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RESEARCH

AI classification of knee prostheses from plain radiographs and real-world applications

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Abstract

Purpose Total knee arthroplasty (TKA) is considered the gold standard treatment for end-stage knee osteoarthritis. Common complications associated with TKA include implant loosening and periprosthetic fractures, which often require revision surgery or fixation. Challenges arise when medical records related to the knee prosthesis are lost, making it difficult to plan for revision surgery effectively. This study aims to develop an artificial intelligence (AI) system to classify the types of knee prosthetic implants using plain radiographs.

Methods This retrospective experimental study includes seven types of knee prostheses commonly used in our hospital. The artificial intelligence (AI) system was trained using YOLO (You Only Look Once) version 9, utilizing a dataset of 3228 post-operative and follow-up knee arthroplasty X-ray images. The plain radiographic images were augmented, resulting in a dataset of 25,800 images. Model parameters were fine-tuned to optimize performance for implant classification.

Results The mean age of the patients was 62.8 years. Right knee arthroplasty was performed in 48.3% of cases, while left knee arthroplasty was performed in 51.7%. The images of knee prostheses comprised 50.9% of the dataset from the anteroposterior (AP) view and 49.1% from the lateral view. The AI model demonstrated exceptional performance metrics, achieving precision, recall, and accuracy rates of 100%, with an F1 score of 1. Additionally, the area under the curve (AUC) of the receiver operating characteristic (ROC) curve was calculated to be 100%.

Conclusion This AI model successfully classifies knee prosthetic implants from plain radiographs. This capability serves as a valuable tool for surgeons, enabling precise planning for revision surgeries and periprosthetic fracture fixation surgery, ultimately contributing to improved patient outcomes. The high accuracy achieved by the AI underscores its potential to enhance surgical efficiency and effectiveness in managing knee arthroplasty complications.

Keywords Knee arthroplasty · Knee prosthesis · Revision knee surgery · AI classification model · YOLO · Medical AI

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Introduction

Total knee arthroplasty (TKA), or total knee replacement (TKR), stands as the standard treatment for end-stage knee osteoarthritis [1, 2]. However, patients often surpass the lifespan of the prosthesis, necessitating revision surgery. Common reasons for revision include implant loosening due to aseptic loosening from prolonged use and septic loosening from periprosthetic joint infection (PJI) [3–6]. Additionally, periprosthetic fractures, particularly around the femoral side, can also require revision surgery [7, 8].

A knee prosthesis typically consists of four main components: the femoral component, tibial component, patellar component, and polyethylene liner. Ensuring compatibility among these components from the same manufacturer and product line is essential for achieving optimal outcomes. Addressing implant loosening generally involves replacing the affected component. Knowledge of the specific implant brand and series prior to revision surgery facilitates a more straightforward procedure by allowing for the targeted replacement of the affected part. Conversely, the lack of such information complicates the surgery, often necessitating the replacement of all components, even if they remain stable [9, 10]. In cases of periprosthetic fracture, familiarity with the femoral prosthesis design enables surgeons to choose for less invasive and more stable fixation methods such as intramedullary nails over plates. For example, the cruciate-retaining (CR) design of the femoral component allows using a retrograde intramedullary nail, but the posterior stabilized (PS) design may not, depending on the manufacturer [11–13].

Typically, the type of implant can be identified by reviewing medical records. However, challenges exist in retrieving this information. First, the transition from paper-based to electronic records can lead to missing data during the transfer process. Second, some hospitals may have policies that limit record retention to 5 or 10 years, potentially resulting in lost data for older procedures [14–16]. Finally, patient transfers between hospitals without accompanying medical records further complicate the process. Failure to obtain this information may necessitate referring patients back to their previous hospital or a tertiary care center for total revision surgery [17]. This can result in increased costs, prolonged treatment duration, and potentially adverse outcomes [18].

The advent of artificial intelligence (AI) has revolutionized various medical disciplines, including orthopedics and radiology. Machine learning (ML) and convolutional neural networks (CNNs) have emerged as invaluable tools, assisting clinicians in achieving superior patient outcomes. Recent advancements in AI have demonstrated significant potential in orthopedic research, particularly in the areas of object detection and classification. Various studies have successfully applied deep learning algorithms to identify and categorize orthopedic conditions, such as fractures and joint abnormalities, with remarkable accuracy. For instance, algorithms have been developed that can analyze radiographic images to detect specific types of fractures, achieving sensitivity and specificity rates that surpass traditional diagnostic methods [19–22].

Additionally, these AI-driven approaches facilitate real-time analysis, enabling clinicians to make timely decisions during patient evaluations. Such innovations not only enhance diagnostic precision but also support surgical planning by providing detailed insights into the conditions being treated. The final aim of these AI innovations is to help improve patient outcomes [23–26].

This study aims to harness AI technologies to accurately identify and classify types of knee prostheses, thereby enhancing treatment efficacy and improving patient outcomes. The final goal is to develop a web-based application that can be freely used by clinicians. Unlike previous studies, this research utilizes YOLO (You Only Look Once) for convolutional neural networks (CNNs), which may offer improved speed and accuracy in real-time implant identification.

Methods

Data set preparation

This retrospective study was approved by the Khon Kaen University Ethics Committee for Human Research (approval No. HE674020). Unilateral and bilateral anteroposterior (AP) and lateral radiographs of patients aged at least 18 years old who underwent total knee arthroplasty operations between January 2016 and June 2024 were collected from the Picture Archiving and Communication System (PACS) of Srinagarind Hospital. Srinagarind Hospital is a university teaching hospital and Level 1 trauma center, capable of providing tertiary care, performing numerous primary knee arthroplasties, and conducting revision knee surgeries, including those referred from nearby rural hospitals due to the complexity of the procedures. This hospital is affiliated with the Faculty of Medicine, Khon Kaen University, Thailand.

Radiographs with previous surgical fixation, unicondylar knee replacements, revision knee replacements, and very poor image quality were removed by consensus of the P.T. (Radiologist) and N.T. (Orthopedist). Subsequently, using the tools in the PACS system, each radiograph was carefully de-identified to remove patient name, age, sex, and radiograph date. Next, we converted each radiograph to JPEG format with an image size of 1024×1024 pixels and a file size of around 90 KB, ensuring adequate windowing, contrast, and exposure. Verification of implant manufacturers and implant design was cross-checked and confirmed using paper medical records, uploaded documentation in the hospital's database system, and electronic medical records.

To prevent underfitting and overfitting during model training, a total of seven different types of knee prostheses were used, for which the raw data images exceeded 300 in each group. From all corrected medical records, a total of 3,228 radiographic images were collected, including 1,642 anteroposterior (AP) views and 1,586 lateral views. Each AP or lateral radiograph was counted as a single image. Additionally, in follow-up cases, only one view (typically AP) was sometimes requested based on the clinical need. Hence, the ap and lateral radiograph numbers are not the same.

The knee radiograph images were randomly divided into three different datasets: 80% for the training set, 10% for the validation set, and 10% for the test set. All images from the same patient were placed within a single set to prevent data leakage from the training set to the test set. The seven types of knee prostheses are sourced from four industry-leading manufacturers: NexGen (Zimmer Biomet), Persona (Zimmer Biomet), Vanguard (Zimmer Biomet), Legion (Smith & Nephew), Gemini CR (Link), Gemini PS (Link), and Sigma PFC (Johnson & Johnson).

Data annotation and augmentation

Bounding boxes covering all areas of the knee prostheses were created by N.T. (Orthopedist) using annotation tool program Roboflow in a private workspace, available from https://roboflow.com.

The images in the training set (2580 radiographs) were augmented by rotation, horizontal flipping, and contrast adjustment, resulting in 25,800 images. This augmentation was done to ensure that the training data set is sufficiently large and representative of real-world x-ray images, thereby maximizing the learning capabilities of the AI model. No augmentations were performed in the validation set and test set to ensure the correctness of the AI performance.

Training AI model

This study employed the YOLOv9 model M (medium), an advanced AI architecture renowned for its precision in detecting and classifying objects. We selected this framework due to its high accuracy. The training platform was based on Visual Studio Code software, which supports Python. All training processes were conducted on our private computer to ensure the security of the dataset and patient information.

By utilizing version 9, we were able to adjust parameters such as batch sizes and epochs and conduct hyperparameter tuning to optimize the model's performance. We used a batch size of 16 and trained for 80 epochs, employing the stochastic gradient descent (SGD) optimizer with a patience parameter set to 0 for hyperparameter tuning with a momentum value of 0.937 and a learning rate of 0.01.

The training process was conducted on a system running Microsoft Windows 10, equipped with a 16-core Intel i7-13,700 processor operating at a maximum frequency of 5.2 GHz, along with two NVIDIA RTX 3060 GPUs, each with 24 GB of memory. Python-3.10.12 torch-2.0.1 + cu118 Visual Studio Code – Oct 2024 (version 1.95.3) was used.

The workflow process is illustrated in Fig. 1.

Model testing and statistical analysis

The test set comprised 320 images of knee prosthesis radiographs, including 160 anteroposterior (AP) views and 160 lateral views, with a balanced distribution across seven types of prostheses. The model detected and classified each image, identifying the regions of the knee prostheses using bounding boxes and specifying the seven classifications of prosthesis types.

The statistical analysis involved measures of precision, recall (sensitivity), accuracy, F1 score, and the receiver operating characteristic (ROC) curve. These metrics provided a comprehensive evaluation of the model's performance in accurately identifying and classifying knee prostheses in the test set.

External validation

To ensure the generalizability and applicability of the AI model in real-world scenarios and to prevent overfitting, external validation was performed using independent data from Phramongkutklao Hospital and Provincial Hospital. Due to the institution's data-sharing policy with hospitals, we were unable to receive the external validation test set at our premises. Instead, we sent the trained model to Phramongkutklao Hospital and Provincial Hospital for testing.

The model was evaluated using three types of knee prostheses from Phramongkutklao Hospital, specifically: 24 radiographs of the NexGen prosthesis (Zimmer Biomet), 126 radiographs of the Legion prosthesis (Smith & Nephew), and 44 radiographs of the Sigma PFC prosthesis (Johnson & Johnson). Four additional types from Provincial Hospital were included: 25 radiographs of the Persona prosthesis (Zimmer Biomet), 24 radiographs of the Vanguard (Zimmer Biomet), 16 radiographs of the Gemini CR (Link), and 22 radiographs of the Gemini PS (Link).

The unbalanced nature of the external test set is not a concern, as it is not used for training and thus will not cause overfitting or underfitting of the model. The model was tested on the dataset as received, simulating real-world

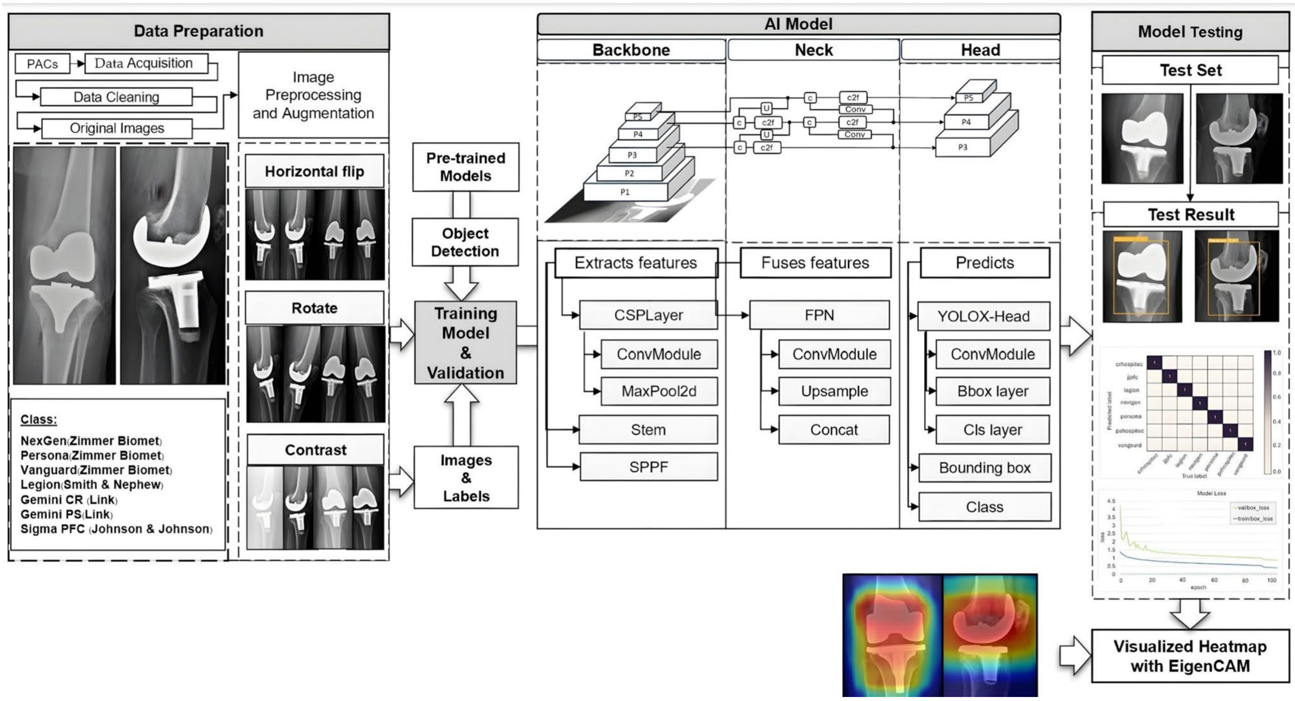

Fig. 1 Flowchart of the Workflow from Data Preparation to AI Model Building, Training, and Testing, Including a Visualized Heatmap

conditions and providing a more authentic evaluation of the model's performance.

Result

The study included a total of seven types of knee prostheses: NexGen (Zimmer Biomet), Persona (Zimmer Biomet), Vanguard (Zimmer Biomet), Legion (Smith & Nephew), Gemini CR (Link), Gemini PS (Link), and Sigma PFC (Johnson & Johnson). The dataset comprised 3,228 radiographs, with 870 radiographs (26.9%) obtained from male patients and 2,358 radiographs (73.1%) from female patients. The mean age of the patients was 62.8 years. Right knee arthroplasty was performed in 48.3% of cases, while left knee arthroplasty was performed in 51.7%. The knee prosthesis images were composed of 50.9% from the anteroposterior (AP) view and 49.1% from the lateral view. Demographic data of the patients and implants are presented in Table 1.

The model detected prostheses using bounding boxes that encompassed the entire implant area and classified the implant type in both anteroposterior (AP) and lateral radiograph views. A confidence threshold of 0.25 was used, and when multiple objects were detected, the single highest confidence value was taken as the output. The percentage value accompanying each classification indicates the model's confidence, with higher values reflecting greater certainty that the bounding box contains an object, as illustrated in Fig. 2.

The AI model achieved a precision of 100%, recall of 100%, accuracy of 100%, and an F1 score of 1, as shown in Table 2. Additionally, for the ROC analysis, we utilized the area under the curve (AUC), which was calculated to be 100% for the

Table 1 Demographic Data Including Sex, Age, Side, and Type of Knee Prosthesis

	Sex			Age	Side		X-ray	
	Male	Female	Total		Right	Left	AP	LAT
NexGen (Zimmer Biomet)	137	366	503	52–82(64)	236	267	272	231
Persona (Zimmer Biomet)	102	296	398	50–84(65)	223	175	203	195
Vanguard (Zimmer Biomet)	145	383	528	52–78(61)	238	290	275	253
Legion (Smith & Nephew)	114	307	421	49–81(62)	198	223	211	210
Gemini CR (Link)	106	351	457	49–77(61)	265	192	229	228
Gemini PS (Link)	128	334	462	47–81(63)	180	282	222	240
Sigma PFC (Johnson & Johnson)	138	321	459	54–78(64)	220	239	230	229

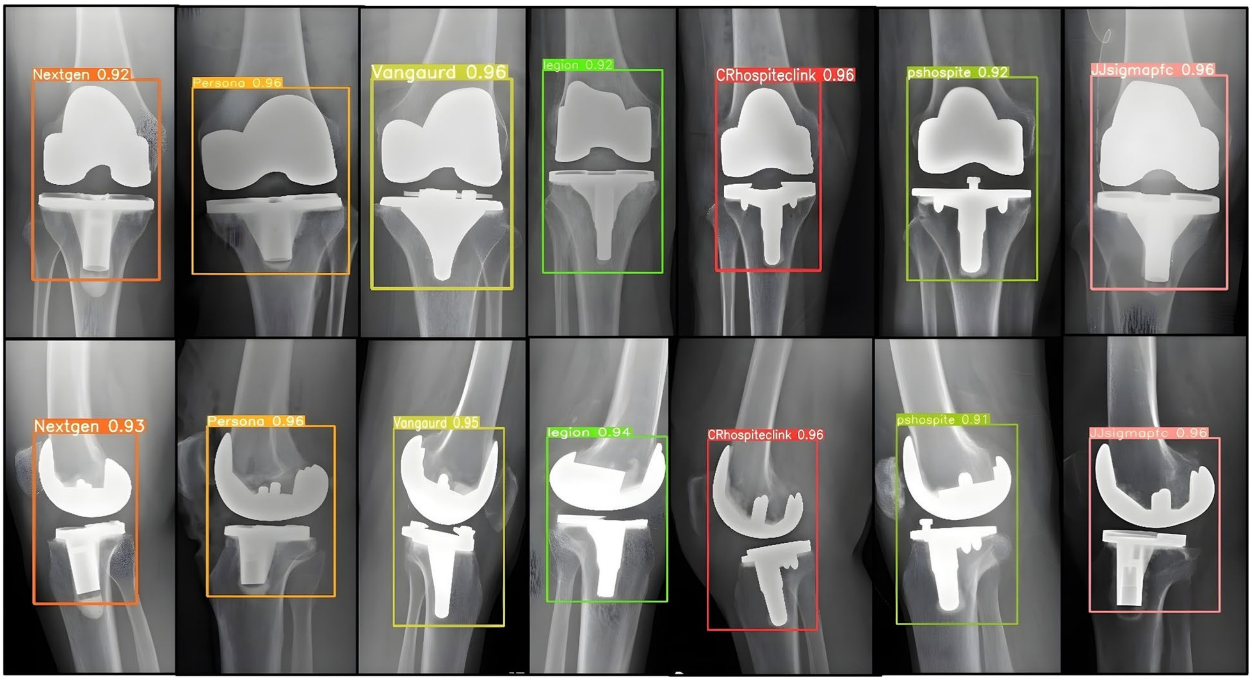

Fig. 2 Example Radiographs with Bounding Boxes Indicating Correct Predictions for Each Type of Knee Prosthesis

Table 2 AI Model Performance for the Classification of Each Type of Knee Prosthesis

Knee prosthesis	Testing X-ray (n)	Sensitivity (%)	Specificity (%)	Accuracy (%)
NexGen (Zimmer Biomet)	AP 25	100	100	100
	LAT 25			
Persona (Zimmer Biomet)	AP 20	100	100	100
	LAT 20			
Vanguard (Zimmer Biomet)	AP 26	100	100	100
	LAT 26			
Legion (Smith & Nephew)	AP 21	100	100	100
	LAT 21			
Gemini CR (Link)	AP 23	100	100	100
	LAT 23			
Gemini PS (Link)	AP 23	100	100	100
	LAT 23			
Sigma PFC (Johnson & Johnson)	AP 23	100	100	100
	LAT 23			

test set. Please refer to Fig. 3 for a graphical representation. In the external validation, our AI model accurately identified all types of knee prostheses with 99.84% accuracy.

The identified images are displayed in Fig. 4, and the results are summarized in Table 3.

Discussion

The AI knee prosthetic classification model developed in this study demonstrates exceptionally high performance,

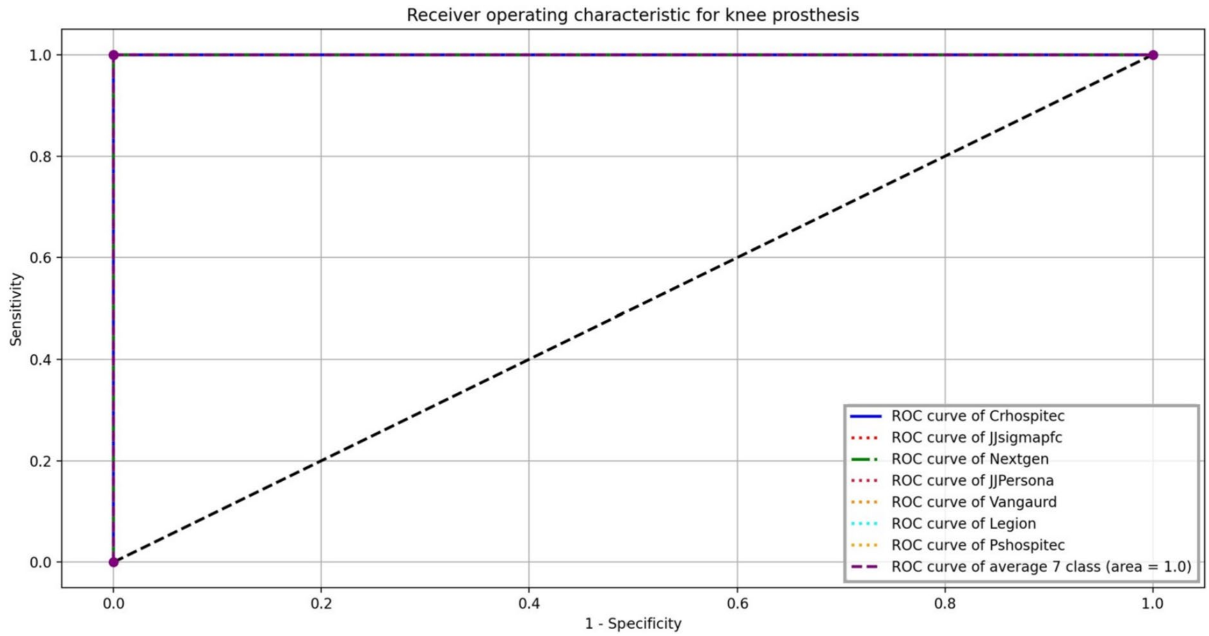

Fig. 3 ROC Curves for AI Model Performance in Classifying Total and Each Type of Knee Prosthesis

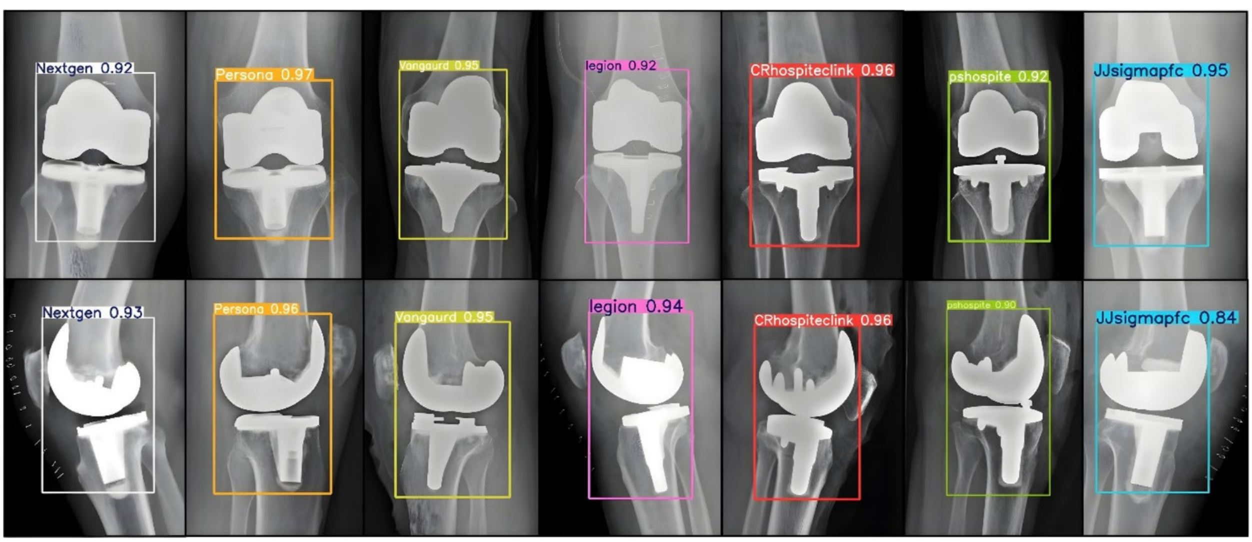

Fig. 4 Externally Validated Radiographs with Bounding Boxes Indicating Correct Predictions of Knee Prosthesis Types

achieving an accuracy of 100% in detecting and classifying types of knee prostheses. This performance is consistent across both the test set and the external test set from another institute. The data are well-subgrouped, ensuring that there is no leakage of training set data into the validation and test sets. The use of an external test set confirms that the model is not overfitted.

Previous work has shown that human doctors could not identify the type of knee prosthesis in 10% of pre-operative cases and 2% of intra-operative cases, leading to prolonged surgical time and increased healthcare costs [17, 18]. This model effectively identifies the type of knee prosthesis solely through the evaluation of X-ray images. This supports the hypothesis that computer vision may help improve the accuracy and efficiency of knee prosthesis identification [27–29].

Previous studies on using AI for knee prosthesis detection have reported varying levels of accuracy with different models. The VGG19 model achieved an accuracy of 83.95%, while the ResNet152 model achieved 91.98%. The most recent model, which combines ResNet50, VGG16,

Table 3 External Validation Results of AI Performance for Classifying Each Type of Knee Prosthesis

Knee prosthesis	Testing X-ray (n)	Sensitivity (%)	Specificity (%)	Accuracy (%)
NexGen (Zimmer Biomet)	AP 12 LAT 12	100	100	100
Persona (Zimmer Biomet)	AP 13 LAT 12	100	100	100
Vanguard (Zimmer Biomet)	AP 12 LAT 12	100	100	100
Legion (Smith & Nephew)	AP 63 LAT 63	100	100	100
Gemini CR (Link)	AP 8 LAT 8	100	100	100
Gemini PS (Link)	AP 11 LAT 11	90.91	100	99.28
Sigma PFC (Johnson & Johnson)	AP 22 LAT 22	97.73	100	99.64
All	281	98.37	100	99.84

and Inception V3, achieved an accuracy of 97.4% [30, 31]. These models have established a strong foundation for knee prosthesis classification by AI. Building upon this progress, our model achieves a new state-of-the-art performance with 100% accuracy.

It is not unexpected that our model achieves 100% accuracy, given the rapid advancements in technology and artificial intelligence models. We employ the latest version of the YOLO (You Only Look Once) algorithm available at the time. YOLO has been effectively utilized for tasks such as

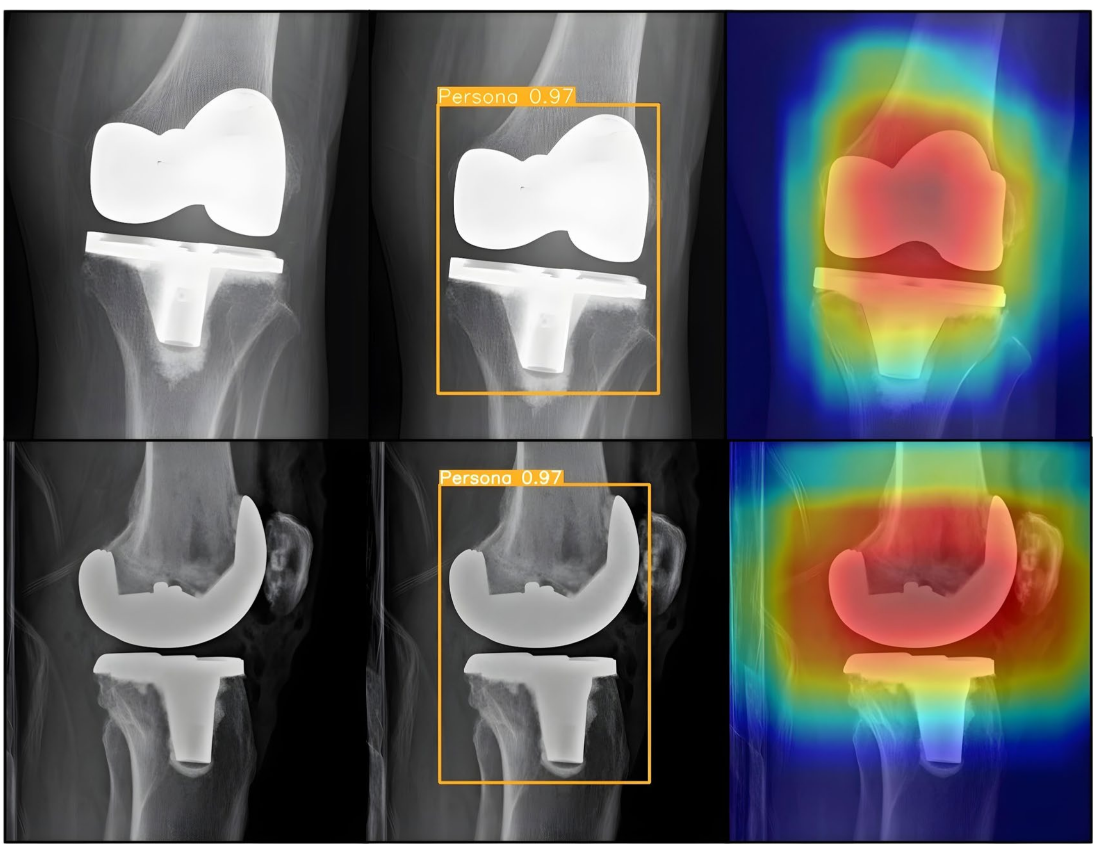

Fig. 5 Heatmap Generated by EIGEN-CAM Showing Areas of Significant Model Consideration Alongside Radiographs of Knee Prostheses and AI Results with Bounding Boxes

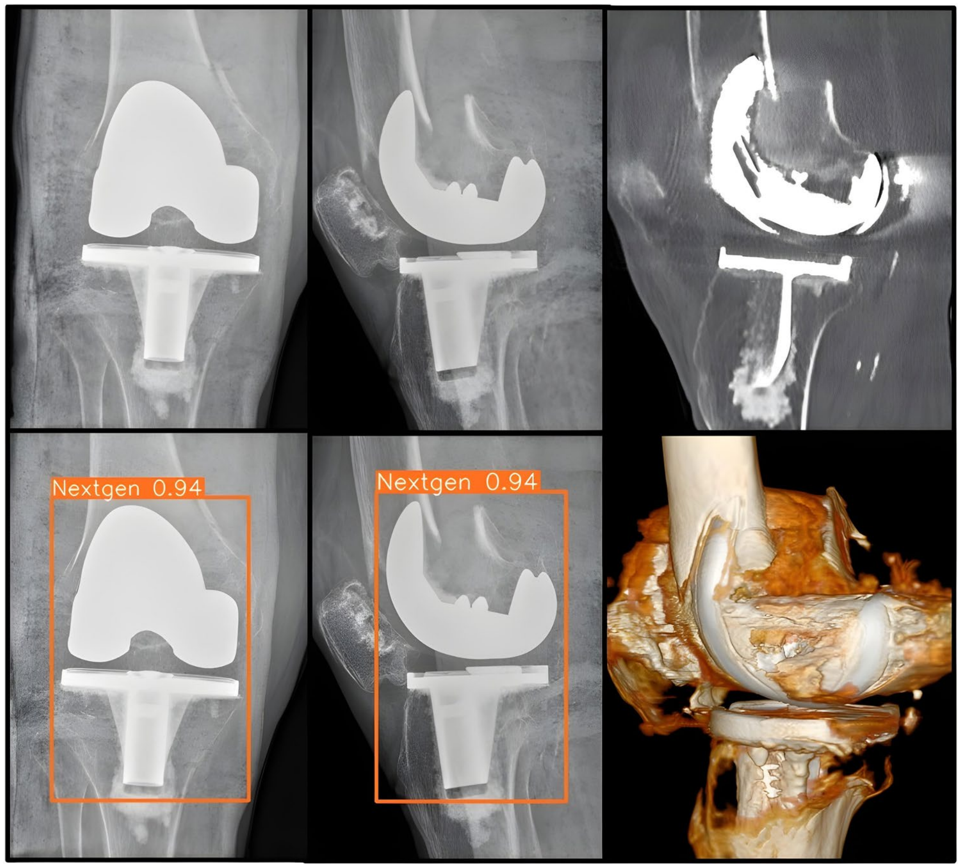

Fig. 6 Radiograph and CT Images of the Case, Along with AI Results Displayed in Bounding Boxes Identifying the Type of Knee Prosthesis As NextGen

detecting and classifying various medical conditions, including fracture detection, cancer detection, and other diseases, demonstrating its robustness and efficiency in clinical settings [32–34].

While some may argue that we have overfitted due to achieving 100% accuracy, overfitting occurs when a model learns the training data too well, capturing noise and outliers rather than general patterns, which can lead to poor performance on unseen data [35]. However, external validation test sets from other institutions consistently demonstrate our model's ability to maintain 99.84% accuracy, indicating that it generalizes effectively and is not merely memorizing the training data. Another explanation could stem from this theory: the prosthesis, characterized by its high metallic density on radiographs, exhibits exceptional radiopacity, making it a highly distinguishable object in computer vision tasks [36]. This distinctiveness contributes to the model's accuracy.

Further reasons for the success of the model may arise from the meticulous data preparation and annotation performed on a case-by-case basis. Without the assistance of AI for annotation, all bounding boxes in every image were carefully created by human doctors. These tasks consumed a significant amount of time—approximately two years—underscoring the critical importance of data quality in our research. As the common saying in the research world goes, "garbage in, garbage out."

Not only is the model successful, but we have also implemented it for real-world use by developing an easy-to-use, free web-based application available at https://indie-ct.enit.kku.ac.th/ai/kneeprosthesisV9. The application provides both visual and textual outputs, displaying an annotated image of the predicted prosthesis type along with a text summary of the top predictions.

One of the primary challenges affecting human doctors' trust in artificial intelligence (AI) is the "black box" nature of AI models. Understanding how convolutional neural networks (CNNs) interpret images and the features they learn from visual data is crucial for comprehending their predictions. In this context, explainability tools are crucial for helping users understand how these models process data and make decisions.

Class activation mapping (CAM) is a technique used to visualize which regions of an image contribute most to a deep learning model's predictions, helping to "open up" the AI black box. In our study, we employed EIGEN-CAM, an

Fig. 7 Postoperative Radiograph After Fixation of the Periprosthetic Fracture with Plates and Screws Showing Evidence of Bone Union and Intact Prosthesis

extension of CAM that uses principal component analysis to generate more precise activation maps.

EIGEN-CAM serves as a significant explainability tool by visualizing the regions of an image that contribute most to a model's decision-making process. By generating heatmaps that highlight areas of high activation, EIGEN-CAM aligns with human visual comprehension, allowing practitioners to see which features the model considers important [30, 37]. This capability enhances transparency and fosters trust in AI systems by providing insights into their decision-making processes, as shown in Fig. 5.

Example of successful cases using our AI model implemented in clinical practice:

First Case: An elderly woman who underwent total knee arthroplasty (TKA) 10 years prior presented with a periprosthetic fracture. Unfortunately, her medical records had been destroyed, preventing us from determining the type of implant. However, our web-based AI model successfully identified the implant as the NexGen from Zimmer Biomet. CT images of this case showed that the implant remained stable with the distal femur, but there was minimal area for fixation, as shown in Fig. 6.

Therefore, we aimed for fixation and prepared for a revision if necessary. Our hospital exclusively uses the posterior stabilized (PS) design of NexGen, so this information from the AI model guided us to utilize a plating system instead of a nail. For the backup system, we prepared the NexGen revision system; in case the fixation plan failed, we could replace only the femoral prosthesis. Fortunately, we were able to treat the patient with open reduction and internal fixation (ORIF) using plates and screws. Six months postoperatively, the fracture had healed, and the patient regained her pre-accident mobility, as shown in Fig. 7.

Second Case: An 80-year-old woman, who underwent bilateral knee replacements three years ago, presented with a periprosthetic fracture of the right knee. During the preoperative conference, even the senior orthopedic arthroplasty staff were unable to definitively identify the implant. To assist in this identification, we utilized our web-based AI knee prosthesis classification system, which predicted that the implant was a Sigma PFC (Johnson & Johnson). Upon reviewing her medical records, we confirmed that the knee prosthesis matched the AI's prediction. Notably, our institution exclusively uses the cruciate-retaining (CR) design of the PFC. A CT scan revealed that the implant remained stable with respect to the distal femur, as shown in Fig. 8. Given the CR design of the prosthesis, we opted for a retrograde nail due to its minimally invasive nature and superior strength compared to a plating system. The surgery proceeded successfully. Following the operation, the patient engaged in a rehabilitation program and was able to perform partial weight-bearing ambulation with a walker prior to discharge, as shown in Fig. 9.

In our example cases, we demonstrate that even in instances of periprosthetic fractures, knee rotation, angulation from fractures, and artifacts from casting, the model can accurately classify the type of implant. It is important to note that the training set consisted of images without fractures, exhibiting good alignment, no rotation, and no artifacts that could interfere with implant identification. However, in real-world applications, periprosthetic fracture cases can also be utilized, highlighting the robustness of the AI model. This showcases the model's impressive capability to perform accurately even under challenging conditions.

A key limitation of our study is that our model can only recognize the types of implants it has been trained on. It will predict one of the predefined classes based on the training data received. Other types beyond these seven, such as those produced by Exactech, MicroPort, Medacta, and Arthrex, will not be predicted correctly due to the absence of corresponding training data. Consequently, it may misclassify implants outside its training set as one of the nearest similar types. This limitation is common in classification models and can lead to inaccurate information for clinicians.

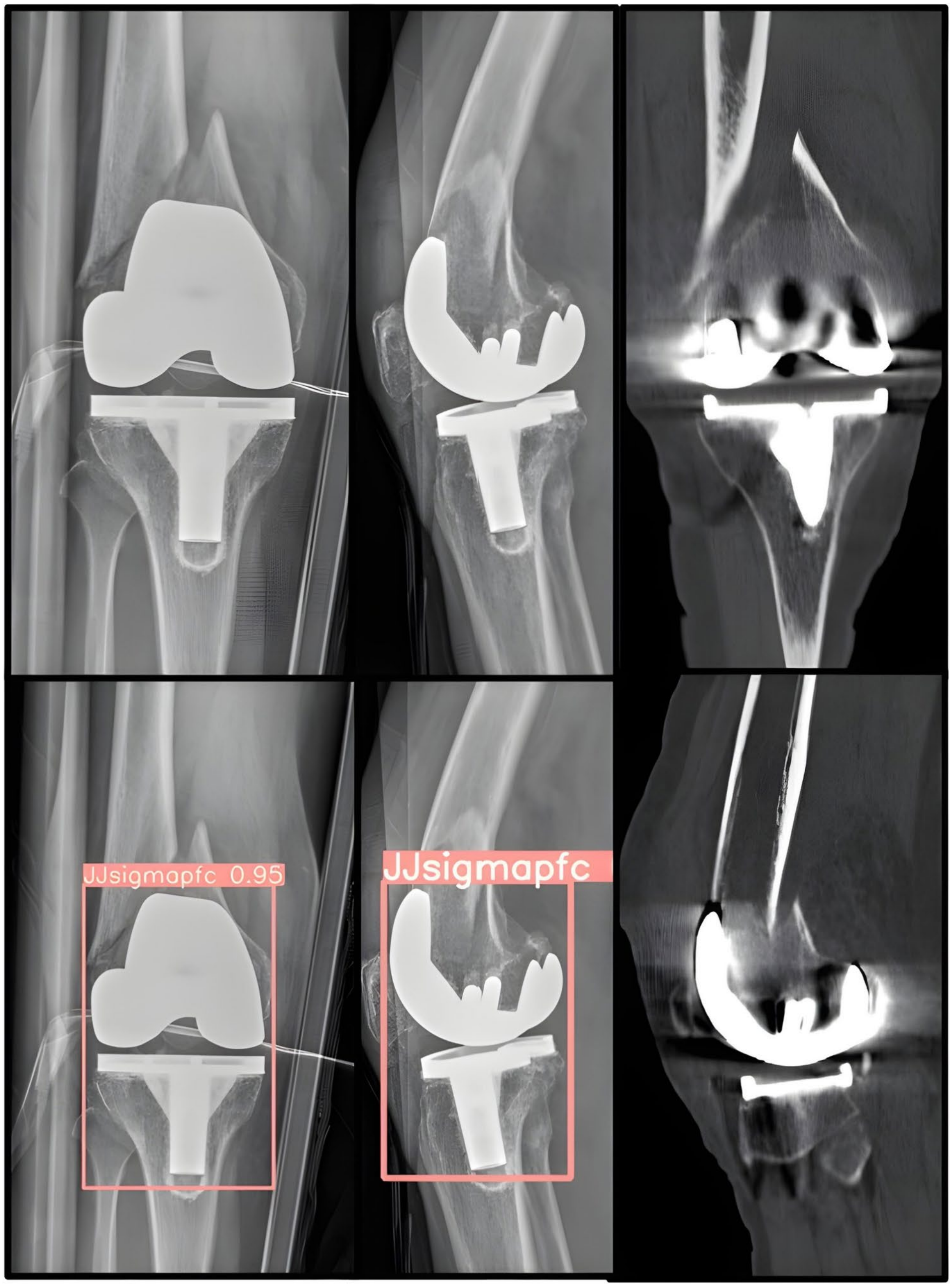

Fig. 8 Radiograph and CT Images of the Case, Along with AI Results Displayed in Bounding Boxes Identifying the Type of Knee Prosthesis As JJ Sigma PFC

Therefore, physicians using this model need to be aware of this constraint.

Future efforts to enhance the AI model will involve comprehensive training on all available knee prosthesis models worldwide. This can be achieved through data exchange facilitated by multi-center collaboration, involving partnerships with prosthetic companies globally. Successful completion of this initiative would enable the development of a globally applicable AI knee prosthesis classification model, which could then be integrated into user-friendly platforms such as web applications or smartphone apps, ensuring widespread accessibility and high-performance effectiveness. If successful, the benefits will be realized for patients, including enhanced safety and cost-effectiveness.

Conclusion

The AI model we developed achieves 100% accuracy in classifying types of knee prostheses. Its successful real-world clinical implementation aids surgeons in planning surgeries effectively. Future research should expand to include all types of knee implants worldwide, with the aim of creating

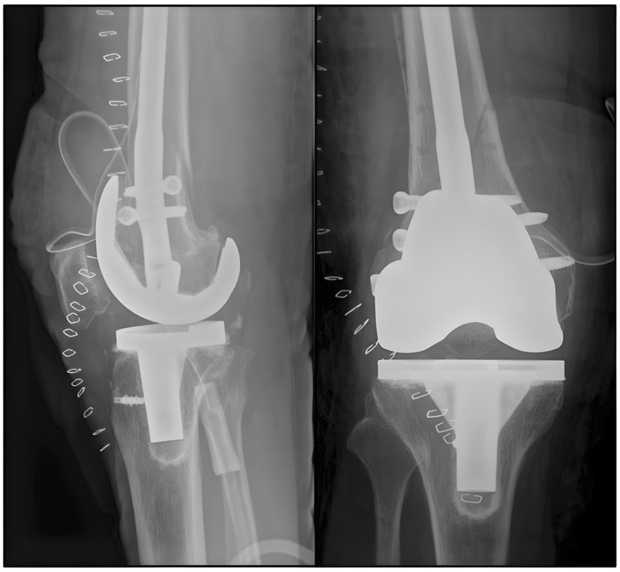

Fig. 9 Postoperative Radiograph After Fixation of the Periprosthetic Fracture with Retrograde Nail and Intact Prosthesis

a user-friendly application that is accessible globally to improve patient outcomes.

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Author contribution All authors designed the protocol, read, and approved the final P.T.: Conceptualization, research design, data collection, data analysis, performed experiments, and manuscript writing. O.P.: Data collection and interpretation of the data. K.W.: Data collection and interpretation of the data. R.A.: Research design, data analysis, summarization of results, and feedback. P.S.: Analyzed the data, and performed experiments W.L.: Reviewed, provided feedback, and assisted with the discussion part. N.T.: Research design, performed experiments, statistical analyses, incorporated feedback from all authors, and wrote the abstract and manuscript with final approval.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interests The authors declare no competing interests.

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