JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

DEEP LEARNING BASED KNEE PAIN CLASSIFICATION X-RAY USING IMAGES

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Abstract-- Millions of people worldwide suffer from knee pain, which is a common and incapacitating symptom that frequently indicates underlying illnesses such arthritis, rheumatoid arthritis, and osteoarthritis (OA). For planning therapy and patient care management to be successful, accurate diagnosis of these disorders is essential. Medical imaging is essential to the diagnosis process since it gives doctors detailed information on joint abnormalities and structures, especially when it comes to X-ray imaging of the knees. Deep learning approaches have transformed medical image analysis in recent years, bringing up a paradigm shift in the way medical practitioners interpret diagnostic images. Deep learning algorithms have proven to be exceptionally effective in automating image interpretation activities, which improves the efficiency and accuracy of diagnosis. Inspired by deep learning's potential in medical image processing using CNN's, this study offers a novel approach for classifying knee pain using X-ray pictures. More specifically, Grade 0, Grade 1, Grade 2, Grade 3, and Grade 4 are the five different diagnostic groups into which our approach attempts to classify knee X-ray pictures. We achieve this by utilizing power pretrained models, such as VGG12, ResNet50, DenseNet, and EfficientNet, which are well-known for their efficacy in picture classification tasks.

Keywords : OA, arthritis, deep learning, CNN.

I.INTRODUCTION

Knee pain is a common and serious symptom faced by millions of people worldwide. It can indicate problems such as arthritis, fractures, and osteoarthritis, which must be identified accurately to plan treatment and manage patient care. Medical imaging, especially X-ray imaging of the knees, is crucial in diagnosis, providing detailed information about joint structures. Recently, the emergence of deep learning has revolutionized medical image analysis, offering healthcare professionals a new way to read images correctly. Deep learning algorithms have demonstrated remarkable ability in automating image interpretation tasks, making the diagnosis process more accurate and efficient. This study proposes a new method for classifying knee pain using X-ray images. Our model aims to categorize knee X-ray images into different grades, ranging from Grade 0 to Grade 4. To achieve this, we use pretrained models such as VGG12, ResNet50, DenseNet, and EfficientNet, known for their image classification abilities

During the training of the model, we utilized various pre-trained models to classify knee pain caused by Osteoarthritis into different grades ranging from Grade 0 to Grade 4. We even included Grade 5, which doesn't exist. Grade 0 represents a healthy knee image with no signs of Osteoarthritis. Grade 1, called "Doubtful," indicates joint narrowing with osteophytic lipping, hinting at early stages of Osteoarthritis. Moving to Grade 2, named "Minimal," shows definite osteophytes and possible joint space narrowing, indicating further advancement of the issue. Grade 3, labeled as "Moderate," comes with multiple osteophytes, clear joint space narrowing, and mild sclerosis, indicating a moderate level of Osteoarthritis. Lastly, Grade 4, known as "Severe," displays large osteophytes, significant joint narrowing, and severe sclerosis, pointing to an advanced stage of Osteoarthritis with extensive structural changes in the knee joint. By using these grades, it is possible to assess the severity of Osteoarthritis in knee images, which can help with treatment decision-making and patient management.

Transfer learning is a technique in deep learning that offers significant advantages by utilizing pre-trained neural network architectures that were trained on large datasets like ImageNet to tackle new tasks with less labeled data. This approach allows knowledge from one area to be transferred to another, resulting in quicker convergence, reduced computational resources, and improved generalization performance. By fine-tuning pre-trained models on specific datasets or using feature extraction, transfer learning helps to efficiently utilize learned representations for various applications like image classification. Our choice of models includes VGGNET, RESNET50, DenseNet121, and EfficientNetB0.

Our primary objective was to demonstrate the effectiveness of our deep learning model in accurately identifying knee X-ray images among various diagnostic types through rigorous and validated trials. Our ultimate goal is to equip healthcare professionals with the necessary resources to promptly diagnose and treat individuals suffering from knee pain with accuracy, objectivity, and efficiency.

X-ray images are typically provided as hard copies or X-ray films, and our dataset is an electronic replica of these films. In X-ray images, osteoarthritis, which causes knee pain, is indicated on a pain scale of 0 to 4. Each photograph in the file is labeled with a grade from 0 to 4: Grade 0, Grade 1, Grade 2, Grade 3, and Grade 4.The dataset consists of the folders train, val and test. Each of the three folders consists of other 5 folders named Grade0, Grade1, Grade2, Grade3, Grade4.

The folder train is user for training the dataset, folder val is used for validating the trained model and test folder is used to test the efficiency of the trained model. The images present in the val folder are Unseen images for the trained model, means these images are not used for the training the model. The dataset consists of images for both knees of both left leg and right leg.

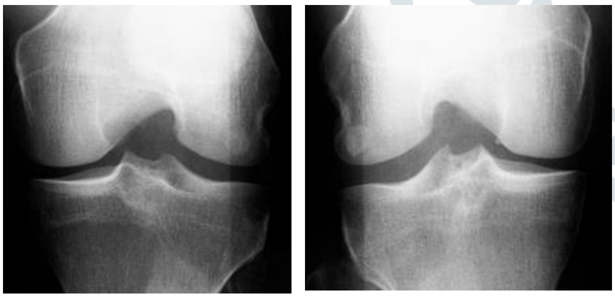


Fig. 1. knee x-ray image of the left and right knee classified as Grade0

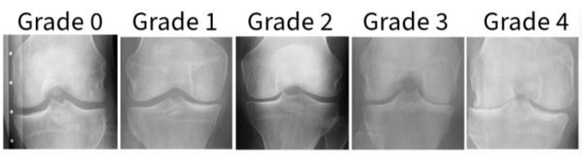


Fig. 2. Sample Images of Grade 0, Grade 1, Grade 2, Grade 3, Grade 4 classified images.

Our findings highlight the promising potential of deep learning-based approaches in enhancing the diagnosis and management of knee-related conditions. By accurately distinguishing between various knee pathologies, including different stages of osteoarthritis, our model offers valuable insights to healthcare practitioners, facilitating informed decision-making and personalized patient care strategies.

II.LITERATURE SURVEY

The continuous loss of cartilage within the knee joint is the hallmark of knee osteoarthritis, a persistent degenerative joint ailment. The damaged knee stories ache, stiffness, decreased mobility because of this deterioration. commonplace causes of knee osteoarthritis encompass growing older, sluggish put on and tear at the knee joint, and joint trauma or damage. weight problems, genetics, overuse of the joint, and positive jobs requiring repetitive knee moves are threat factors for osteoarthritis of the knee. human beings may additionally suffer worsening symptoms as the illness worsens, including hassle walking, climbing stairs, or going about their regular business. at the same time as there may be no treatment for knee osteoarthritis, there are numerous treatments that could assist control signs and decorate great of lifestyles, such as ache control, bodily remedy, exercising, and weight manage. Osteoarthritis (OA) is expected to impact one in three human beings sooner or later of their lives [3]. A meniscus tear, cartilage breakage, reduced synovial fluid, and narrowing of joint area are some of the preliminary symptoms of arthritis. it could also affect systems and organs like the skin, heart, and lungs in both males and females, but it generally influences center-elderly women extra often [1]. Over half of of these 65 years of age and above have as a minimum one joint stricken by OA. by 2030, nearly 25% of usa citizens might be over sixty five, growing their risk of getting OA. Older adults' high-quality of lifestyles is considerably impacted through knee osteoarthritis (OA). Even worse, there may be presently no recognized remedy that could sluggish down or even reverse the innovative structural deterioration related to knee OA [3].

on the subject of figuring out knee osteoarthritis (OA) from scientific imaging facts, such X-rays and MRI scans, deep getting to know algorithms have validated significant promise. Deep studying algorithms can routinely extract good sized traits from snap shots by using utilizing convolutional neural networks (CNNs) [2]. This permits for the correct category of numerous tiers of knee OA primarily based on radiographic effects [2]. those fashions can apprehend patterns connected to osteophytes, sclerosis, narrowing of the joint area, and different ordinary modifications in knee joints that imply the severity of osteoarthritis. huge-scale datasets of annotated knee pictures also can be included into deep studying techniques to beautify model performance and generalization. Deep mastering-based classification algorithms have the capability to assist physicians with diagnosis, monitoring the path of the disease, and directing individualized treatment plans via providing brief and correct opinions of the severity of knee OA.

An efficient deep learning approach called transfer learning is widely used to categorize medical imaging data [8]. Using convolutional neural network (CNN) architectures that have already been trained on huge datasets such as ImageNet, VGG16, transfer learning allows applying learned features to new tasks that have a limited amount of labeled data [8]. Transfer learning models can automatically extract relevant information from knee X-rays or MRI images and adapt their learned representations to the situation, facilitating the accurate classification of different OA severities in the context of knee OA categorization [8]. Pretrained models can learn task-specific features by fine-tuning them on datasets using robust feature representations obtained from diverse image data. This method improves classification performance while speeding up model training, even with limited annotated datasets. Disease prediction and classification based on deep learning relies heavily on medical imaging such as MRI and X-ray [6]. Deep learning algorithms are particularly good at identifying complex patterns and features in medical images, making it possible to accurately diagnose and classify a wide range of diseases using different modalities. Convolutional Neural Networks (CNNs) can analyze X-rays and discover irregularities in bone structure that could be signs of disorders such as osteoarthritis or fractures. Similarly, deep learning models in MRI images are able to identify minute tissue changes, lesions or anomalies associated with musculoskeletal diseases, cancer or neurological diseases. Deep learning algorithms can learn to interpret complex medical images with high accuracy by leveraging large annotated datasets, transfer learning, and advances in model architecture. This capability will help healthcare workers with early disease detection, treatment planning and monitoring. X-ray is considered a more practical and affordable method of analyzing the knee, which allows the bone structure to become visible than MRI and CT scans [6].

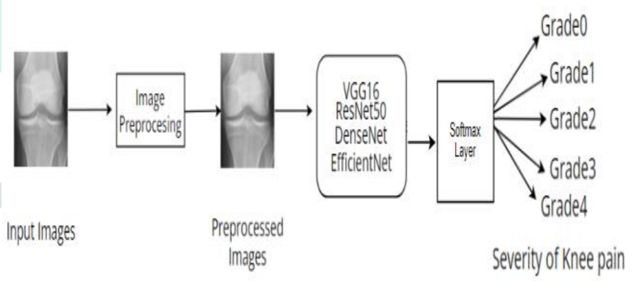
In healthcare, X-rays, MRIs, CT scans and ultrasounds are stored and transmitted using DICOM (Digital Imaging and Communications in Medicine) images [15]. In addition to image data, DICOM files also contain metadata and other study identifiers, imaging parameters, and patient demographics related to medical imaging studies.Digital images of knee radiographs are initially stored in DICOM format, but can be quickly converted to the widely used JPG format for further use [15]. The Kellgren-Lawrence (KL) classification system [2] is the industry standard used by medical professionals to categorize the degree of osteoarthritis of the knee on radiographs. The Kellgren and Lawrence (KL) severity grading system was adopted in 1961 in accordance with WHO guidelines. The KL system divides it into five classes, ranging from 0 to 4, according to the severity of knee OA [1].

The dataset we used to train the knee pain classification model comes from the OAI [3]. The authors [11] investigate the use of computer-supported methods in the diagnosis of leukemia. An aggregation-based deep learning model was proposed to classify leukemic B-lymphoblasts using an automated method that can distinguish between cancer and healthy cells. The CNNs that were pretrained and fine-tuned were used in the proposed model to extract features. Deep learning was used by the authors [12] to analyze glioma tumors. A multi-class model was built that used SVM for classification and deep learning for feature extraction.Thus, we used pre-trained deep learning-based models such as VGG16, DenseNet, ResNet50, EfficientNet [11] to classify knee pain using X-ray images.

To be consistent with the architecture of the model, all input images for deep learning models must have the same size. This is known as fixed input dimensions. Standardizing image sizes guarantees consistency in the input data, making it easier to apply neural network layers and allowing for a smooth integration into the model. When training and inferring models, keeping the image size constant promotes effective memory use and computational performance. Because fixed-size images provide batching and parallel processing, training times are shortened and scalability is enhanced. For training the model, all the images in the dataset are brought to a standard size of 224*224*3 pixels [6].

III. PROPOSED MODEL

This research for the classification of Knee pain using X-ray images used Deep Learning based classification models like VGG16, ResNet50, DenseNet121, EfficientNet . The architecture of the proposed model is shown in Fig. 4



Fig, 3. The Architecture of the Proposed Model

Firstly, the knee pain classification model takes x-ray images as inputs. These input images are of different sizes. For a deep learning model, to effectively work the input images must be in same size. So, the images are pre-processed before training the model to get better results. Once the input images are pre-processed and resized to desired size, the images are given to the pretrained models like VGG16, ResNet50, DenseNet121, EfficientNet. Thirteen convolutional layers and three fully linked layers make up the sixteen layers of VGG16. VGG16 is renowned for its max pooling layers, compact 3x3 convolutional filters, and consistent architecture. The model can extract high-level features from photos because it has been pre-trained on the ImageNet dataset. ResNet50 is known for its creative use of residual connections, which, by reducing the vanishing gradient issue, enable the training of extremely deep neural networks. Deeper model optimization and training are facilitated by the network's ability to learn residual functions thanks to these residual connections. A deep convolutional neural network architecture known as DenseNet is distinguished by its densely linked layers. Every layer in DenseNet gets feature maps from every layer that came before it and sends its own feature maps to every layer that came after it in a dense block. A convolutional neural network called EfficientNetB0 seeks to combine cutting-edge performance with extremely efficient model parameters. Its foundation is a brand-new compound scaling technique that scales depth, width, and resolution consistently. Because of its streamlined architecture, EfficientNetB0 provides higher accuracy while being smaller and faster than earlier versions.

Once the model gets trained the output of the models are given to the SoftMax layer which classifies the x-ray images into 5 classes Grade 0, Grade 1, Grade 2, Grade 3 and Grade 4. The dataset which is used for the training consists of 5 classes named Grade 0, Grade 1, Grade 2, Grade 3 and Grade 4. Grade 0 has 2286 images, Grade 1 has 1046 images, Grade 2 has 1516 images, Grade 3 has 757 images, and Grade 4 has 173 images. Grade 0 signifies a healthy knee image, showing no signs of osteoarthritis. Moving up the scale, Grade 1, labelled as "Doubtful," suggests potential joint narrowing with the presence of osteophytic lipping, indicating early stages of osteoarthritis. Progressing to Grade 2, termed as "Minimal," there is a definite presence of osteophytes, along with possible joint space narrowing, indicating further advancement of the condition. Grade 3, categorized as "Moderate," presents with multiple osteophytes, clear joint space narrowing, and mild sclerosis, reflecting a moderate level of osteoarthritis. Finally, Grade 4, described as "Severe," demonstrates large osteophytes, significant joint narrowing, and severe sclerosis, indicating an advanced stage of osteoarthritis with substantial structural changes in the knee joint. For training the model, as a part of preprocessing, all the images in the training dataset are resized to a standard size 224*224*3 pixels. This standard size is essential for the running the deep learning models.

The pre-processed images are given to the pretrained models for training. While training the pretrained models we use the already existing parameters of the pre-trained model and we finetuning the pretrained model by training it on x-ray image dataset. While training on the X-ray image dataset, the parameters of the model get finetuned. We discard the output layer of the pretrained model and added a dense layer containing 512 perceptrons with the 'relu' as activation function. Relu is commonly used as activation function in the hidden layers because it helps in addressing the vanishing gradient problem, imparts non-linearity to the network and it is faster to compute. To avoid overfitting, we added a dropout layer before the output layer with parameter 0.5. This helps in reducing the model overfitting. We added a custom output layer with 5 Perceptrons with activation function softmax which is used to classify the images into our five distinct classes Grade 0, Grade 1, Grade 2, Grade 3 and Grade 4. The softmax activation function is usually used in the output layer of a neural network for multiclass classification tasks.

We generated the classifier for knee pain using the Adam optimizer, which optimizes the learning rate individually for each parameter by estimating the first and the second moments of the gradient. As a result, Adam can process multiple gradients and learning rates per parameter that facilitates the convergence and improves generalization. The learning rate for the model was set to 0.001. We chose the categorical cross-entropy as the loss function because our model is the multi-class classifier. The categorical cross-entropy is determined as a negative logarithm of the likelihood of the observed data at the predicted probabilities.

$$\text{Categorical Crossentropy} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{C} y_{ij}\log(p_{ij})$$

.

IV. Results and Discussion

After training the model on pretrained models VGG16,ResNet50,DenseNet121, EfficientNet, the models are evaluated using a test dataset. The dataset used for the testing is not part of the training dataset which means that the model is not trained on these images and these images are completely new for the model. It is essential that the images used for training must not be used for testing the model. The images used for testing the model consists of 5 classes. 639 images of Grade 0, 296 images of Grade 1, 447 images of Grade 2, 223 images of Grade 3 and 51 images of Grade 4.

The test results of the 4 trained models are given below

1.VGG16 Model

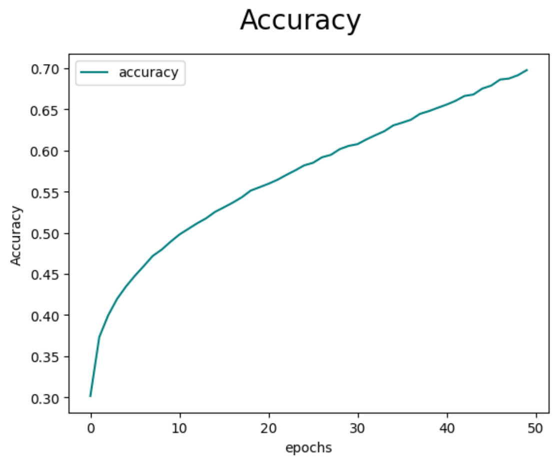


Fig. 4. VGG16 Model Accuracy

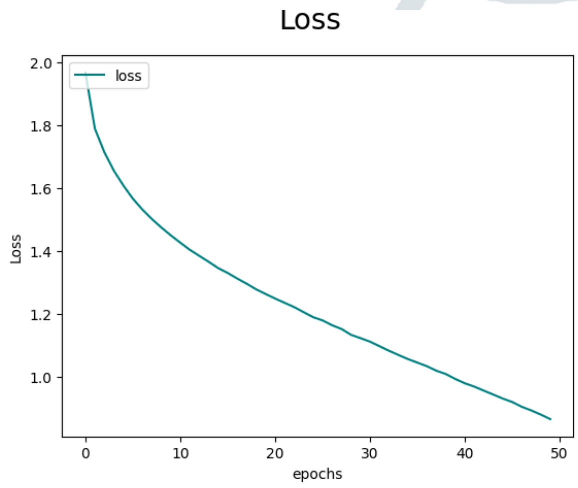


Fig. 5. VGG16 Model Loss

The knee pain classifier using VGG16 pretrained model trained for 50 epochs and gave accuracy of 69.77% with the loss 30.49%. Precision of the model is 57.14% and recall is 39.37%.

2. RESNET50 Model

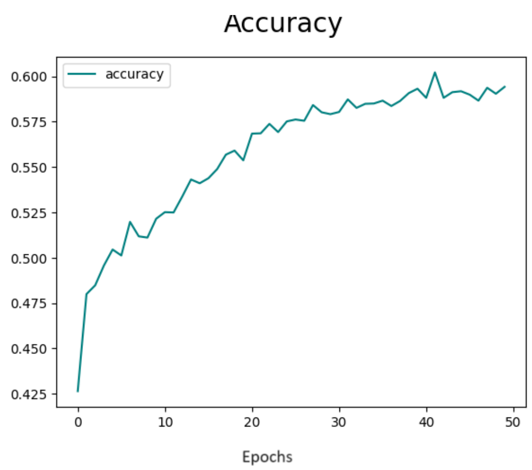


Fig. 6. RESNET50 Model Accuracy

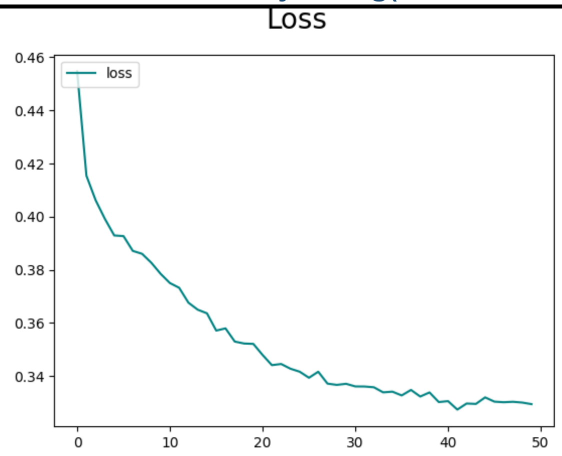


Fig. 7. RESNET Model Loss.

The knee pain classifier using ResNet50 pretrained model trained for 50 epochs and gave accuracy of 59.46% with the loss 32.49%. Precision of the model is 58.66% and recall is 44.98%.

3.DENSENET121

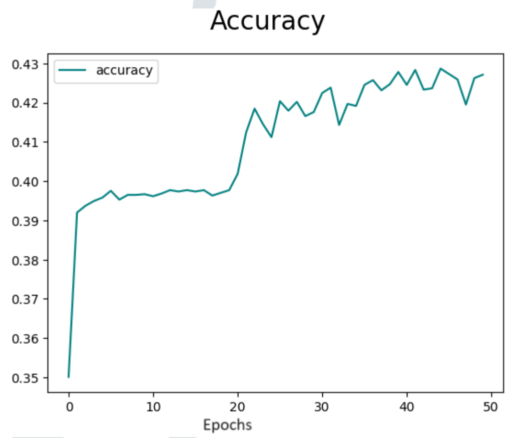


Fig.8.RESNET50 Model Accuracy.

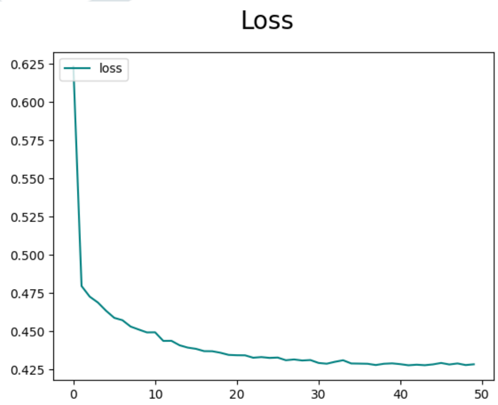


Fig. 9. RESNET Model Loss

The knee pain classifier using DenseNet121 pretrained model trained for 50 epochs and gave accuracy of 42.71% with the loss 32.95%. Precision of the model is 7.38% and recall is 2.19%.

4. EFFICIENTNETB0

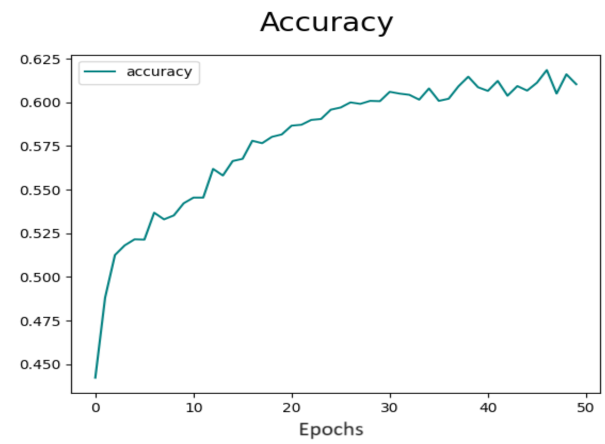


Fig. 10. EFFICIENTNETB0 Model Accuracy

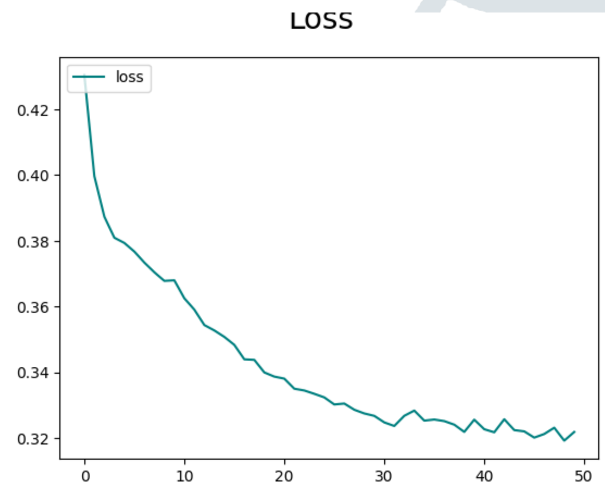


Fig. 11. EFFICIENTNETB0 Model Loss

The knee pain classifier using EfficientNetB0 pretrained model trained for 50 epochs and gave accuracy of 61.02% with the loss 34.18%. Precision of the model is 41.86% and recall is 22.58%.

Model	Accuracy	Precision	Recall	Loss
VGG16	0.6977	0.5714	0.33937	0.3049
ResNet50	0.5946	0.5866	0.4498	0.3295
DenseNet121	0.4271	0.0738	0.0219	0.4282
EfficientNetBo	0.6102	0.4186	0.2258	0.3418

Table1. Metrics of Various Models

From the above table, The model VGG16 performed better compared to DenseNet121, ResNet50 and EfficientNetBo.

V. CONCLUSION

This research work addresses the Classification of knee pain caused by Osteoarthrites into 5 severity levels Grade 0, Grade 1, Grade 2, Grade 3, and Grade 4. This classification is done by using deep learning based pre-trained models. Various Classification models using VGG16, ResNet50, DenseNet121, EfficientNet has been trained among them VGG16 performed better than other models with accuracy of 69.77%. This paper presents the potential of classifing the Knee pain caused by Osteoarthrites, a prevalent and debilitating condition affecting millions worldwide using advanced neural network architectures and innovative techniques such as transfer learning and image preprocessing.

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