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

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Abstract: The study aims to detect knee osteoarthritis using X-ray knee pictures. The initiative employs X-ray pictures to accurately diagnose osteoarthritis, a widespread and cost-effective knee joint health test. The accuracy and precision of image-processing-based knee osteoarthritis detection approaches are lacking. A innovative and personalized knee osteoarthritis detection and classification method is proposed to address the limitations of existing methods. The method requires creating a customized CenterNet, a cutting-edge object identification architecture. This CenterNet uses pixel-wise voting to extract features at a granular level. The project customizes CenterNet to improve knee osteoarthritis detection accuracy and reliability. The model uses DenseNet201 for feature extraction. DenseNet's tightly linked layers reuse features and reduce gradient concerns. DenseNet201 is used to obtain the most representative knee sample characteristics to improve feature extraction. The suggested approach aims to accurately detect knee osteoarthritis in X-rays. To go beyond detection, the model will use Kellgren and Lawrence (KL) grading to determine osteoarthritis severity. This holistic approach provides a deeper understanding of the condition, improving diagnosis and therapy. The project presents an integrated strategy employing powerful classification models (Xception, InceptionV3), efficient object detection methods (YOLOv5, YOLOv8), and a Flask-based front end. This method uses advanced categorization and detection algorithms to create a safe and smooth testing environment.

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

1. INTRODUCTION

Knee osteoarthritis (KOA) is an ongoing joint condition brought about by knee ligament weakening. Joint breaking, enlarging, distress, and inconvenience moving are KOA side effects. Serious KOA side effects can prompt falls, knee cracks, and appendage hindrance [1]. X-ray, X-beam, and CT filters are utilized to analyze knee issues. Likewise fitting for KOA assessment are X-ray and CT checks [2], [3]. The knee joints are obviously noticeable with intravenous difference [4]. These techniques have critical costs, longer assessment times, and wellbeing risks incorporate renal inadequacy [5]. Consequently, there ought to be KOA evaluation techniques that don't need a differentiation specialist and include less time and cash. Subsequently, X-rays are a less expensive and more straightforward means to see bone designs for knee assessment.

While ligament supports adaptability, its misfortune because old enough or injury produces Knee Osteoarthritis. The knee has two bones: tibia and femur. The two bones are associated via ligament. Kellgren and Lawrence (KL) reviewing depends on radiographic KOA classification to evaluate infection seriousness. It has four grades: I, II, III, and IV [6]. Grade I is the mildest disease seriousness and Grade IV is the most extreme. Early ailment determination and classification assist specialists with treating patients effectively. The most predominant reason for KOA is heftiness, and it deteriorates with age. KOA patients normal 45 years of age [7]. KOA people 65 years or more established in the US have been radiographed [6], and very nearly 21 million have the disease [8]. This sickness spreads everyday all through Asia. KOA influences 25% of rustic Pakistanis and 28% of metropolitan Pakistanis [9]. Work out, weight reduction, strolling, and physiotherapy can get KOA also medicine [10]. KOA identification and arrangement techniques incorporate Step Examination, X-ray, Impedance Signs, and so forth [11], [12]. Knee width dividing is critical for KOA seriousness appraisal. Accordingly, X-rays show joint broadness while X-ray estimates ligament thickness and surface quality. Interestingly, bioelectric impedance signals are best for KOA recognition. Minimal expense and simple to utilize [13].

There are ML and DL-based KOA identification and grouping calculations [10], [14], [15], [16], [17], [18]. A model for KOA distinguishing proof and characterization utilizing Pig and CNN crossover highlight descriptors and the KNN bunching strategy was proposed in [19]. The calculation outperformed current strategies with 97.14% accuracy. In this task, we mean to build a profound learning-based strategy with negligible intricacy and more noteworthy exactness for all KOA delivering grades to the KL evaluating framework.

Over the most recent twenty years, division based approaches have filled in pertinence. Pixels portray input test regions. Division partitions an image into regions in view of utilization needs. [20], [21], [22]. Commotion can debase picture quality, yet division based strategies are fundamental for infection distinguishing proof. A computerized division approach will further develop return for money invested determination and exactness in clinical imaging, diminishing missteps and human work. [23], [24], [25]. Profound learning models have been utilized to extricate viable highlights in clinical [26], [27], agricultural[28], reconnaissance [29], and so forth. Although directed approaches are more precise, marking tremendous preparation tests is troublesome. Information might be of many sorts, making naming and getting ready enormous preparation information a continuous interaction.

2. LITERATURE SURVEY

Knee osteoarthritis (KOA) is a degenerative joint condition brought about via ligament misfortune [1, 2, 3, 4, 6]. KOA is perplexing and its pathogenesis is ineffectively perceived, thus specialists require reliable strategies to keep away from finding botches. Public data sets have empowered refined examination in KOA research, but information heterogeneity and high element dimensionality make determination dangerous. This study [3] means to foster a vigorous Feature Selection (FS) procedure that can (I) handle complex datasets and (ii) further develop existing element determination methods for recognizing KOA risk factors. This was finished involving complex information from the Osteoarthritis Drive data set for individuals with and without KOA. The fluffy gathering highlight determination approach consolidates fluffy rationale based channel, covering, and implanting FS calculations. A huge exploratory arrangement with various contending FS calculations and a few notable ML models evaluated the proposed procedure [10], [14], [15], [16], [17], [18]. The top model (Random Forest classifier) grouped 21 gamble factors with 73.55% accuracy. At long last, logic investigation measured the chose qualities' effect on the model's result, assisting us with understanding the best model's dynamic instrument.

Knee joint vibroarthrographic (VAG) signals from delayed knee joint development uncover knee pathology. VAG signals change non-permanently and aperiodically. This study broke down VAG signals utilizing Ensemble Empirical Mode Decomposition (EEMD) and demonstrated a remade signal utilizing Detrended Change Investigation. The proposed procedure [4] trains semi-managed learning classifier models utilizing reproduced flags and inferred entropy values. To evaluate signal intricacy, Tsallis, Change, and Unearthly entropies were extricated. These qualities become Arbitrary Timberland order preparing vectors [32], [33], [34]. This exploration characterized signals with 86.52% exactness. This work could assist with characterizing VAG signals into distorted and ordinary sets for painless knee pre-screening of articular harms and chondromalacia patallae.

Many papers in the beyond four years archived focus subordinate gadolinium statement in grown-ups and kids, apparent as raised signal powers in the globus pallidus and dentate core on unenhanced T1-weighted imaging. Posthumous human or creature examinations have affirmed gadolinium gathering in T1-hyperintensity areas, hoisting gambles for gadolinium-based contrast specialists. Notwithstanding the cerebrum, liver, skin, and bone contain leftover gadolinium. This survey [5] sums up the flow proof on gadolinium statement in people and creatures, assesses the impacts of various kinds of GBCAs on gadolinium affidavit, presents the conceivable entry or freedom component of gadolinium, and examines likely aftereffects and future exploration.

Knee X-rays can be utilized to consequently analyze radiographic osteoarthritis (OA) [31]. Kellgren-Lawrence grouping grades, which address OA seriousness, are utilized for location [6]. The classifier was made utilizing hand sorted X-rays of the initial four KL classes (typical, questionable, least, and moderate). Picture examination includes choosing an assortment of picture content descriptors and picture changes that are helpful for OA recognizable proof in X-rays and weighting them with Fisher scores. A straightforward weighted closest neighbor calculation predicts the KL grade of a test X-ray test. The investigation utilized 350 manual KL-reviewed X-beam pictures. Trial results recommend that moderate OA (KL grade 3) and negligible OA (KL grade 2) might be recognized from ordinary occurrences with 91.5% and 80.4% exactness [10, 16, 46]. Consequently perceived dicey OA (KL grade 1) with 57% accuracy.

A totally constructed computer assisted diagnostic (CAD) framework for early knee osteoarthritis (OA) distinguishing proof utilizing knee X-ray imaging and ML methods is introduced [7]. X-ray pictures are preprocessed in Fourier space with round Fourier channel. The information is then standardized utilizing an exceptional prescient displaying approach in view of multivariate linear regression (MLR) to diminish changeability among OA and sound members. To limit dimensionality, independent component analysis (ICA) is used during highlight choice/extraction. At long last, arrangement utilizes Naive Bayes and random forest classifiers. This special picture based method is applied to 1024 knee X-ray pictures from the OsteoArthritis Drive data set. The proposed OA discovery technique has areas of strength for an order rate (82.98% accuracy, 87.15% sensitivity, and 80.65% specificity).

3. METHODOLOGY

i) Proposed Work:

The suggested method uses a modified CenterNet and a pixel-wise voting technique to extract features from knee pictures automatically. It uses DenseNet201 as the basis network to extract the most representative features from knee data, with an emphasis on accurate knee osteoarthritis (KOA) identification and severity classification using the KL grading system [30]. The project presents an integrated strategy that includes powerful classification models (Xception, InceptionV3), efficient object detection algorithms (YOLOv5, YOLOv8) [46], and a user-friendly front end built with the Flask framework. This technique seeks to capitalize on the merits of advanced classification and detection models while offering a smooth and secure testing environment.

ii) System Architecture:

In this paper, major areas of strength for a discovery component is proposed. The recommended approach might be utilized on inconspicuous knee pictures with various KOA seriousness [45, 55]. Knee imaging' high-layered qualities help recognize and portray disease. The stamped jumping boxes were our return for capital invested for the examples. We shaped highlights utilizing improved CenterNet with DenseNet-201 as the premise organization. DenseNet was picked over ResNet in light of the fact that its thickly connected layers remove the most agent knee joint component. ResNet utilizes skip associations and results from layers 2 and 3. DenseNet likewise has an feature layer (convolutional layer) that catches knee picture low-level highlights, thick blocks, and progress layers between thick blocks. DenseNet addresses includes better compared to ResNet however requires additional handling assets.

Before knee joint component extraction, we gave the democratic capability input bouncing box anticipated utilizing our changed CenterNet to support limitation. Votes from every pixel in the assessed jumping box are utilized to ascertain the ideal bouncing box in view of most noteworthy score. We likewise use information refining to limit model size and move information from a mind boggling model to a conservative one without adding handling assets. Consequently, Mendeley is utilized to make a computerized KOA ailment identification model. We prepared an upgraded CenterNet network [55] utilizing clinical master knee joint examples. These examples are portrayed utilizing KL evaluating frameworks G-I, G-II, G-III, and G-IV. Figure 1 portrays the recommended framework plan. After classifier preparing, photographs are arranged into five classes: Ordinary, G-I, G-II, G-III, and G-IV.

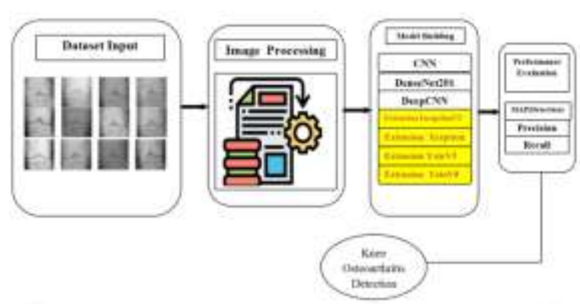

Fig 1Proposed Architecture

iii) Dataset collection:

Acquiring and comprehending the dataset on Knee Osteoarthritis (KOA) [45]. It may entail getting knee X-ray images from a dataset devoted to KOA or using data gathered and preprocessed via Roboflow, a tool that simplifies data preparation for machine learning activities. Exploratory Data Analysis (EDA) may include evaluating data quality, comprehending label distributions, and displaying sample pictures to obtain insight into the dataset's properties.

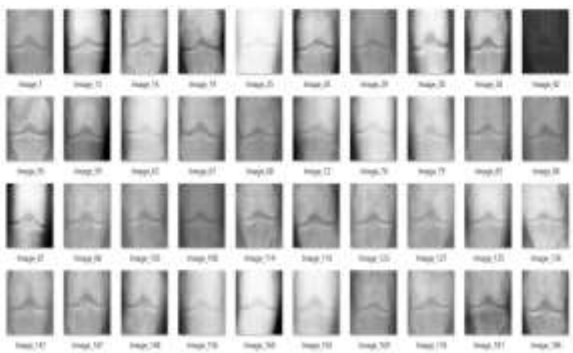

Fig 2 Knee Osteoarthritis Dataset

iv) Image Processing:

Image processing is critical in object recognition in autonomous driving systems, comprising numerous crucial phases. The first phase is turning the input image into a blob object and optimizing it for further analysis and modification. Following that, the classes of items to be identified are defined, outlining the particular categories that the algorithm seeks to recognize. Bounding boxes are also given, defining the regions of interest within the picture where items are anticipated to be found. The processed data is next turned to a NumPy array, which is essential for efficient numerical calculation and analysis.
The following stage is loading a pre-trained model using existing information from large datasets. This involves accessing the pre-trained model's network layers, which include the learnt features and parameters required for accurate object identification. In addition, output layers are extracted, offering final predictions and allowing for successful object discrimination and categorization. Furthermore, the image and annotation files are attached to the image processing pipeline, assuring full information for future study. The color space is altered by converting from BGR to RGB, and a mask is produced to emphasize important characteristics. Finally, the image is scaled to prepare it for further processing and analysis. This complete image processing methodology lays the groundwork for robust and precise object recognition in the dynamic context of autonomous driving systems, hence improving road safety and decision-making capabilities.

v) Data Augmentation:

Data augmentation [25,26] is a key strategy for increasing the variety and robustness of training datasets for machine learning models, notably in image processing and computer vision. To enrich the original dataset, three main alterations are used: randomization, rotation, and transformation.
Randomizing the image increases unpredictability by making random adjustments to brightness, contrast, or color saturation. This stochastic technique allows the model to better generalize to new data and various environmental situations.
Rotating the image entails changing the original image's orientation to differing degrees. This augmentation strategy helps to educate the model to detect objects from multiple angles, imitating differences in real-world circumstances.
Scaling, shearing, and flipping are examples of geometric transformations for images. These changes improve the dataset by adding distortions that match real-world differences in item appearance and orientation. Using these data augmentation approaches broadens the

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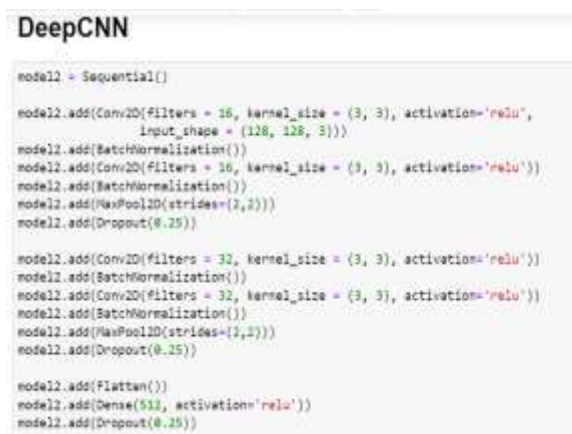
training dataset, allowing the model to learn robust features and patterns. This, in turn, increases the model's capacity to generalize and perform successfully over a wide range of tough test circumstances. Data augmentation is an important method for reducing overfitting, improving model performance, and increasing the overall dependability of machine learning models, particularly in applications such as image recognition for autonomous driving systems.

vi) Algorithms:

CNN (Convolutional Neural Network)- CNNs are a sort of neural network that is for the most part used for picture related errands because of its capacity to learn progressive component portrayals effectively. It incorporates layers like as convolutional, pooling, and completely connected layers. Convolutional layers remove highlights by convolutionalizing learnt channels over input pictures to recognize spatial examples. Pooling layers limit spatial aspects, though completely connected layers order in view of recovered ascribes. CNN is undoubtedly the establishment or a part of the undertaking's model plan. It aids the extraction of highlights from knee X-ray pictures, permitting the model to perceive confounded designs related with knee osteoarthritis [46].

Fig 3 CNN

DeepCNN (Deep Convolutional Neural Network)- DeepCNN alludes to CNN plans with more prominent profundity, which incorporate a few convolutional layers layered successively. More deep plans permit the organization to gain dynamic and complex attributes from input information. [26], [27] DeepCNN might allude to a variety or extension of the venture's conventional CNN engineering. This more definite plan might work on the model's ability to remove nuanced and convoluted attributes from knee X-ray pictures, subsequently expanding the exactness of knee osteoarthritis recognizable proof.



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 design separated by its thick association geography, in which each layer gets immediate contributions from every single going before layer. This design energizes highlight reuse and angle stream all through the organization, bringing about better component spread and relieving the evaporating slope issue. [46] DenseNet201 is probably utilized as the spine or component extractor in CenterNet, a keypoint-based object ID framework. CenterNet's broad component extraction capacities permit it to quickly remove significant elements from knee X-ray pictures. The organization utilizes DenseNet201's thick association

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examples to recognize huge regions or areas related 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 design that utilizes beginning modules, which permit the organization to investigate information at many scales immediately, expanding effectiveness. The extension of InceptionV3 includes its consideration to further develop the model's component extraction abilities. Its multi-scale handling is valuable for acquiring sensitive highlights in knee photographs with 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 design that substitutes customary convolutions with depthwise divisible convolutions, bringing about higher productivity and execution. Xception prescribes its joining to work on the effectiveness of element extraction. Its imaginative convolutional processes help the model catch confounded knee osteoarthritis qualities.

```
# 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 constant item ID framework that depends on the YOLO (You Only Look Once) technique. It changes over a picture into a framework and predicts both jumping boxes and class probabilities. YoloV5 further develops the model's item distinguishing ability. Its ongoing handling considers the fast recognition and limitation of knee osteoarthritis attributes in clinical pictures.

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 word, could allude to a further cycle or upgrade of the Consequences be damned calculation that integrates developments to increment object acknowledgment execution. YoloV8 demonstrates incorporation for upgraded and more intricate item ID, which adds to the model's capacity to perceive knee osteoarthritis qualities with more accuracy and efficiency [46].

YoloV8

```
%cd ..
/
%cd /content/
/content
!pip install ultralytics
```

Fig 9 YOLOV8

4. EXPERIMENTAL RESULTS

Precision: Precision estimates the extent of precisely characterized cases or tests among those classified as certain. Hence, the precision can be determined utilizing the accompanying formula:

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

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

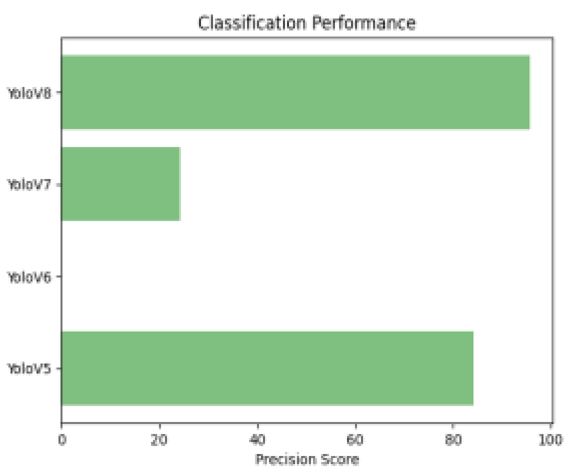

Fig 10 Precision comparison graph

Recall: Recall is an ML metric that evaluates a model's capacity to perceive all occasions of a given class. It is the proportion of accurately anticipated positive perceptions to add up to real up-sides, which gives data on a model's fulfillment in gathering instances of a particular class.

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

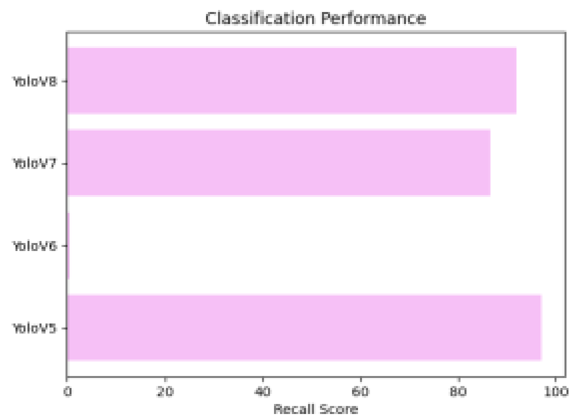

Fig 11 Recall comparison graph

mAP: Mean Average Precision (MAP) is a ranking quality statistic. It takes into account the quantity and location of relevant recommendations on the list. The MAP at K is determined as the arithmetic mean of the Average Precision (AP) at K for all users and queries.

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

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

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

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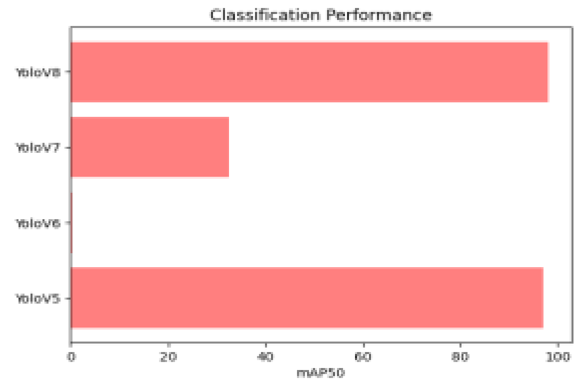

Fig 12 mAP comparison graph

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

Fig 14 Home page

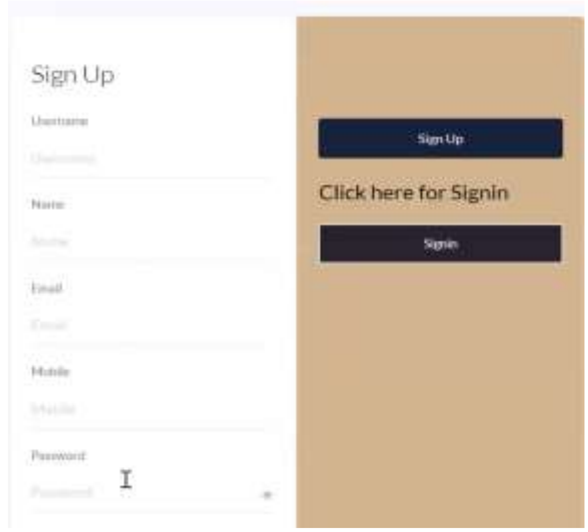

Fig 15 Registration page

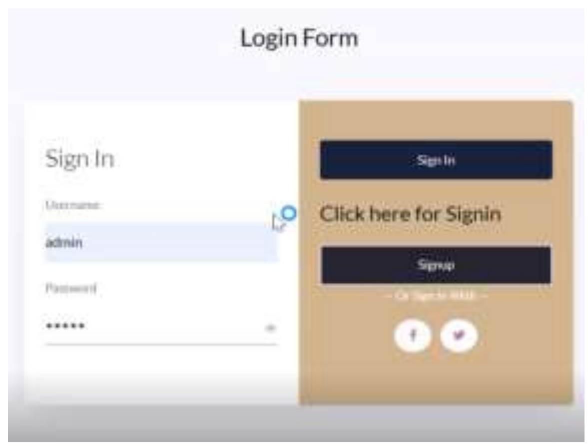

Fig 16 Login page

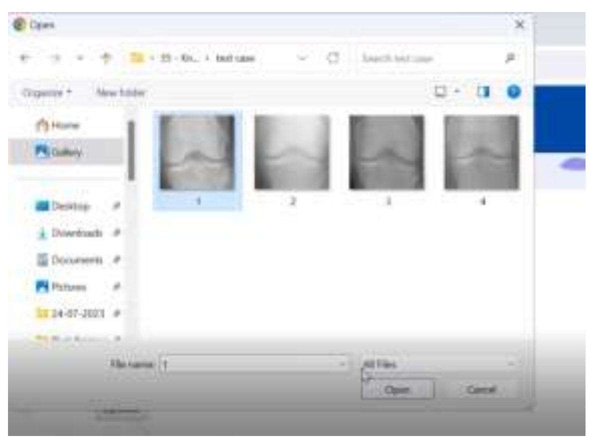

Fig 17 Input image folder

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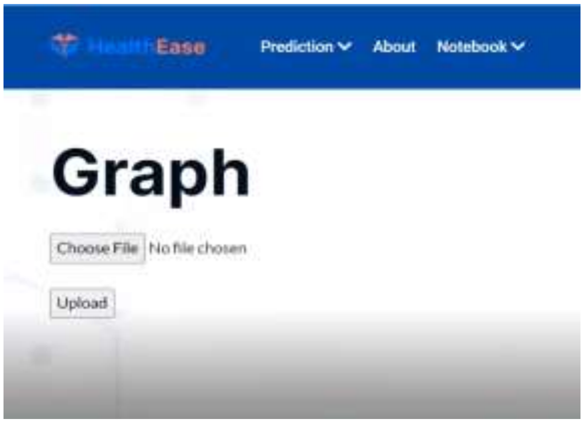

Fig 18 Upload input image

Fig 19 Predict result for given input

5. CONCLUSION

The Knee Osteoarthritis (KOA) detection and classification model, based on an upgraded CenterNet [56] architecture with pixel-wise voting and DenseNet201 as the backbone, has shown promising performance. High accuracy, precision, and recall rates may indicate its ability to recognize and categorize KOA in knee X-ray images. Pixel-wise voting and DenseNet201's dense feature extraction connections boost the model's performance. Pixel-wise voting improves KOA-related region identification, while DenseNet's dense connection patterns enable effective feature extraction from these regions, enhancing the model's capacity to detect subtle KOA patterns. The program accurately identifies the Region of Interest (ROI) in knee X-ray images, indicating KOA [19]. It also extracts and depicts key aspects of these locations. The model's prediction powers and KOA severity categorization depend on this exact feature extraction. Orthopedic surgeons and radiologists are hopeful about the proposed system's early KOA identification and X-ray severity assessment. It gives doctors a trustworthy tool for early diagnosis, enabling rapid intervention and therapy planning for KOA patients. The model generalizes effectively to fresh knee X-ray pictures because to its robustness. Its ability to reliably detect KOA-related traits in new data suggests real-world applications. The suggested technique might simplify KOA diagnosis by employing X-ray images to identify KOA accurately and efficiently. This efficiency can save patients and healthcare personnel time by enabling for faster evaluations and appropriate treatments, enhancing patient care and management.

6. FUTURE SCOPE

The authors pledge to reduce training time and simplify the network in future work to improve the suggested technique's efficiency. This suggests a proactive strategy to refining the model for faster training and simpler network designs, making it more feasible for real-world applications. The authors hope to use the approach for plant disease detection and emotion analysis. This appears to acknowledge the model's adaptability and possibilities beyond knee osteoarthritis diagnosis. The suggested model's versatility allows for innovation and investigation in many fields. Knowledge distillation in the suggested approach allows for knee disease diagnosis research and optimization. Knowledge distillation transfers knowledge from a complicated model (teacher) to a simpler one (student), potentially improving model efficiency without compromising performance. [55] The authors advise improving the model's CenterNet-pixel-wise voting

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architecture. This requires continual attempts to enhance the model's knee image identification and localization. Parameter adjustment, network structure optimization, and sophisticated approaches may be added in the future. Medical applications of deep learning, particularly knee disease diagnosis, are growing. This topic is dynamic, thus future research may investigate new methods and designs. This forward-looking statement stresses innovation and the potential for medical imaging accuracy and efficiency improvements.

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