Siddangouda Hosamani International Journal of Engineering Research and Applications
www.ijera.com
ISSN: 2248-9622, Vol. 10, Issue 11, (Series-III) November 2020, pp. 30-38

RESEARCH ARTICLE OPEN ACCESS

The Mri Knee Pain Classification Using Cnn Algorithm And Segmentation Using Clustering Algorithm

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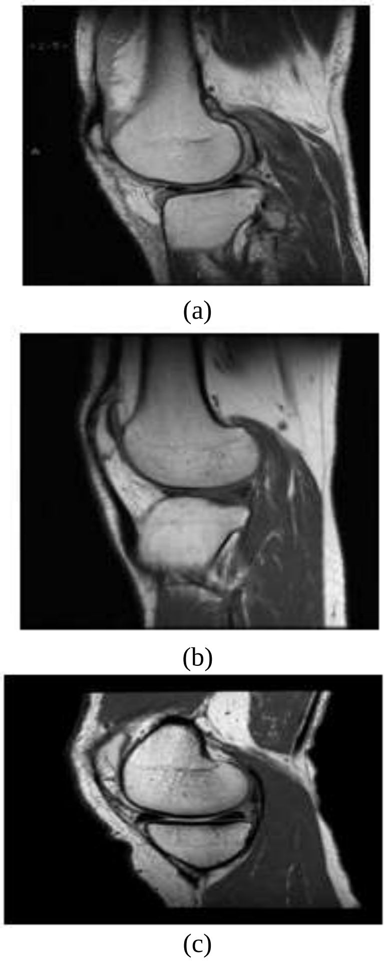
ABSTRACT— The great demand for Magnetic Resonance Imaging (MRI) in the world of medical field has helped the doctors to analyse and detect relevant disease. MRI is not only an effective technique for the assessment of pathology but also a valuable method for tracking the progression of disease. The ability of MRI to provide rapid 3D visualization has led to extensive use of this technology in the diagnosis and therapy of pathologies of different organs that are then used during treatment. Deep learning algorithm for the initial, intermediate and final stages of knee pain is developed. Clustering technique is commonly used in image segmentation in order for users to access a data image to distinguish common preferences and patterns. Clustering is intended to divide a dataset into groups or clusters where similarities between the clusters are minimized while similarities within the clusters are maximized. This work focuses on a convolutionary neural network (CNN) for classification of knee pain and popular K-mean clusters to segment the image. Results of both techniques are presented and accuracy is calculated.
Keywords-pathology;MRI; clustering;CNN;Segmentation

I. INTRODUCTION

The medical imaging technique is used to produce clinically accurate photographs of the actual human body that follow medical standards for diseases and physiology, including anatomy and physiology, to be viewed, treated or analyzed. Although the analysis of the organ and tissues removed can be performed for medical purposes, this is typically not a medical imaging technique but is part of diagnostic pathology. Some of the techniques developed for medical imaging often apply to science and industry. Medical imagery is also used as a practice that creates non-invasively pictures of the inner parts of the body.

The knee is one of the largest joints in the body and one of the strongest. The movement of the body in horizontal (run and walk) and vertical (jumping) directions plays an essential role. Knee pain is a common symptom that affects children and adults alike. Pain evaluation is critical for the aetiology of the underlying disease to be explored further with mechanistic studies in order to evaluate the reaction to therapy interventions. Common complaints: a) A painful, blocked, locked or swollen knee as shown in Fig 1.1.b) Often patients feel as if their knees are going to give up, or they may feel uneasy for their movement[1].



(a)

(b)

(c)

Fig 1.1: (a) swollen knee, (b) locked knee and (c) twisted knee

Typically CNN has three major layer forms, including Convolution, pooling layer and completely linked layers. The input layer is the first step of a CNN. The entry is an picture in gray or RGB. Input is then fed into a convolutionary layer that measures the neuron output, running a dot between the weight and the neurons associated or related areas. The performance of a convolutionary layer shall be [64 x 64 x 8], if the width0 and height0 of the image0 are [64 x 64], with 8 filters. The pooling layer lowers the output by a certain factor from the convolutionary layers. The fully connected layer calculates the training data, resulting in the required output class array[5]. Below figure illustrates CNN architecture.

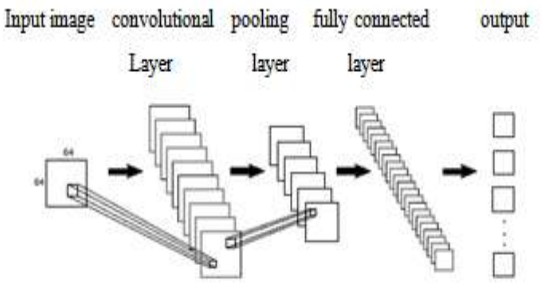


Fig1.2: General architecture of CNN.

Generally Machine learning is primarily aimed at extracting information from an image and these useful information is used further for other tasks following extraction. Few examples may illustrate the argument like pictures used for machine to maneuver through patterns, removal of damaged body organs, etc. Segmentation is the important process toward the interpretation ofimages. Segmentation is the mechanism by which images are partitioned into their components or objects. The entity and boundaries in an image are located and identified. This attempts to segment an image in sub-pieces based on those characteristics. Such characteristics may be based on other thresholds, contours, colors, or other patterns. It therefore helps us to analyze and portray a image easily.

CNNs are a special type of neural network for processing data with defined, grid-like topology. Sources include data from the time series that can be called a 1D grid that takes measurements at regular intervals, as well as image data that can be known as the 2D pixel grid. In practical applications, convolutionary networks were very successful. The term "convolutionary neural network" indicates that the network uses the word "convolution." Specialized form of linear action is Convolution. Convolutionary networks are only neural networks that use convolution in at least one of their layers rather than multiplication of the general matrix.

The input is a tensor with a form (picture numbers) x (image height) x (picture width) x (picture depth) while programming the CNN. Once the image is crossed in form (number of images) x (grid height) x (bandwidth) x (channel maps) it is then abstracted from a feature diagram. The following attributes should be present in a convolutions layer within a neural network:i)Kernels defined in configuration width andheight.ii)The input and output number ofchannels.iii)Output channel size of the convolution filter is equal to that of the input character map number(width).

Image0 Feature0 Extraction0 Using Convolution0

Pixel images can be used as an input to the standard feed-in neural network to address image recognition problems. However, there can be thousands of pixels in even small image sections, resulting in numerous link weight parameters. Various weight parameters have resulted, according to the VC theory, in complex structures which need far more operation to prevent overpowering. In comparison, CNN model sizes are incorporated in smaller kernel filters to facilitate the process of analysis, and CNN sizes are quicker and stronger than conventional neural networks that can be completely connected.

The main feature0 of CNN is evolutionary neuron layers. Input to the convolutionary layer is also considered to be one or more two-dimensional (or channel) matrices, and a number of 2-dimensional matrices are formed. The input and output matrices can differ. The goal of the learning process is to recognize kernel matrices K which will extract good discriminating properties for the classification of images. The context spread algorithm that optimizes weights of the neural network relation can be used as a weight of specific neuron relation to train the kernel matrices and distortions.

Pooling0

There are three phases in a typical layer of a convolutionary network. In the first point, the layer produces several parallel convolutions for a number of linear activations consisting of the standard layer of a convergence network. For the second stage, non-linear activation functions such as the modified linear activation function are done by linear activation. Sometimes this phase is called the level of the detector. In the third section, we use a package function to adjust the level output further. A bundling feature replaces the network output at a specific position with an overview of nearby outputs.A pooling function replaces the output of the net at a certain location with a summary statistic of the nearby outputs. For example the max pooling.

For CNN, pooling layer plays0 an significant role0 for growing the function dimensions.

CNN plays a crucial role in making the bonding layers more functional. To the the number of output neurons to a convolutionary layer, a pooling algorithm should be used to combine the respective elements in the convertion output matrices. The configuration network can provide pooling layers locally or globally to streamline the underlying computing. Through integrating the outputs of neuron clusters at one layer into a single neuron in the next layer, pooling layers minimize data dimension. Local pooling blends tiny clusters, typically 2 x 2. Global pooling operates on the convolutionary layer of all neurons. Further, pooling will measure a limit or an average. Max pooling uses the entire value on the previous layer from each of a cluster of neurons. Average pooling uses the average value in the prior layer from each of a cluster of neurons. Only neurons must be routed to a gradient signal that contributes to the bundling production during error propagation.[6].

ReLU Neuron Activation

For non-linear transfer functions, the position of activation of neurons is used in DNN. The most common functions for activation include sigmoid $f(x) = 1/(1+e{-}x)$ and hyperbolic tangent $f(x) = \tanh(x)$. Tangents are nonlined, saturated functions which, when input increases, reduce the output gradient by zero. Some recent studies have shown that non-saturating,non-linear functions such as corrected linear function $f(x) = \max(0,x)$, improve learning speed and classification efficiency in a CNN0 application. Our CNN model uses the ReLU feature activation of the convolutionary layer. Test results showed that ReLU increases the rating efficiency by 2.5% and converges a network much more rapidly than with Sigmoid.

Linear rectified units are easy to automate when linear units are imitated. A linear unit and a linear unit differ only if a linear unit that is fixed produces nil in half of its domain. This implies that derivatives remain large when a rectified linear unit is operational. The gradients are not only large, they are constant, too. The second derivative of the correction process is approximately 0, and wherever the unit is involved the correction process comes from 1. And the gradient path is much stronger than the activation functions, leading to second-order learning results. Initializing the parameters of a related transformation may be good practice to define all elements in a small positive value like 0.1. It is therefore very likely that linear corrected units will initially be enabled for most inputs and that derivatives will move through in the training system. There are several generalizations of linear rectified units. Most of these generalizations work comparatively with rectified linear units and sometimes better A maxout unit can study a linear convex function with pieces of up to k. Maxout units can therefore be seen rather than simply the relationship between units, as learning how to activate. With enough k, a maxout unit can learn to approximate any convex function arbitrarily. A two-part max-out layer may learn to use the corrected linear enhancement function and a corrective value function, leaky or parametric ReLU in order to implement the same x-function as the conventional layer.For example, the maxout layer is distinct from all other layer types, which ensures that the learning mechanisms are distinct, even in cases in which maxout performs the same x function as in other layer types. A maxout unit requires more regularization, as k weights vectors are not just parameters, but linear corrected ones. If there is a wide variety of training sets and a limited number of pieces per package, they can work well without regularization.

Fully connected layer

Each neuron in one layer is connected to each neuron in a completely connected layer in a different layer. It is basically the same as the traditional neural network (MLP). A completely linked layer is used to identify images across a flattened matrix. The aim of a completely connected layer is to use and classify the results of the convolution process into a label. The output of the convolution is flattened into a single value vector, which is each likely to have a certain feature on a label.

The input values are passed into the first neuron sheet. They are multiplied by weights and are activated in the same way as the classical artificial neural network (usually ReLu). Then they go to the output layer, where each neuron represents a ranking mark. To define the weights most accurately, the fully integrated component of the CNN network goes through its own context propagation cycle. The weights of each neuron give priority to the most suitable mark.

Image Segmentation

Picture segmentation is a process by which the image is divided into several sections. The fundamental aim of this segregation is to allow pictures to be analyzed and interpreted with quality conservation. It is also used to trace the borders of objects within the pictures. The pixels are marked according to intensity and features in this technique. Such pieces reflect the entire original picture and gain its strength and similarity characteristics. The technique of distortion of the image is used to create a 3D body contour for clinical purposes. Segmentation is used for the vision of computers, malignant analyzes of pathogens, tissue sizes, structural and functional measurements and the 3D rendering of techniques.

The segmentation of images is classified into: I local segmentation and (ii) global division.

Especially in a single subdivision, the local segmentation works. In contrast with the global sort, this technique has fewer pixels. The whole picture acts as one unit in the regional segmentation. This method can accommodate more pixels.

The goal of segmentation is to simpler and more effective and easier to analyze the representation of a image. Image segmentation is usually used in order to locate images with objects and borders. More precisely, image segmentation is the process of allocating each pixel in an image with a label that has other pixels with the same label.

The segmentation of images requires the transformation of an image into a series of pixel regions represented by a mask or a labelled image. By separating an image into segments, only the main segments of the image can be processed instead of the entire image. An abrupt discontinuity in pixel values is a typical method that generally indicates edges defining an area. Another that method is the detection of similarities in the image regions. Some strategies that accompany this approach include regional growth, clustering and limitation. Throughout the years, various methods have been developed using domain-specific expertise to effectively address segmentation problems in particular application areas in order to perform image segmentation. Let us therefore continue with a clustering approach in the K- means clustering of image segmentation.

The segmentation of images is a crucial computer vision process. In order to simplify image analysis, the object data is divided into parts. Segments are objects or component parts, which involve collections of pixels or "super-pixels." Photo segmentation classifies pixels into larger parts, which removes the need to consider single pixel as observation units. The effect is a sequence of segments covering the entire image or a set of contours derived from the image. Each area pixel is similar to other characteristics, such as colour, strength or texture, or computed characteristics. Concerning the same feature(s),neighboring regions are substantially different.If the contours after image segmentation can be applied to a stack of images common for medical images the resulting contours can be used with algorithms such as marching cubes for making 3D reconstructions.

Thresholding

The segmentation of thresholds depends on the value for transforming the gray picture to black and white. Many other radiology methods have been used, for example in Otsu and k-means, to restore or reslim images. Thrust method is useful to set the limits in the dark context of solid objects. The threshold techniques allow that variations exist between the intensities of the target and the context. Three kinds of thresholding methods are available. These methods include the global selection threshold, adaptive and histogram-built. Usually global threshold is used for all segmentation technologies which is broader.

A thresholding technique is the simplest method for image segmentation. This method converts a gray image to a binary picture centered on a certain amount of intensity, which is called a pixel black and not a pixel white. The threshold or clip standard is utilized in this approach. One is the global limit and the other is the local limit.

If f(x,y)0 >T then0 f(x,y)=00 else f(x,y)=2550

The most significant thing is that when several levels are selected, the threshold or values are selected. Some common industrial methods include the maximum entropy method, balanced histogram thresholds, Otsu (maximum variance) method, and k-mean clustering.

The main aim of this paper is to classify the knee pain stage of MRI using Convolutional Neural Networks (CNNs) due to the advanced image processing and faster computation feasibility and k-means segmentation is applied to detect the infected region.

Image segmentation can be classified into various categories such as region based, edge based, clustering methods, PDE (Partial Differential Equations) based segmentation techniques [2].With the recent rapid growth of the technological advancements, medical science has also improved. But medical science is dependable on the current improvement of technologies. With this technological improvement it has reached to certain esteem where it can diagnose any diseases in a very less time with full accuracy.

The MRI has become the standard way of studying the knee. In this paper, the magnetic resonance pictures of the knee are pre-processed to identify the pain and then detect the area with an approach to image segmentiation. The identification of infected cells by k-means clustering0 has been carried out.

Narmada M. Balasooriya et al suggested the use of advanced neural networks (CNNs), an algorithm for deep learning with advantages over the simpler and accurate use of neural networks. CNN algorithm will be used for tumor identification when a patient and an advanced CNN model set of MRI images has been developed, trained on cross validation and tested on MRI brain pictures. [4].

Qing Li∗, Weidong Cai et al proposed image classification method using customized Convolutional Neural Networks (CNN) with shallow convolution layer to classify lung image patches with interstitial lung disease. This method gives better classification result than unsupervised RBM neural network[6].

V. Couteaux,, S. Si-Mohamed, et al proposed Automatic knee meniscus tear detection and orientation classification with Mask-RCNN some times this method leads to a class imbalance, hence cascaded the Mask R-CNN into a shallow ConvNet to classifytear orientation[1].

D.Selvaraj et al has segmented skull and CSF(cerebrospinal fluid) from magnetic resonance image of brain. CSF is segmented by orthogonal polynomial transform and this approach is based on intensity based thresholding to get boundaries between cerebrospinal fluid (CSF), Gray Matter (GM) and White Matter (WM).[18]

Natarajan P1 , Krishnan.N et al proposed a technique of Tumor Detection using threshold operation in MRI Brain Images. This approach uses sharpening and median filters, enhancement of image is performed by histogram equalization and segmentation of the image is performed by thresholding[2].

Adhikari et al. have applied cs FCM algorithm on Brain MR Pictures to achieve better output with respect to both qualitative and quantitative tests, including the validity functions in the cluster, the precision of segmentation, tissue segmentation and the operating property of the receptors (ROC) curve on image segmentation outcomes.[15]

Abdel-Maksoud et al. have proposed a hybrid technique that gets the benefits of the K-means clustering for image segmentation in the aspects of minimal computation time. In addition, it can get advantages of the Fuzzy C-means in the aspects of accuracy. In order to have more visualization clearly,Intensity adjustment and 3D evaluation can be done by using 3D slicer.[14]

Juan et al. have proposed the Colored segmentation with K-means clustering algorithms is performed to be highly promising to MRI applications for tracking objects in medical images. The brain areas of a tumor or lesion can be distinguished from the colored picture precisely. Pathologists can discern precisely lesion size and area using this approach.[44].

CLUSTERING TECHNIQUE

In this section we discuss k-means clustering technique and its underlying mathematical model is presented.

K-Means algorithm cluster is an uncontrolled algorithm, which is used to segment the area of interest from the background. It clusters or divides the data into K-clusters or K-centered components. If you have n labelled data, the algorithm is used. The aim is to identify such groups based on a similarity between the data and the number of groups identified by K.

$$J = \sum_{i=1}^{k} \|xi(j) - cj\|2$$

Where j is objective, k is cluster number, n is case number and cj is the centroid for cluster j.

K-means clustering is a method of vector quantification originating from signaling, which aims to divide n observations into k clusters, in which the cluster with the nearest mean is each observation, serving as a cluster prototype.It was proposed to classify specific intensity pixel into pixel groups with associated properties or patterns. K-means clustered algorithm. The basic algorithm for K-Means is the following:

a) Cluster centers, based on a heuristic or random approach, arechosen.

b) Assigning pixels, according to those features, to those cluster centers which have a minimum distance from thatcenter.

c) The sum of all the pixels0 in clusters0 recompose the cluster centers.

d) The last0 two0 steps0 shall be repeated until no further new cluster center is created. Speed, colour , texture, position and so on distinguish the pixels.

II. METHODOLOGY

i.The Proposed CNN model

In this paper, a deep CNN is proposed for accurate knee pain MR image classification. The architecture of the network is mainly based on knee MRI experiments. The software is specifically designed for the classification of knee MRI images. iThe network comprises five layers, two convolutionary, two max pooling layers and one fully linked.

. This network has five layers consisting0 of 2 convolutional0, 2 max pooling0 and 1 fully connected layers.

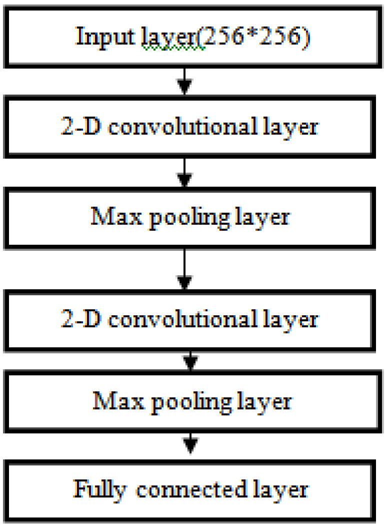


Fig 1.5: Proposed CNN architecture

The images are re-sized in order to reduce the image size and speed of removal in 256 * 256 pixels width and height. There are 3 color channels in each frame. The input consists of two arrays of image pixel values and image tags. When these arrays are fed to the network, the first convolutionary layer passes through them. Within this layer 2-D convolutionary filters are added and for further measurement, a Rectified Linear Unit (ReLU), is enabled. Mathematical definition of the ReLU is shown below Equation,

$$f(x) = max(0, x)$$

Here x is the neural network's net-input. The production of the first layer then is generated to the maximum pooling layer, in which two factors sample the images.

The results are forwarded to next convolution layers, filters and ReLU. To detect an initial stage, intermediate or final stage knee pain level. The increase in filter number in each convolutionary layer guarantees the measurement in each layer of more local features. The default values of 1 are set to shift the filters one pixel a time for every convolutionary layer. This is due to the intricate nature of MRI images being removed. The functionality is removed. The volume parameter for padding is equal to the width and height of the product. The second maximum output of the pooling layer will be fed into the fully connected ReLU layer. The final layer is a completely linked plate.

The trained data set consist of, three stages of Knee pain data. 30 images of stage-1, 78 images of stage-2 and 36 images of stage-3 in Convolutional neural network. When the test data is applied as an input,it is then compared with the trained data to detect the knee pain class as the pain is in initial stage or intermediate stage or final knee pain stage.

ii. PROPOSED SEGMENTATION ALGORITHM

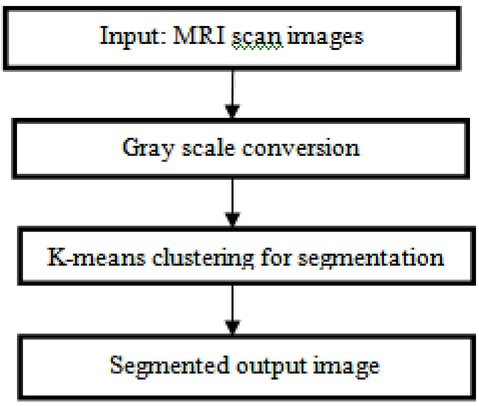


Fig 1.6 Flow chart for segmentation of MRI knee

The next step is to segment the image when the image of the MRI knee pain is identified by using a convolutionary neural network. We can detect the infected area from segmentation. For segmentation of a MR image, the input MR image is taken, Then Gray scale conversion is applied to that image. This MR image is segmented using k-means clustering.

III. SOFTWARE REQUIREMENTS

Python language is a versatile language, highly lightweight and effective for manipulating images, which is associated with the numerical set. Python has the simplicity of Ped in conjunction with the numerical strength and ease of use of MATLAB, but is open source. Compared to compiled languages, source code is usually small for many reasons : high-level information types and operations, no dynamic type declarations, automated meniority management and indented command blocks. The same optimization will cost considerably more time with similar databases and functionalities in C / Ct+. In C / C++ (built-in) there is also a large set of libraries, for Python, that virtually discard the compile / correct / compile method. These features produce a large increase in productivity. The images are shown with the Python Graphic Using Interface (CUI) standard Python module and the features of the Tk package.

TensorFlow is a library open source created for Python by the Google Brain team. In order to allow users to introduce deeper neural networks for work in work areas, including picture recognition, classification and natural language processing, TensorFlow combines different algorithms and modeling. TensorFlow is an efficient system that operates by implementing a collection of mathematical processing nodes called "graphs" for the full set of nodes.The specific requirements are MS Windows and Python 3.7.8 version with CV2 and Numpy libraries.

The machine learning workflow

The training cycle is relatively common for a neural network model and is divided into four phases.

Preparation of data

Next, you must collect and place the data in a way that the network can practice. This ensures that images are collected and labelled. You must even prepare or pre-treat a data set prepared by someone else before you can use the data for training. Even if you download it.For loading the data load_data() command is used.

Creating the model

To construct a neural network model, you have to select various parameters and hyper parameters. Decide about how many layers are to be included in your design, which layer inputs and outputs will be, what sort of activation functions will be used, whether or not you are falling, etc.ReLU is the most common activation and padding ensures that we don't change the image size at all.

Training the Model

Create an instance of the model and paste it with your training data after you have developed your model. When training a model, the biggest consideration is how long the model takes to train. Through determining the number of times to be practiced, you can set the training period for a network.

Model evaluation

The model has been tested in a number of steps. The first phase in the model evaluation is the calculation of model output against an uneducated data collection. The model performance is measured and evaluated by different measurements.

IV. RESULT OF IMPLEMENTATION

i. Data set

Many open repositories provide the data required for this article. MR images are collected from RADIOPEDIA. The data collection collected includes 144 pictures of 17 patients. The photographs must be converted to a normal picture format such as JPEG and classified according to pain in the knees.

ii. Classification Result

Proposed knee MR image classification architecture as mentioned in methodology is applied to determine the stage of knee pain, whether the pain is in initial stage or intermediate stage or in the final stage. The trained data set of a knee pain MR image consist of 30 images of stage-1,78 images of stage2 and 36 images of stage-3.

For test data image classification, two 2D convolution layers are used to perform convolution, two max pooling layers are used to decrease the dimension, ReLU is used as an activation function two to activate the neurons and finally all the neurons combined in a completely connected layer are used to evaluate the stage of knee pain that is to determine the stage of a knee pain. Few classification output of each stage is shown in below figure.

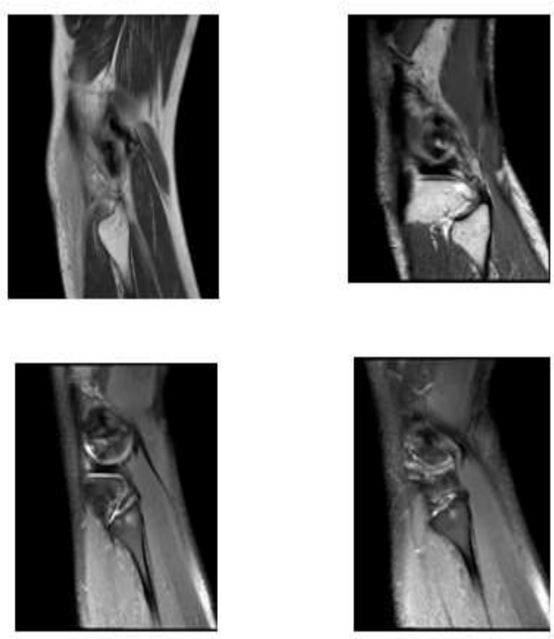


Fig 1.7 Output knee MR images of initial stage

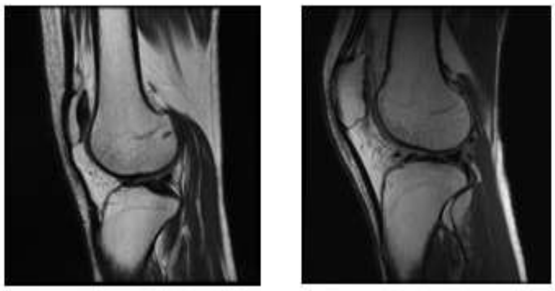


Fig 1.8 Output knee MR images of intermediate stage

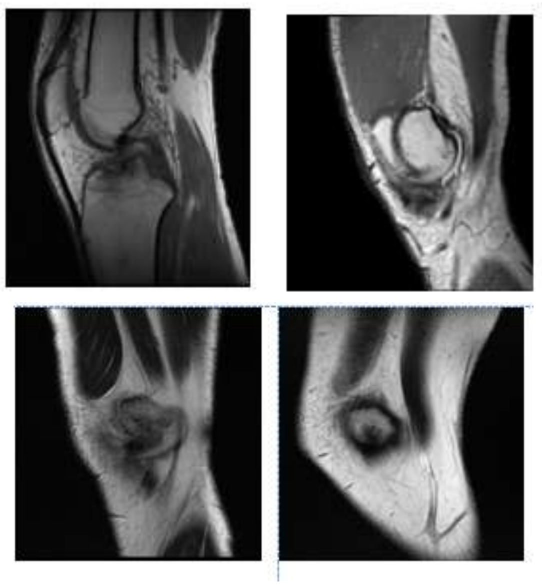


Fig 1.9 Output knee MR images of final stage

From the output of the simulation we can observe that, in initial stage and in final stage the size of knee swelling will be on to lower side hence there will be mild pain, whereas in intermediate stage the size of knee swelling will be on to a bigger side hence the pain will be severe. For the trained data set, the accuracy of proposed model is 99%.

V. RESULTS OF THE SEGMENTATION

When k- means that segmentation is used to classify the infected region, after the identification of any stage of Knee pain. 1)The image is then read and transferred to a matrix shape and image size.2)After this image has been reworked to represent it in a linear manner.3)The k-means algorithm is applied to the original image. The algorithm starts clustering or grouping objects on a basis of features and centroids when k-means is applied to the input image.4) The cluster number is the user input and variable. The target picture becomes clearer with the increase of clusters. (5) The image is then displayed displaying the dead cells of all regular knee cells and showing all cells not known as dead, but impaired due to the faulty regions.

The area that was affected is the highlighted part of the original knee photo. We noticed a minor segmentation of the infected element after using the K-MEANS algorithm with cluster no. 2. However, the image output shows the area of infections being visible or the cells that are affected are segmented from the normal cell when we use the same algorithm with cluster number three. From the method implemented above, we can see that with the identification of infected area the output is so simple as shown in fig. 1.10.

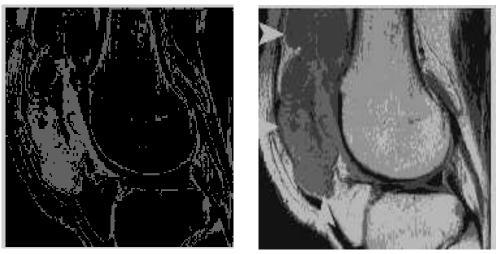


Fig 1.10: Analysis of results obtained by K-Means

VI. CONCLUSION AND FUTURE SCOPE

Convolutionary neural networks are commonly used to identify images. The use of CNNs for the classification of knee pain improves the accuracy of the knee pain stage detection. A less complex CNN model for the classification and estimation of knee pain into three distinct classes of MR pictures is proposed in this project. The accuracy of the model proposed is 99%. In training and testing the pattern, MRI scans of the swollen knee, the locked knee are used.

The segmentation and examination of medical images is very critical for the identification of the infected area. Thus, by applying threshold and segmentation, we have achieved our objective. On the number of MR images in the section of the region concerned, the K-means algorithm was evaluated. The picture shows clearly the infected cells isolated from healthy cells. These methods are very simple and common.

The main approach used for image classification is the evolutionary neural network. This method depends upon the number of convolutionary layer and pooling layer, precision and performance. which can be enhanced by adding additional layer.

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