



# A Survey of Knee Osteoarthritis Assessment Based on Gait

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## Abstract

In today's era of new advancements, diagnosing a pathology at an early stage has given rise to the development of automated diagnostic systems. Knee Osteoarthritis (KOA) being among one of the most painful joint disorders is the root cause for disability, particularly in elderly population. Gait based recognition of KOA is a prominent area that requires deliberations from the end of researchers, academicians and scientists to develop more automated systems that not only offer reliability and accuracy but are also affordable for common man. This article aims to provide an in-depth investigation of efforts directed towards vision-based, sensor-based and hybrid KOA identification. The study is based on the historical data gathered and background obtained viz-a-viz clinical gait analysis. An extensive survey of KOA gait acquisition modalities and feature representation approaches for the purpose of critically examining them are also presented. The study surveys the statistical metrics used for evaluating KOA, considering relevant articles. Based on the survey, this article aims to provide an up-to-date review of machine learning techniques for classification of KOA and healthy subjects. Furthermore, this article also identifies open research challenges existing in the literature that could be explored further for providing more effective KOA analysis. Finally, this article presents the future perspectives and provides an outline of the proposed work for efficient KOA diagnosis based on vision-based gait.

## 1 Introduction

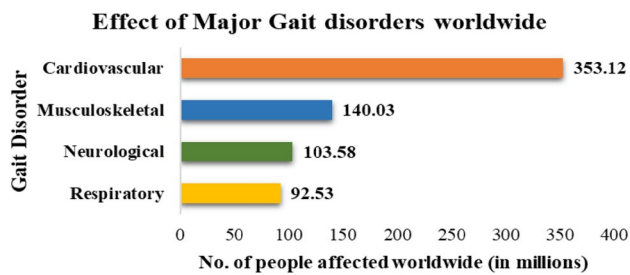
A biometric refers to the measurement of various characteristics of the human body that provides a unique identity to an individual. From recent years, a number of biometrics have been used for diagnostic purposes such as handwriting [1], voice [2–4], iris [5] etc. In the era of modern science and technology, gait as a biometric has gained high popularity in resolving a number of issues. Automating the process of gait analysis plays a vital role in two major application areas: identification of human (authentication purpose) [6, 7] and medical (disease detection) [8–11]. So, gait analysis is mainly concerned with recognizing the walking pattern of an individual using some quantitative measures. Due to distinctive characteristics in gait patterns, positive and negative deviations in a person's gait can be observed and efficiently investigated [12].

The term 'abnormal gait' is often used when a person loses the ability to walk normally. In clinical diagnosis,

human gait analysis can be employed for the identification of various disorders that lead to gait abnormality. Individuals with disturbed gait have altered speed, cadence, limb moments etc. [13, 14] in comparison to ones with a normal gait. Analysis of these abnormalities in gait conditions can provide an effective way of developing new treatment strategies [8] which can help people with better Quality of Life (QOL). Abnormal behavior in gait doesn't arise due to a single condition but involve several pathological diseases such as Musculoskeletal (joint pain, OA, injury) [15, 16], Neurological (Parkinson's, cerebral palsy, other sensory impairments) [17–19] and also diseased health conditions (obesity, respiratory problem, heart attack etc.) [20, 21]. The worldwide data has been provided by Roser et al. [22] on 'Burden of Disease' from (1990–2016) using 'Disability Adjusted Life Years' (DALYs). From all the diseases, we have included aforementioned disorders that may affect the gait of a person. The study revealed that amongst all the considered gait conditions, Musculoskeletal disorders (MSD) shows the highest growth rate after heart diseases as shown in Fig. 1. However, the overall growth rate of cardiovascular diseases seem to be higher but their effect on a person's gait is not tangible. Also, a study by Woolf [23] has revealed high occurrence and burden of MSD across the

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**Fig. 1** Comparative representation of some gait disorders affecting a large population, based on a study [22], measured using DALYs

globe in comparison to other diseases. Therefore, the study of MSDs is taken into consideration and occupy the focus area of study in this article.

MSDs are the conditions often characterized by chronic and long-term pain in any region of Musculoskeletal system (joints, tissues, nerves etc.). Presence of such painful situations hinder the flexibility, stability, mobility and other functional capabilities of a human body [24]. According to ‘Global Burden of Disease’ (GBD) [25], MSD was ranked second due to functional disability caused to the patient’s worldwide. The most common MSD includes Osteoarthritis (OA), injury (joint fracture), back and neck ache [24].

Based on study [26] from (1990–2010), an increase in about 45% abnormality was analyzed due to MSD (primarily due to OA). OA is the common joint disorder causing pain and inflammation in joints. The study [26] estimated OA to grow higher in the coming years with the rise in obesity, injury and aging like factors. Another GBD study [27] from (1990–2015) indicated a rise in OA from 33.6 to 36% (between 2005 and 2015), measured using ‘Years Lived with Disability’ (YLDs).

Recent studies on biomechanical causes in OA mostly focused on analyzing knee joint movement due to its simpler anatomy compared to other body joints [8]. An analysis by the study [28, 29] has shown about 3.8% Global-Age Standardization (GAS) prevalence of KOA higher among female population (about 18%) than males (approx. 9%) over 65 years. Vos et al. [30] reported growth of KOA on 250 million people on global disease survey. Further, KOA requires higher financial dependence for its diagnosis and treatment. Approximately 330\$ billion has been spent on KOA in the USA and further rise has been estimated [28].

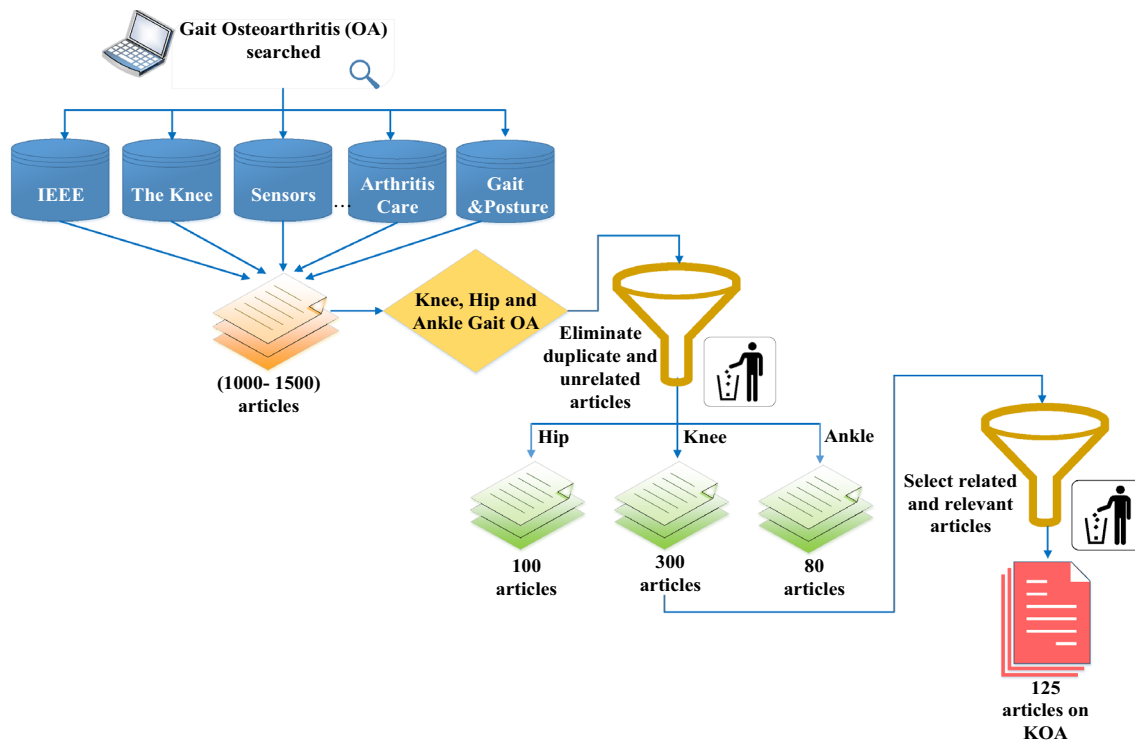
In the field of KOA diagnosis, the use of automated systems employing three types of gait acquisition modalities, i.e. vision-based, sensor-based and hybrid has been given more attention. Recently a study by Derek et al. [16] applied the combination of instrumented gait treadmill and retro-reflective markers to access differences among gait features of KOA and healthy subjects. The use of inverse dynamics successfully achieved an accuracy of 94–98%. The high

potential of hybrid modality for KOA has attracted more researchers towards this. An effort to analyze KOA gait using only sensor based modality was led by Kotti et al. [10] attained high accuracy. Towards vision-based KOA recognition, a commendable work was put forward by Ishikawa et al. [31] using model-based approach. Their study revealed the potential of planar law to measure gait variations. Similarly, the use of the Kinect sensor for KOA gait acquisition by Cui et al. [32] opened new doors towards vision-based model free modality and achieved an accuracy of 97%. Besides these research studies, certain Universities also contributed to the medical field. Recently, in 2018 University of United Kingdom (UK) developed sensor installed clothes for gait capture purposes [33].

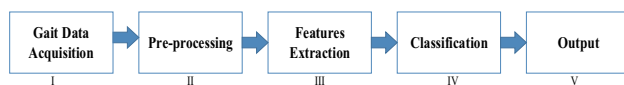
In spite of having huge benefits of vision and sensor-based KOA recognition, several issues have been observed by researchers which make KOA gait analysis a complicated task such as unavailability of KOA database, small sample size [12, 34–36], self-occlusion [37], focus on only few severity levels [16, 38–40], few gait parameters [11, 41] etc. Till now, most of these issues remain unsolved thus opening new research scope in the clinical diagnosis of KOA.

In this article, the entire focus is directed towards broader analysis of KOA considering gait biometric. A systematic review process of the articles is shown in Fig. 2. A literature survey has been performed using highly reputed journals including IEEE, Sensors, The Knee, Osteoarthritis and Cartilage, Gait and Posture, Clinical Biomechanics, Journal of Biomechanics, Advanced Robotics, Arthritis Care and Research etc. Articles are searched using different keywords. Keywords such as ‘osteoarthritis gait’, ‘knee osteoarthritis’, ‘clinical knee osteoarthritis’, ‘vision based KOA’, ‘sensor based KOA’ etc. are incorporated in the search box, also providing a range of years to be searched ‘2000–2018’. On specifying the search string to ‘OA gait’, approximately (1000–1500) articles have been obtained. Further limiting the search string by ‘area tag’ (e.g., knee, hip, ankle OA gait), most of the research articles found to be related with KOA. Finally, after eliminating duplicate and unrelated articles, a total of 125 relevant articles are considered that mainly focused KOA diagnosis based on gait.

The general framework followed for diagnosing KOA using clinical analysis involves five main stages i.e. (1) Gait data acquisition (2) Pre-processing (3) Feature Extraction (4) Classification (5) Output, shown in Fig. 3. Stage-I includes capturing of KOA and healthy subjects gait data using sensor-based [10, 42–44], vision-based [31, 32, 37] and hybrid [14, 36, 45, 46] modalities. In Stage-II, the acquired data is then pre-processed (frame extraction, noise filtering, etc.) to enhance the quality of data. For filtering of gait data, Butterworth (fourth order, zero phase lag) low-pass filter is used by most of the researchers [29, 31, 40, 47]. Stage-III involves acquiring of gait frames and extraction of relevant features



**Fig. 2** A demonstration of the complete systematic review process to obtain relevant KOA articles from (2000–2018), considering reputed journals



**Fig. 3** A pipeline depicting the diagnostic process of knee osteoarthritis (KOA)

such as speed, knee moments, velocity etc. for both KOA and normal subjects, optimized features are then selected using some techniques such as PCA [31] etc. In Stage-IV, the classification among KOA and healthy subjects is performed using statistical measures [42, 44] or machine learning techniques [41, 48]. Stage-V indicates the result of the diagnostic system for KOA diagnosis and accordingly provides a decision regarding the severity of the disease. The detailed description of the aforementioned stages (I, III, IV, and V) is provided in succeeding sections.

### 1.1 Contribution

There are some existing surveys done by different researchers that provided useful reviews on normal as well as pathological gait recognition. A recent review by Prakesh et al. [49] focused on different parameters (such as spatiotemporal, kinetic, kinematic etc.), approaches (vision, sensor-based and hybrid) that are used for human

gait recognition. They had also covered application areas and Machine learning techniques for human identification. Another review by Tao et al. [50] highlighted the efficiency of wearable sensors for gait analysis.

In the clinical field, a review by Herran et al. [51] focused the use of wearable and non-wearable systems and their applicability in diseased gait analysis. Another effort by Ali et al. [52] conducted a systematic review indicating the potential of vision and non-vision based sensors for abnormal gait rehabilitation.

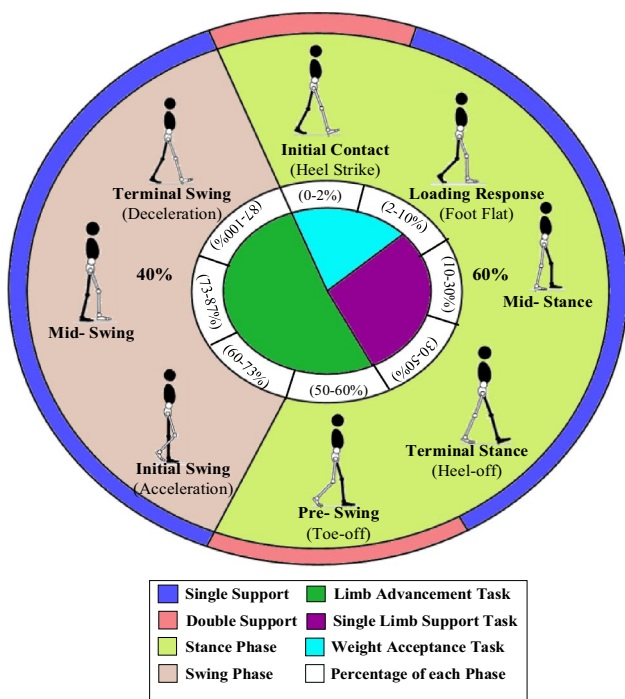
The aim of this article is to perform a systematic survey on different aspects of KOA based on gait. The objective of this article can be understood through the points mentioned under:

1. To the best of our knowledge, this is the first article which provides literature survey of KOA based on gait.
2. The paper comprehensively outlines the evolution of various techniques for clinical gait analysis from the year (2000–2018).
3. Investigated KOA considering more than 100 research articles from journals of repute.
4. The article exhaustively reviews several gait acquisition modalities for KOA, also highlighting their issues and their relative comparison.

5. The article provides a brief description of various performance evaluation statistical methods used for KOA analysis.
6. The paper inclusively surveys a number of KOA feature representation approaches, based on taxonomy shown in Fig. 13.

7. The paper provides an overview of machine learning techniques for the diagnosis of KOA.
8. The article also focuses on the future perspectives that need to be considered for reliable KOA diagnosis.
9. A concise description of the proposed workflow is also given in Fig. 19.

The paper is organized as follows; Sect. 2 presents an overview of human gait analysis including basics of human gait, history of clinical gait analysis and a brief description of Musculoskeletal disorders. Section 3 outlines the evolution of clinical gait analysis technologies. Section 4 describes KOA gait acquisition modalities. Further, feature representation approaches for KOA is defined in Sect. 5. Sections 6 and 7 illustrate evaluation methods and machine learning approaches for KOA analysis. Section 8 discusses future perspectives and proposed work is presented in Sect. 9. At last, Sect. 9 summarizes the whole article in the form of conclusion.

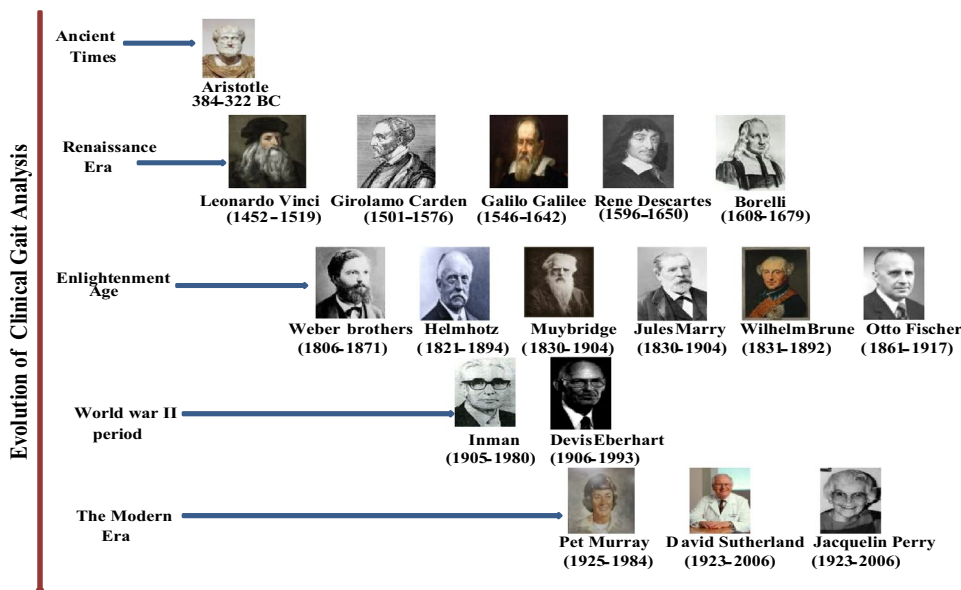


**Fig. 4** Phases and sub phases of the human gait cycle considering the right leg as Ref. [54, 55]. At the bottom, the box indicates the meaning of each color used in the figure

## 2 Overview to Human Gait Analysis

Gait defines the style of walking of humans as well as animals. Human gait analysis is more primarily concerned with the study of human kinetics employing both subjective such as eye and brain of the viewer as well as objective assessment i.e. using various devices and techniques for calculating gesture of body, muscles action and body mechanics [53]. Along with security and clinical applications, gait analysis can be applied in identification of risk injuries (Sports), Robotics research, Rehabilitation etc. In recent years there has been a great interest among researchers and scholars

**Fig. 5** Major contributions in the history of clinical gait analysis. The left side represents the evolution of gait in clinical analysis from Ancient times to The Modern Era. At the right side, key contributors are shown. Some images in this and other figures are from the internet. URL's are provided in "Appendix"



to understand, identify and intellectualize the concepts of biometrics in the field of medicine. By analyzing the walking pattern of a patient clinically, it is possible to perform an early diagnosis of various diseases and accurate differentiation of normal and abnormal subjects. This section provides the description of human gait basics including gait cycle, history of clinical gait analysis and a brief illustration of Musculoskeletal disorders focusing primarily on Knee Osteoarthritis (KOA).

## 2.1 Basics of Human Gait

In a normal human being, gait activity occurs smoothly using two limbs where one limb supports another without losing balance. However, this simple looking walking involves complex events. These events happen in a sequence which repeats itself to create ambulation and forms the gait cycle. In this section, an explanation of phases and sub-phases involved in human gait cycle is presented (using different colors) in Fig. 4. Also, brief detail about percentage contribution of each phase in total gait cycle is provided.

### 1. Human gait cycle

Taking right leg as reference, the period initiating from heel strike of one extremity (right) to the occurrence of the same event of other lower extremity (left), is named as Gait Cycle [54]. On the other hand, if it ends with other lower extremity different from that of starting one, is known as Stride. Three essential combination of human body parts-lower extremity, pelvis and spinal column are responsible for the occurrence of the gait cycle [49].

Typically, Gait cycle is divided into two principle phases namely Stance Phase and Swing Phase. Stance phase means in-touch with the ground, i.e. when foot remains in contact with the floor (lime color), as shown in Fig. 4. It shares about 60% in forming the gait cycle. On the completion of the Stance phase, immediately foot goes in the air (away from the ground) referred to as Swing Phase (tan). It contributes almost 40% in the gait cycle. So, the whole summation of above two phases makes a complete gait cycle [56]. In total, Perry et al. [55] divided gait cycle into eight sub-phases out of which first five belongs to Stance phase and remaining three to Swing phase, implies in Fig. 4. The subsequent aggregation of all phases attain three important tasks-Weight Acceptance (WA) (aqua), Single Limb Support (SLS) (dark purple) and Limb Advancement (LA) (green) [49, 54].

First two sub-phases of Stance phase are: Initial Contact also known as heel Strike, occurs when the foot first touches the ground and contributes nearly (0–2%) of the gait cycle. The second one is Loading Response also known as foot flat, in which the whole weight has to be acknowledged by the reference leg. When this phase takes place, foot become flat

and shares (2–10%) of the total gait cycle. These two sub-phases lead to the accomplishment of the first task i.e. WA.

Then the next two (third and fourth) sub-phases of Stance phase begins-specifically Mid-Stance, which represents the midway of the whole Stance phase. It starts when the limb other than reference leg is raised and maintained over the forefoot and covers about (10–30%) of the gait cycle. Another phase i.e. Terminal Stance (heel-off) indicates that the heel is actually trying to leave the floor and adds (30–50%) of the gait cycle. These two sub-phases of Stance phase completes the second task of (SLS). Final (fifth) sub-phase of stance phase: Pre-Swing (toe-off) occurs when toe leaves the ground and forms (50–60%) in the gait cycle. This phase initiates last task i.e. (LA) and is continued through three (sixth, seventh and eighth) other sub-phases of Swing phase.

In Swing phase, Initial Swing is considered as the first sub-phase in which the person tries to accelerate the extremity ahead and shares (60–70%) of the total gait cycle. Likewise, mid-stance phase of stance phase, other phase known as Mid-Swing referred as the midpoint of Swing phase and shares (73–87%) of the gait cycle.

Following the Mid-Swing phase, the last phase of Swing phase i.e. Terminal Swing occurs. In this phase, an effort is made to stop the limb for next heel strike for the preparation of next Stance phase and commit (87–100%) of total gait cycle [49, 54]. The Period of Double support (DS) can be seen in first and fifth phase (rose) while the period of Single Support (SS) extends from second to the fourth phase and continued from sixth to eighth phase (blue), shown in Fig. 4. Therefore, the gait cycle plays a vital role in the identification of individual gait patterns either normal or with some pathological disorder such as KOA.

## 2.2 History of Clinical Gait Analysis

The understanding of walking developed today is not influenced by a single era of study but involves a long history. How does walking happen? What are the parameters and phases involved in it? People have been reasoning since the earlier times [57]. In this section, the information about work done in the medical area from Ancient times to The Modern Era, by some major contributors is provided and summarized in Fig. 5.

In Ancient era, by raising certain relevant queries about the manner of walking of human beings, Aristotle (384–322 BC) [57, 58] has set the basis for further evaluation in gait analysis and became the first person who contributed towards gait by giving his work in ‘Gait of Animals’. He examined and outlined the human movements based on which various new theories developed on human and animal’s locomotion.



After Aristotle's work, during the Renaissance era, Vinci (1452–1519) [58] focused on the mechanics of the human body during different activities such as walking, upstanding etc. Cardano (1501–1576) [58] contributed his work towards human body's 3D joint angles to analyze the movement. Then the concept of modern scientific methods was put forward by Galilei (1546–1642) [57, 58] who was a physician. Similarly, another work by Descartes (1596–1650) [57] on Cartesian coordinates added a new advancement in the assessment of clinical gait. Out of all the related work done during renaissance era, one of the tremendous contributions was laid by Borelli et al. (1608–1679) [57–59] on 'Motion of Animals' and is considered as the first researcher to conduct experiments on gait analysis. Borelli's study on muscle movements and body mechanics came with a new conclusion that external load applied to muscles is considerably less than the forces between the muscles.

After that, the age of enlightenment began with the work of Weber brothers (1806–1871) [57, 60]. They were the first to inspect the human gait analysis in 'Mechanics of Human Walking Tools' (Mechanik der Menschlichen Gelerzeuge). Their efforts towards constructing a model to give a clear description of the behavior of limbs at different time and relationship between variations in step length and cadence provided great insight in clinical gait assessment.

Afterward, Helmholtz (1821–1894) and Carlet (1845–1892) [58] has carried their researches and involvement towards this field also shown in Fig. 5. Muybridge et al. (1830–1904) [61] and Marey et al. (1830–1904) [62] contributed substantially to this new findings and developing field of gait biometric by giving their work in 'The Human Figure in Motion' and 'Animal Mechanics'. Muybridge (a leading American photographer) used his photography techniques to capture gait. Later Marey's efforts to capture several images on a single photographic plate by developing a shutter had successfully overcome the Muybridge's flaws and used it for pathological gait study [62].

In the same era, Braune (1831–1892) and Fischer (1861–1917) [58, 63] became the first to direct the tridimensional mathematical investigation of human gait and their effort published in the book 'Der Gang des Menschen' (1895–1904). They made an effort to study mass, volume and center of mass for three male adults and also enhanced the use of regression equations to estimate various parameters of the body.

Gait analysis in the clinical application set up great strides in later half of the twentieth century [64]. In the period of World War II, Inman (1905–1980) [65] and Eberhart (1906–1993) [66] emerged with new and splendid understanding concerning to human locomotion. Their aim was to treat world war retired soldiers for providing gait rehabilitation to them.

At the end of World War II, Murray (1925–1984) [58, 67] was the first researcher to quantify the kinematics of body segment in more than one plane during walking. She made intriguing research for worldwide studies in the medical field. The concept of interrupted lights was used to capture the gait of 60 normal males in both sagittal and traverse plane [57].

In the modern century, major contributions to the development of clinical gait have been made by two surgeons namely Sutherland and Perry (1923–2006) [57]. Development of Electromyography (EMG) electrodes by Sutherland [58] for gait measurement using EMG proved to be a successful tool for disease investigation in clinical research. They established the gait enquiry library [64] and have also given division in the phases of the gait cycle.

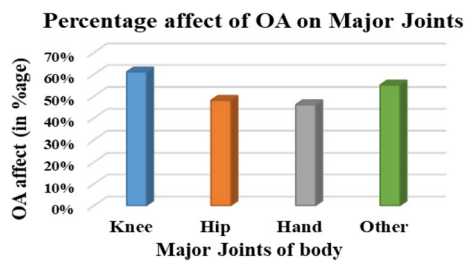
Therefore, clinical gait analysis has emerged as a new area for academia and researchers to produce more investigative outcomes towards early detection of the disease.

### 2.3 Overview of Musculoskeletal Disorders (MSD): KOA

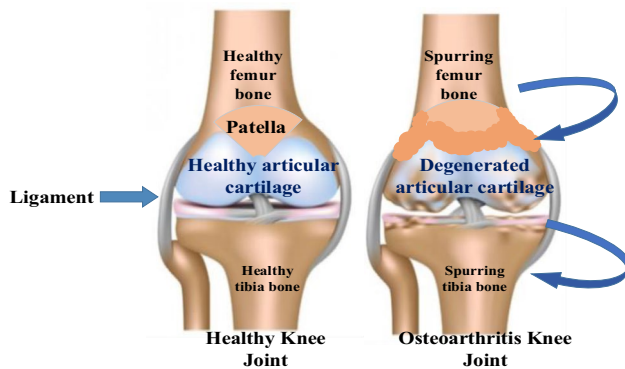
The human body is just like a network that consists of bones, joints, muscles, nerves, other tissues and supporting structures collectively named as Musculoskeletal System (MSS) [68]. The occurrence of any condition (e.g. injury, physical abnormality) which directly or indirectly affects the parts of such system, is termed as Musculoskeletal disorders (MSD) such as arthritis, Osteoporosis, back pain etc. [69]. These disorders causes pain and effects the walking of a person.

This section provides a brief outline of MSD, giving special preference to Osteoarthritis (OA) considering knee i.e. Knee osteoarthritis (KOA), affecting a large population. Arthritis is a MSD that mainly causes inflammation of joints and besides affecting older population, children and young people are also prone to the disease [70]. Among all arthritis's (such as Osteoarthritis (OA), Rheumatoid Arthritis (RA), Gout etc.), OA is the most common type degrading people lives gradually. In a systematic analysis on the global burden of disease study from (1990–2016) [71], it is analyzed that OA shows a high rise in affecting population between the period 2006 and 2016 i.e. 31.5% as compared to other types of arthritis and MSD's. OA typically referred to as degenerative joint disorder/wear and tear disease [64, 72, 73] initially begins with affecting a few joints (medial compartment) and when progresses to severe stages, it destroys other joints of the body including knee, hip, hand, feet and spine [70]. In OA, the joint becomes unstable and loses its range of movement, even then many people do not complain about pain in that joint. Thus, diagnosing OA in early stages is a very difficult task [70].

A 2012 study by Turkievicz et al. [74] investigated the present and future effect of OA on healthcare considering



**Fig. 6** Representation of percentage effect of OA on various joints of the body including knee, hip, hand and other, based on study [74]



**Fig. 7** A pictorial view of healthy unaffected knee joint (left) and knee joint affected by OA (right) [78]

OA population aged greater than 45. The analysis reveals that out of three most effected joints of the body i.e. knee, hip and hand, greater effect was seen on the knee (almost 61%) followed by the hip joint (48%). Hand OA contributed 46% and 55% by other joints (shoulder, ankle, elbow, foot, jaw and polyarthritis nodes) as shown in Fig. 6.

Another study by Gabriel et al. [75] has provided an evidence of knee as the most affected joint attacked by OA compared to hip and hand joints. KOA is a very common cause of gait disorder that affects whole joint [76] and leads to serious treatment such as Total Knee Replacement (TKR) [77].

A joint basically provides a point where two bones meet and are held by a fibrous elastic tissue known as ligament. Figure 7 gives a visual description of differences between a healthy and OA knee joint. In the knee joint, two bones namely femur and tibia are connected with the help of ligament. In a healthy knee (left), cartilage prevents two bones from sliding each-other by providing joint space. Also synovial fluid provides nourishment to the bone and helps in normal walking. When KOA occurs, healthy articular cartilage starts deteriorating, get reduced, become hard and rough, ends of bone swells and take knobby shape [70] as shown in Fig. 7 (right). Also, synovial membrane thickens increasing the amount of synovial fluid which starts releasing toxin substances and reduces joint

space between two bones. As a result of which, during walking, bones rub each other and cause pain to a person.

The causes behind occurrence of KOA still remain hidden. However, some factors such as obesity, aging, excessive joint load, injury can be considered as its main causes [76]. Several studies have revealed that aging is the important risk factor that contributes to KOA and women are more prone to the disease than men [69]. In a health 2000 Examination survey [76], it was concluded that persons with age group (55–74) and mostly females frequently comes under the effect of KOA [70]. The reason may be more susceptibility of KOA for degradation and damage of cells [77].

Therefore, In KOA, destruction of knee joint leads to an abnormal gait, referred to as Antalgic gait. A person with this gait try to put less load on the more affected knee to avoid pain thus have more swing than stance phase in gait cycle [79].

### 1. Clinical Measurements for KOA Diagnosis

In Clinical diagnosis of KOA, radiographs (X-rays, MRI) of a patient's knee gives the evidence of the presence or absence of KOA. Once diagnosing its presence, doctors grade the disease on some clinical radiograph classification systems to assess its severity. Currently, there are almost 30 such systems available to grade KOA severity including Kellgren-Lawrence Scale (K–L scale), Visual Analogue Scale (VAS), Knee injury and Osteoarthritis Outcome Score (KOOS), SF-36 questionnaire, Western Ontario and McMaster Universities Osteoarthritis Index (WOMAC), Boston Leeds OA Knee Score (BLOKS) etc. Amongst the existing grading scales, K–L scale is typically used for assessment of KOA severity by assigning grades from 0 to 4, due to its easiness in understanding and usage [76]. The whole description about the meaning of each grade in K–L scale is presented in Table 1.

However, the use of these clinical grading measures for KOA seems to be good but only involves subjective assessment. Radiographic scores and patients reported pain need not to correlate with each-other that leads to an inaccurate diagnosis of KOA. Therefore, objective and quantitative measurements of KOA should be performed for proper diagnosis of KOA. Using gait as a measure for KOA, can provide a Quality of Life (QOL) to people suffering from KOA and help in gait rehabilitation.

## 3 Evolution of Technologies for Clinical Gait Analysis

A technology refers to equipment or device evolved from technical knowledge in order to solve numerous problems. Due to its larger benefits, one of its application areas is in

**Table 1** Meaning of different scores for grading OA (knee) severity according to Kellgren–Lawrence Scale (K–L scale) [8, 76, 80]

K–L scale grades	Meaning
Grade 0-no OA	No evidence of the presence of radiographic OA
Grade 1-unsure OA	Doubtful joint space reduction, possible development of osteophytes
Grade 2-mild OA	Possible joint space lessening and sure osteophyte formation
Grade 3-moderate OA	Definite joint space narrowing, multiple osteophytes, and some sclerosis
Grade 4-severe OA	Higher osteophytes, severe sclerosis and sure bone deformity

medical for recognition of a disease efficiently. This section provides a brief description of the evolution of numerous technologies invented by different researchers from ancient time to modern era [81] and are used for clinical gait analysis. Figure 8 provides a visual representation of technologies developed from the 1800s to 2018.

The foundation of clinical gait analysis was led by efforts of Braune and Fischer [82] in the 1800s, by applying Geissler tubes. They focused on determining individual joint angles such as flexion, extension, adduction, abduction etc. using the idea of differences in angular rotation of joints and body segments that differentiates a normal gait from an abnormal one. The use of Geissler tubes however shown efficiency in estimating kinetic data of subject but required a large number of hours for patients gait acquisition and further calculations. Another advancement in this area was made by Carlet [57] (student of Jules Marey) in (1849–1892). Carlet developed insole pressure shoes with the aim to perform Ground Reaction Force (GRF's) measurements when foot of the subject comes in contact with the ground.

Afterward, in the 1940s Elbeherdt and Iman [66, 82] took forward the clinical research by using the principle of interrupted lights. The joint angles were calculated by a series of dots formed by slotted plates/disks rotating in front of the camera at fixed intervals of time. Since these angles were manually computed so it was not appropriate for medical applications. Both Geissler tube and interrupted light methods were based on old photography. The discipline of gait enquiry was then lifted ahead by Inman and Colleagues [81] in (1944–1947) with the invention of Kinesiological Electromyography (KEMG). They employed KEMG in combination with 3-Dimensional (3D) force to investigate the muscle movements and strength between normal subject and the ones with the disorder. Abnormal interrupted lights activity potential was then analyzed using a system known as Electromyographs. The used procedure though helped in reducing the synchronization error [81] but the insertion of electrodes in the body to measure EMG signals was very painful for the subjects. In the 1950s, Goddard [81, 83] had revolutionized the world of clinical gait analysis by introducing inertial sensors i.e. accelerometers, gyroscopes etc. These Inertial Measurement Units (IMU's) were fixed to different body parts of subjects in order to compute the

linear acceleration as well as the angular position of the body. However, these units had high potential in capturing sufficient clinical gait data but was bulky, expensive and caused difficulty to subjects in wearing IMU's.

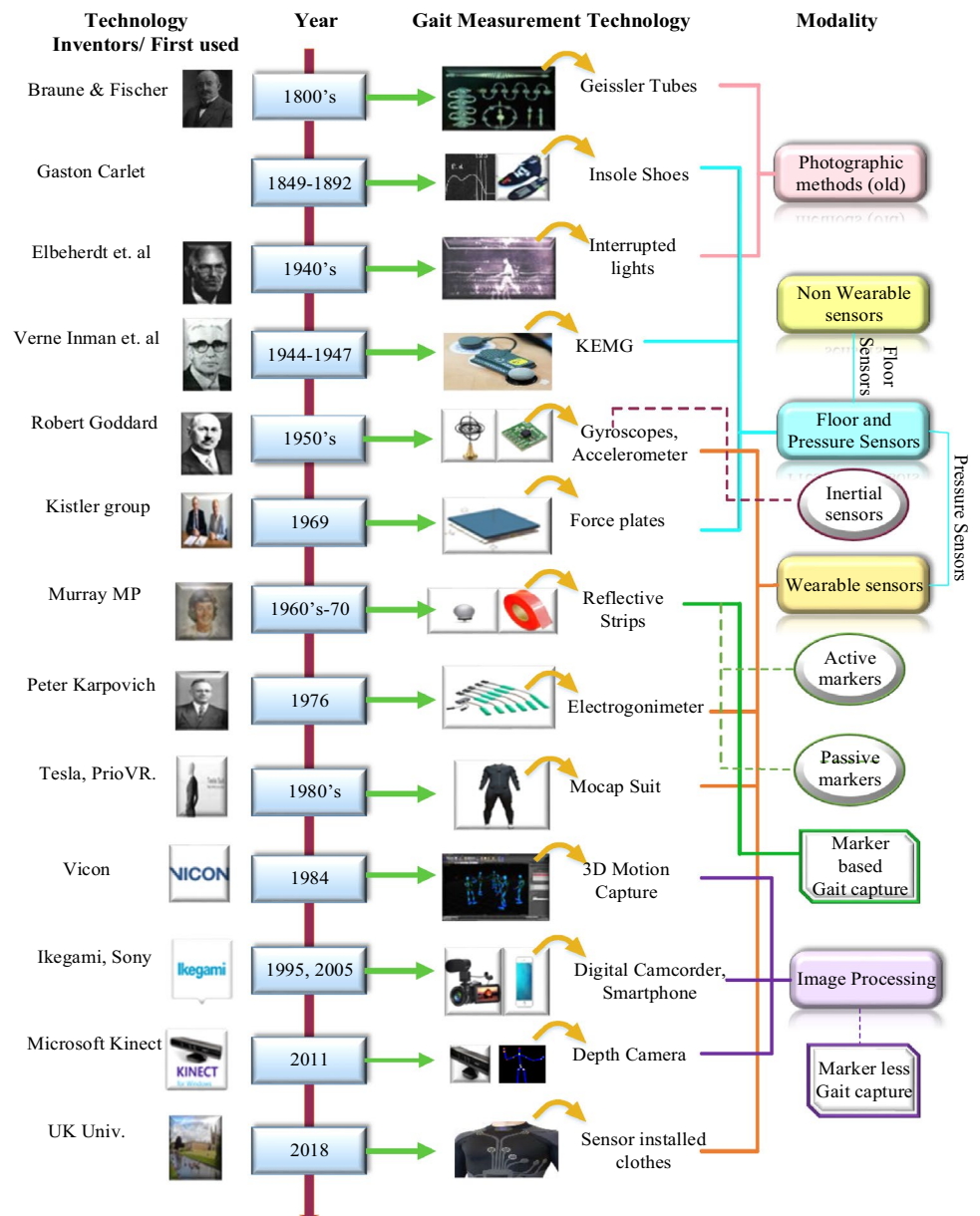
Afterwards, a new technology emerged that has changed the face of clinical gait analysis i.e. Kistler force plates. These force plates were launched by Kistler group [57, 64] in 1969 to measure GRF's from the surface. These devices had the ability to acquire total XY and vertical forces conveyed by foot while walking. The invention of KEMG, insole pressure shoes, and force plates constitute force and pressure sensors which in turn are wearable (e.g. insole shoes) and non-wearable (e.g. Kistler plates) shown in Fig. 8. The name of a great researcher Murray [82] gave a new insight to this area by inventing an effective, easily employable and low-cost technology of retro reflective strips in the 1960s–1970s. Reflective markers (either passive-covered with retro-reflective material or active-LED's itself) were devices attached to different parts of the human body which then acts as landmarks to calculate the joint angles from photographs taken. Measurements were performed by connecting these stripes to body extremities of normal (men, women) and pathological diseased patients. This technology contributed towards marker-based gait capture [84].

In 1976, the very first researcher to make use of the electrogoniometer technique to enable joint angles recording in an easy way was Karpovics brothers [82]. The main advantage was its cost-effectiveness and its ability to continuously measure joint angles. Afterward, in the 1980s Motion capture suit shortly known as Mocap suit [85] was developed by Virtual Programming languages (VPL) that was competent enough to record the actions of the wearer. Other companies had also put forward this technology into a new form such as Tesla, prior Virtual reality (VR) etc. in the market.

In 1984, one of the eminent technologies was founded by Vicon [64] which enabled acquiring and capturing the 3D motion. Vicon was chiefly the video-based motion capture system to reflect infrared light of passive targets attached to the area of interest on the body. In the period of (1995–2005) Digital camcorders and Smartphone's [64] had completely modernized the world. This discovery (by Sony, Ikegami etc.) made it easier to capture the motion of the human body with high accuracy and reliability. Mobile devices such as smartphones have been used to use the accelerometer data.



**Fig. 8** A Visual Representation of the evolution of various technologies for clinical gait analysis. Left side depicts the name of the inventor with the year and the right side shows a list of clinical gait measurement technologies and types of modality under which they fall



Research towards the medical field didn't stop here but a new technology was put forward by Microsoft (MS) Kinect with the invention of the depth camera in 2011 [64]. This device had the capability to capture only that portion of the body in which the researcher was interested by constructing a skeleton structure of the body. The three technologies discussed earlier i.e. Vicon 3D Motion system, Digital camcorders, Smartphone's and depth camera were based on the concept of image processing. They directly capture gait of a patient without the use of markers on the body thus known as mark-less motion capture technology.

Recently in 2018, a new sensor installed clothes have been developed by the researchers in the University of

UK [33] for clinical gait assessment. These clothes are equipped with highly specialized internal sensors to access the entire motion of the body. This new invention contributed immensely towards the enhancement of clinical research. The technologies such as inertial sensors, electrogoniometer, Mocap suit and sensor installed clothes are wearable sensors i.e. in order to use them, it is necessary to attach them to the subject's body.

Therefore, invention and development of the abundant technologies have opened new doors towards medical applications for diagnosis of various gait disorders such as Musculoskeletal, neurological diseases etc. The detailed explanation of all the technologies is presented in Sect. 4.

## 4 Gait Acquisition Modalities for Diagnosis of Knee Osteoarthritis (KOA)

Data acquisition primarily defines the process of collecting sufficient information using different modalities. The success of a system relies on this acquired data. A modality is simply the way through which relevant data can be obtained. One of its major roles can be seen in capturing clinical gait of people suffering from KOA. In recent years, a number of KOA gait acquisition modalities have been developed based on different gait parameters such as Knee Adduction Moment (KAM), Knee Flexion Moment (KFM) etc. that enabled KOA effective diagnosis. Data acquisition in KOA is based on the technologies discussed in Sect. 3.

In this section, a systematic description about various KOA gait acquisition modalities from recent 15 years is summarized in Tables 2 and 3, based on proposed hierarchical taxonomy shown in Fig. 10. To get deep insight through these modalities, a complete illustration of each is presented. In this article, KOA acquisition modalities are classified into three broad categories namely Vision-Based, Sensor-Based and Combined/Hybrid. Approx. 125 research articles are found on KOA from 2004 to 2018, out of which 90 are based on Hybrid modality, 32 are Sensor-based and rest are Vision based, shown in Fig. 9.

### 4.1 Vision-Based

Since assessing an individual's gait with naked eyes is very challenging, the use of an optoelectronic system is required [52]. Vision-based modality make use of the analog or digital camera to capture and analyze the gait cycle. Once KOA gait is acquired, digital image processing techniques such as Time-of-Flight (TOF) and several methods including threshold, range imaging, background subtraction are used to perform measurements on recorded gait data [51]. This modality is further classified into two major sub-categories based on the use of markers i.e. model-based and model-free, shown in Fig. 10.

#### 4.1.1 Model-Based

This modality is based on modeling the human body to extract relevant KOA clinical gait. Initially, a set of retro-reflective markers is fastened to the human body which provides the position of indicator points to determine angles of joints. Then a video-based optoelectronic system such as VICON, Polaris etc. is employed to detect the location of indicated body landmarks [108]. Retro-reflective markers thus used for this purpose are categorized into two classes [49]:

- (i) *Passive markers* These are the spherical, rounded or square devices coated by a reflective scotch lite tape layers. On emitting light by LED's equipped camera, these devices reflect the light back indicating the position of body landmarks.
- (ii) *Active markers* These markers are LED's itself that are attached to the subject's body and releases light. Infrared light signals are released by the camera to determine the backscattering produced by LED's markers giving the exact location and position of landmarks on the body.

Ishikawa et al. [31] proposed a study with an objective to analyze the angle of elevation made by KOA patients and healthy controls during walking. They employed an eight markers plug-in-gait marker set and a nine cameras VICON Mocap system. Results demonstrated the applicability of planar law to patients and achieved increased accuracy- $0.69 \pm 0.14$ , (Area under Curve) AUC- $0.69 \pm 0.767$ , precision =  $0.84 \pm 0.23$ , recall- $0.57 \pm 0.26$ , F-measure- $0.66 \pm 0.15$  than previous method and Threshold =  $8.56 \pm 1.80$ .

Model-based modalities however, achieve high accuracy by giving correct location of body landmarks but require the use of controlled and complex laboratories to achieve KOA gait acquisition purpose.

#### 4.1.2 Model Free

To overcome the limitations of model-based modality, model-free also known as holistic or appearance based modality has been developed. Model-free modality doesn't employ markers on patient's body but only utilizes a single video camera such as Kinect V2 etc. to capture KOA gait. Existing details about the subject's body are not required and the main focus is given to shape, observing the point of camera and appearance. Firstly, videos are captured using a camera and then background subtraction is done to extract the silhouette image in order to again capture again shape and motion parameters [108].

Verlekar et al. [37] developed a single 2D video camera based system to allow automatic diagnosis and classification of gait pathologies using foot (step length and symmetry, foot fraction, normalized step count, speed) and body (amount of movement during gait, the center of gravity shifts and trunk orientation) related features. The proposed system using Support Vector Machine (SVM) outperformed the existing markerless two-dimensional (2D) video-based systems by attaining an accuracy of 98.8% and proved its reliability in the diagnosis of different pathologies including the knee. Though system achieved high accuracy but was susceptible to some flaws such as inability to analyze

**Table 2** Shows sensor-based gait capturing modality used for KOA recognition with accuracy rate

S. no.	References/year	Acq. sensors				Resource	Dataset	Accuracy	Key findings	Remarks
		F	I	EM	EG O					
1	M.Kotti et al. [10]/2017	✓				Two kistler force plates Piezoelectric F	47 KOA subjects and 47 HC	72.61% ± 4.24%	Rule based (Random forest) approach can be used for reliable clinical measure	Less than half of subject's tested for KOA No validation of method against X-rays
2	A. Elbaz et al. [44]/2014	✓				A walking mat (GaitMatIII system)	2911 KOA patients	89.5% for F 90.8% for M	Proposed method correlates with radiographic evaluation, level of pain, function and TKR	Conducted only SPT gait analysis BMI and age were excluded
3	Collins et al. [86]/2011	✓				A force plate An electromagnetic tracker	35 KOA subjects	-	Increased knee flexion and reduced KAM in KOA	Tested only subjects with medial knee OA
4	Liikavaio et al. [87]/2010	✓	✓	✓		3 triaxial accelerometers 2 force plates Bipolar S-electrodes	54 M with KOA, 53 HC	-	SMA and GRF parameters exhibited only minor diff. between two groups	Only males were recruited No calculation for preferred gait speed
5	Moustakidis et al. [88]/2010	✓				Bertec platform	24 patients with KOA, 12 HC	93.44%	Results demonstrated the efficacy of proposed approach	Impact of speed on KOA was not investigated
6	Ronen D et al. [11]/2009	✓				Awalking mat (GaitRite system)	45 M and 85 F with KOA	-	Gender differences indicated significant changes in gait patterns	Kinetic analysis of patients was not performed -Consideration of only bilateral KOA
7	Neila M et al. [89]/2008	✓				Integration of 2 kistler force platforms and treadmill	42 participants (16 HC, 26 KOA)	91%	Wavelet representation revealed its validity for classification	Availability of only small samples of GRF measurements
8	Pazit L et al. [34]/2007	✓				A Kistler force platform	13 with PFPS, 5 KOA, 20 TKR	85–92%	SVM showed high efficiency in recognizing pathological gait changes.	Small number of OA patients
9	John et al. [90]/2004	✓		✓		A force platform S-EMG electrodes Eelectromagnetic Mocap's	24 KOA subjects, 24 HC	-	Results depicted KOA subjects have less excursion, reduced peak GRF's	Utilized large no of devices -Load distribution was not calculated
10	Dylan et al. [15]/2017	✓	✓			4 synchronized IMU's A level treadmill	39 KOA adults	81.7% with 3 sensors 80.0% with 2 sensors	Simplified two sensor solution provided best ideal configuration	Only focused hip strengthening exercise interventions Additional data collection was required

Table 2 (continued)

S. no.	References/year	Acq. sensors				Resource	Dataset	Accuracy	Key findings	Remarks
		F	I	EM	EG O					
11	Kun.H et al. [91]/2015	✓		✓		3 OPAMI A goniometer	10 HC(5 M, 5 F)	Exercise: 97.29% Pos- ture: 88.26%	Proposed mechanism was feasible in clinical health intervention	HC were experimented only System's perfor- mance can be affected by changing sensor wearing posture
12	Ana T et al. [92]/2015	✓				2 I 3 walkers	11 KOA patients (3 M, 8 F)		SW and RFS provided best stability and gait closer to normal ones	High risk of error may caused due to neglect- tance of instructions to patients for using walkers
13	L Atallah et al. [93]/2014	✓	✓			A light weight ear worm IS 2 force plates, a tread- mill	14 HC, 50 with knee and hip OA		Proposed method had feasibility in real life environment for diagnosis	Use of controlled, fixed speed -High mis- match between ages of patient's and HC
14	Ian M.C et al. [94]/2013	✓				4 IMU's	23 KOA patients, 21 HC	Specificity: 0.783 Sen- sitivity: 0.952	Results depicted sig- nificant differences between both groups	Evaluation of knee joint structural changes were missing
15	Stijn B et al. [95]/2012	✓				A 3D I	20 KOA, 30 HC		Measures of time yielded highest capa- bility to differences between groups show- ing reliability of I	Underestimation problem
16	Brunton et al. [42]/2012	✓				A 3D I	20 HC, 40 with hip and KOA		Gait parameters only moderately correlated with classic outcome scores.	Considered only few gait parameters
17	Hubley-Kozey et al. [43]/2015		✓			S-EMG electrodes	38 KOA, 41 HC		Moment and speed was altered between ses- sions of both groups	Mismatch between ages of both groups
18	Tine et al. [96]/2015		✓	✓		Bipolar S-EMG elec- trodes 2 EGM's	11 F KOA, 11 F as HC		H-reflex was seen as important measure for analysis	Small Sample size
19	Hubley-Kozey et al. [97]/2008		✓			Silver chloride S-EMG electrodes	51 KOA subjects	Variance = 97%	Technique used provided a novel approach to quantify synergistic co-activity	Involved complex pro- cedure
20	Shari et al. [98]/2007		✓			Surface, needle EMG A Kin COM dynamom- eter Tera record- ing electrodes -A pedometer	21KOA subjects, 18 HC		Results indicated lower knee ext. strength and S-EMG amplitude in KOA but high muscle force	Involved only tibiofemo- ral knee joint



**Table 2** (continued)

S. no.	References/year	Acq. sensors				Resource	Dataset	Accuracy	Key findings	Remarks
		F	I	EM	O					
21	Daniela et al. [12]/2013		✓			2 Electrogoniometers Arduino Mega 2560 plate	5 KOA patients, 7 HC	–	KOA subjects had less max flexion (69.01°) and max amplitude (51.73°) than healthy ones	Very small sample size Effect of speed on gait biomechanics was not discovered
22	M.M et al. [48]/2017		✓			8 Insole sensors	14 KOA patients, 14 HC	SVM-100% LR-95% MLP-95% TBC-100%	Tree based classifiers (TBC) showed high potential for classifying both groups	Need to validate long term benefits of study
23	H. Arita et al. [99]/2016		✓			Insole type pressure sensor	22 KOA patients	–	Positive correlation of gait speed, TUG and negative correlation of step length, KFA with JKOM total score	Experimented only severe KOA patients
24	Jeroen et al. [100]/2013		✓			A Smart garment with ACS	10 volunteers	RMSE = 1° MAE = 3°R <sup>2</sup> > 0.99	ACS shown potential in long-term clinical monitoring	Doesn't offer high standard of information as dynamic assessment
25	Rita et al. [101]/2011		✓			Zebiris CMS-HS Ultra-sound based triplets A treadmill	20 HC, 90 KOA patients	–	KOA gait variability is gender dependent	Involved only SPT gait data Didn't consider mild KOA

Acronym of words used in table: Floor sensor (F), Inertial Sensor (I), Electromyography (EM), Electrogoniometer sensors (EG), Other sensors (O), Male (M), Female (F), Knee Osteoarthritis (KOA), Healthy Control (HC), RMSE (Root Mean Square Error)

**Table 3** Shows Combined KOA gait acquisition modality with accuracy rate

S. no.	References/year	Resource	Dataset	Accuracy	Key findings	Remarks
1	Derek et al. [16]/2018	Retroreflective spheres Dual belt treadmill (GaitRite™)	74 moderate KOA subjects	94%-98%	Both CP and ID had high potential to calculate knee moment outcomes	Only moderate severity was considered
2	Metcalfe et al. [102]/2017	Plug-in gait marker set 12 Vicon MX2 cameras 3 AMTI force plates	20 KOA, 20 HC	OA and normal Knee: 95%, 92.5%	Focused rehabilitation proved to be useful to optimize outcomes	Selection of people with only single joint disease
3	Jun Sun et al. [103]/2017	24 reflective markers IDEEA3 GO Pro Hero3	23 KOA patients, 12 HC	–	Results showed the reliability of IDEEA3 for efficient use in KOA analysis	Restricted motion analysis system recording space
4	Angkoon et al. [41]/2016	8 camera Vicon Mocap system 9-mm retroreflective markers A treadmill (Bertec)	100 KOA (45M, 55 F), 45 HC (18M, 25 F)	98–100%	Gender should be considered while investigating KOA	Only focused joint kinematic data
5	Hiroki.M et al. [104]/2015	Reflective markers An accelerometer, a dynamometer CM-200 sonometer MC-780A BCA	91 KOA (22M, 69 F)	–	Results demonstrated strong association between KOA and falling risk	Possibility of selection bias
6	Shawn.F et al. [40]/2015	A plug-in gait marker set 2 Bertec force platforms 8 camera Vicon Mocap system	17 with KOA,SRKI and 36 with KOA,NSRKI	–	SRKI was associated with alterations in joint	Only included patients with medial compartment KOA
7	Favre et al. [13]/2014	A force plate Cluster of retroreflective markers An optoelectronic Mocap system	110 (29 young adults, 27 HC, 28 moderate, 26 severe KOA)	–	Less extension and Increased KAM was associated with KOA	- Cross-sectional study - Chances of undiagnosed KOA in healthy ones
8	Jessica et al. [35]/2013	Reflective markers 9-camera Mocap system (Qualisys) A multi-component force plate	43 KOA patients	–	In each gait trail, only KAM showed repeatability	Small number of participants
9	Metcalfe et al. [36]/2013	12 Vicon MX2 camera system 3 AMTI force plates Reflective marker set EMG electrodes	9 KOA subjects, 24 HC	–	In spite having unilateral KOA, abnormal loading was present in both limbs than controls	Small sample size
10	Mark.W.C et al. [14]/2012	2 force plates A Vicon system Reflective markers	91 KOA patients and 31 HC	–	Greater trunk lean towards more affected knee and less flexion in KOA	Cross-sectional study
11	Marius.H et al. [105]/2012	A 6 camera 3D Mocap's 2 AMTI force plates A plug-in gait marker set	137 medial KOA patients	–	Negative correlation shown between pain and loading by less severe and positive between severe between pain and KAM impulse	Cross-sectional study design

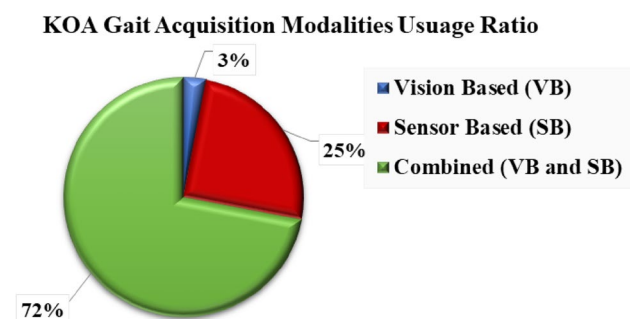
**Table 3** (continued)

S. no.	References/year	Resource	Dataset	Accuracy	Key findings	Remarks
12	Astephen et al. [38]/2011	Optotrack™ 3020 Mocap system AMTI force plate Active markers EMG electrodes	40 KOA patients	–	Gait speed was determined as an important variable to calculate radio-graphic pain	Severe knee OA patients were not involved
13	Nigar.S.K et al. [106]/2010	Computer interfaced camera's Reflective markers A force platform	More than 150 KOA subjects	80%	Combination of classifiers have great potential to provide in high classification rate	Relationship between gait adaptation and disease severity was not determined
14	Ershela et al. [64]/2009	A motion analysis system AMTI force plates Reflective markers An orthotrack system	26 males and 30 females with KOA	–	Highlighted the gait variations among M,F	Only severity level matched participants were chosen
15	Deluzio et al. [46]/2007	An Optoelectronic system 6 infrared light emitting diodes A force platform	50 end stage KOA patients 63 HC	92%	Results depicted the usefulness of combination of two statistical techniques	Cross-sectional study
16	Nigar.S.K et al. [107]/2006	A Vicon Mocap system Force plates	139 KOA patients, 20 HC	87–92%	Amalgamation of MLP's can be successfully applied for correct gait disorder diagnosis	High Complexity of used approach
17	Astephen et al. [39]/2005	Optoelectronic system 6 infrared light emitting diodes A force plate	50 patients with severe KOA, 63 HC	> 90%	Results showed the capability of multidimensional technique for gait pattern classification	Only severe level KOA patients were involved

Acronym of words used in table: Male (M), Female (F), Knee Osteoarthritis (KOA), Healthy Control (HC), Self-Reported Knee Instability (SRKI), Non Self-Reported Knee Instability (NSRKI)

arm movement in silhouette image, requirement of a high resolution camera.

In another study, Cui et al. [32] proposed a method for reliable and accurate gait analysis of KOA patients using a single Kinect sensor consisting of depth sensing RGB-D camera to capture the depth information of joints of patient's body. Kinematic, kinetic and spatiotemporal features were



**Fig. 9** A depiction of usage proportion of each modality for KOA gait acquisition

determined and Dynamic Time Wrapping (DTW) was used for calculation of knee joint angles. DTW is a method for distance calculation that performs a non-linear transformation to minimize the cost function. Applying SVM for classification results in high efficiency of Kinect in KOA diagnosis with an accuracy rate of 97%.

Thus the combination of model-based and model-free modalities constituted video based non-wearable mode for KOA gait acquisition and assessment. In recent years, a very few research is focused on using this modality for KOA diagnosis. Vision-based modalities offer direct capturing of KOA gait without the involvement of subjects and don't require putting devices over the body. So there is greater need to consider these modalities for further KOA investigations.

## 4.2 Sensor-Based

Another important KOA gait acquisition modality is based on the use of sensors which are attached to the human body. These are further classified into two sub-categories on the

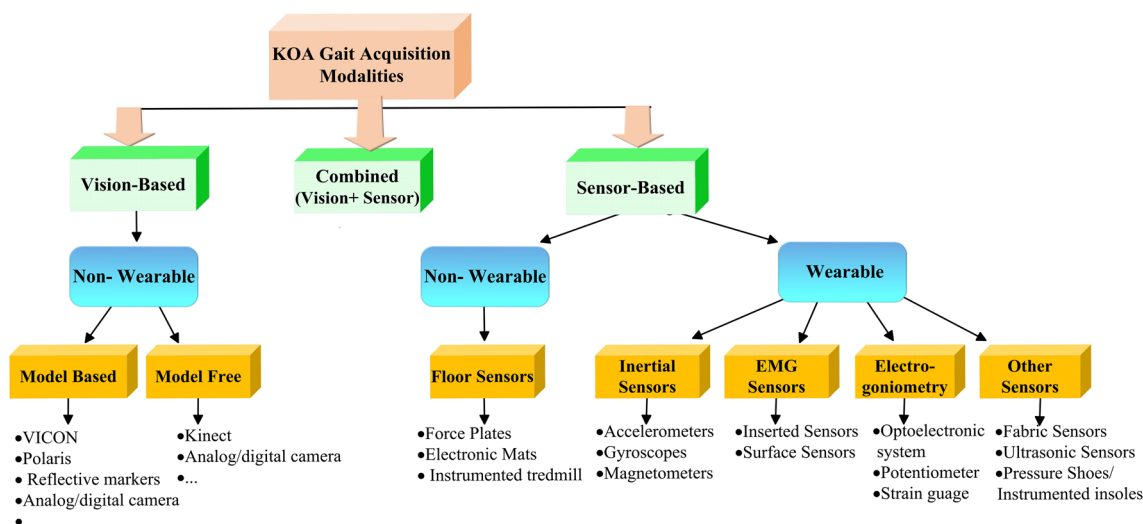


Fig. 10 Gait acquisition modalities for knee osteoarthritis (KOA) diagnosis

basis of their ability to be worn on the subject's body namely Non-wearable sensors and Wearable Sensors.

#### 4.2.1 Non-wearable Sensors (NWS)

This KOA gait sensing modality can't be worn on the body using these sensors, the diagnosis of KOA is performed on the basis of forces obtained from contact between foot and ground. Floor Sensors are used in NWS for the acquisition of KOA gait parameters.

- (a) Floor Sensors (FS)—These are the non-wearable sensors which make use of force sensors embedded in floor platform thus named as floor sensors. The force sensor platforms such as force plates, electronic and pressure mats, instrumented treadmill have the potential to directly make the estimate of the force vector. Transducers provide the GRF's on which measurements are performed. At last, the obtained forces are transformed into electrical signals to compute Center of Pressure (COP). An example of such an electronic floor sensor used in the research study of Southampton University is shown in Fig. 11.

Kotti et al. [10] proposed a system to determine the reliability of rule-based approach for comparison of 47 KOA and healthy subjects. They made use of two Kistler force plates on 6 m long walkway having piezoelectric three-component force sensors to collect subject's data. A 5-fold cross-validation (CV) accuracy of  $72.61\% \pm 4.24\%$  was achieved, employing Random Forest regression learning approach.

In other work, Elbaz et al. [44] used a computerized walking mat (GaitMatMII system) and successfully classified the KOA male and female (including 2911 knee OA patients). An accuracy of 89.5% for females and 90.8% for males was achieved using K-means method and Classification and Regression Tree (CART) model.

With the integration of 2 Kistler force platforms and a treadmill, Mezghani et al. [89] proposed to develop a system to differentiate KOA and healthy subjects. Using GRF's parameters and Nearest Neighbor Classifier, overall accuracy of 91% was achieved.

#### 4.2.2 Wearable Sensors (WS)

In contrast to NWS modality, another modality seeking attention for KOA gait collection is wearable sensors. In order to enable the gait to be captured using wearable sensors, a subject has to wear the sensor on the body. Wearable sensors based modality is further subdivided into different types on the basis of their function.

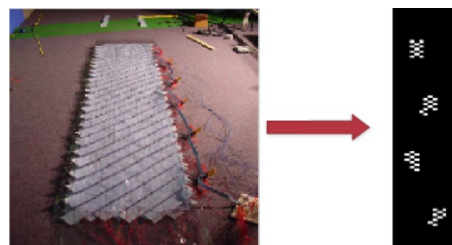


Fig. 11 A prototype of floor or pressure mat (left) and the corresponding recorded footsteps on the instrumented mat (right), taken from [109]. Reproduced with the permission from Southampton University



(a) *Inertial Sensors (IS)* These are the electronic equipment's established on the concept of inertial measurement. The measurement of subject's body can be performed by employing three main devices such as accelerometer (measures acceleration), gyroscopes (angular velocity), magnetometers (magnetic force computation) and sometimes combination of all three. Using IMU's, it is possible to perform linear and angular measurements efficiently [110]. Tereso et al. [92] proposed a study to examine the Spatiotemporal, posture and fall-related features in KOA patients after Total Knee Arthroplasty (TKA). Crutches, standard walker (SW) and Rollator with Forearm Supports (RFS) were used to check their capability in KOA rehabilitation and the gait was recorded using two inertial sensors. MANOVA with repeated measures shown the differences among all the spatiotemporal features ( $p < 0.05$ ). Also, SVM predicted the best stability using SW and RFS in which gait of patients was more closely related to normal ones and revealed the importance of time in gait evaluation.

In other work, Bolink et al. [95] aimed to examine the biomechanical gait features of KOA patients using only a single inertial sensor. An enhanced 3D inertial sensor configuration of gyroscope and accelerometer was applied to analyze spatiotemporal as well as kinetic features. Results indicated the potential of inertial sensors in KOA and analyzed that KOA subjects walk with less speed, flexion and more trunk lean.

(b) *Electromyograph (EMG Sensors)* EMG sensors are the devices used to inspect the muscles electrical activity using a device known as Electromyographs. In KOA, muscle electrical signals representing electrical activity and muscle patterns of patients varies to a larger extent. These patterns represent the strength of muscles and enable the computation of different gait characteristics. EMG sensors perform their function either using inserted sensors, consisting of wire or needle/surface electrodes made up of integral electrodes.

Kozey et al. [43] intended to determine the changes occurring in the knee of 38 KOA patients with time as compared to healthy controls. Surface EMG electrodes were used to analyze lower limb motion, GRF's and other kinetic moments. Using inverse dynamics and Principle Component Analysis (PCA), it was analyzed that changes in gait speed (1.25–1.17 m/s from baseline to follow up) and muscle activity ( $p < 0.05$ ) for both groups varied due to age and other related factors.

Again, in another study, Kozey et al. [97] tried to characterize the knee joint muscles pattern in 51 patients with severe KOA using some pattern recognition methods. Electromyographic data was collected for patients using Silver chloride surface EMG (S-EMG) electrodes. About 97% of the variance and differences in EMG waveform was detected using Analysis of Variance (ANOVA) models which indicated that people with KOA walk with low velocity than healthy subjects.

(c) *Electrogoniometry (EGM Sensors)* These sensor-based modalities are used to quantify joint angles of the body such as ankle, knee, hip etc. repeatedly without any interruption. Based on analyzed fluctuations in angle, these type of modalities are capable of measuring the amount of deviation in the physical signal. Two types of electrogoniometer were in major use including Potentiometer-attached with the joints rotator points but due to its bulky nature induce frustration in ambulation. Another was Strain Gauges, also known as the flexible electrogoniometer made of flex spring with plastic and blocks on each end. These devices were light weighted, portable and can be applied easily [82]. So, in spite of having great potential of measuring joint angles these devices are very painful to wear.

The use of EGM can be seen in the study performed by Tarnita et al. [12]. They tried to examine flexion–extension moments, angles between KOA and healthy group by collecting kinetic and kinematic data using a treadmill and two electrogoniometers. Statistical analysis revealed that Knee OA subjects had less max flexion (69.01 deg.) for affected knee and max amplitude (51.73 deg.) than healthy ones. Also, the healthy knees of the patients shown less flexion than the other group.

(d) *Other Sensors* Irrespective of all the non-wearable sensor modalities discussed above, there are few other preferred for capturing KOA gait. This includes pressure shoes, Ultrasonic sensors and Smart garments. Pressure shoes, also known as instrumental insoles are positioned within the confines of shoes inside and impart the weight or load information applied on sensors. Organero [48] presented a study to evaluate the efficiency of eight insole pressure sensors embedded inside the shoes in KOA investigation. KOA and healthy control group was identified based on different types of classifiers i.e. SVM, Logistic regression model, Multilayer Perceptron (MLP) and Tree-based classifier. Average heel, mid-foot and forefoot pressure was determined and results demonstrated the efficacy of tree-based classifier than all other classifiers.

Ultrasonic sensors are used to achieve gait related parameters such as the number of steps, stride length and other related characteristics. Kiss et al. [101] focused on examining the relation between gait variability of KOA patients and its severity. Patients were strictly instructed to walk at three different speeds to assess the effect of speed on KOA subject's gait, with different severities. An ultrasound-based system (a triplet of UV sensors) was used to analyze gait motion. The study outcome indicated that variations of gait among different severities of KOA are gender dependent and should be considered carefully while analysis of KOA.

Finally, we included smart garments also named as sensing fabrics in this category. They are specially designed by the aggregation of sensing technology and fabric in which sensors are infused in normal fabrics and have flexibility. Bergmann et al. [100] made an effort to propose a new clothing sensor system in which sensors were installed inside the clothes. Knee joints measurement was performed to compare the proposed system with a gold standard system. The coefficient of determination more than 0.99 between two systems shown the reliability of the proposed system for KOA monitoring.

Chen et al. [91] developed a mechanism to evaluate three rehabilitation exercises namely Short Arc Exercise (SAE), Straight Leg Raise (SLR) and Quadriceps Strengthening Mini-squads (QSM) for KOA patients using the combination of three OPAM inertial sensors and a goniometer. Results demonstrated high potential in KOA assessment by providing exercise classification accuracy of 97.29% and posture and classification accuracy of 88.26%.

Table 2 gives the description of work done on sensor based modalities either used alone or in combination with other sensors and attained accuracy.

Data reveals that much of the research is focused on using FS due to its tremendous capability of directly capturing the gait parameters without involvement of any complex procedure for the patient but they are very expensive to use. Out of 32 articles on sensor-based modality, 11 are FS based, 8 are IS based, 6 are EMG, 4 on other sensors and 3 on EGM based, showing more focus on FS. Percentage Utilization of different sensors in Sensor-Based (SB) modality is defined in Fig. 12.

### 4.3 Combined

Apart from these modalities, most of the studies are focused on using the amalgamation of properties and characteristics of sensor-based and vision based modalities [111–113]. The purpose was to capture the advantages of both suppressing their drawbacks. Metcafe et al. [102] evaluated KOA subjects by collecting data using twelve VICON MX2 cameras, three AMTI force plates and a plug-in marker set attached to subject's. The combination of modalities to capture KOA

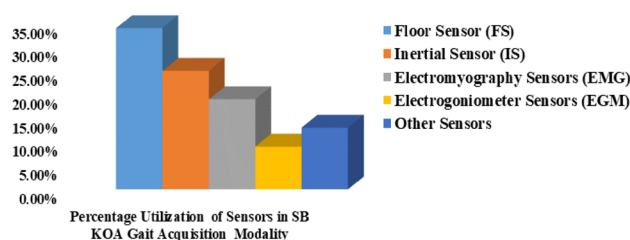


Fig. 12 Description of percentage use of various sensors in sensor-based KOA gait capturing modality

gait yielded an accuracy of 95% and 92.5% for affected and unaffected knees.

In another research, Phinyomark et al. [41] proposed a study to investigate the effect of gender on 100 KOA gait subjects. The data was acquired using a combination of 8 camera VICON Mocap system, 9 mm retroreflective markers and a Bertec treadmill. Using SVM to differentiate both groups based on kinematic joint parameters successfully gained an accuracy of 98–100%. Results have shown the relevance of gender for gait variations in KOA and healthy subjects.

Another study by Koktas et al. [106] used a combination of vision and sensor-based modality to analyze gait variations among 150 KOA subjects with different severity levels. Reflective markers, a force platform and a set of video camera was used to perform measurements while walking. Outcomes demonstrated the potential of pooled classifiers (Decision Trees and Multilayer perceptron) in KOA analysis with a success rate of 80%.

Table 3 provides the summary of combined i.e. vision based and sensor based modalities along with the key findings and accuracy rates. The analysis of considered state-of-art literature indicated much of the focus on combined gait acquisition modalities for KOA diagnosis. About 72% of research seen to be done on this modality, reflecting its potential in KOA diagnosis as depicted by Fig. 9. Since the combination of different modalities offer additional data of the subject to be captured and analyzed and may offer more diagnostic accuracy for KOA identification. So these modalities are preferred by most of the studies to enable more effective KOA analysis but are also limited by large space and heavy set-up requirements.

## 5 Feature Representation Based on KOA Gait Acquisition Modalities

A feature is a distinctive characteristic that provides a unique identity to a person. Based on this unique attribute, it is possible to determine abnormal conditions of an individual. Various approaches can be used to represent different gait features in KOA. An approach is simply the method, as a

result of which relevant features can be determined for efficient diagnosis. In OA, gait features such as Knee Flexion Moment (KFM), Knee Flexion Angle (KFA), speed, stance and swing time etc. has a great significance to enable proper detection of the disease.

In this section, a complete description of various approaches for identifying unique KOA gait features are given. A taxonomy is formed for KOA gait features under different approaches as depicted in Fig. 13. Tables 4 and 5 summarized various KOA feature representation approaches used alone or in combination by different studies.

Based on taxonomy shown in Fig. 10, different KOA features can be extracted and used. We have categorized these approaches into six main sub-categories [49] i.e. anthropometric, spatiotemporal, silhouette, kinematic, kinetic and hybrid. Here different colors are used to clearly explain which KOA gait feature data is captured by what modality. At the leftmost top of Fig. 13 inside a large rectangular box, three small square type boxes in the first row (purple, green and grey) indicates that employing vision based modality using markers for KOA gait acquisition, results in features of three approaches-anthropometric, spatiotemporal and kinematic. Similarly, small square boxes in the second row (purple, green, grey and orange) represents that using data acquired by vision-based marker-less/model-free modality, four parameters can be extracted under four approaches i.e. anthropometric, spatiotemporal, kinematic and silhouette based features. Alike square boxes in the third row (purple, green, grey and pink) depicts four features-anthropometric, spatiotemporal, kinematic and kinetic features that can be extracted using sensors based data recording. Lastly, blue box in the last row representing the consolidation of all the gait approaches features (anthropometric, spatiotemporal, kinematic, kinetic and silhouette) inside a small rectangular box, that can be obtained using two or more categories of modalities (vision based+ sensor based) together. Further investigation of these approaches for KOA analysis is as follows:

### 5.1 Anthropometric

This approach involves KOA demographic data features that represent the quantification of the size of the human body, as each and every individual has own body structure and properties. It involves age, weight, height, BMI, gender, rating score, disease duration etc. to use in KOA analysis. For reliable KOA diagnosis, it is necessary to consider all the aspects of a person, so this data is recorded for each individual involved in the study.

In Asay et al. [35] study, demographic data of KOA patients and healthy subjects such as age, weight, height, BMI was recorded for accurate analysis of both the groups.

Also, WOMAC and Visual Analog Scale (VAS) pain scores were used to grade the KOA severity.

In another work, Monil et al. [123] collected the information about KOOS pain score, height, weight, BMI, age and gender of healthy, Medial KOA and subjects with lateral KOA. The purpose was to only involve the matched demographic data of healthy and KOA individuals.

### 5.2 Spatio-temporal

This is the most widely used approach to facilitate KOA diagnosis. As name suggests, the features used in this approach can be used to characterize or distinguish gait patterns by extracting stance and swing phase related time and distance measurements [133]. This includes stride length, step length, step width, traversed distance etc. as the spatial (distance) features and stride, step period, cadence, velocity, Single Limb Support (SLS), Double Support (DS) etc. as temporal (time) features. Out of the considered features, stride length parameter is of utmost importance since it represents one gait cycle length which can be effectively employed for diseased gait diagnosis in KOA.

Sun et al. [103] proposed a study to analyze and evaluate the correctness of IDDEEA3 system against Go Pro Hero3 high speed camera. Five spatiotemporal features (gait cycle, velocity, cadence, step length, and step counts) of 23 KOA subjects and 12 healthy controls were extracted to evaluate the new system's performance. The error was estimated to determine the differences in measurements using the formula:

$$E(\%) = \frac{\sum MR - GPR}{\sum MR} * 100\% \quad (1)$$

$$E(\%) = \frac{\sum GPR - IDEEA3}{\sum GPR} * 100\% \quad (2)$$

where  $E$  denotes error,  $MR$  is the motion results,  $GPR$  refers to Go Pro results and  $IDEEA3$  represents IDEEA3 system results. The results obtained for IDDEEA3 were consistent with the Go Pro camera (e.g. gait cycle, cadence measurements with high speed camera and IDDEEA3 system were  $0.913 \pm 0.06$  and  $0.916 \pm 0.065$ ,  $131.991 \pm 9.243$  and  $131.625 \pm 9.748$ ) which indicates the high capacity of the proposed system to determine spatiotemporal features for KOA diagnosis.

In another article, Elbaz et al. [44] used spatiotemporal gait features (velocity, cadence, step and stride lengths, base of support, step time, swing time, stance time, SLS time, DLS time) for KOA assessment. Using k-means clustering and CART model, they were successful in classifying male KOA patients with an accuracy of 90.8% and females with 89.5%. Outcomes demonstrated

**Table 4** Spatiotemporal, Kinetic, Kinematic and Silhouette-based KOA feature representation approaches

S. no.	References/year	Gait approach	KOA gait features	Evaluation method/classifier	Clinical rating scale	Tool used	Accuracy
1	Jun Sun et al. [103]/2017	Spatio-temporal	Gait cycle, cadence, step length, velocity, step count	Paired t-test CCC ICC T-test	–	SPSS	–
2	Serkan et al. [114]/2014		Cadence, velocity, double step length, double step time, double support time, single step time, step length, stride length, stride time, stance phase length	Kolmogorov-Sminrov/Shapiro-Wilk's test Kruskal-wallis test	K-L scale	SPSS	–
3	A. Elbaz et al. [44]/2014		Velocity, cadence, step and stride lengths, base of support, step time, swing time, stance time, SLS time, DLS time	Chi-sq. test Kruskal-wallis test K-means clustering method •Classification and regression tree (CART) model	K-L scale WOMAC index SF-36 VAS scale	R 2.11.1	89.5% for F 90.8% for M
4	Brunton et al. [42]/2012		Walking speed, step duration, step length, walking time	Pearson's coefficient	WOMAC index AKSS score	SPSS	–
5	Ronen et al. [11]/2009		Absolute and normalized velocity, cadence, step length, norm SL, swing and stance phase, SLS, DLS, base of support, foot placement angle	Independent t-tests	WOMAC score SF-36 K-L scale	SPSS 14.0	–
6	Tanmay et al. [37]/2018	Silhouette	Amount of body movement, center of gravity shifts, Torso Orientation (TO) and feet related features	Two sample t-test 5 F-CV SVM	–	–	–
7	Yuki.I et al. [31]/2017	Kinematic	Elevation angle, representation angle, approximate angle and knee flexion angle	T-test Accuracy (ACC) Precision (PRE) Recall (REC) F-measure ROC	–	SIMM	–
8	Derek.J.R et al. [16]/2018	Kinetic	Peak KAM, KAM impulse, peak FM, sagittal and frontal plane moments	Pearson's Correlation coefficient.	KOOS score	Minitab 18	94%–98%



Table 4 (continued)

S. no.	References/year	Gait approach	KOA gait features	Evaluation method/classifier	Clinical rating scale	Tool used	Accuracy
9	Margarita.K et al. [10]/2017		Vertical, anterior, posterior and medio-lateral GRF parameters-Push off time and slope	Specificity Sensitivity Accuracy F1 score 5 F-CV Spearman correlation Random Forests Regression algo	-	Matlab 2012b	72.61% ± 4.24%
10	Dylan.K et al. [15]/2017		Hip adduction, Hip flexion, hip extension-rotation, core stability	PRO measures ANOVA	-	Matlab 9.0	sensors 3: 82% sensors 2: 80%
11	Derek.R et al. [115]/2017		EMG signals, net external sagittal and frontal plane reaction forces, amplitude and waveform features, knee flex/extension, sagittal plane motion	KS test Levene's test ANOVA Bonferroni's correction	K-L scale KOOS score WOMAC index	Matlab 2015b	-
12	Mario et al. [48]/2017		Pressure on sole-avgerage heel, midfoot and forefoot pressure, knee forces, peak values	T-test Variance Mahalanobis distance SVM	-	Kinematix	SVM-100% LR-95% MLP-95% TBC-100%
13	C.L et al. [43]/2015		Lower limb motion, GRF's, KAM, KFM, knee rotation moment, medial hamstrings muscle activity	Logistic Reg. and MLP Tree based classifier EM clustering algo ANOVA	K-L scale	-	-
14	Tine et al. [96]/2015		H-reflex modulation (Hmax), muscl co-activation (Mmax), foot switch and EMG signals, sample entropy	Largest Lyapunove exponent T-test Confidence Interval (CI)	KOOS score VAS scale	-	-
15	Shawn et al. [40]/2015		External moments, ROM, hip, knee and ankle excursion moments, knee extension strength, total support moment	Indep. sample t-tests Confidence Interval (CI) Logistic Regression Model	WOMAC index	Stata 11.2	-
16	E.F et al. [116]/2014	Kinetic	KAM, KFM, GRF's	Shapiro-Wilk test Post hoc pre region analysis Point Cluster Technique Regression	K-L scale	SPSS 21	-
17	K.M et al. [117]/2014		KAM, Knee external strength, power, loading magnitude	Regression	KOOS score	Visual 3D	-

Table 4 (continued)

S. no.	References/year	Gait approach	KOA gait features	Evaluation method/classifier	Clinical rating scale	Tool used	Accuracy
18	Andrew et al. [118]/2013		Muscle EMG signals, GRF's, internal, medial and lateral contact forces	Kruskal–Wallis test Tukey's honestly significant difference test Linear Regression	–	–	–
19	M.O et al. [119]/2013		Knee ROM, muscle strength, peak joint moments	PCC One-way ANOVA	–	–	–
20	Collins et al. [86]/2011		Electrical stimulation, KAM, ext. adduction moment, knee abduction moment, knee flexion	T-test ANOVA	K–L scale	–	–
21	Moustakidis et al. [88]/2010		Ground Reaction Forces (GRF's), peak moments	Sensitivity Specificity Total accuracy 10 F-CV Fuzzy Decision tree based SVM classifier	K–L scale	–	93.44%
22	Tuomas et al. [87]/2010		3D GRF's, muscle activation, initial peak acceleration.	Student t-test Mann–Whitney test One way ANOVA Kruskal–Wallis test	K–L scale VAS scale	SPSS	–
23	Joseph et al. [120]/2009		Sagittal plane kinetics-KAM, knee excursion, knee joint reaction forces, Center of pressure (COP)	MANOVA MANCOVA Hierarchical Regression	K–L scale KOOS score	SPSS 15	–
24	Neila et al. [89]/2008		3D GRF's, coefficient of ploygon expansion and wavelet decomposition,	Specificity Sensitivity Accuracy Max leave one out Cross validation	ACR criteria	–	91%
25	Cheryl et al. [97]/2008		EMG profile, knee flexor, knee extensor, plantar extensor moments	Nearest Neighbour classifier ANOVA	K–L scale	Matlab 7.0	Variance = 97%
26	Pazit et al. [34]/2007		GRF magnitude, time for peak GRF, posterior and anterior peaks, velocity	ROC Accuracy Sensitivity Specificity LOO CV Multiclass SVM classifier	–	–	85%–92%
27	Shari et al. [98]/2007		EMG signals, muscles contaction	Chi-sq. test T-test	K–L scale	SPSS 6.2/7.0	–

**Table 4** (continued)

S. no.	References/year	Gait approach	KOA gait features	Evaluation method/classifier	Clinical rating scale	Tool used	Accuracy
28	Walker et al. [121]/2001		ROM, knee flexion and extension	Student t-test Bonferroni correction Variance	-	-	-
29	Hurwitz et al. [122]/2000		External moment and forces, KAM, KFM, KEM	PCC Bonferroni's correction Paired t-tests Kruskal–Wallis test	K–L scale	-	-

Acronym of words used in table: Concordance Correlation coefficient (CCC), Range of Motion (ROM)

the importance of spatiotemporal features in KOA identification.

A study by Falconer et al. [134] presented a very simple, inexpensive method to identify 43 KOA subjects. Spatiotemporal features (step length, cadence, stride width and velocity) were analyzed using footprints obtained by a runway of carbon paper. Results depicted reliability of the used method for KOA recognition purpose.

### 5.3 Silhouette

This approach is used to represent silhouette features. These features are the result of employing model free Marker less approach for KOA gait acquisition. The silhouette attributes are extracted directly from image plane known as Silhouette image and include the shape of silhouette, body posture observing Center of Gravity (COG) shifts, torso orientation, height, width of Bounding Box (BB), Gait Energy Image (GEI), etc.

Verlekar et al. [37] successfully employed automatic recognition of gait pathological disorders using body and feet related features. After extracting silhouette using background subtraction, a body related feature i.e. Amount of Movement (AOM) was measured that describes the amount of motion in arms and lower limbs during walking. To calculate AOM, initially the silhouette was cropped for each frame, numbered from (1 to Q) and then averaged to estimate GEI (Gait Energy Image) over half cycle. At last, AOM was estimated using Shannon entropy defined as

$$AOM_{VB} = - \sum_j Q_j \log_2 Q_j \tag{3}$$

In Eq. 3,  $Q_j$  is the probability indicating  $j$  is equal to the distance among two neighboring pixels and  $AOM_{VB}$  denotes the amount of movement. The study provided good results (about 98.8% accuracy) but overlapping problem made the shape and movements of upper and lower extremity unclear.

### 5.4 Kinematic

Kinematic approach especially includes the motion parameters that allows the gathering of motion as well as geometric details of the human body [50]. These features are obtained using markers and vision based modality. To analyze them, retro reflective markers may be active or passive are attached to the human body. Based on the position of such landmarks, various features are extracted including joint angles are extracted such as Knee Flexion angle (KFA), knee Abduction Angle (KAM), joint positions, acceleration, motion trajectories etc. for further calculations [49, 133].

**Table 5** Hybrid KOA feature representation approaches

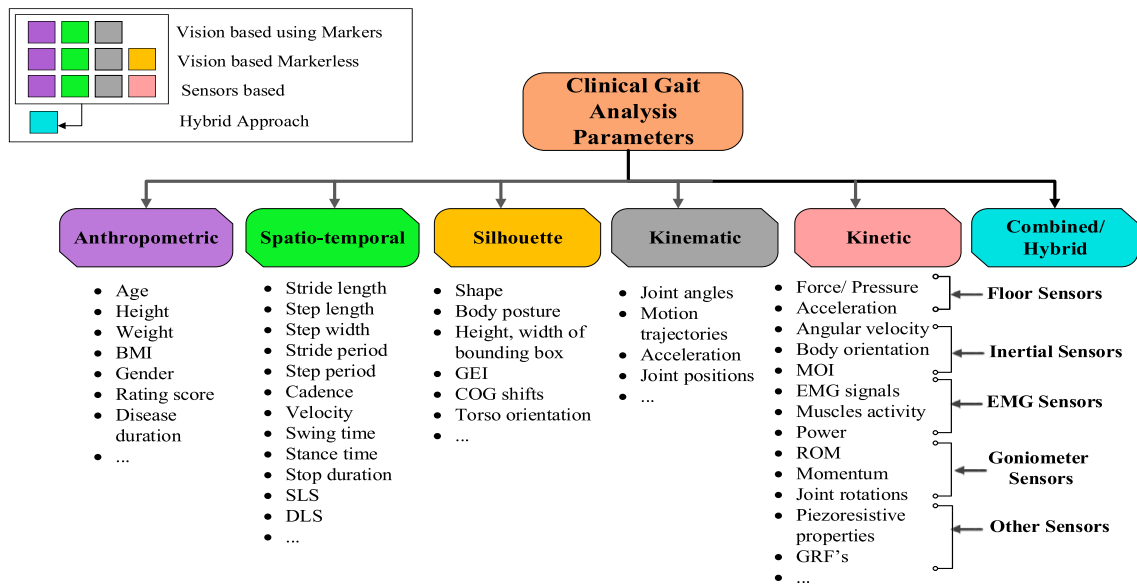
S. no.	References/year	KOA gait features	Evaluation method/classifier	Clinical rating scale	Tool used	Accuracy
1	Karia et al. [123]/2018	Foot length, foot width, KAM, KAA, COP	Bonferroni's correction T-tests	KOOS ques	SPSS 20	–
2	Annalisa et al. [124]/2018	Knee excursion angles, external knee moments	Independent t-test KS test Levene's test MW test Visual 3D	K–L scale	SPSS	–
3	Armaghanet al. [47]/2017	KAM, KAM impulse, KFM, peak KFA, internal–external rotations, VGRF's, heel-strike, toe-off, walking speed, stance time	ANOVA GEEs KW test Signed rank test	K–L scale BLOKS score	Matlab 7.14.0	–
4	Paterson et al. [125]/2017	KAM, KAM impulse, peak KFM, peak KFA, varus-valgus angle and thrust, peak VGRF's, norm walking speed	Chi-sq. test T-test Regression models	WOMAC index K–L scale	Matlab	–
5	Metcafe et al. [102]/2017	EMG data, hamstrings co-contraction, gait speed, cadence, step width, stance percent, hip, knee KAM and impulse	T-tests MW test Cardiff and Dampster-Shafer	WOMAC index	SPSS	For affected. Knee-95% For unaffected. Knee 92.5%
6	Angkoon et al. [41]/2016	KFM, KFA, KAM, walking speed, ROM angles, max–min angles,	ANOVA Support Vector Machine (SVM)	K–L scale	3D gait s/w	98–100%
7	Stephen et al. [126]/2016	Peak sagittal angles, moment and peak frontal moment, ROM, walking speed/velocity, isokinetic strength	ANOVA	WOMAC index	Visual 3D	–
8	Arita et al. [99]/2016	Gait speed, TUG outcomes, step length, KFA, Joint motion angles	TUG test	K–L scale WOMAC index SF-36 VAS score	–	–
9	Chang et al. [127]/2015	Peak KAM, KAM impulse, peak KFM, gait speed	GEEs ICC CV Logistic and linear Regression	WOMAC index WORMS score K–L scale	Matlab	–
10	Hiroimi et al. [104]/2015	Muscle strength, gait speed, step length, gait variability, muscle mass, kyphosis	T-test Multiple Regression	VAS scale	SPSS	–
11	Lysney et al. [128]/2014	External KAM & HAM, KFA & HAA, EMG forces, GRF's	SW test Levene's test Two-way ANOVA	K–L scale	Sigma Plot v.11.0	–
12	Julein Favre et al. [13]/2014	Flex/Ext angles, ant/post. displacement, KFM, KEM, gait speed, heel strike, mid-stance	ANOVA Post hoc Turkey test Bonferroni's correction	K–L scale	Matlab R2010b	–
13	Jessica et al. [35]/2013	KFM, KAM, peak vertical GRF, gait speed, step length, cadence	ANOVA LSD ICC	WOMAC index VAS score	Matlab R2009a	–
14	Farokhi et al. [129]/2013	Knee joint angles, external knee joint moments	Ind. sample t-test	K–L scale	STATA V-11.2	–



**Table 5** (continued)

S. no.	References/year	KOA gait features	Evaluation method/classifier	Clinical rating scale	Tool used	Accuracy
15	Simic et al. [130]/2013	KAM, KAM impulse, KAI, KEM, KFM, GRF's, gait speed, step width, step length	ANOVA Linear Regression	WOMAC index K-L scale	GenStat	–
16	Cheryl H et al. [131]/2013	EMG signals, KF and KE ROM, ankle plantar flexion, gait speed	Paired t-tests SEM	K-L scale	Matlab 7.4	–
17	Deepak K et al. [132]/2012	KAM, muscle force, penetration angles, speed/velocity, medial and lateral joint loads	RMS	K-L scale KOOS score	SIMM tool	–
18	Stijn B et al. [95]/2012	Locomotion, STS, block stepping, ROM	PROM Performance based test T-test ROC	K-L scale	SPSS	–

Acronym of words used in table: Least Significant Difference (LSD), Mann-Whitney Test (MW), Generalized Estimating Equations (GEEs), Standard Error of Measurement (SEM), software (s/w), Time-up and Go (TUG)



**Fig. 13** Various KOA gait features representation approaches obtained using different acquisition modalities

Ishikawa et al. [31] used angular parameters such as elevation angles, flexion angles to analyze the subject's gait presented in Fig. 14.

Elevation angles are made in sagittal plane between segment and Y-direction. Similarly, knee flexion angles are made between the thigh and shank portions. The differences among these angles made by subjects during locomotion provided important evidence of planar law applicability for KOA diagnosis ( $p < 0.01$ ) with cumulative ratio greater than 0.98.

### 5.5 Kinetic

The kinetic approach is related to the features that embrace the study of forces and moments which are caused by the movement of body segments during walking. These features give attention to the forces produced by the interaction of foot and ground. There are different sensors that can be used to capture kinetic data. Each sensor has its own capability such as force, acceleration can be obtained using floor sensors, angular velocity and Moment of Inertia (MOI) etc. can be produced by inertial sensors. Similarly, EMG and goniometer sensors provide EMG signals,

muscles activity, range of motion (ROM), momentum etc. Other sensors such as smart garments, insole shoes are capable of recording Ground Reaction forces (GRF's) and other data.

In Kotti et al. [10] study, a system was proposed that takes kinetic features such as GRF's as input and produces not only output diagnosing KOA but also illustrates the set of rules through which the decision was reached. A rule-based approach was applied and evaluated for KOA detection. Results showed the high capability of used approach for KOA by giving an accuracy of  $72.61\% \pm 4.24\%$ .

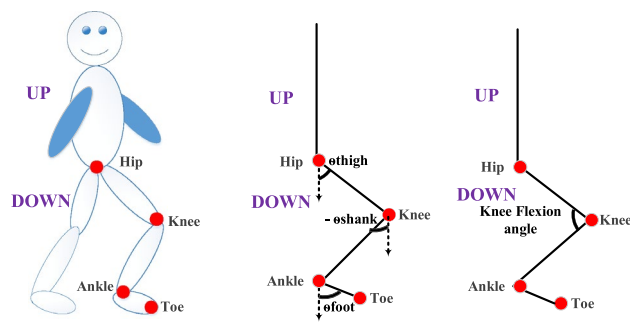
Organero et al. [48] used insole pressure shoes to study an important kinetic feature, i.e. pressure and to check their effectiveness in analyzing patients with mild KOA. The study concluded that the pressure for each mean foot strike in stance phase was greater in patients with KOA as compared to healthy controls indicating the potential of insole pressure shoes in recognizing the effect of KOA on walking.

Table 4 summarizes recent studies from 2000 to 2018 which have used spatiotemporal, kinematic, silhouette and kinetic approaches for KOA detection with accuracy rate. Here, except disease rating scale, no other anthropometric approach feature has been shown in the tables since it is considered by almost all the studies. Data indicates the large use of kinetic approach for KOA gait features representation as it provides direct measurements of knee joint forces, muscles activities during walking. Kinetic approach however can be effective in KOA analysis but the interpretation of the extracted gait features in the form of signals offer high complexity.

## 5.6 Combined/Hybrid

Instead of considering only a small number of features for evaluation, it is more reliable to utilize the combination of features such as spatiotemporal in combination with silhouette, kinematic and kinetic and many more for better KOA assessment. In this section, we analyzed the hybrid approach for the demonstration of KOA gait features. Table 5 gives the summary of recent studies on hybrid approach considering accuracy and classifier used to extract a combination of KOA gait features for successful diagnosis.

Sacco et al. [135] proposed a new KOA analysis cheap footwear named Moleca in combination with passive reflective markers. The objective was to determine the effect of used footwear and other modalities on KAM during stair descent. Kinematic and kinetic features such as joint centers, GRF's were analyzed for evaluation of KOA. Results highlighted that for all foot wear, patients with KOA shown higher KAM (for barefoot-233.3%,  $p=0.028$ , Moleca-379.2%,  $p=0.004$  and High Heeled-217.6%,  $p=0.007$ ) compared to healthy controls. The knee load was similar with barefoot and Moleca for all the stances but



**Fig. 14** A representation of elevation and flexion angles considered by the study [31], using a human body structure model (a). UP denotes upper part of the body including-head, arms, and torso while DOWN represents lower body section including-hip, knee, ankle, thigh, and toe. In stick (b),  $\theta_{thigh}$ ,  $\theta_{shank}$  and  $\theta_{foot}$  are three elevation angles made between hip and knee joint, knee and ankle joint, ankle joint and toe in vertical direction. c represents knee flexion angle made between thigh and shank

greater with high heeled during early stance. Thus, study demonstrated the efficiency of Moleca foot ware in KOA identification.

In another study, Monil et al. [123] proposed to analyze the combination of kinematic and kinetic features for medial, lateral KOA and healthy subjects including KAM, KFA for relative comparison with Center of Pressure (COP). Using logistic regression it has been analyzed that for healthy controls, Knee Adduction Angle (KAA) remains almost zero (an ideal value for a normal person), highest for medial KOA group i.e. 5.1 degrees and very small for lateral KOA, almost - 3.5 degrees. Similarly, highest Knee Adduction Moment (KAM) was offered by medial KOA subjects than healthy controls and smaller by lateral KOA group. Also, results indicated less reliability of COP in KOA diagnosis.

In recent years from 2000 to 2018, about 104 articles related to different KOA gait feature approaches are obtained excluding anthropometric since this general data is used in all the articles. Out of the total 104 studies, 75 are based on hybrid features, 22 are focused on kinetic features, 5 on spatiotemporal and rest on kinematic and silhouette features. Percentage usage of each is represented in Fig. 15.

Table 5 illustrates the findings of the selected articles (out of the total 75 articles) with rate accuracy and tool used. Data shows heavy research on hybrid approach features due to more accurate KOA analysis. Therefore, the research articles discussed in this study reflect extensive research on hybrid KOA features approach as it allows more features of the person to be extracted. Extracting a large number of features and then optimizing them may automatically lead to enhancement in system's performance.

## 6 Performance Evaluation Methods in KOA Diagnosis

After selecting some optimized features, at last the performance of the diagnostic system is evaluated by employing some statistical methods. These methods are the assessment tests having a powerful capability to measure the accuracy of a system. In KOA, these measures were applied to check the efficiency of the used model to classify normal and abnormal gait.

In this section, a simple and broad description of commonly used statistical measures for KOA analysis is presented. Over time, a number of KOA performance evaluation measures have been developed and used by researchers [44, 48, 103, 115] shown in Fig. 16 to check the overall accuracy of the system.

Broadly statistical measures are classified into two main types: parametric, which makes the assumption on data to be normal (e.g. mean, standard deviation (SD), *T* test, ANOVA, Pearson’s Correlation Coefficient (PCC), Intraclass Correlation Coefficient (ICC)/Coefficient of variation etc.) and the other: non-parametric, which doesn’t make any assumption related to data so known as distribution less test (e.g. Chi sq. test, Kruskal–Wallis (KW) test, Kolmogorov–Smirnov (KS) test etc.) [136].

Confusion Matrices and Cross-validation (CV) are other vital measures used in recent studies for performance validation of the model [31, 37]. Also, two important evaluation measures i.e. Mean, and Standard Deviation are examined to be considered by almost all the studies. Thus, available data indicated the high potential of statistical metrics to evaluate the performance of KOA gait analysis system. A very frequently applied tests for evaluation purpose includes:

### (A) Chi Square Test

Chi<sup>2</sup>-test evaluates the inherent variability by comparing collected data and data that was restructured with predict.

Based on results (0–1) obtained from the test, it is convenient to accept or reject the hypothesis (a mere statement may be true or false) [44, 98, 125]. To interpret this non-parametric statistical method, a general equation is used which simply states that Chi<sup>2</sup> value is the sum of observed data/freq. squared divided by expected data.

$$\chi_{chi}^2 = \sum [(f_{ob} - f_{ex})^2 \div f_{ex}], \tag{4}$$

where  $f_{ob}$  and  $f_{ex}$  denotes observed and expected frequency,  $\chi_{chi}^2$  denotes Chi<sup>2</sup> test value and  $\Sigma$  represents the sum of all the values obtained by performing computations on  $f_{ob}$  and  $f_{ex}$ .

KOA Gait Feature Representation Approaches

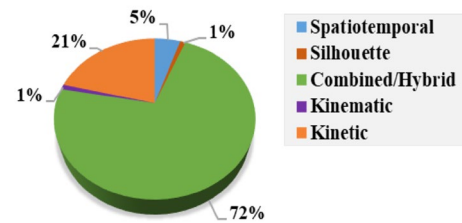


Fig. 15 Usage of each approach (in %) for KOA features representation

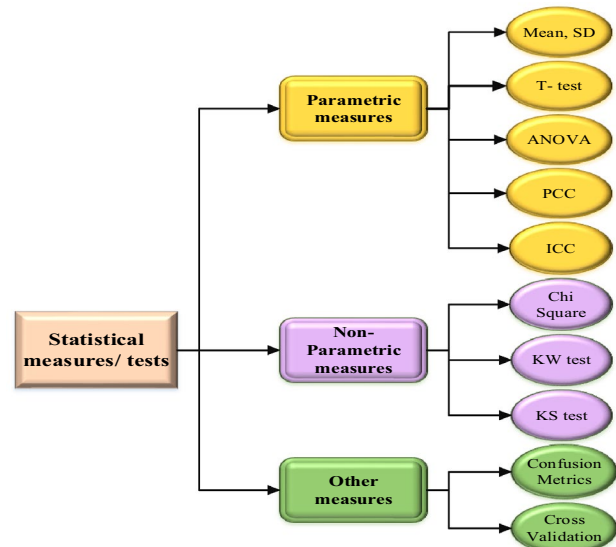


Fig. 16 Description of common performance evaluation statistical measures used for KOA analysis

### (B) ANOVA

If the size of the population becomes large (more than two), Analysis of Variance (ANOVA) provides the best solution by examining total amount of variation within each sample. ANOVA, a statistical technique specially designed to test whether the mean of more than two population is equal or not [15, 41, 43, 46, 87, 96, 115, 119, 135]. Considering the population A and other population X, the method can be given as

$$\bar{A} = \hat{X} \tag{5}$$

where  $\bar{A}$  denotes group A mean  $\hat{X}$  is the group X mean. An ANOVA can be one-way [87, 119] (includes single classification criteria with 1 independent variable and 2 levels) or two-way [128] (two classification criteria with 2 independent variable and multiple levels).

(C) Intra-class Correlation Coefficient (ICC/IC)

An inferential statistic which is used when a unit is arranged in groups and quantitative assessment is performed on it, is known as Intra-class Correlation Coefficient. 1 value of ICC indicates a close relation between elements of group and 0 indicates no relatedness [103, 134]. Considering a dataset with  $P$  paired data items ( $v_{q,1}, v_{q,2}$ ) for  $q = 1 \dots P$ , Mathematically, ICC can be defined as

$$s = \frac{1}{Pr^2} \sum_{q=1}^P (v_{q,1} - \bar{v})(v_{q,2} - \bar{v}) \tag{6}$$

where

$$\bar{v} = \frac{1}{2P} \sum_{i=1}^n (\bar{v}_{q,1} + \bar{v}_{q,2}) \tag{7}$$

$$r^2 = \frac{1}{2P} \left\{ \sum_{q=1}^P (v_{q,1} - \bar{v})^2 + \sum_{q=1}^P (v_{q,2} - \bar{v})^2 \right\} \tag{8}$$

Here,  $s$  denotes the ICC value,  $r^2$  is the variance and  $\bar{v}$  represents the mean of the dataset.

(D) Pearson Correlation Coefficient (PCC)

PCC, the most commonly used statistical measure for correlation analysis, is also referred to as Interclass or Product Moment Correlation Coefficient. PCC is applied to measure the strength of linearly related variables [16, 42]. The value of this coefficient ranges from  $-1$  to  $+1$ . Given  $X$  and  $Y$  as the paired classes, consisting of  $k$  pairs,  $s_{xyp}$  can be presented as

$$s_{xyp} = \frac{\sum_{j=1}^k [(\hat{x}_i - \bar{x}_v)(\hat{y}_i - \bar{y}_v)]}{\sqrt{\sum_{j=1}^k (\hat{x}_i - \bar{x}_v)^2 * \sum_{j=1}^k (\hat{y}_i - \bar{y}_v)^2}} \tag{9}$$

where

$$\bar{x}_v = \frac{1}{k} \sum_{j=1}^k \hat{x}_i, \tag{10}$$

$$\bar{y}_v = \frac{1}{k} \sum_{j=1}^k \hat{y}_i \tag{11}$$

Here  $\hat{x}_i, \hat{y}_i$  represents the individual sample points of the class,  $\bar{x}_v, \bar{y}_v$  are their respective mean  $k$  denotes the sample size,  $j$  is the number of elements in two classes and  $s_{xyp}$  is the PCC value.

(E) t-Test (Student’s t-test)

Like ANOVA, T-test also referred to as Student’s T-test is used to check whether the mean of two groups are equal or not. To analyze this, T-score is calculated which is the difference between two groups divided by the difference between both groups. A small value of T-score indicates similarity between groups and vice versa. The particular choice of t-test depends on whether two samples are unpaired (independent) or paired (dependent) [11, 40, 48, 49, 87, 94, 102, 135].

Thus, T-test can be classified as: Independent (unpaired) [32, 124] which requires two samples to be tested at once so it is necessary to firstly determine the variance for both groups and the other is Dependent (paired) [131] in which one group is tested twice. So, before and after conditions encountered in this test.

(F) Mean and Standard Deviation (SD)

Mean being an important statistical measure provides the average of given data observations [11, 44, 103, 114, 134]. E.g.,  $X$  is the dataset having values  $x_1, x_2 \dots x_{n_v}$ , then mathematically, it can be given as

$$\bar{X}_m = \frac{\sum_{i=1}^{n_v} \hat{X}}{n_v} \tag{12}$$

where  $\hat{X}$  represents the individual value of data,  $n_v$  denotes the number of observations of data and  $\bar{X}_m$  is the mean value.

Similarly, SD gives an estimate of variability in data indicating how much value is far or close to the central mean. A small value of SD means closeness of data go mean and vice versa. If  $\hat{X}$  denotes the individual value of dataset  $X_1, X_2 \dots X_n$  and  $\bar{X}_m$  is the mean of the whole dataset; SD can be presented as

$$\sigma_{SD} = \sqrt{\frac{\sum_{i=1}^{n_v} (\hat{X} - \bar{X}_m)^2}{n_v}} \tag{13}$$

Here,  $n_v$  refers to the number of values in the dataset.

(G) Kolmogorov–Smirnov Test (KS)

Commonly known as KS test, is a non-parametric statistical test and is entirely agnostic. Given two sets of a dataset, KS test tries to examine whether the considered dataset varies significantly or not [35, 116, 118, 124, 128]. This test don’t require the data to strictly follow the normal distribution assumption. Thus, the basic purpose is to determine overall shape differences of the two samples, considering univariate and continuous data. The test statistic  $D_{ks}$  can be defined as

$$D_{ks} = \max_1 \leq \hat{Y} \leq N_T \left[ F_T(\hat{Y}_{i_0}) - \frac{i_0 - 1}{N_T}, \frac{i_0}{N_T} - F_T(\hat{Y}_{i_0}) \right] \tag{14}$$

where  $N_T$  is used to represent total count of data for distribution,  $i_0$  denotes the frequency of observation and  $F_T(\hat{Y}_{i_0})$  symbolize input numbers.

(H) Kruskal–Wallis Test (KW)

KW test, a non-parametric test also named as one-way ANOVA on ranks have one dependent and one independent variable. In the situation where data fails to fulfill the assumption of one-way ANOVA, this test is applied [47, 122]. The test determines significant differences between two or more groups, making no specific supposition about normality. Mathematically,

$$H_{kw} = (N_p - 1) \frac{\sum_{j=1}^q n_j (\bar{S}_j - \bar{S})^2}{\sum_{j=1}^q \sum_{v=1}^{n_j} (S_{jv} - \bar{S})^2} \tag{15}$$

where

$$\bar{S}_j = \frac{\sum_{v=1}^{n_j} S_{jv}}{n_j} \tag{16}$$

$$\bar{S} = (N_p + 1) / 2 \tag{17}$$

Here,  $n_j$  symbolizes the number of observations in group  $j$ ,  $S_{jv}$  denotes the rank of observation ‘ $v$ ’ from group ‘ $j$ ’,  $N_p$  is the total number of observations,  $\bar{S}_j$  represents average range of all observations in group ‘ $j$ ’ and  $\bar{S}$  is the average of all the  $S_{jv}$ .

(I) Confusion Metrics

From recent years, a number of classification models have been developed such as SVM, Decision Trees etc. for KOA diagnosis. To evaluate the performance of such models, confusion matrices are the most widely used measures.

Confusion matrix involves four important identities [31, 88, 89, 107]:

True Positive ( $X_{TP}$ ): total number of positives truly classified as positive.

True Negative ( $X_{TN}$ ): total number of negatives truly classified as negative.

False Positive ( $X_{FP}$ ): total number of positives wrongly classified as positive.

False Negative ( $X_{FN}$ ): total number of negatives wrongly classified as negative.

In general, these metrics can be represented as

$$\text{Sensitivity/Recall/TPR}(v_R) = \frac{X_{TP}}{X_{TP} + X_{FN}} \tag{18}$$

$$\text{Specificity/TNR} = \frac{X_{TN}}{X_{TN} + X_{FP}} \tag{19}$$

$$\text{Precision}(v_P) = \frac{X_{TP}}{X_{TP} + X_{FP}} \tag{20}$$

$$\text{NPV} = \frac{X_{TN}}{X_{TN} + X_{FN}} \tag{21}$$

$$\text{FNR} = \frac{X_{FN}}{X_{FN} + X_{TP}} \tag{22}$$

$$\text{FPR} = \frac{X_{FP}}{X_{FP} + X_{TN}} \tag{23}$$

Here Eqs. (18)–(23) represents True Positive Rate (TPR), True Negative Rate (TNR), Positive Predicted Value ( $v_p$ ), Negative predicted Value (NPV), False Negative Rate (FNR) and False Positive Rate (FPR).

Based on these evaluation metrics parameters, accuracy and F-score can be easily determined and given as

$$\text{Acc}_t = \frac{X_{TP} + X_{TN}}{X_{TP} + X_{TN} + X_{FP} + X_{FN}} \tag{24}$$

(J) F-Score is the beneficial performance measure for multiclass classification. Taking precision and recall into consideration, Total F-score is measured [135]. Highest value can be 1 implies higher predictive capability of classifier and the lowest can be 0 i.e.  $0 \leq F_{SC} \leq 1$ . In scientific terms, it can be presented as

$$F_{SC} = 2 * \left( \frac{v_P * v_R}{v_P + v_R} \right) \tag{25}$$

where  $v_p$  and  $v_r$  denotes precision and recall. Therefore, confusion metric [31] (error metric) gives the estimate of performance by calculating positives and negatives in data. When some conducted to analyze the performance of a model, the probability of occurrence of Type-1 ( $\alpha$ ) (discarding a claim when it is true) and Type-2 ( $\beta$ ) (accepting a claim when it is false) errors get increased. In this case, a formula is applied to correct the error rate known as Bonferroni’s correction (BC) [13, 121, 122, 137]. The use of such correction reduces the size of critical  $\alpha$ , thus suppressing the effect of error occurred due to  $X_{FP}$  and  $X_{FN}$  in data. BC formula can be defined as



$$\alpha_{BC_{new}} = \frac{\alpha_{org}}{K} \quad (26)$$

where  $\alpha_{BC_{new}}$  implies new alpha to correct Type-1 error,  $\alpha_{org}$  indicates error alpha and K is the number of comparisons.

Once the statistical performance measures have been applied, the obtained results are analyzed using ROC [31, 34, 95] referred to as Receiver Operating Curve. ROC thus provides the common way to visualize the accuracy of a binary classifier and gives the value called AUC (Area under Curve). The curve is plotted between TPR (drawn on Y-axis) and FPR (drawn on X-axis) i.e. sensitivity versus (1-specificity). A value of 1 represents the best AUC and worst by 0.5. So, higher the AUC, better is the test.

Yuki Ishikawa et al. [31] used ROC curves to analyze the performance of the system on applying planar law for KOA identification, displayed in Fig. 17.

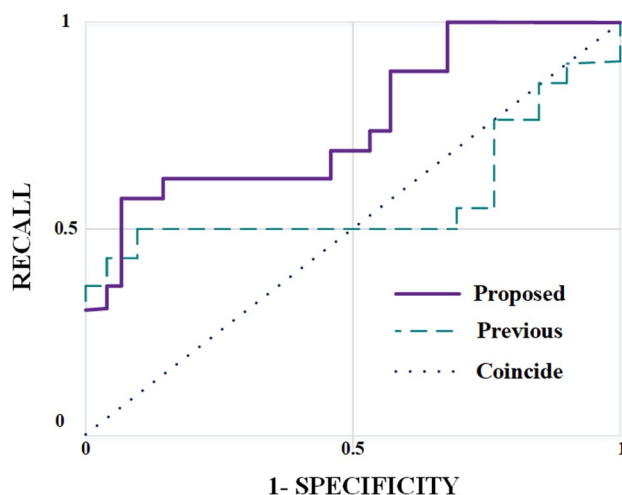
Various studies included cross-validation [10, 32, 34, 91] as an important statistical validation technique. The scheme provides an estimate for selecting best fit model thus achieving good results.

## 7 Overview of Machine Learning Techniques (MLT) in KOA Diagnosis

In the present era of automated diagnosis, the use of Machine Learning is increasing day by day. This is the key enabler of Artificial Intelligence (AI) where the purpose is to create intelligent machines like humans, by artificially incorporating knowledge in them. Machine learning techniques consist of a set of algorithms that have the capability to perform different tasks and achieve reliable accuracy by learning through examples.

In a diagnostic system, final stage consists of using a classifier to enable the identification process. The features extracted in previous steps acts as input to train the classifier. The accuracy of the system depends upon how well the training is performed. Machine learning developed its root in various fields to solve important problems such as business, science, industry, medical and other applications. In medical, diagnosis of a disease is a no more difficult task due to high efficiency of machine learning techniques. It has shown its greater usage in recent years to enable accurate detection of KOA and their proper rehabilitation. A pictorial demonstration of percentage usage of different techniques is also presented, from (2007–2017), indicating its potential to provide a robust solution to problem KOA diagnosis.

Machine learning techniques can be broadly categorized into two sub-categories i.e. Supervised and Unsupervised.



**Fig. 17** Describes the outcome of existing (blue dotted line) and proposed method (bold purple line) by ROC curve, taken from ref [31]. Y-axis represents specificity and X-axis indicates sensitivity. The threshold change between 0 and 50 considered as 0.01. Upper area (left) shown better differences between the two and coincide condition is depicted by the small dotted black line. (Color figure online)

Supervised Machine Learning techniques (SMLT) are further based on classification techniques [49] and regression learning models. Similarly, unsupervised Machine Learning Techniques (USMLT) include clustering and association methods. Since clustering techniques are used by most of the studies so we will only focus them. Some researchers have combined both types of learning techniques to get enhanced performance, known as Hybrid machine learning technique.

### 7.1 Supervised Machine Learning Techniques (SMLT)

Supervised machine learning is the task of determining a function from a labeled data (having independent and a dependent variable). It involves the use of a supervisor to train the classifier with a set of inputs as well as their corresponding outputs. The model is trained on the labeled dataset, so it can predict the outcome of out-of-sample data. The main purpose of using this type of learning is to reduce the chance of occurrence of an error. Various classifiers are used under supervised learning such as Supervised Machine Learning (SVM), Random Forests (RF), Decision Trees (DT), Artificial Neural Network (ANN), Regression Models, for KOA classification.

*Support Vector Machine (SVM)* is most commonly used for diagnosis of KOA. It can be viewed as frontier which best segregates two classes of labeled data using the

concept of hyper-plane. The main objective is to design a hyper-plane that classifies all training vectors in two classes. They have the greater capability to work with a large number of features without involving complex computations. Phinyomark et al. [41] applied SVM to analyze kinematic differences between male and females for both KOA and healthy and classification accuracy of 98–100% was achieved. In another work, Levinger et al. [34] used the concept of SVM and multiclass SVM to identify people with TKR, KOA and PFPS. According to the study, SVM for data classification can be represented as:

$$S_{\text{new}} = \{(u_1, v_1), (u_2, v_2) \dots (u_n, v_n)\} \quad (27)$$

where  $u_i$  is the element of  $Z^n$

$$v_i = \{1, -1\}$$

Here,  $u_i$  represents vectors containing gait features,  $v_i$  denotes corresponding class labels (+1 means disease and -1 indicated healthy). They also employed modified SVM to differentiate data with more than two classes such as the involvement of different subject groups. Considering 'm' classes in the dataset, a combination of  $m(m-1)/2$  SVM classifiers were used to build modified SVM. An accuracy of 85–92% was achieved using SVM. On applying modified SVM, an enhanced accuracy was seen on test data indicating the potential of SVM in KOA detection.

Decision Tree (DT): classifier is based on flowchart-like structure where each internal node represents a test on the attribute and each branch indicates the outcome of test. DT have high potential in handling both numerical as well as categorical data and requires very little effort for data preparation. In KOA decision analysis, it can be used to visually and explicitly represent decisions and for identification and classification of KOA. A study by Organero et al. [48] successfully classified KOA patients from healthy controls using different classifiers such as SVM, a combination of LR and MLP, EM clustering and DT. Out of all the classifiers, DT has shown high performance with a classification rate of 100%. Another study by Chen et al. [91] checked rehabilitation accuracy of three different exercises—SAE, SLR and QSM in KOA patients. DT outperformed KNN with an accuracy rate of 98–100% for KOA rehabilitation.

Random Forest (RF): are the most popular and powerful SMLT which are capable of performing both classification and regression tasks. RF technique creates a forest with a number of decision trees. This is mostly preferred when a large dataset with higher dimensionality is present. In KOA diagnosis, it is proved to be a successful technique having numerous benefits.

Kotti et al. [10] using RF regressors and cross-validation achieved an accuracy of  $72.61\% \pm 4.24\%$  for identification of KOA and healthy subjects. Results demonstrated the high capability of RF rule-based approach in clinical KOA diagnosis.

Artificial Neural Network (ANN): is based on the biological structure of the human brain. As brain consists of billions of neurons that work in combination with each other i.e. receiving input, processing it and producing output. Achieving this functioning artificially is known as ANN. In ANN, a node which is the replica of a neuron in the brain, receives input from the external environment, processes it and gives the desired output. In KOA diagnosis, Multi-Layer Perceptron (MLP) ANN are mostly considered due to greater capability to deal with large computation problems. MLP is a perceptron network having multiple layers i.e. input, output, and more than one hidden layers. A research work by Favre et al. [13] applied a feed-forward MLP having one hidden layer for KAM computations in KOA and healthy controls. The network was trained using back propagation algorithm. The similarity between KAM curves of both groups shown the efficiency of ANN for a broader evaluation of KOA. In another study, Koktas et al. [107] proposed a study to analyze several ensemble techniques to develop a semi-automated system for diagnosis of people with KOA. Kinematic and Spatiotemporal features were used to train a set of MLP's for classification of 110 KOA and 91 healthy subjects. Results demonstrated the efficiency of used MLP's combination in KOA investigation with success rate of 87–92% was attained.

Again, Koktas et al. [106] presented a study to evaluate the performance of mixed classifiers in identification of KOA using vision and sensor based technologies. A Decision tree (DT) classifier build with the MLP successfully achieved the purpose by giving an accuracy of 80%. Munoz et al. [48] tried to investigate the asymmetry in pressure to analyze the differences in gait of KOA and healthy controls. Sensors embedded shoes were used and evaluation was performed using a bundle of classifiers. The combination of logistic regression and MLP attained an accuracy of 95%, closer to that of DT, reflecting its potential in KOA detection.

Regression Learning Models: are one of the important supervised machine learning algorithms used by various studies to classify KOA patients [10, 44, 125, 127]. Different types of regression models have been used to achieve KOA classification task. A linear regression model having a 1:1 relation between dependent and independent variables applied by Mayera [118] diagnosis. In contrast to the linear model, multiple regression having one dependent and more than one independent variables was used in the study of Matsumoto et al. [104]. They investigate the relation between

KOA and variations in gait with a risk of falling in KOA adults.

Another useful classification model in supervised learning is the logistic regression model. In these models, prediction of output is transformed using a non-linear function called the logistic function. Farrokhi et al. [40] used multiple regression to successfully investigate the relation between stability and level of pain in KOA subjects. Similarly, the use of hierarchical regression models which involve running independent variable one at a time or in sets, made by some researchers. A study by Zeni Jr et al. [120] employed hierarchical regression to test the effect of different walking speeds on biomechanical variations in KOA subjects having different severities.

## 7.2 Unsupervised Machine Learning Techniques (USMLT)

Unsupervised machine learning techniques are considered when data in the training set is unlabeled i.e. there are no training examples available to train the model [49] and no corresponding label that is paired with the samples. In this case, to evaluate the model how well it is performing, other similarity measures such as cosine similarity, Mahalanobis distance [48] can be used. In recent years, several unsupervised clustering techniques are used for the diagnosis of KOA such as K-means, Expectation–maximization (EM) clustering algorithm, Fuzzy models etc. These techniques form clusters of data in dataset based on their similarities and dissimilarities and lead to the diagnosis of diseased and healthy ones.

Chen et al. [91] explored the KNN clustering technique to classify exercise type for KOA patients after rehabilitation using three devices and achieved 94% accuracy. In another study, Organero et al. [48] used EM clustering technique to diagnose early-stage KOA subjects. Similarly, a point cluster technique was applied in a study by Chehab et al. [116] to estimate gait variations among KOA and healthy controls for reliable diagnosis.

Some studies utilized the combination of two or more techniques to achieve an improved accuracy rate. In a work, Koktas et al. [106] proposed to combine decision trees with MLP to achieve better accuracy. A success rate of 80% was achieved on KOA subjects.

## 7.3 Hybrid Machine Learning Techniques (HMLT)

In spite of combining similar type of machine learning techniques to each-other (e.g. SMLT with another SMLT), a semi-supervised machine learning platform was developed by some researchers using the combination of SMLT and

USMLT [49]. This learning approach has the great potential to deal with limited data with high efficacy. A hybrid machine learning approach was adopted by Moustakidis et al. [88] combining fuzzy decision tree-based SVM (Fuzzy DT-SVM) classifier to investigate KOA subjects with different severity levels. The used combination yielded an improved accuracy of 93.44%.

A brief summary of mostly adopted machine learning techniques for KOA diagnosis considering their significant benefits (+) and drawbacks (–) is defined in Table 6.

Based on the available data from 2007 to 2017, usage ratio of machine learning classifiers for identification of KOA, shown in Fig. 18. It is analyzed that about 81% of research focused on using SMLT, 16% on using clustering based USMLT and only 3% towards hybrid techniques. Out of the total percentage usage in SMLT, almost 41% of work done considering regression learning models, 16% on SVM, 9% towards DT. ANN contribution is seen to be approx. 12% and 3% studies used RF for KOA identification.

Therefore, the State-of-art survey indicates the usefulness of SMLT for diagnosis of KOA due to its several benefits such as easiness in understanding, specific nature, well-known input data and more accuracy.

## 8 Future Perspectives

The necessary prerequisite, fundamental to any research is to qualitatively and quantitatively examine, analyze and explore the existing literature and identify the gaps in the previous studies. This forms the baseline for carrying out research and for proposing a model/approach to overcome the challenges identified. This section provides an insight to the existing methodologies/approaches by doing their critical analysis considering their scope in future. KOA gait recognition though has gained huge popularity due to a plethora of benefits it aims to provide to clinicians but the scope of improvement with the existing approaches still remain large which attracts researchers and academicians towards this field of study to provide better and more robust automated systems. Unresolved issues in KOA analysis that pose main challenge towards effective KOA diagnosis need to be addressed. They are as follows.

### (A) Gait Dataset Creation

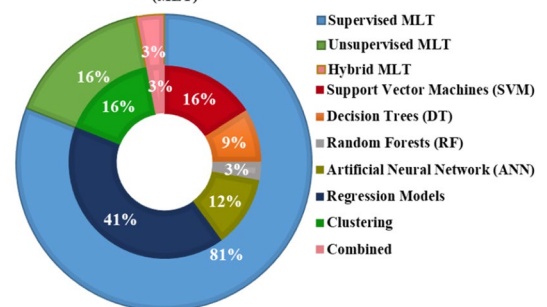
To initiate any detection or classification task, it is necessary to have a proper set of related data. The performance of the entire system depends on the availability of dataset. Thus, one of the main perspectives is to create a clinical gait dataset and make it public to researchers for further investigations. It is pertinent to mention here that no dataset is publicly available for KOA. Some of the datasets

**Table 6** Mostly adopted Machine learning techniques for diagnosis of KOA, from 2000–2018

S. no.	Type of learning	Technique	References	Remarks
1	Supervised	Support Vector Machine (SVM)	[32, 34, 37, 41, 48]	(+) Use of kernel function to solve any complex problem (+) Reduces chance of overfitting (-) Low performance on large datasets (-) Can't able to deal with noisy data (-) Difficulty in choice of kernel function.
2		Decision Trees (DT)	[48, 91, 106]	(+) Easily interpretable and very compact (+) Can handle irrelevant and missing data (-) Unstable and often inaccurate (-) Involves high computations
3		Random Forest (RF)	[10]	(+) Efficiently handles non linear problems also (+) Accurate and low computational cost (-) High risk of Overfitting (-) Difficulty in making interpretations
4		Artificial Neural Network (ANN)	[13, 48, 106, 107]	(+) Ability to deal with incomplete and noisy data (+) High fault tolerance (-) Requires large dataset to work (-) Sometimes, take huge training time
5		Linear, multiple, logistic, hierarchical regression	[10, 40, 44, 48, 104] [38, 45, 117, 118, 120] [125, 127, 130]	(+) Easy and straightforward (+) Ability to avoid overfitting (-) Much affected by outliers presence in data
6	Unsupervised	K-means, expectation–maximization (EM) clustering	[44, 48, 89, 91, 106]	(+) Fast, simple and flexible algorithm (+) Can handle missing data values (+) Efficiently fix mixture distributions (-) Difficulty in specifying number of clusters (-) Very slow convergence
7	Hybrid	Fuzzy DT-SVM	[88]	(+) Highly efficient with high-dimensional problems (+) Reduces complexity and overfitting problems (-) Require large calculations

used in earlier studies were self-created and are currently unavailable. Also, they involve some crucial drawbacks such as less number of KOA subjects i.e. very small sample size, consideration of only single gender etc. They are not reliable for pathological gait analysis. In other words, there is less dataset on gait considering pathological diseases compared to other biometric. So, the research can be directed towards the creation of a new dataset including both normal and abnormal KOA gait samples. The clinical records of KOA like many other diseases, exhibit a striking disparity between the genders and reflects females affected adversely with the disease in comparison to male counter parts. Genetic and hormonal factors are the main causes responsible for the disparity. In addition to factors such as knee injury, genetics or obesity that directly influence knee mobility; the aging process too leaves an impression due to changes in the musculoskeletal system that increases the tendency of KOA. Therefore age and gender of subjects is crucial for the study so as to investigate the effect of these

PERCENTAGE USAGE OF EACH MACHINE LEARNING TECHNIQUE (MLT)



**Fig. 18** A pictorial representation of usage rate of different Machine Learning Techniques (in %age) from 2007 to 2017

parameters on KOA susceptibility and how it affects the knee, over a period to develop KOA.



### (B) Self-occlusion Avoidance

In an abnormal gait such as KOA, sometimes the problem of self-occlusion is observed. It refers to a condition when the differentiation between left and right limb becomes very difficult during abnormal walking. Due to self-occlusion, false recognition rate increases that affect the overall classification accuracy. So the focus of researchers can be directed towards solving this problem by splitting the subject under study to multiple components and then reconstructing the occluded body parts using efficient and appropriate approaches.

### (C) Background Modelling

Background Modelling is a crucial task in a recognition process. Extraction of foreground from background effectively needs complete and proper understanding of background subtraction techniques and its applicability. In previous work, it is examined that the major cause of inaccurate classification results is due to the use of inappropriate foreground detection methods. Verlekar et al. [37] employed background subtraction cues to extract silhouette images from background for further processing. From extracted silhouette, amount of body movement, COG shifts, Torso Orientation (TO) and feet related features were then extracted and analyzed. Lack of efficiency in earlier steps lead to inaccurate results in later stages. So the future work can be focused towards the use of appropriate background and foreground segmentation methods for effective KOA detection.

### (D) Feature Space Reduction

Using a large number of features and achieving good results is not much of worth as it costs on the performance and scalability. Feature space reduction is the process of selecting features in such a way that dropping some of the irrelevant variables among all, does not affect the overall performance of the system.

Kobsar et al. [15] and Derek et al. [115] applied the Principle Component Analysis (PCA) for feature selection to enable better classification accuracy. Another work by Hubley et al. [43] also used PCA to select lower limb features from Ground Reaction Forces (GRF's) and EMG data. Thus using a single robust and hybrid approach that helps in feature dimensionality reduction by selecting the best optimized features is the major concern of this article.

### (E) Severity Level

The proper diagnosis of a disease is not possible unless it is checked for all the severity levels. Factors such as peripheral joint involvement, patient's assessment of

severity of disease, physical examination on the basis of health assessment questionnaire, laboratory tests etc. need to be considered for holistic evaluation and assessment of the severity of the disease. Recent studies indicate that KOA patients show different gait characteristics at different stages of the disease. Several researchers analyzed KOA at only one or two severity levels thus not considering all that need to be focused. Chang et al. [127] conducted a study for diagnosis of KOA considering only early stage patients. Duffell et al. [128] also experimented mild stage patients to analyze knee Osteoarthritis. Therefore, future work should take into consideration the examination and assessment of knee OA disease at different stages of severity in order to cover each and every aspect of abnormal change.

Furthermore, Table 7 summarizes the limitations and future work of some latest KOA articles, in various journals from 2014 to 2018. The table discussed reflects the grey areas that still require deliberations from the side of the research community.

## 9 Proposed Work

Based on the aforementioned future perspectives, we have planned to direct our efforts on clinical gait recognition considering KOA patients with different severities and normal healthy subjects. Following objectives are considered for the proposed work:

1. Creating a new dataset of KOA subjects having different severity levels and healthy controls based on age and gender.
2. Collecting KOA and healthy gait data considering sagittal plane from left to right and right to left, shown in Fig. 19.
3. Perform pre-processing by applying a method to remove noise from acquired data (i.e. filtering of data) and segment the object to build a geometrical model.
4. We adopted a model-based approach due to its high efficiency in detecting body joints, no need of color contrast, overcomes background cluttering problem.
5. Extract subjects gait features using model-based approach for identification of diseased and normal persons.
6. Use nature-inspired or hybrid approaches to optimize features for their reliable selection.
7. Perform evaluation of proposed system using a robust classifier giving high and improved accuracy rate for differentiating KOA and healthy ones.
8. Perform comparative analysis for diagnosis of severity level based on proposed model-based approach and clinical radiographic grading score.



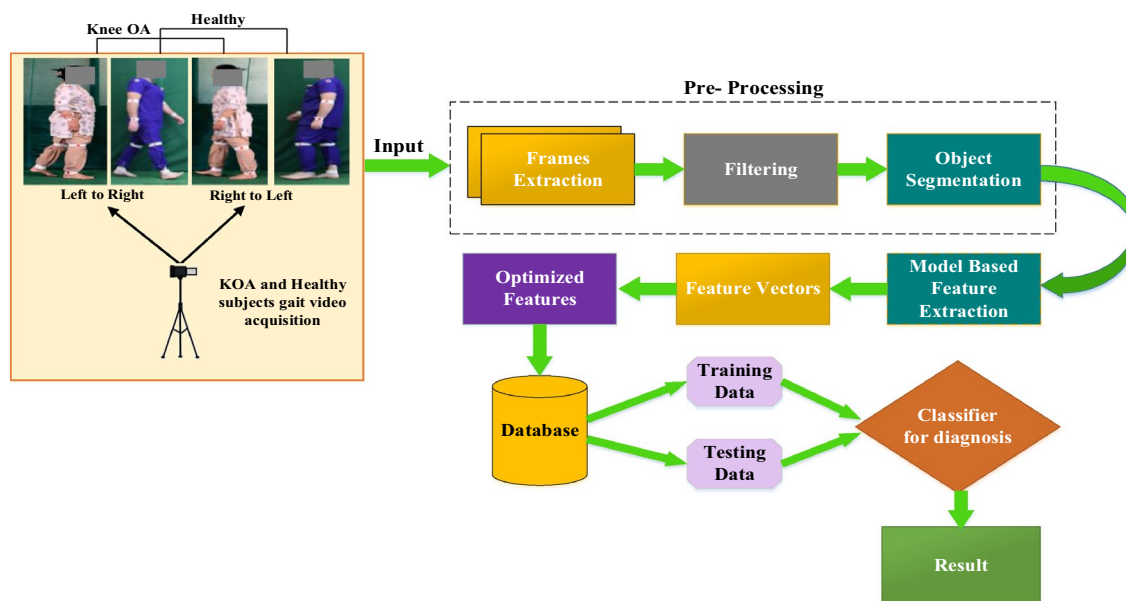
**Table 7** Year wise summary of future work proposed from 2014 to 2018

S. no.	References/year	Bottleneck	Future perspective
1	Tanmay et al. [31]/2018	Disease samples were experimented only	Need to work on: Real patients, Severity level and overlapping problem
2	Karia Monil et al. [123]/2018	Small number of osteoarthritic patients	Analysis of KAM and COP correlation with bony morphology, knee alignment and disease severity is require and large samples should be taken
3	Annalisa Na et al. [124]/2018	Small number of samples Cross-sectional study design Controlled gait speed	Required further analysis of distal and proximal joint gait features along with sex, age, speed
4	A.J Metcalfe et al. [102]/2017	Small sample size with single joint disease	Future work should be directed on large and more representative population
5	M. Hall et al. [138]/2017	Cross-sectional study Great risk of Type 1 error Inaccurate pedometer meas	Longitudinal study is needed to validate results
6	Kade L. et al. [139]/2017	Recreation of virtual gait markers	Need to validate findings using other knee and foot models
7	D Rutherford et al. [140]/2017	Non-consideration of healthy subjects radiographs	Relationship analysis of ageing and KOA is required
8	Jun Sun et al. [103]/2017	Limited motion analysis system recording surface	Focus on other clinical gait features rather than only SPT is obligatory
9	Ashutosh et al. [141]/2016	Small size of KOA participants	Need to analyze the results with large KOA population
10	Stephen et al. [126]/2016	Exploratory nature of study Didn't used any modelling approach	Changes in physical activity patterns need to be explored
11	Kathleen et al. [142]/2016	Small sample size Less similarity in body mass of obese group	Results need to be further verified using large samples
12	Angelos et al. [143]/2016	Included less participants Prone to artifact problem	Further investigation of results is required: in free-living environment in females also
13	A.H Chang et al. [127]/2015	A long-follow up time was needed for assessment of KOA (mild)	Need to inspect the effect on gait in moderate and severe stages Of KOA also
14	Tine Alkjaer et al. [96]/2015	Very limited sample size	Variations in result should be considered for large sample of KOA
15	Hiroimi et al. [104]/2015	Cross-sectional study design Subjective assessment of Kyphosis Chances of selection bias	Clarification of relationship among different gait variables is required
16	Shawn Farrokhi et al. [40]/2015	Subjects with medial compartment KOA were studied only	Efforts should be made to study the affect of other factors and diseases causing knee instability
17	Kun-Hui Chen et al. [91]/2015	Very small sample size	Effect on system's performance due to change in sensor position need to be focused and validation of results should done taking real KOA patients
18	Hublely et al. [43]/2015	Large age differences b/w KOA and healthy subjects	Variations in result should be analyzed when considering age matched controls
19	Sparling et al. [144]/2014	Complicated and costly analysis (multiple force plates)	Further work can be performed on kinematic based recovery for KOA patients
20	Atallah et al. [93]/2014	Larger age difference between groups Used fixed speed, controlled environment	Investigation on head rotations can be performed
21	Calder et al. [117]/2014	Only patients with medial KOA were taken for study	Further studies can be expanded considering comparison with asymptomatic controls

## 10 Conclusion

In clinical practice, automated diagnosis of KOA through biometric gait is an evolving research area drawing the attention of huge researchers. Development of gait

biometrics as a diagnostic tool for KOA has changed the face of subjective clinical assessment. This article provides a comprehensive survey that shows the extent of work done on sensor-based, vision-based and hybrid KOA gait recognition highlighting the most significant one.



**Fig. 19** Workflow of proposed system for KOA and healthy subject's identification. Left part of the figure represents gait samples of KOA and healthy subjects with two view directions (left–right and right–left) in the sagittal plane

The survey summarizes the efforts made by major contributors from ancient times to the Modern era in the medical field. The gait acquisition modalities, feature representation approaches, evaluation methods, and machine learning techniques have been discussed in detail.

Data analysis reveal that even vision-based modality for KOA diagnosis is highly accurate and cost-effective but suffers from certain drawbacks such as overlapping, requirement of large space and high precision cameras etc. Sensor-based modality, however, performs well but is also constrained by factors such as high cost, large time and power consumption, wearing difficulty, etc. The survey done on articles published during the period from 2000–2018 on above-mentioned modalities found approximately about 70% research articles, devoted to hybrid modality for KOA study. Among sensor modality, force sensors in particular being the most utilized sensors due to its capability to directly capture the gait data.

Further, the recent research statistics indicate achieving good measures of accuracy when sensor and vision based modalities are used individually. However, an amalgamation of vision and sensor based modalities definitely provide an edge over the modalities when used individually. Higher efficiency in capturing large and more relevant KOA gait data is the key factor attributed to better performance accuracy. Literature thus clearly reveals the potential of combined features for better KOA diagnosis.

Furthermore, extracting a single feature from KOA gait results in average accuracy of around 85 to 90%. This accuracy rate can further be improved by using an

appropriate fusion of KOA gait features as it can help in reducing misclassification rates. The article inclusively surveys statistical methods and classification techniques used for KOA analysis. Based on the number of articles received from recent years, most researchers have used supervised learning (regression learning models) to classify KOA and healthy subjects with high performance.

From the state-of-art approaches, tailor made specifically for gait based KOA analysis, it can be concluded that certain gaps exist that open up the scope of further research and investigations required for future work in this direction. Challenges such as absence of publicly available KOA gait dataset, consideration of few severity levels and only medial knee compartment, self-occlusion etc., ignored in the previous studies have to be further deliberated upon. Finally, this article provides useful references to get in-depth insight of research towards KOA diagnosis via gait analysis.

## Compliance with Ethical Standards

**Conflict of interest** The author's declare that they have no conflict of interest.

## Appendix

The URLs for the images taken from the internet and used in this article are provided below.

Figure 5: <http://www.clinicalgaitanalysis.com/> <https://en.wikipedia.org/wiki/Aristotle> <https://www.leonardodavinci.net/> <https://www.onthisday.com/people/girolamo-cardano> <https://www.historyonthenet.com/galileo-galilei/> <https://www.biography.com/people/ren-descartes-37613> [https://commons.wikimedia.org/wiki/File:Portrait\\_of\\_Giovanni\\_Alfonso\\_Borelli\\_Wellcome\\_L0010325.jpg](https://commons.wikimedia.org/wiki/File:Portrait_of_Giovanni_Alfonso_Borelli_Wellcome_L0010325.jpg) <https://thomasjohnston.wordpress.com/category/postage-stamps/page/2/> <https://www.thefamouspeople.com/profiles/hermann-von-helmholtz-4828.php> [https://en.wikipedia.org/wiki/Eadweard\\_Muybridge](https://en.wikipedia.org/wiki/Eadweard_Muybridge) <https://sheridanphothistory.wordpress.com/page/2/> <https://me.queensu.ca/People/Deluzio/JAM/files/Baker.pdf> <https://me.queensu.ca/People/Deluzio/JAM/files/Baker.pdf> <https://ouhsc.edu/bserdac/dthompson/web/gait/knematics/saunders.htm> <https://www.nap.edu/read/4779/chapter/14> <http://www.clinicalgaitanalysis.com/history/modern.html> <https://www.legacy.com/obituaries/sfgate/obituary.aspx?n=david-h-sutherland&pid=17877856> <https://ptceu.wordpress.com/2013/05/01/in-celebration-of-my-friend-and-mentor-dr-jacquelin-perry/>.

Figure 7: <https://www.dovemed.com/diseases-conditions/osteoarthritis-of-the-knee/> Figure 8: <https://me.queensu.ca/People/Deluzio/JAM/files/Baker.pdf> <https://www.nap.edu/read/4779/chapter/14> <https://ouhsc.edu/bserdac/dthompson/web/gait/knematics/saunders.htm> [https://en.wikipedia.org/wiki/Robert\\_H.\\_Goddard](https://en.wikipedia.org/wiki/Robert_H._Goddard) <http://www.oemupdate.com/feature/kistler-group-acquires-ios-gmbh/> <http://www.clinicalgaitanalysis.com/history/modern.html> <https://www.digitalthcommonwealth.org/search/commonwealth-oai:73666c049> <https://ar-conf.ru/en/news/pochuvstvuyte-virtualnie-obyaty-tesla-suit-na-ar-conference-30543> <https://news.creativecow.net/company.php?folder=Vicon> <https://www.mediaproductionshow.com/exhibitors/ikegami/> <https://www.dualshockers.com/microsoft-discontinuing-original-kinect-models-for-windows-pc-in-2015/> <https://www.telegraph.co.uk/education/universityeducation/8742154/Top-UK-universities-in-world-rankings.html> [http://physics.kenyon.edu/EarlyApparatus/Static\\_Electricity/Geissler\\_Tubes/Geissler\\_Tubes.html](http://physics.kenyon.edu/EarlyApparatus/Static_Electricity/Geissler_Tubes/Geissler_Tubes.html) <https://www.mdpi.com/1424-8220/14/2/3362/html> [https://www.researchgate.net/publication/301935875\\_Human\\_Gait\\_and\\_Clinical\\_Movement\\_Analysis](https://www.researchgate.net/publication/301935875_Human_Gait_and_Clinical_Movement_Analysis) [http://dynamolab.umed.pl/?page\\_id=34&lang=en](http://dynamolab.umed.pl/?page_id=34&lang=en) <https://www.amazon.co.uk/Tobar-01544-Gyroscope-Silver-10cm/dp/B000H6W52S> <https://www.sparkfun.com/products/retired/692> <https://www.amti.biz/fps-guide.aspx> <http://www.bleng.com/traditional-reflective-markers> <https://www.uline.ca/Product/Detail/S-17177/Vinyl-Safety-Reflective-Tapes/Reflective-Tape-3-x-10-yds-Red> <http://www.taheeltech.com/product/goniometers/> <http://www.phasespace.com/suits.html> <https://vizworld.com/2012/08/vicon-showcase-motion-capture-products-siggraph2012/> <https://www.amazon.in/Camcorders-Camcorder-Digital-External-Microphone/dp/B076DXMXMR> <https://www.dhgate.com/product/2017-anti-blue-light-screen-protector-for/402728044.html> <https://www.generationrobots.com/en/401430-microsoft-kinect-sensor.html> <https://www.microsoft.com/en-us/research/project/kinect-for-windows-sdk-beta/> <https://www.ordineinfermieribologna.it/2016/il-futuro-con-gli-wearable-ecco-la-maglietta-che-rileva-il-ritmo-cardiaco-e-lo-trasmette.html>.

<https://www.shutterstock.com/imagevector/vector-flat-cartoon-lens-photo-camera-777796435>.

Figure 37: <https://www.shutterstock.com/imagevector/vector-flat-cartoon-lens-photo-camera-777796435>.

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