International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(2s) 2026 pp. 181-190
https://doi.org/10.70917/ijcisim-2026-2073
Article

DEEP LEARNING BASED HKA ANGLE ASSESSMENT FOR DETECTION OF CHANGES IN KNEE JOINT ALIGNMENT

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Abstract: Changes in knee alignment takes place with the occurrence of Knee Osteoarthritis. Malalignment of knee is evident when Hip knee ankle angle of an individual changes from its neutral position. The aim of the research is to study the lower-extremity using deep learning for detection of changes in joint alignment. In this study, a dataset of 340 images of scanograms was created. A deep learning model based on Renet-18 with transfer learning is implemented for analysis of left leg and right leg separately. Hip knee ankle angle is measured using landmarks on centre of Femur, centre of knee and centre of ankle. Depending on the HKA angle, knee alignment is decided as Varus, Valgus or Neutral. Results obtained by our deep learning model differed from radiologist's predictions by ±2° for right leg and ±3° for left leg. The model could achieve Intra Class Correlation Coefficient (ICC) of 0.92 and Pearson Correlation Coefficient (r) of 0.94 in HKA analysis. Along with HKA angle analysis, model is trained to evaluate leg length and discrepancy between left and right leg. This deep learning technique enables precise predictions of HKA and leg length enabling the healthcare providers for early and fast decision making.....

Keywords: Deep learning, Resnet, Knee Osteoarthritis (KOA), Medical image analysis, Scanogram...

1. Introduction

Knee OA is a degenerative joint disorder occurring in older population which decreases quality of life by causing mobility issues. Variations in knee alignment increases the severity of Knee OA. Knee malalignment also results into changes in load distribution on the knee joint. One of the important parameters for assessing knee alignment is Hip Knee Ankle angle. Inward or outward angulation of knee joints causes changes in HKA, resulting into Knee Osteoarthritis. Outward angulation of knee bones is termed as varus knee and inward angulation of bones is called valgus knee. Traditionally, the HKA angle is measured manually by orthopedicians using full leg X-rays called scanograms. This process is dependent on marking the landmarks on center of knee joint, center of femoral head and center of ankle joint, which is prone to error. So automated measurement of HKA is necessary to improve accuracy and save the time of measurement [1][2].

Full leg X-rays have proven more useful in detection of HKA instead of plane knee X-rays [3]. Fully automatic analysis of full leg X-rays is reliable and fast [5]. Misalignments of knee angle results into changes in ankle line orientation [7]. HKA angle ranging from −3° to 3° should be considered as neutral knee [8]. There is direct relationship between HKA angle and Knee OA severity. As HKA angle increases, knee OA severity also increases [11].

In order to determine knee OA severity, several studies have been carried out using joint space narrowing. There is limited work carried out on detection of varus and valgus using HKA angle analysis. To address these challenges a deep learning based approach in automatic landmark detection using medical images is required. ResNet-18 is a powerful variant of CNNs providing high computation efficiency and effective feature extraction capability making it suitable for medical image analysis. In this study, we propose an automated system for detecting HKA and classifying the images into varus, neutral and valgus using scanograms.

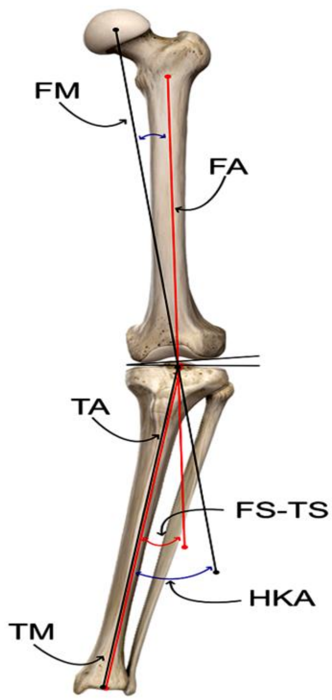


Fig. 1 Landmarks for calculating HKA angle. FM is femoral mechanical axis, TM is tibial mechanical axis, FA is femoral anatomical axis, TA is tibial anatomical axis; HKA is hip–knee–ankle angle, FS–TS is femoral-shaft–tibial-shaft angle [32].

In our approach we are detecting knee alignment thereby measuring knee OA severity and reduce human error in measurements. This will support clinicians in early intervention and planning of treatment. The contributions of this study includes (i) the use of Resnet-18 has evolved as a fast and reliable detector for anatomical regions of full-leg X-rays, (ii)automatic computation of HKA (iii) deciding the class (varus/neutral/valgus) depending on HKA angle computation (iv) automatic computation of leg length and determining discrepancy.

2. Related Work

Wang et. al. [1] proposed CNN based module to analyze knee radiographs from the Osteoarthritis Initiative (OAI) database for predicting Hip Knee Ankle angle and femorotibial angles. 6149 individuals were accessed to obtain mean absolute error 0.8° for femorotibial angles and 1.6° for HKA angle. This technique led to fast and reliable prediction of HKA and FTA. Tack et. al. [2] proposed YoLoV4 based fully automated module to locate regions of interests of Hip, Knee and Ankle in full-leg radiographs. HKA angle was computed and obtained an average mismatch of 0.72°. Babazadeh et. al. [3] proposed to measure accuracy of Computer based tomography for detection of ROI in Hip, Knee and Ankle. For measurement of leg alignment, Long Leg Radiographs are more reliable as compared to Computer Tomography. Sheehy et. al. [4] proposed the use of long leg radiographs for determining leg alignment and joint space narrowing. He demonstrated the use of Global Scale, KL grading Scale and Composite Scale to determine severity of KOA. Shock et. al. [5] proposed the use of long leg radiographs for determining leg alignment using U-Net convolutional neural network. The module achieved Inter reader correlation coefficient from 0.918- 0.995 and intra class correlation coefficient of 0.87–0.99. Nam et. al. [6] proposed the use of deep learning algorithm for predicting lower limb alignment using knee radiographs. 2410 radiographs were used analyzed using HRNET technique to predict weight bearing line ratio. Hodel et. al. [7] proposed to determine the relationship between frontal and axial leg alignment. Authors stated that increase in knee valgus increases Ankle joint line orientation. Rosa et. al. [8] proposed the use of meta-analysis to determine Frontal and Sagittal Knee Alignments. The study found HKA angle between −2.91° to 7.94° for male cases and −5.32° to 3.98° for female cases. Graden et. al. [9] determined true mechanical alignment using standard AP radiographs and Full-Limb X-rays. Authors proposed the use full limb X-rays gave better results than standard AP radiographs. Erne et. al. [10] proposed the use of masked R-CNN for predicting lower limb alignment using full leg radiographs. Different knee angles like mMPTA, mLDFA, mLDTA are computed in the study.

Colyn et. al. [11] determined the variations in knee alignment parameters in a varus knee. Results showed that increase in HKA angle, increases the arthritic progression with changes in MTPA and JLCA. Chen et. al. [12] calculated changes in patella position from center of knee joint to measure the inter-rater dependability and intra-class correlation coefficient. Moon et. al. [13] proposed the use of YoLoV5 for automatic detection of lower limb alignment. 450 long leg radiographs were accessed to determine Concordance correlation coefficient, Pearson correlation coefficient and Intraclass correlation coefficient of different knee parameters. Salzlechner et. al. [14] proposed the use CNN for predicting mechanical leg alignment using knee X-ray images. The implemented model achieved a 74-86% Sensitivity and 79-90% Specificity. Pei et. al. [15] proposed use of deep neural network for automated measurement of HKA using lower limb X-rays. 398 patients were examined and the model showed high consistency in determining HKA angle. Gielis et. al. [16] predicted HKA angle from standard knee radiographs of 100 patients. The Pearson Correlation for HKA was 0.90 and for FTA was 0.83. Sosdian et. al. [17] proposed to determine varus and valgus thrust in individuals with severe knee osteo arthritis using 3D Gait analysis. Clement et. al. [18] proposed that there exists a mild to moderate correlation between static HKA and the dynamic HKA for varus knees, and no correlation between the static HKA and dynamic HKA for valgus knees. Sheehy et. al. [19] determined the relationship between FS-TS and HKA angle using long limb radiographs from the multicenter osteoarthritis (MOST) study. Results show that offset between FS-TS and HKA increases with use of shorter shaft length in Varus knee. Stotter et. al. [20] evaluated HKA of 190 long leg radiographs using AI based software. Mean difference between the AI-based software and manual observer was 0.5° or less for all measurements.

Nijjar et. al. [21] proposed the use of YOLOV3 algorithm for detection of varus and valgus in knees. Detection is based on calculating the distance between two ankles and the distance between two knees. Chen et. al. [22] proposed the use of deep learning method for detection of leg alignment. The study was carried on 8878 radiographs from OAI dataset. The model indicated an absolute error of 0.98° for varus and 2.3° for valgus measurement. Nguyen et. al. [23] proposed the use of CNN for detecting varus and valgus in knee. The model demonstrated an absolute error of 1.5° in 82% cases. Hafliger et. al. [24] proposed the use of Deep CNN for detection of leg alignment using full leg X-rays. Study was carried on 112 patients achieving excellent agreement (ICCs > 0.9) with manual annotations. Lee et. al. [25] proposed the use of deep learning technique based on U-Net for leg length determination. 2767 full leg scanograms were used in the study which achieved mean error of 0.17cm from manual measurements. Lassalle et. al. [26] proposed the use of AI based software for automatic leg length detection. Study was carried out on 175 full leg scanograms achieving an intra-class correlation coefficient of 0.9. Gyftopoulos et. al. [27] proposed the use of CNN for various Musculoskeletal Imaging which determined knee angles, OA severity and bone damage. Zheng et. al. [28] proposed the use of deep CNN for detection of leg length discrepancy using full leg radiographs. The algorithm was 96 times faster than radiologists in calculations and achieved Pearson coefficient of 0.84. Lezak et. al. [29] reviewed the use of CNN for detection of leg length discrepancy using full leg radiographs. Parameters taken for comparison included mean absolute error and intra class correlation coefficient. Li et. al [30] established the tolerance range for joint line orientation angle using finite element analysis. The study performed analysis of HKA and various knee angles. Dobler et. al. [31] proposed the use of long leg radiographs for determining leg discrepancy. The study obtained Higher Pearson correlation coefficients and ICCs in normal-weight compared to overweight patients.

3. Materials And Methods

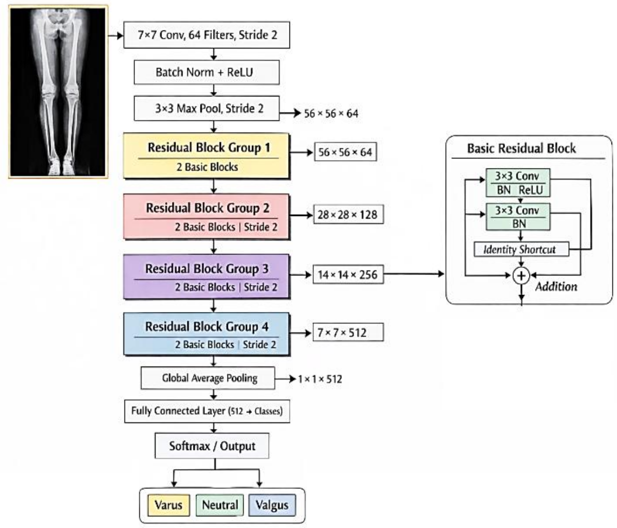


Fig. 2 Architecture of proposed model

Figure 2 demonstrates the detailed architecture of our proposed model. Our model uses Resnet-18 for automatic detection of HKA and leg length. The ability of Resnet to identify edges and bone contours is extremely helpful in HKA assessment. A ResNet-18 model was used to implement transfer learning using dataset of Scanograms. While the final fully connected layers were refined using scanogram images to accomplish knee alignment classification and HKA angle prediction, the earlier convolutional layers were kept for general feature extraction. Here's a breakdown of its working:

Convolution Layer: A Scanogram is a full leg X-ray which demonstrates Hip joint, Femoral shaft, Knee joint, Tibial shaft, Ankle joint. The 7×7 kernel has a large receptive field which is helpful for detecting bone orientation and limb alignment. The 7×7 convolution reduces spatial resolution and provides the necessary down sampling to lower the computational cost. The 7×7 convolution learns for general limb orientation.3×3 kernels are excellent in detecting bone center and shaft center line. They also detect small angular changes which is an important feature for determining HKA. The 7×7 convolution learns for detecting varus/valgus accurately.

Residual Block Group: Residual Block Group1 has an input-output size of 56 × 56 × 64 and is useful in locating joints and long bones which is important in HKA angle determination. Residual Block Group2 has an input-output size of 28 × 28 × 128 and is useful in determining lateral or medial deviation of knee bones from mechanical axis. Residual Block Group3 has an input-output size of 14 × 14 × 256 and is useful in determining angular variations across the knee. Residual Block Group4 has an input-output size of 7 × 7 × 512 and is useful in bifurcation of HKA into varus knee, neutral knee or valgus knee.

Batch Normalization: Batch normalization layers are required after each convolutional layer to normalize the distribution of features. This is especially true for scanogram images due to the significant inter-subject and acquisition-dependent variation in intensity values. Applying batch normalization effectively allows for appropriate learning of residuals while maintaining the geometric alignment cues required for appropriate classification of malalignment of knees.

ReLU layer: The use of ReLU activation functions follows the steps involving batch normalization and residual addition to provide non-linearity while eliminating irrelevant responses of features. This ensures effective modeling of intricate geometric relationships in scanograms that involve varus-valgus malalignment of knees.

$$\mathrm{ReLU}(x)=\max(0, x) \quad (1)$$

where, ReLU(x) is the output with input x.

Global Average Pooling: The global averaging pooling is applied to the last convolutional feature maps to obtain a reduced representation that includes spatial information. It is a less complex operation that improves model robustness to spatial changes, ideal for classifying knee malalignment with HKA based on overall geometry information.

$$\mathrm{GAP(F)}=\frac{1}{\mathrm{H*W}}\sum_{\mathrm{i=1}}^{\mathrm{H}}\sum_{\mathrm{j=1}}^{\mathrm{W}}\mathrm{F(i,j)} \qquad (2)$$

where, F is single feature map produced by Resnet, H is Height of the feature map, W is Width of the feature map.

Softmax Layer: The softmax layer is used to transform the outputs of the connected layers into class probabilities. In detection of knee alignment, our classes are varus, neutral, and valgus knee. This probabilistic output is a mutually exclusive classification and provides confidence scores for assessment of HKA angle for predicting knee malalignment.

$$\mathrm{Softmax(Li)} = \frac{e^{Li}}{\sum_{j=1}^{3} e^{Lj}} \qquad (3)$$

where, Li = output score for class i

4. Experimentation

The proposed algorithm of Resnet-18 Classifier is implemented using multi core Intel Processor, NVIDIA RTX 4050 GPU, 16GB RAM, Windows 11 operating system with CUDA-enabled for deep learning implementations. The software used for implementation of proposed model is AWS Deep Learning AMIs with pre-installed frameworks of Python 3.x. The Resnet-18 Classifier is our proposed model designed for the finding HKA angle and predicting the class Varus, Valgus or Neutral. The flow diagram for training and testing the proposed model is as shown in Figure 3.

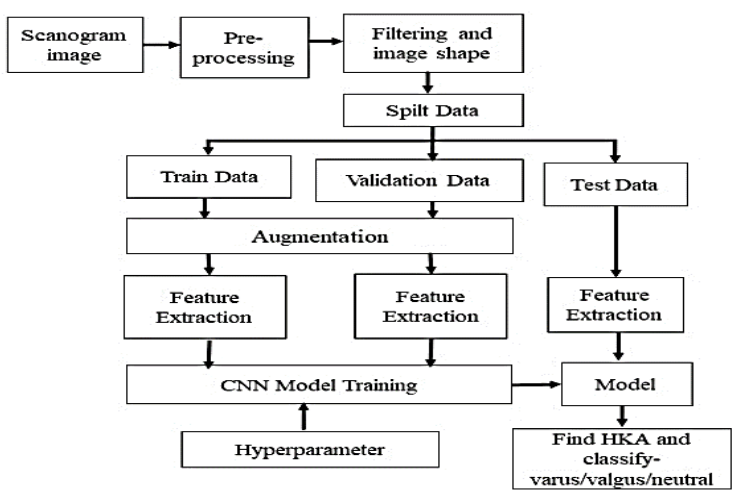


Fig. 3 Flow diagram for training and testing

Dataset: 340 images of Scanograms (full leg X rays) are collected from nearby hospitals. A dataset indicating the center of Femur, center of Knee and center of Ankle is prepared for detection of HKA angle. Using HKA angle joint alignment ie- varus, vulgus and neutral is predicted. Analysis of left leg and right leg is performed separately. Distance from femur head to center of knee is termed as femur length and distance from center of knee to ankle is termed as tibia length. Leg length is calculated by summing femur length and tibia length. Discrepancy in right and left leg length is predicted by our model from leg lengths obtained.

5. Results and Discussion

5.1. Training Phase

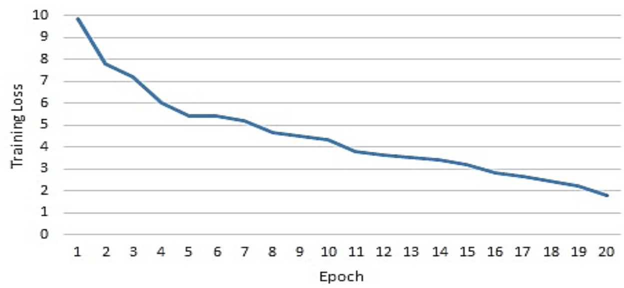
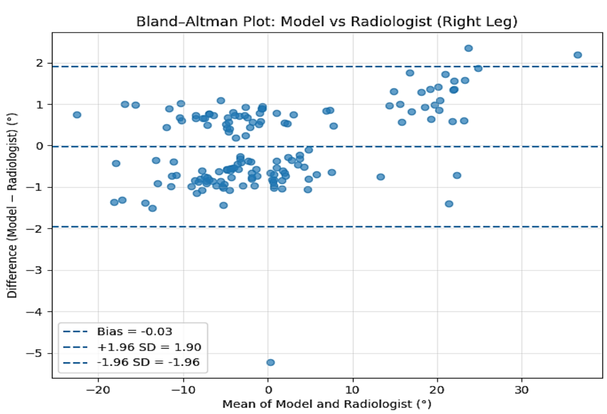


Fig. 4 Training loss Vs Epoch

Figure 4 shows the decreasing pattern of training loss as epochs increase. Initially loss reduces rapidly indicates model learns basic image features. In middle stage learning becomes slower but model identifies more complex anatomical relationships. By epoch 20 the training loss is lowered significantly, indicates model is fine tuning parameters, reducing errors in training phase and becoming stable in predicting knee alignment.

5.2 Comparison of Models Performance with Radiologists Evaluation



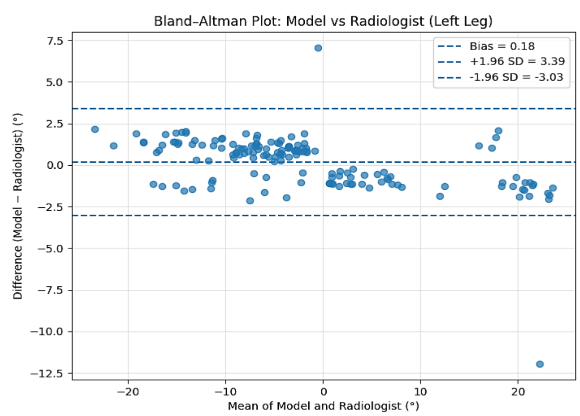


Fig. 5 Comparative evaluation of Hip Knee Ankle angle by Radiologist and proposed model

Figure 5 shows details of manual and automatic assessment of HKA angle by radiologist and our proposed model. For right leg analysis, our model achieved a bias of -0.03° indicating it neither overestimates nor underestimates the results. Upper limits of agreement are 1.90° and lower limits of agreement is -1.96°; this indicates 95% of our models predictions differ from radiologists predictions with less than ±2°.For left leg analysis, our model achieved a bias of 0.18° indicating the ability to correctly predict the results. Upper limits of agreement are 3.39° and lower limits of agreement is -3.03°; this indicates 95% of our models predictions differ from radiologists predictions from ±3°.

Resnet-18 based model is trained using scanograms. Our proposed model identifies the alignment between center of femur, center of knee and center of ankle. Resnet-18 based machine learning model predicts the knee alignment viz- Varus, Valgus and Neutral. Figure 6 demonstrates HKA angle less than -3° are termed as Varus, HKA angle more than +3° are termed as Valgus and HKA less than ±3° are termed Neutral. In order to determine HKA angle between center of femur, center of knee and center of ankle is calculated (θ). For Varus alignment, Hip Knee Ankle angle is termed negative as it is less than 180°. For Valgus alignment, Hip Knee Ankle angle is termed positive as it is more than 180°. For Neutral alignment, Hip Knee Ankle angle lies between ±3°.

Hip Knee Ankle angle = θ - 180°

As per medical analytics, knee alignment is very closely related to existence of knee osteoarthritis. Larger the HKA (Varus or Valgus) more is the prevalence of knee osteoarthritis. Our model identifies the existence of Knee osteoarthritis through changes in knee alignment

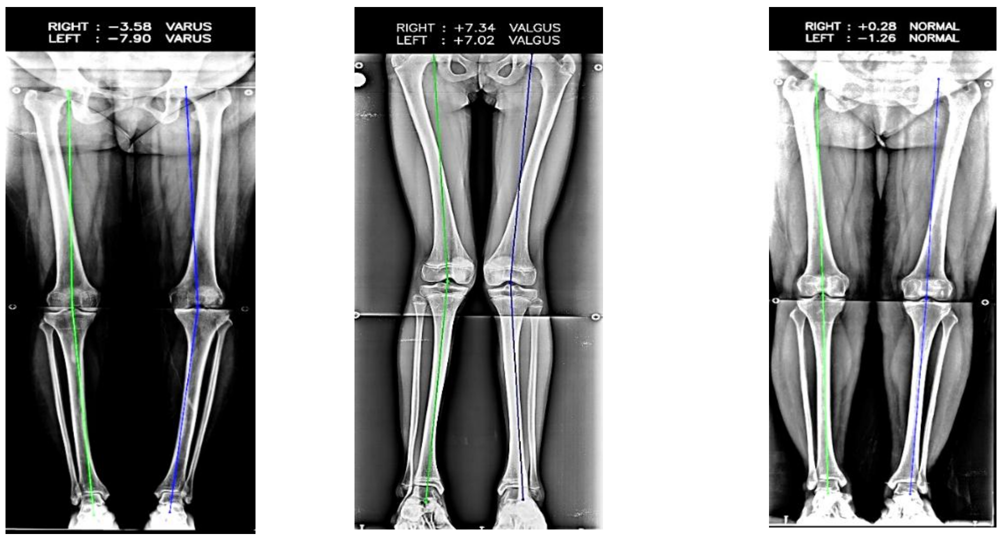


Fig. 6 Results obtained by our model demonstrating knee alignment

5.3 Analysis of Leg length

Figure 7(a) demonstrates positive linear relationship between left and right femur. Pearson correlation coefficient r=0.903 indicates as length of right femur increases, length of left femur increases proportionately. Coefficient of Determination (R2=0.815) is strong, indicating our models predictions are consistent. Figure 7(b) shows Tibia scatter plot, Pearson correlation coefficient of r=0.941 and Coefficient of Determination R2=0.886 is achieved. Figure 7(c) shows Leg length scatter plot, Pearson correlation coefficient of r=0.963 and Coefficient of Determination R2=0.928 is achieved. Figure 7(d) shows Bland-Altman plot for leg length analysis. Our model achieved a bias of 0.22cm indicating the ability to correctly predict the results. Upper limits of agreement is 3.31cm and lower limits of agreement is -2.87cm; this indicates 95% of our models predictions for right leg differ from left leg predictions from ±3cm.

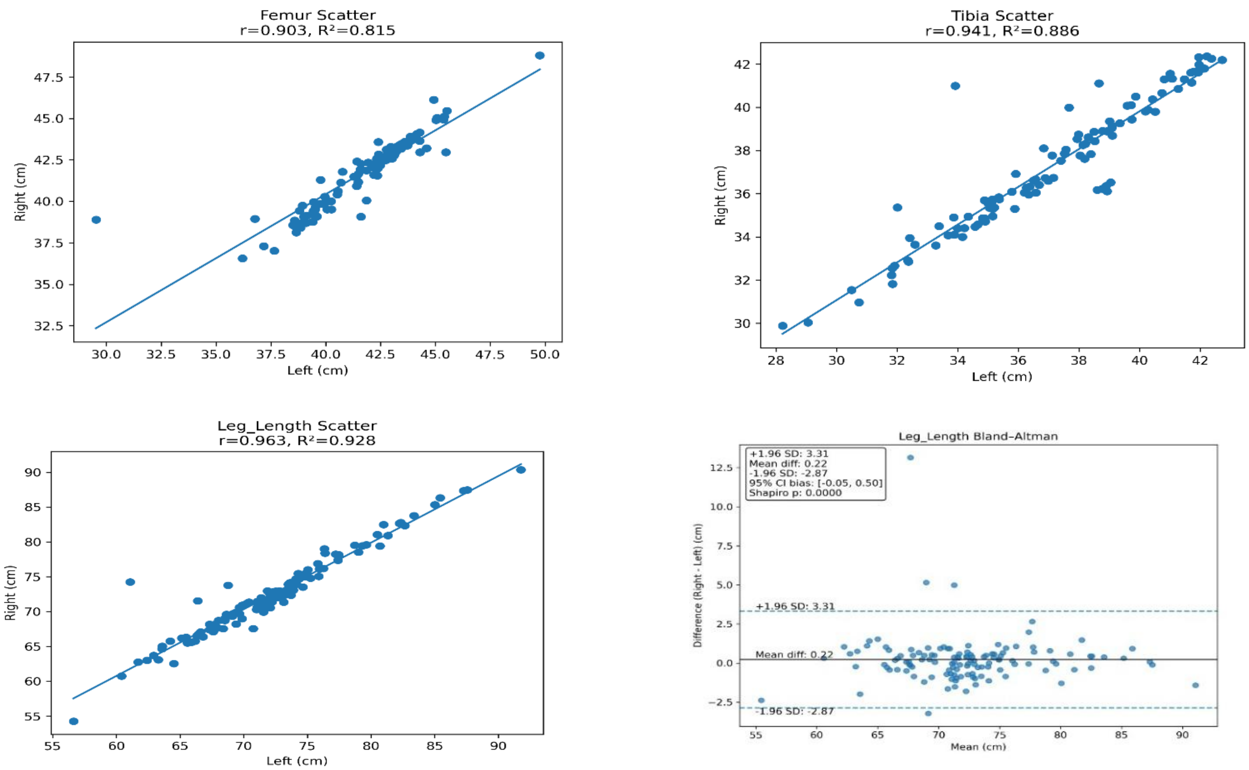


Fig. 7 (a) Femur scatter plot (b)Tibia scatter plot (c) Leg length scatter plot (d) Bland-Altman plot for Comparative evaluation of left Vs right leg

Comparison of Proposed model with other Researchers

Table 1. Comparison of proposed model

Research	Modality	Intra class Correlation Coefficient			Pearson Correlation Coefficient		
		HKA	**Femur length**	**Tibia Length**	**HKA**	**Femur length**	**Tibia Length**
[1]	Full limb radiographs	0.80	-	-	-	-	-
[2]	Full leg Xray	0.97	-	-	-	-	-
[5]	Full leg Xray	0.94	-	-	-	-	-
[16]	Standard knee radiographs	0.90	0.87	0.87	0.90	0.88	0.88
Proposed Model	**Scanograms**	**0.92**	**0.94**	**0.94**	**0.94**	**0.92**	**0.92**

Table 1 demonstrates comparison of our model with other research models. Research [1] used full limb radiographs with densenet-121 for HKA analysis. The model could achieve ICC value of 0.8 for HKA analysis. Research [2] used full leg X-rays with YoLov4 for determining HKA. The model could achieve ICC value of 0.97 for detection of HKA. Research [5] used full leg X-rays with UNet CNN for determining HKA. The model could achieve ICC value of 0.94 for detection of HKA. Research [16] used Standard knee radiographs for determining ICC value for HKA, Femur length and Tibia length. Researchers could achieve ICC of 0.90 for HKA, 0.87 for Femur length and 0.87 for Tibia length. Pearson correlation coefficient 0.90 for HKA, 0.88 for Femur length and Tibia length was achieved by the researchers. Our proposed model used Scanograms with Resnet-18 for analysis. The model achieved

ICC of 0.92 for HKA, 0.94 for Femur length and Tibia length. Pearson correlation coefficient 0.94 for HKA, 0.92 for Femur length and Tibia length was achieved by our model. The proposed model achieved excellent agreement and strong correlation attributed to residual learning attributes of Resnet-18. Model could produce high ICC value attributed to stable feature learning in limited data size. Our proposed model could achieve high Person r as Resnet-18 correctly identified edges, bone contours and anatomical landmarks.

6. Conclusion

This study explored the potential of Resnet classifier for automated analysis of HKA angle. The objective was to determine changes in joint alignment and predict knee alignment viz- Varus, Valgus and Neutral. Variations in knee alignment is an important indicator for existence of knee osteoarthritis. Along with leg alignment model could precisely predict leg length and its discrepancy. The model was implemented using NVIDIA RTX 4050 GPU with 16GB RAM and CUDA-enabled deep learning implementations. Results obtained by our model differed from radiologists predictions by $\pm 2°$ for right leg and $\pm 3°$ for left leg. The model could achieve ICC of 0.92 in HKA analysis and 0.94 in leg length measurement. The model could achieve Pearson's r of 0.94 in HKA analysis and 0.92 in leg length measurement. Our model produces result that have high agreement with clinical measurements indicating greater consistency and reliability. Our model automatically detects knee malalignment thereby reducing manual workload of radiologists and orthopaedic surgeons. The model can help doctors with preoperative planning and deformity assessment. The future work is to use diverse dataset of scanogram images to improve generalization capability of the model. Also, advance deep learning architectures can be explored to improve HKA analysis and detect additional knee parameters.

Conflict of interest

The authors declare no conflict of interest.

Acknowledgement

The authors would like to thank Dr. Mayur Kapse, Orthopaedic Surgeon, Maharashtra for providing clinical insights and assisting in estimation of HKA angle from scanograms in this study..

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