Transfer Learning based AlexNet framework to Predict Knee osteoarthritis Evolution

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ABSTRACT

Knee osteoarthritis (KOA) is a disease that grows in incidence and frequency with increasing age, to the point where in people over the age of 60, around 10% of men and 13% of women have symptomatic KOA. The illness may also affect other joints in the body. The number of persons in the age group that is associated with the most severe symptoms of KOA is continuing to rise as the population continues to age. Initially, 3D-KOA dataset is considered, which has the properties of magnetic resonance imaging of knee disorders. Then, principal component analysis (PCA) is applied, which normalized all the records in the dataset and eliminated the missing values, unknown values. Here, the PCA is also dimensionality reduction method, which extracted the statistical features from the dataset. Then, multi scale residual network (MSRN) is used to upgrade the low-resolution features into higher resolution features, which boosts the probabilities. Finally, transfer learning (TL) based AlexNet model is used to classify the normal and abnormal stages of KOA using MSRN features. The simulation results shows that the proposed model outperformed in terms of accuracy, sensitivity, specificity, as compared to existing methods.

Keywords: Knee osteoarthritis, radiography data, transfer learning, principal component analysis, multi scale residual network,

1.0 INTRODUCTION

The KOA, also known as "Degenerative Joint Disease" or "Wear and Tear arthritis," is the most common musculoskeletal disorder, and it primarily affects weight-bearing joints such as the hip, knee, spine, feet, and finger. KOA may be caused by several factors, including age, hereditary predisposition, injury, hormone problem, recurrent damage to joint, uric acid, and diabetes. KOA is a condition that typically affects older people because of the wear and tear that occurs on the protective tissue that lies between joints (cartilage). However, KOA can affect younger people because of joint injury or the repetitive joint stress that comes from overuse. A study found that KOA was the 11th greatest worldwide impairment factor in 2017, affecting 303 million individuals all over the world. The cost of treatment for KOA is about around 19,000 dollars per year, and as a result, it constitutes a significant financial burden for the globe currently.

KOA is one of the most common types of joint pain. Degenerative alterations in the bones, cartilage, menisci, ligaments, and synovial tissue define this chronic and severe joint condition [1]. Osteoarthritis is a kind of this condition. According to the definition provided by the American Rheumatism Association (ARA) [2], KOA is a heterogeneous group of conditions that can cause joint symptoms and signs that are associated with defective integrity of cartilage, in addition to related changes in the underlying bone and at the joint margin. In other words, KOA is a condition that can be caused by several different conditions. Over 250 million individuals, or about 4% of the total population of the globe, are afflicted with KOA, making it the most prevalent of the 50 illnesses and injuries that are the most frequent sequelae of accidents in the world. It is linked to factors such as age, obesity, previous injuries to the joints, occupational factors, and genetics. Walking is a daily activity that places a significant amount of demand on the knee joint; hence, if KOA sets in, it will be exceedingly painful and difficult to walk. It is essential to get a diagnosis of KOA early on, before the condition progresses to a more critical stage, so that this outcome may be avoided. The primary way for diagnosing KOA is using joint X-rays [3]. At the present time, the Kellgren and Lawrence (KL) classification is the clinical tool that is utilized most of the time for making a radiographic diagnosis of KOA. In most cases, the KL classification is used primarily within the realm of KOA. Joint X-rays are given a grade that ranges from 0 to 4, which the researchers associated to the growing severity of KOA [4]. A grade of 0 indicates that there is no evidence of KOA, while a grade of 4 indicates that severe KOA is present.

According to the research that has been done, a significant proportion of the cost of treatment is caused by a lack of awareness on the part of patients and an inability to diagnose symptoms at an early stage, when there is a greater chance of mitigating the effects of the condition or delaying its progression toward permanent disability [6]. Therefore, the only alternatives available for maintaining a healthy life are an early diagnosis and behavioral therapies [7] since joint replacement surgery remains the sole solution at the advanced stage of KOA. Imaging techniques in medicine have been used to aid in the early detection of KOA [8]. It is now being used effectively in a wide variety of applications, including the diagnosis, monitoring, and even treatment of many medical diseases. Rapid advancements in processing power, software, and medical imaging methods have greatly increased the potential for using artificial intelligence (AI) in a wide range of radiological imaging activities, including prediction, diagnosis, risk assessment, detection, and therapeutic response [9]. The inside structures of the body may be seen thanks to medical imaging, which generates these images.

The novel contributions of the article are as follows:

- The 3D-KOA dataset is evaluated, which has magnetic resonance imaging characteristics for knee diseases.
- PCA is used to normalise all the records in the dataset and remove missing or unknown values.
- MSRN is then utilised to convert the low-resolution data into higher-resolution features, increasing the probability.
- TL-AlexNet model is employed to categorise the normal and pathological phases of KOA.
- The simulation results reveal that the suggested model beat current techniques in terms of accuracy, sensitivity, and specificity.

Rest of the article is organized as follows: Section 2 contains about the detailed analysis of existing surveys. Section 3 provided the details of proposed method. Section 4 contains the details of results, followed by comparison. Finally, section 5 concludes the article.

2.0 LITERATURE SURVEY

Sivakumar, et al. [11] proposed the AlexNet model to classify the severity of KOA. However, physicians are put under a tremendous amount of strain, and the fact that there are tiny differences between phases as well as many x-rays might cause them to make mistakes in judgement. The KOA severity may be classified manually, semi-automatically, or automatically using plain radiographs, as recommended by Saini et al. [12] for the reader's consideration. In this narrative review paper, we have reported current improvements in the severity assessment of KOA using X-ray data.

A TL method for learning KL severity assessment of KOA was developed by Helwan et al. [13]; it makes use of a very deep wide residual learning-based network (WRN-50-2), which is trained using X-ray plain radiographs from the KOA Initiative (OAI) dataset. Using radiographic data, Yunus et al. [14] developed a classification and localization approach for the KOA method, and that method is provided here in this study. After converting the two-dimensional radiograph data into three dimensions, LBP features are then retrieved, each with a dimension of 59. The PCA method is then used to pick the features with the highest quality that fall within the range. Sarvamangala et al. [15] suggested using CNNs to grade the severity of KOA. The implementation of the recommended model makes use of CNNs that have been pretrained in addition to multiscale convolutional filters. MCBCNN was developed with the aid of three pretrained CNN models, namely mobileNet2, resNet50, and inceptionNetv3, which were used throughout the process.

A KOA KL grade prediction model and a follow-up management plan prediction model were developed by Wo et al. [16] to reduce the amount of time that KOA patients had to wait for treatment and to decrease the worsening of patients' symptoms as a result of delayed treatment. A KOA KL grade prediction model was created by Wo et al. [17] to reduce the amount of time that OA patients must wait for treatment and to decrease the worsening of patients' symptoms because of delayed therapy. To this research, the data classification work is handled by the Xception model, while the Region of Interest (ROI) extraction duty is handled by the Mask R-CNN algorithm. Challenges in Deep Learning Applied to Knee Joint Magnetic Resonance Imaging were suggested by Kadar et al. [18]. On the other hand, reading and analyzing knee MRIs takes a significant amount of time and might lead to an incorrect diagnosis. Wang et al. [19] introduced an innovative learning system that dynamically divides the data into two categories based on how reliable they are. In addition, we propose a hybrid loss function to assist CNN in learning from both sets in the appropriate manner. We place an emphasis on the usual samples and maintain control over the implications of instances with a low level of confidence using the technique that has been presented.

The KOA Prediction was a concept that was suggested by Hirvasniemi and colleagues [20]. This test set included MRI and X-ray image data, in addition to clinical risk factors at baseline. The participants were not given access to the ground truth outcomes, which were defined as whose knees acquired incident symptomatic radiographic KOA within 78 months of starting the study. Chang et al. [21] used a convolutional Siamese network to correlate MRI data from the KOA Initiative (OAI) with chronic, unilateral knee pain. The researchers looked at the difference in function between the painful knee and the unaffected knee.

Deep learning approach using the YOLOv3 model and VGG-16 was used in Huu, et al [22] suggested methodology to assist medical professionals in automatically identifying KOA on X-ray data. Following this step, the YOLOv3 model is trained using the input of a preprocessed dataet. After that, it makes an automated prediction about the position of the knee joint on the X-ray data. Morales Martinez et al. [23] introduced the idea of learning KOA imaging biomarkers from a spherical encoding of the bone surface. A total of 41822 merged spherical maps were used, each labeled with a Kellgren-Lawrence grade for radiographic OA, to train a CNN classifier model to detect OA based on bone shape learning properties. Martinez et al. [24] put out the idea of using spherical encoding for the discovery of KOA biomarkers. In addition, the radiographic score is the clinical standard for the diagnosis of KOA. This score indicates the severe pathological phases of the disease, which sometimes include permanent damage. An automatic segmentation approach of the knee bone was suggested by Adeola et al. [25] based on a Deep Learning CNNs architecture. This method was developed using MRI slides as the source material.

3.0 PROPOSED METHOD

The KOA is a primary cause of illness and disability, and it imposes enormous costs to society and the economy. It was estimated that arthritis cost the United States $336 billion in 2004, which is equivalent to 3% of the country's gross domestic product. KOA is the most frequent type of arthritis. Current therapeutic options for KOA of the knee are limited to those that provide only symptomatic relief. The KOA is the most frequent kind of musculoskeletal illness for which there is no known cure. The prediction of the progression of KOA is a very difficult and pressing issue that, if solved, has the potential to hasten the development of disease-modifying drugs and, ultimately, to aid in the prevention of the millions of total joint replacement surgeries that are performed each year. This study will provide a multi-modal TL-based KOA progression prediction model utilizing the AlexNet framework. The model will make use of raw radiography data (MR or X-ray), the findings of a clinical examination, and the patient's prior medical history.

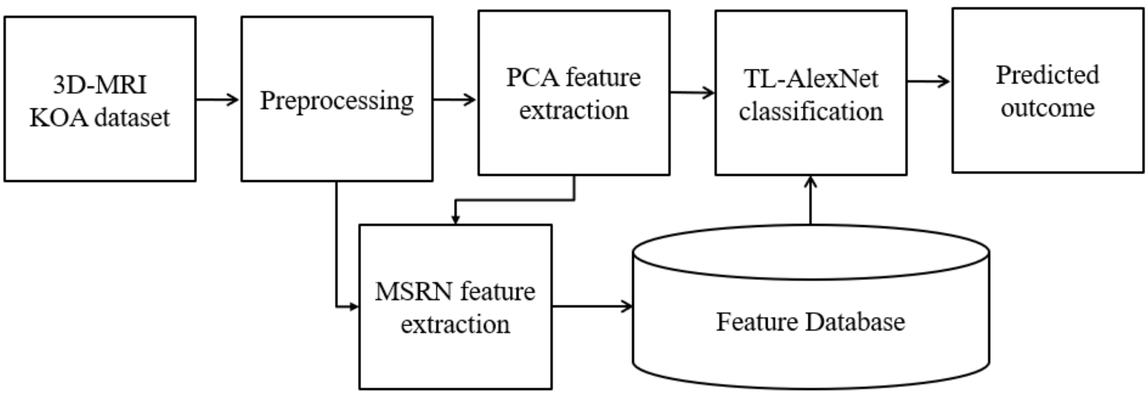

Figure 1. Proposed Block diagram.

Figure 1 shows the framework of proposed model. It considers the 3D-KOA dataset, which is similar to MRI in its ability to detect knee problems. The dataset was then standardized by using principal component analysis, which also accounted for missing and unknown values. The PCA was used to extract statistical characteristics from the dataset, making it a dimensionality reduction approach as well. The chances are then increased by using MSRN to transform the low-resolution characteristics into high-resolution ones. Finally, MSRN characteristics are applied in a TL-AlexNet model to categorize KOA into normal and pathological phases. The simulation results demonstrate the superior accuracy, sensitivity, and specificity of the proposed model compared to the state-of-the-art approaches.

3.1 PCA feature extraction

There are eight key parameters that might possibly have an influence on the feature propagation characteristics of an explosion generated by coal dust. One of these aspects is the amount of coal dust in the atmosphere. Even if there is some connection between these factors, the impact that each of them has on the qualities of feature propagation might vary based on the circumstances. If the results of the tests conducted on these significant components are used straight, then there will be a substantial amount of error created in the construction of a prediction model. As a result of this, the development of a prediction model will take much more time. As a direct consequence of this finding, the technique of PCA has been used throughout this study. The primary goal of this strategy is to lessen the dimensionality of the multivariate data while at the same time guaranteeing that the recovered main components are independent of one another in terms of their correlation levels. As a direct result of this modification, the predictive power of the model will therefore be elevated to a higher level. Figure 3 offers a graphical depiction of the phases of computation used in PCA. These stages are then deconstructed into their component pieces in the following steps.

Step 1: Determine the eight factors that have the most significant influence on the characteristics of explosive feature propagation for eleven different kinds of coal dust samples. This will serve as the starting analytical variables for the study.

Step 2: Based on the variables that were employed in the beginning, determine the covariance matrix for the principal component extraction.

Step 3: We are required to do the calculations necessary to determine the eigenvalues of the covariance matrix as well as the eigenvectors that are regarded as standard for the matrix.

Step 4: In accordance with the presumption that the cumulative variance contribution rate ought to approach 85%, one determines the number of principle components, and one generates an expression of primary components. This is done to construct the principal components.

Step 5: After the fundamental components have been identified, the training of the MRCN will then be carried out in line with those components.

3.2 MRCN feature analysis

Using low-resolution photos as input, feature analysis may recover high-resolution data that is related to the original image. The term "super resolution" is used to describe this method, which has the potential to revolutionize several industries. Figure 2 illustrates the topology of the deep learning network model that was developed by MSRN, which is based on feature extraction process.

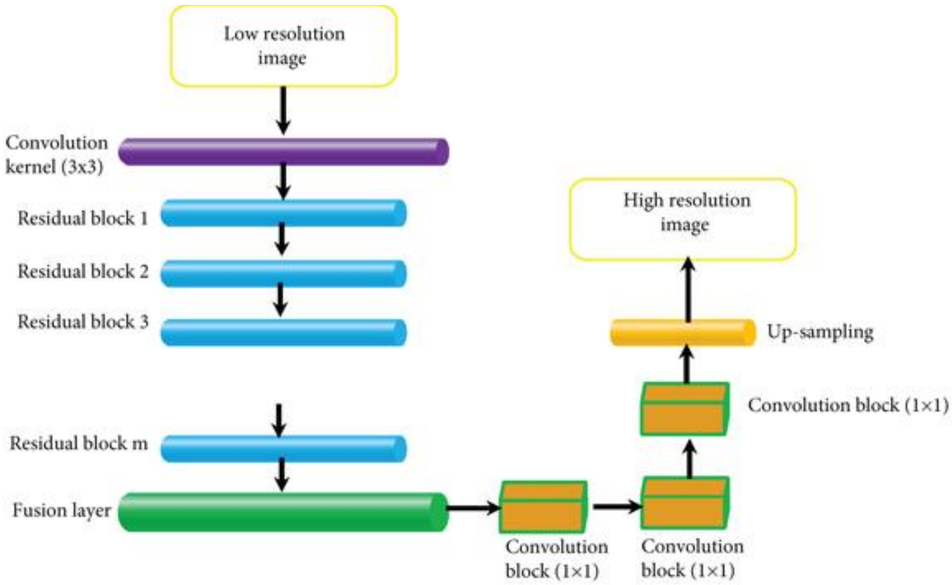

Figure 2. MSRN feature extraction.

In this configuration, local residual learning has the potential to both lessen the computational burden placed on the network and boost its overall performance. The extraction of data features via multiscale feature fusion may be done in a variety of proportions, and it enables shared feature information across distinct branches. The operation may also be stated in the following format.

$$F_1 = \lambda(\alpha_{3*3}^{1} * H_{m-1} + c^1) \tag{1}$$

$$G_1 = \lambda(\alpha_{5*5}^{1} * H_{m-1} + c^1) \tag{2}$$

$$F_2 = \lambda(\alpha_{3*3}^{2} * [F_1, G_1] + c^2) \tag{3}$$

$$G_2 = \lambda(\alpha_{5*5}^{2} * [G_1 F_1,] + c^2) \tag{4}$$

$$F' = \propto_{1*1}^{3} * [F_2, G_2] + c^2 \tag{5}$$

Here, λ and $\propto$ are the weighting factors; what is the standard deviation; superscripts 1, 2, and 3 indicate the layers in which it is positioned; and G_1 indicate the size of the convolutional kernel respectively; H is shorthand for the RELU function; and F_1 stand for the operations that are performed on series; and c^1denotes the number of network feature graphs.

3.3 TL-AlexNet classifier

The TL is a method for collecting deep features from pre-trained CNN models. The use of TL in computer vision helps save time since it enables us to construct an accurate method of constructing a model by using a model that has been trained for one issue as a starting point for a second problem that is linked to the first. Problems in computer vision and natural language processing are often tackled by applying deep learning to pre-trained models as the foundation for model parameters. Therefore, it is simple for the algorithm to modify the weights of the training set in such a way that they are in line with the requirements of the new domain by making just minor adjustments. A classification model, for example (radiographs), is based on pre-trained models that were obtained from extremely large dataets within the field of computer vision.

Because of this, TL can function because it makes use of patterns that are acquired through the process of addressing a variety of issues. Because of this, you won't have to start completely over from square one. There are often two approaches used, when using TL to problems involving computer vision: To begin, homogeneous TL is used in situations in which both the source domain and the destination domain share the same feature space. The suggested approach makes advantage of this kind of TL. Second, heterogeneous TL takes place when the source and destination do not have feature spaces that are comparable to or identical with one another. The network model only makes use of a single scale convolution kernel to extract image features while attempting to collect high-frequency information from low-resolution data. As a result, a significant amount of the images' details would be missed. As a result, using the model presented above as a foundation, this investigation extends it by adding three branch networks on varying sizes. Figure 3 shows the architecture of TL-AlexNet.

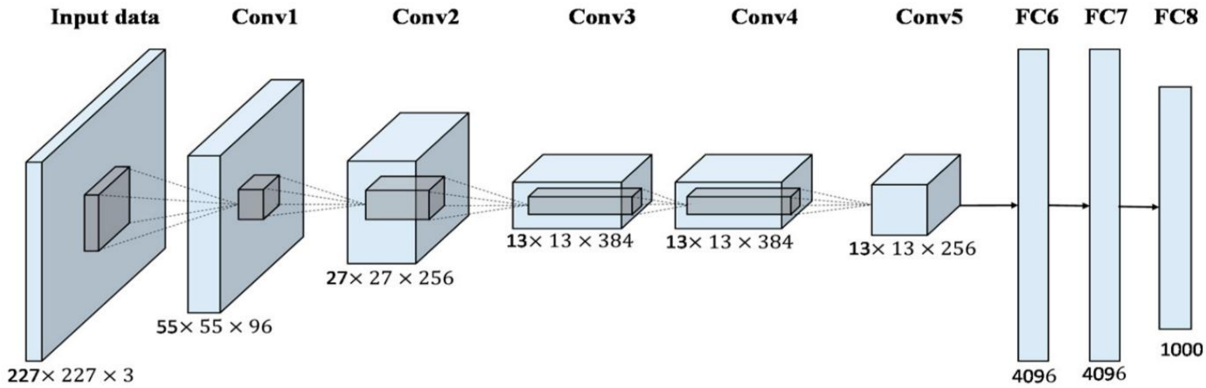

Figure 3. TL-AlexNet classifier.

The model described above can-do classification reconstruction of Y channels as well as converting RGB data into Ycbcr images. Assuming for the sake of argument that a data has K channels, the model may be stated as follows.

$$\hat{\delta} = argmin_{\delta} \frac{\sum_{i=1}^{L} \Re*(F_{\delta}(Im_i^{LRI}),Im_i^{HRI})}{L} \quad (6)$$

$$\delta = \{\alpha_1, \alpha_2, \cdots \alpha_n, c_1, c_2, \cdots c_n\} \quad (7)$$

where represents the weight and deviation of the network, represents the total quantity of data inputs, and is the loss function to minimize the gap between the low-resolution and high-resolution feature pictures. The network structure of the model is mostly made up of three blocks: the multiscale feature extraction block, the broad residual block, and the multiscale reconstruction block. This is one possible way to describe the multiscale feature extraction component.

$$U_{MF} = CON_{MF\times3}(Im^{LRI}) \quad (8)$$

Here, $CON_{MF\times3}$ denotes the extraction of features using the branch network of 3.The broad residual module is responsible for carrying out tasks such as feature fusion, wide residual feature extraction, local residual learning, and global residual learning. A possible expression for the broad residual feature extraction is as follows:

$$F_1 = Z_{gn}(\alpha_{3*3}^1 * H_{m-1} + c^1) \quad (10)$$

$$G_1 = Z_{gn}(\alpha_{5*5}^1 * H_{m-1} + c^1) \quad (11)$$

$$F_2 = \lambda(\alpha_{3*3}^2 * [F_1, G_1] + c^2), \quad (12)$$

$$G_2 = \lambda(\alpha_{5*5}^2 * [G_1 F_1,] + c^2) \quad (13)$$

Here, Z_{gn} shows that the feature graph was normalized by using the group normalization layer, the meanings. Following is an expression that may be used to describe the fusion process.

$$F' = \propto_{1*1}^3 * [F_2, G_2] + c^2 \quad (14)$$

To gain more specific information, local residual learning may help to enhance the transfer of feature information and gradient flow within the network. This is something that can be described as follows:

$$H_m = F' + H_{m-1} \quad (15)$$

Here, H_m stands for local residual learning, and as we'll see below, using global residual learning may help solve the problem of gradient disappearance throughout the network's training phase.This problem occurred because local residual learning did not consider global residual learning.

$$U_{GR} = U_{MF} + H_M \tag{16}$$

Here, U_{GR} denotes the overall residual learning of the population. In the end, a multiscale reconstruction is performed, and the completed data may be described in the following way:

$$IM_{re} = U_{3*3}\left(v_{ups,\times 3}(U_{GR})\right) \tag{19}$$

where IM_{re} indicates the final super resolution data that was rebuilt after all the pixels had been processed.

4.0 RESULTS AND DISCUSSIONS

This section gives the detailed analysis of simulation results. All the simulations are carried out using Spyder-Anaconda software tool. The programming language also used python, which is software primitive coding.

4.1 Dataset

The system is based on deep learning. We gather information, such as the 2874 X-ray data of knees that were collected from the OAI dataet, which is a sizable collection of information pertaining to joints and knees. In this study, the chiropractors at Bach Mai Hospital are responsible for labelling and analyzing all the data, which will then be preprocessed using the PCA algorithm so that the data quality may be enhanced.

4.2 Classification performance.

Table 1 shows the performance of proposed KOA detection using TL-AlexNet for various performance metrics. Table 1 compares the performance of proposed TL-AlexNet classifier is improved as compared RNN [20], CNN [23], ResNet [25]. Here, proposed method improved accuracy, and all other metrics like Accuracy, Sensitivity, Specificity, Precision, Recall, F1-score, and False acceptance Ratio (FAR).

Table 1. Classification performance comparison of various approaches.

Metric	RNN [20]	CNN [23]	ResNet [25]	Proposed MBRS-FCRN
Accuracy	90.240	94.881	94.267	99.34
Sensitivity	91.419	94.565	93.750	99.37
Specificity	91.795	93.527	94.204	99.687
Precision	92.170	94.089	93.394	99.67
Recall	91.174	94.553	94.457	99.68
F1-score	91.755	94.432	95.344	99.234
FAR	90.974	94.225	93.080	99.45

Table 2. X-ray images-based classification performance.

Metric	KOA [11]	OAI [13]	LBP [14]	Proposed MBRS-FCRN
Accuracy	90.32	94.39	93.87	99.25
Sensitivity	92.54	93.72	98.16	99.59
Specificity	96.00	92.60	94.56	99.51
Precision	96.83	92.38	95.15	99.22
Recall	95.92	95.74	93.38	99.65
F1-score	92.63	98.61	95.62	99.41
FAR	97.89	97.42	97.53	99.05

Table 3. Radiographic data-based classification performance.

Metric	WRN [13]	PCA [14]	MCB-CNN [15]	Proposed MBRS-FCRN
Accuracy	90.68	90.34	93.94	99.14
Sensitivity	96.06	93.97	93.37	99.84
Specificity	92.98	97.70	92.65	99.34
Precision	98.62	92.10	97.05	99.06
Recall	98.33	96.30	93.07	99.56
F1-score	98.41	96.34	91.72	99.74
FAR	97.27	94.59	92.64	99.79

Table 4. Motion quality-based classification performance.

Metric	ROI [17]	OAI [21]	VGG-16 [22]	Proposed MBRS-FCRN
Accuracy	96.35	91.56	96.02	99.47
Sensitivity	91.16	94.29	90.28	99.63
Specificity	98.96	98.80	96.89	99.29
Precision	90.95	93.20	95.34	99.26
Recall	96.62	98.17	90.60	99.50
F1-score	96.91	97.63	90.83	99.15
FAR	93.95	97.78	93.89	99.40

5.0 CONCLUSION

This article was aimed to develop the KOA prediction and progression using TL models. Consideration is given to the 3D-KOA dataet, which may be characterised as having the characteristics of magnetic resonance imaging of knee diseases. The PCA method is then used, which resulted in the standardisation of each record within the dataet as well as the removal of any uncertain or missing values. In this case, PCA is a technique for dimensionality reduction that was used to extract the statistical characteristics from the dataet. The low-resolution features are then upgraded to higher resolution features with the help of MSRN, which ultimately results in an increase in the probability. In conclusion, a TL-AlexNet model is used to the MSRN characteristics for the purpose of classifying the normal and pathological phases of KOA. The simulation results show that the proposed model outperformed state-of-the-art methods in all three metrics. Advanced transfer learning and optimization models may be used to further boost the effectiveness of this endeavor.

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