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Deep Convolutional Neural Network Classifier for Effective Knee Osteoarthritis Classification

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Abstract— Millions of people are affected by the disease Knee Osteoarthritis, and the prevalence of the condition is steadily increasing. Knee osteoarthritis has a significant impact on people's lives by generating increased worry, mental health disorders, and physical problems. Early detection of knee osteoarthritis is critical for decreasing disease consequences, and numerous studies are being conducted to classify knee osteoarthritis. In this study, the deep CNN classifier is used to classify knee osteoarthritis, which effectively extracts the features required for disease classification more efficiently. The preprocessing of the data, which is done in three processes such as Circular Fourier Transform, Multivariate Linear Function, and Histogram Equalization, is particularly important in this research since it aids in obtaining more efficient information about the image. The deep CNN classifier's weights and bias deliver better and desired classification results while spending less time and storage. The proposed deep CNN classifier attained the Accuracy of 94.244%, F1 measure of 94.059%, Precision of 94.059%, Recall of 93.586%.

Keywords- Knee Osteoarthritis, classification, deep Convolutional Neural Network classifier, preprocessing, weight, bias.

I. INTRODUCTION

The prevalent chronic ailment characterized by degenerative knee joint disease, or knee osteoarthritis, is brought on by the usage and abuse of the femur and tibial bones' ligaments [7][1]. A defective knee joint may be caused by several conditions, including rheumatoid arthritis, haemophilia, gout, osteochondritis, knee injuries, and deformities. However, osteoarthritis is the most common reason for knee illness [8][3]. Although the scientific community has expended plenty of time and energy on Knee osteoarthritis research, early detection, diagnosis, and treatment of Knee Osteoarthritis is still present as significant challenge. In the field of detection of knee osteoarthritis, many researchers have used artificial intelligence (AI) techniques due to the concurrent development in computational power, the accumulation of large datasets, and the necessity to address the issues [9][4]. Subchondral sclerosis the thickening of bone, joint space narrowing the irregular distance in the joints, and osteophytes, the formation of lumps are three primary radiographic indicators of osteoarthritis in human knees that are distorted [10]. Joint space narrowing, generally called cartilage loss, is one of these and is thought to be the primary symptom of osteoarthritis [11][3]. As they have been mentioned in the pertinent contemporary research [12][4], the living style of individuals, weight, age, gender, and knee traumas are the risk factors for knee osteoarthritis.

Osteoarthritis, the most common form of arthritis, is a degenerative disorder of the articular cartilage that decreases joint comfort and mobility while also lowering sovereignty and general quality of life. [6]. One in three people at their age of 60 worldwide have osteoarthritis, which is the most common form of degenerative joint disease [22][1]. More than 250 million people globally suffer from osteoarthritis, which costs 1-2% of the country's GDP. [2][3].

The number of people who have knee osteoarthritis is anticipated to rise as the world's population gets older [13][2]. Before the initialization of treatment for the knee osteoarthritis the condition of the normal or older patient or a sport person should be identified as symptomatic or asymptomatic so that the treatment could be provided according to the situation. A variety of risk factors for knee osteoarthritis have now been identified using various categories in studies undertaken over the previous three decades. Those factors are body's metabolism, heredity, obesity, bone density, muscular weakness, and joint laxity, as well as factors related to the workplace, physical activity, sports, and joint traumas [21][6].

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The primary goal of the study is to use the deep CNN classifier to categorise knee osteoarthritis.

Deep CNN classifier is highly utilized for the classification because the classifier extracts more significant features from the image without human intervention. The availing of pretrained Resnet-101 model reduces the time consumption and the preprocessing using the circular Fourier transform, multivariate linear regression and histogram equalization effectively enhances the intensity, contrast and extracts the region of interest and the following are the research's primary contributions:

Deep CNN classifier: Deep CNN classifier effectively extracts the features present in the image and effectively classifies the knee osteoarthritis so that the treatment could be given according to the necessity.

- The image used is enhanced in terms of intensity, contrast, and the artifacts are efficiently removed using the multivariate linear regression, circular Fourier transform and histogram equalization.
- The complexity of the network and the time constraints are effectively reduced using the pretrained resnet-101 model.

The manuscript is structured as follows: The Literature Review is enumerated in section 2 through the existing methods along with their cons, pros, and challenges. The methodology used for the classification of knee osteoarthritis along with the architecture of deep CNN is interpreted in section 3. The results acquired and interpreted in section 4 demonstrate the effectiveness of the suggested model, a brief comparative discussion is interpreted in section 5 and the conclusion and future scope of the research is particularized in section 6.

II. LITERATURE REVIEW

Most individuals are afflicted by knee osteoarthritis, making it a prominent disease. Nevertheless, because of the complicated bone pattern, it is difficult to detect and classify knee osteoarthritis, and the numerous methods used for categorization are shown below.

Currently used classification techniques include Mohamed Yacin Sikkandar *et al.* [1] used a segmentation method relying upon local centre and classified the knee osteoarthritis using deep CNN classifier. The classification is made according to the grades allotted for the knee osteoarthritis and the grading of knee is performed through the features extracted. Although the grading of osteoarthritis was performed the interpretation of how the decision made was not distinct. Soon Bin Kwon *et al.* [2] availed the radiographic and gait analysis data for the purpose of automatic classification of knee-osteoarthritis and graded the knee osteoarthritis using Kellgren -Lawrence grading system. The main advantage of this method is the usage of gait data that helps in the identification of the severity of the knee osteoarthritis. But the complexity of the gait data and the smaller data acts as a disadvantage. Mahrukh Saleem *et al.* [3] analyzed the radiological symptoms based on the X-ray images and the quality of the images are also enhanced for better identification. The knee region was extracted without manual intervention and provided, and this method reduced the responsibility of the medical professional but whenever there is a slight change in the size or variation could cause problems. Christos Kokkotis *et al.* [4] mainly focused on the feature selection of knee osteoarthritis relying upon the fuzzy logic mechanisms and the usage of multidimensional data that provided increased performance and reduced complexity. The factor that contributes to the outcome is not validated was a disadvantage and the availing of fuzzy network allows the selection of informative features robustly. Shivanand S. Gornale *et al.* [5] eliminated the unnecessary distortions and identified the geometric transformation of the cartilage region and the Hu's invariant moment helps in the attainment of rotated version of the image. Two classifiers, such as K-NN and decision trees, are used to categorise the segmented regions, although the method is ineffective for distorted images.

2.1 Challenges:

The challenges to be overcome in this research are,

- In some data the space between the bones is difficult to identify especially if the image is present in the anterior view [1]. Early detection of this osteoarthritis disease is really a challenging task since in most of the cases the symptoms are mild along with that long term diagnoses also possess challenges [4].
- An artificial neural network's problematic task is that a large amount of data must be used to train it, and the decision-making process is typically perceived as paradoxical, making it challenging to understand [1].
- Identifying the variation between the muscle and the cartilage sound is difficult that initiates complexities while detecting the knee osteoarthritis [2]. The process of extracting the region of interest for the knee osteoarthritis classification is a strenuous task [5].

III. METHODS

3.1 Proposed Deep CNN Classifier for classification of knee osteoarthritis:

The primary goal of the study is to use the deep CNN classifier to categorise knee osteoarthritis. The Osteoarthritis Initiative (OAI) database serves as the initial source for the data collection.[14] and then the preprocessing is performed to make

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the data more suitable for the training of the classifier. The preprocessing of the data is performed using three significant steps such as Circular Fourier Transform, Multivariate Linear Enhancement, and Histogram Equalization that enhances the quality of the image. After preprocessing the data are fed forwarded to the pretrained resnet-101 model that effectively extracts the features and reduces the complexity and time constraints of the network. Finally, the features are trained using the deep CNN model that effectively performs the classification of knee osteoarthritis and the schematic representation of the methodology is shown in figure 1.

3.2 Input for Knee Osteoarthritis:

The input for the classification of the knee osteoarthritis is obtained from the OAI database that consists of the images in the form of magnetic resonance imaging and radiographs and is mathematically represented as follows,

$$I = \{H_{uv}\} \tag{1}$$

here, H designates the number of images in the database and u denotes the magnetic resonance imaging and v designates the radiographs.

3.3 Preprocessing of Knee Osteoarthritis Data:

Preprocessing is mostly used to transform raw data into a comprehensible format and helps in effective data training. Through preprocessing, the data are trained to fit the essential requirements, and the region of interest is also extracted. Here, the preprocessing is carried out in three steps: circular Fourier filtering, multivariate linear regression, and histogram equalization.

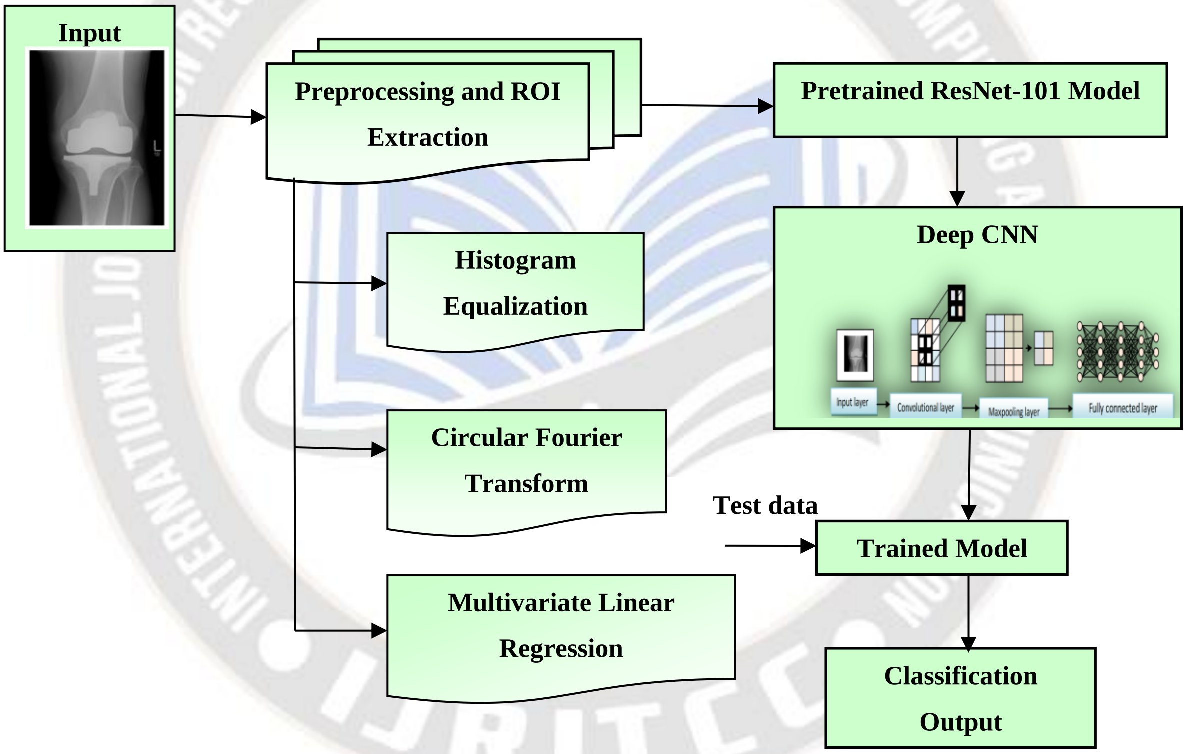

Fig. 1: Schematic representation of the Knee osteoarthritis classification model

3.3.1 Circular Fourier Transform:

The essential information needed from the region of interest is filtered in this Fourier domain to remove the redundant information so that the complexity of the region could be reduced. The regions for the determination of knee osteoarthritis are categorized in to two distinct regions based on the cut of frequencies k. If the obtained frequency (k_l) is lower than k, the region is unaffected and if the obtained frequency (k_h) is higher than k then the region is considered as the affected knee osteoarthritis region. Hence, the application of this filter helps to characterize the affected and unaffected region.

3.3.2 Multivariate Linear Regression:

Intensity normalization using MLR reduces the artifacts in the ROI and inter-subject variability. To ensure comparability both within and across the images of the many subjects in any image analysis with more than one subject, intensity normalization is an important technique. The strength of the relationship between the variables is given by the multivariate linear

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regression, especially the relationship between the dependent and independent variables are determined. This helps to predict the outcome of the variables and is formulated using the formula,

$$D = G\lambda + E \tag{2}$$

here, D represents the response variables, E designates the vector of error terms, the vector of regression coefficient is given by λ, and the vectors of the regressor values are given by G.

3.3.3 Histogram Equalization:

The usage of histogram equalization is to enhance the contrast of the image because the contrast of original images is considerably low. The enhancement of the images automatically enhances the tibial trabecular bone pattern through the process of improving high frequencies and reducing the other frequencies.

3.4 Pretrained Resnet 101 Model for Feature selection:

The main purpose of resnet-101 is the selection of features and the ResNet model avoids the problem of vanishing gradient. Resnet-101 is a pretrained model consists of the output from trained millions of images and hence the usage of this pretrained model reduces the time complexity of the network. The complexity of the resnet-101, a convolutional neural network with 101 layers, is decreased by applying the proper filters to the feature maps. The rennet-101 trains the images without increasing the error percentage that helps in determining an efficient output.

3.5 Deep CNN classifier for the classification of knee osteoarthritis:

The deep CNN classifier is used to categorise osteoarthritis because it can automatically learn the fundamental filters without incurring large costs. Deep CNN classifier makes the training of the network faster and efficient and minimises the complexity of the network. The input layer, Convolutional layer, maxpooling layer, and fully connected layer make up the deep CNN. The Convolutional and the maxpooling layers alone consist of the learning parameters during the training process and the detailed description of individual layers are enumerated in below sections. Figure 2 depicts the deep CNN classifier's schematic representation.

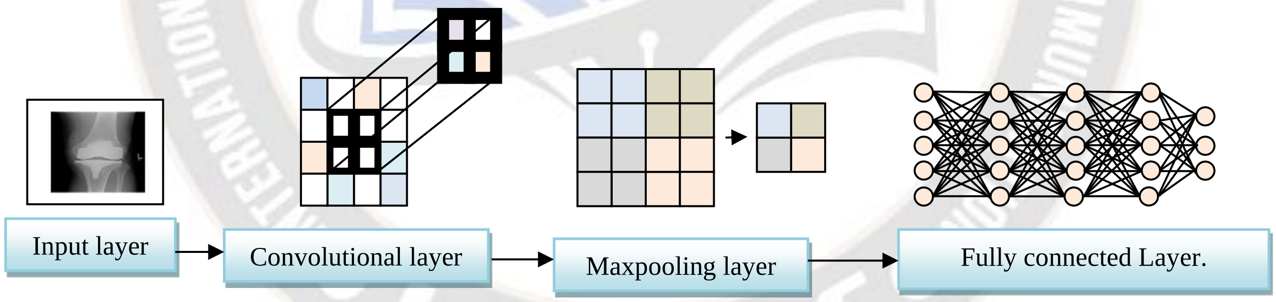

Fig. 2: Architecture of deep CNN for knee osteoarthritis classification

3.5.1 Input layer:

The input layer contains the data needed to classify the input, which typically includes the image's pixel matrix.

3.5.2 Convolutional layer:

The Convolutional layer consists of k-learnable filter and each filter consists of bias and weight. The obtained input from the input layer is multiplied by the weights and the tuning is performed in the classifier for attaining desired output. The bias in the layer represents the difference between the desired output and the current output. The tuning of the weight and bias parameter helps in achieving the classification results without complexities and the output from the Convolutional filters are mathematically represented by,

$$\left(F_{\alpha}^{j}\right)_{C,F} = \left(Q_{\alpha}^{j}\right)_{C,F} + \sum_{f_1=1}^{h_1^{f_1-1}} \sum_{f_2=-h_1^n}^{h_1^n} \sum_{f_3=-h_2^n}^{h_2^n} \left(W_{\alpha,f_1}^{j}\right)_{a,b} * \left(F_{f_1}^{n-1}\right)_{C+\beta,F+\delta} \tag{3}$$

here, the fixed feature map from the n^{th} Convolutional layer is given by $\left(F_{\alpha}^{j}\right)_{C,F}$ from the n^{th} Convolutional layer centered

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at C,F. The weight W^{j}_{α,f_1} and bias $F^{n-1}_{f_1}$ of the classifier, f_1, f_2, f_3 indicates the individual feature maps and these feature maps forms the output of the Convolutional layer.

3.5.3 Maxpooling layer:

Maxpooling is a pooling layer that extracts the maximum region from the feature maps that are necessary for knee osteoarthritis classification. Down sampling operation is performed for minimizing the special size and the significant information alone are concerned.

3.5.4 Fully connected layer:

The fully connected layer receives the feature maps from the pooling layer and generates the final output classification in this fully connected layer. The output from the fully connected layer is given by,

$$\left(FCL^{j}_{\alpha}\right)_{C,F} = \lambda\left(F^{j}_{\alpha}\right)_{C,F} \text{ with}$$

$$\left(F^{j}_{\alpha}\right)_{C,F} = \left(Q^{j}_{\alpha}\right)_{C,F} + \sum_{f_1=1}^{h_1^{f_1-1}} \sum_{f_2=-h_1^n}^{h_1^n} \sum_{f_3=-h_2^n}^{h_2^n} \left(W^{j}_{\alpha,f_1}\right)_{a,b} * \left(F^{n-1}_{f_1}\right)_{C+\beta,F+\delta} \tag{4}$$

The final classification of data is performed by the fully connected layer with high efficiency. The results obtained for the classification of knee osteoarthritis is interpreted in below section.

IV. RESULTS

The sections below exhibit the findings for the classification of knee osteoarthritis using deep CNN classifier.

4.1. Experimental setup:

The research based on the classification of knee osteoarthritis is conducted using the MATLAB software in Windows 10 operating systems, and the effectiveness of the research is demonstrated using the metrics accuracy, F1-measure, precision, and recall. The results demonstrate the effectiveness of the research.

4.2. Dataset description:

The osteoarthritis initiative database comprised of the data gathered from 4,796 subjects and 26,626,000 images, which assisted multiple researchers in learning more about the knee osteoarthritis disease. The parameters accuracy, F1 measure, precision and recall are measured for revealing the efficacy of the model, which are described below.

Accuracy: Accuracy measures the number of instances that correctly recognized the knee osteoarthritis and is measured using,

$$Acc = \frac{T_{pos} + T_{neg}}{T_{pos} + T_{neg} + F_{pos} + F_{neg}} \tag{5}$$

***F1-measure*:** F1 measure provides the measure of the harmonic mean between the precision and recall and is given by,

$$F1_{measure} = \frac{2*\left(Pre*Rec\right)}{\left(Pre+Rec\right)} \tag{6}$$

Precision: The precision measures the difference between the relevant instances and retrieved instances and is given by,

$$Pre = \frac{T_{pos}}{T_{pos} + F_{pos}} \tag{7}$$

Recall: The number of positive instances correctly identified by the proposed method is measured using recall and is given by,

$$Rec = \frac{T_{pos}}{T_{pos} + F_{neg}} \tag{8}$$

4.3 Comparative analysis for the proposed knee osteoarthritis classification model:

The comparative analysis for the deep CNN classifier is performed to explicit the superiority of the proposed model and is performed based on the k-fold and training percentage values.

4.3.1 Comparative Methods:

Random forests [15], Decision trees [16], Support Vector Machines (SVM) [17], K-nearest Neighbor (KNN) [18], and Neural Networks (NN) [19] are some of the comparison techniques utilised to assess the proposed deep CNN classifier.

4.3.2 Comparative analysis based on k-fold:

Figure 3 shows the comparison analysis based on the k-fold values 4, 6, 8, and 10 for the metrics accuracy, F1 measure, precision, and recall.

For the simplified view, the improvement rate obtained by the proposed deep CNN classifier while compared with existing methods is enumerated.

Figure 3 (a) shows the accuracy obtained by various methods and the proposed deep CNN attained an improvement of 3.21 % while compared with NN classifier during the k-fold 10.

Figure 3 (b) indicates the f1-measure obtained by the methods for the k-fold value 10 and an improvement rate of 3.217 % is obtained by the proposed deep CNN classifier, while compared with NN classifier.

The precision values acquired by the proposed deep CNN classifier are shown in Figure 3 (c), and an improvement rate of 2.99% is achieved at the k-fold value of 10 when compared to NN classifier.

Figure 3 (d) lists the measured recall values. As compared to the NN classifier, the proposed deep CNN improved by 3.23% during the k-fold value of 10.

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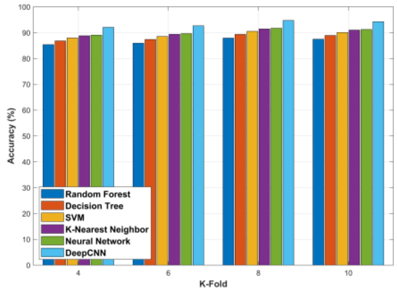
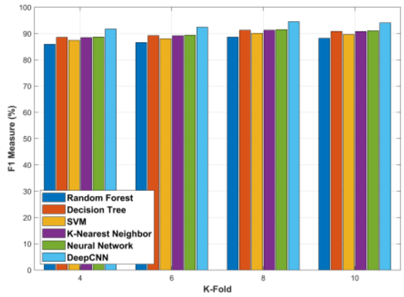


a)



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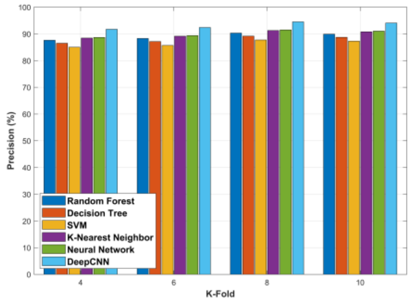

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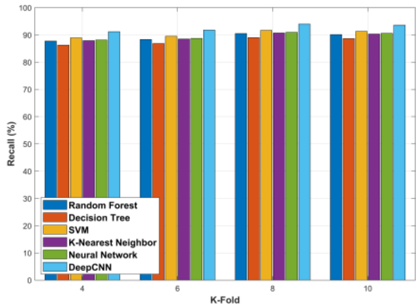


d)

Fig. 3. Comparative analysis of the proposed deep CNN based on k-fold a) Accuracy b) F1 Measure c) Precision d) Recall.

4.3.3. Comparison Evaluation Using Training Percentage:

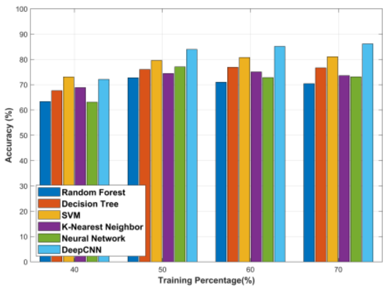
The metrics accuracy, F1 measure, precision, and recall are measured using the training percentages of 40%, 50%, 60%, and 70%, as shown in figure (4). For the simplified view, the improvement rate obtained by the proposed deep CNN classifier while compared with existing methods is enumerated.

Figure 4 (a) shows the accuracy obtained by various methods and the proposed deep CNN attained an improvement of 15.1 % while compared with NN classifier during 70 % of training data.

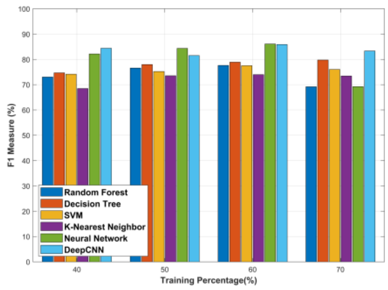
Figure 4 (b) indicates the f1-measure obtained by the methods for the training percentage 70 and an improvement rate of 16.9 % is obtained by the proposed deep CNN classifier, while compared with NN classifier.

The proposed deep CNN classifier's accuracy values are displayed in Figure 4 (c), and a comparison with the NN classifier shows an improvement rate of 1.16% at training percentage 70.

Figure 4 (d) lists the measured recall values, and when compared to the NN classifier, the proposed deep CNN showed a 16.9% improvement during training percentage 70.



a)



b)

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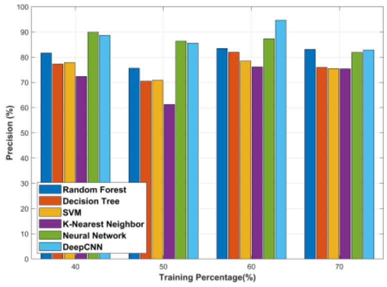
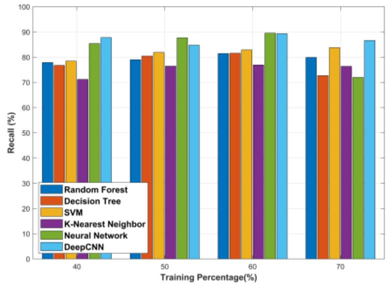


c)



d)

Fig. 4. Comparative analysis of the proposed deep CNN based on training percentage a) Accuracy b) F1 measure c) Precision d) Recall.

V. DISCUSSION

The values at which the proposed deep CNN classifier attained best values are enumerated in table 1. The deep CNN achieved the value of 94.244 % accuracy, 94.059 % f1 measure, 94.059 % precision and 93.586 % recall values when the k-fold value is 10. Similarly, the accuracy of 86.126 %, f1 measure of 83.330 %, precision of 82.840 % and 86.629 % for recall is obtained. The best values are obtained because of the learning of complex parameters without consuming large time, effective feature extraction made by the proposed deep CNN classifier.

The lack of any optimization techniques used to fine-tune the classifier is one of the proposed work's limitations. If optimization techniques had been used, the outcomes would have been more accurate and superior.

Table 1: Comparative discussion of proposed deep CNN based knee osteoarthritis classification model.

Method/ metrics	**K-fold**				**Training percentage**			
	Accuracy	**F1 measure**	**Precision**	**Recall**	**Accuracy**	**F1 measure**	**Precision**	**Recall**
Random forests	87.452	88.184	89.874	90.112	70.413	69.205	83.105	79.864
Decision tree	88.904	90.810	88.727	88.630	76.659	79.746	75.942	72.687
SVM	90.051	89.652	87.275	91.283	81.046	76.038	75.477	83.759
KNN	90.974	90.790	90.790	90.317	73.579	73.450	75.373	76.359
NN	91.218	91.033	91.246	90.560	73.114	69.241	81.871	71.983
Deep CNN	94.244	94.059	94.059	93.586	86.126	83.330	82.840	86.629

VI. CONCLUSION AND FUTURE SCOPE

The knee osteoarthritis classification using proposed deep CNN classifier is performed in this research. The knee osteoarthritis greatly impacts the lifestyle of people and causes fatigue, anxiety, and financial loss, affects the performance of work and so on. Osteoarthritis of the knee can be more effectively treated, and its effects lessened to a larger extent by early detection and classification. The usage of deep CNN classifier automatically extracted the features, reduced the computational time, and enhanced speed of classification, which helps in effective classification of the disease. The proposed deep CNN classifier's effectiveness is demonstrated by measuring the parameter metrics accuracy, f1 measure, precision, and recall, which achieved values of 94.244%, 94.059%, 94.059%, and 93.586% in terms of k-fold and 86.126%, 83.330%, 82.840%, and 86.629% in terms of training percentage, respectively. The authors want to work on a real-time dataset in the future with exact severity rating. The research's future focus could be on severity categorization with highly effective results.

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