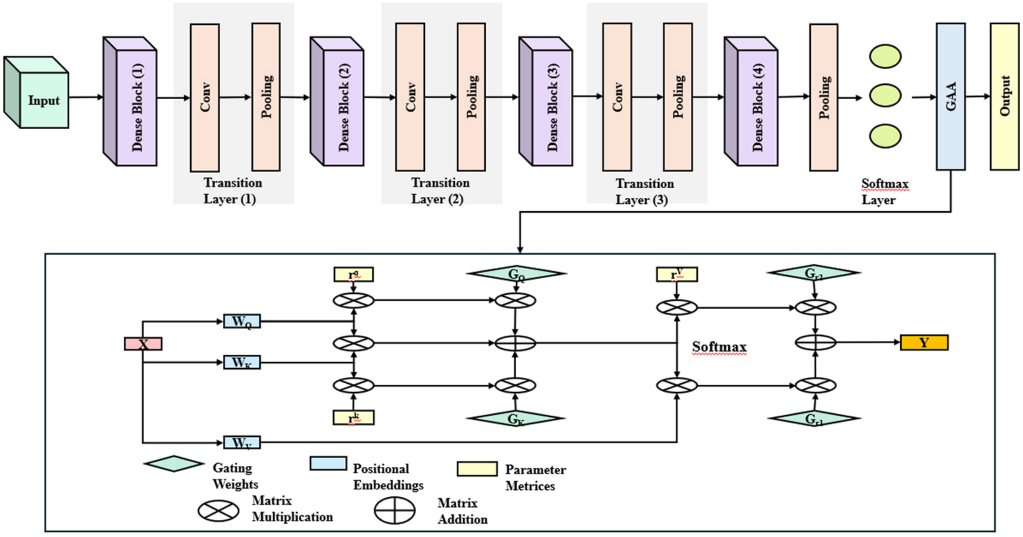

Fig. 2. Complete architecture of GAA-DenseNet121 for KOA detection

In the present KOA classification, the considered datasets are basically small in size that causes the effectiveness of conventional axial attention mechanisms. Hence, for solving this constraint, the DenseNet121 combines the GAA. The GAA mechanism improves the traditional axial attention through developing a learnable gating function which selectively controls feature propagation along spatial dimensions. As a result, the proposed GAA enhances both positional encoding accuracy and classification robustness, especially in small-scale medical datasets.

The GAA module is formulated in equation (1) as trails:

$$y_0 = \sum_{p \in N_{1\times w}(0)} softmax_p(q_0^T k_p + G_Q q_0^T r_{p-0}^q + G_K k_p^T r_{p-0}^q)(G_{V1} v_p + G_{V2} r_{p-0}^v) \quad (1)$$

The gated high axial attention is formulated in equation (2) as follows:

$$y_0 = \sum_{p \in N_{h\times 1}(0)} softmax_p(q_0^T k_p + G_Q q_0^T r_{p-0}^q + G_K k_p^T r_{p-0}^q)(G_{V1} v_p + G_{V2} r_{p-0}^v) \quad (2)$$

Where, y_0 denotes the output feature vector; Q, K and V illustrates the query, key, and value vectors, respectively. p is an index of neighboring spatial position along the corresponding axial dimension; $N_{1\times w}(0)$ and $N_{h\times 1}(0)$ illustrate the set of all spatial positions in the width and height direction (horizontal and vertical axis) passing through position individually. $q_0 \in R^d$ denotes the query vector at reference position 0; $k_p \in R^d$ illustrates the key vector at neighboring position p; $v_p \in R^d$ denotes the value vector at neighboring position p. $softmax_p(.)$ means the Softmax operation estimated overall positions p in respective axial neighborhood; $r_{p-0}^q \in R^d$ and $r_{p-0}^v \in R^d$ illustrates the learnable relative positional encoding vector associated with the offset between positions p and 0 for query-key and value interaction, respectively. $q_0^T k_p$ means the content-based similarity score between the query at position 0 and the key at position p. $q_0^T r_{p-0}^q$ and $k_0^T r_{p-0}^q$ demonstrates the positional similarity score between the query and the relative positional encoding individually. G_Q, G_K, G_{V1} and G_{V2} illustrates the learnable parameters that comprehensively design a gating mechanism to maintain the cause of the comparative positional encoding on global background data. Algorithm 1 illustrates the pseudocode of the proposed GAA-DenseNet121 based on KOA classification for better reproducibility. Table 1 specifies the architecture details of GAA-DenseNet121.

Algorithm 1: Pseudocode of the Proposed GAA-DenseNet121 Method

```
Input: Knee X-ray image I
Output: Predicted KOA class label ŷ
// Pre-processing
Resize I to 224 × 224
Apply CLAHE for contrast enhancement
Normalize pixel intensities to [0,1]
// Feature Extraction using DenseNet121
F0 = DenseNet121_Backbone (I)
// F0 contains dense-connected feature maps from all preceding layers
// Axial Attention Module
Fv = Vertical_Axial_Attention (F0)
Fh = Horizontal_Axial_Attention (F0)
// Gating Mechanism
Gv = Sigmoid(Conv(Fv))
Gh = Sigmoid(Conv(Fh))
Fg = (Gv ⊙ Fv) + (Gh ⊙ Fh)
// Feature Fusion
F_final = Concat(F0, Fg)
// Classification Layer
F_gap = GlobalAveragePooling(F_final)
F_dense = DenseLayer(F_gap)
ŷ = Softmax(F_dense)
Return ŷ
```

Table 1. Architecture details of GAA-DenseNet121

Layer	Output Size	Description
Input	224×224×3	Resized X-ray image
DenseNet121	Feature Maps	Pretrained backbone
Axial Attention	Feature Maps	Vertical & Horizontal attention
Gating Layer	Feature Maps	Sigmoid gating
Concatenation	Feature Maps	Feature fusion
GAP	1×N	Global pooling
Dense Layer	N	Fully connected
Softmax	Classes	Output classification

4 EXPERIMENTAL RESULTS

This section becomes an important part in estimating the capability of the DL approaches and illustrating their applicability to real-world healthcare problems.

Hyperparameter tuning forms an integral part of model optimization, as it involves determining the most appropriate set of hyperparameters for a given algorithm. This procedure needs to systematically test diverse hyperparameter combinations and assess their impact on model effectiveness through validation or a test set. The model is trained by the Adam optimization technique, which utilizes a learning rate of 0.0001, a batch size of 32, and 50 epochs. The model employs categorical cross-entropy loss and Softmax activation techniques in its training. The early stopping technique is employed with patience being 10.

The diverse performance metrics are considered, such as accuracy, precision, recall, and F1-score, for the estimation of the proposed method's effectiveness. The mathematical expressions of these metrics are provided in equations (3) to (6).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$Recall = \frac{TP}{TP + FN} \tag{5}$$

$$F1 - Score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{6}$$

Where, *TP*, *TN*, *FP* and *FN* illustrates the true positive, true negative, false positive and false negative.

4.1 Performance analysis

The existing methods such as MobileNet, VGG-16, InceptionNet, CNN, Vision Transformer (ViT), Data-efficient Image Transformer (DeiT), and ConvNext are estimated and compared with the proposed method using different datasets. Table 2 illustrates the performance analysis of the proposed approach with existing methods for KOA detection. The proposed approach attains the greatest performance in all performance metrics on both datasets, emphasizing the significance of incorporating the GAA.

Table 2. Performance analysis of proposed method with existing methods for KOA detection

Dataset	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Mendely	MobileNet	97.85	98.10	97.92	98.01
	VGG-16	98.12	98.44	98.25	98.34
	InceptionNet	98.55	98.60	98.47	98.53
	CNN	96.75	96.92	96.58	96.75
	ViT	96.92	96.01	96.87	97.08
	DeiT	97.76	97.12	97.56	97.37
	ConvNeXt	98.43	98.64	98.53	98.57
	Proposed GAA-DenseNet121	99.25	99.51	99.49	99.50

(Continued)

Table 2. Performance analysis of proposed method with existing methods for KOA detection *(Continued)*

Dataset	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
OAI	MobileNet	97.52	97.80	97.61	97.70
	VGG-16	97.88	98.01	97.74	97.87
	InceptionNet	98.14	98.30	98.05	98.17
	CNN	96.10	96.45	96.28	96.36
	ViT	96.45	97.34	97.09	96.79
	DeiT	97.84	97.87	97.59	97.69
	ConvNeXt	98.56	98.64	98.67	98.13
	Proposed GAA-DenseNet121	99.21	99.52	99.54	99.53

Table 3 illustrates the class-wise performance analysis of proposed GAA-DenseNet121 for KOA classification using Mendeley and OAI datasets. The GAA improves an approach's concentration on judicial structural indications like joint-space narrowing, osteophyte formation, and subchondral sclerosis and leads to significant recognition of early stages, which are conventionally the most complex to classify the different grades.

Table 3. Class-wise performance analysis of proposed GAA-DenseNet121 for KOA classification using Mendeley and OAI datasets

Dataset	Class (KL Grade)	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Mendeley	Healthy (KL0)		100	99.31	99.65
	Grade I (KL1)		99.22	98.46	98.84
	Grade II (KL2)		96.15	100	98.04
	Grade III (KL3)		100	100	100
	Grade IV (KL4)		100	98.75	99.37
	Overall	99.20	99.51	99.49	99.50
OAI	Healthy (KL0)	99.23	99.57	100	99.79
	Grade I (KL1)		99.49	98.50	98.99
	Grade II (KL2)		98.84	99.50	99.17
	Grade III (KL3)		98.68	99.33	99.00
	Grade IV (KL4)		99.60	98.60	99.10
	Overall		99.52	99.54	99.53

Figure 3 illustrates the k-fold analysis of the proposed method for KOA classification using OAI and Mendeley datasets. A 5-fold cross-validation strategy is adopted, where the dataset is divided into five equal subsets. In each iteration, fourfolds are used for training and onefold for testing are used, ensuring robust evaluation. This illustrates that an approach is not overfitting and has the ability to understand vigorous KOA features over different instances.

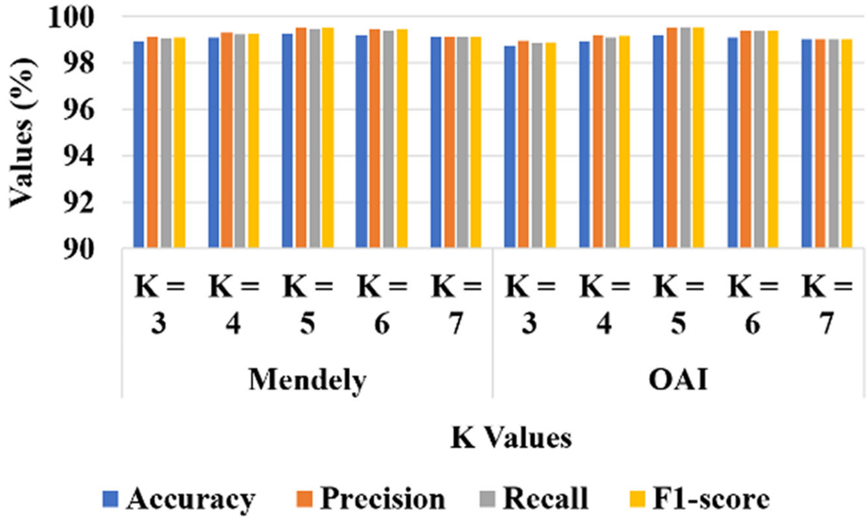

Fig. 3. K-fold analysis of the proposed method for KOA detection

Table 4 illustrates the cross-dataset analysis of the proposed method with existing methods for KOA classification using OAI and Mendeley datasets. The cross-dataset analysis illustrates the effective generalization capability of the proposed GAA-DenseNet121 over different imaging conditions and annotation styles. Training on Mendeley and testing on OAI attains 98.95% accuracy, whereas the reverse setup reaches 99.10%, representing superior feature transferability.

Table 4. Cross-dataset analysis of the proposed method with existing methods for KOA classification using OAI and Mendeley datasets

Dataset	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Trained on Mendely: Tested On OAI	MobileNet	95.42	95.88	95.61	95.74
	VGG-16	96.18	96.55	96.40	96.47
	Inception-Net	96.75	97.05	96.92	96.98
	CNN	94.88	95.12	94.95	95.03
	ViT	95.38	96.02	95.24	95.78
	DeiT	96.47	96.37	96.47	96.42
	ConvNeXt	97.84	97.14	97.57	97.32
	Proposed GAA-DenseNet121	98.95	99.20	99.12	99.16
Trained on OAI: Tested on Mendeley	MobileNet	95.85	96.14	95.98	96.06
	VGG-16	96.40	96.72	96.58	96.65
	Inception-Net	97.02	97.38	97.20	97.29
	CNN	94.52	94.78	94.60	94.69
	ViT	96.48	95.58	94.81	95.93
	DeiT	97.58	96.39	95.93	96.08
	ConvNeXt	98.47	98.47	97.46	97.78
	Proposed GAA-DenseNet121	99.10	99.35	99.30	99.32

Table 5 illustrates the statistical analysis and computational complexity of the proposed method with existing methods. In spite of having a larger architecture than MobileNet or CNN, the GAA-DenseNet121 attains a comparable inference time because of effective feature reutilization, minimizing duplicate computation. The memory consumption is moderate and crucially less than large networks such as VGG-16 and InceptionNet. The statistical significance of the proposed approach is estimated through a two-tailed paired t-test and one-way ANOVA. The t-test compares the performance of the proposed GAA-DenseNet121 model with every existing approach over different experimental runs, assuming that the performance scores are approximately normally distributed. The statistical analysis considers different hypothesis-testing frameworks: two-tailed p-tests and one-way ANOVA. The p-test estimates a null hypothesis (H_0) that the proposed model presents no significant enhancements across previous approaches, against the alternative hypothesis (H_1) that it attains statistically meaningful gains. A p-value below 0.05 resulted in rejection of H_0. The reported p-values demonstrate the statistical significance of the performance enhancement attained through the proposed GAA-DenseNet121 approach compared to existing approaches. In this research, a significance level of 0.05 is adapted. Since each acquired p-value for the proposed approach is less than 0.05, the null hypothesis (H_0), which assumes no significant difference between models, is rejected.

Table 5. Statistical analysis and computational complexity of the proposed method with existing methods

Dataset	Methods	Inference Time (s)	Memory Size (GPU)	Training Time (s)	P-test	ANOVA
Mendely	MobileNet	0.011	1.5	680	0.041	0.049
	VGG-16	0.019	2.4	910	0.038	0.044
	InceptionNet	0.021	2.8	1020	0.034	0.040
	CNN	0.014	1.9	580	0.052	0.058
	ViT	0.012	1.8	578	0.047	0.053
	DeiT	0.011	1.7	575	0.043	0.047
	ConvNeXt	0.010	1.5	570	0.035	0.044
	Proposed GAA-DenseNet121	0.008	1.2	560	0.028	0.031
OAI	MobileNet	0.012	1.7	690	0.046	0.055
	VGG-16	0.020	2.5	940	0.042	0.047
	InceptionNet	0.023	2.8	1045	0.039	0.043
	CNN	0.019	1.6	960	0.029	0.067
	ViT	0.019	1.5	910	0.028	0.063
	DeiT	0.015	1.4	840	0.027	0.054
	ConvNeXt	0.012	1.2	810	0.026	0.043
	Proposed GAA-DenseNet121	0.009	1.0	770	0.025	0.033

Figure 4 illustrates the ablation study of the complete proposed method with individual baseline approaches. The baseline DenseNet121 employs better but fails to modeling the subtle KOA indications. Incorporating GAA into DenseNet121 enhances the overall performance through improving directional feature learning along key joint regions. This enables an approach to better emphasize clinically crucial structures like osteophytes and joint-space narrowing.

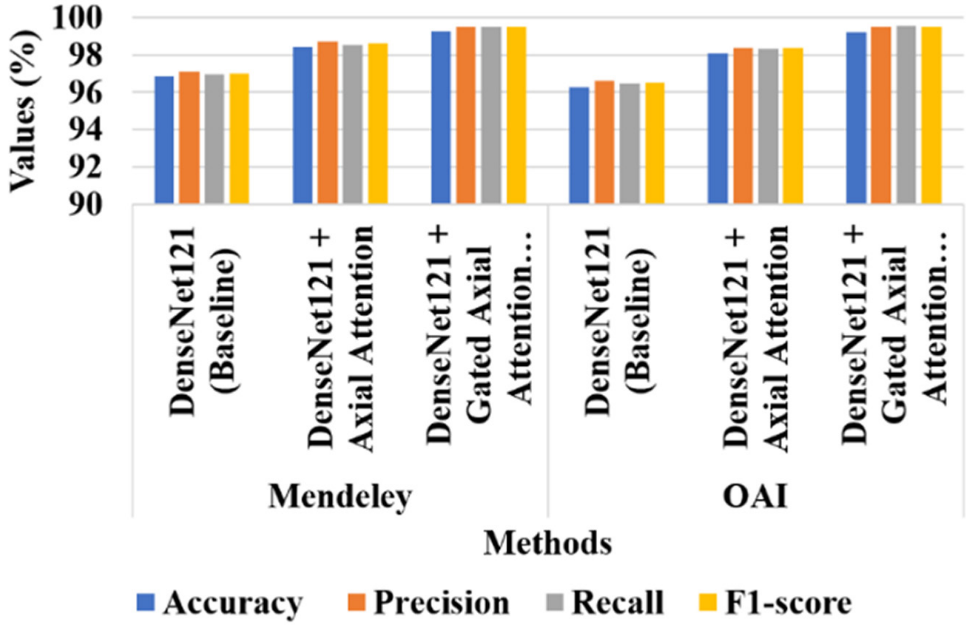

Fig. 4. Ablation study of the complete proposal with individual baseline approaches

Figures 5a and b illustrate the confusion matrix of the proposed KneeOsteoNet method for KOA detection. The confusion matrix provides a detailed breakdown of classification outcomes produced by the GAA-DenseNet121 model, including true positives, true negatives, false positives, and false negatives. It clearly shows how accurately the model identifies osteoarthritis cases and normal knees.

Figures 6a and b demonstrate the receiver operating characteristic (ROC) curves of the proposed KneeOsteoNet method using different datasets. The proposed KneeOsteoNet approach achieves the better AUC, illustrating the higher discriminative capability. The curves illustrate better discriminative performance over each KL grade, with AUC values close to 1.0.

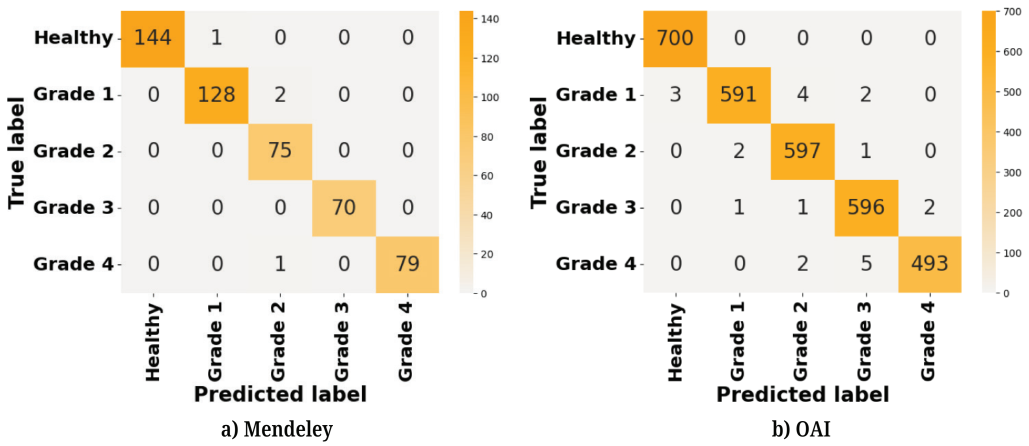

Fig. 5. Confusion matrix of the proposed KneeOsteoNet method for KOA detection

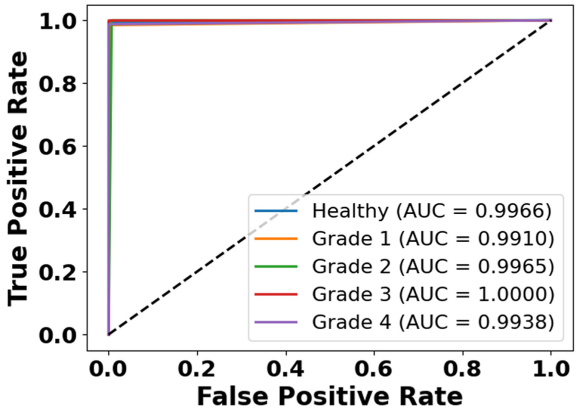

Fig. 6. (a). ROC of the proposed KneeOsteoNet method for KOA detection: Mandeley

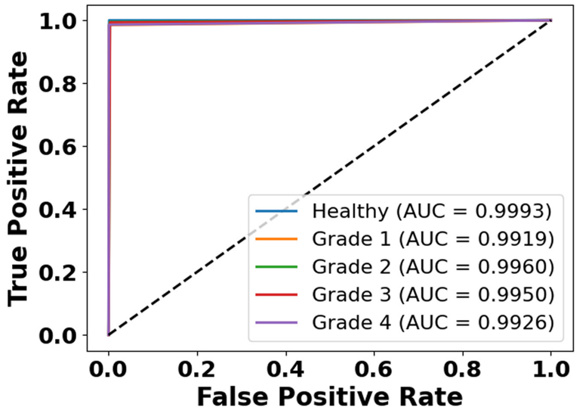

Fig. 6. (b). ROC of the proposed KneeOsteoNet method for KOA detection: OAI

4.2 Comparative analysis

Table 6 illustrates the comparative analysis of the proposed method with existing methods for KOA using OAI and Mendeley datasets. The decimal value of existing methods such as Ensemble [25] is converted into a percentage for uniformity with the proposed method and for better understanding.

Table 6. Comparative analysis of proposed method with existing methods for KOA using OAI and Mendeley datasets

Dataset	Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Mendely	CenterNet [21]	99.14	99.45	99.42	99.44
	Ensemble method [22]	98.90	–	–	–
	Proposed KneeOsteoNet	99.25	99.51	99.49	99.50
OAI	CenterNet [21]	99.14	99.45	99.42	99.44
	DRAE + Deep Siamese [23]	79.02	81.17	75.12	79.98
	12-layer CNN [24]	92.3	96.11	97.05	–
	Ensemble [25]	98	98	96	97
	OsteoHRNet [26]	71.74	–	–	–
	Proposed KneeOsteoNet	99.21	99.52	99.54	99.53

4.3 Discussion

The suggested GAA-DenseNet121 model offers remarkable improvement in detecting KOA by increasing the precision (~99%) and interpretability. The model addresses the limitations of the previous deep learning models by increasing the sensitivity towards early KOA and removing background noise through a Global Attention Augmentation (GAA) module. DenseNet121 facilitates effective reuse of features, while the gating mechanism allows focusing on the clinically significant areas such as joint space narrowing and osteophytes.

The model shows excellent results when tested on different datasets (OAI and Mendeley) through k-fold and cross-dataset validation. This shows that there is no overfitting, as the results remain consistent. Furthermore, the heatmaps of attention and Grad-CAM visualization increase interpretability by emphasizing clinically significant areas.

4.4 Misclassification analysis

The confusion matrix analysis demonstrates that most misclassifications occur among adjacent KL grades, especially KL1–KL2 and KL2–KL3, because of subtle and overlapping radiographic features such as timely joint-space narrowing and osteophyte formation. Although the proposed GAA approach enhances the attention to clinically relevant regions, some limitations remain. The model relies only on X-ray images without incorporating clinical data, and performance was influenced through dataset size and class imbalance. Moreover, borderline cases with fewer visual differences are still challenging to classify. Future work will concentrate on integrating the multimodal data and enhancing the fine-grained feature discrimination.

5 CONCLUSION

The proposed study presents a GAA-DenseNet121 algorithm that is designed to identify KOA from X-ray images using DenseNet121 along with GAA modules. It is highly accurate with high consistency when tested on the OAI and Mendeley databases, including early-stage KOA. Future directions may include the use of multiple modalities and explainable AI techniques.

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