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KNEE OSTEOARTHRITIS PREDICTION DRIVEN BY DEEP LEARNING AND THE KELLGREN-LAWRENCE GRADING

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A B S T R A C T

Degenerative osteoarthritis of the knee (KOA) affects the knee compartments and worsens over 10–15 years. Knee osteoarthritis is the major cause of activity restrictions and impairment in older persons. Clinicians' expertise affects visual examination interpretation. Hence, achieving early detection requires fast, accurate, and affordable methods. Deep learning (DL) convolutional neural networks (CNN) are the most accurate knee osteoarthritis diagnosis approach. CNNs require a significant amount of training data. Knee X-rays can be analyzed by models that use deep learning to extract the features and reduce number of training cycles. This study suggests the usage of DL system that is based on a trained network on five-class knee X-rays with VGG16, SoftMax (Normal, Doubtful, Mild, Moderate, Severe). Two deep CNNs are used to grade knee OA instantly using the Kellgren-Lawrence (KL) methodology. The experimental analysis makes use of two sets of 1650 different knee X-ray images. Each set consists of 514 normal, 477 doubtful, 232 mild, 221 moderate, and 206 severe cases of osteoarthritis of the knee. The suggested model for knee osteoarthritis (OA) identification and severity prediction using knee X-ray radiographs has a classification accuracy of more than 95%, with training and validation accuracy of 95% and 87%, respectively.

1. INTRODUCTION

The most prevalent form of joint disease, osteoarthritis (OA), it impacts 10-15% of individuals all over the world and can result in long-term pain as well as other problems (Conaghan et al, 2015). In 2015, according to estimates from the World Health Organization, 9.6% of men and 18.0% of women who were 60 years of age or older had symptoms of OA. 25% of those with symptomatic OA are unable to carry out their daily tasks, and 80% of those with mobility limitations. The results of 2012 (KNHANES) illustrated the fact that people aged 50 even older are 3.3% of men and 16.0% of women had OA (Neogi 2013). According to the size of the elderly population, osteoarthritis prevalence may rise as the average life expectancy gradually rises. In

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addition to having an impact on an individual's physical and mental health, OA also places a strain on society and the economy. The main signs and symptoms of OA are pain and stiffness in the joints, as well as movement restrictions. Previous studies have shown that the most important risk factors for developing osteoarthritis are smoking, having a metabolic condition, being older, being overweight, being of a different gender or ethnicity, having poor muscle function and not getting enough nutrients. Because osteoarthritis is condition that develops over time as well as hinders cartilage function that cannot be returned to its condition before it was injured, prevention must be the primary emphasis of treatment (Norman et.al, 2015). The physical well-being of people as well as communities is therefore more dependent than ever on early examination and diagnosis. The three-dimensional structures of knee joints can be reflected using MRI technology (Nacey et al, 2017). Due to the high cost of the examination and the fact that MRI is only offered in large medical facilities, it is not appropriate for use in the routine diagnosis of knee osteoarthritis. Therefore, the X-ray has become the best model for the screening of knee osteoarthritis for the reason that it is risk-free, has a low cost, and is accessible to a vast number of individuals. Figure 1 illustrates both the samples and the standards for each grade level.

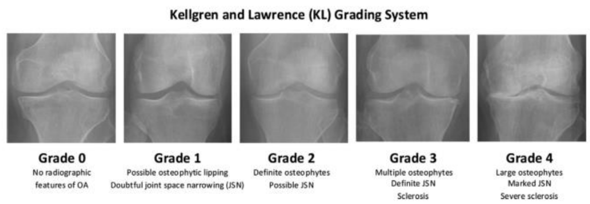

Figure 1. KL grading for samples of knee joints

The KL classification only applied in the context of knee osteoarthritis (OA), as stated in the information that was provided in their initial study (Guan et al, 2020) as in Figure 1. In the beginning stages of the KL classification, anteroposterior radiographs of the knee were taken to describe the condition. A number between 0 and 4 was assigned as the grade for each radiograph. Radiographs are the method of choice for knee osteoarthritis (OA) classification. These radiographs make use of the Kellgren-Lawrence (KL) grading, which uses a scale from 0 to 4, where 0 represents normal, 1 represents doubtful symptoms of OA, 2 represents mild OA, 3 represents moderate OA, and 4 represents severe OA (Kellgren & Lawrence, 1957). KL grades are normally issued to each knee joints within a relatively short amount of time following a doctor's examination of a knee X-ray The expertise and attentiveness of the attending physicians have a significant impact on the reliability of the diagnosis. In addition, the standard for determining a student's grade in KL is extremely vague. As an illustration, the presence of questionable joint space nodules and the likelihood of osteophytic lipping are two of the requirements for the KL grade 1 designation. When evaluating that knee joint at different points in time, even the same doctor may come to a different conclusion regarding the patient's KL grade. According to research (Guan et al, 2020), the KL intra-rater reliability falls somewhere in the range of 0.67 to 0.73. We have a theory that the low assurance of the grading done by physicians is because of the ambiguity of the test, which causes the knee joint's KL grade to be misidentified as one of the grades that are closer to it.

Deep learning has been the most important contributor to the overall progress that has been made in the health informatics (Lim et al, 2019). In that, the primary focus is on the analysis of huge amounts of dataset in order to enhance medical decision support technologies and keep track of patient data for both assurance and patient access to healthcare services. Electronic health care metrics are extremely main resources of patient data. These datasets hold data on the patient's prognosis, diagnostic procedures, treatments and care plans, immunization documents, allergy information, diagnostic images, and lab tests, amongst other aspects of the patient's medical history. These large datasets could be effectively analyzed to yield important insights into the management of diseases (Antony et al, 2017). Knee osteoarthritis (OA) is another condition that primarily affects people over the age of 55, with an increased prevalence in those over the age of 65 (Postler et al, 2018). According to the projections of researchers, there will be 130 million people affected by knee OA worldwide by the year 2050. However, OA of the knee can be stopped from progressing, and people's quality of life can be improved if it is detected and treated early (Wang et al, 2021). Many of the earlier studies had shortcomings, such as using a limited number of osteoarthritis-related variables or not having access to a sufficient amount of data. As a result, research must be conducted to develop a tool on large amounts of data in order to predict the osteoarthritis, which contributes to the difficulty a disease presents for society. The purpose of the study is to build a deep learning approach that employs information about medical treatment and patterns of healthy behavior to identify the presence of OA. The risk of osteoarthritis developing in hips and knee joints is higher (OA) than other joints in the body because they are the ones that bear weight. On the other hand, the cartilage tissue surrounding each and every joint in the body is somewhat susceptible to change and damage. The proposed system is helpful for analyzing factors that are associated with osteoarthritis and developing a model that can predict the progression of osteoarthritis.

2. LITERATURE

Due to the speedier diagnosis and higher rate of early identification, there is a great demand for an automatic grading of knee severity. This is due to a shortage of radiologists, especially in remote areas and the lengthy process involved in analysing X-ray pictures of the knee. Because of this, a great number of computer-aided diagnosis (CAD)-based radiology methods are suggested to identify and evaluate knee osteoarthritis (Anifah, L et al, 2013) (Kotti et al, 2017) (Wahyuningrum et al, 2016). The application of deep learning and machine learning techniques in the field of medical imaging has increased recently. These methodologies allow for the problem-solving of classification (Varma et al, 2019) (Abd Ghani et al., 2020), detecting (Lim et al., 2019) (Kubkaddi & Ravikumar, 2018), and other related problems with no need for the expertise of a radiologist (Wang et al, 2020) (Praveena et al, 2020). Determining the level of severity of osteoarthritis of the knee can be accomplished through classification by noting the alterations in the knee joints spaces and the growth of osteophytes (Gan et al., 2021) (Ebrahimkhani et al., 2020). A developed scoring system for predicting radiographic and symptomatic knee OA [F. (Eckstein et al., 2021) risks by making use of artificial neural networks (ANN) from a survey. In a multipurpose bio-medical image classifier it was referred (Razmjoo et al., 2020) to categorise knee OA images (Tiulpin et al., 2018) (Tack, 2018) and for CAD-based early identification of knee OA (Ebrahimkhani et al., 2020). Features that are manually constructed and retrieved from unprocessed and modified images are used by WND-CHARM (Razmjoo et al., 2020) (Tiulpin et al., 2018).

To be more specific the design and implementation of DL-based detection algorithms were effective in determining the severity of knee osteoarthritis (Varma et al., 2019). In addition to this, even though it doesn't involve human feature engineering, they demonstrate performance in the biological sector of X-ray analysis. This is due to the fact that feature engineering occurs inadvertently in training phase, when the model is adjusting its system parameters to suit the relevant data. On the other hand, in order to produce the desired results, the data must be modified beforehand using a specialised feature engineering or training technique in order to employ any of the basic machine learning algorithms. When compared the traditional ML algorithms, amount of computational power and resources that DL algorithms typically demand can be considered excessive. In addition, it leads to overfitting if it is given too little data to work with. Additionally, there are several varieties of DL, such as TL based CNN (Wang et al., 2020), Resnet, Inception, that produce impressive results in computer vision. In addition, an innovative method for evaluating the severity of knee OA based on X-ray images was also proposed (Antony et al., 2017). In order to train FCNN to quantify the of knee osteoarthritis, KL grades served as training input. osteoarthritis Study, also known as MOST, were chosen in order to evaluate the efficacy. When the statistical findings of this approach were compared to those of other ways that were currently in use, it was found that this method had advancements in accuracy rate, recall, F1 score, and precision (Norman et al., 2019).

Based on the KL grading method, a novel strategy has been developed to evaluate osteoarthritis (OA) in knee X-rays. This technique employs neural networks to adopt supervised procedures for exact identification from the original X-rays (Norman et al., 2019). They said the method could be used as assistance to physicians in the process of diagnosis that is very reliable. The KL grading method was followed alongside two CNNs to determine the level of knee osteoarthritis (Chen et al., 2019). The images of the knee joint that were detected were then classified by making use of modified ordinal loss evaluation and then CNN is performed. These CNNs included different versions of YOLO, DenseNet, VGG, ResNet, and InceptionV3. A CAD method for the faster identification of knee osteoarthritis that utilises digital knee X-ray pictures and few ML algorithms are described (Brahim et al., 2019).

Convolutional neural networks (CNNs) lately surpassed numerous methods in image processing. CNNs are taught efficient for feature sets that are ideally suit for fine-grained classification (Nguyen et al., 2020) We previously showed that utilising transfer learning, pre-trained CNNs like the VGG 16-Layers network (Shamir et al., 2009), the VGG-M-128 network (Neogi, 2013), and the BVLC reference CaffeNet (Conaghan et al., 2015) trained on the ImageNet LSVRC dataset (B. Norman et al., 2019) may be improved for knee OA image classification. (Conaghan et al., 2015). In the past, (Ebrahimkhani et al., 2020) suggested using template matching as a method to automatically detect and extract the knee joints. It takes a long time for this method to process large datasets like OAI, and it has poor accuracy and precision when it comes to detecting knee joints.

In general, DL and ML approaches multiple bone illnesses have been diagnosed using in the methods that have been referred by previous works that have been published in (Christodoulou et al., 2019) (Du et al., 2018) (Hirvasniemi et al., 2022). When it comes to classification into binary categories, these methods have proven to be effective. On the other hand, owing to the fact that they are not applicable to the classification tasks of knee OA, this method achieved an accuracy of 68% (Wang et al., 2012). Therefore, it is challenging to recommend a useful instrument for the early categorization of osteoarthritis of the knee. Therefore, for the purpose of enhancing performance in classification, an approach that makes use of both types of learning is essential.

3. PROPOSED SYSTEM

Knee X-rays were taken from a dataset that was available to the general public and used by us: An Initiative for Osteoarthritis (OAI) (https://data.mendeley.com/datasets /t9ndx37v5h/1/). We outline an approach to use deep learning to predict knee OA from X-rays. The classifier was created using X-rays that had been manually categorised into the following stages: normal, mild, moderate, severe, and doubtful. First, a set of picture methods used to evaluate and image changes that are helpful for detecting OA are found. After that, weights are assigned to this feature representation in order to make the detection process more accurate. The experiment's dataset included 3300 knee X-ray images fully connected layer, FC layer adds a bias vector after multiplying the input by a weight matrix. There is at least one completely linked layer following the convolutional and down sampling layers. The detection is based on the classification of the VGG16 model, which corresponds to the various stages of the severity of OA.

The suggested system is useful for computer-aided diagnosis. Osteoarthritis is typically detected visually by looking at medical images, because early-onset osteoarthritis is difficult to detect manually, even in its tiniest progression. This is how artificial intelligence works. The creation of an osteoarthritis clinical decision aid shows significant promise when using the proposed system mode VGG16. Among the most impressive vision model topologies available at this time the convolution neural net (CNN) architecture known as VGG16 (Lim et al., 2019). The notable characteristic of VGG16 is that it gave higher importance to have convolution layers that are 3x3 and that it always used the same padding and maxpool layers that were 2x2 respectively. The convolution and max pool layers are arranged in precisely the same manner throughout the architecture. It concludes with three fully connected layers (FC). This system model is simple to use and serves as an excellent foundation for learning. The schematic methodology is shown in Figure 2.

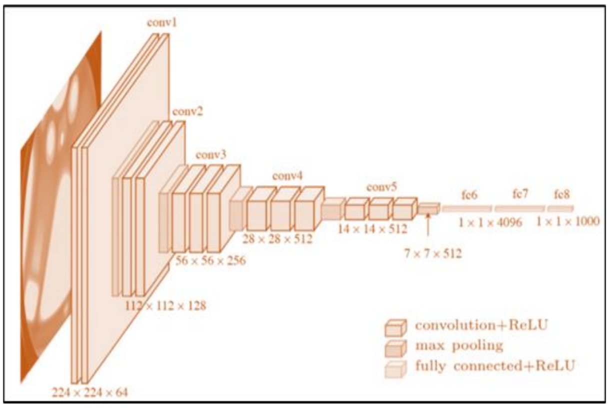

Figure 2. A Schematic Methodology for Proposed Classification (VGG16) (Lim et al., 2019)

The proposed system outperforms all other models currently in use, with an average training accuracy of 95% and a maximum validation accuracy of 87%. The suggested system model can be trained beforehand using ImageNet. The suggested system proved to be an effective methodology that will be crucial in effectively monitoring and identifying knee osteoarthritis conditions.

The proposed algorithm is composed of the following steps:

1. Getting the Knee OA data set, bringing in library files and making a personalized dataset.
2. Pre-processing the images – Resizing and normalizing the images to 224 x 224.
3. Prepare Data Loader.
4. Training the system using VGG16 and SoftMax.
5. Teach the model by pulling out features.
6. Getting the properties from several VGG layers
7. KL grading.
8. Get Execute the model, and plot the graphs to evaluate the accuracy and loss.
9. Saving the Trained Model.

Convolutional neural networks in terms of image recognition, they excel. The convolution operation, which sets CNN apart from conventional neural networks, is the crucial component to comprehend. CNN repeatedly scans an image after it is input to look for specific features.

4. EVALUATION PARAMETERS

All stages of a Disease Management (DM) programme are fraught with concerns about diagnostic or predictive accuracy, which ultimately have a big impact on how effective the programme is. A few applications where accuracy evaluation is helpful, if not essential, involve things like the detection of patients who are already sick, predictive modelling of future health status and costs, and risk stratification.

The sensitivity, recall, and F-measure performance metrics, which are also known as accuracy, recall, and accuracy, were used to evaluate the knee OA classifier models. First off, accuracy is calculated as the proportion of correctly categorized cases to all cases. As a result, it computes to evaluate the total effectiveness of the suggested method, which is based on the information, and which may be mathematically expressed as Equation (1).

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \qquad (1)$$

Instances that are correctly classified as positive are denoted by the terms TP (true positive) and FN (false negative). On the other hand, instances that are incorrectly classified as positive are denoted by the term FP (false positive), and instances that are correctly classified as negative are denoted by the term TN (true negative).

The term "sensitivity" or "recall" in Equation (2) is a predictive measure that estimates the likelihood of discovering all positive units in the dataset. As a consequence of this, it refers to the percentage of patients across all relevant occurrences for whom an accurate prediction may be made. The F-measure, which is also referred to as the F-score in Equation, takes into account both precision and recall (3).

$$Sensitivity\ or\ Recall = \frac{TP+TN}{TP+FN} \quad (2)$$

$$F - measure = \frac{(2\ X\ Precision\ X\ Sensitivity)}{Precision+Sensitivity} \quad (3)$$

A brief theoretical overview of the techniques employed by the suggested approach. CNN is most well-known and fiercely applied algorithms in DL (Antony et al., 2017). Which, in comparison to its forerunners, has the main advantage automatic recognition of the relevant features without human participation. It takes its cues from the visual system of the human brain. CNNs are created to give computers the ability to perceive the world similarly to how humans do. CNNs have applications in a variety of fields, including natural language processing, picture classification, and image recognition.

4.1 Convolutional Layer

CNN gets its name from the "convolution" procedure that occurs in the convolutional layer, which is also the primary layer of the network. Additionally, kernel convolution is a crucial component of a number of other computer vision techniques. It is crucial to the functioning of CNN, which uses a number of convolutional filters referred to as kernels. This method involves applying a kernel or filter—a small number matrix—to our image and then transforming it using the values of the filter. In addition, each filter is linked to a specific matrix that performs a convolution operation on the input image. This is known as the convolution matrix. In order to generate the output feature maps, the input image is convolved with these filters first. This formula is utilized in the process of computing feature map values, as demonstrated by Equation (4).

$$F[m, n] = (I * K)[m, n] = \sum_i \sum_j K[i, j]I[m - i, n - j] \quad (4)$$

The letter K stands for the kernel, and the letter I for the input image. The indices of the rows and columns of the result matrix are represented by the symbols m and n, respectively. An output feature map was produced by us through the use of a convolutional approach. The equation for the convolution layer reveals how many of the input feature maps are combined to produce each output feature map.

4.2 Activation Layer

The activation layer, often referred to as the nonlinear layer (Ebrahimkhani et al., 2020), comes immediately after each convolution layer. The primary function of the system that this layer is added to is to perform linear computations; the nonlinearity that is intended to be added is the purpose of this layer. For instance, adding a convolutional layer on top of an activation layer that uses a rectified linear unit, or ReLU, increases the amount of nonlinearity in the input data and changes any negative input values to positive numbers. This is because the ReLU outputs 0 for any input that is negative. The key benefit of using ReLU rather than one of the other activation functions is that it decreases the amount of work that must be done by the computer. Therefore, CNN with ReLU is more expedient and less difficult in the present circumstance. Mathematically, it can be expressed by the usage of Equation (5).

$$f(j) = \max(0, j) \quad (5)$$

4.3 Pooling Layer

In CNN architectures, subsampling or pooling layers are usually present in addition to the convolution layers. Each feature map undergoes its own processing, which is determined by the convolution layer. In order to lower the likelihood of overfitting and improve the quality of retrieved features, pooling methods limit the spatial size of the feature map. Maximum pooling and average pooling are the two strategies for pooling that are used the most frequently (Zeiler & Fergus, 2014). The two different methods of pooling are shown in Figure 3.

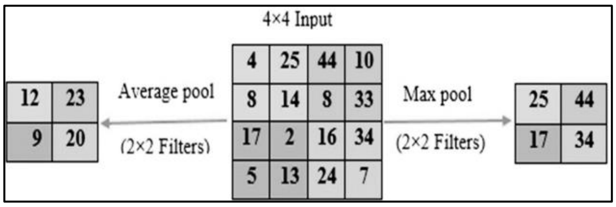

Figure 3. Input of Two layers (Zeile, 2014)

4.4 Fully Connected Layer

The outputs of the convolution and pooling layers permit us to extract high-level features from the input images. However, combining fully connected (FC) layers may be significantly more beneficial because it is also a low-cost way to learn the nonlinear combinations of these characteristics. This could have a significant impact on the accuracy of the model. A potential classification score is produced by the FC layer, which combines the convolution and pooling layers. This score is used for labelling the input images that are found in the input layer. After the FC layer has sent the two-dimensional result to the output layer, the output layer can make a prediction regarding the input class label by employing a sigmoid function or a soft max. Equations (6) and (7) demonstrate a Softmax and sigmoid activation function mathematically.

$$\boldsymbol{\sigma}(\boldsymbol{x}) = \frac{e^{x_j}}{\sum_{k=1}^{k} e^{x_k}} \quad (6)$$

$$\boldsymbol{f(y)} = \frac{\mathbf{1}}{\mathbf{1}+\boldsymbol{e^{-y}}} \tag{7}$$

In this particular instance, x and y stand for the values that are obtained from the neurons that are located in the output layer. When referring to a multiclass classification, the number of output classes is denoted by the letter k. (x) represents the predicted probability that the test input belongs to class j, and one way to think about it is in this way. Another way to think about it is as follows. The CNN model also computes, with the help of the loss function, the extent to which an estimated value varies from the value that is being seen in the data. In doing so, it contributes to the process of establishing what a sound mode prediction might be. The Conv Net configuration is shown in Table 1.

Table 1. Conv Net Architecture (K. Simonyan & Zisserman, 2014)

Conv Net Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
Input (224 X 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
Soft-max					

5. RESULTS AND DISCUSSIONS

The proposed architecture was put into force in Python. First, importing the required libraries, which include keras for the purpose of constructing the primary model, sklearn with the goal of partitioning the data that is utilized for training and testing, PIL for the purpose of converting images into arrays of numbers, and various other libraries such as pandas, numpy, matplotlib, and tensorflow. We obtain the X-ray images as well as the labels associated with them. The images should then be pre-processed for scaling and resized to dimensions 224 x 224 in order to facilitate recognition of each image. The images are then converted into a numpy array.

VGG16, FC layer and flask are used to implement the architecture. Tensor flow serves as the back end for the frame work. Kaggle has ImageNet pre-trained weights dataset. Immediately following the pre-processing of a knee X-ray image of any size for VGG16. The dataset used contains 3300 digital Knee X-ray. During the testing period, the X-ray picture of the knee is enhanced, stabilized, and then concatenated by the pre-processing technique that was used while the training period.

Compiling the model and applying it with the fit function are the next steps. A batch size of six. After that, we will plot the graphs to determine the degree of accuracy and loss. The average accuracy of our validation was 0.87%, while the average accuracy of our training was 0.95%. As a result, the proposed method is having the AUC of 0.950 which indicates that testing model is perfect. The proposed system achieves the highest accuracy of validation accuracy of 87%, and the average training accuracy of 95%. When compared to versions of ResNet or DenseNet, the improved VGG16 model has the highest identification capability, illustrating how dependent CNN models are on the recognition challenge in question. Figure 4 illustrates the declines in accuracy, training, and validation that take place over the course of the epochs. Figure 5 presents the confusion matrix, which categorizes knee osteoarthritis according to KL grade.

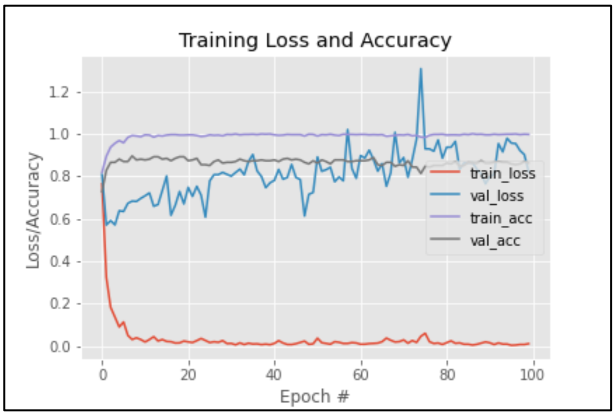

Figure 4. Epoch-based training and validation accuracy

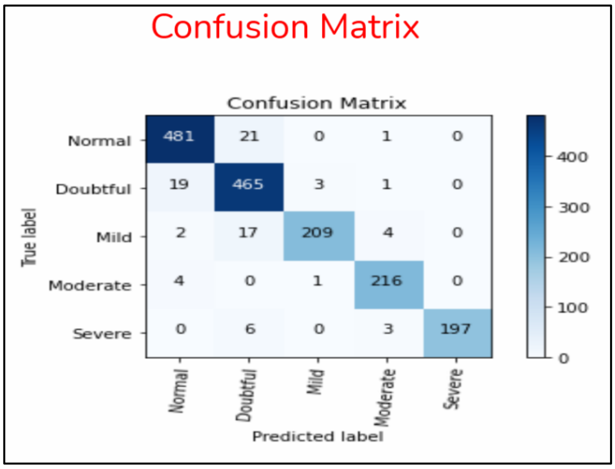

Figure 5. The KL grading confusion matrix of proposed method

6. CONCLUSIONS

In this research, an effective method for determining the severity of knee osteoarthritis from X-ray images by making use of DL convolutional neural networks for the goal of extracting features is proposed. These networks are used in order to break down the image into its component parts. In order to make the most of OAs in order to achieve its goal of having the ability to identify multiple features from knee X-ray. The DHL-I model that has been proposed makes use of a convolutional neural network that has been pre-trained. Deep learning was used to implement a VGG 16 model-based system to predict knee osteoarthritis. Knee images of various sizes and shapes have been used as input to train the system. According to the results of the experiments, the suggested DHL-I model exhibited good levels of accuracy when processing training data as well as testing data. The proposed system has a validation accuracy of 87% and an average training accuracy of 95% for detecting the presence and absence of knee osteoarthritis. The specificity achieved in the proposed work is 95%, demonstrating fewer false predictions. In addition, when it comes to determining whether or not an individual has knee osteoarthritis, the suggested method has a validation accuracy of 87 percent and an average training accuracy of 95 percent. We predict that the use of this computer-assisted diagnostic tool will greatly increase the efficiency and precision with which OA patients are diagnosed.

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