



Artificial Intelligence in Automated Identification of Prosthesis with Focus on Total Shoulder Arthroplasty Implants: A Survey

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ABSTRACT

Arthroplasty is a surgical technique that involves modifying, realigning, and replacing a bone's broken surface with a human-made, durable substance to alleviate discomfort and reestablish joint functionality. Knee, hip, and shoulder replacement are all examples of Arthroplasty surgery. Total Shoulder Arthroplasty is a procedure that is commonly performed to treat injured shoulder joints. Injuries, calcification, deterioration in the shoulder cartilage tissue, injury to surrounding bones, and severe arthritis are all common causes of shoulder damage and malfunction. There are currently several manufacturers of shoulder prostheses who create various types of this prosthesis to match varied conditions and patients. When the quality of the prosthesis deteriorates years after replacement, reoperation and revision may be required. Finding the model, structure, and prosthesis manufacturer to position them correctly is the main surgical stage to reduce the usual issues. The patient and the primary doctor at the other location or country may not be aware of the prosthesis model and manufacturer in cases where a patient migrates from the place or country where surgery was performed. As a result, determining the model of the prosthesis and the manufacturer requires a thorough inspection and visual comparison of radiological pictures. This method delays reoperation and correction, is time-consuming, and is error-prone. Numerous studies have shown how to use different deep learning approaches to categorize implants based on their manufacturer and identify the type and structure of the implants. Researchers have offered a number of detection models for the duration of stay in the hospital, payment schemes, practical results, and patient expectations, and so on, with the need for more optimal solutions. However, no complete evaluation of the automatic prediction, identification, and classification of prosthesis based on manufacturer exists. As a result, this study discusses the various detection models utilized in arthroplasty. The review also provides an overview and taxonomy of arthroplasty, as well as research gaps and prospects.

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INTRODUCTION

Arthroplasty is a surgical technique that involves the modification, realignment, and

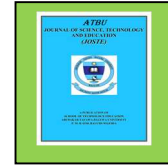
replacement of a bone's broken surface with a human-made, durable substance to alleviate discomfort and reestablish joint functionality.

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Knee, hip, and shoulder replacement are all examples of Arthroplasty surgery. (Aresti, Kassam, Bartlett, & Kutty, 2017). Arthroplasty is used to treat disorders that cause osteoarthritis, rheumatoid arthritis, osteonecrosis, joint traumas, and so forth. Cemented, uncemented, and hybrid joint prostheses are the surgical methods utilized in arthroplasty. (Boyle, Zhu, Frampton, Vane, & Poutawera, 2022).

Both cemented and uncemented prostheses have significantly reduced advanced arthroplasty and joint discomfort. One of the best orthopedic therapies for restoring joint function and minimizing discomfort in patients with a variety of illnesses, such as osteoarthritis and osteonecrosis of the femoral head and neck fractures, is arthroplasty with a prosthesis. (Kelly et al., 2022). A few months to a year after the remodeling, realignment, and replacement procedure, patients reported less pain in the damaged area; however, some of them also reported decreased mobility, long-term muscle weakness in one area of the body, and dissatisfaction with their ability to perform daily tasks. Total Shoulder Arthroplasty is a procedure that is commonly performed to treat injured shoulder joints. Injuries, calcification, deterioration in the shoulder cartilage tissue, injury to surrounding bones, and severe arthritis are all common causes of shoulder damage and malfunction. This injury causes serious stress and shoulder dysfunction. When shoulder joint injury persists, a surgical procedure may be used to alleviate pain and restore movement to the patient's shoulder. (Borjali et al., 2021). The injured joint is separated and replaced with an artificial prosthetic joint during the TSA process. (Yilmaz, 2021). X-ray implant graphics are used to examine the suitability of the artificial prosthesis prior to surgery and to check the correctness of the artificial prosthesis placement after surgery. There are currently several manufacturers of shoulder prostheses who create various types of this prosthesis to match varied conditions and patients. When the quality of the prosthesis deteriorates years after replacement, reoperation and revision may be required. Finding the model, structure, and

prosthesis manufacturer to position them correctly is the main surgical stage to reduce the usual issues. The patient and the primary doctor at the other location or country may not be aware of the prosthesis' model and manufacturer in cases where a patient migrates from the place or country where surgery was performed. As a result, determining the model of the prosthesis and the manufacturer requires a thorough inspection and visual comparison of radiological pictures. This method delays reoperation and correction, is time-consuming, and is error-prone. (Borjali, Chen, Muratoglu, Morid, & Varadarajan, 2020).

Numerous studies have shown how to use different deep learning approaches to categorize implants based on their manufacturer and identify the type and structure of the implants. Recently, deep learning techniques such as ResNet, Convolutional Neural Network (CNN), Neural Network, VGG, GoogleNet, and Inception have been utilized to automatically identify implant maker. (Hadj Saïd, Le Roux, Catherine, & Lan, 2020). These methods have been used as feature extractors to improve the accuracy of implant identification and classification. (Borjali et al., 2020).

Researchers have offered a number of detection models for duration of stay in hospital, payment scheme, practical result, and patient expectations, and so on, with the need for more optimal solutions. However, no complete evaluation of the automatic prediction, identification, and classification of prosthesis based on manufacturer exists. As a result, this study discusses the various detection models utilized in arthroplasty. The review also provides an overview and taxonomy of arthroplasty, as well as research gaps and prospects. The remainder of this work is structured as follows: The second section provides an overview of arthroplasty, the third section includes a synthesis of many predictive and detecting models used in arthroplasty, the fourth section covers research gaps and opportunities, and the fifth chapter concludes the survey.

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LITERATURE REVIEW

In this section, we provide an in-depth examination of artificial intelligence methods utilized in the prediction and detection of arthroplasty. Arthroplasty is a surgical procedure to reduce pain and restore joint function that involves modifying, realigning, and replacing a damaged bone's surface with a synthetic material. Knee, hip, and shoulder replacement are all common Arthroplasty procedures. Arthroplasty is used to treat disorders that cause osteoarthritis, rheumatoid arthritis, osteonecrosis, joint traumas, and so forth.

Overview of Arthroplasty

There are two types of arthroplasty prostheses: cemented and uncemented. Poly-Methyl-Methacrylate (PMMA) is used as a grout

in cemented prostheses to create an interlocking fit between cancellous bones and the prosthetic. Bone is biologically fixed to a surface layer of the prosthesis in uncemented hips. To establish initial attachment, a prosthesis that is slightly larger than the prepared bone bed is inserted, compression hoop stresses are produced, and a so-called press-fit is obtained. The taxonomy of arthroplasty shown in Fig. 1 from the perspective of the surgeon and the patient is based on the type of surgery, cost of the procedure and any necessary medication for the duration of the patient's stay in the hospital, patient satisfaction following the procedure, the number of surgical revisions necessary after the initial procedure, the patient's length of stay, implant stability, fracture risk, and complications related to the procedure.

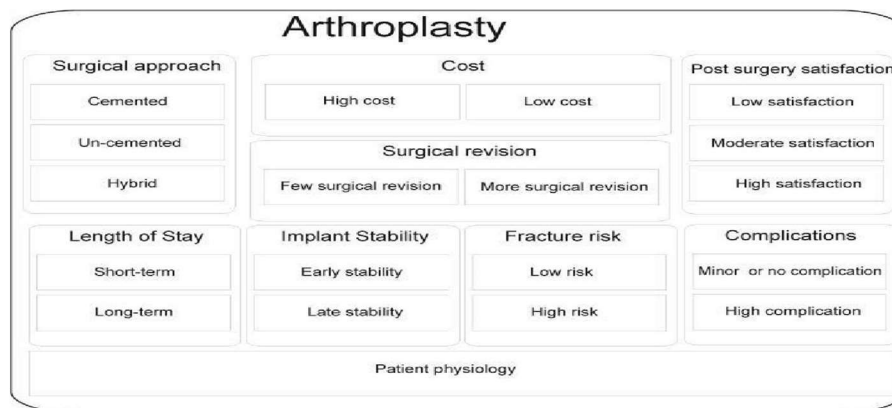


Fig. 1: The classification of arthroplasty from the perspectives of the surgeon and the patient

As a result, Table 1 compares the two surgical techniques for arthroplasty: cemented prosthesis and uncemented prosthesis in terms

of materials utilized, patient stay time, surgical revision, cost, fracture risk, and comorbidities.

Table 1: A comparison of cemented and uncemented prostheses

S/No	Parameter	Cemented Prosthesis	Uncemented Prosthesis
1	The material utilized	Poly Methyl Meth Acrylate (PMMA)	Bone
2	Stability	Earlier stability in recovery process	Late stability in recovery
3	Surgical revision	Few revisions	More revisions
4	Fracture risk	Increased fracture risk	Low fracture risk
5	Risk of	Equal risk of infection	

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6	infection Management of fracture	Less difficult	Difficult
7	Success rate	Less success rate	Higher success rate
8	Complications	More complications may occur	Few complications
9	Survival rate	far above the acceptable limit	Marginally inferior
10	Patients' category	Older aged and weak bone patients	Young aged patients

Overview of Arthroplasty Prediction and Detection Models

Currently, orthopedic surgeons are more concerned with the surgical approach to be used in treating patients, minimizing the risk of fracture, infections, complications, and the number of surgical revisions, whereas patients are more concerned with the amount of time they will need to spend in the hospital, the surgery's results, the financial implications of the surgery, and the medications. Many prediction models based on Machine Learning have been proposed by computer scientists. Deep Learning, Hybrid algorithms, Transfer Learning, and Ensemble algorithms were used to estimate the duration of stay, surgical technique, cost implications, and other requirements for patients undergoing arthroplasty.

Machine Learning

Machine learning is the study of computer algorithms that provide systems the ability to automatically learn from experience. It is generally seen as a subset of artificial

intelligence. (Deng, 2018). The systems are outfitted with machine learning algorithms that allow them to make decisions on their own without the need for human intervention. These decisions are made by discovering significant underlying patterns in huge, complex data sets. Machine learning algorithms are classified into three types: supervised, unsupervised, and reinforcement learning (Dhanaraj, Rajkumar, & Hariharan, 2020). These classifications are based on the learning approach, the types of data input and output, and the types of issues solved. A few hybrid strategies and other commonly used techniques allow for the spontaneous growth of machine learning problem types.

Deep Learning

Deep learning is a machine learning method that employs multiple-layer neural networks. These many processing layers learn representations of the input at various degrees of abstraction in order to interpret the incoming data.

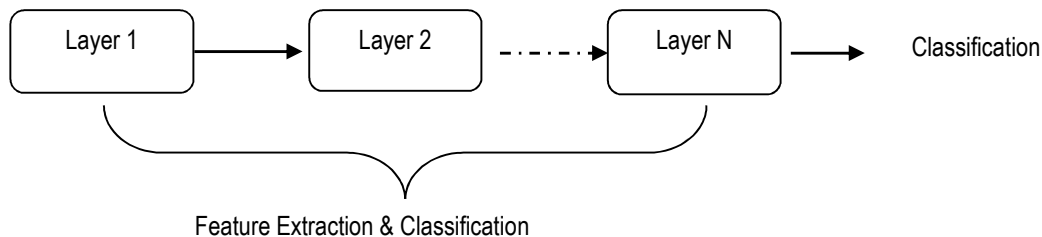


Figure 1. Overview of Deep learning (Mathew, Amudha, & Sivakumari, 2021)

Ensemble Learning

Using the machine learning model known as ensemble learning, multiple learners

are trained to solve the same issue. They outperform individual learning algorithms in terms of prediction performance. Base students are

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often a group of kids who make up an ensemble. The capacity for generalization of an ensemble is

often much greater than that of the base learners.

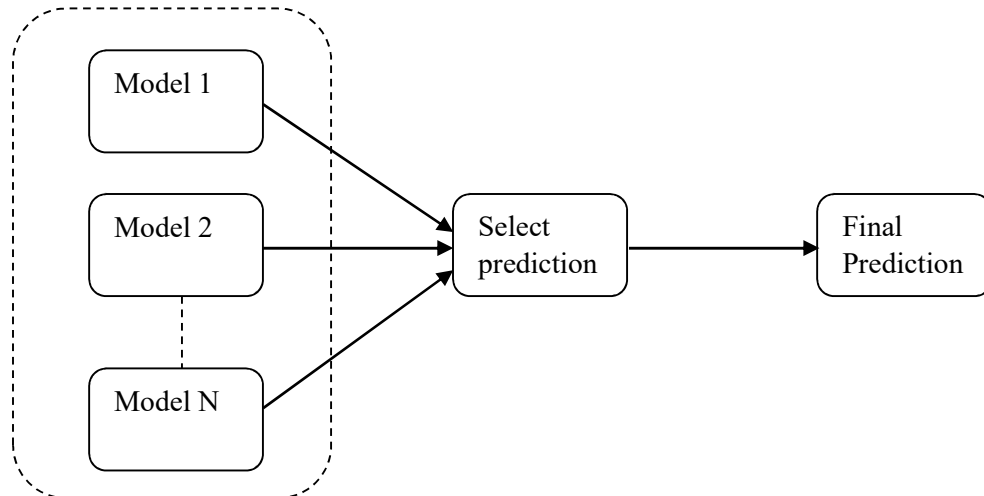


Figure 2. Overview of Ensemble Learning (Sagi & Rokach, 2018)

Transfer Learning

Transfer learning is the process of testing a developed algorithm on an unrelated but related task (Schiller, Huber, Dietz, & André, 2020). Because the fundamental idea is to transfer information from one supervised learning

job to another, additional labelled data from a different but related activity is usually required. One disadvantage of this method is that the new supervised learning tasks require more labeled data than unlabeled data.

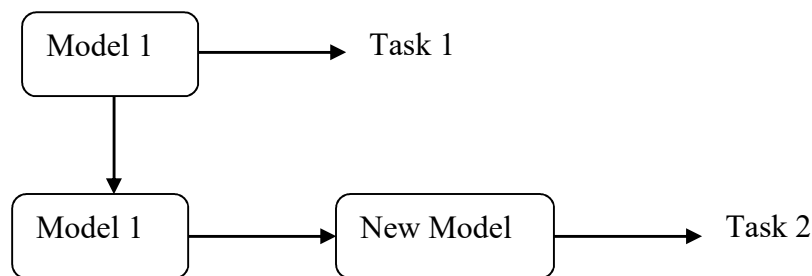


Figure 3: Overview of Transfer Learning (Zhuang et al., 2020)

Application of Prediction and Detection Models

In this section, we will look at the many applications of arthroplasty prediction models, as well as the model's prediction parameters and the surgical stage at which it is applied.

A. Surgical Approach Prediction Model

The patient's physiology and any related chronic condition will determine whether to use a cemented or uncemented method. Age, bone and muscle quality, related chronic illnesses, among other factors, all have an impact on the surgical technique. Prediction models for

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surgical approaches take into account the patient's aforementioned characteristics and forecast an appropriate strategy for the patient's recovery of joint function. The method chosen affects how long a patient stays in the hospital.

B. Model for Predicting Stay Length

The length of stay for a patient is the whole period of time they will be having arthroplasty. Age, gender, chronic diseases related, comorbidity status, APR degree of illness, kind of admission, number of associated diagnoses, etc. are all factors that are taken into account by the length of stay prediction model to determine how long it will take for a patient to be admitted and discharged. When a patient is admitted to the hospital, this paradigm is typically used. The surgical method is among the most crucial elements in determining the patient's duration of stay.

C. Risk Prediction Model

The risk prediction model anticipates the outcome of the surgery. The technique used determines the result of the procedure. the related chronic condition, and complications. Both the surgeon and the patient are concerned

about the danger and outcome of the surgery. As a result, an effective prediction model is critical.

D. Model of Cost Prediction

The price of arthroplasty varies according to the patient. The amount charged to the patient is determined by the type of procedure and length of stay in the hospital. The parameters in surgical approach prediction models define the surgical approach, while the parameters in the length of stay prediction model determine the patient's length of stay. This means that the surgical method and duration of stay are the primary parameters for the cost prediction model. In addition, problems seen after surgery may be included. The cost prediction model is a technique that estimates the financial impact of arthroplasty surgery and medicines administered to patients prior to stabilization.

Table 2, summarizes the models proposed by researchers in their research effort. The overview comprises the recommended procedure or algorithm, a prediction model (surgical approach, duration of stay, risk/outcome of the surgery), and operation kinds based on surgery site (total knee, total hip, or total shoulder).

Table 2: Summary of detection models by algorithm proposed, prediction model and operation type based on the location of the surgery.

S/No	Reference	Algorithm Applied	Prediction Model				Type of Operation based on Location		
			Surgical	LoS	Risk	Cost	TKA	THA	TSA
1.	(Anis et al., 2020)	Personalized prediction tool regression	X	X	✓	X	✓	X	X
2.	(Ramkumar, Karnuta, et al., 2019)	Artificial (ANN) Network	X	✓	X	✓	X	✓	X
3.	(Ricciardi et al., 2020)	Machine learning Image processing approach	✓	✓	✓	X	X	✓	X
4.	(Tolk et al., 2020)	Multivariable Image processing technique and regression analyses	X	X	✓	X	✓	X	X
5.	(Taaffe et al., 2001)	Classification and regression tree	X	X	✓	X	✓	X	X

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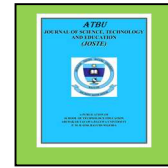
		(CART) analyses and logistic regression							
6.	(Liu et al., 2021)	Linear regression and multivariate logistic Regression	X	X	✓	X	✓	X	X
7.	(Venäläinen et al., 2021)	Multivariable regression Lasso	X	X	✓	X	X	✓	X
8.	(Simmen et al., 2008)	Logistic regression model	X	X	✓	X	X	X	✓
9.	(Alshahwani, Dungey, Lillie, Krikler, & Plakogiannis, 2021)	Risk assessment and prediction tool	X	✓	X	X	✓	✓	X
10.	(Halawi et al., 2015)	Multivariable logist	X	✓	X	X	X	✓	X
11	(Karhade, Schwab, & Bedair, 2019)	Stochastic gradient boosting (SGB), Random Forest, Support Vector Machine (SVM), Neural Network, and Elastic-net Penalized Logistic Regression (ENPLR)	X	X	✓	X	X	✓	X
12.	(Karnuta et al., 2020)	Neural Network	X	✓	✓	✓	X	X	✓
13.	(Oosting et al., 2016)	Risk Assessment and Predictor Tool (RAPT) and Performance-based Functional Tests	X	X	✓	X	X	✓	X
14.	(Petis, Howard, Lanting, Somerville, & Vasarhelyi, 2016)	Logistic regression	X	✓	✓	X	X	✓	X
15.	(Li et al., 2021)	Random Survival Forest (RSF) algorithm	X	X	✓	X	X	✓	X
16.	(Kugelman et al., 2021)	XGBoost (eXtreme Gradient Boosting)	X	✓	✓	X	X	✓	X
17.	(Ramkumar, Navarro, et al., 2019)	Naïve Bayesian Model	X	✓	✓	✓	X	✓	X
18.	(Baessler et al., 2021)	Pair wise analysis, Linear Regression	X	X	✓	X	X	X	✓

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19.	(Sniderman et al., 2021)	Least Absolute Shrinkage Selection Operator (LASSO)	X	X	✓	X	X	✓	X
20.	(Gabriel et al., 2019)	Multivariable logistic regression, Point based calculator	X	X	✓	X	X	✓	X
21.	(Kumar et al., 2021)	XGBoost machine learning technique	X	X	✓	X	X	X	✓
22.	(Polce et al., 2021)	stochastic gradient boosting, Random Forest, Support Vector Machine, Neural Network, and Elastic-net Penalized Logistic Regression	X	X	✓	X	X	X	✓
23.	(Chen, Papuga, Nicandri, Miller, & Voloshin, 2019)	Patient-Reported Outcomes Measurement Information System (PROMIS)	X	X	✓	X	X	X	✓
24.	(Dacombe et al., 2020)	Simple descriptive statistical analysis using Microsoft Excel	X	X	✓	X	X	X	✓
25.	(Sivasundaram et al., 2019)	Multivariable logistic regression	X	X	✓	X	X	X	✓
26.	(Gronbeck, Cote, & Halawi, 2019)	Multivariable logistic regression	X	X	✓	X	X	✓	X
27.	(Kim et al., 2018)	Outpatient Arthroplasty Risk Assessment (OARA)	X	✓	✓	X	X	✓	X

Length of Stay (LoS), Total Knee Arthroplasty (TKA), Total (THA), Total Shoulder Arthroplasty (TSA),
 X=(N/A) and ✓=(yes)

As seen in Table 2, the bulk of the models concentrated on the surgery's risk and outcome. Few research has focused on the length of stay of patients. The cost implications of the operation and medicine, and surgical strategy prediction. It is also worth noting that only a few of the detection models incorporated data from complete shoulder arthroplasty and knee arthroplasty. While the bulk of studies use data from complete hip arthroplasty. As a result, in the next subsections, we will look at a few relevant studies that focus on the identification and classification of shoulder implant manufacturers using radiographic imaging.

RELATED WORK

Numerous studies have been proposed in this context, for example, (B. Kim & Kim, 2019) suggested a proprietary Convolutional Neural Network model for shoulder implant manufacturer categorization. When compared to pre-trained models, the model produced encouraging results. "VGG-16, VGG-19, ResNet-50, ResNet-152, NasNet and DenseNet." To train their model, Le Van, C et al, 2021 collected shoulder implant pictures from several manufacturers.

Urban et al., (2020) suggested using X-Ray pictures to automatically detect and segment Total Shoulder Arthroplasty (TSA) implants. To

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find the implant in this study's work, the authors used the hough transform approach. They next used simple seeded region growth for picture segmentation. This technique had a 94% accuracy rate, which was an encouraging result. Six implants from three manufacturers were depicted in panoramic radiograph images using the You Only Look Once (YOLO3) version 3 algorithm. (Lunati, Wilson, Farley, Gottschalk, & Wagner, 2021). The accuracy of this approach was 72%.

Paul et al., (2020), segment the panoramic implant images and then utilize the typical pre-trained models (VGG-16 and VGG-

19) to identify the wide implant graphics using the transfer learning approach. However, in this study, the VGG-16 and VGG-19 networks fail to recognize the un-cropped panoramic implant images.

In order to distinguish between the various models of the Total Hip Arthroplasty (THA) prosthesis. Šarić, Šimunović, Vukelić, Šimunović, & Lujčić, (2018) presented a deep Convolution Neural Network paradigm. The model was tested using orthopedic surgeons' responses, and the results show promise in terms of speed and accuracy when compared to the surgeons' responses.

Table 3: Summary of the state-of-the-art

S/N	Author	Year	Title	Model Used	Result	Issues/Gap
1	(Yilmaz, 2021)	2021	Shoulder implant manufacturer detection by using Deep Learning: Proposed Channel Selection Layer	Convolution Neural Network (CNN)	The accuracy of 97.2% was achieved, which is better than the benchmarked approaches	The size of the dataset was limited to generalize the model
2	(Vo, Vo, & Le, 2022)	2021	A robust framework for shoulder implant X-ray image classification	X-Net with Squeeze and Excitation (SE) Net	The model improves the performance of the prediction	The region under curve is highly dependent on the dataset
3	(Stark, 2018)	2018	Automatic detection and segmentation of shoulder implants in X-ray images	Hough transform and Seeded region growing	The approach outperforms the outcome of the manually segmented ground truth images	Require a lot of hyper-parameters turning
4	(Yi et al., 2020)	2020	Automated detection and classification of shoulder arthroplasty models using deep learning	Deep Convolutional Neural Network (DCNN)	The approach was able to achieve high accuracy in terms of identification and classification	Requires cross-dataset validation to design a comprehensive classification framework
5	(Zhou & Mo, 2021)	2021	Shoulder implant X-ray manufacturer classification: exploring	Vision Transformer	The approach perform self-attention	The approach requires large amount of data to

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			with vision transformer		across patches of pixels	learn from scratch
6	(Le Van, Bao, Puri, Thao, & Le, 2021)	2021	Detecting lumbar implant and diagnosing scoliosis from vietnamese X-ray imaging using the pre-trained api models and transfer learning	Pre-trained API's	The pretrained API performs better than the benchmarked approach	The approach takes longer time to converge
7	(Borjali et al., 2021)	2021	Comparing the performance of a deep convolutional neural network with orthopedic surgeons on the identification of total hip prosthesis design from plain radiographs	Convolution Neural Network	The method takes lesser time to make predictions as compared to the surgeon	It requires a lot of datasets to be effective
8	(Borjali et al., 2020)	2020	Detecting total hip replacement prosthesis design on plain radiographs using deep convolutional neural network	Deep Convolution Neural Network	The model achieved 100% accuracy on the dataset	Requires cross-dataset validation to design a comprehensive classification framework
9	(Urban et al., 2020)	2020	Classifying shoulder implants in X-ray images using Deep Learning	Deep Convolutional Neural Network	Achieve accuracy of 80% using 10-fold cross validation	It requires a lot of datasets to be effective
10	(Sivari, Güzel, Bostanci, & Mishra, 2022)	2022	A Novel Hybrid Machine Learning Based System to Classify Shoulder Implant Manufacturers	DenseNet201 + Logistic Regression	The proposed hybrid machine learning algorithms achieve the goal of low cost and high performance compared to other studies in the literature	selection of useful features was not done for classification which can decrease the performance of the proposed method
11	(Geng et al., 2023)	2023	Development of a machine learning algorithm to identify total and reverse shoulder arthroplasty	convolutional neural network (CNN)	the model performed with an overall accuracy of 93.9% with	The method may be augmented with the addition of more implant types

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			implants from X-ray images		positive predictive value, sensitivity and F-1 scores of 94% across 10 different implant types (4 reverse, 6 anatomical)	
12	(Zhou & Mo, 2021)	2021	Shoulder Implant X-Ray Manufacturer Classification: Exploring with Vision Transformer	Vision Transformer, transfer learning, VGG-16, ResNet-50 and Inception-V3 architecture.	deep learning method is proven to be successful in the classification of shoulder implant's manufacturers	an assistant tool of classifying shoulder implants was not considered
13	(Kunze et al., 2023)	2023	Artificial intelligence for automated identification of total shoulder arthroplasty implants	DL algorithm	A DL model demonstrated excellent accuracy in identifying 22 unique TSA implants from eight manufacturers	The class imbalance in learning was resolved
14	(Sultan et al., 2021)	2021	Artificial Intelligence-Based Recognition of Different Types of Shoulder Implants in X-ray Scans Based on Dense Residual Ensemble-Network for Personalized Medicine	ensemble of convolutional neural networks (CNNs)	The experimental results showed that DRE-Net achieved an accuracy of 85.92%, which were higher than those of the state-of-the-art methods	High the training time
15	(Porhemmat, 2020)	2020	Classification of Shoulder Implants in X-ray Images Using Deep Learning	deep convolutional neural networks	deep convolutional neural networks outperform other	The class imbalance in learning was resolved

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				classifiers significantly if and only if out-of domain data such as ImageNet is used to pre-train the models	
16	(Karaci, 2022)	2022	Detection and classification of shoulder implants from X-ray images: YOLO and pretrained convolution neural network-based approach	YOLO and pretrained convolution neural network	The highest classification performance was achieved in the cascade DenseNet201 model with an accuracy rate of 84.76%. The size of the employed dataset was limited
17	(Sultan et al., 2022)	2022	Artificial Intelligence-Based Solution in Personalized Computer-Aided Arthroscopy of Shoulder Prostheses	ensemble network called the Inception Mobile Fully-Connected Convolutional Network (IMFC-Net)	The proposed model is efficient and can minimize the revision complexities of implants Despite the augmentation of the dataset, the class imbalance problem still persists

Research Gap and Opportunities

According to the review, few studies focused on patient duration of stay, cost implications of the operation and medicine, and early prediction of surgical technique. It is evident that there are few prediction models for predicting surgical approach, which serves as the foundation for other prediction models such as surgery outcome, patient length of stay, and cost of surgery and medication. The development of effective surgical approach prediction models that take into consideration parameters such as age, gender, underlying disorders, and so on will be a fantastic research opportunity.

Furthermore, based on the review presented, the author observes that few researchers have applied deep learning concepts to predict the manufacturer of prosthesis prior to revision. For example, the study in (Urban et al., 2020) proposed deep convolutional neural

networks to identify should implant. Promising detection rate was achieved by the CNN model. However, the techniques were trained using a little dataset that resulted to poor approximation and high variance estimation of model performance. Furthermore, the research ignores segmentation in the preprocessing stage which degraded the performance (Du, Cao, Liang, Chen, & Zhan, 2020). Additionally, the model treats all the features (relevant and irrelevant features) of the shoulder implant equally resulting in poor computational time and less accuracy (X. Liu et al., 2016). Hence, Attention mechanisms can be added to deep learning models to focus the attention of the model to specific parts of data thereby addressing the challenges identified in the literature (Urban et al., 2020). Therefore, this study focuses on developing a deep learning model for the automatic detection and classification of prosthesis based on

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manufacturer using an improved convolutional attention model.

It is also worth noting that only a few of the detection models incorporated data from complete shoulder arthroplasty and knee arthroplasty. While the bulk of studies use data from complete hip arthroplasty. As a result, in the next subsections, we will look at a few relevant studies that focus on the identification and classification of shoulder implant manufacturers using radiographic imaging.

The survey also reveals that there is no one model or instrument for predicting surgical strategy, surgical outcome, duration of stay, and surgical and drug costs. Creating a single model for predicting surgical strategy, surgery result, patient length of stay, and surgery cost will be another exciting research opportunity.

Furthermore, the majority of the algorithms proposed in the literature use the notion of deep learning to forecast the manufacturer of prosthesis. These strategies train the suggested models using a small dataset, resulting in poor approximation and high variance prediction of model performance. Second, in order to acquire the best weights, the models need a significant amount of hyper parameter turning. To address the data limitation, it is necessary to investigate the possibilities of the transfer learning notion in this concept.

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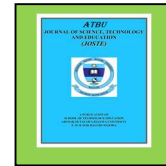
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