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REVIEW **OPEN ACCESS**

Contemporary Machine Learning Approaches Towards Biomechanical Analysis in the Diagnosis and Prognosis Prediction of Knee Osteoarthritis: A Systematic Review

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Abstract
Introduction: Knee Osteoarthritis (KOA) is the second most reported condition for persons 50 years and up; approximated by the continuous degradation of the knee, and eventually extending to the debilitation of biomechanical gait parameters. Inconsistencies with existing diagnostic methods mean that Machine Learning (ML) has been leveraged in creating gait-based predictive models in relation to KOA. The purpose of this study is to explore existing literature with camera and sensor-based methodologies, along with the employed algorithms in the diagnosis and prognosis prediction of KOA.
Methods: Searches for literature were accomplished on Google Scholar and PUBMED databases using relevant keywords, within a time frame of 2010 - 2023. Information pertaining to the data collection method, algorithm used, and model performance was collected.
Results: After the initial search of 1132 articles, the selection process yielded 22 articles for further review. Of the 22 articles, 10% focused on the prediction of patient outcomes and disease prognosis, while 90% focused on the initial diagnosis or severity prediction of KOA. 28% of the reviewed literature utilized sensor-based technology for biomechanical gait parameter collection, while the remainder utilized a more traditional camera-based approach. While evaluatory metrics varied between studies, of the studies with reported accuracy metrics (n=11), camera-based models had on average a higher accuracy compared to sensor-based algorithms, 92.05% compared to 67.96%, respectively.
Discussion: Support Vector Machine (SVM) was found to be the most common algorithm used within the reviewed studies, and had the highest accuracy on average, possibly attributed to the ability of the algorithm to manage small yet high dimensional datasets. The difference in accuracy between camera-based and sensor-based approaches was determined to be statistically significant through application of a Mann-Whitney U Test. While sensors have a reduced quantity of features capable of being measured, it is a more applicable technology for clinical application, indicating an area for future development.
Conclusion: Overall, literature concerning the binary classification of symptomatic KOA provided high accuracy, yet further validation to minimize overfitting is required. Furthermore, areas for prognosis prediction and multiclass classification of KOA severity remain as areas for further development.

Keywords: machine learning; biomechanical analysis; gait-based analysis; knee osteoarthritis

Introduction

Knee osteoarthritis (KOA) is one of the most common debilitating musculoskeletal diseases in the world and is the second most reported condition for persons over 50 years of age [1]. While previously believed to be characterized by the degeneration of cartilage, novel evidence supports the characterization as a polymorphic disease of the whole joint, where an array of etiological causes results in the progressive degradation of the knee [2]. While the pathophysiology of the condition is not well understood, it can be approximated as the remodeling of the subchondral bone following the degradation of the cartilage [2, 3]. As such, the progressive loss of cartilage volume results in a degenerative disease that gradually affects virtually all biomechanical metrics, resulting in the altered gait of affected patients [4]. Currently, no curative treatments exist, and existing therapies focus on the maintenance of patient quality of life, bar severe cases where joint replacement through either total or unicompartmental knee arthroplasty is applied [5]. Epidemiologically, KOA is estimated to affect over 7% of the global population, with higher prevalence in countries with a higher median age and obesity rates [6]. With the increasing age of the Canadian population, the prevalence of KOA is expected to increase along with the estimated direct costs of the condition, going from 2.9 billion in 2010 to an estimated 7.6 billion in 2031 [7].

Contemporary diagnosis of KOA is done using radiographic images, where the Kellgren and Lawrence (KL) grading system is the most accepted tool by physicians. The system is a 5-grade scale that determines the severity of KOA based on the visual inspection by physicians of radiographs [8]. However, this method of diagnosis has several problems. For one, the KL classification method is liable to subjectivity, where interobserver and even intraobserver analysis of radiography have a lack of reliability in the assignment of KL grades [5]. Furthermore, the degree of knee degradation may not correlate to the degree of pain experienced by the patient, where patients diagnosed with a higher severity of KOA may experience very little pain, and vice versa [2, 9]. Moreover, this method is unable to distinguish high-risk patients, who may be subject to a rapid prognosis of the condition called accelerated KOA (10). Finally, the accessibility of radiography comes into question for low-income patients, who may not be able to access such diagnostic tools [11].

Due to the increasing prevalence of KOA, the associated economic costs, and flawed existing approaches, it is important to explore alternative options for diagnosis and progression prediction. Enter gait-based diagnosis of KOA, a relatively novel non-invasive approach that utilizes the declining gait function of patients suffering from KOA to make predictions on the severity and progression of the disease [12]. Existing studies have shown that alterations in the temporospatial and biomechanical parameters have been positively correlated to increasing severity of KOA [13]. While traditional approaches towards gait analysis utilize motion capture and cameras to capture parameters, often with high accuracy in laboratory settings, contemporary advancements in wearable sensor technology have facilitated a remote, cost-effective, and accessible method, often at the cost of accuracy and depth of information [14]. The ability for biomechanical data to be applied towards the diagnosis and prognosis prediction for KOA can increase accessibility for patients, and allow for earlier access to treatment, possibly relegating KOA to a preventable disease in the future [15]. Due to the complexity and quantity of associated data, gait-based analysis is vastly improved with the implementation of machine learning (ML) to create predictive models. ML describes the integration of computer algorithms and datasets to generate models capable of accurate predictive tasks, where the models employed by literature, associated cross-validation, and metrics for evaluation in tables 1, 2, and 3, respectively. As most studies employ hospital databases, ML can be leveraged to generate predictive models that account for all relevant features [16]. Contemporarily, there are no studies that exclusively focus on the applications of ML toward biomechanical-based analysis of KOA. As such, the objective of this study is to review the cutting-edge approaches toward gait-based KOA diagnosis and prognosis prediction, with a specific focus on the ML models used.

Table 1. A Brief Summary of Machine Learning Algorithms Utilized by Literature Explored within this Study

Model	Description
Random Forest (RF)	A supervised learning algorithm that utilizes individual decision trees and cumulative voting to reach a final prediction [17].
Support Vector Machine (SVM)	A supervised learning model that is used for regression or classification by finding the best hyperplane that maximizes the distance between features to maximize the generalization of the model [18]. Datasets with overlapping targets can result in increased error.
Extreme Learning Machine (ELM)	A feedforward neural network with a single layer of hidden nodes, assigned random weights [19]. Facilitates extremely fast learning speeds, and greater generalization ability.
Decision Tree (DT)	A simple predictive model where nodes of a decision tree propose an attribute, edges have “answers” to such attributes, and leaves with classification labels [17].
Neural Network (NN)	A model containing layers of interconnected neurons that find patterns in the input data to perform classification tasks. • Multi-layer Perceptrons are a type of neural network with multiple layers of neurons and are used for complex pattern recognition. Applying backpropagation, the weight of each node is adjusted internally [17]. • Convolutional Neural Networks utilize connected layers and pooling layers to reduce the total number of dimensions [20]. Applied towards image and video analysis. • Long-Short Term Memory is a type of recurrent neural network that is effective at remembering sequential data long-term [21].
Logistic Regression (LR)	Logistic Regression is used for classification and predicting a binary outcome based on predictor variables [17].

Model	Description
K-Nearest Neighbors (kNN)	A supervised learning classification algorithm that uses the proximity of existing data points within an *n*-dimensional space to make predictions about input data. Accuracy heavily depends on the quality of training data and can fluctuate based on the assigned *k*-neighbors [17].
Naive Bayes (NB)	A classification algorithm that assumes feature independence and calculates the probability of an event using the Bayes Theorem, suitable for small databases [22]. In the event of closely related features, it can result in reduced accuracy.
Adaptive Boosting (AdaBoost)	An algorithm that combines many "weak" performing classifiers to create a strong classifier using sequential weight adjustments [17].
Extreme Gradient Boosting (XGBoost)	A scalable algorithm that uses gradient boosting, a technique where weaker decision trees are combined with stronger ones to make predictions [17].
Stacked Ensemble	An algorithm that involves aggregating predictions from multiple machine learning models. • Super learning, one of the most advanced methods, involves creating a library of candidate algorithms, and the combination of the best learners into an ensemble [23].

Table 2. A Brief Summary of Cross Validation (CV) Techniques Utilized by Literature Explored within this Study

Technique	Description
Hold-Out Method	The simplest method, in which the primary data set is split into a training and test set.
Leave One Out Cross Validation	Often used for smaller datasets, LOOCV evaluates the training dataset *n*-times, where *n* represents the number of features in the dataset. Each feature is left out once and used as a test set [24].
k-Fold Cross Validation	A resampling technique that is done by splitting the dataset up into *k*-groups, where each group serves as the validation set once to be used for model evaluation against the remaining data [25].

Table 3. A Brief Summary of Performance Metrics Utilized by Literature Explored within this Study

Metric	Description
Accuracy	The measure of the number of correct predictions out of all predictions made.
Precision	The measure of the ratio between true positives and the total number of positive cases predicted.
Area Under the ROC Curve (AUC)	The measure of model performance when given a random positive example and a random negative example, aggregated across all classification thresholds.
Specificity	The probability of a positive test result, or the proportion of true positive examples correctly identified by the test.
Sensitivity	The probability of a negative test result, or the proportion of true negative examples correctly identified by the test.
Matthews Correlation Coefficient (MCC)	The measure of the difference between predicted values and actual values.

Methods

Searches for peer-reviewed literature published between 2010 and 2023 were conducted on Google Scholar and the PubMed databases, using the keywords: "gait analysis," AND "knee osteoarthritis," AND "machine learning," along with their related synonyms. Such keywords were searched for "anywhere in the article," and "in all fields" on Google Scholar and PubMed, respectively. Following the initial search, there were a total of 1132 articles. Following the manual screening of titles and abstracts by a single reviewer, a total of 58 results were obtained for full article screening, all subject to the exclusion criteria, as follows:

- Any studies pertaining to ML applications exclusively towards medical imaging were disregarded from this study.
- Literature analyzing the application of ML in patient gait retraining, or biomechanical analysis following Total or Unicompartmental knee arthroplasty were excluded, as this falls outside of the scope of this review.
- Other literature reviews or meta-analyses were not evaluated.

Following the application of the exclusion criteria, there were a total of 22 articles that were included in the literature review. See Figure 1 for a detailed description of the selection process.

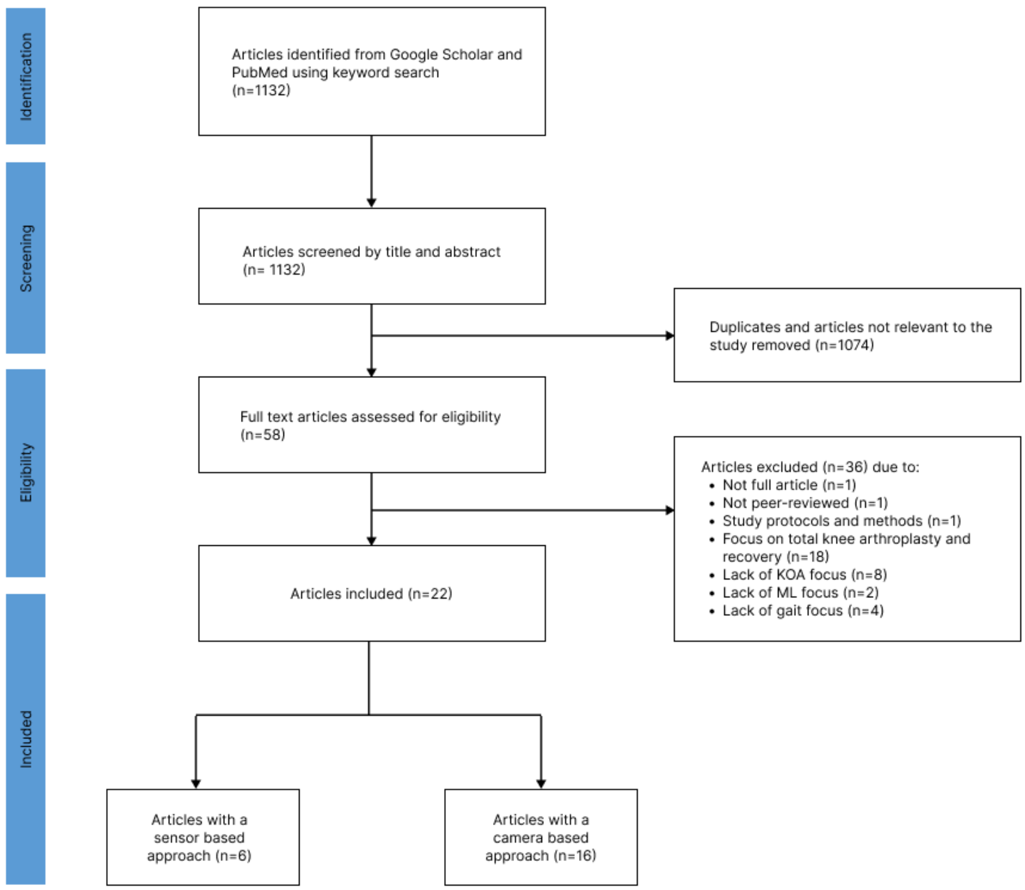

Figure 1. A PRISMA flow diagram of the article selection process (figure created in Figma).

The Kruskal-Wallis Test was then used to compare the accuracies for more than two independent groups of machine learning models. This test is ideal as it is less sensitive to irregularities in data and can handle the varying sample sizes among the different models. The Mann-Whitney U Test was used to assess the statistical difference between two independent groups, camera-based and sensor-based approaches to KOA detection, as this test is ideal for small sample sizes.

Results

Of the 22 studies that were considered within this review, it was identified that 16 (73%) studies utilized a camera-based approach, while 6 (27%) utilized a sensor-based approach. As such, this study will evaluate each of these approaches separately. Literature with a camera-based approach is summarized in Table 4, while literature with a sensor-based approach is listed in Table 5.

Table 4. Studies with ML Towards the Diagnosis and Prediction for KOA using Cameras

Reference	Methodology	Performance	Notable findings
(Kwon et al., 2020a) [26]	ML Model: • RF Dataset: • Gait database with a total of 375 subjects and associated WOMAC indexes. Validation: • Hold-out method, 70-30 split.	RMSE value of 17.38 R value of 0.741	Multiclass classification through prediction of WOMAC index with associated gait features
(Kwon et al., 2020b) [27]	ML Model: • SVM Dataset: • Gait database with a total of 364 subjects, KL ranging from 0-4. Validation: • Hold-out method, 70-30 split.	AUC for predicting: KL 0: 0.934 KL 1: 0.802 KL 2: 0.846 KL 3: 0.774 KL 4: 0.967	A multiclass classification through the combination of both gait and radiographic features in predicting a specific KL score of patients.
(Köktas et al., 2010) [28]	ML Model: • MLP decision tree Dataset: • Unspecified Validation: • 10-fold CV	0.80 ACC on average for the combined MLP decision trees.	Determination of KL class, normal, mild, moderate or severe using a decision tree with MLP at the leaves.
(Chen et al., 2020) [29]	ML Model: • Hybrid model of LSTM network and SVM Dataset: • Data is collected from 19 asymptomatic and 19 patients with KOA. Validation: • 5-fold CV	ACC of 0.988	Able to determine and distinguish asymptomatic patients from KOA patients with a high accuracy.
(Bosel et al., 2020) [30]	ML Model: • 3D NN Dataset: • 86 individuals partook in the study, 64 with KOA ranging from 1-3, and 22 asymptomatic subjects. Validation: • 10-fold CV	Peak values for ACC: 0.85, SEN of 0.73, SPF of 1.0, PRC of 1.0.	Prediction of Knee adduction moment for patients only from 2D videos, with a high peak ACC.
(Zeng et al., 2022) [31]	ML Model: • LR Dataset: • Total of 528 asymptomatic patients, and 306 symptomatic patients were used in the training set. Validation: • n/a	The best performing model was the conjoint model of angular, translational and composition data for the 6DOF, with a ACC of 0.889, SEN of 0.921, and a SPF of 0.967	Creation of 4 separate LR models in diagnosing patients with KOA using 3D gait parameters

Reference	Methodology	Performance	Notable findings
(Kour et al., 2022) [32]	ML Model: • KNN, LR, RF, SVM Dataset: • 50 total patients with KOA, separated into mild, moderate and severe populations, and 30 healthy subjects. Validation: • 5-fold CV	KNN had the highest metrics, ACC of 0.924, SEN of 0.916, SPF of 0.939, PCN of 0.909 in prediction KOA.	The model was able to use simple spatiotemporal data from video recordings to make predictions on both KOA diagnosing and severity.
(Aljaaf et al., 2016) [33]	ML Model: • RF, MLPNN, Decision tree Dataset: • 31 patients with Alkaptonuria induced KOA Validation: • Hold-out method, with a 70:30 split.	MLPNN r^2 of 0.8616, AUC of 0.874.	The MLPNN was able to quickly be trained and accurately predict the knee abduction moment for KOA patients.
(Cui et al., 2018) [34]	ML Model: • SVM Dataset: • 19 asymptomatic and 19 symptomatic patients Validation: • 10-fold CV	Average ACC of 0.97	Using 14 gait features, the model provides a non invasive, low cost analysis of gait for the pre-diagnosis of OA.
(Zeng et al., 2023a) [35]	ML Model: • A NN integrated with PSR and ITD Dataset: • 22 patients with KOA, and 28 age matched asymptomatic persons, from the Guangzhou General Hospital Validation: • 2-fold and LOOCV	ACC of 0.92	High accuracy and ability to pre diagnose patients with KOA
(Kwon et al., 2019) [36]	ML Model: • RF Dataset: • Total of 227 unilateral KOA patients, and an unreported number of asymptomatic volunteers. Validation: • 10-fold CV	AUC for KL 0: 0.974, KL 1: 0.992, KL 2: 0.845, KL 3: 0.894, KL 4: 0.905	Identified Knee extension moment and rotational moment as key features, alongside 20 other features that can be used as biomarkers in discrimination KOA severity.
(Costello et al., 2023) [37]	ML Model: • Ensemble model where candidate learning models are weighed using "super learning." Dataset: • 947 total participants all with a KL of 0-2, who were invited to 2-	Median AUC of 0.73	Created a cutting edge ensemble model capable of prognosis prediction for KOA patients. Identified 10 features with the highest VIM (variable importance measure)

Reference	Methodology	Performance	Notable findings
	year follow ups from their initial doctor consultation. Validation: • 5-fold CV on all candidate learning models		
(Emmerzaal et al., 2022) [38]	ML Model: • LR Dataset: • 51 total participants, 12 asymptomatic patients, 20 unilateral Hip OA patients and 19 unilateral KOA patients. Validation: • 5-fold CV	1.0 classification accuracy for distinguishing KOA from asymptomatic patients.	Using kinematic data from patients ascending stairs, the model achieved a perfect overall accuracy when employed on the test dataset.
(Yoo et al., 2013) [39]	ML Model: • SVM Dataset: • Patients were taken from the Yonsei University RI, 20 asymptomatic controls, and 13 patients with KOA who had sustained follow ups over a 7 year period. Validation: • LOOCV	ACC for detecting KOA: 0.974, pain prediction: 0.833, Radiographic severity: 0.833, unfavorable outcomes: 0.692	The model was successfully able to predict the prognosis of KOA patients with a high accuracy, using minimally invasive features in making predictions (time for stair ascent, etc).
(Zeng et al., 2023b) [40]	ML Model: • SVM, KNN, Naive Bayes, DT and Ensemble learning based AdaBoost (ELA) classifier Dataset: • 26 patients with KOA and 26 asymptomatic controls Validation: • Two-fold and LOOCV	SVM with LOOCV had an ACC: 1.0, SEN: 1.0, MCC: 1.0 SVM with 2-fold CV had an ACC: 0.923,SEN: 0.923, and MCC: 0.846.	RQA and fuzzy entropy were used to help classify gait patterns, which has never been considered (to the best of the authors' knowledge at the time the article was published)
(Long et al., 2017) [41]	ML Model: • KNN Dataset: • 84 asymptomatic participants and 41 people with KOA Validation: • CV (did not specify further)	Using biomechanical parameters: AUC of 0.92, while using all biomechanical parameters + QOL: AUC 1.00	This study measures a large-scale model in the prediction of KOA, using KOOS and QOL as features in classification.

Abbreviations used: Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Sensitivity (SEN), Multi-Layer Perceptrons (MLP), Neural Network (NN), K-Nearest Neighbours (KNN), Long-Short Term Memory (LSTM), Specificity (SPF), Precision (PRC), Accuracy (ACC), Matthews Correlation Coefficient (MCC), Area Under Curve (AUC), Extreme Learning Machine (ELM), Recurrence Quantification analysis (RQA), Six-Degrees of Freedom (6DOF), Cross validation (CV), Phase Space Reconstruction (PSR), Intrinsic Time-Scale (ITD), Leave One Out Cross-Validation (LOOCV), Knee Injury and Osteoarthritis Outcome Score (KOOS), knee related Quality of Life (QOL)
*KOOS is a quality-of-life measure that can potentially be used to predict early OA onset

Table 5. Studies with ML Towards the Diagnosis and Prediction for KOA Using Wearable Sensors

Reference	Methodology	Performance	Notable findings
(Yang et al., 2020) [42]	ML Model: • SVM Dataset: • 84 KOA patients + 97 asymptomatic patients Validation: • 5-fold CV	In classifying asymptomatic vs KOA patients, ACC of 0.928, SPF of 0.949, SEN of 0.912. In classifying KOA severity, ACC: 0.812 using 72 features, 0.856 using 10 optimal features	This study discusses the importance of feature selection in KOA severity classification (by removing unnecessary gait features)
(Bacon et al., 2022) [14]	ML Model: • Stacked ensemble model created using "super learning." Dataset: • Total of 2066 participants, with 271 with unilateral KOA, 268 with bilateral KOA, and the rest asymptomatic. Validation: • 5-fold CV	AUC: 0.75	The study found that people who are at risk of developing or who have KOA have lower step regularity (asymmetry of the center of mass) and lower gait regularity (less adaptable to external disruptions to walking)
(Almuhammadi et al., 2022) [43]	ML Model: • OA-Pain-Sense (ML framework to assess HKOA pain scores; it uses LR, SVM, KNN, DT, RF and XGB) Dataset: • 53 patients with hip (n=26) and knee (n=25) OA, and 27 asymptomatic controls Validation: • 5-fold cross validation	In classifying KOA vs. asymptomatic controls, XGB had the highest accuracy of 0.767	Top ten features that contribute to KOA vs healthy classification (in order of importance): gait velocity, cadence, stride time, stride length, step length, step time, step count, stride count, swing time Var, Terminal Double Support Time Var
(Wang et al., 2022) [44]	Model: • RF, AdaBoost, SVM Dataset: • 18 patients with Knee OA and 22 control subjects Validation: • Hold-out method, 70-30 split.	SVM had the highest ACC of 0.931, with an AUC of 0.98.	This study measured the Piezoresistive pressure features for patients when walking to predict KOA, using low-cost, convenient insoles. This would be combined with speed-based features of patients, leading to the highest accuracy and model performance.
(Snyder et al., 2023) [45]	Model • Feed forward NN, CNN, and Recurrent NNs Dataset: • 9 asymptomatic female subjects Validation: • LOOCV	Highest accuracies for predicting the KAM was the CNN, with a R value of 0.96, and RMSE of 0.47	This study aimed to predict KAM (Knee Adduction Moments), which is a factor associated with KOA. They did the study on healthy female participants.
(Xia et al., 2022) [46]	Model • SVM, DT, RF, Voting classifier (based on SVM, DT and RF), and CNN Dataset: • 36 individuals who had KOA and 14 asymptomatic participants Validation: • LOOCV	Using three IMU sensors, the highest performance was using the Voting classifier, with an AUC of 0.82 and SEN of 0.86.	This study found that three sensors provided a more accurate classification; combining IMU sensors on the upper-end limbs and lower-end limbs resulted in the highest model performance.

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Abbreviations used: Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Sensitivity (SEN), Multi-Layer Perceptrons (MLP), Neural Network (NN), Convolutional Neural Network (CNN), K-Nearest Neighbours (KNN), XGBoost (XGB), Decision Tree (DT), Specificity (SPF), Precision (PRC), Accuracy (ACC), Area Under Curve (AUC), Inertial Measurement Unit (IMU)

Study Characteristics

There were only 2 studies that focused on the prediction of KOA prognosis, with the remaining 20 focused on the initial diagnosis of KOA in patients. Of the 22 articles reviewed, the number of participants ranged from 31 to 2066, with an average of 250 participants. The average number of KOA patients was 85, with a range of 13 to 539, while the average number of asymptomatic patients was 165, with a range of 12 to 1527. Specifically, for studies that utilized a camera-based approach, the average number of KOA patients was 58 with a range of 13 to 306, while the average number of asymptomatic patients was 79 with a range of 12 to 528. In studies employing a sensor-based method, the average number of KOA patients was 140, with a range of 18 to 539, while the average number of asymptomatic patients was 337, with a range of 14 to 1527. The ratio of KOA to asymptomatic patients is close to 1:1 in many of the studies, with many studies matching each KOA participant with an asymptomatic counterpart (. Seven studies were excluded from this calculation as two had unreported participant data and the remaining five only included participants from one category, either KOA patients or those who were asymptomatic. The average age of KOA patients in the studies was 59.7 with a range of 41.6 to 73.4. The average age of asymptomatic patients in the study was 51.7 with a range of 24.7 to 69.4. The number of studies published each year increased over time. There was one article published in 2010, one in 2013, and one every year from 2016 to 2019. In 2020, there were 5 articles, and 11 were published between 2022 and 2023. This increasing trend is indicative of both the increasing interest in this topic and the innovations made within ML.

Descriptive Statistics

The literature analyzed within this study utilized a variety of metrics for gauging model performance. Using the eleven studies that provided accuracy metrics in models accomplishing binary classification of asymptomatic to symptomatic KOA participants, the mean accuracy was calculated for each algorithm. The mean values were further separated into camera-based and sensor-based approaches (Table 6). Of the cumulated articles, the most successful algorithm was the Support Vector Machine (SVM) on average, achieving a mean accuracy of 90.28%. Conversely, the worst-performing models were Decision Trees (DT) and Random Forest (RF), both attaining a mean accuracy of 78.95%.

Table 6. Mean Accuracies of Various ML Models for Camera-Based, Sensor-Based, and Overall KOA Detection

	Camera Mean Accuracy (%)	Sensor Mean Accuracy (%)	Overall Mean Accuracy (%)
Random Forest	78.92*	78.97	78.95
Support Vector Machine	95.30	81.92	90.28
Logistic Regression	91.73	63.64*	84.71
K-Nearest Neighbors	96.20	55.45*	86.01
Decision Tree	98.08*	59.82*	78.95
Overall	92.05	67.96	83.78

*Based on one study (not a mean)

Statistical Analysis

The Kruskal-Wallis Test was performed to determine if there were any statistically significant differences in the classification accuracies of the most popular ML models utilized by literature explored within this review. The accuracies of the RF, SVM, Logistic Regression (LR), K-Nearest Neighbors (kNN), and Decision Tree (DT) algorithms were collected from all associated studies (n=11). The test resulted in an H-statistic of 2.200 and a p-value of 0.699, suggesting that there is no statistically significant difference in model performance when detecting KOA (Table 7).

Table 7. Results of the Kruskal-Wallis Test for Model Accuracy

H-statistic	p-value	alpha
2.200	0.699	0.05

The Mann-Whitney U Test was performed to determine if there were any statistically significant differences in the overall model accuracies of camera-based and sensor-based approaches. The accuracies of the RF, SVM, LR, kNN, and DT algorithms were aggregated and separated by approach. The same eleven studies used in the Kruskal-Wallis Test were used in this analysis. The test resulted in a U-statistic of 90.0 and a p-value of 0.0032, suggesting that camera accuracies are significantly higher than sensor accuracies (Table 8).

Table 8. Results of the Mann-Whitney U Test for Camera vs Sensor Overall Model Accuracy

U-statistic	p-value	alpha
90.0	0.0032	0.05

Discussion

This review summarized the key findings and analyzed the performance of various ML models in the diagnosis and prognosis of KOA, using biomechanical data from patients. Camera-based approaches were documented separately from sensor-based approaches to provide insight into their differences and to evaluate the feasibility of wearable sensor technology for patients at risk for KOA. The statistical findings provide a quantitative measure of algorithm analysis across studies and provide insight into the relative importance of model selection and source of data for KOA detection.

Support Vector Machines (SVM) were found to have the highest overall model accuracy (90.28%) out of the studies that predicted KOA from symptomatic and asymptomatic patients. SVMs were also the most commonly used algorithm for the literature reviewed in this article (n=7). In a review by Kokkotis et al. (2020) on ML techniques for the diagnosis and prediction of KOA, SVMs were also found to be the most commonly used algorithm across all investigation domains concerning KOA, namely regression, classification, optimum post-treatment planning techniques and segmentation of magnetic resonance images [12]. This can be attributed to the generalization capabilities of SVMs with limited yet high-dimensional data [17]. In the context of studies explored in this review, many employed a small sample cohort. This possibly subjugates such studies to the “curse of dimensionality,” in which the limited data points compared to the thousands of unique features extracted from the biomechanical gait, including but not limited to the velocity, cadence, time, length, and swing, results in a reduced ability to generalize [47]. As SVMs work by finding an optimal separating hyperplane that maintains the maximum distance from all classes, this allows them to work better with smaller datasets because this distance prevents overfitting [48]. In addition, they rely on the points closest to the plane, called support vectors, which prevent them from being influenced by all data points and thus allow better generalizability. By using support vectors, SVMs are better able to capture overall patterns in the data and respond effectively to unseen observations.

In contrast, the Random Forest and Decision Tree algorithms performed the poorest overall, with both averaging an accuracy of 78.95%. This can be explained by the limited capacity of these models to handle the high dimensionality of gait data [17]. Decision trees are simple models that are best suited for numerical or categorical data, and are prone to overfitting when dealing with more complex data [49]. While random forest models are less likely to overfit, their performance tends to decline when the number of predictor variables is significantly larger than the number of observations, a characteristic common for the studies reviewed [50].

In general, camera-based approaches had a higher mean accuracy than studies that employed a sensor-based approach. Studies that used a camera to capture gait information had an overall mean of 92.05%, which is 24.09% higher than the mean accuracy of sensor-based studies, which had an overall 67.96%. This is supported by the Mann-Whitney U Test, a statistical test that is used to assess the difference between two independent groups, which in this instance, refers to the accuracies of the two respective approaches. Results confirmed that camera accuracies were statistically higher than sensor accuracies. The test yielded a p-value of 0.0032, which when compared against a conventional alpha level of 0.05, results in the rejection of the null hypothesis, instead suggesting that the camera-based approach has a significantly higher accuracy when compared to the sensor-based approach. Traditionally, camera-based approaches utilize motion capture technology, consisting of high-speed cameras and reflective markers to measure the biomechanical gait data of patients [51]. While this can yield a high number of possible spatiotemporal features for analysis and high model accuracy from such features, the resources needed for such an approach mean it is not currently feasible for clinical applications [52]. Kour et al. (2022) and Bosel et al. (2020), as explored within this review, have utilized simple 2-D video camera apparatus to gather biomechanical data, indicating possible areas for future inquiry [32, 30]. Recent exploration of inertial sensor-based methods presents a more clinically applicable approach, in which wearable sensor technology is used to track and measure patient biomechanical data outside of a laboratory setting [14]. However, this alternative often comes at the expense of quality and the number of features able to be collected [52]. As such, camera-based approaches offer high-quality data and a vast amount of possible features, resulting in a statistically higher model accuracy when compared to sensor-based approaches in this review. Yet it is important to note that sensor-based approaches provide other merits, such as possible wide-scale clinical application.

The Kruskal-Wallis Test was performed to determine if there was a statistically significant difference between the accuracies of five different algorithms. Due to the lack of statistical significance found when conducting the Kruskal-Wallis Test, these findings imply that the type of algorithm chosen is potentially less critical than other factors such as feature selection and the source of data. To support the latter point, the Mann-Whitney U Test highlighted a clear statistical significance between camera and sensor data, which underscores the importance of data sources in predictive accuracy. Although there isn't a statistical significance in model accuracies across different models, this does not imply that consideration in this aspect is arbitrary. As illustrated in the mean accuracies (Table 8), there are still differences shown between models based on their ability to handle high-dimensional data and their tendency to overfit. In addition, while these findings propose the usage of camera-based systems over sensors for KOA detection, it is important to acknowledge that the sample size used in the analysis was small and thus may not be completely reflective of all existing literature on the subject.

A common limitation among the studies reviewed in this article is overfitting due to small study cohorts. Overfitting occurs when a model fits too closely with its training data, preventing it from being able to make accurate predictions on new, unseen data. Since the small number of participants recruited in each study may not fully represent the diverse population of individuals who are affected or at risk of KOA, this can limit the ability for the results of these studies to be generalized to broader populations. Furthermore, almost all models developed were binary classifiers of symptomatic KOA, compared to only three models capable of multiclass classification of KOA severity. Kwon et al., 2020b, and Kwon et al., (2019) were two studies that created models capable of multiclass classification of KL severity (0-4) using biomechanical data [27, 36]. The former study utilized the integration of both radiographic features and gait parameters to achieve a relatively high model Area Under the Curve (AUC), ranging from 77.4% - 96.7% for the classification of KL scores between 0 - 4. This feat signifies a significant improvement on previous multiclass models, capable of an average accuracy of only 66.7%, when trained solely on radiographic data [53]. In addition, only two studies explored within this review focused on the prognosis projection of KOA, where the majority of studies instead focused on the initial diagnosis of KOA, largely attributed to the complex methodologies of associated studies [37]. However, recent prognosis-based literature has returned optimistic results, in which related models achieved an AUC of 0.73 [37]. All in all, while significant innovation has been achieved in biomechanical-based predictive models, there still exists room for future investigation and development.

The RMSE score for the Snyder et al. (2023) study was significantly lower than the RMSE score of the study conducted by Kwon et al. (2020a), which included both male and female subjects. This discrepancy can potentially be attributed to the fact that use of birth control reduces estrogen levels in women and thus can be an extraneous factor in the KOA detection being higher than normal.

Conclusions

The use of ML techniques in the diagnosis and prognosis of diseases has seen a surge in recent years. This review provides insight into the existing body of research around the implementation of ML in the diagnosis and prognosis prediction of KOA. One of the insights that emerged from this review concerns the importance of the data collection method in determining the accuracy of models, when compared to algorithm selection. Through the exploration of both camera-based and sensor-based approaches toward the collection of biomechanical data, statistical analysis demonstrated that camera-based approaches had on average significantly higher accuracies, of 92.05% compared to 67.96%. This knowledge can also guide further research directions toward optimizing data collection methods in sensors, possibly facilitating their implementation on a clinical scale. Moreover, current prognosis-based studies have average model performance, where alongside the shortage of such articles, indicate another area for future development. While improvements in model performance are necessary, the integration of ML in the diagnosis and prognosis prediction for KOA can facilitate early diagnosis of patients, helping patients get the treatment they need.

List of Abbreviations Used

ACC: accuracy
AUC: area under curve
CNN: convolutional neural network
CV: cross validation
DT: decision tree
ELM: extreme learning machine
IMU: inertial measurement unit
ITD: intrinsic time-scale
KNN: K-nearest neighbors
KOOS: knee injury and osteoarthritis outcome score
KL: Kellgren and Lawrence grading system
LSTM: long-short term memory
LR: logistic regression
LOOCV: leave one out cross validation
MCC: Matthews correlation coefficient
MLP: multi-layer perceptrons
NN: neural network
PRC: precision
PSR: phase space reconstruction
QOL: knee-related quality of life
RF: random forest
RQA: recurrence quantification analysis
SEN: sensitivity

SPF: specificity
SVM: support vector machine
XGB: XGBoost
6DOF: six-degrees of freedom

Conflicts of Interest

The authors declare that they have no conflict of interests.

Ethics Approval and/or Participant Consent

This study did not require ethics approval or participant consent as it is a systematic review and only considered secondary data.

Authors' Contributions

MZ: Made contributions to the design of the study, collected and screened data, analyzed studies, drafted the manuscript, and gave final approval of the version to be published.
SY: Made contributions to the design of the study, analyzed studies, conducted statistical tests on data, drafted the manuscript, and gave final approval of the version to be published.

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