KL Grade Classification of Knee Osteoarthritis using Convolutional Neural Networks and CBAM

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Abstract- Knee osteoarthritis is a prevalent musculoskeletal disorder that predominantly affects the elderly population and is typified by the gradual deterioration and attrition of articular cartilage in the knee joint. One commonly employed technique to evaluate the extent of knee osteoarthritis is the Kellgren-Lawrence (KL) grading system, which evaluates joint space narrowing, osteophytes, sclerosis, and bony deformity visible on radiographic images. The purpose of this study is to compare and contrast the Knee Osteoarthritis KL grade classification performance of various architectures of Convolutional neural networks including ResNet-34, DenseNet-121, VGG-19 and Inception-V3. The Osteoarthritis Initiative (OAI) dataset was chosen as the primary dataset for our research. In this study, osteoarthritis is classified solely based on radiographs (X-RAY) of the knee obtained in a bilateral posteroanterior projection with fixed joint flexion. We investigate the effectiveness of the Convolution Block Attention Module on these architectures for knee osteoarthritis severity level. We merged KL scale grades 0 and 1 into a single category which resulted in a 11.84 % improvement in accuracy without losing any essential data. We observed that DenseNet-121 with CBAM performed the best among all the models, achieving an accuracy of 86.714% with highest per class accuracy of 93.15% achieved on Grade 0.
Index Terms- Knee Osteoarthritis, Kellgren-Lawrence scale, Convolution Block Attention Module, DenseNet, ResNet, VGG, Inception

I. INTRODUCTION

Knee osteoarthritis [1] is a multifactorial degenerative disorder that poses a significant health burden in the aging population worldwide. This illness is most prevalent in individuals between the ages of 45 and 80, particularly women. Articular cartilage damage is the hallmark feature of this condition, detecting and grading the severity of osteoarthritis is of utmost importance. Articular cartilage is a firm, elastic tissue that serves as a cushioning mechanism at the ends of bones in joints. The primary symptoms of knee osteoarthritis include pain, stiffness, swelling, and limited mobility. Swelling is often caused by inflammation within the joint, leading to the knee feeling warm and tender to the touch. Furthermore, restricted mobility can impede the ability to carry out routine activities such as walking, climbing stairs, or bending down.

Several factors can contribute to the development of knee osteoarthritis, including age, genetics, obesity, previous knee injuries, and certain occupations or sports that involve repetitive stress on the knee joint. As individuals age, the natural wear and tear of cartilage in joints can lead to osteoarthritis. Additionally, genetics may also play a contributory role in the onset of the condition. There is an increased susceptibility for individuals who have a familial background of knee osteoarthritis to develop the ailment themselves. Moreover, obesity places excess strain on the knees, hastening the cartilage breakdown process.

The detection and classification of knee osteoarthritis are crucial for several reasons. Firstly, as there are no known medical means available till now that can regrow the articular cartilage, healthcare providers need to determine the appropriate treatment plan for each individual. The degree of knee osteoarthritis severity can vary considerably, and treatment options will hinge on the level of progression. For instance, mild cases may be managed with lifestyle modifications and physical therapy, while severe cases may necessitate surgery. Secondly, tracking the progression of knee osteoarthritis can help healthcare providers identify potential complications or comorbidities that may arise, such as joint deformities or nerve damage. Finally, early detection of knee osteoarthritis can enhance outcomes and potentially delay the need for more invasive treatments. By routinely assessing the levels of knee osteoarthritis, healthcare providers can facilitate effective condition management and improve the quality of life of patients.

Knee osteoarthritis can be diagnosed and evaluated via various methods, including clinical examination, imaging techniques such as X-rays and MRI, and biomarker analysis. X-rays are a widely-used diagnostic tool in the detection of this disease. X-rays facilitate the visualization of joint space narrowing and bone spur development, contributing to the accurate diagnosis of the condition. The severity of knee osteoarthritis can be evaluated using the radiographic Kellgren-Lawrence grading scale [2]. Narrowing of joint space, osteophytes, sclerosis, and bone deformity are some of the characteristics that contribute to a diagnosis. The KL grading system is widely used in both clinical practice and research to assess the degree of knee osteoarthritis. This system classifies the condition of the joint in five grades (0-4) (Fig. 1).
A score of 0 suggests no osteoarthritis, whereas a score of 4 implies severe osteoarthritis.

- Grade 0: a knee joint without any radiographic evidence of osteoarthritis

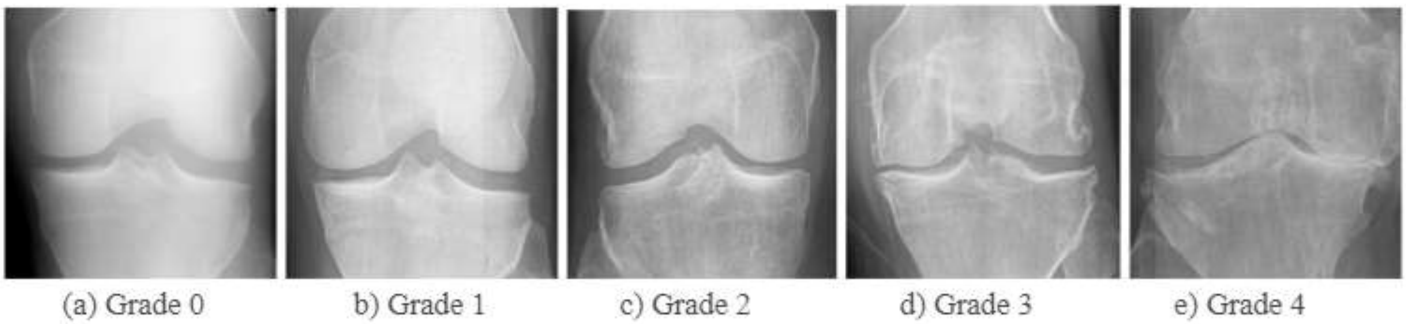


Fig. 1. Knee X-Ray images of various KL grades from OAI dataset

- Grade 1: some suspicion of osteoarthritis with probable osteophytes and narrowing of joint space
- Grade 2: a concrete diagnosis of osteoarthritis including mild narrowing of joint space and some osteophytes.
- Grade 3: indicative of moderate to severe narrowing of joint space, numerous osteophytes, and possible sclerosis.
- Grade 4: severe narrowing of joint space, huge osteophytes, acute sclerosis, and potential bony deformities.

Here, it is important to note that the KL grading system is based solely on radiographic findings and does not take into account other factors such as pain, functional impairment, or patient-reported outcomes. As such, it is just one aspect of a comprehensive assessment of osteoarthritis in the knee joint.

II. LITERATURE REVIEW

The state-of-the-art studies have investigated the use of CNNs [3] for knee osteoarthritis classification and severity grading using radiographic images. These studies have shown that CNNs can achieve high accuracy in automatically classifying knee osteoarthritis severity based on radiographic images [4].

Attention-based CNN for KL Grade Classification: Data from the Osteoarthritis Initiative [5]

In this study, the authors brought to the table Residual Neural Network (ResNet) [6] to identify the knee joint in radiographs, and a Convolutional Block Attention Module (CBAM) [7] was then integrated to provide automatic KL-grade prediction. This study used a Residual Neural Network (ResNet) model in tandem with a Convolutional Block Attention Module (CBAM) to achieve the most exceptional performance in automated KL-grade classification. This is shown by noticeably improved metrics like Mean Squared Error (MSE), multi-class average accuracy, and Quadratic Kappa score. This method's increased performance may be ascribed to the use of sophisticated preprocessing techniques and improvements to knee joint localization, which have improved the model's efficacy and accuracy in comparison to earlier methods. With a mean squared error of 0.36, a quadratic Kappa score of 0.88, and a multi-class average accuracy of 74.81%, the suggested model significantly outperformed previously published results. This represents a significant advancement in automated KL-grade classification using deep learning techniques.

Using compression and excitation blocks to improve the accuracy of automatic classification of osteoarthritis of the knee using convolutional neural networks [8]

In this research study the author undertook an investigation to assess the efficacy of integrating compression and excitation blocks into ResNet and DenseNet [9] convolutional neural networks, with the aim of improving the classification accuracy of knee osteoarthritis. The outcomes of this inquiry evinced a significant improvement of 1-3% in the quality of OA classification, as appraised on the KL scale, without significant deviations from conventional methods. In addition, the study revealed that incorporating grades 0 and 1 of the Kellgren-Lawrence (KL) grade into a single class conferred a remarkable 12.74% augmentation in the precision of osteoarthritis KL grade classification, while simultaneously retaining indispensable disease-related data.

To further elevate the performance of the classification model, a novel approach was employed, which entailed an ensemble of three convolutional networks adopting the DenseNet-121 architecture with compression and excitation blocks. This innovative technique culminated in a striking classification accuracy of 84.66%, which surpasses the outcomes of previous studies and illuminates the tremendous potential of integrating squeeze and excitation blocks [10] in the realm of deep learning algorithms for osteoarthritis classification

Fully automatic knee osteoarthritis severity grading using deep neural networks with a novel ordinal loss [11]

In this research, the author sequentially deploys two deep CNN models to autonomously estimate the knee osteoarthritis intensity, as determined by Kellgren-Lawrence scale. Firstly, a specialized YOLOv2 [12] (one stage) network is employed to detect knee joints determined by the size distribution of knee joints with modest variance. Secondly, the most widely used CNN models have been fine-tuned, including variations of ResNet, VGG [13], and DenseNet as well as Inception-V3 [14], to categorize the joint pictures using a new, configurable ordinal loss. Misclassifications with bigger distances between the predicted and actual KL ratings are assigned a higher penalty. The Osteoarthritis Initiative (OAI) baseline X-ray images are utilized for assessment. When it comes to identifying the knee joint, the authors achieved a mean Jaccard index 0.858. The model with the proposed ordinal loss has the maximum classification accuracy (69.7%) and the lowest mean absolute error (MAE) (0.344) on the knee KL grading test. Superior results are achieved in both the KL grading of the knee and the identification of the knee joint.

III. DATA

There are several standard datasets available for knee osteoarthritis grading, including:

1. The Osteoarthritis Initiative (OAI) dataset [15], which contains an archive of clinical data of 4796 patients.
2. MOST (Multicenter Osteoarthritis Study) dataset, which includes data on 3026 patients.
In addition, recently the dataset is gaining popularity.
3. CHECK (Cohort Hip & Cohort Knee), which is the result of a long-term follow-up of patients with early symptoms of osteoarthritis of the knees and hips in the Netherlands and consists of more than 3000 x-rays of various parts of the body (lateral and frontal projections of the knees, hips, x-rays of the hands, etc.).

However, during experiments, it was found that the CHECK dataset contains a large number of markup errors, and access to the MOST dataset is limited due to the termination of funding and reorganization.
Therefore, we selected the OAI dataset as the primary dataset for our study. This set contains information on 4796 patients aged between 45 to 79 years, followed up for 14 years. In addition to radiographs of the knee joint, the dataset also contains information on various measurements, the presence of osteophytes, narrowing of the intra-articular space and stages of osteoarthritis obtained from several independent experts.
In our study, the classification of osteoarthritis is carried out only on radiographs (X-RAY) of the knee joint obtained in a bilateral posteroanterior projection with fixed joint flexion.

This set was randomly divided into training, validation and test sets. samples in the proportion 7: 1: 2.

The dataset obtained was highly imbalanced. We used Data augmentation to address the severe imbalance in the obtained dataset. To get this effect, we flipped the original data horizontally, randomly scaled and rotated it (by a slight angle), then adjusted the hue, saturation, and brightness of the images. The final resolution of the photograph, after all the adjustments, was 224x224 pixels. Over the course of model training, all augmentation steps were executed at random.

IV. METHODOLOGY

In our model we implemented various architectures of convolutional neural networks including DenseNet, ResNet, VGG and Inception-V3. We modified the structure of these models and added a novel attention mechanism [16], Convolution Block Attention Module (CBAM) (Fig. 2). The architecture of the network includes multiple convolutional layers, followed by attention layers, and then fully connected layers.

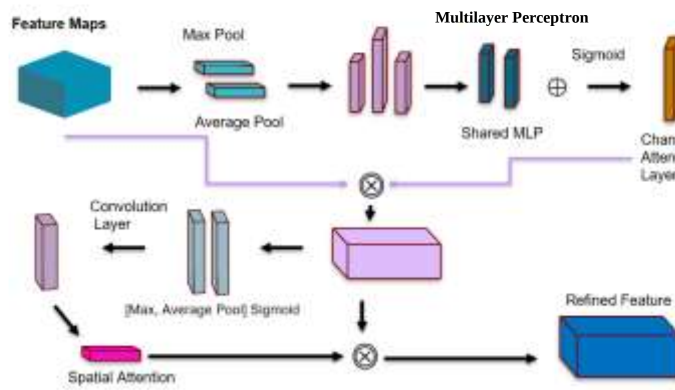


Fig. 2. architecture of convolutional block attention module

In order to boost the efficiency of convolutional neural networks (CNNs), CBAM was developed as a neural network module. Both a channel attention module and a spatial attention module make up the CBAM module. Using the channel attention module, you may selectively highlight important channels while suppressing less informative ones, therefore capturing the interdependencies across feature channels in a convolutional layer. An important part of the spatial attention module is its ability to selectively highlight useful spatial locations while suppressing less informative ones, thereby capturing the interdependencies between spatial places in a feature map.

We employed a DenseNet-121 architecture with CBAM for the classification task (Table 1). We obtained images of 224x224 pixels with 3 channels after data augmentation on the OAI dataset to handle the problem of dataset imbalance. The pixel values were further normalized in the range [0,1] to ensure that they are within a consistent range. The initial layer is a 7x7 convolutional layer with 64 filters with stride 2 and valid padding, followed by batch normalization [17] and ReLU activation function. The output is passed through a max pooling layer with a 3x3 window and stride 2.

The architecture (Fig. 3) consists of a series of four such dense blocks each consisting of 6, 12, 24, and 16 layers respectively, with a growth rate of 32. After each dense block, the feature maps are passed through a Convolutional Block Attention Module (CBAM) module. The channel attention branch of CBAM learns

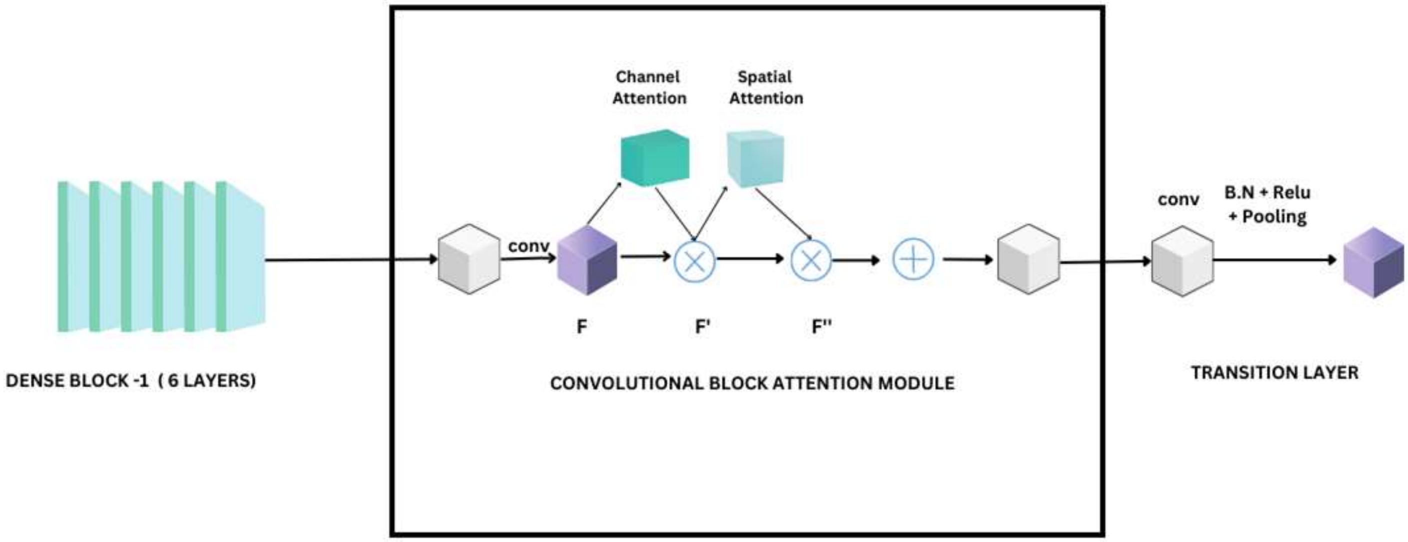


Fig. 3. Model Architecture

to focus on important features by analyzing the interdependencies between different channels in the feature maps. It uses a global pooling operation to aggregate the feature maps across spatial dimensions, followed by a series of fully connected layers to compute a set of channel-wise attention weights. These weights are then used to scale the feature maps before passing them to the next layer. The spatial attention branch of CBAM learns to focus on important regions by analyzing the interdependencies between different spatial locations in the feature maps. It uses a series of convolutional layers to compute a set of spatial attention maps, which indicate the importance of each spatial location in the feature maps. These attention maps are then used to modulate the feature maps, allowing the model to selectively attend to important regions.

The outputs of the channel and spatial attention branches are combined using element-wise multiplication, resulting in a set of attention-modulated feature maps that are more discriminative and informative than the original feature maps. By incorporating both channel and spatial attention, CBAM can effectively capture both global and local dependencies in the feature maps.

There are 3 transition blocks, each consisting of a convolutional layer, batch normalization (B.N.), ReLU activation, average pooling, and reduction in the number of filters by a factor of 0.5. The Global average pooling layer reduces the spatial dimensions of the output feature maps to a single vector.

Finally, a Dense layer is added that applies a fully connected layer with 5 output nodes and SoftMax activation is employed for classification. We compile the model using the Adam optimizer [18] with a learning rate of 0.0001 and categorical cross-entropy loss, which is a commonly used loss function for multi-class classification tasks such as KL grading.

Layer Type	Output Shape	Filters	Kernel Size	Stride	Padding
Input	(224, 224, 3)				
Conv2D	(112, 112, 64)	64	7x7	2	same
BatchNormalization	(112, 112, 64)				
ReLU	(112, 112, 64)				
MaxPooling2D	(56, 56,64)		3x3	2	same
Dense Block 1	(56, 56, 256)	32	1x1		
CBAM	(56, 56, 256)				
Transition Layer 1	(28, 28, 128)				
Dense Block 2	(28, 28, 512)	64	1x1		
CBAM	(28, 28, 512)				
Transition Layer 2	(14,14, 256)				
Dense Block 3	(14,14, 1024)	128	1x1		
CBAM	(14,14, 1024)				
Transition Layer 3	(7,7, 512)				
Dense Block 4	(7,7, 2048)	256	1x1		
CBAM	(7,7, 2048)				
Average Pooling	(1, 1,2048)		7x7		
Flatten	2048				
Dense	5 (KL grades)				

Table 1: The network structure of the DenseNet-121 architecture with CBAM blocks. The input shape of 224x224x3 is first passed through a convolutional layer with 64 filters, followed by batch normalization and ReLU activation, followed by max pooling, Dense Blocks with CBAM, and Transition Layers.

After implementing the above model for various CNN architectures, we found that in order to streamline the classification process and improve the focus on osteoarthritis detection, we can merge KL grades 0 and 1 into a single category. This decision was based on the fact that these two grades are often considered similar in terms of the absence of osteoarthritis. We took care to maintain consistency with the original KL grading scale by leaving the remaining categories untouched.

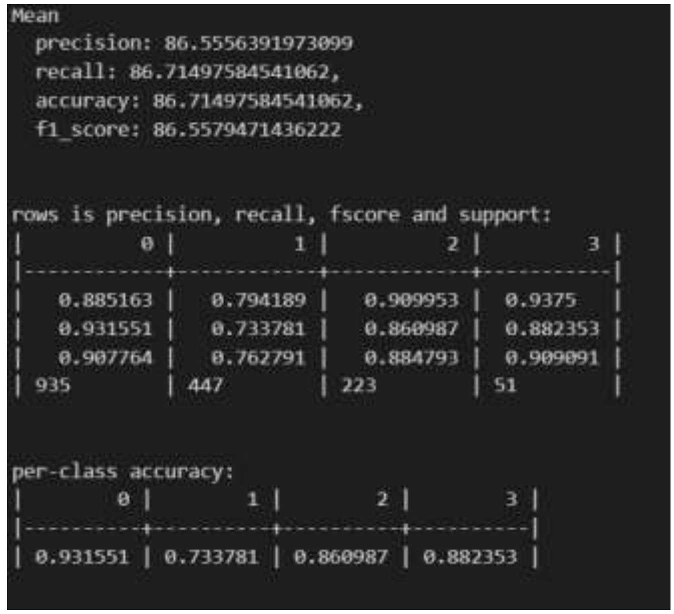
Combining 0 and 1 grade on KL grading in knee osteoarthritis is a common practice in medical imaging due to several reasons. Firstly, the cartilage thickness and radiographic findings of 0 and 1 grades are very similar, making it difficult to distinguish between the two grades. Secondly, combining these grades can increase the sensitivity of the classification model and reduce the chances of false negatives. This is particularly important in early stages of the disease where minor changes in the cartilage can be missed by radiologists. Moreover, combining 0 and 1 grades can simplify the classification process, as it reduces the number of categories in the grading system, making it easier for radiologists to interpret and report their findings. Overall, combining 0 and 1 grade on KL grading in knee osteoarthritis is a practical and effective approach that can improve the efficiency and accuracy of the diagnosis and treatment of the disease.

V. RESULTS

To comprehensively evaluate the performance of various models for KL grading of knee osteoarthritis on the OAI dataset, we conducted a comparative analysis of ResNet-34, DenseNet-121, VGG-19, and Inception-V3. These models were chosen based on their established efficacy in image classification tasks and their proficiency in handling large, complex datasets. The evaluation was performed using multiple performance metrics, including overall accuracy, precision, recall, and F1-score, for each model on the OAI dataset. Our findings revealed that DenseNet-121 outperformed the other models and was the most accurate for KL grading of knee osteoarthritis from X-rays. The obtained results demonstrate the potential of deep learning models in diagnosing knee osteoarthritis, which could aid healthcare professionals in developing personalized treatment plans and improving patient outcomes.

In this work, we studied the effect of incorporating an attention mechanism into our models, and also investigated the effect of merging two classes in our classification task. We first evaluated all the models without any attention block, and compared their performance. Next, we added a CBAM attention module after each layer, and again compared the results. Our findings showed that the inclusion of the CBAM attention module led to a significant improvement in model accuracy, with an average increase of about 3%.

Moreover, we also examined the effect of merging two classes in our classification task. Specifically, we merged grade 0 and grade 1 into a single class, and compared the accuracy with the original class distribution. Our experimental results revealed a significant increase in accuracy of about 11.34% when the two classes were merged.



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Mean
  precision: 86.5556391973099
  recall: 86.71497584541062,
  accuracy: 86.71497584541062,
  f1_score: 86.5579471436222

rows is precision, recall, fscore and support:
|          0 |          1 |          2 |          3 |
|------------+------------+------------+------------|
|   0.885163 |   0.794189 |   0.909953 | 0.9375     |
|   0.931551 |   0.733781 |   0.860987 | 0.882353   |
|   0.907764 |   0.762791 |   0.884793 | 0.909091   |
| 935        | 447        | 223        | 51         |

per-class accuracy:
|        0 |        1 |        2 |        3 |
|----------+----------+----------+----------|
| 0.931551 | 0.733781 | 0.860987 | 0.882353 |
```

Fig. 4. Results obtained on the DenseNet-121 model + CBAM for the case of 4 classes

The performance of the DenseNet-121 model with CBAM and an amalgamation of 0-1 KL grade is illustrated in Fig. 4. The model shows an accuracy of 86.714% and also shows the class wise accuracy, precision, recall, support and F1-score obtained by this architecture.

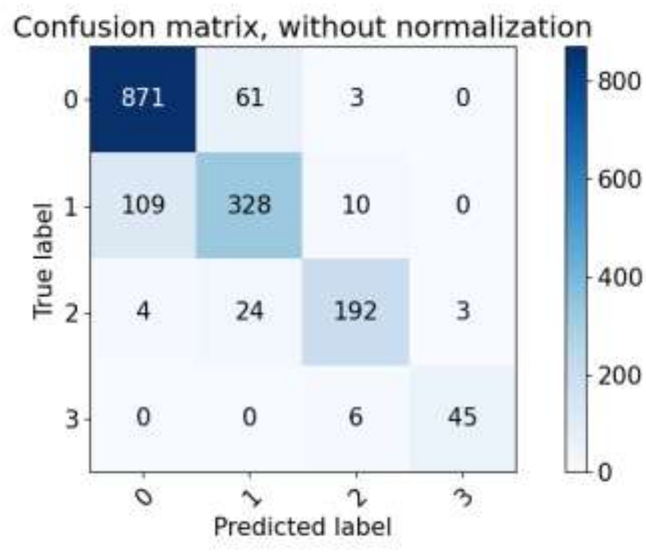

Fig. 5. confusion matrix obtained on the DenseNet-121 model + CBAM for the case of 4 classes

The confusion matrix (Fig. 5) shows that the models are better at predicting classes 2 and 3 compared to classes 0 and 1, which is expected given the imbalance of the dataset. The effectiveness of a machine learning model for classification tasks may be measured using a confusion matrix. The model's predicted values are compared to the actual values of the test data, and the resulting comparison forms the matrix. The matrix's columns display the predicted values, while the rows display the actual ones. True positives, False positives, True negatives, and False negatives make up the four quadrants of the confusion matrix.

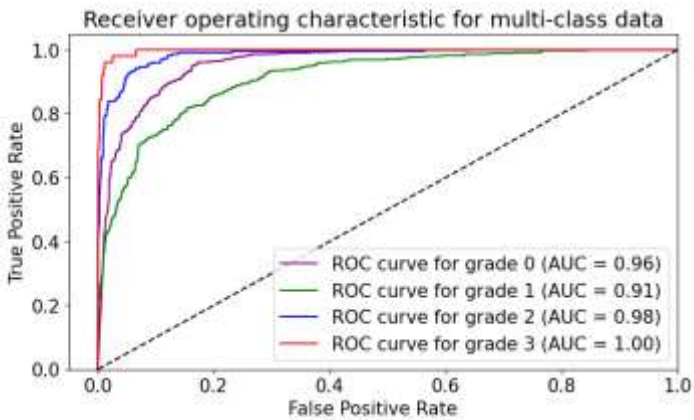

Fig. 6. ROC curve obtained on the DenseNet-121 model + CBAM for the case of 4 classes

Model	Accuracy	Precision	Recall	F1-Score
DenseNet-121-CBAM	0.867	0.865	0.867	0.865
ResNet-34 CBAM	0.835	0.852	0.827	0.839
Inception-V3 CBAM	0.804	0.834	0.821	0.827
VGG-19 CBAM	0.781	0.773	0.795	0.783

Table 2: Result obtained on various CNN architecture + CBAM for the case of 4 classes

As illustrated in Table 2, DenseNet-121 with CBAM performed the best among all the models, achieving an accuracy of 86.7% while VGG-19 with CBAM yielded the lowest accuracy of 78.1%.

Our study has implications for the diagnosis of knee osteoarthritis, as our models can be used to automate the process of KL grading from X-ray images, providing a more objective and efficient diagnostic tool for healthcare professionals. Additionally, our research highlights the potential of using CBAM in conjunction with deep learning models for medical image analysis.

VI. CONCLUSION

In conclusion, this study was designed to comprehensively evaluate the performance of four deep learning models, ResNet-34, DenseNet-121, VGG-19, and Inception-V3, for KL grading of knee osteoarthritis on the OAI dataset. The study also aimed to investigate the effect of integrating an attention mechanism into the models and merging two classes (grade 0 and grade 1) in the classification task.

The results of the study demonstrate the potential of deep learning models in accurately diagnosing knee osteoarthritis. DenseNet-121 outperformed the other models, demonstrating superior accuracy for KL grading of knee OA from X-rays. This suggests that deep learning models could be a valuable tool for improving the accuracy of knee OA diagnosis, which could lead to more effective treatment plans and better patient outcomes.

Moreover, the inclusion of a CBAM attention module after each layer significantly improved the performance of the models, resulting in an approximate increase in accuracy of 3%. This finding suggests that incorporating attention mechanisms into deep learning models can improve their performance in medical image analysis tasks. In addition, merging grade 0 and grade 1 into a single class resulted in a significant increase in accuracy of approximately 11.34%. This suggests that simplifying the classification task by merging classes can lead to more accurate results.

The study highlights the potential of using deep learning models in diagnosing knee osteoarthritis, which could aid healthcare professionals in developing personalized treatment plans and improving patient outcomes. The use of CBAM in conjunction with deep learning models for medical image analysis is also demonstrated as a promising avenue for future research.

ACKNOWLEDGMENT

We offer our deepest appreciation to the individuals and organizations whose persistent support was crucial to the completion of our research endeavor. We would like to express our gratitude to our esteemed supervisor, Professor Manoj Kumar, whose exceptional guidance, support, and encouragement proved invaluable throughout the project. His expertise and insights were critical in helping us design and execute our research. Furthermore, we are grateful to the Delhi Technological University for their significant assistance in various aspects of the project, including the provision of necessary hardware and software. Finally, we would like to acknowledge the unwavering support and encouragement from our families and friends throughout the project's duration. Their steadfastness, patience, and understanding were integral in our ability to complete this work. We remain deeply grateful to all those who contributed to the accomplishment of this research project.

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