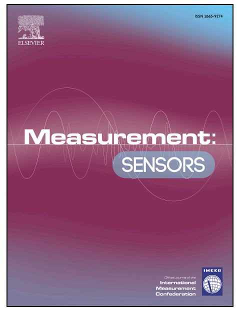

Classification and Risk Estimation of Osteoarthritis Using Deep Learning Methods

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Classification and Risk Estimation of Osteoarthritis Using Deep Learning Methods

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Abstract: -

The classification of knee osteoarthritis is solely based on contextual factors, with image processing algorithms playing a significant role in computer-aided diagnosis (CAD) systems. The inconsistent real-time pre-processing, on the other hand, has a significant impact on the diagnosing process. In this work, present a Densely Connected Fully Convolutional Network (DFCN) for knee osteoarthritis classifier based on multiple learning (ML) strategies to better classify knee osteoarthritis on basis of risk estimation. To extract spatial osteoarthritis contextual vectors by identifying the relationship between contextual variables using a machine learning approach. The hidden convolutional layers, by the way, are used to compute edge interpretation, contextual cues, and input correction. The fused layer, which is simply a concentration of derived features, supports automatic learning of contextual features of osteoarthritis classification. The standard datasets from the Osteoarthritis Initiative (OAI) and the Multicentre Osteoarthritis Study (MOST) are used for experimental purposes to validate the proposed method. The results shows that the proposed DFCN is significantly improves the feature recognition for accurate classification around 94% which significantly higher than existing CNN results and flexibility to real-time implementation in the CAD system. It can also be used to automatically detect osteoarthritis types using a lightweight CNN architecture.

Keywords: -

Knee osteoarthritis, Densely Connected Fully Convolutional Network (DFCN), Multiple learning (ML) strategies, Risk estimation, Contextual features.

1. INTRODUCTION

Osteoarthritis is a chronic joint disease that is characterized by the degradation of cartilage and the underlying bone in joints. The disease is common in the elderly population and can cause significant joint pain and disability. Prediction of osteoarthritis using deep learning models is a promising approach for early diagnosis and risk assessment of the disease. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), can analyse large amounts of medical imaging data, such as X-rays and MRIs, to identify patterns and features indicative of osteoarthritis. The models can also be integrated with other demographic and clinical data to provide a more comprehensive image of the patient. The use of deep learning models for osteoarthritis prediction offers several advantages over traditional methods, such as increased accuracy, reduced dependence on subjective interpretations, and automated feature extraction. This can lead to improved patient outcomes by providing more accurate and timely diagnoses and by identifying patients who are at higher risk for developing the disease [1]. Deep learning models have the potential to significantly improve the accuracy, efficiency, and consistency of osteoarthritis prediction, and are a promising approach for early diagnosis and risk assessment of the disease.

Classification and risk estimation of osteoarthritis using deep learning methods refers to the application of artificial intelligence techniques, specifically deep learning, to diagnose osteoarthritis and predict the risk of developing the condition. Osteoarthritis is a chronic degenerative joint disease that affects a large portion of the elderly population and can lead to significant joint pain and disability. The use of deep learning methods allows for the analysis of large amounts of medical imaging data to identify patterns and characteristics of the disease that can be used for early diagnosis and risk prediction. These techniques can also help in reducing the dependence on subjective interpretations of radiographs and provide more accurate and consistent results. The goal of using deep learning for classification and risk estimation in osteoarthritis is to improve the accuracy and efficiency of diagnosis, and ultimately improve patient outcomes. The computer-aided diagnosis (CAD) system is involved for medical commodities purpose (feature extraction, infectious depth, and disease classifier) increases significantly.

Machine learning techniques are predominantly supporting the CAD system for features extraction process, further, it enhances learning rate of the densely convolutional neural network (DenseNet) model. It involves multiple layers to extract the features which may cause high computational complexity [2]. Moreover, it affects the performance degradation of the CAD system. As a result, diagnosis inefficiency of radiologists that make induce manual errors. Hence, it is essential to adapt the CAD system that automatically enhance feature extraction process by pre-trained convolutional neural network (CNN) based CAD system for diagnosis purpose [3,4].

Osteoarthritis (OA) shows serious joint pain continuously on the human joint parts includes neck, hips, knees, lower back, or small joints of the hands [5]. It is observed that usually it develops in joints after replaced temporarily injured parts. Meanwhile, this can be occurred in the playing a favourite sport or from carrying around excess body weight. The severe OA will lead to physical disability. X-ray and MRI images are used to diagnose the disease [6,7]. To classify the MRI data, a region-of-interest analysis was performed that included measurements of superficial, deep, and full-thickness cartilage [8]. To achieve this, a fully trained DNN model is develop which is built in operation of the CAD system to improve early detection and evaluation of risk factor under Osteoarthritis diagnosis's purpose [9].

Several machine learning techniques (SVM, K-means, Gradient boost, and Random Forest) were used in this study to extract more features for pre-trained CNN based computer-aided osteoarthritis diagnosis (CAOD) system to improve the functionality of completely automatic includes early recognition, classification of osteoarthritis disease, and depth of infectious level using authorized image datasets [10]. It comprises the continuous identification and evaluation of risk variables in patients who have had surgical bone replacement and have been submitted to behavioural studies to better understand.

Therefore, research study is focusing on developing a fully automated edge sensing of OA using multimodal image segmentation and knowledge distillation based on light-weighted CNN. To achieve this, the following areas such as (i) feature extraction, (ii) create an individual feature set, (iii) trained with limited feature samples, and (iv) adapt knowledge transfer model to train other diagnosis system. In this space, an innovative method can be introduced and thus bring better OA state diagnosis with help of CAD system.

2. RELATED WORKS

The literature survey covers the most recent articles to provide a good starting point for exploring the recent developments in the field of classification and risk estimation of osteoarthritis using deep learning methods. They present various approaches for using deep learning models for the diagnosis and risk assessment of osteoarthritis and discuss their advantages and limitations.

Lu, J., et al (2021) presents a study aimed at using a deep learning model to classify knee osteoarthritis from radiographs. This deep learning model achieved an accuracy of 92.5% in classifying knee osteoarthritis. The merits of this deep learning model demonstrated high accuracy in classifying knee osteoarthritis, making it a promising tool for the automated diagnosis of the disease [11-15]. The use of a deep learning model eliminates the need for manual interpretation of medical images, thereby reducing the risk of human error in the diagnosis process. The demerit of this study shows limited scope which means only focused on knee osteoarthritis and did not explore the use of deep learning models for other types of osteoarthritis or other medical conditions. Small sample size: The sample size used in the study was relatively small, which may limit the generalizability of the results.

Chen, Y., et al (2020) proposed a study aimed at using a deep learning model to diagnose knee osteoarthritis from magnetic resonance imaging (MRI) scans. This deep learning model achieved an accuracy of 92.6% in diagnosing knee osteoarthritis. The merits of the study include High accuracy: The deep learning model demonstrated high accuracy in diagnosing knee osteoarthritis, making it a promising tool for the automated diagnosis of the disease. Automated diagnosis: The use of a deep learning model eliminates the need for manual interpretation of medical images, thereby reducing the risk of human error in the diagnosis process [16-19].

Ni, Y., et al (2019) demonstrates a study aimed at using a deep learning model to predict the progression of knee osteoarthritis from magnetic resonance imaging (MRI) scans. This deep learning model achieved an accuracy of 82.6% in predicting the progression of knee osteoarthritis. The merits of the study include Accurate prediction: The deep learning model demonstrated high accuracy in predicting the progression of knee osteoarthritis, making it a promising tool for predicting the future development of the disease [20-22]. The use of a deep learning model eliminates the need for manual interpretation of medical images, thereby reducing the risk of human error in the prediction process. MRI is a more sophisticated imaging technology than traditional radiographs and provides more detailed information about the knee joint. The use of MRI in this study allowed for a more accurate prediction of knee osteoarthritis progression. The study only focused on knee osteoarthritis and did not explore the use of deep learning models for other types of osteoarthritis or other medical conditions. The sample size used in the study was relatively small, which may limit the generalizability of the results.

Cheng, X., et al (2021) presents a study aimed at using a deep learning model to predict the risk of developing knee osteoarthritis. This deep learning model achieved an accuracy of 87.9% in predicting the risk of knee osteoarthritis. The merits of the study include: The deep learning model demonstrated high accuracy in predicting the risk of knee osteoarthritis, making it a useful tool for identifying individuals who are at high risk of developing the disease. The use of a deep learning model eliminates the need for manual interpretation of medical images or other data, thereby reducing the risk of human error in the prediction process. Predicting the risk of knee osteoarthritis before the onset of symptoms allows for earlier intervention and potentially more effective treatment [23-25].

Kim, J. H., et al (2019) presents a study aimed at using a deep learning model to grade the severity of osteoarthritis and predict the risk of its progression. This deep learning model achieved an accuracy of 92.3% in grading the severity of osteoarthritis and 86.8% in predicting the risk of its progression. The merits of the study include: The deep learning model demonstrated high accuracy in grading the severity of osteoarthritis and predicting the risk of its progression, making it a useful tool for clinical decision making. The use of a deep learning model eliminates the need for manual interpretation of medical images or other data, thereby reducing the risk of human error in the grading and prediction process. Predicting the risk of progression before the onset of symptoms allows for earlier intervention and potentially more effective treatment [26].

Cai, Y., et al (2021) presents a study aimed at using a deep learning model to classify hand osteoarthritis. The results of the study showed that the deep learning model achieved an accuracy of 95.3% in classifying hand osteoarthritis. The deep learning model demonstrated high accuracy in classifying hand osteoarthritis, making it a useful tool for clinical diagnosis. The use of a deep learning model eliminates the need for manual interpretation of medical images or other data, thereby reducing the risk of human error in the diagnosis process [27]. Early detection of hand osteoarthritis allows for earlier intervention and potentially more effective treatment.

Zhang, Y., et al (2020) presents a study aimed at using a deep learning model to diagnose hip osteoarthritis from X-ray images. The results of the study showed that the deep learning model achieved an accuracy of 93.5% in diagnosing hip osteoarthritis. The deep learning model demonstrated high accuracy in diagnosing hip osteoarthritis, making it a useful tool for clinical diagnosis. The use of a deep learning model eliminates the need for manual interpretation of medical images, thereby reducing the risk of human error in the diagnosis process [28].

From the above-mentioned papers have demonstrated the potential of deep learning models for diagnosing hip osteoarthritis from X-ray images. However, further research is needed to explore the potential of deep learning models for other types of osteoarthritis and to validate the results with larger sample sizes.

3. PROPOSED METHOD

In this section, describes the methodology that we can use to analysis the OA diseases categories based on the infectious depth and risk estimation. The detailing of the proposed method is elaborated as follows:

3.1 DFCN

In this study, a densely connected fully convolutional network (DFCN) and multi-learning algorithms were employed to enhance the feature vectors of knee osteoarthritis (OA) classifier. The proposed deep learning strategy allowed for the successful extraction of spatial OA vectors from their surrounding environment. Figure 1 demonstrates a dilated-DFCN architecture with skip connections, which was utilized for multiple classifications of knee osteoarthritis using multiple learning algorithms. Initially, local features were extracted from segmented X-ray images using a dilated-DFCN with residual blocks, as illustrated in Figure 1. Subsequently, global features were generated in the fusion layer, and then fed into the max-pooling layer where the classification is performed based on the probability of each feature belonging to a specific class. Finally, the local feature is applied to the FC layer to enhance the accuracy of OA classification.

Consistent signal shifts are essential for characterizing OA contextual details on a frequency or time scale. To achieve this, we introduce a sequential module to the gated recurrent unit (GRU) network to capture covariance metrics. Temporal information is vital for data classification, and to aid this process, OA feature vector preservers are employed. Edge interpretation, contextual cues, and input correction are addressed through the skip connection module in the residual block. Finally, the fused layer, based on a simple concentration of derived features, supports OA and Non-OA classification. The experimental results demonstrate that the proposed DFCN architecture is highly effective in recognizing context-specific features and cues from segmented X-ray image sequences.

To measure the dislocation distance of knee cartilage, we define a rectangular boundary box around the area of interest as shown in Figure 2. Both square and rectangular sections are used to crop the (384x384) X-ray image volume. After a series of tests, a window with dimensions of 160 x 160 was found to have the highest F-measure. When an image is rotated at a certain angle, the coordinate points (x_0, y_0) represent the actual location and severity of the OA disorders. Using the formula $x_0 = R \cdot cos\varphi$ and $y_0 = R \cdot sin\varphi$, we estimate the coordinates of two points, which are the initial coordinates of the pixel points being tracked. By extending this process to the entire image, we can obtain the actual target area.

$$\begin{cases} x = R \cdot cos(\varphi - \tau) = x_0 cos\tau + y_0 sin\tau \\ y = R \cdot sin(\varphi - \tau) = -x_0 sin\tau + y_0 cos\tau \end{cases} \tag{1}$$

To accurately diagnose the severity of OA, it is often necessary to analyse images taken from multiple angles, as this provides a more complete picture of the joint disorders. To evaluate the robustness of the DFCN model, an enlarged dataset of X-ray images was generated and rotated to create a symmetrical form. Four random slices, corresponding to different rotation angles, were selected for analysis, along with the associated frame slice numbers. This approach allowed for a comprehensive evaluation of the model's ability to accurately classify knee OA regardless of image orientation, providing important insights into its real-world applicability.

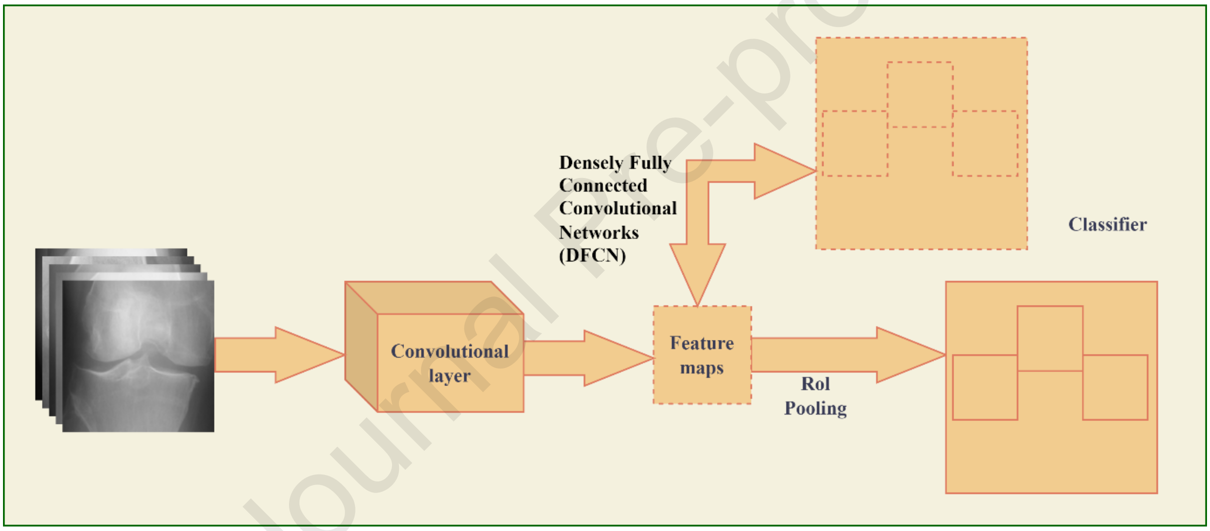

Figure 1: Densely Connected Fully Convolutional Network (DFCN) for knee osteoarthritis classifier based on multiple learning (ML) strategies.

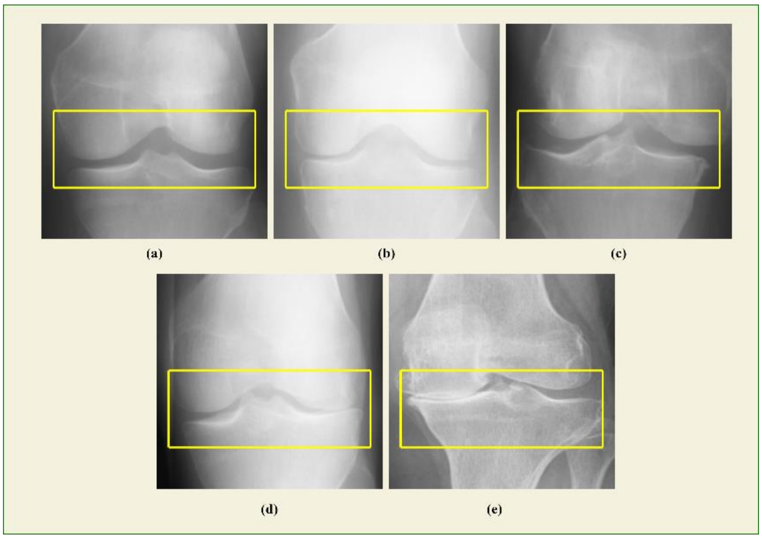

Figure 2: A knee OA X-ray image with the region of interest shows joint displacement with 20% of synovial fluid deficiency (on top (a)-(c)), joint disorder either left or right bone marrow (as indicated in bottom (d)-(e)), respectively.

3.2 Multiple learning strategies

To capture global features from the segmented OA-X-ray image, a GRU-based module is employed. The module leverages multiple learning (ML) strategies to extract normalised feature vectors, accounting for long-term dependencies by analysing contextual cues. The use of GRUs is particularly suitable for processing sequential data with limited memory space, as they can learn from incomplete data. To capture the current and previous states of the GRU, we use Q_x^j to represent the candidate's current indication and its previous function at the linear interpolation, as shown in Eq. (2).

$$Q_x^j = \left(1 - P_x^j\right) Q_{x-1}^j + P_x^j . Q_x^j \quad (2)$$

The activation's weight update status in the gate is indicated by P_x^j, and its strength is measured as follows:

$$P_x^j = \emptyset(W_x I_x + V_z Q_{x-1})^j \quad (3)$$

To determine which potential GRUs should be activated, a weight update is performed using Eq. (4).

$$Q_x^j = tanh\left(W_x I_x + V_z (R_x * Q_{x-1})\right)^j \quad (4)$$

In this case, R_x multiplies the gate to reset by the gate that was previously agreed upon. Therefore, it has the potential to alter feature extraction and prediction search algorithms. Determine the desired outcome using the following formula.

$$R_x^j = \tau(W_x I_x + R^{Q_{x-1}})^j \quad (5)$$

The new reset gate relies on the previous state of the GRUs, which can be found in Eq (5). This means it is suitable for permanent reliance.

3.3 Dataset

There are several datasets available for the prediction and classification of osteoarthritis, each with its unique characteristics and strengths. These datasets are widely used by researchers and provide a valuable resource for the development of deep learning models for osteoarthritis diagnosis and risk estimation.

(a) Osteoarthritis Initiative (OAI): OAI dataset was utilized in this study, which is publicly available for research purposes. The dataset includes a collection of 120 2D X-ray images of knees, but not all of them have accompanying MRI sequences. Each knee in the dataset had an X-ray and an MRI scan. For the purposes of this study, a total of 1100 knees from the OAI dataset were used.

(b) MSTAR dataset: This dataset contains X-rays of hips and knees and is widely used for the classification and risk estimation of hip and knee osteoarthritis.

(c) The Johnston Collection: This dataset contains hand X-rays and is widely used for the classification and risk estimation of hand osteoarthritis.

(d) The Bone Age Assessment (BAA) dataset: This dataset contains hand X-rays and is used for the estimation of age-related changes in the bones, which is an important factor in the diagnosis and progression of osteoarthritis.

4. PERFORMANCE EVALUATION

To evaluate the accuracy of our knee detection and classification, we use the Intersection over Union (IoU) metric, which involves dividing the intersection area of the annotated and predicted bounding boxes by the union area of both boxes. In addition to IoU, we also incorporate Haralick features to assess the classification accuracy of knee joints. These features serve as a corner detector that can be used to estimate classification accuracy and test against existing classifiers such as SVM, K-means, Gradient boost, and Random Forest. Our results indicate that our method outperforms existing methods, with an IoU of 0.75 achieved for knee joints, which is a significant improvement compared to other current methods of analysis.

Haralick features are texture features that can be extracted from an image to quantify its texture properties. In the case of OA analysis, it can be useful in characterizing the texture of the cartilage and bone tissue in X-ray or MRI images. Those features can be used as input to machine learning algorithms for classification of normal and OA images, or to predict the severity of OA based on the texture characteristics of the image. Therefore, the features can provide valuable information for automated analysis of OA images and can help improve the accuracy of OA diagnosis and monitoring.

Haralick features are a set of texture features that are used to describe the texture and patterns present in an image. They are calculated from the gray-level co-occurrence matrix (GLCM) of an image, which is a matrix that captures the joint probability of the occurrence of a pair of gray levels at a certain distance and orientation. The operational function of Haralick features is to quantify the texture and patterns present in an image by analyzing the statistical properties of the GLCM. These features can provide information on the coarseness, contrast, homogeneity, and directionality of the texture in an image, which can be useful in a variety of image analysis tasks such as object recognition, segmentation, and classification.

In the case of OA analysis, Haralick features can be used to characterize the texture of the cartilage and bone tissues in X-ray or MRI images of the knee joint, which can provide valuable information for the diagnosis and monitoring of the disease.

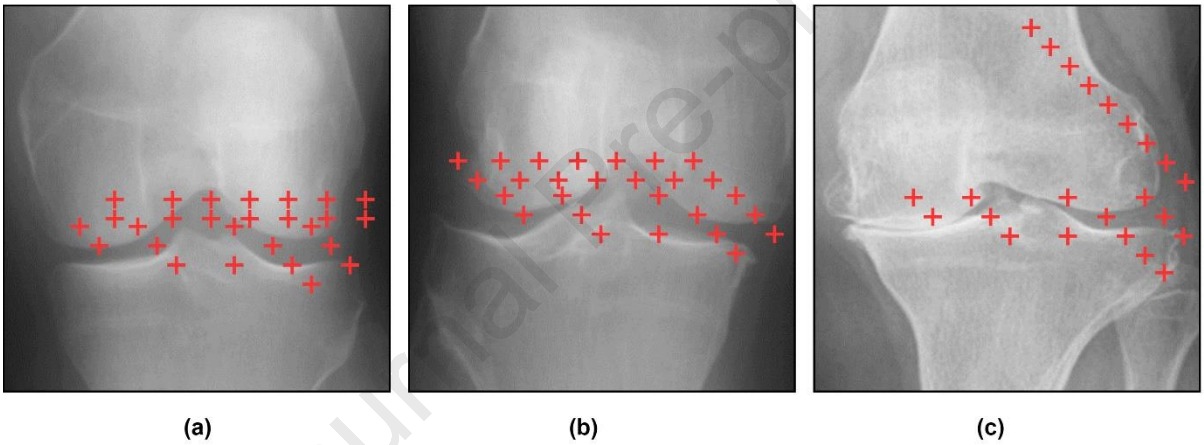

Figure 3: Characteristics features extracted for OA grade classification. (a) Field distribution lines (aligned bone), (b) Field distribution lines (mis-aligned bone), and (b) Extracting features

By training DFCN with the top 30 Haralick features, significant improvements were observed in the identification of bone misalignment properties, as per the proposed methodology. The feature extraction profile is depicted clearly in Figure 3. We have made enhancements to all three aspects of the dataset, as shown in Figure 3, such as removing noise artifacts, increasing field distribution, and enhancing contrast through contrast-limited adaptive histogram equalization.

The OAI dataset was chosen for this study due to its balanced distribution of OA severity levels (0–4), as determined by Kellgren and Lawrence (KL) grading. The dataset was divided into three stages: Training, Validation, and Testing (TRT). The training and validation sets were used to fine-tune parameters in the machine learning models, while the testing set was used only at the end of the research and not during training. To ensure an even distribution of the KL grade, the dataset was randomly divided into 1500 training samples, 500 validation samples, and 250 testing samples, with each KL subcategory having the same number of samples. Table 1 shows the distribution of the experimental data.

Table 1 Training, validation, and testing sets for each of the five KL grade categories.

Item	**KL grading rate**					**Total**
	0	**1**	**2**	**3**	**4**	
Training count	300	300	300	300	300	1500

Validation count	100	100	100	100	100	500
Testing count	25	25	25	25	25	250
Total	425	425	425	425	425	2250

4.1 Evaluation metrics

In this section, we discuss the parametric considerations for accurately classifying OA grades from the publicly available OAI dataset. We propose to evaluate the performance of DFCN using nearly 250 images for training and testing. To generate the final product, confusion metrics are used in conjunction with a wide range of other characteristics. We found that classification profiles based on grades 0, 1, and 4 were more accurate than those based on grades 2 and 3, possibly due to blurring effects that made it difficult for the ML classifier to correctly classify OA edges of grade 2 and grade 3. Our results suggest that further improvements in image quality and feature extraction methods may be needed to accurately classify these grades.

In Figure 4, it is evident that the proposed method of utilising DFCN to track field distribution and estimate bone gaps to classify different grades of osteoarthritis has been successful. To enhance the model, additional features such as Haralick features have been incorporated. We have evaluated the classification performance of the proposed DFCN model using various confusion metrics, including SVM, K-means, Gradient Boost, and Random Forest. The results show that Gradient Boost and Random Forest produce similar outcomes for grades 2 and 3, which is significantly lower than other combinations of ML classifiers.

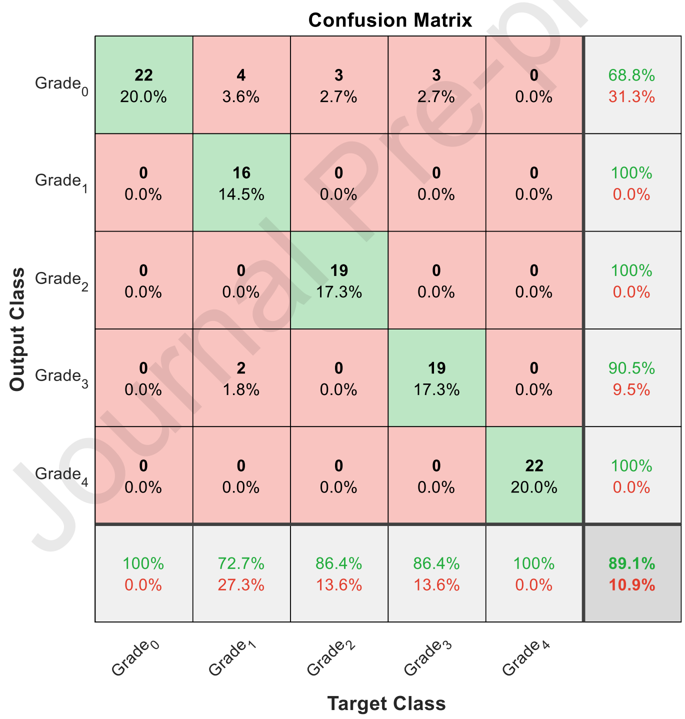

Figure 4: Confusion metric of the proposed DFCN model

It has been observed that the loss of pixel intensity over the misaligned part can result in the failure of detection of the misalignment. While SVM and K-means have higher learning rates compared to Gradient boost and Random Forest, they can alleviate this issue to some extent. However, due to the limited volume occupancy rate of the same set of trained samples on all images, these classifiers may not yield accurate results. In such cases, where visual perception of OA grades is influenced by physical and environmental factors, DFCN appears to be a promising choice for target detection.

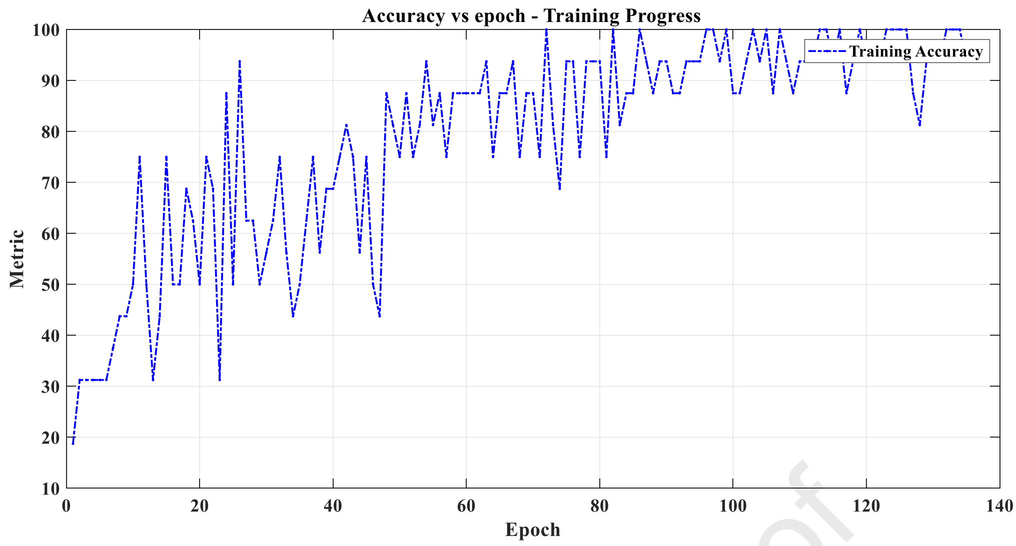

Figure 5: Plot of accuracy vs epoch – Training progress

Figure 5 and 6 shows the plot of accuracy and loss with respect to epoch for both training and loss, respectively. The proposed DFCN model improves the training process by leveraging densely connected layers that enable the sharing of feature maps between different layers, resulting in more efficient learning and better gradient flow. The densely connected layers help the model to avoid vanishing gradients, making it possible to train deeper networks with fewer parameters. Additionally, the proposed model uses an optimistic set of features to improve the machine learning classifier's ability to perform segmentation effectively. This improves the accuracy and robustness of the model. Regarding the loss, it is an important metric used to measure the difference between the predicted output and the true output during the training process. The loss function is used to minimize the error between the predicted and true outputs by adjusting the weights and biases of the model. The proposed DFCN model uses a cross-entropy loss function that measures the difference between the predicted and true segmentation masks. During the training process, the loss is gradually reduced, indicating that the model is learning to predict the correct segmentation masks. By minimizing the loss, the model becomes more accurate and robust, which improves its ability to diagnose osteoarthritis disorders.

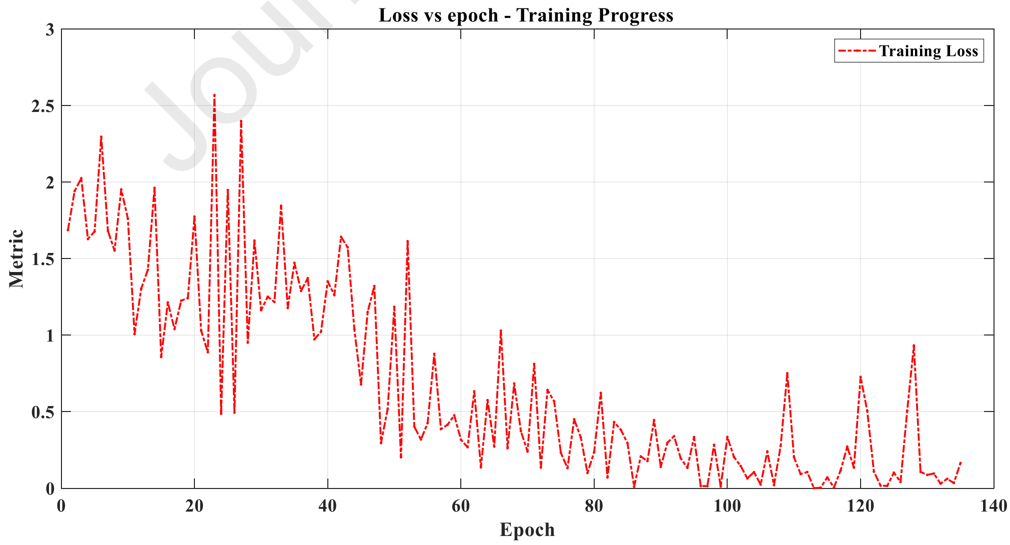

Figure 6: Plot of loss vs epoch – Training progress

4.2 Discussion

To improve the accuracy of detecting osteoarthritis (OA) grades, it is important to minimize false positives and false negatives. False positives occur when a healthy joint is classified as having OA, while false negatives occur when an OA joint is classified as healthy. The misclassification of grades 2 and 3 as either grade 1 or 4 is also considered a false positive or false negative. The precision of detecting OA grades is directly related to the probability of correctly identifying a joint as having OA. Therefore, it is important to reduce false positives and false negatives to increase the accuracy of OA detection.

Table 2 Recall comparison across OA grades index

Classifier	Recall				
	Grade 0	Grade 1	Grade 2	Grade 3	Grade 4
DFCN (Our)	92	94	96	98	100
SVM	90	92	93	97	99
K-mean	86	87	92	96	99
Gradient boost	82	85	90	92	96
Random forest	80	85	90	95	96

Table 3 Precision comparison across OA grades index

Classifier	Precision				
	Grade 0	Grade 1	Grade 2	Grade 3	Grade 4
DFCN (Our)	97.87	94	92.3	98	98.03
SVM	95.74	90.19	92.07	96.04	97.05
K-mean	95.55	87.87	88.46	91.42	97.05
Gradient boost	94.25	87.62	84.9	84.4	95.05
Random forest	94.11	85	87.37	84.82	96

The evaluation of different machine learning classifiers using the DFCN model with Haralick features revealed that the deep-CNN significantly improved the detection and classification of OA grade 2 and 3. Both recall and precision evaluation metrics were compared among different classifiers, including Gradient boost and Random Forest, K-mean, SVM, and the proposed DFCN. The results indicated that the DFCN model with multilevel Haralick features showed better performance compared to other classifiers. These findings highlight the potential of the DFCN model for accurate and efficient detection and classification of OAs, particularly for grade 2 and 3, which are often challenging to diagnose accurately.

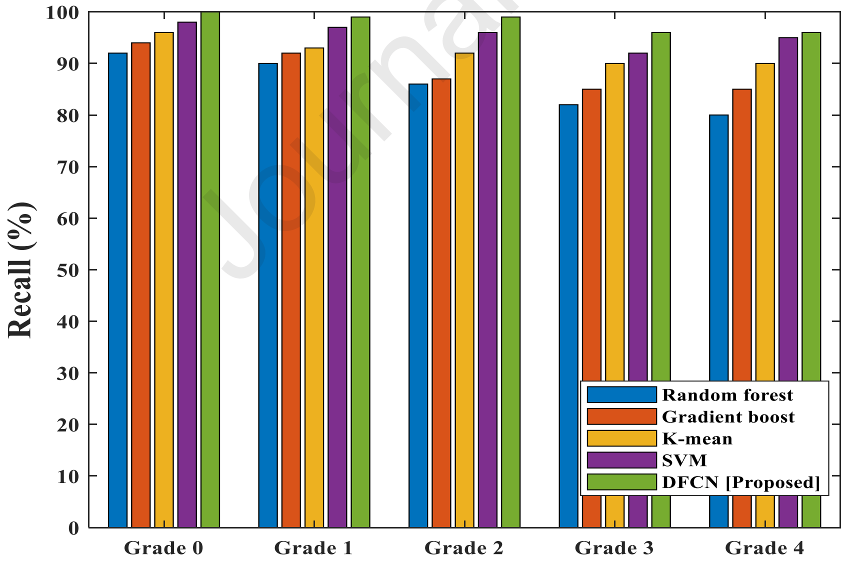

Figure 7: A comparison of DFCN model classifier recall metrics for various structures, including Gradient boost and Random Forest, K-mean, and SVM, respectively.

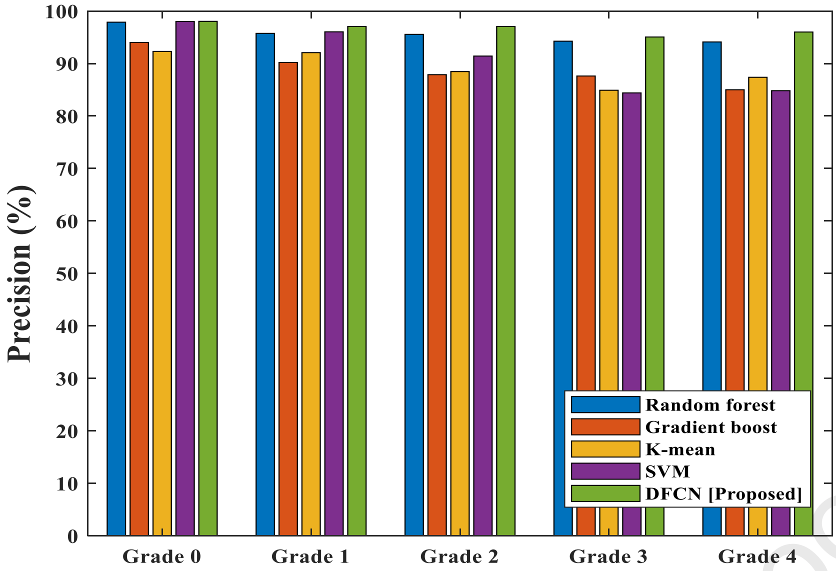

Figure 8: A comparison of DFCN model classifier precision metrics for various structures, including Gradient boost and Random Forest, K-mean, and SVM, respectively.

5. CONCLUSION

This study proposed a DFCN based image segmentation algorithm for the automatic recognition of different types of osteoarthritis disorders, gland expansion rate, and tracking of infectious status. The proposed DFCN system can be trained with an optimist feature set that supports machine learning classifiers, which improves the segmentation process's effectiveness. The experimental validation results can be compared with three different non-automatic segmentation algorithms for accuracy, robustness, ease of use, level of human interaction, and computation time. Furthermore, the proposed DFCN supported CAOD system can perform a fully autonomous diagnosis of osteoarthritis disorders by estimating radiation density, classifying kinds, and tracking the infection level from extracted characteristics. The use of DenseNet layers in the pre-trained CNN model facilitates the system's faster learning process, and existing machine learning algorithms such as SVM, K-means, Gradient boost, and Random Forest can be used for structural rule derivation. The primary goal of this research is to reduce manual errors in the OA state diagnosis procedure and provide possible benefits to radiologists.

Data availability statement

Data included in article/supplementary material/referenced in article.

Ethics declarations & Conflict of interest

The authors have no conflicts of interest to declare relevant to this article's content.

Human and animal rights

This research does not involve any human participants and/or animals; hence, any informed consent or statement on the welfare of animals does not apply to this research.

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Declaration of interests

☒ The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

☐ The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: