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HUMAN GENDER CLASSIFICATION USING KINECT SENSOR: A REVIEW

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1. INTRODUCTION

Gender classification using Kinect sensors is an important topic in computer vision and biometrics. The Kinect sensor, which was developed by Microsoft for gaming, can capture both RGB and depth data simultaneously as it can provide more information about the subject's facial features and body skeleton joints than traditional 2D cameras. This makes it an attractive tool for many potential applications, including security systems, marketing research, and healthcare. Therefore, research in this area can have a significant impact on various fields and improve the accuracy and efficiency of gender classification.

Recent advances in computer vision and machine learning have made it possible to automatically recognize gender from visual data, such as images or videos using the Kinect sensor and shown favorable results (Wolfshaar, J. van de, Karaaba, M. F., & Wiering, M. A, 2015). As the demand for human gender classification methods continues to grow, and by leveraging the sensor's ability and Machine learning algorithms, such as deep learning and support vector machines, researchers are exploring and developing advanced a variety of algorithms and techniques to enhance the accuracy and efficiency of gender classification systems. These algorithms not only take into account facial features but also consider body shape (skeleton) and posture, providing a comprehensive approach to gender classification. Furthermore, there are ethical and social implications of gender classification technology that need to be considered, such as privacy and discrimination concerns (Zhang, Y. Liu, A. Li and M. Wang, 2014). In this work, a review of gender classification features, challenges and limitations of using features for gender classification, methods and approaches for Gender Classification, public Kinect Databases, and the most related articles from 2023 to 2015 are presented.

2. GENDER CLASSIFICATION FEATURES

The human face holds a very important quantity of attributes and information about the individuals, such as expression, ethnicity, gender, and age. Human beings can analyze this information easily, but not that easy for machines (Khalifa, T. A. M., 2016).

There are different features used for gender classification, including the following:

- Face features: These are the features derived from the shape, texture, color, and expression of the human face. They can be global or local, depending on whether they consider the entire face or specific regions or landmarks. Face features can be extracted using various methods, such as wavelet transform, Eigenfaces, gait energy images, etc. (Alghaili, M., Li, Z., & Ali, H. A., 2020).
- Body features: These are the features derived from the posture, shape, size, and movement of the human body. They can be static or dynamic, depending on whether they consider the body at rest or in motion. Body features can be extracted using various methods, such as skeleton joints, light points, angles, distances, etc. (S. Kumar, S. Singh, and J. Kumar, 2019), (Zhang, C., Ding, H., Shang, Y., Shao, Z., & Fu, X., 2018).
- Biological features: These are the features derived from the intrinsic characteristics of the human body, such as fingerprint, iris, skin color, voice, etc. They can be more robust and reliable than appearance-based features, but they may require more specialized devices or techniques to capture and process them (Mali, V. Y., & Patil, B. G., 2019).
- Social network features: These are the features derived from the online behavior and interactions of human users, such as profile information, posts, comments, likes, etc. they can provide rich and diverse information about the gender identity and preferences of the users, but they may also pose privacy and ethical issues Alghaili, M., Li, Z., & Ali, H. A., 2020).

Facial features are considered the most important features that have a unique characteristic to distinguish one individual from another can be Naturel, X., Chateau, T., Duffner, S., Garcia, C., & Blanc, C., 2018), Facial texture (Vaitonytė, J., Blomsma, P. A., Alimardani, M., & Louwerse, M. M , 2021), Facial hair (Dixson, B. J., & Brooks, R. C., 2013), (Goodwin, N. L., Nilsson, S. R. O., & Golden, S. A, 2020), and Jawline (Lambros, V., & Amos, G, 2020). By analyzing these features, machine learning algorithms can be trained to accurately identify the gender of a person and used in various applications based on the Kinect sensor and other technologies.

3. CHALLENGES AND LIMITATIONS OF THE FEATURES USED IN GENDER CLASSIFICATION

The features used for gender classification are not always reliable indicators, many individuals do not conform to traditional gender norms, and their features may not fit the typical profile of a male or female. Several challenges and limitations need to be considered. The following are some of the most significant ones (Anderson, M., & Toor, S, 2019):

- The features may not capture the diversity and complexity of gender identity and expression, which may not be binary or consistent with physical appearance. This may lead to misclassification or exclusion of individuals who do not conform to the gender norms or expectations of the system.
- The features may be affected by various factors, such as illumination, pose, occlusion, expression, aging, makeup, hairstyle, clothing, accessories, etc., these factors may introduce noise or variation in the feature extraction and classification process, resulting in lower accuracy or robustness.
- The features may be biased or discriminatory due to the quality and quantity of the training data, the choice of the feature descriptors and classifiers, or the evaluation metrics and criteria. These biases may cause the system to perform differently or unfairly on different groups of people based on their race, ethnicity, age, culture, etc.

Additionally, there are more challenges such as variability in facial features for example, some men may have softer facial features that resemble those of women, and some women may have more pronounced facial hair or a wider jawline. Age and ethnicity can further complicate gender classification for example, older men may have more prominent wrinkles and sagging skin, and people of different ethnicities may have different facial features that are not characteristic of their gender. Limited training data, machine learning algorithms for gender classification require large amounts of training data to achieve high accuracy. There are also worries about the algorithm's accuracy and the possibility of data exploitation (Lin, F., Wu, Y., Zhuang, Y., Long, X., & Xu, W., 2016), (Scheuerman, M. K., Paul, J. M., & Brubaker, J. R, 2019), (Benitez-Quiroz, C. F., Srinivasan, R., Feng, Q., Wang, Y., & Martinez, A. M, 2017), (Hassanat, A. B., Albustanji, A., Tarawneh, A. S., Alrashidi, M., Alharbi, H., Alanazi, M., … Prasath, V. B. S., 2021).

4. METHODS AND APPROACHES USED FOR GENDER CLASSIFICATION

Computer vision includes methods and techniques for understanding, analyzing, and extracting patterns from images. These patterns could be a shape, speech signal, fingerprint image, a handwritten word, environment, or a human face (Khalifa, T.A.M, 2016). There are several methods used for gender classification. It refers to the various techniques and algorithms used to predict the gender of an individual based on certain characteristics or features. These features such as facial geometry, voice characteristics, linguistic patterns, or physiological measurements predict an individual's gender (Rai, P., Khanna, P., 2012). Classification methods used in gender classification with Kinect sensor technology include feature-based methods, appearance-based methods, and model-based methods. Feature-based methods use specific facial features to determine genders, such as the shape of the jawline or the distance between the eyes. Appearance-based methods use the overall appearance of the face to determine gender, while model-based methods use statistical models to classify gender. The methods and approaches used for gender classification, include machine learning algorithms, statistical models, and deep learning techniques. Furthermore, gender classification can be a controversial topic due to the complex nature of gender identity and expression. It is important to approach gender classification with sensitivity and caution and to avoid reinforcing harmful gender stereotypes or biases (Swaminathan, A., Chaba, M., Sharma, D. K., & Chaba, Y, 2020).

Most of the existing methods involve the use of machine learning algorithms to analyze the features of a person to determine their gender using generally standard databases having high-resolution aligned frontal faces (Tilki, S., Dogru, H. B., Hameed, A. A., Jamil, A., Rasheed, J., & Alimovski, E, 2021). The methods and approaches used the following analysis in their work:

Facial feature analysis: This involves analyzing facial features such as the shape of the jawline, the distance between the eyes, and the presence or absence of facial hair to predict an

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individual's gender. One study used this approach and achieved an accuracy rate of 97% on a dataset of 3,500 images of faces (Swaminathan, A., Chaba, M., Sharma, D. K., & Chaba, Y., 2020).

- Voice analysis: This involves analyzing the pitch, tone, and other acoustic features of an individual's voice to predict their gender. One study achieved an accuracy rate of 99.13% using this approach on a dataset that contained 1652 data from more than 250 speakers and tested them with 400 male and 400 female voices (Badhon, S. M. S. I., Rahaman, M. H., & Rupon, F. R, 2019).
- Linguistic analysis: This involves analyzing language use patterns such as word choice, sentence structure, and use of pronouns to predict an individual's gender. Researchers used this approach and achieved a good accuracy rate on a dataset of Twitter posts (O'Dea, B., Larsen, M. E., Batterham, P. J., Calear, A. L., & Christensen, H., 2017), (Cao, Y. T., & Daumé, H., III, 2021).
- Machine learning algorithms: This involves using various machine learning such as, support vector machines (SVMs), CNN (convolutional neural networks), Random Forest (RF), K-nearest neighbors (KNN), and others (Tuda, M., & Luna-Maldonado, A. I., 2020).
- Physiological measurements: This involves analyzing physiological signals such as electroencephalography (EEG), electrocardiography (ECG), and electrodermal activity (EDA) from an individual's gender for gender classification (Zhang, X., Javed, S., Dias, J., & Werghi, N., 2021).

Almost all of the methods and algorithms used different classifiers which are trained and tested by facial or body features that are already extracted. The classification follows standard steps that a classifier takes images randomly from a training set as test images and uses the rest as the training set, then it compares these images with all other images, this is called Leave-One-Out (LOO) technique (K. Y. Chang and C. S. Chen,2015), (Pan, Hongyu, Hu Han, Shiguang Shan, and Xilin Chen, 2018), (SVM) (Liu, H., Lu, J., Feng, J., & Zhou, J., 2017), (Boutellaa, E., Hadid, A., Bengherabi, M., & Ait-Aoudia, S, 2015), (Ahmed, M. H., & Sabir, A. T., 2017), Convolutional Neural Networks (LUN, ROANNA Z., 2018), and Local Binary Patterns (LBP).

5. PUBLIC KINECT DATABASES

Various types of databases or datasets can be used for gender classification. The choice of dataset depends on the specific research question and the type of physiological measurement being used. The following are types of database\datasets:

- Physiological signals dataset: this includes physiological signals such as electroencephalography (EEG), electrocardiography (ECG), electrodermal activity (EDA), and functional magnetic resonance imaging (fMRI)). (Botvinik-Nezer, R., Iwanir, R., Holzmeister, F., Huber, J., Johannesson, M., Kirchler, M., ... & Schonberg, T., 2019). These datasets are often collected from a group of individuals in controlled settings while performing specific tasks. Swaminathan, A., et al. used a Physiological signals dataset for emotion analysis (Swaminathan, A., Chaba, M., Sharma, D. K., & Chaba, Y., (2020), (Behnke, M., Buchwald, M., Bykowski, A., Kupiński, S., & Kaczmarek, L. D., 2022).
- Speech dataset: this dataset records the individual's voice from their speaking used for gender classification depending on vocal features like pitch and intonation (Elsisi, M., Mahmoud, K., Lehtonen, M., & Darwish, M. M. F., 2021).
- Health-related dataset: this database is collected from medical records, genetics, and lifestyle factors are included in this kind of collection used to classify gender based on the treatments of the person's medical record (Zhao, Yunpeng, Yi Guo, Xing He, Yonghui Wu, Xi Yang, Mattia Prosperi, Yanghua Jin, and Jiang Bian., 2020).
- Body database: this type of database consists of face and skeleton features, categorize into two separate databases: Face database and Skeleton database, both of which are widely used in the researches for various (C. Cao, Y. Weng, S. Zhou, Y. Tong, and K. Zhou, 2014).

One of the most important and recent features used in face applications are facial features. The following are the most publicly available Kinect face databases:

i. FaceWarehouse Database: 150 people from 7 to 80 years old are included in the database. 19 more expressions in addition to the neutral expression had their RGB-D data recorded. It can be used to determine identity, gender, and age, and it is most effective for expression recognition evaluation. (C. Cao, Y. Weng, S. Zhou, Y. Tong, and K. Zhou, 2014), FaceWarehouse Dataset | Papers with Cod.

ii. CurtinFaces Database: the Kinect sensor was used to capture nearly 5000 photographs of 52 participants for the database, both in RGB and depth maps. There are 42 male and 10 female participants. This one is the most difficult Kinect face database used to recognize, identity, gender, ethnicity, and expression (Patrick Peursum, “CurtinFaces Database”, Curtin University).

iii. Delhi (IIIT-D) database: there are 106 male and female subjects in the database provided by the Indraprastha Institute of Information Technology. The largest Kinect face database in terms of subjects is IIIT-D, this database is utilized for face detection, identity, and gender recognition because the photos are not segregated (Goswami, G., Bharadwaj, S., Vatsa, M., & Singh, R., 2013).

iv. ICT-3DHP dataset: It is gathered using the Microsoft Kinect sensor and includes 14k depth maps and RGB images split into 10 series. The image has a 640 × 480-pixel resolution. Each individual wears a white headgear with the gadget attached to it; it is visible in both depth and RGB frames. Further, the dataset is inadequate for deep learning methods due to the small number of participants and frames (T. Baltruˇsaitis, P. Robinson, and L.-P. Morency, 2012).

v. FLORENCE superface: It consists of both low- and high-resolution 3D scans with the goal of evaluating cutting-edge, resolution-dependent 3D face recognition technologies. A 2D-3D video sequence obtained using the Kinect is included in the collection. (F. Principi, S. Berretti, C. Ferrari, N. Otberdout, M. Daoudi, A. Del Bimbo, 2021), (S. Berretti, A. Del Bimbo, P. Pala, 2021).

vi. IKFDB RGB-D face database: It is a color-depth face features database that is made to cover Middle-Eastern face types and subtle facial expressions. It was built using data from Iranian participants of all genders and ages (Mousavi, S.M.H., Mirinezhad, S.Y., 2021).

vii. RGB-D Face Dataset: it contains 640x480 RGB and depth images of 15 people with different facial expressions, several applications, including face identification, age estimates, recognition of facial expressions, and facial micro expressions, use RGB-D face datasets. They are also used in 3-D modeling and reconstruction, augmented reality, industry, medicine, human-computer interaction (HCI), robotics, and more (Alexandre Lopes, Roberto Souza, and Helio Pedrini, 2022).

viii. EURECOM Kinect Face Dataset (EURECOM KFD): it has another name Kinect FaceDB, 52 individuals, 14 women, and 38 men have multimodal facial images in the dataset that were collected using Kinect sensors. Two sessions are used to collect the data, each at a distinct time of about 14 days with nine facial expressions captured in various conditions (Min, R., Kose, N., & Dugelay, J.-L, 2014).

ix. SASE DB database: this database is an RGB and depth image, captured from 32 men and 18 women in various subjects (age, race, and hairstyle). Also, the rotation angles are taken into account, SASE DB facial expressions are more variable and complex and used both for HPE and expression recognition (Lüsi, I., Junior, J. C. J., Gorbova, J., Baró, X., Escalera, S., Demirel, H., & Anbarjafari, G., 2017).

Kinect face databases or datasets are used for various tasks, including face recognition, facial expression analysis, and gender classification, also can be used for various other research applications. Researchers must ensure that the use of these datasets is done ethically and with appropriate consent from the participants. On the other hand, many researchers built their own face database and used it in desired on-line and off-line applications.

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6. RELATED LITERATURE REVIEW

Recent studies from researchers have shown promising results in gender classification, they used different features in their work such as facial, skeleton joint's, skeleton angles between joints, and body movement features. The following are reviews of the most recent research using Kinect sensor technology:

Azhar, M. et al. (2023), presents an approach to classify a human gender classification by analyzing the lower body joints. They used two publicly available multi-view gait databases (CASIA-B, UET-B) (Wang, Z., & Tang, C, 2021), (Elharrouss, O., Almaadeed, N., Al-Maadeed, S., & Bouridane, A, 2021). The classification approach is a Random Forest (RF) algorithm that uses an ensemble of decision trees to classify a new sample based on the majority vote of the trees. The accuracy of the proposed system is 99.35% for normal walking conditions, 98.75% for wearing a coat condition, and 97.92% for carrying a bag condition (Azhar, M., Ullah, S., Ullah, K., Rahman, K. U., Khan, A., Eldin, S. M., & Ghamry, N. A., 2023).

Azhar, M. et al. (2022), introduced a Microsoft Kinect-based, 3D, real-time, multi-view, limited feature-based gender classification system. Also, they used the mentioned two databases CASIA-B, and UET-B. The gait data that was gathered at run time is used in the paper's statistical model, which is based on binary logistic regression. SVM is a supervised learning algorithm that uses to separate the data into two classes (male or female) based on their gait features. The system's performance is assessed in the study using data from 80 users, and it has a 97.50% accuracy rate (Azhar, M., Ullah, S., Raees, M., Rahman, K. U., & Rehman, I. U, 2022).

Azhar, M. et al. (2022), proposed a method for gender classification by gait analysis of total body joints, The database used is CASIA-B, which is publicly available and provides a multi-view gait database that contains 124 subjects walking in 11 views and under three conditions (normal, wearing a coat and carrying a bag). The classification approach is K-nearest neighbors (KNN) uses the distance between the feature vectors to assign a class label to a new sample based on the majority vote of its k-nearest neighbors. The accuracy of the proposed system is 99.19% for normal walking conditions, 98.39% for wearing a coat condition, and 97.58% for carrying a bag condition (Azhar, M., Ullah, S., Ullah, K., Syed, I., & Choi, J., 2022).

B. Kwon et al. (2021), proposed a novel gait feature called joint swing energy (JSE) for gender classification based on 3D human skeletons. JSE measures how far each body joint deviates from anatomical planes during walking. Also introduces a new method to obtain anatomical planes from 3D gait sequences. Four publicly available datasets Skeleton databases (A, B, C, D) are used (Andersson, V., & Araujo, R, 2015), (Guffanti, D. A., Brunete, A., & Hernando, M, 2020), (Kastaniotis, D., Theodorakopoulos, I., Theoharatos, C., Economou, G., & Fotopoulos, S., 2015), (Kastaniotis, D., Theodorakopoulos, I., & Fotopoulos, S., 2016), and four machine learning algorithms they called JSE-(KNN), JSE-(NB), JSE-(SVM) and JSE-(DT). They show that JSEs can distinguish between male and female walkers and uses them to train machine learning algorithms for gender classification. The accuracy of JSE-(KNN) is 100% with DB (C), JSE-(NB) 94.33% with DB (D), JSE-(SVM) 94.33% with DB (B), and JSE-(DT) 90.38% with DB (B) (Kwon, B., & Lee, S, 2021).

Xu, C. et al. (2021), proposed a real-time system to classify gender and estimate age based on gait by using a single image. They proposed to use a CNN method to implement stand-alone and client-server online systems. By utilizing Microsoft Kinect v2 to capture single-depth images extracting walking persons' training and evaluating the CNN method on OUMVLP Takemura, N., Makihara, Y., Muramatsu, D., Echigo, T., & Yagi, Y, 2018), which is one of the biggest gait datasets in the world (contains various subjects of (5,193 females and 5,114 males), it rang age from 2 to 27 age. They improved the performance through the experiments and compared it with the benchmark algorithms. As they mentioned, their approach meets the requirements of an online real-time online system (Xu, C., Makihara, Y., Liao, R., Niitsuma, H., Li, X., Yagi, Y., & Lu, J., 2021).

Zhang, X. et al. (2021), suggested a deep learning-based method for classifying human gender on RGB-D database images using a body-joint attention technique. The 115 cases (64 men and 60 women) were captured with a Kinect V2 camera in a variety of perspectives, positions, and scales. A body-joint concentration module that captures the inter-dependent information from the two modalities is used to merge the features collected from RGB and depth pictures using CNN with two separate branches. The suggested technique outperforms state-of-the-art techniques in three different test sets that comprise standing, walking, and interacting postures, obtaining accuracy of 96.3%, 93.9%, and 94.1% on the three test sets, accordingly (Zhang, X., Javed, S., Obeid, A., Dias, J., & Werghi, N, 2021).

Zhang, X. et al. (2020), suggested using an RGB-D image with deep learning to classify gender. They automatically detected the head regions on the images using a head detector based on YOLO (Redmon, Joseph, and Ali Farhadi, 2017) and then independently extracted features from the head and the body as a whole using two CNN classifiers based on VGG19, trained the model on the Hollywood head dataset (Vu, T. H., Osokin, A., & Laptev, I., 2015). The authors employ both local and global information for gender classification and combine the findings of the two classifiers to arrive at the final prediction. A difficult gender dataset comprised of many perspectives, postures, and scenarios of people standing, moving, and conversing is utilized to evaluate the proposed method. The achieving accuracy of 93.8%, 90.6%, and 91.9% on the three test sets, respectively (Zhang, X., Javed, S., Obeid, A., Dias, J., & Werghi, N., 2020).

Do, T.D. et al. (2020), presented a method for real-time gender classification based on gait information. Using average, energy-gait images in their method enables the method to be effective and resistant to changes in vision. In order to reduce interference in the classification process, the technique builds a distance signal to remove any areas with an attachment (carried objects, worn coats), which is done during the testing step. Multiple-view-dependent classifiers trained in SVM with the CASIA Dataset B database achieved an accuracy of 98.8% classification (Do, T. D., Nguyen, V. H., & Kim, H., 2020).

D. Guffanti et al. (2020), presented a non-invasive system for gait analysis and gender classification. The gait is recorded using multiple depth V2 sensors to build a dataset of gait data obtained from 81 individuals, including 41 males and 40 females who walked at a self-selected speed across a 4.8-meter walkway from different viewpoints. The classification method involves extracting gait features from the video data and training an SVM method to predict gender based on the gait features. The proposed system achieves an accuracy of 99.7% for gender classification (Guffanti, D., Brunete, A., & Hernando, M., 2020).

Kitchat, K. et al. (2019), proposed a gender classification approach using observation angle-based GEIs (Gait Energy Images) from a gait silhouette. Their approach includes two models: the gender classification model and the observation angle classification. 10 observation angle-based GEIs were generated to predict gender, the GEIs are then used as inputs for the gender classification model for both the observation angle classification model and the gender classification model utilizing CNNs. The experiments are done on the SIIT-CN-B (freestyle walk) dataset collected by the staff of CN (Cholwich-Nirattaya) lab., sing Kinect for Xbox 360 and CASIA-B datasets. The proposed methods perform well with freestyle walks which contain a viewpoint issue. The proposed model achieves 90.74% accuracy in the freestyle walk dataset (SIIT-CN-B) and 97.58% with CASIA-B fixed-direction walk dataset (Kitchat, K., Khamsemanan, N., & Nattee, C., 2019).

Camalan, S. et al. (2018), presented 3D anthropometric measurements from individuals to detect gender. They used a 3D camera in the Microsoft Kinect V1 for recognizing the posture and features classification they used body metrics. To classify the gender, SVM, and KNN is used to classify genders and ANN with parameters. A database they used is collected by them from sixteen volunteers (31 males and 29 females, all of them 20-60 years old captured by the Kinect. Used this database in the approach. While, for validation the Leave One Out method. The accuracy achieved is 96.77% (Camalan, S., Sengul, G., Misra, S., Maskeliūnas, R., & Damaševičius, R, 2018).

Kharchevnikova, A. et al. (2018), in their paper that was also included in a chapter book, proposed a modern deep CNN to review the issue of age and gender detection algorithms for video data. To aggregate decisions for individual frames, they gave a comparative analysis of classifier fusion techniques. To increase the age and gender identification accuracy, they implemented a video-based recognition system with some aggregation techniques. Using the IJB-A, Indian Movies, and Kinect datasets, an experimental comparison of the suggested method with conventional simple voting is offered. It is shown that, for gender recognition and age prediction, respectively, the geometric mean and mathematical expectation of the outputs at softmax layers of the convolutional neural networks yield the best accurate results (Kharchevnikova, A. S., & Savchenko, A. V., 2018).

Ahmed, M. et al. (2017), proposed an approach to classify gender based on gait utilizing a Kinect sensor. They built their database using a Kinect sensor from 18 participants (9 male and 9 female), all of them walk 10 times in front of the Kinect sensor from the side view (90°) to provide a total of 180 records. A set of the feature is used (Dynamic Distance Feature (DDF)'. They used three classification methods, SVM, KNN, and LDC tested based on skeletal data provided by Microsoft Kinect. The accuracy achieved is 90.0%, 96.67%, and 91.1% respectively for the three methods (Ahmed, M. H., & Sabir, A. T., 2017).

Yildirim, M. et al. (2017), proposed a feature extraction strategy based on maximal inter-class variance (MICV) as a technique for classification. Absolute disparities between the mean values of the male and female class features are discovered after calculating the intra-class-based means of all 60 features. The ones that differ by an amount greater than a predetermined percentage are regarded as distinguishing characteristics and are used for class representation. employed Multilayer Perceptron for training and testing while conducting their experiments and benchmarking using Genetic Algorithm on the publicly available dataset UPCV gait collected by Microsoft Kinect (Kastaniotis, D., Theodorakopoulos, I., Economou, G., & Fotopoulos, S, 2013), comprising 5 gait sequences from 30 participants. The accuracy is 96.67% on 60 subjects from the database (Yildirim, M. E., Ince, O. F., Ince, I. F., Salman, Y. B., Park, J.-S., & Yoon, B.-W., 2017).

Bachtiar, M. et al. (2016), the authors emphasized biometric characteristics such as a person's physical attributes or behavior. One distinctive aspect of human behavior is the way people walk, and this characteristic can be used to classify gender. This study suggests several factors to distinguish between gender-based gaits. These characteristics are derived from the skeleton that the Kinect camera provides. The breadth of the foot when walking, the width of the swing arm, and the high ankle when elevated off the ground are the three gait characteristics that were measured out of the four. The breadth between two feet (from left ankle to right ankle) is the final characteristic. The result, these features to 80% can be used to identify the gender of a person (Bachtiar, M. M., Nuzula, F. F., & Wasista, S, 2016).

Azzakhnini, S. et al. (2016), the authors studied and compared some popular techniques for gender recognition and investigated which combination of face descriptors, feature selection methods, and learning techniques are best suited to better exploit RGB-D images. Combining two RGB-D Kinect databases: the EURECOM Kinect database and CurtinFaces database, the resulting dataset consists of 572 images of 104 individuals with variations in expressions and illumination from 80 males and 24 females. Two classifiers: support vector machines (SVM), and AdaBoost (AB) are used for gender. The accuracy for AB is 96.59, and 97.15 for SVM classifiers (Azzakhnini, S., Ballihi, L., & Aboutajdine, D., 2016).

Antony, J. et al. (2016), the authors proposed a method for face and Gender recognition. In this proposed method, they used Random Decision Forest (RDF) and Naïve Bayes (NB) to develop a model for their work for face and gender classification, these both are trained separately using IIIT-D RGB-D database. The process of Gender recognition is done by using the DCT (Discrete cosine transform) feature extraction and PCA (Principal Component Analysis) for dimensionality reduction, a Nave-Bayes classifier used in training, then the system classifying the gender from the input image. The accuracy is 88.271% for gender classification (Antony, J., & Prasad, J. C., 2016).

Andersson, V. et al. (2015), proposed the use of anthropometric features, including the average length of each body part and average body height, for gender classification to demonstrate the usefulness of anthropometric features, the authors tested three machine learning algorithms, including SVM, K-nearest neighbor (KNN), and multi-layer perceptron (MLP) classier, on their skeleton dataset. According to their results, the MLP classier showed the best performance, achieving a gender classification accuracy of approximately 61% (Andersson, V. O., Amaral, L. S., Tonini, A. R., & Araujo, R. M, 2015).

Miyamoto, R. et al. (2015), proposed a method using 3D position information of body joints obtained by the Kinect v2 sensor directly as a feature vector. The lengths of the feature vectors varied according to the length of the input skeleton sequences. The authors applied linear interpolation to the sequences to make their lengths equal. They trained an SVM classifier using the feature vectors and evaluated it on their dataset consisting of twelve people (six males and six females). According to their results, the SVM classifier achieved a classification accuracy of 99.12% Miyamoto, R., & Aoki, R, 2015).

Linder, T. et al. (2015), presented a tessellation learning method for gender classification in 3D point clouds RGB-D data from the side and back captured by them using Kinect sensors from individuals, they learned the classifier on the Kinect v2 data using a HOG baseline, compared with other deep learning methods, Convolutional-recursive neural networks (CRNN) and Hierarchical matching pursuit (HMP) and SVM. The best accuracy was 91% on standing people Linder, T., Wehner, S., & Arras, K. O, 2015).

Eltaher, M. et al. (2015), proposed a method for human gender classification based on gait features from a video stream. A Kinect sensor is used to collect silhouettes of a walking human pattern, extracting two gait features which are Gait Energy Image (GEI) to signify an appearance-based gait and Denoised Energy Image (DEI) to eliminate the noises from GEI. To get the gait features, they used feature vectors with small dimensions and SVM for the classifier with the gait-based feature vector. The obtained accuracy is up to 87% (Eltaher, M., Yang, Y., & Lee, J., 2015).

Boutellaa, E. et al. (2015), presented a system for face analysis that includes: identity, gender, and ethnicity and explores the usefulness of the depth images provided by the Kinect sensors. They used local feature extraction methods (LBP, LPQ, HOG, and BSIF) to encode shape, face texture, and shape. Their experiments are done on three Kinect face databases publicly available which are: CurtinFaces, IIIT-D, and FaceWarehouse. The best results they obtained in their experiments after applying the four methods on the three databases for gender classification is with the HOG classifier on the Curtinface database which reaches up to 89.1% (Boutellaa, E., Hadid, A., Bengherabi, M., & Ait-Aoudia, S, 2015).

From the above literature view, the authors used various types of features, databases\datasets, and methods\approaches. The accuracies obtained also, are various. As seen in **Table 1**, the study's findings revealed numerous factors in the accuracy of the Kinect sensor-based gender classification system. It is crucial to remember that the effectiveness of such techniques can change based on the algorithms and machine learning models used, the quality of the data gathered by the Kinect sensor, and other factors. To determine the precise accuracy of a particular method for gender classification utilizing a Kinect sensor, more investigation and testing are required.

Table 1. Comparison of the most related articles based on database, classification method, and accuracy

Publications	Databases / Datasets	Features	Methods / Approaches	Accuracy %
Azhar, M. et al. (2023)	CASIA-B, UET-B	Lower body joints	Random forest (RF)	99.35 for normal walking condition, 98.75 for wearing a coat condition, 97.92 for carrying a bag condition
Azhar, M. et al. (2022)	CASIA-B, UET-B	Multi view body joints	SVM	97.50
Azhar, M. et al. (2022)	CASIA-B	Total body joints	K-nearest neighbors (KNN)	99.19 for normal walking condition, 98.39 for wearing a coat condition, 97.58 for carrying a bag condition
B. Kwon et al. (2021)	Publicly available skeleton databases (A, B, C, D)	Joint swing energy	JSE-(KNN), JSE-(NB), JSE-(SVM), JSE-(DT)	100 with DB (C), 94.33 with DB (D), 94.33 with DB (B), 90.38 with DB (B).

Publications	Databases / Datasets	Features	Methods / Approaches	Accuracy %
Xu, C. et al. (2021)	Publicly available OUMVLP	Gait	CNN	-
Zhang, X. et al. (2021)	RGB-D database	Body joints	CNN	96.3
Zhang, X. et al. (2020)	Hollywood head dataset	Head &body	CNN	93.8
Do, T.D. et al. (2020)	CASIA-B	Gait	SVM	98.8
D. Guffanti et al. (2020)	Self-captured database	Gait	SVM	96.7
Kitchat, K. et al. (2019)	SIIT-CN-B Self-captured dataset, CASIA-B datasets	Gait	CNN	90.74, 97.58
Camalan, S. et al. (2018)	Self-captured database	Body metrics	SVM, KNN, ANN	96.77
Kharchevnikova, A. et al. (2018)	IJB-A, Indian Movies database, & Kinect datasets	Gait	CNN	84
Ahmed, M. et al. (2017)	Self-captured database using Kinect sensor	Gait	SVM, NN, LDC	90.0, 96.67, 91.1
Yildirim, M. et al. (2017)	UPCV dataset	Gait	Genetic Algorithm	96.67
Bachtiar, M. et al. (2016)	Self-captured skeleton database	Gait	Euclidean distance	80
Azzakhnini, S. et al. (2016)	EURECOM CurtinFaces	Face	SVM AdaBoost (AB)	97.15, 96.59
Antony, J. et al. (2016)	IIIT-D, RGB-D	Face	Naïve Bayes (NB)	88.271
Andersson, V. et al. (2015)	Self-captured Skeleton dataset	Body skeleton	SVM KNN MLP	61
Miyamoto, R. et al. (2015)	Self-captured Skeleton dataset	Body joints	SVM	99.12
Linder, T. et al. (2015)	Self-captured Skeleton dataset	3D point clouds	HOG baseline	91.00
Eltaher, M. et al. (2015)	Self-captured Skeleton dataset	Gait	SVM	87
Boutellaa, E. et al. (2015)	CurtinFaces, IIIT-D, and FaceWarehouse	Face	LBP, LPQ, HOG, and BSIF	89.1

7. CONCLUSIONS

The Kinect sensor is increasingly useful in recent years for a variety of tasks, such as classifying and identifying human gender. Despite the lack of specific search results, the purpose of this study is to provide a broad overview of the methods and approaches used in this field from 2023-2015. Researchers have developed machine learning models and algorithms to reliably classify and identify gender based on human body characteristics and movements using the depth and RGB data from the Kinect sensor. This technology has many advantages over other traditional technologies, including price, speed, accuracy, and non-invasiveness, it can be used in real-time applications like interactive gaming, security, and targeted advertising have all seen beneficial effects using these techniques. The accuracy of gender classification with a Kinect sensor depends on the quality of data captured and the algorithm used for analysis. Also, there are some limitations and challenges in implementing the technology. As the technology continues to improve, the future of gender classification technology is promising, with advancements in AI and machine learning making it more accurate and reliable and there is an expectation to see even more exciting applications for the Kinect Sensor in the future.

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