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KNEE OSTEOARTHRITIS DETECTION USING AN IMPROVED CENTERNET WITH PIXEL-WISE VOTING SCHEME

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Abstract: The primary objective of the project is to identify and diagnose knee osteoarthritis using knee images obtained through X-ray scans. X-ray images are a common and cost-effective modality for examining knee joint health, and the project focuses on leveraging these images for accurate detection of osteoarthritis. Current methods for knee osteoarthritis detection, which rely on image processing techniques, face challenges in terms of accuracy and precision. The project acknowledges the shortcomings of existing approaches and seeks to overcome these limitations by introducing a novel and customized technique for improved detection and classification of knee osteoarthritis. The proposed technique involves the development of a specialized CenterNet, a state-of-the-art object detection architecture. This CenterNet is tailored with a pixel-wise voting scheme, a method that allows for the extraction of features at a granular level. By customizing the CenterNet in this way, the project aims to enhance the accuracy and reliability of knee osteoarthritis detection. The model incorporates DenseNet201 as the base network for feature extraction. DenseNet is known for its densely connected layers, which promote feature reuse and alleviate gradient-related issues. By utilizing DenseNet201, the model aims to capture the most representative features from knee samples, enhancing the robustness of the feature extraction process. The overarching goal of the proposed model is to achieve accurate detection of knee osteoarthritis in X-ray images. Moreover, the model intends to go beyond detection by determining the severity level of osteoarthritis using the Kellgren and Lawrence (KL)

grading system. This comprehensive approach ensures a nuanced understanding of the disease, aiding in more effective diagnosis and treatment planning. The project proposes an integrated strategy involving advanced classification models (Xception, InceptionV3), efficient object detection methods (YOLOv5, YOLOv8), and a user-friendly front end developed using the Flask framework. This approach aims to leverage the strengths of sophisticated classification and detection models while providing a seamless and secure testing environment.

Index terms - *Machine learning, detection performance, HCI, classification, deep learning, multi-scale features.*

1. INTRODUCTION

Knee Osteoarthritis (KOA) is a chronic joint disease due to the worsening of articular cartilage in the knee. The symptoms of KOA comprise joint noises due to cracking, swelling, pain, and difficulty in movement. Moreover, the severe symptoms of KOA may cause fall incidents i.e. fracture in the knee bone that ultimately results in disability of leg [1]. Various imaging techniques which have been employed for the analysis of knee disease include MRI, X-ray, and CT scans. Furthermore, MRI and CT scans are also considered suitable for KOA assessment [2], [3]. They are accompanied using an intravenous contrast agent [4] which provides a clear view of Knee joints. However, these approaches are associated with high costs, increased examination time, and potential health risks such as patients with renal inadequacy [5]. Therefore, there should be some techniques for the assessment of KOA that can be employed without the contrast agent and require minimum expense, and time of examination. Therefore, an X-ray is considered a more feasible way to provide bony structure visualization and is a less expensive approach for knee analysis.

Cartilage helps in flexible movement, however, when it decreases with age or any accidental loss, it causes the disease Knee Osteoarthritis (KOA). The Knee joint is composed of two bones i.e. tibia and femur. Both of these bones are joined with the thick material that is called cartilage. The severity of the disease is measured through a grading system known as Kellgren & Lawrence (KL) which is based on the radiographic classification of KOA. It comprises of 4 grades i.e. Grade I, Grade II, Grade III, and Grade IV [6]. Grade I shows the lowest severity of the disease whereas Grade IV refers to the highest severity level. Early detection and the classification of disease help physicians to treat patients with a high success rate. The most common cause of KOA is being overweight and the disease progresses towards higher grade with the age. Moreover, the average age of forty-five years of KOA patients has been reported in [7]. In the USA, patients of KOA having an age of 65 years or above have been assessed for KOA through radiography [6] and more than twenty-one million people have this disease [8]. In Asian countries, this disease has been spreading day by day. In Pakistan, 25% of the rural area and 28% of the urban population has KOA disease [9]. Besides medication, KOA can be treated through exercise, weight reduction, walking, and physiotherapy [10]. There exist various techniques for KOA detection and classification such as Gait Analysis, MRI, Impedance Signals, etc. [11], [12]. Knee joint width space is an important key factor to assess the KOA severity. Therefore, X-rays help in the visualization of joint width space and MRI assesses the cartilage thickness and complete surface condition. On the other side,

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bioelectric impedance signals are the most useful approach for detecting the KOA. It requires a low expense and is easy to employ [13].

There exist various ML and DL-based methods for the detection and classification of KOA [10], [14], [15], [16], [17], [18]. In [19], a model has been developed for KOA detection and classification based on the hybrid feature descriptors such as HOG and CNN employed with the KNN clustering algorithm. The algorithm outperformed the existing techniques, attaining an accuracy of 97.14%. However, in this study, we aim to develop a system based on deep learning that has low complexity and gives better accuracy for all grades of KOA rendering to the KL grading system.

The advancement in segmentation based techniques has also gain importance in last two decades. The images pixels are pictorial elements to discern the various regions of the input samples. Segmentation is a technique to divide the whole image into various regions based on the application requirement [20], [21], [22]. These segmentation-based techniques play a vital role in detection of diseases, however quality of images may be impacted due to noise. Therefore, to minimize the errors and human effort in medical imaging, an automated segmentation technique will provide better accuracy and ROI selection [23], [24], [25]. Deep learning models have been employed for various purposes to extract the efficient features i.e. medical [26], [27], agriculture [28], surveillance [29], etc. Although, the supervised methods provide better accuracy, however the challenging task is to label the training samples of large number. Additionally, data may have different types, therefore to label and prepare the large training data is never-ending task.

2. LITERATURE SURVEY

Knee Osteoarthritis (KOA) [1, 2, 3, 4, 6] is a degenerative joint disease of the knee that results from the progressive loss of cartilage. Due to KOA's multifactorial nature and the poor understanding of its pathophysiology, there is a need for reliable tools that will reduce diagnostic errors made by clinicians. The existence of public databases has facilitated the advent of advanced analytics in KOA research however the heterogeneity of the available data along with the observed high feature dimensionality make this diagnosis task difficult. The objective of the present study [3] is to provide a robust Feature Selection (FS) methodology that could: (i) handle the multidimensional nature of the available datasets and (ii) alleviate the defectiveness of existing feature selection techniques towards the identification of important risk factors which contribute to KOA diagnosis [3]. For this aim, we used multidimensional data obtained from the Osteoarthritis Initiative database for individuals without or with KOA. The proposed fuzzy ensemble feature selection methodology aggregates the results of several FS algorithms (filter, wrapper and embedded ones) based on fuzzy logic. The effectiveness of the proposed methodology was evaluated using an extensive experimental setup that involved multiple competing FS algorithms and several well-known ML models [10], [14], [15], [16], [17], [18]. A 73.55% classification accuracy was achieved by the best performing model (Random Forest classifier) on a group of twenty-one selected risk factors. Explainability analysis was finally performed to quantify the impact of the selected features on the model's output thus enhancing our understanding of the rationale behind the decision-making mechanism of the best model.

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Knee joint vibroarthrographic (VAG) signals acquired from extensive movements of the knee joints provide insight about the current pathological condition of the knee. VAG signals are non-stationary, aperiodic and non-linear in nature. This investigation has focussed on analyzing VAG signals using Ensemble Empirical Mode Decomposition (EEMD) and modeling a reconstructed signal using Detrended Fluctuation Analysis (DFA). In the proposed methodology [4], we have used the reconstructed signal and extracted entropy based measures as features for training semi-supervised learning classifier models. Features such as Tsallis entropy, Permutation entropy and Spectral entropy were extracted as a quantified measure of the complexity of the signals. These features were converted into training vectors for classification using Random Forest [32], [33], [34]. This study has yielded an accuracy of 86.52% while classifying signals. The proposed work can be used in non-invasive pre-screening of knee related issues such as articular damages and chondromalacia patallae as this work could prove to be useful in classification of VAG signals into abnormal and normal sets.

In the past 4 years, many publications described a concentration-dependent deposition of gadolinium in the brain both in adults and children, seen as high signal intensities in the globus pallidus and dentate nucleus on unenhanced T1-weighted images. Postmortem human or animal studies have validated gadolinium deposition in these T1-hyperintensity areas, raising new concerns on the safety of gadolinium-based contrast agents (GBCAs). Residual gadolinium is deposited not only in brain, but also in extracranial tissues such as liver, skin, and bone. This review [5] summarizes the current evidence on gadolinium deposition in the human and animal bodies, evaluates the effects of different types of GBCAs on the gadolinium deposition, introduces the possible entrance or clearance mechanism of the gadolinium and potential side effects that may be related to the gadolinium deposition on human or animals, and puts forward some suggestions for further research.

We describe a method for automated detection of radiographic Osteoarthritis (OA) in knee X-ray images [31]. The detection is based on the Kellgren-Lawrence classification grades, which correspond to the different stages of OA severity [6]. The classifier was built using manually classified X-rays, representing the first four KL grades (normal, doubtful, minimal and moderate). Image analysis is performed by first identifying a set of image content descriptors and image transforms that are informative for the detection of OA in the X-rays, and assigning weights to these image features using Fisher scores. Then, a simple weighted nearest neighbor rule is used in order to predict the KL grade to which a given test X-ray sample belongs. The dataset used in the experiment contained 350 X-ray images classified manually by their KL grades. Experimental results show that moderate OA (KL grade 3) and minimal OA (KL grade 2) can be differentiated from normal cases with accuracy of 91.5% and 80.4%, respectively [10, 16, 46]. Doubtful OA (KL grade 1) was detected automatically with a much lower accuracy of 57%.

This paper presents a fully developed computer aided diagnosis (CAD) system for early knee OsteoArthritis (OA) detection using knee X-ray imaging and machine learning algorithms [7]. The X-ray images are first preprocessed in the Fourier domain using a circular Fourier filter. Then, a novel normalization

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method based on predictive modeling using multivariate linear regression (MLR) is applied to the data in order to reduce the variability between OA and healthy subjects. At the feature selection/extraction stage, an independent component analysis (ICA) approach is used in order to reduce the dimensionality. Finally, Naive Bayes and random forest classifiers are used for the classification task. This novel image-based approach is applied on 1024 knee X-ray images from the public database OsteoArthritis Initiative (OAI). The results show that the proposed system has a good predictive classification rate for OA detection (82.98% for accuracy, 87.15% for sensitivity and up to 80.65% for specificity).

3. METHODOLOGY

i) Proposed Work:

The proposed system introduces an innovative approach centered around a customized CenterNet with a pixel-wise voting scheme for automated feature extraction from knee images. It leverages DenseNet201 as the base network to capture the most representative features from knee samples, with a focus on accurate knee osteoarthritis (KOA) detection and severity classification based on the KL grading system [30]. The project proposes an integrated strategy involving advanced classification models (Xception, InceptionV3), efficient object detection methods (YOLOv5, YOLOv8) [46], and a user-friendly front end developed using the Flask framework. This approach aims to leverage the strengths of sophisticated classification and detection models while providing a seamless and secure testing environment.

ii) System Architecture:

In this work, a robust framework for the detection of KOA is suggested. The proposed system can be employed on unseen knee images having varying severity levels of KOA [45, 55]. The high-dimensional features play a significant role in the recognition and characterization of disease in knee images. We fed the samples having the annotated bounding boxes as a region of interest (ROI). We utilized improved CenterNet using DenseNet-201 as the base network for feature formation. The reason behind choosing the DenseNet over ResNet is to extract the most representative feature from the knee joint due to densely connected layers. However, ResNet employs skip connections and attains output from the second and third layers. Moreover, DenseNet contains a feature layer (convolutional layer) capturing low-level features from knee images, several dense blocks, and transition layers between adjacent dense blocks. Although, DenseNet requires high computational power, however, it provides better feature representation than ResNet.

Before, the feature extraction phase from the knee joint, we improved the localization results by giving input bounding box predicted from our customized CenterNet to the voting function. The voting function computes the best bounding box by taking votes from each pixel from the estimated bounding box and gives an output of the best bounding box based on maximum score. Additionally, to reduce the size of the model and to transfer the knowledge from a cumbersome model to a compact one without increasing the computational power, we have introduced knowledge distillation. Therefore, an automated model for the detection of KOA disease is employed using the dataset i.e. Mendeley. We trained an improved CenterNet network [55] over the various knee joints samples attained from the medical

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experts. Moreover, these samples are characterized rendering to the KL grading systems such as G-I, G-II, G-III, and G-IV. The architecture of the proposed system is shown in figure 1. After the training of the classifier, classification is performed and images have been characterized into five classes i.e. Normal, G- I, G-II, G-III, and G-IV.

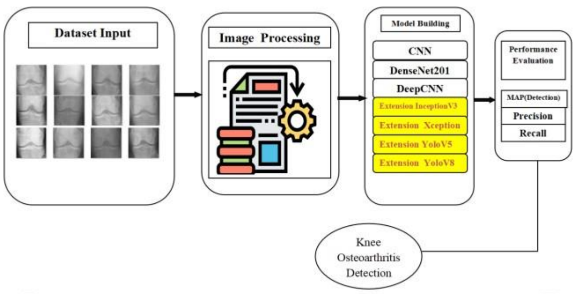

Fig 1Proposed Architecture

iii) Dataset collection:

Acquiring and understanding the dataset related to Knee Osteoarthritis (KOA) [45]. It might involve obtaining knee X-ray images from a specific dataset dedicated to KOA or utilizing data obtained and preprocessed from Roboflow, a platform that facilitates data preparation for machine learning tasks. Exploratory Data Analysis (EDA) may include assessing data quality, understanding label distributions, and visualizing sample images to gain insights into the dataset's characteristics.

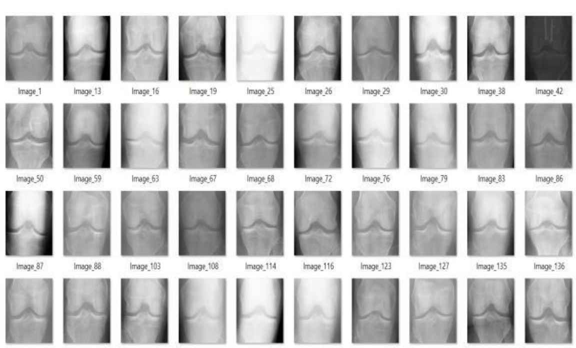

Fig 2 Knee Osteoarthritis Dataset

iv) Image Processing:

Image processing plays a pivotal role in object detection within autonomous driving systems, encompassing several key steps. The initial phase involves converting the input image into a blob object, optimizing it for subsequent analysis and manipulation. Following this, the classes of objects to be detected are defined, delineating the specific categories that the algorithm aims to identify. Simultaneously, bounding boxes are declared, outlining the regions of interest within the image where objects are expected to be located. The processed data is then converted into a NumPy array, a critical step for efficient numerical computation and analysis.

The subsequent stage involves loading a pre-trained model, leveraging existing knowledge from extensive datasets. This includes reading the network layers of the pre-trained model, containing learned features and parameters vital for accurate object detection. Additionally, output layers are extracted, providing final predictions and enabling effective object discernment and classification.

Further, in the image processing pipeline, the image and annotation file are appended, ensuring comprehensive information for subsequent analysis. The color space is adjusted by converting from BGR to RGB, and a mask is created to highlight relevant features. Finally, the image is resized, optimizing it for further processing and analysis. This comprehensive image processing workflow establishes a solid foundation for robust and accurate object detection in the dynamic context of autonomous driving systems, contributing to enhanced safety and decision-making capabilities on the road.

v) Data Augmentation:

Data augmentation [25,26] is a fundamental technique in enhancing the diversity and robustness of training datasets for machine learning models, particularly in the context of image processing and computer vision. The process involves three key transformations to augment the original dataset: randomizing the image, rotating the image, and transforming the image.

Randomizing the image introduces variability by applying random modifications, such as changes in brightness, contrast, or color saturation. This stochastic approach helps the model generalize better to unseen data and diverse environmental conditions.

Rotating the image involves varying the orientation of the original image by different degrees. This augmentation technique aids in teaching the model to recognize objects from different perspectives, simulating variations in real-world scenarios.

Transforming the image includes geometric transformations such as scaling, shearing, or flipping. These alterations enrich the dataset by introducing distortions that mimic real-world variations in object appearance and orientation.

By employing these data augmentation techniques, the training dataset becomes more comprehensive, allowing the model to learn robust features and patterns. This, in turn, improves the model's ability to generalize and perform effectively on diverse and challenging test scenarios. Data augmentation serves as a crucial tool in mitigating overfitting, enhancing model performance, and promoting the overall reliability of machine learning models, especially in applications like image recognition for autonomous driving systems.

vi) Algorithms:

CNN (Convolutional Neural Network)- CNN is a class of neural networks primarily used for image-related tasks due to its ability to effectively learn hierarchical representations of features. It comprises layers like convolutional, pooling, and fully connected layers. Convolutional layers extract features by convolving learned filters across input images to capture spatial patterns. Pooling layers reduce spatial dimensions, and fully connected layers perform classification based on extracted features. In the context of the project, CNN likely forms the basis or a component of the model architecture. It aids in feature extraction from knee X-ray images, enabling the model to identify intricate patterns associated with Knee Osteoarthritis [46].

```
model1 = Sequential()

# convolutional layer
model1.add(Conv2D(50, kernel_size=(3,3), strides=(1,1), padding='same', activation='relu', input_shape=(128, 128, 3)))

# convolutional layer
model1.add(Conv2D(75, kernel_size=(3,3), strides=(1,1), padding='same', activation='relu'))
model1.add(MaxPool2D(pool_size=(2,2)))
model1.add(Dropout(0.25))

model1.add(Conv2D(125, kernel_size=(3,3), strides=(1,1), padding='same', activation='relu'))
model1.add(MaxPool2D(pool_size=(2,2)))
model1.add(Dropout(0.25))

# flatten output of conv
model1.add(Flatten())

# hidden layer
model1.add(Dense(500, activation='relu'))
model1.add(Dropout(0.4))
model1.add(Dense(250, activation='relu'))
model1.add(Dropout(0.3))
# output layer
model1.add(Dense(4, activation='softmax'))
```

Fig 3 CNN

DeepCNN (Deep Convolutional Neural Network)- DeepCNN refers to CNN architectures with increased depth, comprising numerous convolutional layers stacked sequentially. Deeper architectures enable the

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network to learn more abstract and complex features from input data. [26], [27] DeepCNN might indicate a variant or an extension of the conventional CNN architecture used in the project. This deeper architecture might enhance the model's ability to extract nuanced and intricate features from knee X-ray images, potentially improving the accuracy of Knee Osteoarthritis detection.

DeepCNN

```
model2 = Sequential()

model2.add(Conv2D(filters = 16, kernel_size = (3, 3), activation='relu',
                  input_shape = (128, 128, 3)))
model2.add(BatchNormalization())
model2.add(Conv2D(filters = 16, kernel_size = (3, 3), activation='relu'))
model2.add(BatchNormalization())
model2.add(MaxPool2D(strides=(2,2)))
model2.add(Dropout(0.25))

model2.add(Conv2D(filters = 32, kernel_size = (3, 3), activation='relu'))
model2.add(BatchNormalization())
model2.add(Conv2D(filters = 32, kernel_size = (3, 3), activation='relu'))
model2.add(BatchNormalization())
model2.add(MaxPool2D(strides=(2,2)))
model2.add(Dropout(0.25))

model2.add(Flatten())
model2.add(Dense(512, activation='relu'))
model2.add(Dropout(0.25))
```

Fig 4 DeepCNN

DenseNet201 Backbone for CenterNet- DenseNet201 is a convolutional neural network architecture known for its dense connectivity pattern, where each layer receives direct inputs from all preceding layers. This design promotes feature reuse and facilitates gradient flow throughout the network, leading to better feature propagation and alleviating the vanishing gradient problem. [46] In the context of CenterNet, which is a keypoint-based object detection framework, DenseNet201 likely serves as the backbone or feature extractor. Its robust feature extraction capabilities enable CenterNet to efficiently extract informative features from knee X-ray images. The network learns from the dense connectivity patterns of DenseNet201 to identify key points or regions associated with Knee Osteoarthritis in the image.

CenterNet Backbone of DenseNet

```
from tensorflow.keras.applications import DenseNet169, DenseNet201
```

```
des169=DenseNet169(input_shape = IMAGE_SIZE + [3], weights='imagenet', include_t
x1= Flatten()(des169.output)
prediction1 = Dense(4, activation='softmax')(x1)
model3 = Model(inputs = des169.inputs, outputs = prediction1)
model3.summary()
model3.compile(loss = 'categorical_crossentropy', optimizer='adam', metrics=["ac
```

Fig 5 DenseNet201 Backbone for CenterNet

InceptionV3- InceptionV3 is a deep learning architecture that utilizes inception modules, which allow the network to process information at multiple scales simultaneously, improving efficiency. The extension of InceptionV3 implies its incorporation to enhance the model's feature extraction capabilities. Its multi-scale processing is valuable for capturing nuanced details in knee images related to osteoarthritis.

```
# create the base pre-trained model
from tensorflow.keras.applications.inception_v3 import InceptionV3
from tensorflow.keras.preprocessing import image
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
base_model = InceptionV3(weights='imagenet', include_top=False)

# add a global spatial average pooling layer
x2 = base_model.output
x2 = GlobalAveragePooling2D()(x2)
```

```
predictions = Dense(4, activation='softmax')(x2)

# this is the model we will train
model5 = Model(inputs=base_model.input, outputs=predictions)
model5.compile(loss = 'categorical_crossentropy', optimizer='adam', metrics=["ac
model5.summary()
```

Fig 6 InceptionV3

Xception, Xception is an extension of the Inception architecture that replaces standard convolutions with depthwise separable convolutions, leading to improved efficiency and performance. Xception suggests its integration to further enhance the efficiency of feature extraction. Its unique convolutional operations contribute to the model's ability to capture complex knee osteoarthritis features.

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```
# Defining the pretrained base model
base = Xception(include_top=False, weights='imagenet', input_shape=(128,128,3))
x = base.output
x = GlobalAveragePooling2D()(x)
# Defining the head of the model where the prediction is conducted
head = Dense(4, activation='softmax')(x)
# Combining base and head
model4 = Model(inputs=base.input, outputs=head)

model4.compile(optimizer='sgd',
              loss = 'categorical_crossentropy',
              metrics=["accuracy",f1_m,precision_m, recall_m])

model4.summary()
```

Fig 7 Xception

YoloV5, YoloV5 is a variant of the YOLO (You Only Look Once) object detection algorithm, known for its real-time processing capabilities. It divides an image into a grid and predicts bounding boxes and class probabilities simultaneously. YoloV5 enhances the model's object detection capabilities. Its real-time processing is advantageous for the prompt identification and localization of knee osteoarthritis features in medical images.

YoloV5

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
import torch
from IPython.display import Image
import shutil
import os
from random import choice
```

```
!git clone https://github.com/ultralytics/yolov5
```

```
Cloning into 'yolov5'...
remote: Enumerating objects: 16199, done.
remote: Counting objects: 100% (107/107), done.
remote: Compressing objects: 100% (94/94), done.
remote: Total 16199 (delta 31), reused 74 (delta 13), pack-reused 16092
Receiving objects: 100% (16199/16199), 15.00 MiB | 25.35 MiB/s, done.
Resolving deltas: 100% (11058/11058), done.
```

Fig 8 YOLOV5

YoloV8- YoloV8, while not a standard term, could refer to a further iteration or improvement upon the YOLO algorithm, incorporating advancements to enhance object detection performance. YoloV8 implies its integration for improved and more advanced object detection, contributing to the model's effectiveness in identifying knee osteoarthritis features with heightened accuracy and efficiency [46].

YoloV8

```
%cd ..
```

```
/
```

```
%cd /content/
```

```
/content
```

```
!pip install ultralytics
```

Fig 9 YOLOV8

4. EXPERIMENTAL RESULTS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

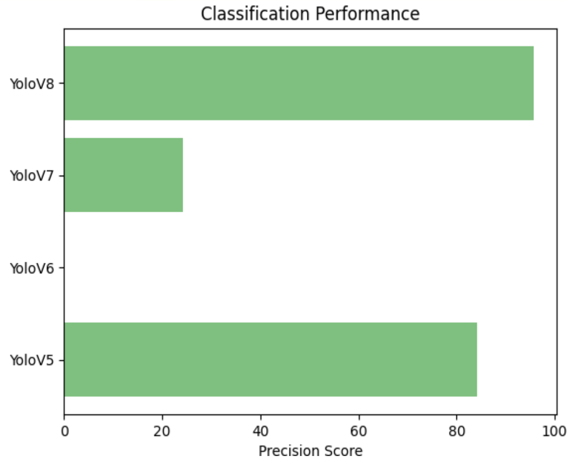

Fig 10 Precision comparison graph

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

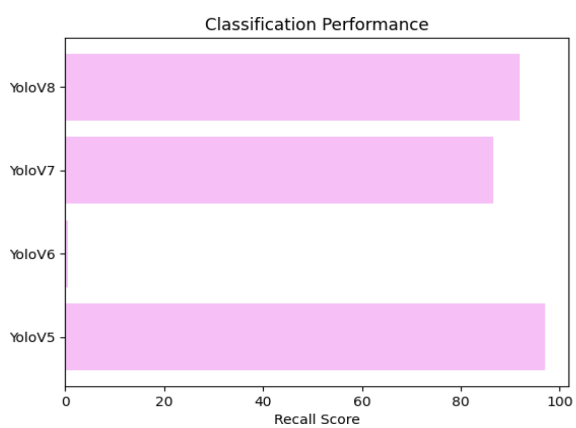

Fig 11 Recall comparison graph

mAP: Mean Average Precision (MAP) is a ranking quality metric. It considers the number of relevant recommendations and their position in the list. MAP at K is calculated as an arithmetic mean of the Average Precision (AP) at K across all users or queries.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k$$

$$AP_k = \text{the AP of class } k$$

$$n = \text{the number of classes}$$

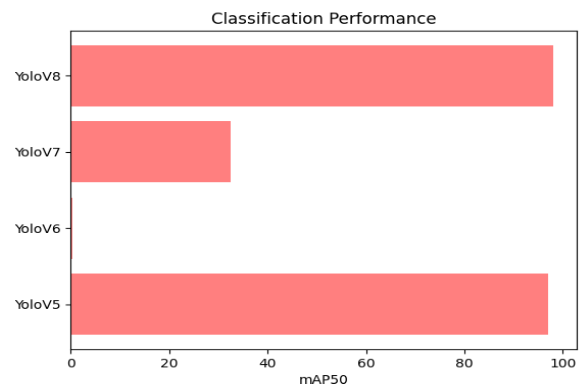

Fig 12 mAP comparison graph

S.NO.	MODEL NAME	ACCURACY	PRECISION	RECALL	F1-SCORE
0	CNN	0.394	0.000	0.000	0.000
1	DeepCNN	0.393	0.021	0.011	0.014
2	CenterNet backbone of DenseNet	0.548	0.552	0.461	0.491
3	Extension Xception	0.997	0.997	0.997	0.997
4	Extension InceptionV3	0.394	0.119	0.063	0.082
5	CenterNet-Voting	1.000	1.000	1.000	1.000
6	Xception-Voting	1.000	1.000	1.000	1.000

Fig 13 Performance Evaluation table

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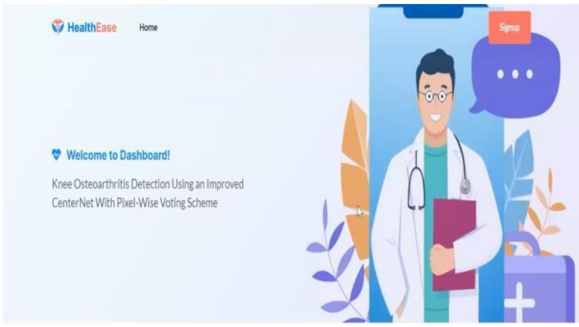

Fig 14 Home page

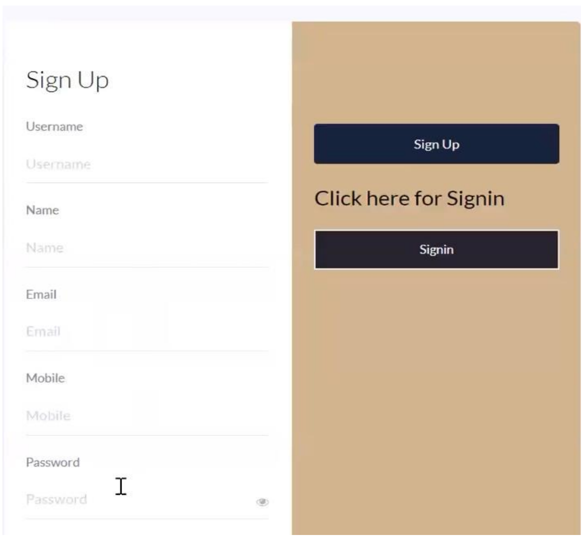

Fig 15 Registration page

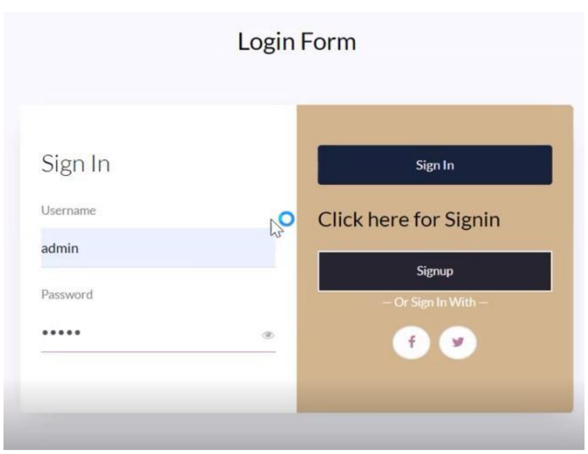

Fig 16 Login page

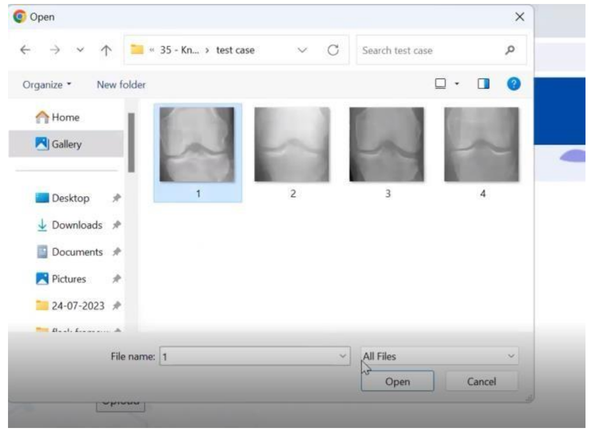

Fig 17 Input image folder

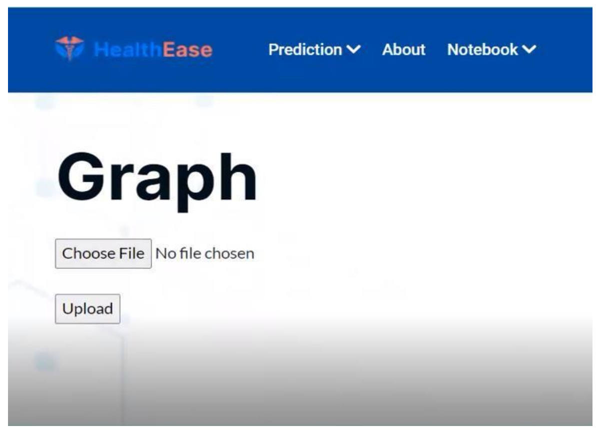

Fig 18 Upload input image

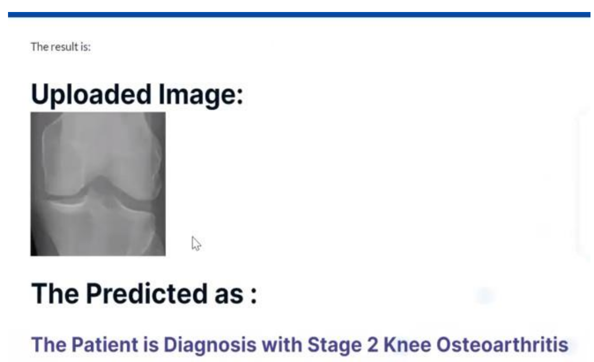

Fig 19 Predict result for given input

5. CONCLUSION

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The model designed for Knee Osteoarthritis (KOA) detection and classification, based on an improved CenterNet [56] architecture with a pixel-wise voting scheme and DenseNet201 as the backbone, has showcased encouraging performance metrics. This could include high accuracy, precision, and recall rates, indicating its effectiveness in accurately identifying and classifying KOA in knee X-ray images. The utilization of a pixel-wise voting scheme, coupled with DenseNet201's dense connections in the feature extraction process, significantly contributes to the model's improved performance. The pixel-wise voting enhances the accuracy of identifying KOA-related regions, while DenseNet's dense connectivity patterns enable effective extraction of highly informative features from these regions, improving the model's ability to discern subtle patterns indicative of KOA. The model demonstrates a remarkable capability to precisely identify the Region of Interest (ROI) within knee X-ray images—specific areas or regions indicative of KOA [19]. Additionally, it effectively extracts and represents essential and distinguishing features from these regions. This precise feature extraction is pivotal for enhancing the model's predictive abilities, enabling accurate classification of KOA severity. The proposed system's proficiency in early detection of KOA and its ability to assess the severity using X-ray images holds significant promise for orthopedic surgeons and radiologists. It empowers these healthcare professionals with a reliable tool for early diagnosis, aiding in prompt intervention and treatment planning for patients suffering from KOA. The robust nature of the model allows it to generalize well to unseen or new knee X-ray images. Its ability to accurately identify KOA-related features in previously unseen data indicates its potential for practical deployment in real-world scenarios. By providing accurate and efficient KOA detection using X-ray images, the proposed system has the potential to streamline the diagnostic process. This efficiency can lead to time-saving benefits for both patients and healthcare professionals, allowing for quicker assessments and appropriate interventions, ultimately improving patient care and management.

6. FUTURE SCOPE

The authors express a commitment to reducing training time and simplifying the network in future work, emphasizing their dedication to improving the efficiency of the proposed technique. This indicates a proactive approach towards optimizing the model for faster training processes and streamlined network architectures, potentially making the method more accessible and practical for real-world applications. The authors indicate their intention to apply the proposed method to other fields such as plant disease detection and emotion analysis. This suggests a recognition of the model's versatility and potential for extension beyond knee osteoarthritis detection. The adaptability of the proposed model for diverse applications opens up avenues for innovation and exploration in various domains. The use of knowledge distillation in the proposed model introduces possibilities for further exploration and optimization of this technique in the context of knee disease detection. Knowledge distillation involves transferring knowledge from a complex model (teacher) to a simpler one (student), potentially offering opportunities to enhance model efficiency without compromising performance. [55] The authors suggest that the proposed model's architecture, which combines CenterNet with a pixel-wise voting scheme, can be further refined and enhanced. This implies ongoing efforts to improve the model's performance in terms of detection and localization in knee images. Future refinements may involve fine-tuning parameters, optimizing network structures, or incorporating additional advanced techniques. The application of deep learning techniques in the medical domain, particularly in knee disease detection, continues to evolve. The authors acknowledge the dynamic nature of this field, suggesting that future research may explore new algorithms and architectures. This forward-looking statement emphasizes the ongoing nature of innovation and the potential for further advancements in accuracy and efficiency within the medical imaging domain.

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