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Leveraging Machine Learning and Deep Learning Techniques to Identify Deformation in Knee for Assisting Replacement Surgery

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Abstract: The rise in knee injury has increased and hence the need for advanced technology is needed to reduce the duration of recovery required to cure the knee replacement. This work first introduces the knee replacement issue and then tries to review the work that has been carried out in this regard. This paper also tries to produce the detection for knee replacement with more accuracy using the science of Deep Learning which is extended version of Machine Learning. This work focuses on detection of Deformation in Knee using three methods i.e. Convolutional Neural Network, Transfer Learning and the proposed method based on enhancement of VGG16. A comparative analysis is made based on performance metrics that shows the proposed model outperforms the rest two in terms of these metrics. The proposed method achieves an accuracy of 94.5%, surpassing CNN's 91.2% and Transfer learning 92%.

***Keywords**: comparative, replacement, VGG16, Deformation*

1. Introduction

The human body highly depends on the knee for its movement in lifting and bending. Hence, knee is one of the most vital element of human body for its proper functioning to support daily life work to be performed by human. The knee lies at middle of the human body's leg which articulates between the patella, tibia as well as femur. There are situations like age, accidents, malnutrition, etc. which deteriorates the knee functionality. The medical science has huge work on the knee injury. Moreover, when the knee is not in a potion to be repaired easily, there is need for knee replacement, or knee arthroplasty. Moreover, in order to treat the advanced osteoarthritis (KOA), the use of Total Knee arthroplasty is considered as part of the surgery [1]. Total Knee arthroplasty (TKA) is has been considered as one of the most widely accepted solution to treat KOA and this would highly impact the need for adopting TKA with more precise and accurate diagnostics as there are high risk of failure and revision involved when considering TKA a [2, 3]. Revision is required in many case after surgery when there is a case of loosening which increase more complications [3]. The dwelling of longer life expectancy, occurrence of loosening and the proliferation in TKA make a major reason for interest in the field of orthopedic for knee replacement treatment. The delay in diagnosis may result in more complication, revisions of surgery and also result in permanent damage which may result in permanent damage in sense of recovery. Also, the prolonged walking because on non-diagnosis of KOA may result in loss of bone stock as well it may also lead to damaging of soft tissues that surrounds the knee area, it may also damage the ligaments used to bind bones and muscles.

If a system is developed which can automatically detect the loosening process which is initial symptoms in KOA may reduce the burden for the orthopedic surgeon and it may also provide more accurate diagnosis parameters that could be adopted for TKA. Though, loosening is one of the difficult task to be diagnosed, still may attempts are made by analyzing scintigraphy, MRI as well as fluorodeoxyglucose-positron emission tomography (FDG-PET) in order to understand loosening which is be very costly and as well as has less accuracy [4]. In addition, due to these multiple imaging modalities, there could be need of for further blood tests, repeating of imaging of the patients and also there could be need for unnecessary revision [4].

The use of advanced technologies like Artificial Intelligence (AI) could be a major breakthrough in analyzing or diagnosing the KOA at earlier stages and also provide the more accurate diagnosis in comparison to the traditional methods. Artificial

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Intelligence refers to develop the capability of the machine that could simulate like human intelligence in sense of thinking, reasoning and could also have learning capability like human [5]. Moreover, AI have the capability to make decision and improve its performance using various algorithms that it incorporates. There are various concepts of AI such as Machine Learning (ML), Neural Network (NN), Deep Learning (DL), Natural Language Processing (NLP) and many others [6].

Machine Learning (ML) is the subdomain of AI which has the capability of learning without being programmed in explicit manner. The ML has implementation in research and that too in healthcare sector. ML is majorly categorized as Supervised Machine Learning (SML), Unsupervised Machine Learning (UML), Semi-Supervised Machine Learning (SSM)and Reinforcement Learning (RL).

Supervised Learning uses concept where the training is done over the Labelled Dataset (LD). These LD have both input as well as output parameters [7]. While SML uses LD, the UML uses Unlabeled Dataset (UD) [8]. UML tries to discovery patterns as well as relationship using UD. The main aim of using UML is to identify the hidden patterns, similarities as well as cluster available in the UD.

Semi-Supervised Learning (SSL) works in the intermediate concept of both SML and UML and it uses both LD as well as UD [9]. This algorithm becomes more vital when LD is very costly, require more time and also need intensive resources. When there are few LD and few UD, the use of Semi-Supervised Learning becomes highly useful. Finally, the Reinforcement Learning (RL) is ML algorithm whose outputs depends upon interaction with the environment [10]. The use of trial, error including delay are the prevalent nature of RL. The best part of the RL is that, it keeps on improving the performance by Reward Feedback (RF) concept.

Neural Network (NN) are used to mimic the complex functionality of human brain using its computational models [11]. The NN consist of neural network have interconnection or the neurons connections which are responsible for learning and processing the signals.

Convolution Neural Network (CNN) is subdomain of Artificial Neural Network where it works by extracting feature matrix data set which are in the form of grids. CNN is having combination of various layers that are input layer, convolution layer, poling layer and finally the fully connected layers [12].

Deep Learning (DL) is one of the major part of ML which lays its mechanism on Artificial Neural Network (ANN) architecture [13]. ANN has interconnected nodes which are known as neurons that work with each other for processing and learning form the provided input. The neuron gets input from its previous layer which is also known as input layer. The output for the previous layer become input for the preceding layer. The layers of DL perform the transformation of input data vis sequence of nonlinear transformation. DL could be implemented for three major concepts that is Supervised, Unsupervised and Reinforcement ML. Transfer Learning is another important concept that could be used in various applications including application in KOA. Transfer learning is very advanced method in ML where the model uses knowledge gained from its previous task to solve the newer one [14].

The introduced topic has been used in this work for laying foundation for research and its processing to achieve the objective of the research paper.

2. Literature Review

Machine Learning has come as one of the major applications in healthcare sector. The ML can detect in automation various medical conditions such as strokes, cancer and other disease with higher level of accuracy [15-20]. Ml has the capability to recognize pattern by traversing superfluous number of LD and UD to make more intelligent decision which may not follow clinical benchmark set by healthcare expert [21]. Shah et al. [21] analyzed the detection of KOA using radiography. Though, the accuracy was not up to the mark because it completely depends upon the type of algorithms adopted, type of dataset used and the computation capabilities utilized.

The use of AI and its subdomain could be vitally used increase the detection accuracy of the KOA and TKA and it provides more useful results that could identify TKA need in very early stage [22]. The models have been developed using ML algorithms to deal and provide assist in pre-TKA prediction and as well as plan to identify useful parameters and metrics of TKA which may include prediction of size for implanting process [23]. ML and DL could also help in reconstruction of three dimensional CT data that could be eventually used to provide facility to robotic assistance based TKA [24]. Moreover, the use of these advanced technology could also help in positioning and alignment for the TKA [25]. The use of ML and DL helps in reducing the labor cost and also reducing the chances of revision of surgery. The use of ML and its subdomain can also be used to calculate in advance the cost of stay in hospital, discharge disposition and various other elements involved in Total Knee Replacement [26]. Moreover, this also significantly impacts the burden of TKA and consequently it affects the decision regarding payment in healthcare services [27 -28].

Tiulpin et al. [29] proposed model based upon Siamese Convolutional Neural Network which was trained over knee radiograph for detection of KOA in elderly people. The model achieved multiclass accuracy of 67 % which is considered significant in comparison to the arthroplasty surgeons. Norman et al. [30] used NN to achieve sensitivity accuracy in range of 69 to 89 percent.

Leung et al. [31] developed model using deep learning where it used to predict the need for the TKA and the performance was better in comparison to previous algorithms used [32]. Heisinger et al. [33] proposed one ML model for anlysis of knee symptomatology used for tackling the TKA. El-Galaly et al. [34] were the first one to propose the detection of TKA for early revisions. The model was proposed and made optimal at that stage based upon preoperative information [34]. But, this could be made more optimal bu using latest models or algorithms of AI.

There are other techniques that were proposed for TKR which consist of regression [35]. However, the use of multivariate model for prediction of TKR has ben also proposed [36]. This shows the need of advanced technologies. The research is optimal during the time of its achievement but for future and in present scenario, there is need of modern models of ML and DL in order to predict TKR more precisely and accurately. Also, various predictive models were developed to that were able to accept clinical inputs as well as demographic information required for TKR [37]. The use of deep learning has acted as one of the solution in order to predict the symptoms for TKR, and the author has also sued the CNN that helped in image classification required for the TKR [38]. Though, again there are scope of improvement when considering the performance matrix that are used in ML. There is again need to imap0lemnt advanced techniques for the TKR issues using ML and DL. The use of DL is also very vital when there are very complex prognostic features whose extraction is viral for TKR. The use of DL was also used as one of the mitigating element in complex situation even in case like Osteoarthritis Initiative (OAI) [39]. Therefore, the use of DL has been suggested in many works where OAI classification as well as progression were required [39]. Therefore, it can be seen that large work done supports the use of ML and DL for the prediction of TKR.

Knee osteoarthritis (KOA) is the root cause for disability for most of the elderly people where the figure is rising continuously [40]. This not only increase burden on individual but also creates economic burden to the nation, where expenditure for product on OA is approximately 1 to 2 percent for entire [41,42]. It has been also noticed that almost 30 percent of the people which are above an age of 60 are mostly suffering from KOA [42]. The increase in stiffness as well decrease in the movement of join are the two main symptoms for OA [43]. When these symptoms go unnoticed, then there is need for TKR. Dysfunction is another aspect of the of OA which consequently result in need for TKR.

The research done in earlier phase and also in the current phase over the prediction for need of the TKR hugely require more precise and early detection for speedy recovery. Also, the use of ML and DL and other advanced algorithm is the need as the figure suggest the rise in OA with the toe to come. Therefore, this section does more descriptive review in order to form the base for the model and solution that would be proposed in the next section [44][45][46].

3. Proposed Methodology

3.1 Data Set:

This work is performed on knee X-ray images and to assess the severity of osteoarthritis using the Osteoarthritis Initiative (OAI) dataset. The link of this dataset is available at Knee X-ray Analysis with ResNet for Osteoarthritis (kaggle.com) . Images are resized to 224x224 pixels to match the input size.

3.2 Data Preprocessing and Data Augmentation: Data augmentation is a technique used to artificially increase the size and diversity of a dataset by creating modified versions of existing images. It is especially useful in training deep learning models to improve their generalization ability and prevent overfitting by exposing the model to varied forms of the same image. Common data augmentation techniques for images include geometric transformations, color adjustments, and other modifications. A few geometric transformations has been performed to artificially increase the dataset in order to manage the class imbalance. Table 1 shows the parameters of data augmentation [47][48][49].

Table1: Parameters for data augmentation

Parameters to Augment Image	Values
Rescaling	1./255
Random Rotations	40
Horizontal Shifts	0.2
Vertical Shifts	0.2
Shear Transformations	0.2
Zooming	0.2
Horizontal Flipping	True

3.3 Data Split: In this process the dataset is divided into training and validation to evaluate model performance reliably. The data is split into 90% for training and 10% for validation.

3.4 Classification Models

This work compares three classification models one is Convolutional Neural Network (CNN) and another is enhanced VGG16 and transfer learning. Both these models are trained using 90% of the dataset and then evaluated and made comparison based on performance metrics like accuracy, precision, recall, F1-Score, sensitivity, specificity [50][51].

VGG16 is a deep convolutional neural network known for its straightforward and consistent design, featuring 16 layers with adjustable weights: 13 convolutional layers and 3 fully connected layers. It is organized into five convolutional blocks, each with 2-3 convolutional layers followed by 2x2 max-pooling layers. The convolutional layers use 3x3 filters with a stride of 1, keeping the spatial dimensions intact while increasing the number of filters from 64 in the initial block to 512 in the later ones. This consistent use of small filters helps capture detailed features like edges and textures and develop more complex representations deeper in the network. Each max-pooling layer halves the spatial dimensions, simplifying the data while preserving essential features, leading to efficient feature extraction. After the convolutional blocks, VGG16 includes three fully connected layers: the first two have 4,096 neurons each and use ReLU activation to introduce non-linearity, aiding in capturing complex feature relationships. The final fully connected layer uses a softmax activation function to classify input images [52].

The enhancement of the VGG16 model involves excluding its top layers and deactivating extra layers, leaving only the batch normalization layers active. Additional layers such as regularizer, dropout layers, and extra batch normalization were added to improve the model's performance and make it a better fit for the dataset. Early stopping is employed to halt training once the model reaches its optimal learning point, preventing overfitting and ensuring efficient training. The learning rate used in the proposed model is 0.0001. Figure 1 shows the proposed model summary for the model.

Model: "model"

Layer (type)	Output Shape	Param #
input_3 (InputLayer)	[(None, 224, 224, 3)]	0
block1_conv1 (Conv2D)	(None, 224, 224, 64)	1792
block1_conv2 (Conv2D)	(None, 224, 224, 64)	36928
block1_pool (MaxPooling2D)	(None, 112, 112, 64)	0
block2_conv1 (Conv2D)	(None, 112, 112, 128)	73856
block2_conv2 (Conv2D)	(None, 112, 112, 128)	147584
block2_pool (MaxPooling2D)	(None, 56, 56, 128)	0
block3_conv1 (Conv2D)	(None, 56, 56, 256)	295168
block3_conv2 (Conv2D)	(None, 56, 56, 256)	590080
block3_conv3 (Conv2D)	(None, 56, 56, 256)	590080
block3_pool (MaxPooling2D)	(None, 28, 28, 256)	0
block4_conv1 (Conv2D)	(None, 28, 28, 512)	1180160
block4_conv2 (Conv2D)	(None, 28, 28, 512)	2359808
block4_conv3 (Conv2D)	(None, 28, 28, 512)	2359808
block4_pool (MaxPooling2D)	(None, 14, 14, 512)	0
block5_conv1 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv2 (Conv2D)	(None, 14, 14, 512)	2359808
block5_conv3 (Conv2D)	(None, 14, 14, 512)	2359808
block5_pool (MaxPooling2D)	(None, 7, 7, 512)	0
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 512)	0
dense_2 (Dense)	(None, 1024)	525312
dropout_2 (Dropout)	(None, 1024)	0
batch_normalization_2 (BatchNormalization)	(None, 1024)	4096
dense_3 (Dense)	(None, 5)	5125

Figure 1: Model summary of Proposed Model

Total params: 15,249,221

Trainable params: 15,247,173

Non-trainable params: 2,048

3.5 Performance Metrics

Accuracy, precision, recall, F1-score, and specificity are key metrics used to evaluate a model's performance. Accuracy provides an overall measure by calculating the proportion of correct predictions out of all predictions. Precision focuses on the accuracy of positive predictions by measuring how many of the predicted positives are actually true. Recall (or sensitivity) assesses how well the model identifies true positive cases, indicating its ability to detect relevant instances. The F1-score combines precision and recall into a single value using their harmonic mean, offering a balanced view when both false positives and false negatives matter. Specificity evaluates the model's effectiveness in correctly identifying negative cases, making it useful in contexts where distinguishing true negatives is important.

3.6 Results and Discussion

The comparative performance evaluation of the proposed method based on transfer learning i.e. enhanced VGG16 against Convolutional Neural Networks underscores the significant advancements in knee joint diagnostics achieved through the new methodology. Table2 illustrates a direct comparison between the proposed method and CNN, highlighting the superior performance of the former across several performance metrics. The proposed method achieves an accuracy of 94.5%, surpassing CNN's 91.2%. This difference signifies a more precise diagnostic capability, which is crucial for accurately assessing knee joint conditions. Precision is another key performance indicator where the proposed method scores 93.8% compared to CNN's 89.5%. Higher precision reflects the method's enhanced ability to correctly identify relevant features and reduce false positives, leading to more reliable diagnostic outcomes.

Similarly, the proposed method excels in recall, with a score of 92.3% versus CNN's 87.8%. This indicates that the new method is more effective in identifying true positives, which is essential for comprehensive diagnostics. The F1-Score, combining precision and recall into a single metric, is also higher for the proposed method at 93.0%, compared to CNN's 88.6%. This shows a balanced performance, integrating both high precision and recall, leading to better overall diagnostic accuracy. Sensitivity, at 90.9% for the proposed method, further demonstrates its ability to detect true positive cases, outperforming CNN's 85.4%. Specificity, which measures the method's ability to correctly identify negatives, is also higher for the proposed method at 95.1% compared to CNN's 92.0%. This indicates fewer false positives, ensuring more accurate diagnostics.

Table 3 provides a comparison between the proposed method and Transfer Learning, showcasing similar improvements. The proposed method's accuracy of 94.5% outstrips Transfer Learning's 92.0%, indicating better overall performance in diagnostic accuracy. Precision, recall, and F1-Score are higher for the proposed method (93.8%, 92.3%, and 93.0%, respectively) compared to Transfer Learning (90.1%, 88.5%, and 89.3%). These results highlight the proposed method's advanced capability in identifying and correctly diagnosing knee joint issues. Sensitivity and specificity are also superior in the proposed method, with scores of 90.9% and 95.1%, respectively, compared to Transfer Learning's 87.6% and 93.2%. These metrics underscore the proposed method's enhanced diagnostic accuracy and reliability, leading to fewer missed diagnoses and incorrect identifications.

In summary, the proposed method demonstrates a marked improvement over both Convolutional Neural Networks and Transfer Learning in key performance metrics. Its higher accuracy, precision, recall, F1-score, sensitivity, and specificity make it a more effective tool for knee joint diagnostics. This comprehensive performance evaluation highlights the advanced capabilities of the proposed methodology, showcasing its potential to deliver more reliable, accurate, and efficient diagnostic results compared to traditional methods. By incorporating sophisticated algorithms and advanced feature processing techniques, the proposed method offers a significant enhancement in medical image analysis, providing valuable insights for the accurate assessment of knee joint conditions.

Table 2. **Performance Evaluation of Proposed Method vs. Convolutional Neural Networks**

Performance Metric	**Proposed Method**	**Convolutional Neural Networks**
Accuracy (%)	94.5	91.2
Precision (%)	93.8	89.5
Recall (%)	92.3	87.8
F1-Score (%)	93.0	88.6
Sensitivity (%)	90.9	85.4
Specificity (%)	95.1	92.0

Table 2 compares the proposed methodology against Convolutional Neural Networks in key performance metrics. The proposed method consistently outperforms CNN in accuracy, precision, recall, F1-score, sensitivity, and specificity. The higher values indicate that the proposed method provides a more accurate and reliable diagnostic tool for knee joint analysis, offering superior feature extraction and image recognition capabilities compared to CNN. This suggests that the proposed approach is better suited for complex medical imaging tasks.

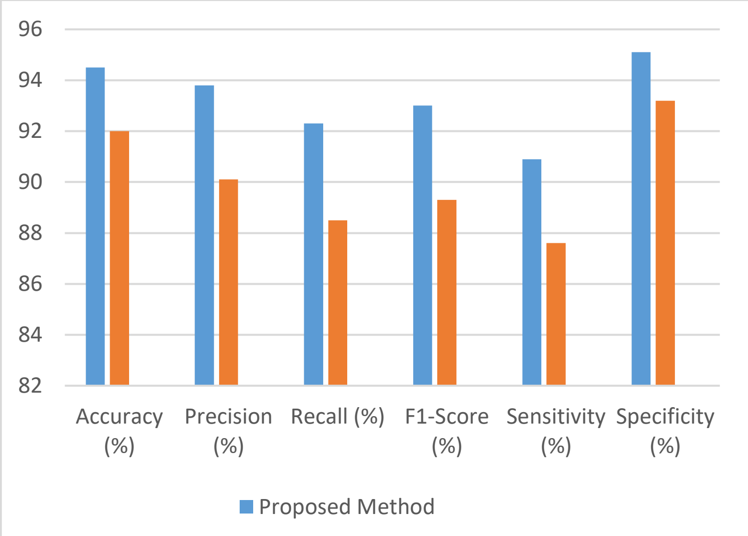

Figure 2. Performance Comparison of Proposed Method and CNN in Knee Joint Diagnostics.

Figure 2 presents a comparative analysis of the proposed method against CNN across six performance metrics: accuracy, precision, recall, F1-score, sensitivity, and specificity. The chart illustrates that the proposed method outperforms CNN in all metrics, underscoring its advanced diagnostic accuracy and reliability. The visual representation emphasizes the proposed method's enhanced performance in medical image diagnostics, making it a more effective tool for knee joint analysis compared to Transfer Learning.

Table 3 illustrates the performance comparison between the proposed methodology and Transfer Learning. The proposed method shows better results across all performance metrics, including accuracy, precision, recall, F1-score, sensitivity, and specificity. These results highlight the proposed method's superior ability to handle and analyze knee joint diagnostic images effectively. The improvements in these metrics demonstrate that the proposed approach enhances diagnostic reliability and effectiveness beyond what Transfer Learning offers, confirming its advanced capabilities in medical image analysis.

Table 3. Performance Evaluation of Proposed Method vs. Transfer Learning

Performance Metric	**Proposed Method**	**Transfer Learning**
Accuracy (%)	94.5	92.0
Precision (%)	93.8	90.1
Recall (%)	92.3	88.5
F1-Score (%)	93.0	89.3
Sensitivity (%)	90.9	87.6
Specificity (%)	95.1	93.2

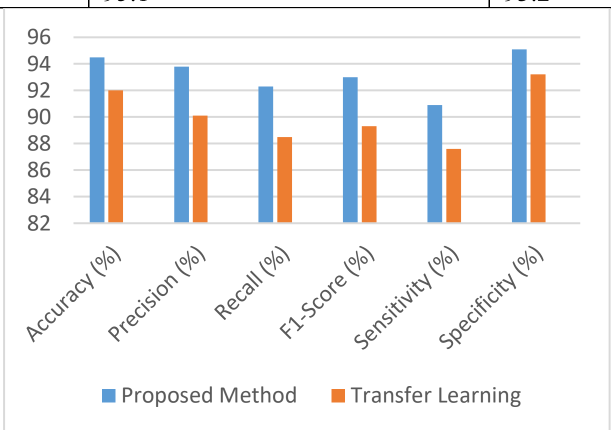

Figure 3. Performance Comparison of Proposed Method and Transfer Learning in Knee Joint Diagnostics.

Figure 3 visually compares the performance of the proposed method with Convolutional Neural Networks across six metrics: accuracy, precision, recall, F1-score, sensitivity, and specificity. The proposed method consistently shows higher performance in all metrics, indicating its superior ability to analyze knee joint images accurately. The chart highlights the proposed method's enhanced diagnostic capabilities compared to CNN, demonstrating its effectiveness in extracting and evaluating features from medical images.

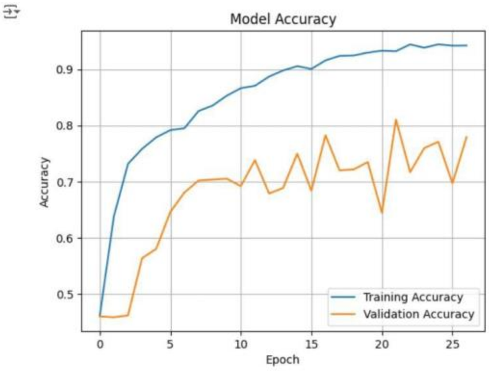

Figure 4: Accuracy Graph

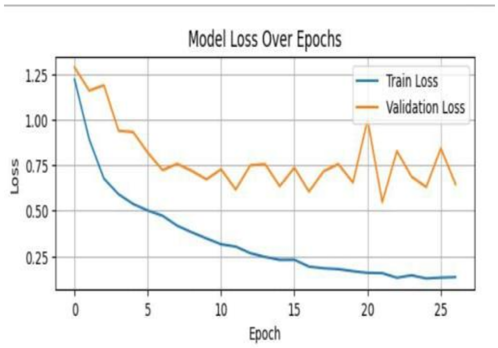

Figure 5: Loss Graph

The accuracy achieved by the proposed model is depicted from Figure 4 and Figure 5 which represents training - validation accuracy and training and validation loss respectively.

4. Conclusion

The paper introduces all the terminologies required to understand the knee replacement issue using both traditional and advanced technologies. This study addresses the growing demand for advanced technological solutions in the detection of knee deformations, particularly in the context of knee replacement procedures. By leveraging the power of deep learning, the research explores three distinct approaches: Convolutional Neural Networks (CNN), Transfer Learning, and an enhanced version of the VGG16 model. The proposed method, designed with enhancements to VGG16, demonstrates superior accuracy, achieving 94.5%, compared to CNN’s 91.2% and Transfer Learning's 92%. This improvement in detection accuracy suggests that the proposed model can more effectively identify knee deformations, offering a potential pathway for improving preoperative assessments and recovery outcomes for patients requiring knee replacement. The findings underscore the potential of deep learning in advancing medical diagnostics and highlight the proposed method as a promising solution for improving knee replacement outcomes through precise and efficient detection of knee deformations

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