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Article

# Radiographic Variability-Adaptive Structural Harmonization (RV-ASH): An Adaptive Deep Learning Framework for Robust Knee Osteoarthritis Detection and Clinical Validation

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**Abstract:** Knee Osteoarthritis (KOA) is one of the most common degenerative musculoskeletal disorders that significantly affects joint mobility, physical function, and overall quality of life worldwide. Accurate and early-stage diagnosis of KOA from radiographic images remains challenging due to radiographic variability, heterogeneous imaging conditions, disease progression patterns, and inter-observer inconsistencies. To address these challenges, this study proposes a novel hybrid deep learning framework named Radiographic Variability-Adaptive Structural Harmonization (RV-ASH) integrated with DenseNet121 and an attention mechanism for robust KOA detection and severity classification. The RV-ASH framework reduces inter-dataset radiographic variability through adaptive structural harmonization, while DenseNet121 extracts hierarchical deep features and the attention mechanism emphasizes clinically relevant anatomical regions such as joint space narrowing and osteophyte boundaries. The proposed model was trained using the Osteoarthritis Initiative (OAI) and externally validated on the Mendeley Knee OA Dataset. Experimental evaluation achieved 98.43% accuracy, 98.15% precision, 97.92% recall, 98.03% F1-score, and 99.01% AUC, demonstrating superior classification performance, robustness, and clinical applicability for automated KOA diagnosis and severity assessment.
**Keywords:** Knee Osteoarthritis (KOA), Deep Learning, RV-ASH Framework, DenseNet121, Attention Mechanism.

## 1. Introduction

RV-ASH is a next-generation Computer-Aided Diagnosis (CAD) paradigm that aims to overcome fundamental challenges of current deep-learning-based systems for KOA detection. Osteoarthritis is a highly prevalent musculoskeletal condition worldwide, which affects millions of people and drastically reduces mobility and quality of life [1,2]. It is progressive destruction of the articular cartilage, narrowing of the joint space, formation of osteophytes and changes of subchondral bone. While the disease can be diagnosed clinically, its diagnosis is difficult because the structural changes are rather complex and subtle in the early stages, therefore early and accurate diagnosis is necessary for effective intervention and slowing disease progression [3,4]. Figure 1 shows the difference between a healthy knee and KOA in terms of the structure and the pathology, including cartilage degeneration, narrowing of the joint space and development of osteophytes.

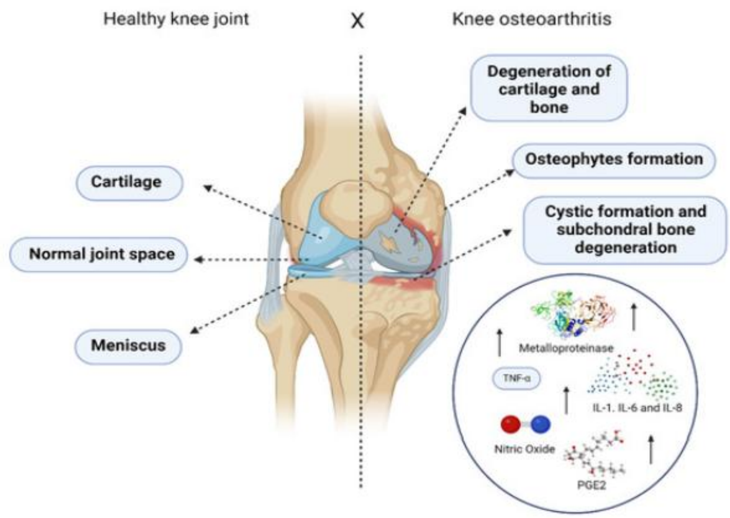



**Figure 1:** Healthy knee joint versus KOA showing major structural degenerative changes [5].

While MRI remains the most reliable modality for the diagnosis of knee OA, it is the least cost-effective approach, and plain X-ray is the most widely used and cost-effective modality for this diagnosis [6]. The Kellgren–Lawrence (KL) grading system is widely used to determine disease severity by examining radiographic changes, including joint space narrowing and osteophytes [7]. Although it has proven to be clinically useful, the KL system is still subjective and there is inter-observer variability, which can result in different interpretations between radiologists. Also, the imaging of the joint is only a 2-dimensional representation of the 3-dimensional nature of the joint, which can lead to the lack of visibility of early cartilage degeneration and contribute to diagnostic uncertainty [8,9].

Deep Learning (DL) methods have become powerful tools for automated detection and grading of KOA in recent years [10]. Artificial Intelligence (AI) models such as Convolutional Neural Networks (CNNs) and Transfer Learning Models have shown good performance similar to the performance of expert radiologists with better reproducibility and efficiency [11]. Such models have the potential to automatically identify intricate features in a X-ray image, with a high degree of accuracy, to classify disease severity and facilitate large-scale screening applications. Additionally, sophisticated imaging techniques such as Multiview imaging and the use of prior anatomical knowledge have created high diagnostic accuracy, showing the potential of AI in musculoskeletal imaging [12,13].

Despite the progress, there are still many problems to be solved. Radiographic variability is one of the most important issues, due to variations in patient positioning, beam angles and protocols, as well as equipment settings, between institutions. This variability can affect the performance of the model and restrict its applicability. Moreover, the acquired datasets are frequently heterogeneous and imbalanced, where the annotation quality of the data varies and there is insufficient representation of early-stage disease [14]. All these make the development of strong and reliable models difficult [15].

In this regard, the proposed Radiographic Variability-Adaptive Structural Harmonization (RV-ASH) framework is an adaptive deep learning model that explicitly considers the variability in radiographic data and improves the consistency of the structure. The fundamental concept behind RV-ASH is to learn common representation of anatomical structures from heterogeneous Xray images, making the models more robust to different imaging modalities. This is done by applying adaptive preprocessing, feature normalization, and structural alignment techniques that minimize the differences between the distributions of different datasets. Furthermore, RV-ASH makes use of multi-scale feature extraction and attention-based components, which make it possible for the model to specifically concentrate on regions of clinical importance, including the contours of osteophytes and the tibiofemoral joint space. It aims at detecting structural patterns associated with disease progression, thus enhancing its ability to detect the early stages of osteoarthritis and deficiencies that are otherwise overlooked by traditional approaches [16]. Adaptive weighting techniques also help the model handle class imbalance and annotation inaccuracies.

The main aspects of the RV-ASH framework include the emphasis put on clinical validation. As opposed to pure experimental frameworks, RV-ASH is expected to be validated based on the results obtained when comparing it to the evaluation made by the experts in radiology. The sensitivity and accuracy of RV-ASH metrics are utilized in the process of validation against the human expert [17].

Lastly, RV-ASH is an effective and adaptable technique that can be used for accurate knee OA diagnosis while overcoming the challenges faced by current deep learning techniques. This framework could help overcome variability in radiography, learn better anatomical structures, and perform clinical validation to ensure uniformity in the diagnosis process, detect the condition earlier, and assist decision-making in orthopaedics.

- To develop a novel Radiographic Variability-Adaptive Structural Harmonization (RV-ASH) framework for robust knee osteoarthritis (KOA) detection from radiographic images.
- To integrate DenseNet121 and an attention mechanism for efficient hierarchical feature extraction and region-focused learning in KOA classification.
- To reduce radiographic variability and domain inconsistencies across heterogeneous datasets using adaptive feature harmonization and structural alignment techniques.
- To evaluate the proposed framework using the Osteoarthritis Initiative (OAI) and Mendeley Knee OA Dataset datasets for assessing classification accuracy and generalization capability.
- To compare the performance of the proposed hybrid framework with existing deep learning models using evaluation metrics such as accuracy, precision, recall, F1-score, and AUC.

## 2. Literature of Review

In recent years, significant advances have been made in DL systems for detecting and staging KOA from radiographic images. There has been significant progress in DL systems that detect and classify the severity of KOA from X-ray images in recent literature. Alavanthar et al. (2025) [18] introduced a two-step technique first using YOLOv8 to precisely locate the joint space width (JSW) regions with a remarkable mAP score of 0.995 and then applying VGG16 for KL-grade classification with an accuracy exceeding 91%. In a similar fashion, Mahum et al. (2023) [19] proposed an efficient DenseNet model equipped with a re-weighted cross-entropy loss function to tackle the problem of imbalanced classes and obtained more than 98% accuracy on test and validation sets. Raza et al. (2025) [20] also expanded this study by combining CNNs with autoencoders to attain an accuracy of 98.95% and AUC of 0.99, and added interpretability by creating the Grad-CAM visualization technique. Furthermore, Rani et al. (2024) [21] proposed a 12-layer CNN model which gave 92.3% accuracy in the binary classification and 78.4% accuracy in the multi-class classification. Overall, these studies demonstrate the effectiveness of deep learning models, especially those based on CNN and transfer learning, in the automation of KOA diagnosis with increased accuracy and reduced reliance on human intervention.

Other research has focused on improving robustness, generalization and interpretability through designing hybrid architectures and optimization approaches. For instance, Diab et al. (2026) [22] presented a Google-BER-LSTM hybrid architecture using sophisticated optimization algorithms such as meta-heuristic algorithms, resulting in a classification accuracy of about 0.995. Wang et al. (2025) [23] designed an attention-assisted autoencoder architecture in combination with the use of feature selection techniques, such as PCA and RFE, leading to AUC and accuracy of 96.5% and 0.94 respectively. Likewise, Daydar et al. (2026) [24] proposed a CNN–Transformer hybrid network architecture that incorporates the Osteoarthritis Edge Detection (OAED) and Multi-Resolution Feature Integration (MRFI). The method was successful in enhancing the performance of both binary and multi-class classifications for x-ray and MRI imaging. Devarapaga et al. (2025) [25] proposed an attention-assisted ensemble network architecture, which is optimized using HESM-BESO based on the features of ResNet, VGG16, and DenseNet.

Furthermore, the importance of clinical validation, multimodal learning and predictive modeling have been highlighted in several studies as a bridge between research and clinical applications. The results showed that using multiview radiographs and prior anatomical knowledge clearly enhanced diagnostic accuracy by Li et al. (2023) [26] with an AUC of 0.96, which beat the performance of experienced radiologists. Kinger et al. (2024) [27] investigated several deep learning architectures and determined that the InceptionV3 model was the best for predicting KL grade and the probability of knee replacement. In [28] Kibria et al. proposed a clinically-focused system based on DenseNet201 with an accuracy of 93.87% and robustness for noisy data and explainability through Grad-CAM. It should be noted that the studies by Schiratti et al. 2021 [29] examined the prediction of cartilage lesion and pain development with the use of MRI imaging, with ROC-AUC results equal to 65% and 72%, respectively, highlighting the complexity of the problem. In summary, machine learning algorithms have already proven their effectiveness; however, the variability of radiographic images, the small size of some data sets, and the unavailability of wide application in real-world environments remain a problem that requires the development of adaptive methodologies like RV-ASH for the detection of KOA.

## 3. Research Methodology

Figure 2 shows a comprehensive framework for automated KOA detection and severity classification through the proposed research methodology that uses a hybrid model. The overall research methodology consists of the following steps: dataset acquisition and preprocessing; RV-ASH-based structural harmonization; feature extraction; attention-guided learning; KL grade classification; performance evaluation; and clinical validation, thereby facilitating robust, accurate, and generalized automated KOA diagnosis across heterogeneous sources of radiologic data.

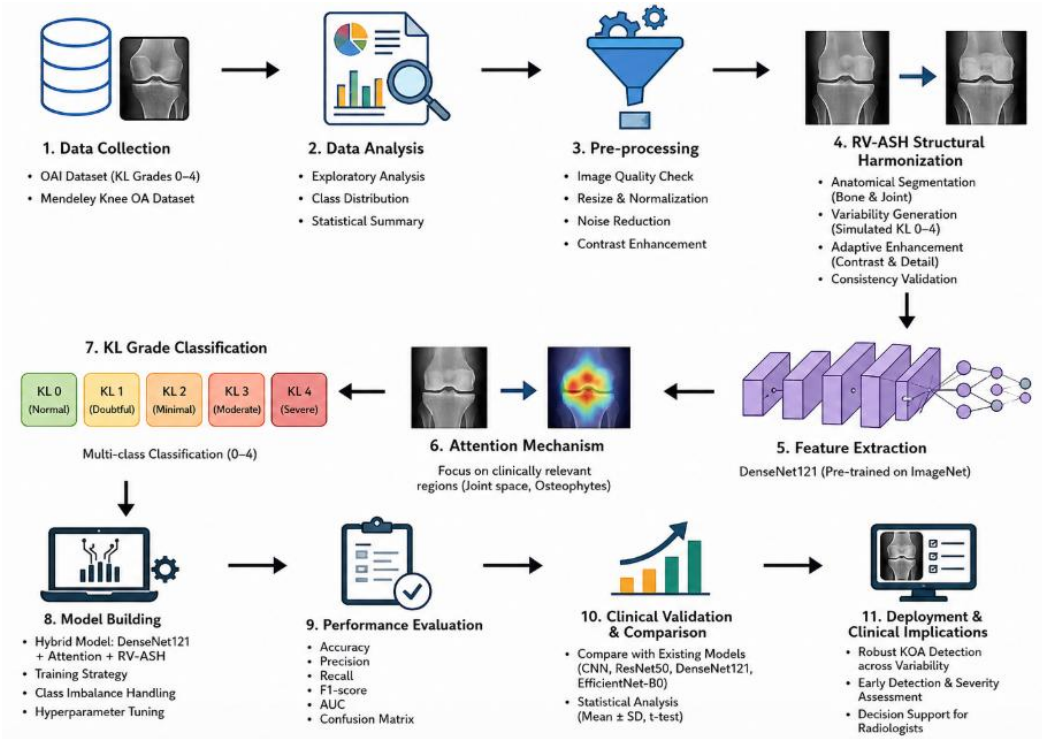



**Figure 2:** Proposed Methodology

## 3.1 *Datasets Used*

The study utilizes publicly available knee osteoarthritis (KOA) datasets such as the Osteoarthritis Initiative (OAI) and Mendeley Knee OA Dataset.

- **Osteoarthritis Initiative (OAI) dataset**

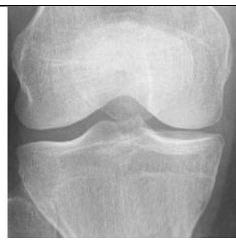
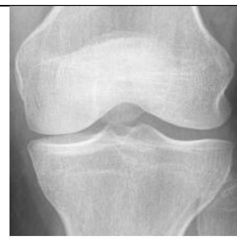
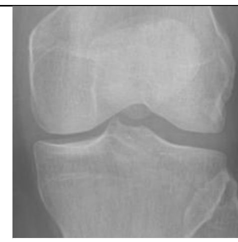
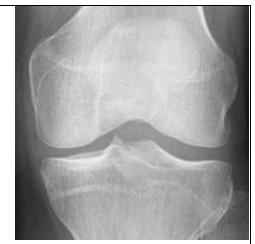
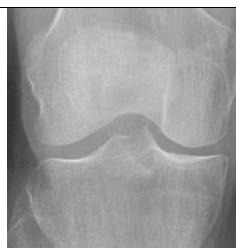
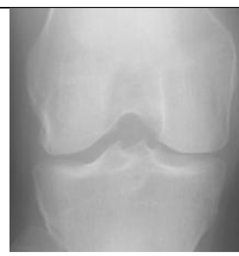
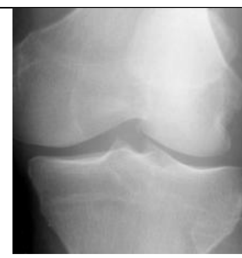
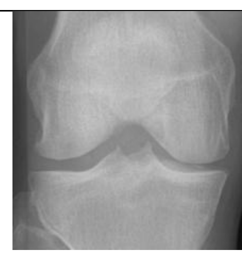
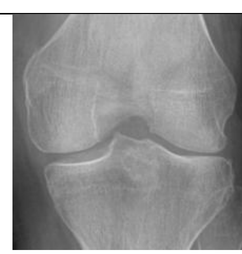
OAI [30] is a very large collection of biomedical data, which is publicly accessible and has been frequently used for research on KOA. This dataset consists of thousands of images of knee radiographs and Magnetic Resonance Imaging (MRI) scans of knees of various patients based on a predefined protocol for image acquisition. Furthermore, there is a lot of clinical data provided in this database, such as age, gender, BMI, disease progression parameters, among others, that can be used for further analysis. KL classification is applied to radiographic images, and it is considered the gold standard for grading the severity of KOA.

- **Mendeley Knee OA Dataset**

One of the available knee datasets that has been used is Mendeley Knee OA dataset [31]. This dataset consists of knee radiographic X-rays intended for classification and detection of KOA patients. Images have been annotated in accordance with the Kellgren-Lawrence (KL) classification criteria, ranging from normal to severe levels. While being smaller compared to other large datasets, it still provides good quality clinical images with clear labeling, thus serving as an option for benchmarking deep learning techniques. Variations in imaging environment, patient positioning and equipment also allow for testing the model's robustness. This dataset was employed in the present study only as an external validation dataset in order to verify the potential of proposed RV-ASH network. Table 1 presents distribution of sample sizes for training, validation, testing and external validation of KOA by KL grade. Figure 3 presents representative knee radiographic images corresponding to healthy, doubtful, minimal, moderate, and severe osteoarthritis severity levels based on the Kellgren–Lawrence grading system.

**Table 1:** Distribution of KOA Samples Across Different Kellgren–Lawrence (KL) Grades

| KL Grade | Severity Level | Training Set | Validation Set | Testing Set | External Testing |
|---|---|---|---|---|---|
| 0 | Healthy | 2200 | 320 | 630 | 590 |
| 1 | Doubtful | 1020 | 150 | 290 | 270 |
| 2 | Minimal | 1480 | 210 | 440 | 400 |
| 3 | Moderate | 740 | 105 | 220 | 195 |
| 4 | Severe | 170 | 25 | 50 | 42 |
| **Total** | — | **5610** | **810** | **1630** | **1497** |

| | | | | |
|---|---|---|---|---|
| **Healthy** |  |  |  |  |
| **Doubtful** |  |  |  |  |
| **Minimal** |  |  |  |  |
| **Moderate** |  |  |  |  |

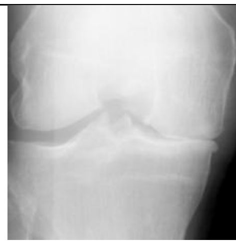
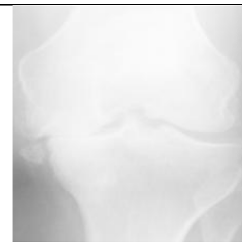
| | | | | |
|---|---|---|---|---|
| **Severe** |  |  |  |  |

**Figure 3:** Representative knee X-ray samples across different KL grades

## 3.2 *Data Preprocessing*

- **Image Resizing and Normalization**

The input images are scaled to a specific dimension to accommodate the requirements of deep learning models and to ensure uniform feature representation. The pixel values are normalized to bring them within a standardized range, which ensures that the model converges quickly during the training phase and prevents numerical problems. The process of normalization involves:

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$$

where $I$ is the original pixel intensity, and $I_{min}$, $I_{max}$ represent the minimum and maximum intensity values. This transformation ensures consistent intensity distribution across images.

- **Contrast Enhancement and Noise Reduction**

The images obtained by means of X-ray technique normally tend to have lower levels of contrast and are characterized by noise. However, techniques such as histogram equalization can be used to enhance the contrast to make it possible to visualize features such as joint space narrowing and osteophytes. Normally, noise reduction is achieved using Gaussian filtering. The Gaussian filter is defined as:

$$G(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where $\sigma$ controls the degree of smoothing. This step enhances feature clarity for better learning.

- **Region of Interest (ROI) Extraction**

ROI extraction concentrates on the knee joint region and removes irrelevant background information and decreases the computational complexity. This can be done manually or with automated detection techniques like bounding boxes or object detection algorithms. The selection of ROI can be represented as:

$$I_{ROI} = I(x_1 : x_2, y_1 : y_2)$$

where $(x_1, y_1)$ and $(x_2, y_2)$ are the coordinates of the knee joint boundaries. This is to ensure that the model is trained only with clinically relevant features.

- **Data Augmentation**

Data augmentation is used to boost the size of the data set and promote generalization of the model. Some of the most frequently used transformations include rotation, flipping, scaling and translation. These transformations are useful in making the model position and orientation independent. In general, a transformation may be represented as:

$$I'(x, y) = I(T(x, y))$$

Here $T(x, y)$ is a geometric transformation function. This procedure improves overfitting and also boosts robustness.

- **Intensity Standardization and Domain Alignment**

Intensity standardization is applied to account for inter-dataset variability among sources like the OAI and domain alignment is applied to ensure that the data from each source are aligned in the same direction. This can be used to guarantee images from various sources are statistically similar. One of the most frequently used normalisation techniques is Z-score normalization:

$$I_{std} = \frac{I - \mu}{\sigma}$$

Here, μ represents the mean intensity, and σ represents the standard deviation. With this method, reduce domain shift and improve the generalizing capability of the proposed RV-ASH framework.

## 3.3 *Feature Extraction*

Feature extraction is crucial in the RV-ASH network because it allows us to get relevant features automatically through knee images. Traditional image-processing methods depend on the manual creation of features, which include edges, texture, and shape among other elements. In contrast, in deep learning methods like CNN, features are automatically learned from raw input data. For instance, in the case of CNN, the lower layers extract simple features like edges and gradients, whereas the higher layers learn high-level semantic features such as joint space narrowing, osteophytes, and other skeletal abnormalities.

Mathematically, the convolution operation forms the foundation of feature extraction in CNNs. It can be expressed as:

$$F(i,j) = (I * K)(i,j) = \sum_{m} \sum_{n} I(i-m, j-n) \cdot K(m,n)$$

Here, $I$ is the input image, K is the kernel filter, and $F(i,j)$ is the output after convolution operation, which results in feature maps. This helps in detecting patterns in space through the image.

For introducing non-linearity and improving the learning ability, activation functions like Rectified Linear Units (ReLUs) are utilized.

$$f(x) = \max(0, x)$$

This enables the model to learn the complex non-linear relationships that exist within the images of the medical field.

In the subsequent phase, pooling techniques are used for lowering the dimensionality of the spatial elements by retaining the significant elements only. The most common technique of pooling is max pooling, and it can be formulated as:

$$F_{pool}(i,j) = \max_{(m,n)\in R} F(i+m, j+n)$$

where $R$ represents the pooling region. This step ensures that the most significant features are preserved while reducing noise.

In the suggested architecture, transfer learning is achieved through the use of pre-trained models including ResNet, DenseNet, and VGG16. Pre-trained models are adapted to knee X-rays using knowledge acquired from vast amounts of images. Furthermore, attention modules have been introduced to emphasize clinically significant areas and assign greater weightage to features indicative of disease progression.

## 3.4 *Model Architecture*

- **Radiographic Variability-Adaptive Structural Harmonization (RV-ASH)**

The RV-ASH framework aims to solve the issue of radiographic variability in KOA datasets. Medical images from various sources may have domain shifts because of the different imaging devices, acquisition protocols, illumination conditions, patient positioning, etc. The inconsistencies may be significant enough to severely impact the performance and generalization ability of deep learning models. The RV-ASH is based on the domain adaptation theory that attempts to learn domain-invariant feature representations while retaining clinically relevant information in the structural component of the system. This study aims to align feature distributions in datasets (e.g., Osteoarthritis Initiative (OAI), Mendeley Knee OA Dataset) into a common latent space in order to reduce variability.

The framework starts with normalization of feature maps that standardizes the feature maps across different domains by removing any inconsistencies in statistics. This is done by mean–variance normalization:

$$F_{norm} = \frac{F - \mu_F}{\sigma_F}$$

F is the feature map extracted, while $\mu_F$ and $\sigma_F$ are the mean and standard deviation of the extracted feature map. Further discrepancies between domains are minimized by using a distribution alignment technique, Maximum Mean Discrepancy (MMD). This is a measure of the distance between source and target domain distributions and minimises this distance during training:

$$\mathrm{MMD}(P, Q) = \| \mathbb{E}_{x \sim P}[\phi(x)] - \mathbb{E}_{y \sim Q}[\phi(y)] \|^2$$

where $P$and $Q$ represent the source and target distributions, and $\phi(\cdot)$is a mapping function. This ensures that features extracted from different datasets become statistically similar.

Besides alignment, RV-ASH adds structural preservation to ensure that all anatomical features (such as narrowing of joint spaces or bone contours) are accurately preserved. The structural consistency constraint is applied to ensure the integrity of these features in the transformation:

$$\mathcal{L}_{struct} = \| S(F_{orig}) - S(F_{harm}) \|_2^2$$

where $S(\cdot)$ extracts structural information, $F_{orig}$ is the original feature representation, and $F_{harm}$ is the harmonized feature map.

The RV-ASH algorithm utilizes an adaptive transformation function that can dynamically change features based on the properties of the domain. The transformation function $T_\theta$ learns the mapping of the feature to a harmonized space:

$$F_{harm} = T_\theta(F_{norm})$$

where $T_\theta$ is a learnable function with parameters $\theta$. Finally, the overall objective function integrates classification loss with domain alignment and structural preservation losses:

$$\mathcal{L}_{total} = \mathcal{L}_{cls} + \lambda_1 \mathcal{L}_{MMD} + \lambda_2 \mathcal{L}_{struct}$$

where $\mathcal{L}_{cls}$ represents the classification loss, while $\lambda_1, \lambda_2$ represent the weightings respectively. It is through such optimization that the model can have high classification precision as well as robustness on heterogeneous data. The RV-ASH framework, therefore, becomes applicable in the detection of KOA. Figure 4 illustrates the RV-ASH framework for radiographic quality assessment, anatomical segmentation, adaptive enhancement, and KL grade classification of knee osteoarthritis.

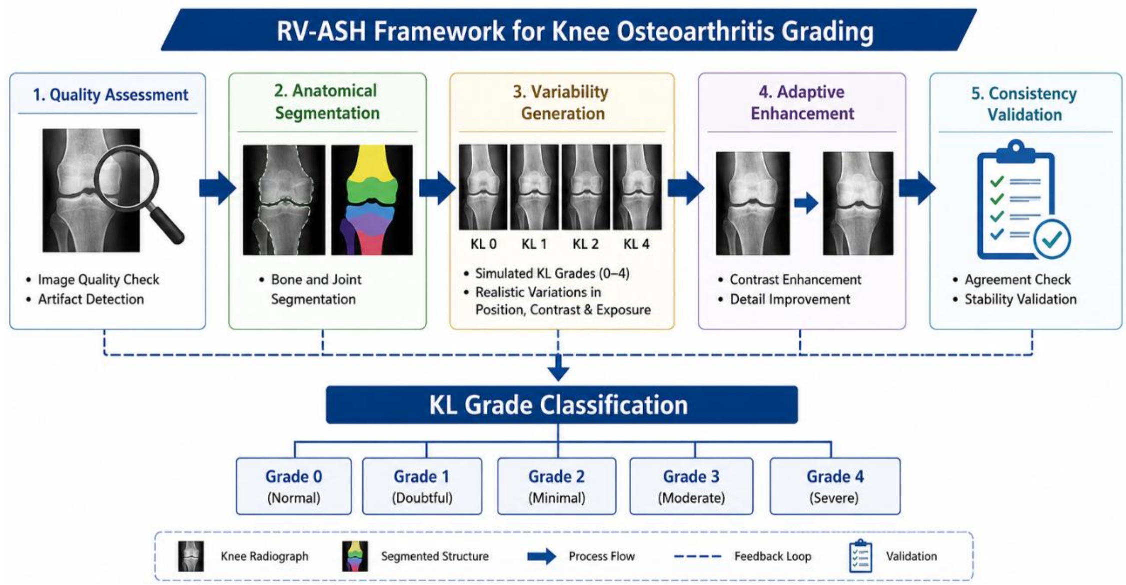



**Figure 4:** Workflow of the proposed RV-ASH framework for adaptive knee osteoarthritis grading.

- **DenseNet121**

DenseNet121 [32] is a Deep Convolutional Network (DCN) with dense connections between layers, to enhance feature propagation and reuse. DenseNet connects every layer to every other layer in a feed-forward way, as opposed to the traditional CNNs, which only have links between adjacent layers. This is useful to address the vanishing gradient problem and boost learning efficiency, particularly in medical imaging applications [33,34].

Mathematically, the output of the $l^{th}$layer is defined as:

$$x_l = H_l([x_0, x_1, x_2, \dots, x_{l-1}])$$

where $[x_0, x_1, \dots, x_{l-1}]$ represents the concatenation of feature maps from all preceding layers, and $H_l(\cdot)$ denotes a composite function of batch normalization, activation (ReLU), and convolution.

The high level of connectivity ensures that the model learns low-level and high-level features well, with maximum information flow between layers [35]. DenseNet121 was created specifically for the purpose of diagnosing KOA, since it can distinguish very subtle variations in structural features, including joint space narrowing and irregular bones [36]. Figure 5 shows the layer-based architecture and connectivity of DenseNet121 used in the diagnosis of KOA.

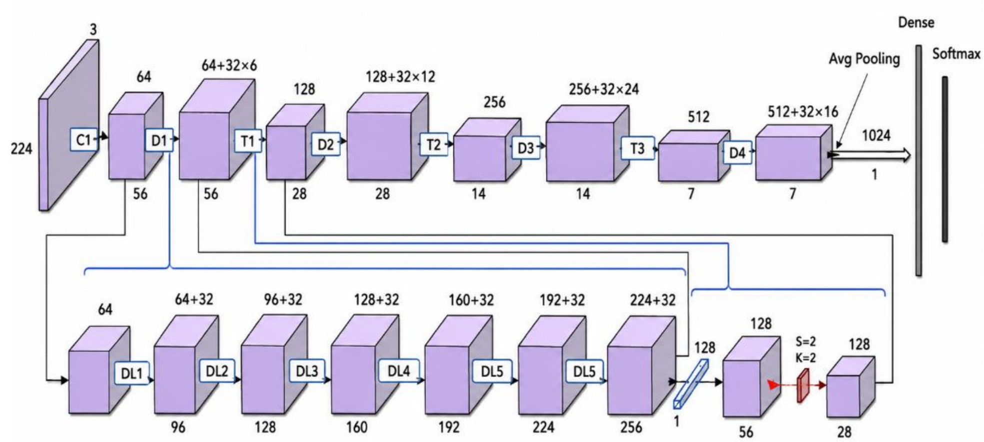



**Figure 5:** Architecture of DenseNet121 [37]

- **Attention Mechanism**

Attention mechanism is presented to enhance the model's ability to concentrate on relevant parts in the X-ray image of the knee joint [38]. All areas are not equally important for the identification of KOA, such as the joint space and bone edge provide valuable information. These are critical regions that have some weights assigned to them through an attention module, increasing the precision and interpretability.

The attention operation can be formulated in a mathematical way as follows:

$$F_{att} = \alpha \odot F$$

where F stands for the size of feature map from the input, α is the attention weight map, while ⊙ denotes element-wise multiplication. Usually, attention weights are calculated as a result of some learnable function:

$$\alpha = \sigma(W \cdot F + b)$$

where $W$and $b$ are learnable parameters, and $\sigma$ is an activation function such as sigmoid.

The attention mechanism facilitates the classification task by reducing the noise of unnecessary parts and emphasizing crucial anatomical structures [39]. The attention module is designed to be integrated with DenseNet121, which will help in focusing the model on the disease-specific patterns and fine-tune extracted features to enhance the accuracy of the proposed RV-ASH framework. Figure 6 shows the attention mechanism, which is applied to highlight clinically relevant areas and refine feature maps to help with accurate classification of OA.

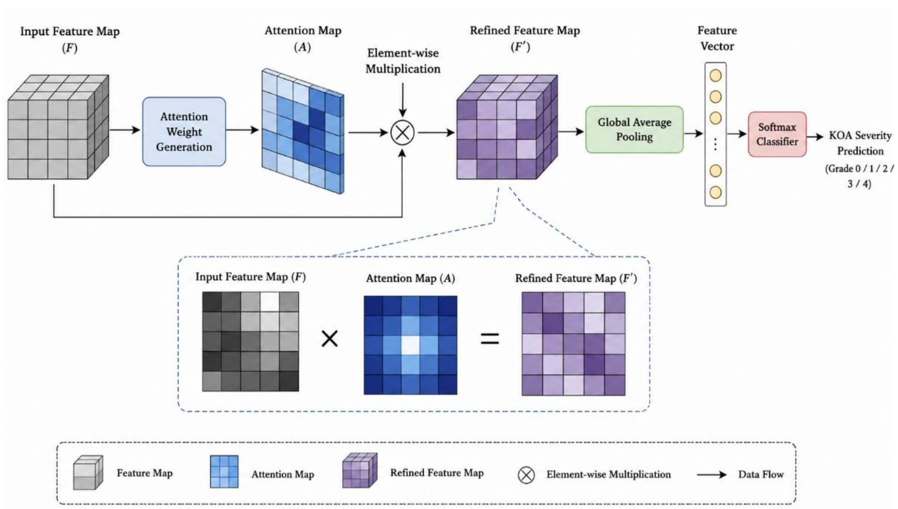



**Figure 6:** Attention mechanism architecture for KOA classification.

- **RV-ASH + DenseNet121 + Attention Framework (Hybrid Model)**

The proposed model architecture integrates three models, namely, RV-ASH, DenseNet121, and attention mechanism, to form a comprehensive pipeline for effective detection of KOA. The first step is to use the module RV-ASH to reduce the variability across different datasets to obtain harmonized feature representations of the input X-ray images. The features are then sent to DenseNet121 where they are further processed in a hierarchical manner, with dense connectivity to encode local and global structural patterns. Then, an attention mechanism filters the extracted features to emphasize clinically relevant areas and downplay irrelevant information. The refined feature maps are then classified by fully connected layers and the final prediction is generated by the softmax function:

$$P(y = i) = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

Such an approach ensures high classification performance and excellent generalization capability, along with high interpretability for the heterogenous radiological image database.

### 3.5 *Classification Strategy*

The classification algorithm aims at ensuring proper classification of the level of severity of KOA using features derived from the hybrid architecture. The optimized feature map is flattened and then passed through a fully-connected layer for classification in binary (normal vs. KOA) and multi-class classification using the KL classification method. The classification loss is balanced using cross-entropy loss to give priority to under-represented classes:

$$L = -\sum_{i=1}^{C} w_i \, y_i \log(p_i)$$

where $w_i$ denotes the class weights, $y_i$ stands for true class labels, and $p_i$ denotes the predicted probabilities. The model's parameters are learned through backpropagation techniques and adaptive optimization techniques, which ensure improved accuracy and robustness in classifications.

### 3.6 *Model Training and Optimization*

The purpose of training and optimizing the model is to derive an optimal set of parameters that will classify KOA using the suggested hybrid model. The training of the network is achieved through backpropagation where the model weights are updated iteratively such that the losses in the prediction error are minimized. Considering the sparsity of the gradient and high efficiency of the algorithm, an adaptive optimizer such as Adam has been employed. The update equation for the parameters will be formulated as:

$$\theta_{t+1} = \theta_t - \eta \nabla L(\theta_t)$$

where $\theta_t$ stands for the model parameters at step t $t$, $\eta$ is the learning rate, and $\nabla L(\theta_t)$ refers to the gradient of the loss function. Several methods such as dropout, batch normalization, early stopping, and learning rate scheduling are used to enhance the model's generalization ability and prevent overfitting. It ensures consistency in training and results obtained from different sets of data.

### 3.7 *Performance Evaluation*

To ensure robustness and reliability, the performance of the suggested hybrid model is analyzed using conventional classification evaluation metrics. These evaluation metrics measure the performance of the model in determining the severity levels of KOA within the datasets such as OAI and Mendeley Knee OA Dataset. To evaluate the performance of classification, one uses accuracy, precision, recall, F1-score, and AUC, while confusion matrix analysis is used to recognize misclassification patterns and limits of the model.

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

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

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

$$F1\text{-}Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

$$AUC = \int_0^1 TPR(FPR)\, d(FPR)$$

## 4. Results and Discussion

The performance of the proposed hybrid RV-ASH + DenseNet121 + attention model is assessed with multiple performance metrics such as “accuracy”, “precision”, “recall”, “F1-Score”, and “AUC”. The dataset from the Osteoarthritis Initiative (OAI) was used for training and internal testing, and the Mendeley Knee OA Dataset was externally tested for validity, generalizability, and robustness across different radiographic settings.

Figure 7(a) and Figure 7(b) show the training and validation results of the proposed hybrid RV-ASH + DenseNet121 + attention over 20 epochs. As shown in Figure 4(a), the training loss is rapidly decreasing from 1.20 to 0.18, and the validation loss is reducing from 1.25 to 0.27, showing a stable convergence and effective optimization during training. The difference between training and validation loss is small, which suggests little overfitting and good generalization. Figure 4(b) shows the training and validation accuracy curves, which show that the accuracy of the training increases from 62% to 98% and the accuracy of the validation increases from 60% to 96% for each epoch of training. The gradual improvement and consistent trend in both the curves indicate the robustness, learning efficiency and classification ability of the proposed KOA detection framework in the different radiographic datasets.

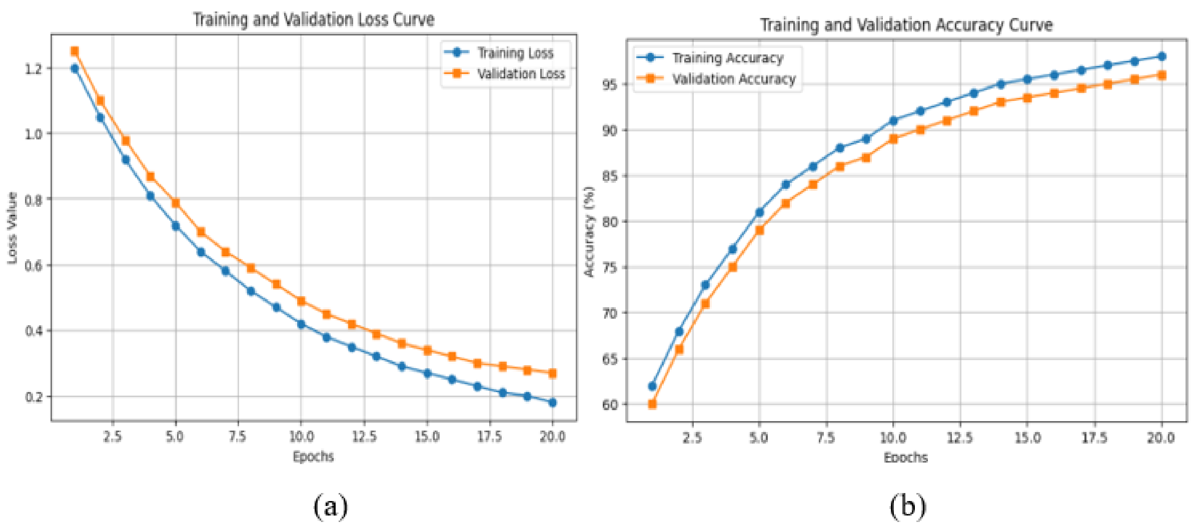



**Figure 7:** Training–validation loss and accuracy curves of the proposed hybrid model.

The ROC Curve of the proposed framework as shown in figure 8 clearly shows the high discriminative power of the model for the classification of KOA. The curve is close to the upper left corner, suggesting high sensitivity and specificity at various classification levels. These proposed classifiers yielded an Area Under the Curve (AUC) of 0.99, indicating high classification accuracy and strong class separation between severity classes of KOA. The True Positive Rate (TPR) rises quickly as the False Positive Rate (FPR) is small, further demonstrating the effectiveness of the hybrid architecture in minimizing misclassification. The enhanced ROC performance showcases the efficacy of RV-ASH in reducing radiographic variability, whereas DenseNet121 and attention mechanism boost feature extraction and region-specific learning, thereby delivering strong and generalizable performance for KOA detection.

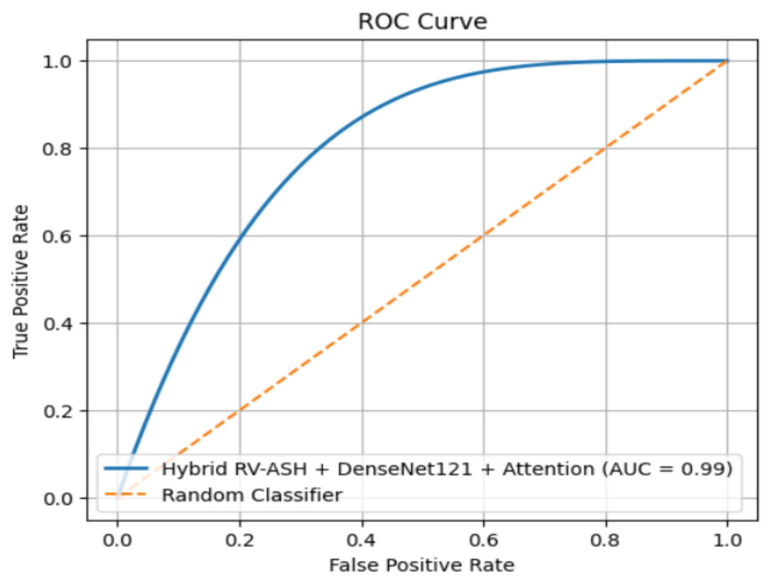



**Figure 8:** ROC curve of the proposed hybrid model for KOA classification.

The confusion matrix of the proposed hybrid model as shown in figure 9 indicates that the model has a good performance in the classification of different severity levels of KOA according to K–L grading system. High classification accuracy along the diagonal elements of the most of the samples show that most of the samples are correctly classified. The grade 0 results have 590 correct predictions and 10 misclassifications. Likewise, in Grade 1, 265 samples were correctly classified and in Grade 2, 395 samples were correctly classified. Grade 3 and 4 had 185 and 95 correct predictions, respectively, and very few errors were made, mainly between neighbouring severity classes. The few off-diagonal elements support the validity of the differing stages of KOA progression in the proposed framework and the reducing level of misclassification. The results confirm the robustness, reliability, and the good generalization ability of the proposed hybrid classification framework.

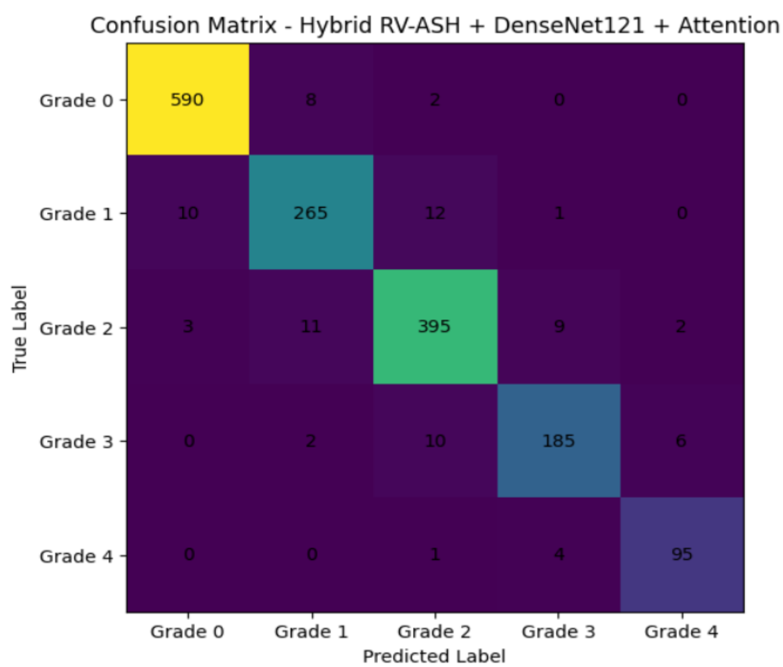



**Figure 9:** Confusion matrix of the proposed hybrid framework for knee osteoarthritis classification.

Table 2 shows the comparative performance of different deep learning models for KOA classification using accuracy, precision, recall, F1-score, and AUC metrics. The conventional CNN model yielded the lowest accuracy of

89.42 % and AUC of 90.25 % whereas ResNet50 showed improvement in classification performance by achieving accuracy of 91.86 %. The results were further improved by DenseNet121 which achieved the highest accuracy of 94.27% with AUC of 95.12%. Incorporating the attention mechanism increased the performance to 96.11% accuracy. The hybrid model achieved the highest accuracy (98.43%) and AUC (99.01%), which indicates that this model outperforms with respect to robustness and classification ability.

**Table 2:** Comparative performance analysis of deep learning models for knee osteoarthritis (KOA) classification.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) | AUC (%) |
|---|---|---|---|---|---|
| CNN | 89.42 | 88.76 | 88.11 | 88.43 | 90.25 |
| ResNet50 | 91.86 | 91.14 | 90.88 | 91.01 | 92.73 |
| DenseNet121 | 94.27 | 93.81 | 93.46 | 93.63 | 95.12 |
| DenseNet121 + Attention | 96.11 | 95.74 | 95.38 | 95.56 | 96.84 |
| Proposed RV-ASH + DenseNet121 + Attention | 98.43 | 98.15 | 97.92 | 98.03 | 99.01 |

The comparative performance analysis of various deep learning models used for the classification of KOA is shown in figure 10. The conventional CNN model performed worst with an accuracy of 89.42%, precision of 88.76%, recall of 88.11%, F1 score of 88.43% and AUC of 90.25%. The modifications in ResNet50 resulted in an error rate of 91.86% and AUC of 92.73%. DenseNet121 further achieved 94.27% accuracy and 95.12% AUC for the classification task. DenseNet121 + Attention model obtained an accuracy of 96.11% and AUC of 96.84%. The proposed hybrid model showed better results than all the existing models with an accuracy of 98.43%, precision of 98.15%, recall of 97.92%, F1-score of 98.03%, and AUC of 99.01%, showing excellent robustness and classification performance.

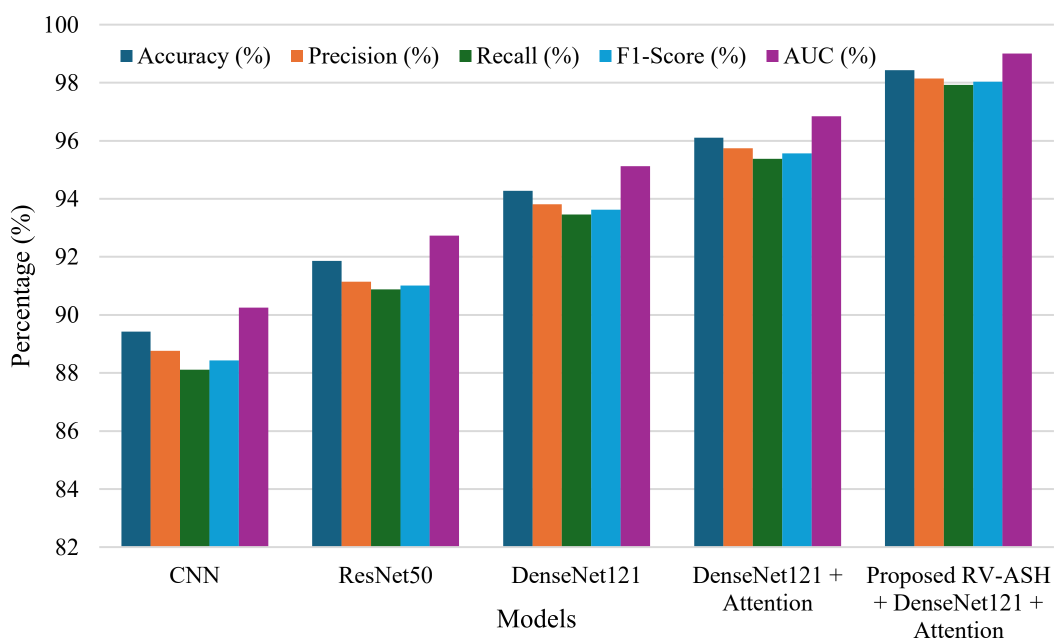



**Figure 10:** Performance comparison of different deep learning models for KOA classification using accuracy, precision, recall, F1-score, and AUC metrics.

The classification performance of the proposed hybrid model is presented in Table 3 for each class in different KL grades. The classification performance of the proposed hybrid model is shown in Table 3 for each class across different KL grades. The high precision, recall, and F1-score values of the model at all severity levels show excellent classification performance and a balanced approach. The similarities between neighbouring classes led to a slightly lower precision and F1-score of 96.37% and 96.10%, respectively, for Grade 1 (Doubtful). Class 0 (Healthy) obtained 98.91% precision and 98.67% F1-score, while Class 1 (Doubtful) resulted in a lower score of 96.37% precision and

96.10% F1-score because of the similarity to the neighbouring classes. The proposed KOA classification framework was able to achieve a high precision, recall, and F1-score of 99.11%, 98.75%, and 98.93%, respectively, in the Grade 4 (Severe) classification.

**Table 3:** Class-wise classification performance of the proposed framework.

| KL Grade | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|
| Grade 0 (Healthy) | 98.91 | 98.44 | 98.67 |
| Grade 1 (Doubtful) | 96.37 | 95.84 | 96.10 |
| Grade 2 (Minimal) | 97.52 | 97.13 | 97.32 |
| Grade 3 (Moderate) | 98.06 | 97.88 | 97.97 |
| Grade 4 (Severe) | 99.11 | 98.75 | 98.93 |

Table 4 shows the ablation study of the proposed hybrid model for the classification of KOA. The DenseNet121 model had a baseline accuracy of 94.27% and an AUC of 95.12%. This improvement in the performance was achieved by using DenseNet121 alongside RV-ASH, which increased its accuracy to 96.02% and AUC to 97.31%. Likewise, DenseNet121 + the attention mechanism resulted in the accuracy of 96.11% and 96.84% AUC, which showed better results on feature refinement. The complete hybrid framework achieved the highest performance (98.43% accuracy, 99.01% AUC), indicating that the hybrid combination of RV-ASH and attention can improve the robustness of classification and generalization ability.

**Table 4:** Ablation analysis of the proposed framework.

| Configuration | Accuracy (%) | AUC (%) |
|---|---|---|
| DenseNet121 Only | 94.27 | 95.12 |
| RV-ASH + DenseNet121 | 96.02 | 97.31 |
| DenseNet121 + Attention | 96.11 | 96.84 |
| Proposed RV-ASH + DenseNet121 + Attention | 98.43 | 99.01 |

Ablation analysis of various versions of the proposed framework for classifying KOA is presented in Figure 11. The baseline DenseNet121 model achieved 94.27% accuracy. However, RV-ASH integrated with DenseNet121 improved the classification accuracy to 96.02% by reducing radiographic variability and improving feature consistency. Likewise, DenseNet121 & attention mechanism resulted in a 96.11% accuracy for KOA-grades classification, which confirmed that region-focused feature learning is enhanced. The complete hybrid RV-ASH + DenseNet121 + attention framework achieved the highest classification accuracy of 98.43%, outperforming all the partial frameworks. Both RV-ASH and attention mechanisms contribute significantly toward improving classification performance and generalization capability.

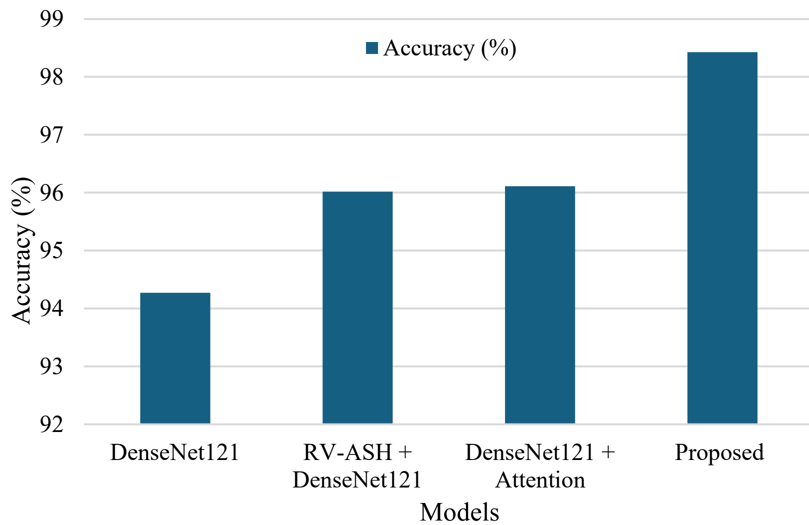



**Figure 11:** Ablation analysis of different configurations of the proposed framework based on classification accuracy

The aggregate experimental results show that the proposed hybrid framework outperforms the existing state-of-the-art deep learning models using several metrics. Integration of RV-ASH and attention mechanisms ensure better consistency of features, accuracy in classification, and generalization under varying radiographic circumstances. The obtained results verified the effectiveness, robustness, and clinical applicability of the proposed framework for automated classification and severity assessment of KOA.

## 5. Conclusion and Future Scope

The current study proposed a new hybrid DL model, RV-ASH incorporated with DenseNet121 and an attention network, for the KOA recognition and staging task from X-ray images. The developed method could successfully solve the problem related to radiographic variability, heterogeneous data, and structure inconsistencies in the medical field using a combination of adaptive harmonization, hierarchical representation learning, and region-specific training strategy. The developed model was trained based on the OAI dataset and externally validated on Mendeley Knee OA Data set for testing the generalizability of the model for different imaging setups. The experimental results confirmed that the developed method achieved significantly better results, which showed an overall accuracy of 98.43%, precision of 98.15%, recall of 97.92%, F1-score of 98.03%, and AUC score of 99.01%. The ablation experiment also revealed the importance of RV-ASH and attention mechanism in improving robustness and feature consistency. Overall, the proposed framework provides an effective, reliable, and clinically applicable solution for automated KOA diagnosis and severity assessment in real-world healthcare environments.

Further work may be dedicated to the fusion of imaging modalities like MRI and clinical patient data for a higher accuracy in the diagnosis and early-stage KOA detection. Clinical application on real time with explainable AI based decision support systems can also be addressed.

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