Journal of Orthopaedic Translation 36 (2022) 177–183

Contents lists available at ScienceDirect

Journal of Orthopaedic Translation

journal homepage: www.journals.elsevier.com/journal-of-orthopaedic-translation

ORIGINAL ARTICLE

A novel image-based machine learning model with superior accuracy and predictability for knee arthroplasty loosening detection and clinical decision making

Lawrence Chun Man Lau [a], Elvis Chun Sing Chui [a,*], Gene Chi Wai Man [a], Ye Xin [a], Kevin Ki Wai Ho [a], Kyle Ka Kwan Mak [a], Michael Tim Yun Ong [a], Sheung Wai Law [a], Wing Hoi Cheung [a], Patrick Shu Hang Yung [a]

[a] Department of Orthopaedics and Traumatology, Faculty of Medicine, The Chinese University of Hong Kong, The Prince of Wales Hospital, Shatin, Hong Kong

A R T I C L E I N F O

Keywords:
Artificial intelligence
Machine learning
Xception model
Predictive modeling
Total knee arthroplasty
loosening

A B S T R A C T

Background: Loosening is the leading cause of total knee arthroplasty (TKA) revision. This is a heavy burden toward the healthcare system owing to the difficulty in diagnosis and complications occurring from the delay management. Based on automatic analytical model building, machine learning, may potentially help to automatically recognize the risk of loosening based on radiographs alone. The aim of this study was to build an image-based machine-learning model for detecting TKA loosening.

Methods: Image-based machine-learning model was developed based on ImageNet, Xception model and a TKA patient X-ray image dataset. Based on a dataset with TKA patient clinical parameters, another system was then created for developing the clinical-information-based machine learning model with random forest classifier. In addition, the Xception Model was pre-trained on the ImageNet database with python and TensorFlow deep learning library for the prediction of loosening. Class activation maps were also used to interpret the prediction decision made by model. Two senior orthopaedic specialists were invited to assess loosening from X-ray images for 3 attempts in setting up comparison benchmark.

Result: In the image-based machine learning loosening model, the precision rate and recall rate were 0.92 and 0.96, respectively. While for the accuracy rate, 96.3% for visualization classification was observed. However, the addition of clinical-information-based model, with precision rate of 0.71 and recall rate of 0.20, did not further showed improvement on the accuracy. Moreover, as class activation maps showed corresponding signals over bone-implant interface that is loosened radiographically, this confirms that the current model utilized a similar image recognition pattern as that of inspection by clinical specialists.

Conclusion: The image-based machine learning model developed demonstrated high accuracy and predictability of knee arthroplasty loosening. And the class activation heatmap matched well with the radiographic features used clinically to detect loosening, which highlighting its potential role in assisting clinicians in their daily practice. However, addition of clinical-information-based machine-learning model did not offer further improvement in detection. As far as we know, this is the first report of pure image-based machine learning model with high detection accuracy. Importantly, this is also the first model to show relevant class activation heatmap corresponding to loosening location.

Translational potential: The finding in this study indicated image-based machine learning model can detect knee arthroplasty loosening with high accuracy and predictability, which the class activation heatmap can potentially assist surgeons to identify the sites of loosening.

Abbreviations: TKA, Total Knee Arthroplasty; CNN, Convolutional Neural Network; AI, Artificial Intelligence; ROC, Receiver Operating Characteristic.

* Corresponding author.
E-mail addresses: lawrencelau@link.cuhk.edu.hk (L.C.M. Lau), elvis_chui@cuhk.edu.hk (E.C.S. Chui), patrickyung@cuhk.edu.hk (P.S.H. Yung).

https://doi.org/10.1016/j.jot.2022.07.004
Received 29 March 2022; Received in revised form 13 June 2022; Accepted 4 July 2022
Available online xxxx

1. Introduction

Total knee arthroplasty (TKA), as one of the most frequently performed operation in orthopedics currently and anticipated to become the commonest elective operation in the near future, can become heavy burdens to the healthcare system with its accompanied risk of failure and revision [1,2]. Loosening is the leading cause of revision among various complications, and it tends to occur many years after the initial surgery [3]. With the summative effect of longer life expectancy, late occurrence of loosening, and increasing number of patients living with TKA, the early detection of loosening in patients with TKA has become a major importance and interest in the orthopedic field. A delay in diagnosis of loosening and hence a prolonged period of walking with an unstable implant can result in loss of bone stock and deterioration of surrounding soft tissues, which may entail a larger scale of revision surgery with poorer outcome. A system that can automatedly detect loosening may relieve the burden of orthopedic surgeons and further safeguard their practice.

As loosening is hard to diagnose, various imaging modalities, such as scintigraphy, arthrogram, MRI and fluorodeoxyglucose-positron emission tomography (FDG-PET) scans, have been investigated and shown various limitations, such as high cost, insensitivity, invasiveness in nature, and low accuracy [4]. Owing to uncertainty in diagnosis by these various imaging modalities, patients would often need further testing like various blood tests, repeated imaging and possibly subsequently false reassurance or unnecessary revision [4].

Machine learning has been successfully applied in various medical field. This includes the automatic detection of strokes, retinopathies, and cancerous histology, with same level of accuracy as the relevant field experts [5–10]. Actualized by advanced computational power, machine learning can self-teach and self-develop its pattern recognition by reading a vast number of relevant labelled images and/or data and does not necessarily follow clinical criteria set by the medical experts. Shah et al. reported an attempt in application of machine learning in detection of arthroplasty loosening using radiographs [11]. However, their model's performance for TKA is relatively poor and it depends heavily on historical, demographic, and comorbidity information, instead of isolated image analysis [11]. However, in reality, many of those cases that had their TKA performed many years ago, especially in outside tertiary referral centers, would often have their historical and demographic information, such as operation details and particulars of surgeons, to be unknown. In addition, the heavy dependence of non-image details would also limit the system ability to work as mass screening or applicable to various joint replacement centers owing to being unavailable or incomplete. Besides, the system reported by Shah et al. failed to indicate the region of the implant–bone interface on determining the position of loosening. This would limit its purpose on providing an accurate position of the loosening for early clinical management.

Therefore, the current study aimed to build and evaluate an optimized image-based machine-learning model that could effectively detect TKA loosening based on radiographs alone. Additional clinical-information-based machine-learning models were developed and combined with image-based machine-learning model for further evaluation and comparison. Class activation heatmap was generated to represent machine-learning model focused on detection of loosening based on analysis of radiographs, and to generate the probability of loosening.

2. Materials and methods

2.1. Ethical statement

This study complied with the Declaration of Helsinki after obtaining approval from the Institutional Review Board of the local institution's Research Ethical Committee (CREC 2018.544).

2.2. Machine learning model

Image-based machine-learning model was developed based on ImageNet which is an open-source project that could classify an Input Image into 1000 separate object categories. The model was trained using approximately 1.2 million images, with another 100,000 images for testing and 50,000 images for validation. In addition, Xception model, an extension of the Inception Architecture which replaced the standard Inception modules with Depthwise Separable Convolutions, was employed [12]. The development of this deep learning-based prosthesis loosening estimating system was based on Xception pre-trained model and a TKA patient X-ray image dataset. In brief, random forest, consisted of a large amount of individual decision trees that operate as an ensemble, were created. Then, each individual tree in the random forest generated a class prediction. Whereas, the class with the most votes became our model's prediction. The process of random forest is shown in Fig. 1. A classification system based on a dataset with TKA patient clinical parameters was developed using random forest classifier.

2.3. Dataset

A total of 440 X-ray images displaying the distal femur and proximal tibia regions of TKA patients, were included in this study. Among these, 206 images were derived from prosthesis loosening patients with TKA loosening. Loosening was diagnosed by intraoperative finding during

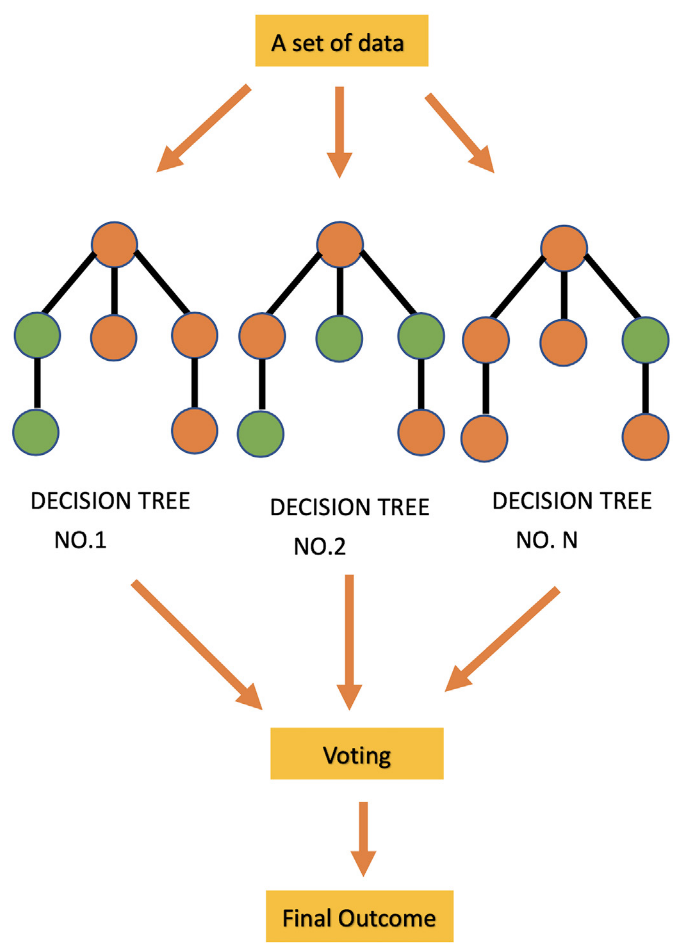

Fig. 1. The above schematic depicts how random forest is undergone. Random forest is composed of individual trees where each of them initially makes a class prediction. When generated predictions from each tree are collected, a general voting will be undertaken where class prediction with the most votes will prevail and be selected as the prediction of our model.

revision surgery of TKA in which the TKA was found loosened from the surrounding bone and with compatible X-ray finding of loosening before surgery. The remaining 234 images were derived from early images (after initial TKA surgery) of patients that have been followed up for 10 years and without TKA loosening. We included X-ray images that have complete coverage of the whole TKA implant, and derived from patients with aseptic loosening of the TKA. We excluded X-ray images that have incomplete coverage of the TKA implant, substandard resolution/saturation and/or brightness, interference by other radio-opaque objects. We also excluded those images that were derived from TKA loosening due to infection or fracture extending into the TKA prothesis. As shown in Fig. 2, convolutional Neural Network (CNN) (Xception Model) was pre-trained on the ImageNet database with python and Tensorflow deep learning library for prediction of loosening.

2.4. Optimization configuration

Stochastic gradient descent (SGD) was used as Optimizer. Momentum set at 0.9. Initial learning rate and the learning rate decay were 0.45 and 0.94 every 2 epochs, respectively. The Xception network was implemented using the TensorFlow framework and trained on Nvidia GTX 1080 Ti GPUs. Data parallelism with synchronous gradient descent was used to achieve the best classification performance. And 5000 iterations (70 h) were undergone for data training process.

2.5. Visualization classification

Class activation maps, shown in Fig. 3, were used to interpret the prediction decision made by CNN. It generated heatmaps representing class activation over input images. A class activation heatmap is a 2D grid of scores associated with a specific output class, computed for every location in any input image, considering the contribution of specific locations to the class. Verification of visualization classification was carried out retrospectively by orthopedic specialists in joint replacement surgery.

2.6. Clinical information based model

A dataset encompassing 4 major areas of clinical details was collected. They were as followed:

(1) patient background: sex, age, body weight, steroid usage, smoker, and medical comorbidities.
(2) pre-operative details of the knee: diagnosis, previous knee operation, pre-operative deformity, degree of deformity, pre-operative flexion contracture and pre-operative flexion range.
(3) operative and post-operative details: side of TKA performed, insert size, degree of distal femur cut, patellar resurfacing, augment and stem usage, operation time, drain output if any, hemoglobin drop, post-operative transfusion, duration of post-operative antibiotics, intra-operative complications, and discharge difficulties.
(4) follow-up details: total duration of follow-up, symptoms, Knee Society knee score and function score (initial and latest), flexion range, tibial, femoral, and overall lower limb alignment.

Data were exploited for training of random forest, a machine learning method.

2.7. Detection comparison benchmark

To setup comparison benchmark, two senior orthopaedic specialists with 15–20 years' experience were invited to join the study for prosthesis loosening assessment from X-ray images for 3 attempts, with each attempt performed separately with a 2-week-interval. During each attempt, 95 X-ray images with knee prosthesis (21.5% of the data in the study) was randomly selected for assessment of prosthesis loosening.

3. Results

Evaluation was run by a single model on a single crop of input X-ray images. Approximately, 75% of X-ray images (345 X-ray images) in the dataset were used as the test set and 25% of X-ray images (95 X-ray images) in the dataset were used as validation set. Only the findings on validation set were reported subsequently. Image-based machine-learning model (Xception Model with pre-trained ImageNet database) was assessed. The current model resulted in precision rate and recall rate of 0.924 and 0.961, respectively (Fig. 4). Accuracy rate of 96.3% for visualization classification was observed. The corresponding sensitivity is 96.1% and specificity is 90.9%. The positive predictive value is 92.4% and the negative predictive value is 95.2% (Table 1). The Receiver Operating Characteristic (ROC) curve for the test output and the Accuracy & Error Graph of the model are illustrated in Fig. 5 and Fig. 6

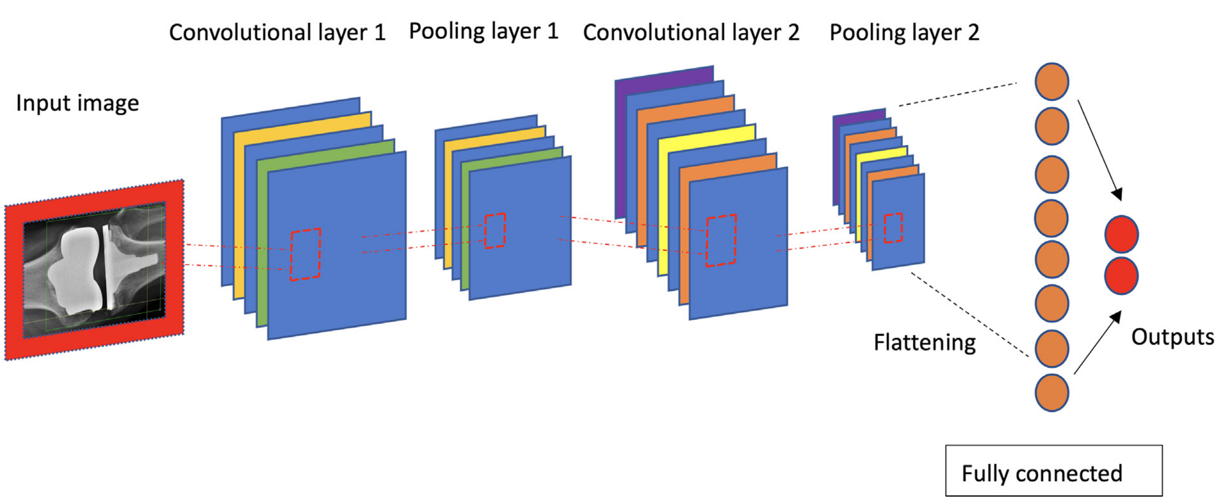

Fig. 2. The Architecture of Convolutional Neural Network (CNN) [30]. At first, the input image – radiographs with TKA will be passed to convolutional and pooling layers. Convolutional layer consists of multiple types of kernel (represented by different colored filters here), each is responsible for extraction of specific image features which allow object categorization. Next, pooling layer where max pooling is carried out. Max pooling is sub-sampling of image outputted from the convolutional layer and the return of maximum aggregate value from matrix in convolutional layer. At the end, the matrix in pooling layer will be processed by the fully connected (FC) layer where flattening is undergone. Flattening is the process where a pooled feature map (vector) is transformed into a column. FC layer also plays a role in determining the probability of the specific class the image is belonged to.

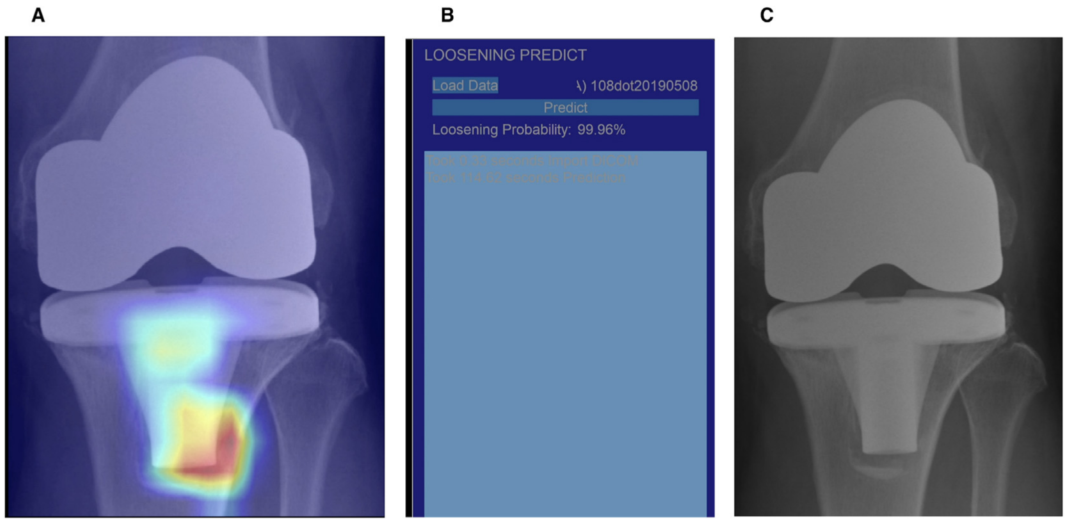

Fig. 3. Diagram of the Machine Learning Process (A) displays class activation map of the TKA X-ray, highlighting region of suspicion by machine learning model (B) Loosening prediction of the X-ray showing probability of 99.96% chance of loosening (C) Same X-ray as shown in Fig. 3A but without the class activation map.

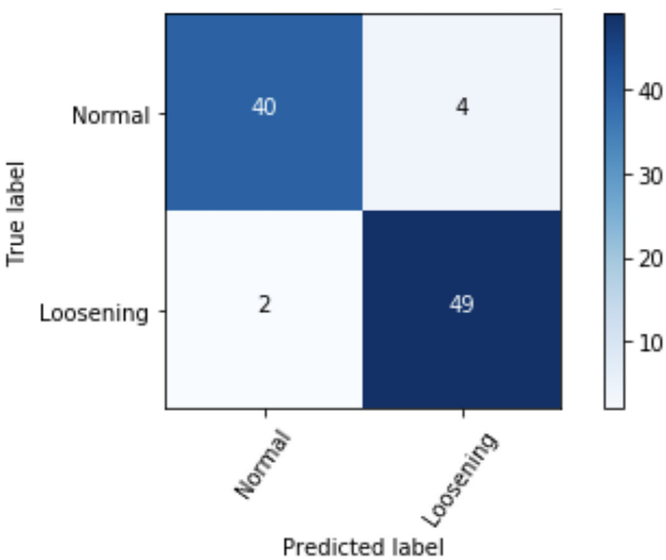

Fig. 4. Confusion Matrix for loosening. Precision rate and recall rate were 0.92 and 0.96 respectively. Accuracy rate of 96.3% for visualization classification was observed.

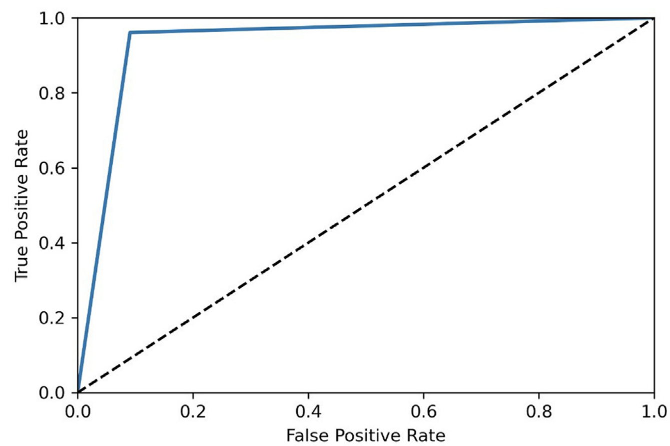

Fig. 5. The Receiver Operating Characteristic (ROC) curve of the test output. The area under the dotted line is 0.5. The Area Under Curve of ROC (blue line) is an indicator of the diagnostic capability of the deep learning model, which is 93.5%.

Table 1
Image-Based Machine Learning Model performance on test set.

Performance criteria	Overall (%)
Accuracy	96.3
Sensitivity	96.1
Specificity	90.9
Positive predictive value	92.4
Negative predictive value	95.2
AUC	93.5

respectively. According to the ROC curve (shown in Fig. 5), it was suggested that the model was with high diagnostic capability as its AUC was greater than 0.9. With respect to the model Accuracy and Error graph (shown in Fig. 6), the model demonstrated high accuracy and low error when undergone for a set amount of epoch.

Clinical-information model (Random forest classifier) was implemented for estimating the occurrence of prosthesis loosening. It resulted in precision rate of 0.71 and recall rate of 0.20. The difference between a combined model of image-based and clinical-information-based model to image-based model alone was insignificant. It was observed that using X-ray images alone as input and deep learning for estimation could achieve greater precision and recall rates, thus a better estimation for prosthesis loosening. Such examples of loosening prediction were shown in Fig. 7. As shown, both the probability of loosening predicted by the model and the class activation maps concentrate on the tibial tray bone-implant interface were found to increase with time (Fig. 7). Importantly, there was a serial increment in the probability of loosening detected by the model in the span of 14 years from initial post-operation to time prior to revision (Fig. 7).

The comparison benchmark set by two senior orthopaedic specialists on detection of prosthesis loosening assessment from X-ray images in 3 attempts are listed (Table 2). The benchmark accuracy by senior orthopaedic specialists ranged from 89.09% to 94.54% in the attempts, suggesting comparable accuracy of the Image-based machine-learning model in this study suitable for clinical use (96.3%). Class activation maps of individual X-ray images were also assessed by orthopaedic surgeons to confirm the relevant sites for clinical consideration.

As there was an increase in probability of loosening on sequential X-rays from initial post-op to time prior to revision in the image series and

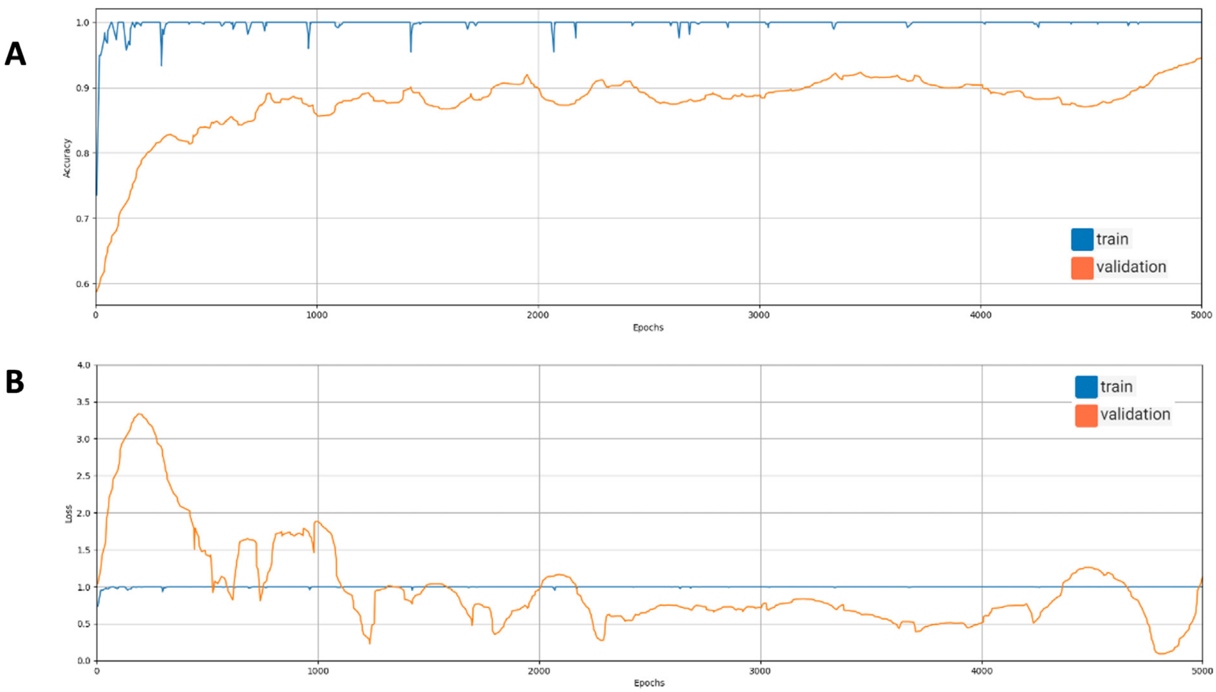

Figure 6. Training accuracy and validation accuracy with respect to epoch (A) It illustrated the training accuracy (blue) and validation accuracy (orange) with respect to epoch (B) It illustrated error during the training (blue) and validation period (orange) with respect to epoch.

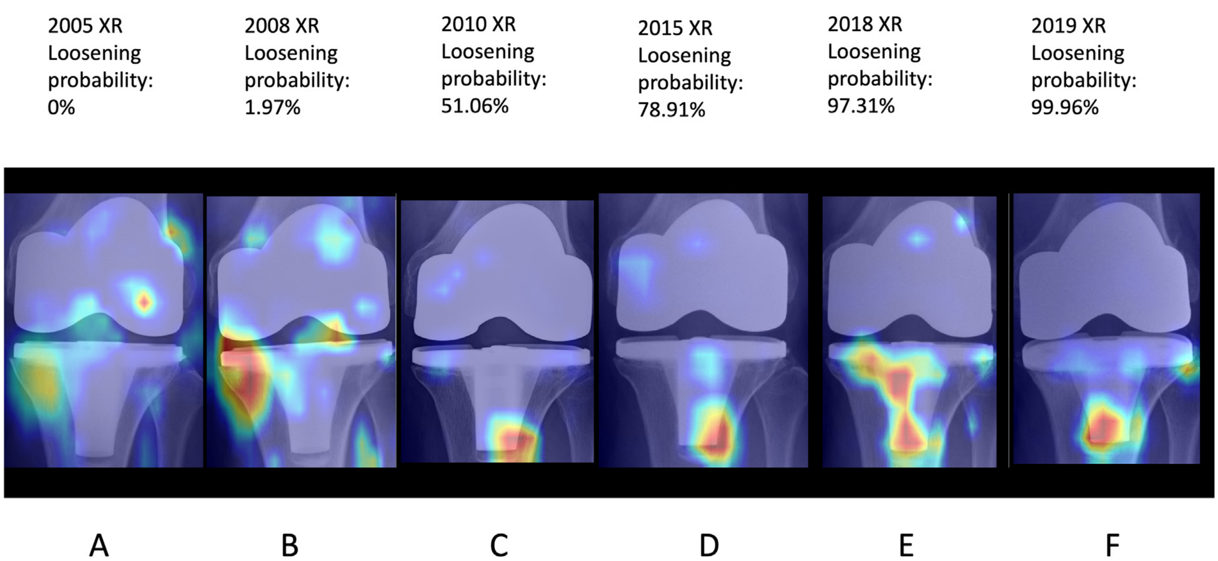

Fig. 7. Recognition of Knee Arthroplasty Loosening by the Machine Learning Model. A-F) Radiographs with superimposed class activation maps, also known as heatmaps, of a single patient taken after initial operation in 2005 to the time prior to revision due to loosening in 2019, with the corresponding time of radiographs taken and probability of loosening were shown. From left to right (i.e. from A to F), the probability of loosening predicted by the model increased with time and the class activation maps increasingly concerned on the tibial tray bone-implant interface with time.

Table 2
Comparison Benchmark of detecting loosening from X-ray by senior orthopaedic specialists.

Attempt	Surgeon 1 Accuracy	Surgeon 2 Accuracy
First	92.72%	90.9%
Second	89.09%	94.54%
Third	93.63%	91.8%

class activation maps, shown in Figs. 3 and 7, this represent the contribution of specific locations to the class which reflect potential sites of loosening under consideration. With increasing probability of loosening, there was trend that there are increasing class activation signals over bone-implant interface that is loosened radiographically. This further confirms that the model indeed utilized a similar image recognition pattern to that of manual human inspection.

4. Discussion

The novel machine learning model developed in this study demonstrated high accuracy and predictability of knee arthroplasty loosening, achieving our initial aim of loosening detection based on radiographs alone. However, additional clinical-information-based machine-learning model combining with image-based machine-learning model do not offer further improvement in detection. On the other hand, the class activation heatmap, representing the machine-learning model focus of loosening detection during radiograph analysis, matched well with the radiographic features used clinically to detect loosening, highlighting its potential role in assisting orthopedic surgeons or radiologists. As far as we know, this is the first report of pure image-based machine learning model on knee arthroplasty loosening detection that demonstrate such high accuracy and also the first report showing relevant class activation heatmap corresponding to loosening location. This is in contrary to previous report by Shah et al. on using machine learning in detection of arthroplasty loosening using radiographs [11]. It showed lower performance for TKA loosening detection and depended heavily on historical, demographic, and comorbidity information instead of isolated image analysis [11]. The improvement could be contributed by the focused training of the machine learning model using TKA X-rays and a difference in the machine learning architecture. Besides those, the quality and quantity of clinical information in both studies are likely different, which possibly generate the difference in performance of the clinical information-based model. However, this difference and difficulty in obtaining similar quality and quantity of clinical information as in Shah et al. study indeed illustrate the reality of developing machine learning model to diagnose loosening would be simpler and easier by using X-rays images alone.

This machine-learning model has huge translational potential in the current healthcare system, given the gigantic amount of TKA being performed globally. Based on a consensus, 1.2 million TKA are performed annually in US alone and is expected to rise to 3.4 million per year by 2030 [1]. With the ever-growing number of TKA being performed, this further implies a likely increase on the number of follow-up cases and patients living with TKA. Despite the advancement of surgical techniques (e.g., use of robot and navigation), some centers have begun to offer lifelong follow-ups for these patients in considering the likelihood on the occurrence of common complications, such as loosening, fracture and wearing, to appear after many years of TKA [3,13–16,31]. This post TKA follow-ups have significant burden to the healthcare systems given the late occurrence of loosening and cumulative increase on the number of patients living with TKA. Herein, the machine-learning model in this study may potentially reduce workloads of surgeons by allowing detection of early TKA loosening to enable prompt follow-up at an earlier stage with less stringent support. In fact, our study noted a phenomenon that there was an increase in probability of loosening on sequential X-rays from initial post-op film to time prior to revision and together with increasing relevant localization of class activation map signals (Fig. 7). This may allow clinicians to focus on potential film and relevant area of loosening earlier than before to facilitate prompt management. However, it currently remains difficult to truly determine whether this model can achieve a clinical benefit on providing earlier diagnosis on TKA loosening when compared to standard clinician-based radiographical diagnosis, which would require a separate cohort with a large sample size for verification.

In an attempt to further enhance the diagnostic performance, we have computed another model based on clinical information. However, this model alone (or in combination with the image-based model) did not outperform the image-based model. The lack of improvement can be attribute to multiple factors. These factors might include variation in surgical procedures, preferred use of specific implant types and loss or alteration in method of documentation. Likewise, high heterogeneities are present in subjective measurements such as the patient-reported outcome measures and knee scores. On the other hand, development of image-based model was based on objective data, which is based on pixels by pixels (with higher visual clarity than human eyes) over the X-rays. Moreover, in-depth analysis was carried out by the “past learning experience” of the model, which far exceeded the power of manual interpretation. It is also possible that the earliest sign of loosening can be detected by the AI prior to patient's report on their bodily sensations using knee scores [17]. Moreover, an image-based machine-learning model alone might actually be easier to be integrated into different clinical practice. As often, the documented clinical information is usually highly heterogenous between different assessors, hospitals, and even healthcare system. To make matter worse, those patients having their TKA to be performed by private sectors or in other part of the world, the clinical information may be lacking or not retrievable. Yet, a standalone image-based machine-learning model can work well in these settings and easily applied to various healthcare system.

Nevertheless, the Image-based machine-learning model developed in this study has a few limitations. Firstly, the TKA X-ray images employed in this study are derived from cemented TKA. Recently, there is a surge of interest in the use of cementless TKA [18]. It is currently unknown the image characteristics of these cementless TKA when they are loosened in the future, and it is unknown whether our model can detect their loosening comparable to detect loosening in cemented TKA. By the same token, if future TKA designs employ a significant different shape and fixation mechanism, the performance of the machine learning model may not be as just as shown in this study. Similarly, this limitation may be applicable on using this model for the detection of unicompartmental knee arthroplasty or TKA with additional implants like a previous high tibial osteotomy plate [19–22]. Secondly, there are upcoming therapeutic modalities to improve bone health, osteoarthritis, and integration of implants that patients with TKA may receive in the future, which includes the use of bisphosphonates and magnesium-based coating over implants [23–28]. Hence, these may lead to subtle alternation of the radiographical appearance of bone, such as increased bone density with bisphosphonates, to potentially affect the detection accuracy of the machine learning model. Although this study has already employed 440 images for the development of the model, using more images may still further enhance the performance of the model. The use on using a larger quantity of images from territory-wide data source can be used toward the verification of the model or to provide more raw images for the training of the model, which these would significantly help to improve the precision of this model [29].

5. Conclusion

The novel image-based machine learning model developed in this study demonstrated high accuracy and predictability of knee arthroplasty loosening. Addition of clinical-information-based machine-learning model did not offer further improvement in detection. Importantly, the class activation heatmap matched well with the radiographic features used clinically to detect loosening, which highlights its potential role to facilitate current clinical practice.

Funding/support statement

The work was supported by the donation of Kai Chong Tong for the project of “Augmented Reality Assisted Orthopaedic Surgical Robot and Artificial Intelligence Assisted 3D Surgical Planning System”.

Declaration of competing interest

The authors have no conflicts of interest to disclose in relation to this article.

Acknowledgements

All persons who have made substantial contributions to the work reported in the manuscript (e.g., technical help, writing and editing assistance, general support), but who do not meet the criteria for authorship, are named in the Acknowledgements and have given us their

written permission to be named. If we have not included an Acknowledgements, then that indicates that we have not received substantial contributions from non-authors.

References

[1] Kurtz S, Ong K, Lau E, Mowat F, Halpern M. Projections of primary and revision hip and knee arthroplasty in the United States from 2005 to 2030. J Bone Joint Surg Am 2007;89(4):780–5.

[2] Klug A, Gramlich Y, Rudert M, Drees P, Hoffmann R, Weissenberger M, et al. The projected volume of primary and revision total knee arthroplasty will place an immense burden on future health care systems over the next 30 years. Knee Surg Sports Traumatol Arthrosc 2021;29(10):3287–98.

[3] Sharkey PF, Lichstein PM, Shen C, Tokarski AT, Parvizi J. Why are total knee arthroplasties failing today–has anything changed after 10 years? J Arthroplasty 2014;29(9):1774–8.

[4] Barnsley L, Barnsley L. Detection of aseptic loosening in total knee replacements: a systematic review and meta-analysis. Skeletal Radiol 2019;48(10):1565–72.

[5] Gayathri S, Gopi VP, Palanisamy P. Diabetic retinopathy classification based on multipath CNN and machine learning classifiers. Phys Eng Sci Med 2021;44(3):639–53.

[6] Jeong S, Son DS, Cho M, Lee N, Song W, Shin S, et al. Evaluation of combined cancer markers with lactate dehydrogenase and application of machine learning algorithms for differentiating benign disease from malignant ovarian cancer. Cancer Control 2021;28:10732748211033401.

[7] Mainali S, Darsie ME, Smetana KS. Machine learning in action: stroke diagnosis and outcome prediction. Front Neurol 2021;12:734345.

[8] Kashi S, Polak RF, Lerner B, Rokach L, Levy-Tzedek S. A machine-learning model for automatic detection of movement compensations in stroke patients. IEEE Transact Emerging Topics Comput 2021;9(3):1234–47.

[9] Li X, Hu X, Yu L, Zhu L, Fu CW, Heng PA. CANet: cross-disease attention network for joint diabetic retinopathy and diabetic macular edema grading. IEEE Trans Med Imag 2020;39(5):1483–93.

[10] Kang YJ, Yoo JI, Cha YH, Park CH, Kim JT. Machine learning-based identification of hip arthroplasty designs. J Orthop Translat 2020;21:13–7.

[11] Shah RF, Bini SA, Martinez AM, Pedoia V, Vail TP. Incremental inputs improve the automated detection of implant loosening using machine-learning algorithms. Bone Joint Lett J 2020;102-B(6_Supple_A):101–6.

[12] Chollet F. Xception: deep learning with depthwise separable Convolutions. Paper presented at: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR); 21-26 July 2017,; 2017.

[13] Lau LCM, Lee WYW, Butler APH, Chernoglazov AI, Chung KY, Ho KKW, et al. Multi-energy spectral photon-counting computed tomography (MARS) for detection of arthroplasty implant failure. Sci Rep 2021;11(1):1554.

[14] Patrick NJ, Man LLC, Wai-Wang C, Tim-Yun OM, Wing CK, Hing CK, et al. No difference in long-term functional outcomes or survivorship after total knee arthroplasty with or without computer navigation: a 17-year survivorship analysis. Knee Surg Relat Res 2021;33(1):30.

[15] Chui EC, Lau LCM, Kwok CK, Ng JP, Hung YW, Yung PS, et al. Tibial cutting guide (resector) holding pins position and subsequent risks of periprosthetic fracture in unicompartmental knee arthroplasty: a finite element analysis study. J Orthop Surg Res 2021;16(1):205.

[16] Qin LY, Wen JZ, Chui CS, Leung KS. Housing design and testing of a surgical robot developed for orthopaedic surgery. J Orthop Translat 2016;5:72–80.

[17] Ho KK, Chau WW, Lau LCM, Ong MT. Traditional Chinese-Hong Kong version of Forgotten Joint Score-12 (FJS-12) for patients with osteoarthritis of the knee underwent joint replacement surgery: cross-cultural and sub-cultural adaptation, and validation. BMC Muscoskel Disord 2022;23(1):222.

[18] Franceschetti E, Torre G, Palumbo A, Papalia R, Karlsson J, Ayeni OR, et al. No difference between cemented and cementless total knee arthroplasty in young patients: a review of the evidence. Knee Surg Sports Traumatol Arthrosc 2017;25(6):1749–56.

[19] Chui CS, Leung KS, Qin J, Shi D, Augat P, Wong RMY, et al. Population-based and personalized design of total knee replacement prosthesis for additive manufacturing based on Chinese anthropometric data. ENGINEERING-PRC 2021;7(3):386–94.

[20] Lau LCM, Fan JCH, Chung KY, Cheung KW, Man GCW, Hung YW, et al. Satisfactory long-term survival, functional and radiological outcomes of open-wedge high tibial osteotomy for managing knee osteoarthritis: minimum 10-year follow-up study. J Orthop Translat 2021;26:60–6.

[21] Ng JP, Fan JCH, Chau WW, Lau LCM, Wan YC, Tse TTS, et al. Does component axial rotational alignment affect clinical outcomes in Oxford unicompartmental knee arthroplasty? Knee 2020;27(6):1953–62.

[22] Ng JP, Fan JCH, Lau LCM, Tse TTS, Wan SYC, Hung YW. Can accuracy of component alignment be improved with Oxford UKA Microplasty(R) instrumentation? J Orthop Surg Res 2020;15(1):354.

[23] Yao H, Xu J, Wang J, Zhang Y, Zheng N, Yue J, et al. Combination of magnesium ions and vitamin C alleviates synovitis and osteophyte formation in osteoarthritis of mice. Bioact Mater 2021;6(5):1341–52.

[24] Dai B, Li X, Xu J, Zhu Y, Huang L, Tong W, et al. Synergistic effects of magnesium ions and simvastatin on attenuation of high-fat diet-induced bone loss. Bioact Mater 2021;6(8):2511–22.

[25] Zhu Y, Huang Z, Wang Y, Xu W, Chen H, Xu J, et al. The efficacy and safety of denosumab in postmenopausal women with osteoporosis previously treated with bisphosphonates: a review. J Orthop Translat 2020;22:7–13.

[26] Li Y, Zhao S, Li S, Ge Y, Wang R, Zheng L, et al. Surface engineering of biodegradable magnesium alloys for enhanced orthopedic implants. Small 2019;15(51):e1904486.

[27] Dreyer CH, Kjaergaard K, Ding M, Qin L. Vascular endothelial growth factor for in vivo bone formation: a systematic review. J Orthop Translat 2020;24:46–57.

[28] Zheng N, Tang N, Qin L. Atypical femoral fractures and current management. J Orthop Translat 2016;7:7–22.

[29] Wong GL, Hui VW, Tan Q, Xu J, Lee HW, Yip TC, et al. Novel machine learning models outperform risk scores in predicting hepatocellular carcinoma in patients with chronic viral hepatitis. JHEP Rep 2022;4(3):100441.

[30] Albawi S, Mohammed TA, Al-Zawi S. Understanding of a convolutional neural network. Paper presented at: 2017. Int Conf Eng Technol(ICET) 2017:21–3. Aug. 2017.

[31] Lau LCM, Ong MTY, Chau WW, Ng JP, Griffith JF, Ho KWK. Avulsion Fracture of Bicruciate Ligament and Patellar Tendon in Bicruciate-Retaining Total Knee Arthroplasty. Arthroplasty Today 2022. In press.