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Identification of Knee Prostheses from Lateral Radiographs Using Deep Learning Techniques

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***Abstract* -** The field of medical imaging has seen significant progress in recent years, particularly with the evolution of deep learning techniques. In the context of arthroplasty, the ability to accurately detect and identify specific implant models is crucial for proper patient care and revision surgery. However, manual identification of implants from radiographic images (X-Ray) takes a lot of time and is affected by manual human error. To solve this, this research proposes a deep learning-based novel approach to automate the identification of Knee arthroplasty implants from Lateral (LAT) view X-ray images of the implant. Pre trained convolutional neural networks are used for this purpose. Best results are obtained using VGG16 which produces a higher accuracy of 81.61% and stronger Area Under Curve (AUC) of 0.9547.

***Keywords*:** Deep learning, Orthopaedics, Knee implant models, Radiographic images, Artificial Intelligence, Biomedical Engineering.

1. Introduction

The identification of the brand of knee arthroplasty prosthesis is very important for planning a revision knee arthroplasty. However, it takes a lot of time and effort to determine the implant brand from a primary knee arthroplasty [1]. The frequency of patients having repeated knee surgeries is rising along with the number of knee operations being performed [2]. Total knee arthroplasty (TKA), a surgical surgery that may be used to treat severe osteoarthritis of the knee, lowers joint damage and enhances overall joint function [3]. This is the most common type of surgery in United States of America [4].

For enhanced quality of revision surgery in cases of total knee arthroplasty failure, accurate preoperative diagnosis is crucial [5]. Deep learning (DL) has been demonstrated to be significantly more effective than manual interventions at improving diagnosis. Deep learning approaches are used to resolve the issue of recognising the producer and model of knee arthroplasty prostheses [6,7] which is the most important and subtle step in planning a revision surgery.

Deep Learning is used in Orthopaedics and helps in multiple ways [8]. Machine learning (ML) is considered a subset of Artificial Intelligence and is also widely used in Orthopaedics [9].

The proposed study focuses on using lateral images to identify knee implant manufacturers and models accurately. By leveraging deep learning models and convolutional neural networks (CNN), the study aims to overcome the challenges and provides accurate and robust results. The study is the first of its kind to leverage upon the LAT images for arthroplasty implant identification.

2. Literature Survey

Anne et al studied all revision TKAs from 2010 to 2015 at their home department regardless of whether it was their first or subsequent revision surgery. The revision cause was evaluated by the physician in the operation report. 312 individuals had TKAs, and the most common causes of revision were aseptic loosening, periprosthetic fracture, and infection [10]. Sukrit et al identifies 6 knee implant models using radiographs of both Anterior Posterior (AP) and Lateral

(LAT) views. Best results were obtained using the DenseNet 201 deep learning model. Accuracy of 96.38% and a sensitivity of 97.2% were obtained in the classification [11]. Samuel et al identified 6 different implant models only using AP view. The system was also able to detect radiographs with no prosthesis. Accuracy of 100 and F1 Score of 1.0 were the best results obtained using Pretrained ResNet18 [12].

3. Dataset Description

This proposed study consists of Lateral (LAT) images of six different classes of orthopaedic implants: Exactech Opterak, Smith and Nephew Legion, Stryker NRG, Zimmer LPS, and Zimmer Persona. The images were collected in a completely anonymized manner without any form of patient details that identifies the patient and their condition. The dataset was preprocessed by removing any images that were of poor quality or showed significant artefacts or distortions. Images are labelled only for the make and model and each image labelling was verified by a senior Orthopaedic surgeon. The table 1 below lists the implants used in the proposed work.

Table 1 : Implants used in the proposed work before augmentation

MAKE	**MODEL**	**TOTAL IMAGES**
Exactech	Opterak Logic	156
Smith and Nephew	Legion	128
Stryker	NRG	101
Zimmer	LPS	100
Zimmer	Persona	168

Fig 1(a-e): Visual Representation of Lateral view of the five Knee Implant classes

The images shown in Fig 1 display the Lateral view of the different implants. There were five classes namely Opterak Logic, Legion, NRG, LPS, Persona respectively labelled as a, b, c, d, and e in the images. In this study, we will only be using the lateral view (LAT) images.

4. Methods And Methodology

4.1 Preprocessing and Training Data Selection

4.1.1 Preprocessing- From the original extreme poor-quality images were removed and only good quality images were used. These images were converted to grayscale before further process.

4.1.2 Training Set - The data was split into ratios of 70-30. 70% of images from the original database were selected for training the model in a random manner. These images undergo the Augmentation techniques to increase their count. Quality of training determines the efficiency of testing and thus images were carefully augmented to increase their count.

4.1.3 Validation Set / Internal Testing Set – Validation set comprises 30% of our unaugmented total data to assess the performance of our model after training. By setting aside this separate subset of data, we can evaluate the model's accuracy and identify any issues with overfitting or underfitting [13] ensuring that it can generalise effectively to new and unseen data.

4.1.4 Data Augmentation - The method of creating additional data samples from existing ones by applying minor modifications to the original dataset is called data augmentation. For this study, different techniques were used to increase the count of training images alone. The images were first converted to grayscale and the images underwent extreme rotation [14] in both positive and negative angles to increase the count of training images. As a result, the number of data samples increased from 758 to above 5000 (On an average 1100 images per implant class).

4.2 Deep Learning Methods: CNN based DL techniques were used for classification of implants. Pretrained DL models such as VGG16 [15] and popular models like VGG19 [16], MobilenetV2 [17] and InceptionV3 [18] were used to identify the implant across five (5) implant classes. These models were pretrained on a larger database called ImageNet [19] and were predominantly used in image classification tasks

4.2.1 Model evaluation - the resulting models were evaluated using various metrics such as precision of classification, accuracy of classification, recall, AUC as well as F1 Score [20]. These metrics allowed for a thorough assessment of the models' ability to correctly identify the various implant designs. These were from test images classified as true positive, false negative, true negative and false positive [21].

4.3 Proposed Model:

The motivation of the proposed study was to create a DL-based approach for identifying arthroplasty implants from lateral images of knee implants. In order to achieve this, the authors employed CNN as the basis for the model. CNNs play a huge role in image classification tasks, as they can identify patterns and features in images that are not readily apparent to the human eye. Transfer learning techniques were refined on a pre-trained CNN on our objective of recognising arthroplasty implants in order to enhance the performance of the model. For this study, four different, highly fine-tuned pre-trained CNN models were used in the study. All the deep learning models used in this proposed work were fine tuned for various parameters such as Learning rate, optimizers, batch size etc [22].

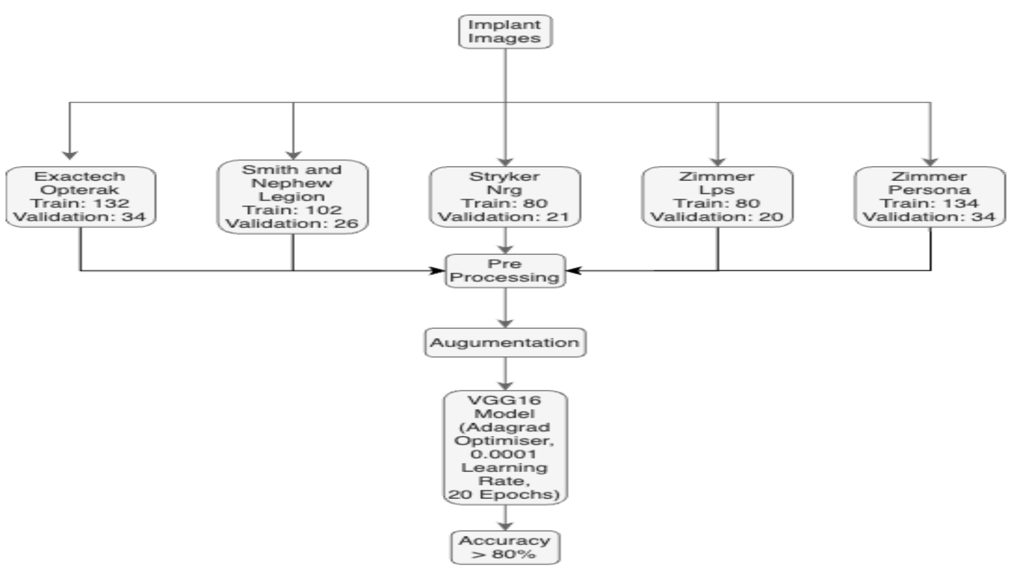


Figure 2: Flowchart of the knee implant identification system

5. Results and Discussions:

5.1 Results of Augmentation of Images:

Figure 3. Visual Representation of Five Different Classes of Augmented Knee Implant Model

Figure 3, displays five augmented knee implant models in the order of Opterak Logic, Legion, NRG, LPS and Persona, respectively labelled as a, b, c, d, and e.

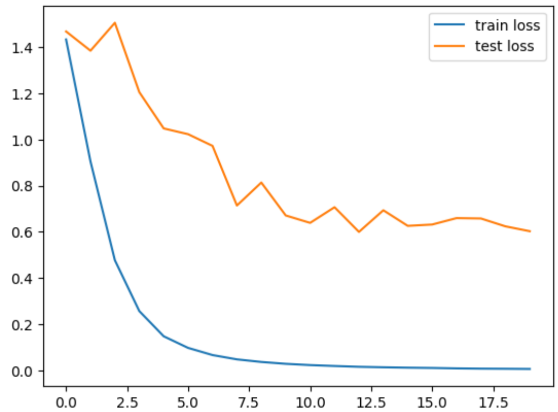
The image serves as a visual representation of different rotation augmentation techniques used in the study.

5.2 Deep Learning Results:

The five implant classes were trained and tested with various pre-trained deep learning models. The best performance was obtained using VGG 16 deep learning model after higher fine tuning. The best combination of hyperparameters that gave results were shown in Table 2.

Table 2: Configuration of the VGG-16 model with highest accuracy.

Model	VGG – 16
Optimiser	Adagrad
Learning Rate	0.0001
Trainable layer	No changes



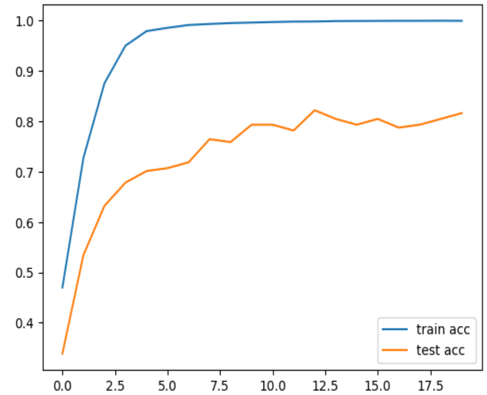


Figure 4: Loss and Accuracy plots of VGG16 Model

Figure 4 shows the plot of both loss and accuracy of both train and test images obtained using the VGG 16 model. Loss increase in both train and test/ validation and accuracy increases steadily.

Table 3: Accuracy and Loss values for classification of Implants across various Deep learning models

Model	**Number of Epochs**	**Accuracy of Training (%)**	**Loss incurred in Training**	**Accuracy of Validation (%)**	**Loss incurred in Validation**
VGG16	20	99.93	0.0059	81.61	0.6030
VGG19	20	93.34	0.0023	72.99	0.9935
Mobilenet	30	95.14	0.2618	70.69	1.2080
Inception V3	20	96.07	0.2561	68.39	1.2106

Table 3 provides the accuracy and loss values for both train and validation sets of the different deep learning models tested. VGG16 outperforms other models with an accuracy of 81.61%

Table 4: Performance metrics for classification of Implants across various Deep learning models

Model	**Epoch**	**AUC**	**Precision**	**Recall**	**F1 Score**
VGG16	20	0.9547	0.8141	0.8161	0.8129
VGG19	20	0.9334	0.7226	0.7299	0.7157
Mobilenet	30	0.8802	0.7600	0.7100	0.6800
Inception V3	20	0.8520	0.7800	0.6800	0.6700

Table 4 summarises the best performance metrics achieved by the models and it is clearly seen VGG16 is better than other 3 DL models.

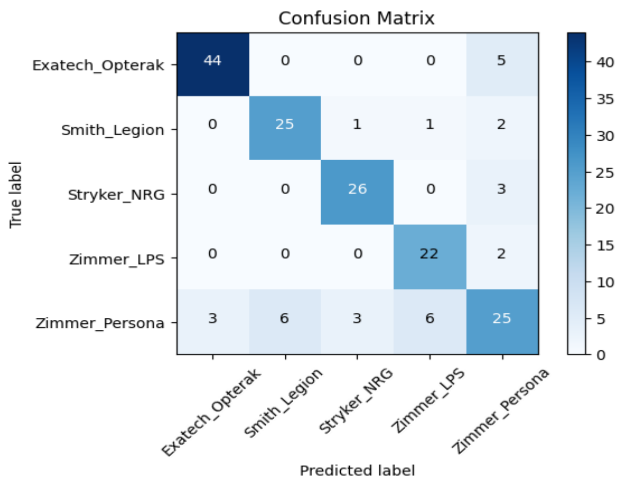


Figure 5: Confusion Matrix of VGG 16 Block Diagram

The confusion matrix of the 5 implant classes performance under VGG16 model are plotted in Figure 5. All the implants suffered minor misclassification and were mostly accurately classified. Optimizers such as Adam [23], SGD [24] and Adagrad [25] were used across the 4 deep learning models. Best results were obtained when trained with 'Adagrad' optimizer and when trained with a learning rate of 0.0001 for VGG16 in classification of 5 total knee replacement implants.

6. Conclusion:

The proposed work uses a novel framework to recognise total knee arthroplasty implants from radiographs and determine their make and model. The work, which is first of its kind, uses only LAT images for both training and testing and identifies the implants with an accuracy of 81.61% and an AUC of 0.9547 respectively. The study which is first of its kind accurately identifies the 5 knee implants only with LAT images. Future work can involve using more implant models and using a general algorithm for both hip and knee implants.

References

[1] Tiwari, A., Yadav, A.K. and Bagaria, V., 2022. Application of deep learning algorithm in automated identification of knee arthroplasty implants from plain radiographs using transfer learning models: Are algorithms better than humans?. Journal of Orthopaedics, 32, pp.139-145.

[2] Kim, B., Lee, D.W., Lee, S., Ko, S., Jo, C., Park, J., Choi, B.S., Krych, A.J., Pareek, A., Han, H.S. and Ro, D.H., 2022. Automated Detection of Surgical Implants on Plain Knee Radiographs Using a Deep Learning Algorithm. Medicina, 58(11), p.1677.

[3] Postler, A., Lützner, C., Beyer, F., Tille, E. and Lützner, J., 2018. Analysis of total knee arthroplasty revision causes. BMC musculoskeletal disorders, 19, pp.1-6.

[4] Sun, X., Wang, J. and Su, Z., 2020. A meta-analysis of total knee arthroplasty following high tibial osteotomy versus primary total knee arthroplasty. Archives of orthopaedic and trauma surgery, 140, pp.527-535.

[5] Baré, J., MacDonald, S.J. and Bourne, R.B., 2006. Preoperative evaluations in revision total knee arthroplasty. Clinical Orthopaedics and Related Research®, 446, pp.40-44.

[6] Jaret M. Karnuta, Hashim J.F. Shaikh, Michael P. Murphy, Nicholas M. Brown, Andrew D. Pearle, Danyal H. Nawabi, Antonia F. Chen, Prem N. Ramkumar, Artificial Intelligence for Automated Implant Identification in Knee Arthroplasty:

A Multicenter External Validation Study Exceeding 3.5 Million Plain Radiographs, The Journal of Arthroplasty, 2023, ISSN 0883-5403,

[7] Ghose, S., Datta, S., Batta, V., Malathy, C. and Gayathri, M., 2020, December. Artificial intelligence based identification of total knee arthroplasty implants. In *2020 3rd International Conference on Intelligent Sustainable Systems (ICISS)* (pp. 302-307). IEEE.

[8] Tolpadi, A.A., Lee, J.J., Pedoia, V. *et al.* Deep Learning Predicts Total Knee Replacement from Magnetic Resonance Images. *Sci Rep* 10, 6371 (2020).

[9] Dossett HG. Machine Learning: the Future of Total Knee Replacement. Fed Pract. 2022 Feb;39(2):62-63. doi: 10.12788/fp.0224. Epub 2022 Feb 14. PMID: 35444380; PMCID: PMC9014939

[10] Postler, A., Lützner, C., Beyer, F., Tille, E. and Lützner, J., 2018. Analysis of total knee arthroplasty revision causes. *BMC musculoskeletal disorders*, *19*, pp.1-6.

[11] Sharma, S., Batta, V., Chidambaranathan, M., Mathialagan, P., Mani, G., Kiruthika, M., Datta, B., Kamineni, S., Reddy, G., Masilamani, S. and Vijayan, S., 2021. Knee Implant Identification by Fine-Tuning Deep Learning Models. *Indian Journal of Orthopaedics*, *55*, pp.1295-1305.

[12] Belete, S.C., Batta, V. and Kunz, H., 2021. Automated classification of total knee replacement prosthesis on plain film radiograph using a deep convolutional neural network. *Informatics in Medicine Unlocked*, *25*, p.100669..

[13] Pothuganti, S., 2018. Review on over-fitting and under-fitting problems in Machine Learning and solutions. *Int. J. Adv. Res. Electr. Electron. Instrumentation Eng*, *7*(9), pp.3692-3695.

[14] Shorten, C. and Khoshgoftaar, T.M., 2019. A survey on image data augmentation for deep learning. *Journal of big data*, *6*(1), pp.1-48

[15] Simonyan, K. and Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.

[16] Sudha, V. and Ganeshbabu, T.R., 2021. A convolutional neural network classifier VGG-19 architecture for lesion detection and grading in diabetic retinopathy based on deep learning. *CMC-Computers Materials & Continua*, *66*(1), pp.827-842.

[17] Sandler, M., Howard, A., Zhu, M., Zhmoginov, A. and Chen, L.C., 2018. Mobilenetv2: Inverted residuals and linear bottlenecks. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 4510-4520).

[18] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. and Wojna, Z., 2016. Rethinking the inception architecture for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 2818-2826)

[19] Deng, J., Dong, W., Socher, R., Li, L.J., Li, K. and Fei-Fei, L., 2009, June. Imagenet: A large-scale hierarchical image database. In *2009 IEEE conference on computer vision and pattern recognition* (pp. 248-255). Ieee.

[20] Vakili, M., Ghamsari, M. and Rezaei, M., 2020. Performance analysis and comparison of machine and deep learning algorithms for IoT data classification. *arXiv preprint arXiv:2001.09636*

[21] Ramanathan, A. and Christy Bobby, T., 2020. Classification of Corpus Callosum Layer in Mid-saggital MRI Images Using Machine Learning Techniques for Autism Disorder. In *Modeling, Machine Learning and Astronomy: First International Conference, MMLA 2019, Bangalore, India, November 22–23, 2019, Revised Selected Papers 1* (pp. 78-91). Springer Singapore.

[22] Yu, T. and Zhu, H., 2020. Hyper-parameter optimization: A review of algorithms and applications. *arXiv preprint arXiv:2003.05689*.

[23] Kingma, D.P. and Ba, J., 2014. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*

[24] Ruder, S., 2016. An overview of gradient descent optimization algorithms. *arXiv preprint arXiv:1609.04747*.

[25] Lydia, A. and Francis, S., 2019. Adagrad—an optimizer for stochastic gradient descent. *Int. J. Inf. Comput. Sci*, *6*(5), pp.566-568.