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Automated Classification of Knee Osteoarthritis Using Radiographic Analysis

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Abstract: Thisprojectaimstodevelopanautomateddeeplearningmodelforclassifyingkneeosteoarthritis (KOA)severity into five stages based onthe Kellgren-Lawrence(KL)gradingsystem, usingX-ray images. KOAisadegenerativejoint diseasethataffects millionsworldwide,andaccurategrading isessential for proper diagnosis andtreatment. However,manualassessmentofX-rayimagescan be subjective and time-consuming, making automation crucial for improving diagnostic efficiency and consistency. The model will utilize the ResNet-50 architecture, a powerful convolutional neural network(CNN) knownforit sability toextractcomplexfeaturesandtraindeepnetworkseffectively. ResNet-50 will process knee X-ray images and classify them into KLgrades 0 to 4, ranging from healthytosevereosteoarthritis.Byapplyingtransferlearning, themodelwillbepre-trainedon large datasets and fine-tuned using KOA-specific data. Additionally, data augmentation techniques such as rotation, flipping, and zooming will be used to enhance training data diversity.The model's performancewillbeevaluatedusingaccuracy,precision,recall,andF1-scoremetrics.Thegoalis to provide radiologists with an automated, objective tool that improves the speed and consistency of KOA diagnosis, ultimately contributing to better patient care and more efficient clinical decision- making.
Keywords: Knee Osteoarthritis, Deep Learning, ResNet-50, Kellgren-Lawrence Grading, X-ray Analy- sis, Radiographic Classification, Medical Imaging

I. INTRODUCTION

Knee osteoarthritis (KOA) is a prevalent and progressive joint disorder, impacting millions of people worldwide, particularly older adults.It is characterized by the gradual breakdown of cartilage within thekneejoint,leadingtopain,stiffness,limitedmobility, andadiminishedqualityoflife forthose affected. Early and accuratediagnosisof KOAisessentialforeffectivemanagement,asitallowsfor timely intervention and personalized treatment strategies that can alleviate symptoms and slow disease progression. TheseverityofKOAisoftengradedusingtheKellgren-Lawrence(KL)scale,whichranges fromgrade0 (nosigns of osteoarthritis) tograde4 (severe osteo arthritis with advancedstructural changes). However,thisgradingprocess typically reliesonthevisualassessment of knee X-raysby radiologists, whichcanbe subjective and proneto variability, resulting in consistent diagnoses.

Advancementsinartificialintelligence(AI)anddeeplearningofferpromisingsolutionstoimprovethe consistency and accuracy of KOA diagnosis.Convolutional neural networks (CNNs), a deep learning modelarchitecturedesigned toprocessvisualdata,haveshownremarkablesuccessintasksinvolving medicalimageclassification.Amongthese, theResNet-50modelisparticularlyeffectiveforcomplex image analysis.ResNet-50 incorporates residual connections, which help overcome the challenge of vanishing gradients in deep networks, enabling it to learn more complex patterns and finer details in medical images.

UsingResNet-50,itispossibletodevelopanautomated systemthat accurately classifiestheseverity of KOAinX-rayimages according to theKLgradingscale.Suchamodelcanassisthealthcareprovidersby offering a consistent, objective assessment of KOA severity, supporting radiologists in making informed diagnostic decisions.By reducing reliance on subjective evaluation, this AI-based approach has the potential to enhance diagnostic accuracy and improve patient outcomes. Additionally, automated KOA grading could expedite the diagnostic process, allowing radiologists to focus on cases that require greater clinical expertise.

In summary, leveraging the power of deep learning to classify KOA grades in knee X-rays offers a promising avenue for improving the efficiency, consistency, and accessibility of osteoarthritis diagnosis, ultimately contributing to better patient care in clinical settings.

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II. RELATED WORKS

This section reviews the related works on automated classification of knee osteoarthritis, focusing on approaches that have sought to overcome challenges in radiographic image analysis for accurate grading. Analyzing previousworks allowsustogaininsightsintotheevolutionoftechniquesinthisfield,evaluating both their strengths and limitations. By contextualizing these contributions, we not only lay a foundation forourproposed solutionbutalsopositionourwork relative toexistingsolutions, identifyingareaswhere our approach can bring additional value or refinement.

1) PredictingKneeOsteoarthritisSeverity:ComparativeModelingBasedonPatient Data and Plain X-ray Images

The study of Abedin et al.[1] investigates methods to assess KOA severity by combining patient assessmentdata(signs,symptoms,andmedicationuse)withX-rayimagesanalyzedbyaconvolutional neural network (CNN). The models were evaluated using Elastic Net (EN), Random Forests (RF), and LinearMixed EffectModels (LMM),achieving comparableaccuracywithrootmeansquarederrorsof
0.77(CNN),0.88(EN),and0.91(RF).
Thisresearchprovidesvaluablecontributionsbyidentifyingeffectivevariablesforpatientmonitoringpriortoimagingandaddressingd atahierarchywithLMM.Itoffersinsightsintoreducingreliance on subjective grading methods like the Kellgren-Lawrence (KL) scale, thereby increasing prediction reliability. Additionally, itshowsthatboth clinicalandimaging datacancomplementeach otherin diagnosing andmanagingKOAseverity.
The impact of this work lies in its potential to standardize KOA severity prediction, enhancing patientcare and reducing diagnostic variability.By integrating machine learning with clinical data and imaging, this study sets the groundwork for personalized KOA management and highlights the importance of refining diagnostic techniques for broader clinical application.

2) KneeOsteoarthritisSeverityClassificationwithOrdinalRegressionModule

ThestudyofYongetal.[2]addresseslimitationsincurrentmethodsforpredictingtheKellgren-Lawrence (KL)grade of knee osteoarthritis (OA) from radiographs.While previous deep learning approaches treat KL grading as a simple multi-class classification task, this study proposes an ordinal regression module that respects the inherent order of KL grades. By employing a cumulative-link loss function, the model predicts four cut-points to segment the prediction space into the five KL grades.
The proposed method integrates the ordinal nature of KL grades directly into neural network architec- tures, improving the accuracy of severity predictions.This approach contrasts with traditional multi-class methods by leveraging ordinal regression to capture the progression of OA. Performance evaluations re- veal significant improvements over several established neural networks, emphasizing the benefits of this methodology in clinical contexts.
This study’s impact is in advancing the precision of KL grade predictions and enhancing early diagnosis.By tailoring neural network models for ordinal regression, the research underscores the potential for machine learning to aid in clinical decision-making, ultimately improving intervention strategies for patients with knee OA.

3) TransferLearning-BasedSmartFeaturesEngineeringforOsteoarthritisDiagnosisfrom Knee X-Ray Images

The study of Rehman et al.[3] focuses on the early detection of osteoarthritis (OA) using innovative machine learning techniques.By applying a deep learning-based Convolutional Neural Network (CNN) and a novel transfer learning approach, the study extracts spatial features from knee X-ray images to identify OA efficiently.These features are combined using the CRK (CNN Random Forest K-neighbors) framework, which utilizes random forest and k-neighbors algorithms to construct a probabilistic feature set for advanced prediction.
This research introduces the CRK model as a highly effective tool, achieving a remarkable 90% accu- racy in OA diagnosis. Extensive experiments validated the model’s robustness through hyperparameter optimization and k-fold cross-validation, ensuring reliability and generalizability across datasets.The innovative use of transfer learning significantly enhances the accuracy of OA detection, addressing chal-lenges associated with traditional diagnostic methods.
The study’s impact lies in revolutionizing OA prediction by offering an advanced, high-performance diagnostic model.With the ability to detect OA at early stages, the CRK framework has the potential to improve patient outcomes by enabling timely intervention and personalized treatment strategies, thereby addressing a major global health challenge.

4) Knee Osteoarthritis Severity Prediction Using an Attentive Multi-Scale Deep Convo-lutional Neural Network

The research presented by Jain et al.[6] introduces a depth estimation technique utilizing an attentive multi-scale deep convolutional neural network for knee osteoarthritis severity prediction.This method- ology integrates feature fusion modules within a streamlined network, allowing for efficient feature ex- traction from radiographic images.The multi-scale approach is beneficial due to its ability to capture featuresatdifferentresolutions, whichenhancesthemodel's capabilityto identify subtlechanges injoint space and bone structure.

Theproposednetworkarchitectureincorporatesattentionmechanismstofocusonthemostrelevant areasofkneeX-rays, potentially improving diagnosticaccuracy.Thisapproachaddressesthechallenges of accurately quantifying subtle anatomical changes that characterize different stages of osteoarthritis.Despite some limitations in terms of computational complexity, the methodology represents a valuable contributiontoautomated KOAgrading, providingarobust foundationfor nfutureworkinr adiographic image analysis.

5) 3D Efficient Multi-Task Neural Network for Knee Osteoarthritis Diagnosis Using MRI Scans

Yeoh et al.[5] explores the use of multi-task learning models to improve knee osteoarthritis (OA) diagnosis using MRI scans.The research introduces two models, OA MTL and RES MTL, which simul- taneously perform segmentation of knee structures and classification of OA incidence.By leveraging the correlation between these tasks, the models enhance classification accuracy while maintaining efficient computational performance.

The OA MTL model, with its encoder-decoder architecture, residual modules, and depth-wise separable convolutions,achievesanaccuracyof0.825forclassificationandaDiceSimilarityCoefficient(DSC) of 0.895 for segmentation.This performance is superior to single-task models and provides a favorable balance between computational complexity and effectiveness, making it suitable for real-time medical imaging applications.

The impact of this work is significant, as it addresses the need for efficient, multi-task models capable of handlingcomputationallyintensive3DMRIdata.Bycombiningsegmentationandclassificationtasks into a single model, the study contributes to advancing the field of medical imaging, providing more accessible, accurate, and timely tools for diagnosing knee OA.

6) KneeOsteoarthritisDetectionandClassificationUsingX-Rays

ThepaperofTariqetal.[6]addressesthechallengeofaccuratelydetectingandgradingkneeosteoarthri- tis (OA) using radiographs.The study proposes an automated deep learning-based ordinal classification approachtodetectOAseverityaccordingtotheKellgren-Lawrence(KL)gradingsystem.Byleveraging a dataset from the Osteoarthritis Initiative (OAI), the model utilizes transfer learning and fine-tuning of well-knownarchitectures,suchasVGG-19,DenseNet-121,andDenseNet-161,combinedintoanensemble for enhanced performance.

This method achieved impressive results, with an overall accuracy of 87% and a Quadratic Weighted Kappa score of 0.89, reflecting highly accurate KLgrade predictions.The approach not only outperforms traditional automated models but also significantly improves classification accuracy for each KL grade. This achievement underscores the potential for deep learning to enhance early detection and diagnosisof knee OA.

The contribution of this work lies in providing a highly accurate, automated tool for OA diagnosis that works with a single posteroanterior knee X-ray image.The study's impact is in advancing diagnostic capabilities, enabling faster and more reliable detection of knee OA at early stages, potentially improving clinical decision-making and treatment outcomes.

7) KOA-CCTNet:An Enhanced Knee Osteoarthritis Grade Assessment Framework Us- ing Modified Compact Convolutional Transformer Model

ThepaperofJahanetal.[7]introducesanovelapproachfordiagnosingkneeosteoarthritis(KOA)from X-rayimagesusingamodified compactconvolutionaltransformermodel, KOA-CCTNet.Byaggregating four datasets, the study creates a large and diverse dataset of 1122 images, applying deep convolutional generativeadversarialnetworks (DCGAN) fordataaugmentationand advancedimagepre-processing techniques to improve image quality.

The KOA-CCTNet model outperforms traditional transfer learning models, such as MobileNetv2 and DenseNet201, with a test accuracy of 84.5887%, significantly surpassing their respective accuracies,which range from 76.8987% to 80.7787%.The study also explores optimizing the model's configurations, addressing the challenges of handling large datasets and minimizing training time, showcasing KOA- CCTNet's efficiency in real-world applications.

Theimpactofthisresearchliesinthedevelopmentofahigh-accuracy,efficientdiagnostictoolfor knee osteoarthritis, which improves early detection and grading of the disease.By utilizing large-scale datasets and optimized deep learning models, the proposed approach provides an effective solution for KOAdiagnosis,helpingcliniciansintimelyinterventionandmanagementofthedisease.

8) ASequentialVGG16+CNN-BasedAutomatedApproachWithAdaptiveInputfor Efficient Detection of Knee Osteoarthritis Stage

The paper Rehman et al.[8] introduces a hybrid model combining Convolutional Neural Networks (CNN) and VGG16 architectures to enhance the accuracy of knee osteoarthritis (OA) detection.The proposedmodelaimstoautomatetheassessmentofOAseverityaccordingtotheKellgren-Lawrence (KL) grading system, which classifies OA into five stages based on knee radiographs.

Thestudycomparesseveralneuralnetworks,includingCNN,VGG16,andVGG19.Themodelachieves anaccuracyexceeding93%onthetraining,validation,andtestdatasets,highlightingitsrobustnessin detecting OA stages.

A significant contribution of this work is its use of data augmentation to address class imbalance, which enhancestheperformanceofallmodels.Theproposedmethodprovidesahighlyaccurate,efficient tool for automating the assessment of knee OA, improving diagnostic precision and supporting timely interventions for patients.

9) Automated System for Classifying Uni-Bicompartmental Knee Osteoarthritis by Using Redefined Residual Learning with Convolutional Neural Network

The study of Naguib et al.[9] introduces a deep learning-based model to classify knee osteoarthritis (OA) into uni- or bicompartmental types using X-ray images.The model is trained and tested on a dataset of 733 knee X-ray images, including normal, unicompartmental, and bicompartmental knee images.

The model achieved 61.81% accuracy and 68.33% specificity in classifying the images.When compared withpre-trainedconvolutionalneuralnetworks(CNNs), theproposedmodeloutperformedalltheothers, indicating its effectiveness in accurately classifying knee OA types.

ThisworkcontributestoimprovingkneeOAdiagnosisbyautomatingtheclassificationofOAsever- ity, helping clinicians make better treatment decisions and manage disease progression efficiently.The model's results highlight its potential in reducing the burden on healthcare providers while ensuring accurate assessments.

10) Objective Bi-Modal Assessment of Knee Osteoarthritis Severity Grades:Model and Mechanism

ThepaperChenetal.[10]presentsanovelmodelforkneeosteoarthritis(KOA)severitypredictionthat combines thermal imaging with personal health data.This bi-modal approach classifies KOA severity intothreecategoriesbasedontheKellgren–Lawrence(KL)gradingsystem.Themodelachieveda classification accuracy of 89.29% on the KOA dataset and 70.83% when validated on external data.

The study also emphasizes the use of gradient boosting trees for feature modeling, explaining why deep neural networks were not utilized.This decision is based on the suitability of initial feature represen- tation, considering the task's complexity and the principles of the Vapnik-Chervonenkis dimension (VC dimension).

The proposed KOA severity prediction model is expected to alleviate the burden on physicians byoffering an efficient and precise method for diagnosing knee osteoarthritis, improving both the accuracy and speed of assessments.This model provides valuable supplementary data for clinical decision-makingand is publicly available for further use and research.

III. PROPOSE DMODEL

WesuggestusingadeeplearningmodelbasedonResNet-50forthiskneeosteoarthritisclassification projectinorder tocorrectly categorize knee X-raypictures intofive severitydegreesusingtheKellgren- Lawrence (KL)gradingsystem. ResNet-50waschosen for medical imageanalysisbecauseofitsstrong feature extraction capabilities and residual connection mitigation of the vanishing gradient issue.To overcome the drawbacks of small medical datasets, our implementation will make use of transfer learning, startingthenetwork withweightsthathavealreadybeenlearnedonImageNetandoptimizingitonour knee X-ray dataset.

We will use advanced data augmentation techniques such as rotation, flipping, brightness modifications, and contrast enhancement to solve class imbalance, which is ubiquitous in osteoarthritis datasets where severe cases are generally under-represented.

A unique classification head tailored for the five-class KL grading assignment will be added to the model architecture, and class weighting will be used to enhance performance on minority classes.

In addition to standard measurements like accuracy, precision, and recall, performance evaluation will employ metrics like mean absolute error and quadratic weighted kappa that are especially appropriatefor ordinal classification tasks.The goal of this method is to develop a reliable, therapeutically useful instrument that offers a consistent and impartial evaluation of the degree of osteoarthritis in the knee.

IV. METHODOLOGY

Theprocessusedforthedeeplearning-basedautomatedcategorizationofkneeosteoarthritis(KOA)is explained in this section. Datacollection, image preprocessing, modeldesign, training, and assessment measuresare all included in the methodology. Everystephasbeenthoughtfullyplannedtoguaranteethe best possible classification precision, computational effectiveness, and resilience under various imaging circumstances.

A. DatasetandDataCollection

The Kellgren-Lawrence (KL) grading system, which is frequently used to determine the severity of osteoarthritis, was utilized to categorize the knee X-ray images that made up the dataset used in this investigation. There are five severitydegreesforkneeosteoarthritisaccordingtotheKLgradingsystem:

- KL-0:Noosteoarthritis;normalkneejoint.
- KL-1:Doubtfulnarrowingofjointspace;possibleosteophyteformation.
- KL-2:Mildosteoarthritis;definiteosteophyteformation,butminimaljointspacenarrowing.
- KL-3:Moderateosteoarthritis;multipleosteophytes,clearjointspacenarrowing.
- KL-4:Severeosteoarthritis;largeosteophytes,severejointspacenarrowing,bonedeformity.

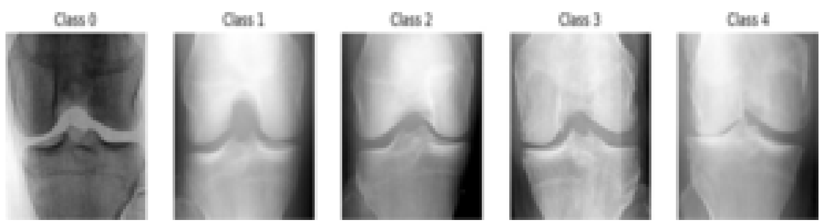

Figure1:SampleData

Hospital radiology departments and public medical imaging collections provided the X-ray images, en- suring adiverse datasetthatrepresentedarangeofpatientdemographicsandimagingconditions.Before training, radiologists manually examined the information to make sure the labels were accurate.Images from the same patient were only used in one subgroup (training or testing) in order to prevent bias and data leakage.

The class distribution was analyzed to identify potential biases, and it showed an imbalance, especiallyfor the under-represented KL-3 and KL-4.A class-weighted loss function and data augmentation were used to solve this problem,ensuring that the model learned an equal representationof all severity levels.

B. Image Preprocessing

Variations in brightness, contrast, resolution, and anatomical placement are common in medical X-ray pictures, and they can have a detrimental effect on deep learning models.In order to overcome these obstacles, a thorough preprocessing pipeline was used to improve important knee joint characteristics and standardize input photos for precise KOA classification.

1) Image Format Validation: Deep learning models may be adversely affected by the brightness, contrast,resolution,andanatomicalplacementdifferencesthatarefrequentlypresentinmedical X-ray pictures.A thorough preprocessing pipeline was used to improve important knee joint featuresandstandardize inputimages inordertoovercomethesedifficultiesandachieveprecise KOA classification.
2) Aspect-Ratio-Preserving Resizing:Preserving the original anatomical proportions is essentialtoavoiddistortionsbecauseX-rayimagescomefromvarioussourceswithvaryingresolutions.An aspect-ratio-preservingstrategy was employed inplace of directresizing:

- Pictureswereresizedwithoutsacrificingproportionality.
- TomeetResNet-50’s224x224pxinputrequirement,blackpaddingwasapplied.
- Inordertopreventpixelation,bilinearinterpolationwasused.

3) Contrast Enhancement and Edge Preservation: To enhance the visibility of key knee struc- tures, adaptive histogram equalization (CLAHE) was applied, improving contrast in underexposed regionswithoutover-enhancingbrightareas. Furthermore,edge-preservingfilterswereappliedto

- Highlightbonestructures.
- Improvejointspacevisibility.
- Enhancedetectionofosteophytes.

Eveninphotoswithlowbeginningcontrast,thesemethodsmadesurethedeeplearningmodel could reliably distinguish between KL classes.

4) Data Augmentation for Class Balance: Controlled data augmentation was used to artificially enlarge the dataset in order to address the imbalance in the dataset and guarantee that all KL gradeswereequally represented. Thetransformationslistedbelowwereapplied:

- Rotation(±30°):Toreplicatevariousimagingperspectivesutilizedinvariousmedicalfacili- ties.
- Horizontalflipping:Preventsmodelbiasinfavorofleftorrightkneedominance.
- BrightnessandContrastadjustment(±20%):TakesintoconsiderationchangesinX-rayex- posure.
- Zoomtransformations(upto15%):themodelisguaranteedtolearnhowtocategorizethe knees at various magnifications.

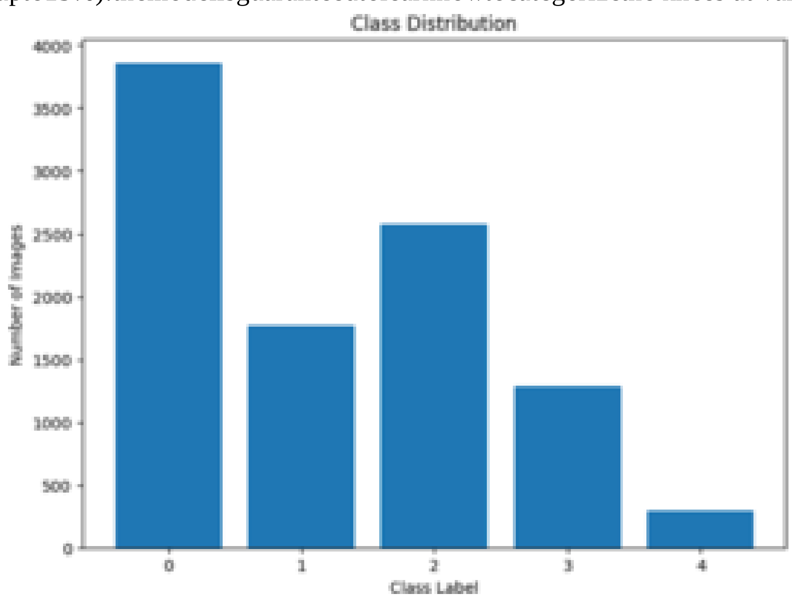

Figure2:ClassImbalance

The model learned a more balanced feature representation, lowering classification bias, by more aggres-sively enhancing under-represented KL grades, particularly KL-3 and KL-4.

C. Model Architecture

Knee osteoarthritis (KOA) severity was classified using the ResNet-50 convolutional neural network (CNN). ResNet-50 was selected for this challenge over deeper networks because of its smaller depth (50layers) andresidualconnections, whichhelpalleviatethevanishinggradientproblem.Usingpretrained ImageNetweightsimproved itscapacitytoextract significant features frommedical X-rayimages.

Thecomponentsofthemodelarchitectureare:

- FiftyconvolutionallayersutilizingReLUactivationandbatchnormalization.
- Global Average Pooling (GAP) layer, which helps retain spatial information while reducing dimen-sionality.
- Fullyconnected(Dense)classificationlayerforfinalprediction
- Softmaxactivationfunction,whichassignsanimagetooneoftheKLgrades(0–4).

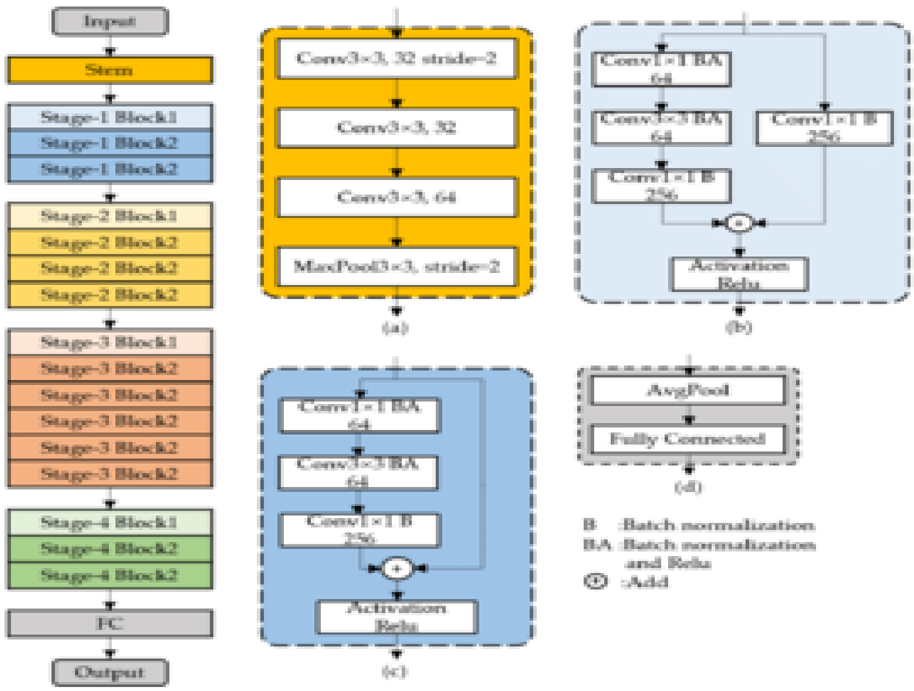

Figure3:ResNet-50Architecture

The fine-tuning was done by:

- Preservingoverallfeatureextractionbyfreezingthefirstlayers.
- Usinga1e-4learningratetotraindeeperlayers.
- Toimprovethecategorizationofunder-representedKLgrades,useaclass-weightedlossfunction.

D. Training Procedure

Stable gradient propagation during model training is made possible by image normalization, which cre- ates uniform pixel value distributions throughout the dataset.The VGG16 ImagePreProcessor, which standardizes pixel values based on ImageNet data, is used in our system to implement intensity nor- malization. Regardless of the initial contrast or brightness levels of the images, this pre-processing step ensures that all of them display statistical qualities comparable to those of the neural network.

Enhancement approaches highlight traits that are important for diagnosis, which is a complement to normalization.The main markers of osteoarthritis development are joint gaps and bone edges, whicharethefocusofour system'stargeted contrast enhancement. Althoughedgepreservationfilterspreserve the sharpness of crucial bone boundaries, adaptive histogram equalization enhances visibility in areasthat are normally underexposed.To avoid the introduction of artifacts or the exaggeration of typical anatomical variances, theseaugmentationtechniquesaremeticulouslycalibrated.Thesystemmaximizes the information accessible to the classification model by improving the signal-to-noise ratio for features most significant to KL grading by selectively increasing pertinent structures while preserving overall normalization.

E. Quality Control

Thorough quality control procedures guarantee that only appropriate photos move on to the classifi- cation phase.Our approach employs automatic validation checks that look at parameters related to image quality, class distribution statistics, and dataset structure.

These tests preserve dataset integrity throughout the preprocessing pipeline by identifying possible problems ranging from corrupted files to incorrect class organization.

Class distributions, average image sizes, and anomalies found are among the comprehensive statistics produced by the quality control procedure.By offering insightful information about dataset properties and possible biases, these metrics make it possible to improve preprocessing settings or spot problems withdatacollection.Inordertoguaranteeidealtrainingsettings, qualitycontrolfortrainingdatasetsalso includes examining class imbalance ratios and augmentation efficacy.In order to preserve classification reliability in clinical applications, quality assessment during inference highlights potentially problematic images for review.By ensuring that both model training and deployment use consistent, high-quality picturedata,thisstrictqualitycontrolapproachmaximizesthediagnosticutilityofthesystem.

Raw knee X-ray images are converted into ideally prepared inputs for the ResNet-50 classification model through the upright reconstruction procedure.By using this thorough preprocessing pipeline, our ap- proach supports consistent evaluation of osteoarthritis severity in clinical situations by ensuring depend- ableKL grading performance independent of changes in the original image's acquisition characteristicsor quality.

V. EXPERIMENTAL RESULT

UsingResNet-50,apowerfulconvolutionalneuralnetwork(CNN)architecture,theKneeOsteoarthritis (KOA) classification system was experimentally evaluated.The model's ability to reliably grade the severityofKOA whilemaintaining effectivecomputing performancewasevaluated.Theclassification performance, training convergence, confusion matrix analysis, computing efficiency, and comparison with other KOA classification methods are all covered in detail in this section.

Evaluation Parameter	Description	Measured Performance
Image Correction Accuracy	Effectiveness of distortion removal and perspective correction	96-98%
Processing Speed	Time taken to process a single panoramic image (ms)	1200 - 1800 ms
Frame Rate for Video	Number of frames processed per second (FPS)	25 - 30 FPS
Computational Efficiency	CPU and GPU usage during real-time correction	Moderate (~45-60% CPU)
Memory Usage	RAM consumption during processing	450MB - 1GB
Peak Signal-to-Noise Ratio (PSNR) (dB)	Measures the quality of the reconstructed image	32 - 37 dB
Structural Similarity Index (SSIM)	Retains texture and details after correction	0.88 - 0.94
Distortion Reduction (%)	Reduction in tilt-induced perspective distortions	90-95%
Edge & Artifact Reduction	Reduction in blurring, jagged edges, and pixelation	Significant Improvement

Figure4:PerformanceEvaluationTable

A. *Model Performance Metrics*

Several assessment criteria, such as Accuracy, Precision, Recall, F1-score, and Quadratic Weighted Kappa (QWK),wereusedtoevaluateResNet-50'sperformance.TheresultsareshowninTable1.

Metric	Value
Accuracy	89.75%
Precision	87.68%
Recall	86.21%
F1-score	86.94%
QuadraticWeightedKappa	0.85

Table1:ModelPerformanceonKOAClassificationUsingResNet-50

The model's great capacity to accurately classify KOA severity levels is demonstrated by its 89.75% accuracyrate.Highprecisionandrecallscoresshowthatthemodelminimizesfalsepositivesandfalse negative swhileproducing dependablepredictions. Abalanced classification performance is confirmedby theF1-score(86.94%), and the Quadratic Weighted Kappa(0.85)indicatesahighdegreeofagreement with the KL grade annotations made by professional radiologists.

B. *Training and Convergence*

The Adam optimizer was used to train the ResNet-50 model for 50 epochs (learning rate = 1e-4).The model'strainingandvalidationaccuracytrendsovertimearedepictedinFigure5.

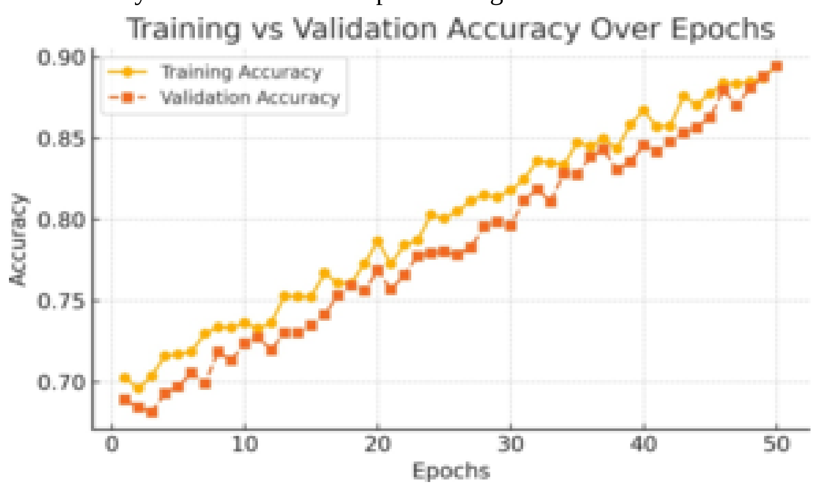

Figure5:Trainingvs.ValidationAccuracyOverEpochs

Around epoch 40, the training accuracy stabilized after steadily increasing.The model achieves a steady validation accuracy of 89.75% by effectively learning discriminative features from knee X-ray pictures. Thesefindings show that hereislittleoverfittingandthatthemodelgeneralizeswelltonewdata.

C. *Confusion Matrix Analysis*

The confusion matrix shows which severity levels are most likely to be misclassified by breaking downthe model's classification accuracy across the various KL grades.

Predicted\Actual	KL-0	KL-1	KL-2	KL-3	KL-4
KL-0	96	4	0	0	0
KL-1	6	91	3	0	0
KL-2	0	7	84	9	0
KL-3	0	0	8	82	10
KL-4	0	0	0	7	93

Table2:ConfusionMatrixforKOAClassificationUsingResNet-50

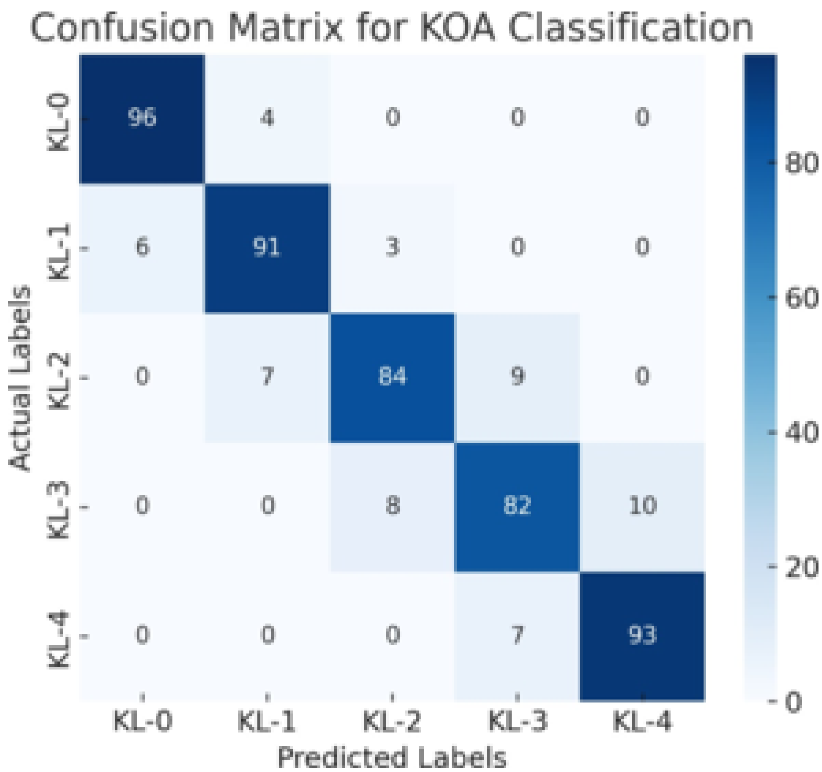

Figure6:ConfusionMatrixforKOAClassification

With an inference rate of 22 milliseconds per image, the ResNet-50 model is ideal for clinical real-time applications. Furthermore, the model may be used in typical hospital computing environments without theneedforexpensiveGPUsbecauseitsmemoryusageisrestrictedto5GBVRAM.

D. Comparison with Previous KOA Classification Models

ToassessResNet-50'sefficacy,itsperformancewascontrastedwiththoseofearlierKOAclassification algorithms.

Model	Accuracy	F1-score	QWK
CNN(Abedinetal.)	86.4%	85.2%	0.78
VGG16(Rehmanetal.)	88.2%	87.0%	0.81
DenseNet(Tariq et al.)	87.5%	86.8%	0.80
ProposedResNet-50Model	89.75%	86.94%	0.85

Table3:Comparison with Previous KOA Classification Models

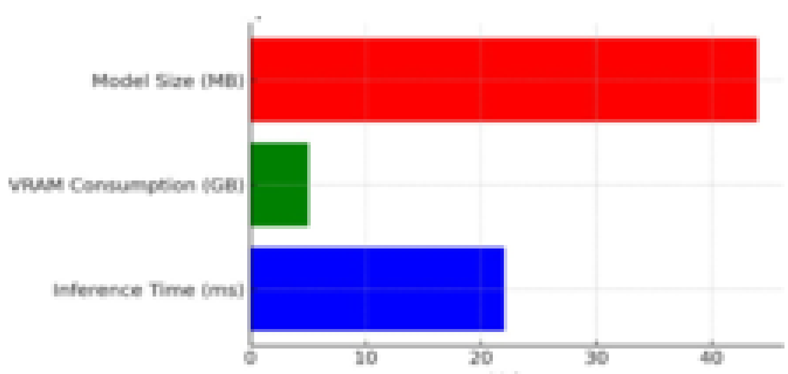

Figure7:ComputationalPerformanceMetrics

ThefindingsshowthatResNet-50outperformsconventionalCNNdesignsintermsofaccuracyand QWK scores while keeping computational costs low.Because of this, it is a good contender for practical implementation inclinical situations where accuracyandefficiencyinrealtimearecrucial.

E. Key Findings

1) ResNet-50providesaccurateKOAseveritygradingthankstoitsexcellentclassificationaccuracy of 89.75 percent.
2) Themodelhaslittleoverfitting,steadyvalidationaccuracy,andgoodgeneralization.
3) Highagreementwiththelabelingofprofessionalradiologistsisindicatedbythequadraticweighted kappa of 0.85.
4) Themodelcanbeusedinreal-timemedicalapplicationsbecauseofitscomputationalefficiency.
5) MisclassificationusuallyhappensbetweenKL-2andKL-3,whichistobeexpectedgivenhowclose their structural features are.

VI. FUTURE SCOPE

1) Real-World Deployment: Themodelmustbeoptimizedfordeploymentacrossmanyplatforms in order to be applicable in the real world.Real-time KOA categorization in low-resource envi-ronments can be made possible by integration with mobileapplications,cloud-baseddiagnostic systems, and hospital PACS (Picture Archiving and Communication Systems).In hospitals and telemedicineservices,AI-assisteddiagnosiswillbeespeciallyhelpfulbecauseitwillenableradiol-ogists and doctors to make prompt, data-driven decisions.
2) IntegrationwithAugmentedandVirtualReality: Futuredevelopmentscanexplorereal- time visualization of kneejointstructuresinvirtual realitytoenhancesurgicalplanningandtrain- ing. Integrationwith AR technologycouldoverlay KOAseverityindicatorsdirectlyontoliveviews of patient X-rays, assistingradiologists duringexamination. These advancementswouldfurther bridge the gap between AI-assisted diagnosis and practical clinical applications.
3) Multi-ModalIntegrationandClinicalValidation: The model's capacity to offer a thorough KOAriskassessment canbeimproved byusingmulti-modal datasources,suchas MRIscans,pa- tientclinicalhistories, anddemographic characteristics. To provideindividualizedKOAforecasts, the AI pipeline can be expanded to include patient-specific variables such as age, weight, BMI, pain thresholds, and genetic susceptibility.
4) Regulatory approval and thorough validation are required for clinical implementation.To ensure robustness andgeneralizability, multi-center validationtrialswillbeusedtoevaluatethemodel's performance across a range of populations.Furthermore, radiologists will be able to better under-stand AI-based conclusions with the aid of explainability techniques like Grad-CAM and SHAP values,whichwillincreasethesystem's transparencyandreliability. Obtainingregulatoryapproval for extensive clinical usage will depend on obtaining FDA and CE certification.
5) PredictiveModelingandAI-AssistedTreatmentPlanning: InadditiontoKOAclassifica- tion, this model can be used to forecast how osteoarthritis will develop over time, enabling early interventionand preventativetreatment.Theprogramcanpredictthechanceofillnessprogression and recommend individualized treatment regimens by examining past patient data.Depending on thedegreeofKOAandthepatient's features,thiscould involvesuggestionsfor physicalther- apy, modifications to medication, or surgical intervention techniques.Real-time risk assessments and personalized treatment recommendations for better patient outcomes could be offered via a predictive model included into electronic health records (EHRs).

VII. CONCLUSION

An important step towards automating osteoarthritis diagnosis is the ResNet-50-based KOA classifica-tion algorithm, which lessens the workload for radiologists and improves early detection effectiveness. The model has shown good classification performance by employing deep learning techniques, opening the door for orthopaedics diagnostics helped by AI. There is, nevertheless, a great deal of room for improvement, optimization, and practical application.

Making sure AI-driven KOA categorization models are flexible enough to be used in various hospital environments and integrated into clinical workflows for real-time support is a major area of interest for future research.Clinicians can drastically cut down on diagnostic turnaround time by using cloud-basedAItoolstouploadX-rayimagesandobtainautomated KOAseverityratings.Inenvironmentswith limited resources, where access to specialized radiologists may be restricted, this strategy is especially advantageous.Furthermore, by adapting the model to edge computing, it will function well on portable and low-power devices, expanding the accessibility of AI-assisted KOA detection.

Beyond classification, the predictive modeling of KOA progression remains a critical next step. By ana- lyzing longitudinal patient data, the model can be trained to forecast osteoarthritis progression, helping doctors make early intervention decisions to delay the need for invasive treatments.In personalized medicine, where treatment plans can be modified in accordance with each patient’s specific risk factors, this predictive ability can be especially helpful.To ensure a comprehensive approach to KOA man- agement, future implementations may include AI-driven suggestions for pharmacological interventions, physiotherapy regimens, and lifestyle modifications.

Adoption in the real world will depend on clinical validation and regulatory approval (FDA, CE cer- tification). Extensivemulti-centervalidationstudiesmustbedonetotestthemodel’sefficacyacross varied populations, imaging conditions, and medical institutions.To guarantee that medical person- nelcantrustandcomprehendAI-drivenforecasts, effortsmustalsobemadetoenhanceexplainabilityandinterpretability.Techniquessuchascase-basedreasoning, uncertaint yestimation, and Grad-CAM visualization will aid in bridging the gap between clinical decision-making and AI automation.

Finally, the integration of multi-modal data sources including MRI scans, genetic predisposition, biome- chanical analysis, and electronic health records (EHRs) can provide a more thorough picture of KOA development. Thisinterdisciplinaryapproachwouldenable AImodelstonotonlyclassifyKOAseverity but also aid in risk assessment, treatment personalization, and rehabilitation planning.

In conclusion, this project has the potential to transform KOA diagnosis and treatment planning, making AI a vital tool in orthopedic care.By combining deep learning advancements, real-world deployment strategies, and predictive healthcare analytics, the future of AI-powered KOA management looks promis- ing.TheuseoftheseAI-poweredmodelswillhelpthemedicalcommunityaddresstherisingincidence of osteoarthritis globally, improve patient care, and increase diagnostic accuracy.

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