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TOPICAL REVIEW

Review and Analysis of Patients' Body Language From an Artificial Intelligence Perspective

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ABSTRACT Body language is a nonverbal communication process consisting of movements, postures, gestures, and expressions of the body or body parts. Body language expresses human feelings, thoughts, and intentions. It also reveals physical and psychological health conditions: abnormal activities inform peoples' health conditions, facial expressions indicate their emotional states and abnormal body actions convey specific diseases' external signs and symptoms. We can observe the importance of studying the body language of people with health conditions through many reports in literature written by healthcare (medical) and artificial intelligence researchers. This paper comprehensively reviews artificial intelligence-based articles that have studied patients' body language. We also conduct different descriptive and exploratory examinations of the findings using data analysis techniques, which provide more authentic domain knowledge of abnormal activities, abnormal body actions, and more precise analysis of methodologies used in machine learning tasks for studying these abnormalities. The paper's results are essential for developing intelligent automated systems that accurately evaluate patients' physical and psychological conditions, precisely identify external signs and symptoms of diseases, and adequately monitor patients' health conditions.

INDEX TERMS Artificial intelligence, body language, abnormal activity, abnormal body action, abnormality detection, machine learning, data analysis.

I. INTRODUCTION

Body language is a collection of bodily actions such as movements, postures, gestures, expressions, tone of voice, proximity, and touch performed by different body parts used in human relations and interactions to convey and express thoughts, intentions, emotions, feelings, and physical conditions. According to Mehrabian, a pioneer researcher of body language, 93% of face-to-face communication constitutes nonverbal signals, which include body actions (55%) and vocal expressions (38%) [1]. Birdwhistell, the developer of kinesics (the study of nonverbal communications), established that more than 65% of communications are made nonverbally [2], [3]. The interaction of body language in communications facilitates speedy and clear information transmission and understanding [4], and it speaks more and better content than verbal language [5]. Because people are not always aware that they are communicating nonverbally, body language is often more honest than an individual's verbal pronouncements [6]. Thus, reading nonverbal cues and signs is crucial for understanding people and establishing human relationships and communication.

Business, trade, politics, security, education, and healthcare are a few of the many sectors of human society where body language plays a significant role in different activities, assisting people in expressing themselves and understanding

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and decoding others. The expressions of confidence, comfort, and attraction through body postures, kindness, seriousness, and other characteristics with facial expressions, attention and respect in eye contact, personality, and physical behaviors in handshakes are key in general business negotiations and communications [7], [8], [9], [10], [11]. Educators' body language affects students' motivation, inspiration, and engagement in teaching and learning settings. On the other hand, understanding students' body language is also important as it reveals students' involvement, attention, understanding, thinking, and feeling during class activities [12], [13], [14], [15], [16]. The ability to interpret body postures, facial expressions, and other bodily cues is crucial in security services, criminal intelligence, and law enforcement [17], [18], [19], [20], [21], [22]. Politicians, in addition to verbal skills, communicate effectively through their body language as it is a powerful tool for expressing their personalities, connecting with people, and influencing the audience's perception through their good public appearance, postures, facial expressions, hand gestures and tone of voice [23], [24], [25], [26], [27].

Body language also plays an important role in the relationships and communications of personnel and patients in healthcare systems [28], [29], [30], [31]. However, the significance of body language in health and medicine is utmostly related to decoding patients' physical and psychological states. Sick people use hand gestures or finger movements to point to pain locations in the body [32], and their facial expressions show pain severity [33]. Several diseases affect different body parts causing abnormalities in their movements, postures, gestures, and expressions. Many papers in the literature have studied the causational relationships of diseases and pains to abnormal body actions, such as abnormal head poses and movements, facial expressions, eye movements, and upper and lower limb movements. For instance, Study [34] reveals that patients with Parkinson's disease (PD) practice delayed initiating movements, slowness, and hesitance. They also show fixed facial expressions, staring, downward and unblinking gaze, stooped and flexed posture, and tremors. Patients with ataxia-telangiectasia experience co-contraction, myoclonus, tremor, dystonic spasms, tonic activity, and other abnormal body postures [35]. According to [36], rigidity, chorea, tics, motor impersistence, rigidity, and choreiform motions are associated with Huntington's disease (HD). Postural deformities such as camptocormia, antecollis, Pisa syndrome, and scoliosis are also found in patients with Parkinson's disease [37]. Moreover, PD patients have less frequent and reduced facial expressions [38]. Work [39] informs that patients with Alzheimer's disease (AD) show increased latency to the initiation of saccades. The results of [40] show that PD patients have difficulty in performing motor tasks such as finger tapping, hand opening and closing, forearm pronation, and supination. Paper [41] highlights that celiac disease is frequently associated with restless leg syndrome (RLS). According to [42], RLS is also associated with type 2 diabetes. Paper [43] demonstrates that there is a substantial relationship between tachyphemia and freezing of gait.

Recent advances in artificial intelligence (AI), especially machine (deep) learning, allow using AI-based technologies in almost all aspects of human life. AI plays a key role in transforming traditional healthcare into smart healthcare, making it more efficient, convenient, and personalized [44]. Smart healthcare systems ?involve automated health monitoring, intelligent diagnosis and treatment, optimized hospital management, best health decision-making, and AI-supported medical research. Nevertheless, the application of AI in healthcare presents ethical dilemmas that require careful consideration and resolution. A primary ethical concern in healthcare AI is *privacy and data security*. As AI algorithms depend on extensive patient data for training and optimization, securing sensitive patient data and limiting access to authorized personnel is essential. Healthcare organizations should enforce rigorous data protection policies like encryption, access control, and routine data audits. Additionally, they should maintain data collection and usage transparency and obtain patient consent for data sharing [45], [46]. Another ethical issue arises from AI algorithms potentially perpetuating *biases and discrimination* in healthcare if trained on biased data or programmed on biased assumptions. To mitigate this, healthcare organizations should ensure AI algorithms are trained on diverse, representative data sets and consistently monitor them for bias and fairness, making adjustments as needed [45], [46], [47]. Furthermore, addressing *accountability and responsibility* is necessary as AI decisions can significantly impact patients' health and well-being. Healthcare organizations should establish distinct lines of accountability and responsibility for AI decisions and maintain transparency regarding decision-making criteria and algorithm functionality [45], [47], [48]. Moreover, concerns exist that AI could entirely replace human healthcare professionals, resulting in losing *empathy and human touch* in healthcare. To address this, organizations should develop AI systems that collaborate with, rather than replace, human professionals, ensuring AI systems include human oversight and control, particularly in critical situations [45], [46], [47]. Healthcare organizations can minimize ethical risks by implementing these measures while maximizing AI's benefits.

Patients' body language analysis using machine and deep learning techniques enhances key dimensions of such systems with intelligently monitoring and evaluating health conditions of patients, identifying external signs and symptoms of diseases and pains, and diagnosing diseases through abnormal body actions such as abnormal postures, movements, gestures, and expressions. We can distinguish two main categories of AI-based research in this domain: the first includes studies that analyze patients' health conditions concerning their activities and movements using machine learning techniques (for instance, see [45], [46], [47]), and the second involves studies that, similar to medical researches, investigate the effects of diseases and pains to body actions to identify abnormality patterns (for instance, see [52], [53], [54], [55]).

In the literature, we can find a few review papers that have addressed to summarize such studies from different perspectives. For instance, report [56] provides an in-depth review of machine learning models that analyze abnormal body actions caused by a large spectrum of neurodegenerative diseases. Another paper [57] analyzes the performance of machine learning algorithms that detect and recognize abnormal motor symptoms of a specific neurodegenerative disease, namely Parkinson's disease, based on time-series data. Review [58] investigates the research frameworks for automated facial pain expression detection using FACS. Recent papers [30] and [31] provide an overview of the role of body language in healthcare and an analysis of computational methods used to detect and recognize healthcare patients' abnormal body activities and actions. Though these reports provide an exhaustive review of methodologies and computational models used in the analyses of causational relationships of diseases and pains with abnormal body actions, they merely focus on *specific diseases* (e.g., neurodegenerative diseases in [56], Parkinson's disease in [57]), *specific abnormal actions* (e.g., hand gestures in [56] and facial expressions in [58]) performed by *specific body parts* (e.g., upper and lower limbs in [30], [56], and [57] and face in [31] and [58]).

However, the comprehensive understanding of the relationships between diseases/pains and patients' body language and the development of reliable AI-powered solutions that identify signs and symptoms of diseases and evaluate and monitor patients' health conditions require a broader and deeper approach to studying and analyzing abnormal activities and abnormal body language of people with health conditions. Since a certain disease may cause abnormalities in movements, postures, gestures, or expressions in *different* body parts as well as a certain abnormal body action may be caused by *different* diseases, such a "clustered" review and analysis approach should focus on determining *all* abnormal body actions performed by *each* expressible body part. As a completion of these ideas, the current study reviews AI-based papers studying patients' body language, and it conducts descriptive and exploratory analyses of the extracted knowledge from the reviewed papers using data analytics techniques.

We investigate the papers that discuss bodily activities (walking, sitting, lying, falling, etc.) of people with health conditions and abnormal body actions of patients with certain diseases or pains. First, we cluster the selected papers for review according to body parts expressing abnormalities in their movements and poses. Second, we subcategorize each cluster into subclusters concerning patient activities and abnormality-causing diseases and pains. This approach provides a clearer focus on smaller targets with the precise classification of problems and their solutions. After identifying the patient activities and the causational relationships of diseases/pains with abnormal body actions, we mine the information related to datasets, data acquisition and preprocessing techniques, methods, and algorithms employed for segmentation, detection, recognition, evaluation, and analysis. We further conduct descriptive and exploratory analyses of the findings to determine useful relations of data types, data acquisition procedures, feature engineering techniques, methods, and algorithms for abnormality detection, recognition, and performance evaluation metrics. We believe this research will support the development of more reliable, intelligent systems that accurately evaluate patients' physical and psychological conditions, precisely identify external signs and symptoms of diseases, and adequately monitor patients' health conditions.

The main contributions of this paper can be summarized as follows:

1. Numerous AI-based papers examining abnormal activities and body actions in individuals with health conditions are reviewed, focusing on the causational relationships between health conditions and body action abnormalities and machine learning approaches for detecting, recognizing, evaluating, and analyzing abnormalities in these relationships.
2. The review findings are organized in separate tables based on the expressive body parts, offering a more comprehensive and clear depiction of the causational relationships between diseases and abnormal body language exhibited by each body part. This organization also identifies and categorizes the relevant machine learning techniques used to study these abnormal body actions in relation to each body part.
3. Utilizing the information presented in the abnormality tables, a dataset encompassing properties, such as abnormal body language, diseases, pain, data types, datasets, data preprocessing techniques, feature engineering processes, machine learning methods, algorithms, performance evaluation metrics, and results, has been created.
4. Exploratory and descriptive analyses are performed on all dataset features, establishing their statistical and relational properties. Consequently, we obtain highly supportive outcomes concerning the most frequently studied diseases, abnormal body actions, causal relationships, and research frameworks.

Further, we describe our review and analysis methodology, which is densely depicted in Figure 1.

Stage 1: **Paper Search and Selection**. We search and select AI papers that discuss the different activities (walking, sitting, running, falling, lying, etc.) of people with some health conditions and patients' abnormal body actions caused by diseases and pains in electronic databases such as SCOPUS, PubMed, ScienceDirect, etc. The search is conducted using the related combinations of keywords such as "*disease*," "*pain*," "*body*," "*head*," "*neck*," "*shoulder*," "*face*," "*eye*," "*limb*," "*upper limb,*" "*lower limb,*" "*arm*," "*hand*," "*leg*," "*foot*," "*finger*," "*movement*," "*pose*," *"posture,"* "*gesture*," "*expression*," "*falling*," "*activity*," "*artificial intelligence*," "*machine learning,"* and "*deep learning*."

Stage 2: **Paper Classification**. The selected papers are classified into three main categories: the papers studying abnormal activities of people with health conditions, the papers studying disease and abnormal body language causational relationships, and the papers studying pain and abnormal body language causational relationships. The papers of these three categories are further divided into subcategories based on the "*expressible*" body parts, i.e., body (general), head, face, eyes, upper limbs, and lower limbs.

Stage 3: **Paper Review**. The review of the papers focuses on identifying diseases/pains and abnormal body language causational relationships, health conditions, body language, datasets, data preprocessing techniques, feature engineering tools, machine (deep) learning methods, algorithms for segmentation, detection, recognition, evaluation, and performance evaluation metrics and results.

Stage 4: **Finding Summarization**. The information extracted from the reviewed papers based on the defined criteria is represented in tables according to the abnormal body movements, poses, and expressions. The obtained knowledge has been organized from the outlook of activities, diseases, and pains within the tables.

Stage 5: **Analysis of Findings**. The review dataset is constructed based on the tables obtained in Stage 4. All dataset features – activities, diseases, pains, datasets, data preprocessing techniques, feature engineering procedures, machine (deep) learning methods, algorithms, methodologies, performance evaluation metrics, and results – are statistically analyzed. *Methodology Similarity Clusters* are defined, and the best methodologies for abnormality pattern detection, recognition, and evaluation are selected.

Stage 6: **Conclusions**. The review study is concluded: the findings have been summarized, and the limitation of the study and future research have been described in detail.

The paper is structured as follows: In Section II, we conduct a comprehensive review of selected research papers that concentrate on the abnormal activities of people with health conditions and patients abnormal body actions caused by diseases and pains. Section III presents a summary of key findings, including health conditions, body language, methodologies, and results, displayed in "abnormality" tables. In Section IV, we provide the results of a detailed descriptive and comprehensive analysis of the statistical properties of the findings. Section V concludes the current study by emphasizing the key outputs. It also explains essential constraints in AI-based research pertaining to patients' abnormal body language and proposes an approach for overcoming these issues.

II. PATIENTS' ABNORMAL ACTIVITIES AND BODY LANGUAGE

In this section, first, we provide an initial insight into different relations among activities, diseases, abnormalities, and other important information discussed in the selected papers for review and analysis using VOSviewer [59] and Mendeley Reference Manager [60]. Then, we review the papers that study different health conditions involving abnormal activities, motions, poses, gestures, and expressions produced by the expressible body parts using machine and deep learning techniques. We review the papers centralizing on body parts, i.e., body, head, face, eye(s), lower limbs, and upper limbs. We focus on abnormal activities, disease and body language causational relationships, data acquisition techniques, data types, datasets, data preprocessing steps, feature extraction and selection procedures, machine learning methods and algorithms, and performance evaluation metrics and results.

A. PRELIMINARY OBSERVATION

From initially collected 180 AI articles that mention diseases, pains, their relationships to patients' body postures and, movements, activities, we selected 84 papers that discussed abnormal activities of people with health conditions and the *causational relationships* of diseases and pains with *abnormal body actions*, i.e., abnormal movements, postures, gestures and expressions performed by the body or any body part. Figure 2 illustrates the initial observation of the reviewed *papers' network*, i.e., the relationships of the diseases, pains, body language, datasets, machine learning methods, and other essential keywords occurring in these papers. This graph is constructed using VOSviewer from the information (keywords) extracted from the titles and abstracts of the papers listed in Mendeley Reference Manager. The graph consists of 101 nodes and 577 edges in 12 clusters. The nodes in the graph represent all the keywords selected, and each node size indicates the total number of occurrences of the corresponding keyword in all papers. The keywords closely related to one another are grouped into clusters of different colors. The edges indicate the relations between keywords. Due to the high number of keywords present, some nodes are congested in a single location resulting in some keywords not being displayed (we refer the reader to Figure S1 to view a more detailed interactive chart). Here, we can observe that the represented relationships of diseases and pains with body postures, movements, expressions, and gestures, patients' activities, data preprocessing techniques, detection, recognition, and analysis methods, and performance evaluation metrics are very complex and highly unstructured, which challenges mining the necessary information and establishing structured and accurate relations of these elements. We unscramble this problem through a scrupulous review and comprehensive data analysis.

B. ABNORMAL BODY MOVEMENTS AND POSES

The following papers have proposed various patient activity detection and recognition systems. Study [61] presents an initial implementation of a patient monitoring system based on support vector machine (SVM) models that can be used for patient activity recognition in case a patient or

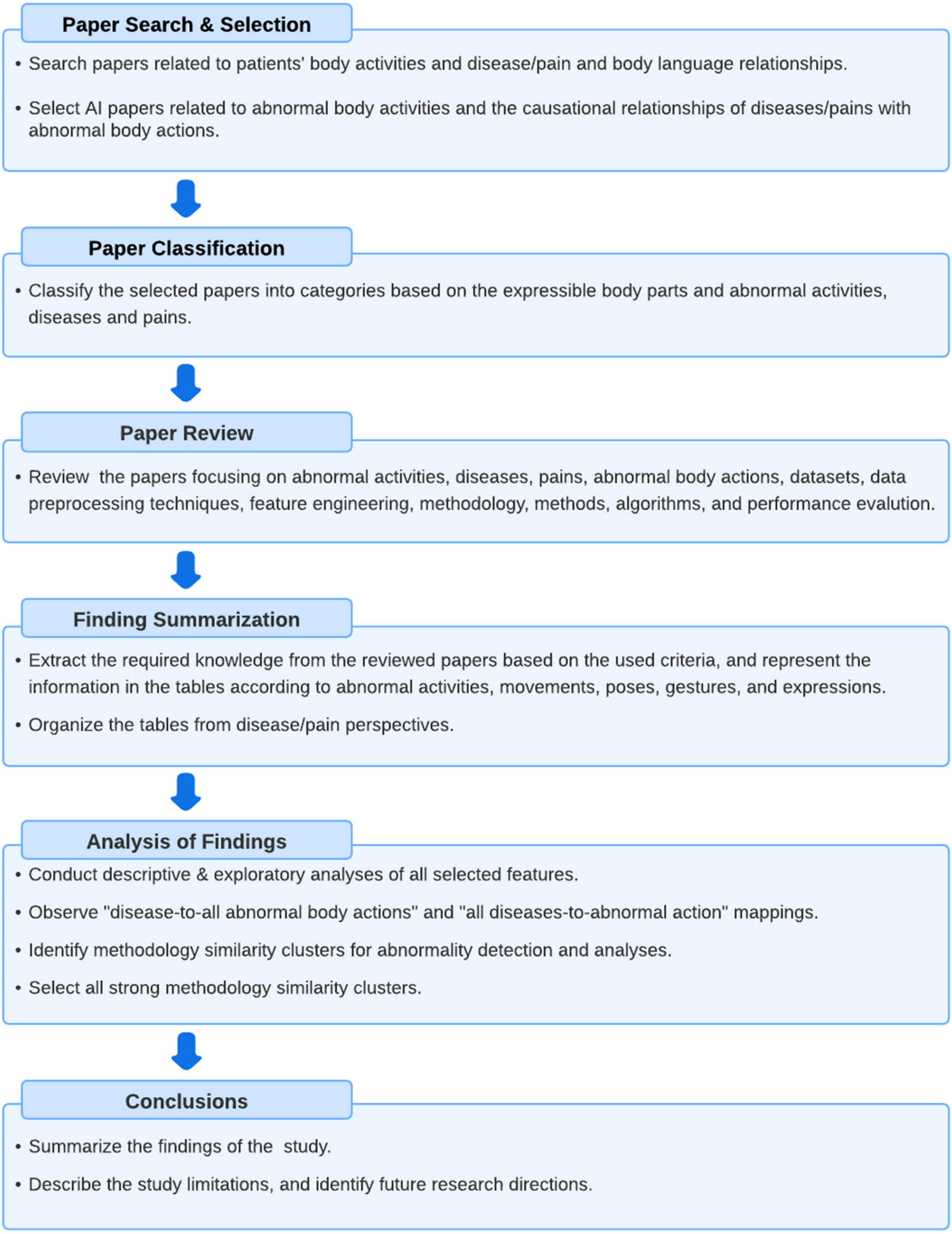

FIGURE 1. The review and analysis methodology: a six-stage process starts with 'Paper Search & Selection' for sourcing relevant papers, then 'Paper Classification' for sorting these papers based on body parts. 'Paper Review' ensures comprehensive understanding, while 'Finding Summarization' distills key points. Subsequently, 'Analysis & Findings' observes and evaluates data, leading to the final stage, 'Conclusions', discussing results and implications.

an elder fall. The paper considers three types of activities: simple walk, simple walk and fall, and simple walk and run, monitored using sensors equipped with accelerometers and microphones. The data classification with the SVM-RBF (radial basis function) kernel produces an accuracy of 96.72% for all activities. Meanwhile, the highest accuracy of 98.2% is detected for the run events. Paper [62] proposes a novel method to detect and record various posture-based events of interest in a typical elderly monitoring application in a home surveillance scenario. These events include standing, sitting, bending/squatting, side-lying, and lying toward the camera. The preprocessed data of 30 video clips with an average duration of 2 minutes and five postures recorded from a fixed camera are inferred using the k-nearest neighbor (KNN) algorithm and evidence accumulation technique. It is shown that the recognition rate of above 90%. Paper [63] aims to unobtrusively monitor elder activity to recognize falls and other health problems. It analyzes the performance of eight machine learning algorithms: SVM, KNN, Random Forest (RF), Bagging, AdaBoost M1, RIPPER Decision Rules, Naïve Bayes (NB) classifier, and C4.5 Decision Trees (DTs) for detecting falling, lying down, sitting down, standing/walking, sitting, and lying. The paper shows that SVM produces the most accurate classifier: the accuracy on clean data was 97.7%, and on noisy data, 96.5%. RF, Bagging, and AdaBoost M1 Boosting closely follow it. Research [64] introduces an activity recognition system based on a nonlinear SVM algorithm to identify 20 different human activities categorized into three classes, motions (jumping, walking, etc.), stationary postures (bending, lying, sitting, etc.), and transitions (standing-to-bend, lying-to-sit, etc.), from an accelerometer and RGB-D camera data. The model achieves the lowest weighted briber score of 0.1700, the highest Macro F1 score of 33.53%, and the highest Micro F1 score of 65.08%.

Among the studies focused on patient activity detection and recognition, we can pay special attention to those investigating patients' falls. The following papers have developed fall detection systems implemented in different situations related to patients and older adults. Paper [65] presents a novel patient fall detection system implementation. The system acquires the data from sensors attached to the legs of the subjects that provide information on walking, walking and falling, and walking and running. SVMs are used to classify the acquired data and determine a fall emergency event. Fall events are detected with an average accuracy of 98.2%, whereas run events were successfully detected at 96.72%. Study [66] introduces a low-cost, non-invasive motion sensing method, mobile infrared silhouette imaging, and sparse representation-based pose recognition for building an elderly-fall detection system. The pyroelectric infrared (PIR) sensor array is used for elderly pose acquisition, and robust fall detection is obtained via sparse representation. The mobile robot undertakes rotary scanning, and the pose of the human body can be recorded as a simple binary silhouette.

Paper [67] presents a depth video-based novel method for human activity recognition (HAR) using robust multi-features and embedded Hidden Markov Models (HMMs) to recognize several daily activities (e.g., sitting down, taking medicine, falling, both hands waving, etc.) of older adults living alone in indoor environments such as hospitals, homes, and offices. The developed model analyzes 705 video sequences of sixteen people's daily activities and demonstrates the accuracy of 94.82% on hospital activities, 95.15% on home activities, and 95.97% on office activities. Research [68] introduces a fall detection system framework based on edge computing. The data obtained from wearable devices is processed on a nearby edge device (e.g., a computer or a mobile device) instead of sending the data to the cloud. The machine learning model enables data analysis and generates real-time notifications for assistance. The research analyzes four types of falls: forward lying (fall forward from standing and use of hands to dampen fall), front knees lying (fall forward from standing with the first impact on knees), sideward lying (fall sideward from standing with bending legs), and back sitting chair (fall backward while trying to sit on a chair). The highest performance of the model over the data obtained with the waist and wrist combination gives 96% precision, 96% recall, and 95.8% accuracy.

The abnormal activities of the patients are the main interest in the following papers. Work [69] proposes a high-speed and robust posture classification algorithm employed in any pervasive patient monitoring system. The algorithm processes twenty images per posture obtained from twenty bed-bound patients to recognize the eight body postures: supine, supine hands on the body, supine-folded leg, supine-crossed leg, right yearner, right fetus, left yearner, and left fetus. The algorithm achieves a total accuracy of 97.1% for all posture classifications. Paper [70] introduces a novel real-time system for recognizing freezing episodes in a standstill state, tremors, and fall incidents commonly seen in PD patients using a 3D camera sensor based on the Microsoft Kinect. The system was tested on seven simulated subjects in 12 events indicating that the design could detect 99% of the falling incidents, 91% of tremors, and 92% of the freezing of gait (FOG) episodes. [50] proposes a semi-automated approach for improving upper body pose estimation in noisy clinical environments. The subject-specific convolutional neural networks (CNNs) analyze videos of seven joints in the bodies of three subjects: head, left/right hands, left/right elbows, and left/right shoulders. The average accuracy for detecting the upper-body features achieves 92%. Paper [71] studies the patients' movement detection problem using ResNet and healthcare personnel movement detection using YOLOv2. The data for the study is collected from the seven wall-mounted depth sensors that capture 3D volumetric images of patients and healthcare personnel. The patients' mobility activities are detected with a mean specificity of 89.2% and sensitivity of 87.2% for overall activities, and the personnel activities are detected with a mean accuracy of 68.8%.

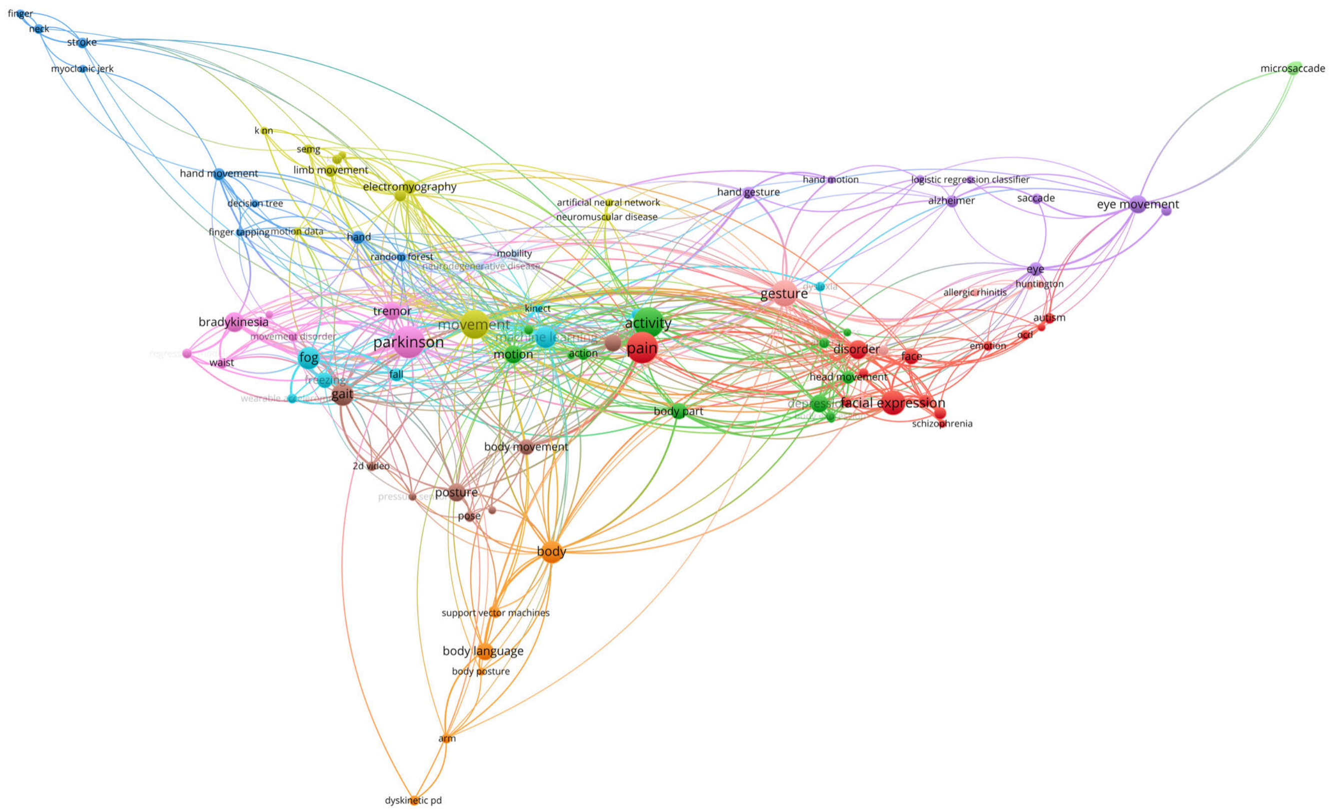

FIGURE 2. **The network of the reviewed papers depicts the initial relationships among diseases, pains, body language, and machine learning methods based on keyword data from the titles and abstracts of reviewed papers, visualized using VOSviewer.**

Study [72] estimates the patient's in-bed motions from pressure sensors' data mapped to images. Five body positions and movements of six subjects on the bed are learned with a hashing-based content retrieval method and CNNs. The former searches a query image in a training hash table and retrieves the nearest neighbor's 3D body poses, and the latter estimates a 3D pose from a pressure image using regression. The results show satisfactory performance with both methods, even in poses where the subject has minimal contact with the sensors.

In-bed motion tracking has grown in popularity for a variety of therapeutic applications. Paper [73] addresses this problem by proposing a deep neural network (DNN)-based framework for 3D posture estimation. A DNN is used to collect a complete body 3D position in the first phase of the approach. This phase includes two networks: the first one extracts the shape (2D pose) and texture feature map with hierarchies from each view separately, and the second network infuses this information from all accessible viewpoints to build the 3D posture, which is then used by a top-down inverse dynamic algorithm to compute the kinetic of the L5/S1 join. The results are verified against a marker-based motion capture system as a baseline. Throughout all datasets, the grand mean SD of the total moment/force absolute errors was 9.06 ($\pm$ 7.60) N·m / 4.85 $\pm$ 4.85 N. Report [74] reviews relevant literature using the methodology of combining expertise and perspectives from physical therapy, speech-language pathology, movement science, and engineering to provide insight into applications of pose estimation in human health and performance. It also focuses on applications in human development, performance optimization, injury prevention, and motor assessment of persons with neurologic damage or disease. It concludes that pose estimation algorithms directly address an essential and widespread need for low-cost, easy-to-use, accessible technologies that enable human movement tracking in virtually any environment, including the home, clinic, classroom, playing field, and other ''in the wild'' settings.

Several machine learning-based researchers have developed intelligent systems that study patients' abnormal body poses and movements with particular diseases, such as PD, HD, schizophrenia, depression, and pains. Paper [53] proposes an automated resting and action/postural tremor assessment using a set of accelerometers mounted on different patient body segments. Estimating tremor type, resting, and action postural and severity is based on features extracted from the acquired signals and HMMs. The method is evaluated using data from 23 subjects (18 PD patients and five control subjects). The proposed model reaches 87% accuracy for tremor severity. The method also discriminates resting from postural tremors and differentiates tremors from other Parkinsonian motor symptoms during daily activities. Research [51] performs a preliminary investigation on the visual-based monitoring behavior of psychiatric patients using surveillance cameras. Patients entering and leaving the room, fighting, sleeping, talking, and breaking out are analyzed through statistics of optical flow vectors extracted from the patient's movements. The classification uses Bayesian classifiers, HMM, and SVMs. For the data set, all the activities considered are successfully detected and classified by approximately 85%.

Study [75] proposes relative body parts and a local motion pattern-based depression detection framework, which analyzes the left and right arm, head, and upper and lower parts of the left and right leg of 30 depressed and 30 healthy subjects. The model first computes relative orientation and radius for detecting the body parts resulting in a histogram of relative parts' motion. Second, space-time interest points are calculated to analyze the motion holistically, and a bag of words framework is learned. Then, two histograms are fused, and a support vector machine classifier is trained. The results show that a bimodal system overcomes the ambiguity in polar histograms and helps maintain spatial information by combining holistic body motion information. Paper [75] studies upper body expressions and gestures' contribution to automatic depression analysis. The significant contribution of this paper lies in creating a bag of body expressions and facial dynamics for assessing the contribution of different body parts for depression analysis. The experiments are performed on real-world clinical data where video clips of patients and healthy controls are recorded during interactive interview sessions.

Work [76] proposes a deep learning method, feed-forward 1D-ConvNet (convolutional network), for detecting FOG episodes in PD patients. The model is trained using a spectral data representation strategy that considers information from previous and current signal windows. The approach is evaluated using data collected by a waist-placed inertial measurement unit from 21 PD patients with FOG episodes. The model achieves 90% for the geometric mean between sensitivity and specificity. Paper [77] develops fast and objective myoclonus quantification methods for myoclonus epilepsy type 1 (EPM1), addressing marked variability problems, which present a substantial challenge in devising treatment and conducting clinical trials. An automatic tool obtains a myoclonic jerk score from video recordings using human body key point detection and human pose estimation. The paper establishes that myoclonic jerks' automated quantification is feasible and consistent with the accepted clinical gold standard quantification method. Research [78] proposes a novel method to automatically detect self-adaptors and fidgeting, i.e., a subset of self-adaptors correlated with psychological distress. The paper processes the dataset containing full-body videos (facial expressions, body motions, gestures, and speech) of 35 people (18 with high distress and 17 with low distress) and self-reported distress labels. It demonstrates that the proposed multi-modal approach combining audio-visual features with automatically detected fidgeting behavioral cues can successfully predict distress levels in a dataset labeled with self-reported anxiety and depression.

A comprehensive review of the computational methods used throughout the neurological spectrum, including Amyotrophic Lateral Sclerosis (ALS), AD, PD, HD, and Multiple System Atrophy (MSA), is presented in [56]. This review covers the computational approaches currently used across the entire neurodegenerative spectrum and the general taxonomy identification of neurodegenerative disorders. Moreover, a detailed analysis of the various modalities and decision systems used for each disease and sleep disorders associated with various diseases is provided. The paper [79] presents a deep learning-enabled assessment framework for the Unified Parkinson's Disease Rating Scale (UPDRS). The dataset includes bradykinesia (BRADY), gait disorders (PIGD), rigidity, tremor, and posture instability. As an ensemble model of ResNet, Spatio-Temporal Graph Convolutional Networks (ST-GCN) and Hierarchical Convolutional Networks (HCN) are used in the assessment process. Using the proposed framework, the highest F1 score obtained was 78%. Paper [80] introduces an approach based on machine learning (ML) and wearable sensors to select the best exercise for detecting PD in patients.

Ten thousand samples are recorded using wireless sensors, with 670 samples per exercise and 126 attributes. Since the data is imbalanced, weights are used to control class distribution. Three base estimators, RF (with multiple parameter options), SVM, and logistic regression (LR), are used for stacking. The final estimator was determined to be LR since it was the most effective in actual use. The best-achieved accuracy through experiments is 67%. Research [81] describes a simple method to detect gestures revealing muscle and joint pain, such as lumbar spondylosis, tennis elbow, plantar fasciitis, etc. The data is acquired using a Kinect sensor from ten subjects. A feed-forward neural network is trained to classify seven body poses and movements. The classification accuracy reaches 91.9%. Work [82] develops a machine learning-based system consisting of an RF and two-stage classification scheme (KNN and HMM) that can continuously detect pain-related behaviors from patients' electromyography (EMG) signals and body movements. The models tested on the Emo-Pain dataset are proved efficient in detecting different body poses and movements such as guarding one-leg stand, abruption one-leg stand, protecting reach forward, guarding sit to stand, etc.

As head movements and body expressions are regarded as indications for depression analysis. In [83], authors examine the significance of upper body expressions for automatically detecting depression cases. A framework based on Space-Time Interest Points (STIP) and a bag of expressions is used. Head movement analysis is conducted for the upper body part by selecting rigid face fiducial points and a novel Histogram of Head Movements (HHM). Spatio-temporal features are subsequently calculated on the aligned face blob video. Next, a histogram and three hard fiducial points represent the frequency of head motions. Experiments are conducted using real clinical data, with video recordings of patients and healthy subjects during interactive interview sessions. Using a range of body expressions, the highest F1 and accuracy scores for depression detection are 80% and 76.7%, respectively. In paper [84], General Movements Assessment (GMA) is conducted on infants with cerebral palsy. Video dataset from MINI-RGBD is utilized with 12 sequences [85]. Two pain pose features are suggested: Histograms of Joint Displacement 2D (HOJD2D) and Histograms of Joint Orientation 2D (HOJO2D). Three ML models, KNN, linear discriminant analysis (LDA), and ensemble learning, are used. The ensemble model achieves the best accuracy of 91.6%.

C. ABNORMAL HEAD POSES AND MOVEMENTS

The study of abnormalities in healthcare patients' head poses, and movements originating from different diseases and pains have also been under the interest of AI researchers. Research [52] investigates vertiginous conditions and other balance issues in otoneurology using a signal analysis approach. To stimulate the vestibulo-ocular reflex, a subject is instructed to shake his head horizontally from the center to the left or right and back to the center based on a set rate. The authors apply DT, SVM, NB, Kohonen networks, and neural networks (NNs) to classify subjects as normal and abnormal. With average accuracies of 89.8% and 89.4%, respectively, the DT and SVM models have outperformed other models by 1-5%. [86] investigates the use of multimodal diagnostic criteria, focusing on electroencephalogram (EEG), and develops an RF classifier to differentiate dementia with Lewy bodies (DLB) from AD. A comprehensive sample of patients was chosen, including 66 subjects from each class (DLB, AD, and normal). Clinical, cognitive, and visual EEG data and neuroimaging and cerebrospinal fluid measures were combined with quantitative EEG (qEEG) measurements. Each tree in the RF is created using a bootstrap sample which yielded to achieve an accuracy of 87% using the proposed model.

The effects of everyday computer use, known as the Computer Vision Syndrome (CVS) system, have been studied using machine learning in [87]. The system calculates the rate at which the eyes blink to detect CVS. CVS is identified if this rate is larger or lower than a threshold value for eye blink rate or head movement detection. A web camera is used to collect data for this system. Using the Haar Cascade classifier, blinks are distinguished from other eye movements from the collected data. Additionally, segmenting head movement using OpenCV is employed. Based on experiments, the proposed algorithm produced 99.95% accuracy. In [88], a deep learning model for abnormal head movement identification is introduced. This model can handle distortion, noise, and different illumination conditions. Normalization and scaling are done in the first step of image preprocessing. Multi-task Cascaded CNNs (MTCNN) with Hare Cascaded are applied in the second stage to detect upper bodies. CNN is used for feature extraction and classification tasks. The Normal Abnormal Head Movement Dataset (NAHM) is gathered to verify the proposed framework, with 98.31% validation accuracy.

D. ABNORMAL FACIAL EXPRESSIONS

The study of abnormal facial expressions is also one of the most investigated areas by AI researchers. Since the face is an important source for expressing emotions, in the following papers, the researchers have studied patients' depression, despair, irritation, sadness, and other negative emotions with or without relating to specific diseases.

Study [89] improves the capabilities of Remote Patient Monitoring Systems (RPMS) by building a more realistic RPMS that considers patients' mental and emotional states. A dataset consisting of 351 digitally captured faces from 27 people is used. Artificial neural networks (ANN) are applied to process images as face details represented by intensities in grayscale mode. Moreover, facial features have been extracted using the active contour model technique. Authors utilized Sobel edge detected images and Laplacian of Gaussian filtered images as starting points. Each control point will go to the least energy point in the eight neighborhoods. To reduce energy points in eight neighborhoods, each control point is moved. Based on the experimental findings, feature expression analysis could be employed to evaluate patients with RPMS's emotional states. The authors of [90] propose a method for identifying performed emotional states based on evaluating body language and gesture expressiveness. Eight emotional states are collected from 10 participants: pleasure, anger, despair, interest, sadness, irritation, pride, and joy. The proposed method is based on both direct and indirect categorization of time series. Eyes Web Expressive Gesture Processing Library computes various expressive motion cues. KNN, DT, and Hidden Naïve Bayes (HNB) models are applied for classification. The best achieved Leave-One-Out Cross-Validation (LOOCV) error value was by the DT model. Reference [91] presents a computational framework that creates probabilistic expression profiles for video data and can potentially help automatically quantify emotional expression differences between patients with neuropsychiatric disorders and healthy controls. The authors applied Active Appearance Model (AAM) for face landmark detection and SVM for facial expression classification. Happiness and neutrality expressions had the highest accuracy scores, 82.0% and 54.5%, respectively.

Facial abnormalities have often been used to evaluate emotional impairment in neuropsychiatric patients. Work [92] develops an automated facial action coding system (FACS) system to analyze dynamic changes in facial actions in videos of neuropsychiatric patients. The introduced method analyzes dynamical expression changes through videos, measures individual- and combined-facial muscle movements through action units (AUs), and performs automatically without an operator's intervention. These advantages facilitate high-throughput analysis of large sample studies on emotional impairment in neuropsychiatric disorders. Paper [93] proposes a facial-expression recognition system to improve healthcare service in a smart city using IoT. The proposed system first extracts sub-bands using applying a bandlet transform to a face image; second, it applies a weighted, center-symmetric local binary pattern (CS-LBP) to each subband block by block resulting in the CS-LBP histograms of the blocks that produce a feature vector of the face image. Lastly, the data is fed into two classifiers: Gaussian mixture model (GMM) and SVM. The scores of these classifiers are fused by weight to produce a confidence score, which is used to make decisions about the facial expression's type. The experiments on a constructed dataset with five types of facial expressions – happy, sad, angry, excited, and neutral produced by 100 male subjects (aged between 18 and 29 years) show that scene contexts can contribute important information to automatically recognize emotional states and motivate further research in this direction.

Research [94] develops a technique for automatically visualizing expressive facial and upper-body motions concerning emotions. A bimodal database (FABO) of 54 videos from four people, 27 for the face and 27 for the body, is utilized. These videos are collected using separate cameras to simultaneously record face and body postures. The developed model is described in two steps: feature-level fusion and decision-level fusion. First, each classifier is trained using only one modality. Second, the authors combined affective body postures and facial expression knowledge at the feature and decision levels. The study's outcomes reveal that the classification of emotions using the two modalities improves recognition accuracy overall, exceeding classification using the face or body modality alone. Paper [54] uses visual scanning behaviors (VSBs) on emotional and non-emotional stimuli to detect apathy in AD patients. Forty-eight AD patients took part in the study. A recurrent neural network (RNN) is used in two ways: first, to discover differences in VSBs between apathetic and non-patients, and second, to define the individual's VSBs in response to emotional and non-emotional stimuli. Vector representations are generated in response to emotional and non-emotional stimuli. After that, using a Logistic Regression classifier, patients are classified as either apathetic or non-apathetic based on the distance between these vector representations. The first method produces an Area Under the ROC Curve (AUC) gain of 0.074, whereas the second one yields an AUC gain of 0.814.

Study [95] suggests a novel approach for calculating the usefulness of visual information collected from face stimuli for emotion detection. The study targets a population consisting of 21 patients with autism spectrum disorder (ASD). Face stimuli are fused using a Gaussian fixation distribution estimate, giving more detail in the face part. During the emotion detection, participants with autism have fixations on the bottom parts of their faces and are less focused on the eyes than the usual subjects. This method attains an accuracy of 90% for ASD emotion detection and 92% for routine people emotion detection. Paper [96] presents EMOTIC, a dataset of images of people in natural and different situations annotated with their apparent emotions. The EMOTIC database combines two types of emotion representation: 26 discrete categories and the continuous dimensions of Valence, Arousal, and Dominance. A statistical and algorithmic dataset analysis and annotators' agreement analysis are also presented. Few CNN models are used for emotion recognition, combining the information of the person bounding box with the information present in the scene context. The results show that scene contexts can contribute important information to automatically recognize emotional states and motivate further research in this direction.

The following papers mainly focused on depression detection and analysis through facial expressions. Study [97] examines the association between changes in the intensity of depressive symptoms over time and facial expression. Videos captured from 34 individuals are analyzed, with manual and automatic approaches employed to analyze facial expressions. The automatic method registers faces based on landmark points recorded using AAM. Next, the frames are matched using a gradient-descent function and mapped to reference points using a 2D similarity transformation. This study shows the effectiveness of automatic methods in both behavioral and clinical sciences. The authors of [98] are motivated by the abundance of stress and anxiety feelings to build a model for stress detection using video recordings. The videos captured from 23 adults are used for analysis where participants range in age from 10 to 45. The examined features comprise heart rate calculated using camera-based photoplethysmography, mouth activity, head motion parameters, and eye-related events. Sequential backward selection (SBS) and sequential forward selection (SFS) techniques are used for feature selection. KNN, Generalized Likelihood Ratio, SVM, NB classifier, and AdaBoost classifier are employed for the classification step. The Adaboost classifier demonstrated a superior classification accuracy, reaching a 91.68% accuracy rate.

Paper [99] introduces a model for the early detection of possible depressed patients. This model investigates whether there are differences in facial expression alterations between depression patients and healthy persons in the same situation. Video samples of 26 depression patients and 26 healthy people are obtained from Shandong Mental Health Center in China as part of the data collection process. A person-specific AAM model extracts the important facial features from the captured videos based on the viola-Jones face detector. Thereafter, a support vector machine is applied to recognize depression based on the movement variations of the eyes, brows, and corners of the lips. The covered facial expressions are sadness, disgust, fear, neutrality, anger, surprise, and happiness. The proposed model achieved an accuracy of 78% and an F1 of 79.2%. Work [100] examines the difficulties in recognizing facial expressions in traumatic brain injury (TBI) patients in a realistic context. To collect data from TBI patients, scenarios were developed using video recordings. A deep learning model composed of Long Short-Term Memory (LSTM) and CNN extract spatio-temporal information for face frames and the Supervised Decent Method (SDM). An AUC value of 75.26% is obtained using the proposed model.

Automatic pain detection is an emerging area of investigation in healthcare. The variation in facial expressions often provides a clue for the occurrence of pain and its level. The main interest of the following papers is the automatic detection of ''pain'' facial expressions. The UNBC-McMaster Shoulder Pain Expression Archive Database is presented and evaluated in [101]. The paper uses video records of individuals who experienced shoulder pain. Each arm was subjected to eight unique motions during the motion testing: flexion, abduction, and internal and external rotation. The test recordings covered 129 participants with shoulder pain and produced 200 recordings. The SVM model is utilized for classification to provide a baseline for this database. Other pain expression detection studies later used the UNBC-McMaster Shoulder Pain Database. In [102], a computer vision system is presented to analyze face characteristics to detect video pain expressions. To get a discriminative representation of the face, authors extracted shape information using a pyramid histogram of oriented gradients (PHOG) and appearance information using a pyramid local binary pattern (PLBP). First, faces in videos are detected and tracked using the Viola-Jones object detection model. When a face is identified, the framework splits it into two equal portions to treat each portion of the face equally; the top half of the face has the eye regions and wrinkles on the upper area of the nose, while the bottom part has the mouth regions and the lower part of the nose. PHOG and PLBP are then used to extract and concatenate facial features. Second, the classification step is applied using a set of ML models, including RF, SVM, DTs, and KNN. The UNBC-McMaster Shoulder Pain dataset is used to examine the effectiveness of the suggested model. The KNN model achieved the highest accuracy result, 96%, even with limited data collection.

Paper [103] proposes an automated pain detection framework from specific facial features. The framework uses iterative shape alignment based on Procrustes analysis and texture wrapping techniques to extract a facial region. It uses Gabor feature extraction and feature compression with Principal Component Analysis (PCA) to determine the pain. Further, SVMs are used to classify between painful and non-painful faces and four pain levels. The method achieves 87.23% accuracy for detecting pain at the frame level and 82.43% for classifying the frames between four pain levels. The success rate of the methodology for pain detection at the image level is 95.5%. Study [104] develops a healthcare framework for recognizing patient states using the GMM. The suggested framework handles two types of inputs: video and audio, both obtained via multi-sensory environments. This framework starts by recognizing faces in videos and identifying key frames. These are then transformed to grayscale mode and subjected to local ternary patterns (LTP). Afterward, face histogram features are computed and fed into the GMM classifier. The system accordingly showed accuracies of 99.9%, 99.5%, and 98.8% in the normal, pain, and tension states. [58] reviews 114 research papers that have contributed to automated pain detection, with a focus on (1) the framework-level similarity between spontaneous automated facial expression recognition (AFER) and automated pain detection (APD) problems; (2) the evolution of system design, including the recent development of deep learning methods; (3) the strategies and considerations in developing a FACS-based pain detection framework from existing research, and (4) introduction of the most relevant databases that are available for AFER and APD studies.

Accurately determining pain levels in children is difficult, even for trained professionals and parents. The facial activity provides sensitive and specific information about pain, and computer vision algorithms can help automatically detect Facial AUs defined by the FACS. Paper [105] uses a simple ANN with one hidden layer to recognize pain using facial AUs coded by a computer vision system embedded in the i-Motions software package. It also analyzes the relationship between i-Motions (automatically) and human (manually) coded AUs. It identifies that AUs coded automatically differ from those coded by a human trained in the FACS system and that the human coder is less sensitive to environmental changes. The paper also considers a transfer learning method to enable more robust pain recognition performance. This method improves the AUC on independent data from new participants in our target domain from 0.67 to 0.72. Research [106] proposes a DeepPain model for facial expression classification. The model detects pain using facial expressions such as joy, surprise, anger, contempt, fear, sadness, and disgust. CNN is used first to learn face attributes from the VGG model, coupled to an LSTM to leverage the temporal correlation between video frames. The canonically normalized appearance of each image is compared to taking the entire image. To evaluate the Deep Pain model, UNBC-McMaster painful dataset is used, which contains recorded videos for 25 patients who had shoulder pain. This model obtained an AUC of 89.6% when training a CNN end-to-end to conduct pain-level estimates, improving to 93.3% when that same CNN is utilized to extract features to train the LSTM. Additionally, this model achieved 97.2% accuracy when tested on the CK+ face expression classification dataset.

E. ABNORMAL EYES MOVEMENTS

The most abnormal eye movements caused by neurological diseases, such as Alzheimer's and Parkinson's diseases are studied in the following papers. In [107], the features of the various components of fixational eye movements are investigated. To obtain data, 16 macular disease observers and 14 older people with normal vision used a Rodenstock scanning laser ophthalmoscope for 30 seconds to fixate a small cross. A multiple linear regression model is used to evaluate the obtained data. Results demonstrated that the intensity of microsaccades has a significant role in restricting fixation persistence. Paper [108] introduces a statistical model that uses eye-tracking data to predict readers with and without dyslexia. This model is built on an SVM applied in binary classification mode. A dataset including 1,135 eye tracker readings of Spanish speakers aged 11 to 54 with and without dyslexia is used to train the SVM model using ten folds cross experiments. All readings by the same user are placed in the same fold, resulting in an equal number of readings classified as participants with and without dyslexia in each fold. The proposed model achieves an accuracy of 80.18%. Work [109] suggests an approach for detecting early-stage cognitive impairment cases. Eye movements are modeled using linear mixed-effect models (LMM). The authors conducted a case-control study with 20 patients with suspected AD and 40 normal control patients. Data is evaluated using linear mixed-effects models, revealing that eye movement behavior while reading can identify whether a person suffers from cognitive impairment. The study results are compatible with previous findings that AD patients have visual memory recognition problems and abnormalities in processing speed and visual short-term memory, even in the early stages of AD.

According to cognitive theories, attentional biases are essential in maintaining obsessive-compulsive symptoms (OCS). Therefore, an eye-tracking method is developed to investigate attentional biases regarding OCS in [110]. In the proposed model, eye-tracking measurements of the attention problems served as the main variables in simple linear regressions with OCS severity as the predictor. Findings showed that OCS severity significantly predicted longer fixations on obsessive-compulsive disorder (OCD) signals, evidence of the maintenance attentional bias. Paper [111] examines the correlation between eye-tracking measures and common visual cognitive tests in Young-onset Alzheimer's disease (YOAD) patients. The study covers 57 participants: 21 normal controls and 36 YOAD patients. Three eye-tracking tests are held on participants, including fixation, pro-saccade, and smooth pursuit. The implemented method consists of three parts. First, HMM is employed as a fitting model for eye tracking (up, down, left, right, and fixed). Second, feature extraction is performed using the fitted model to generate individual feature vectors. Finally, a classification step is performed using the obtained feature vectors. Using cross-validation tests, this approach achieved an accuracy of 95%. Authors of [112] develop a deep learning-based architecture for classifying eye movements. The suggested architecture uses recurrent temporal information-collection layers and deep CNNs for extracting visual features. Standard web cameras are used to capture the dataset images for training and validation, which are then automatically preprocessed using specialized software.

When applied to real-time tests, the developed architecture's overall accuracy on the validation set reached 92% and 88%. A Mann-Whitney-Wilcoxon test revealed that AD patients have to move their face and eyes concurrently in the vertical direction, but cognitively normal persons did not. While most studies on the influence of Parkinson's disease on eye movements have focused on rapid eye movements during sleep, resting-state eye movements are explored in [113]. Vertical electrooculography (VEOG) is employed on 27 PD patients in both the OFF and ON medication states to record the motions. Extracted features from the frequency-, time-, and frequency-time domains of the VEOG time series are used to classify data. The effectiveness of the classification process is measured using a range of classifiers, including decision trees, KNN, SVM, and error-correcting output code-SVM. The suggested model obtained discrimination accuracies for the OFF and ON states, 69.10% and 87.27%, respectively.

F. ABNORMAL UPPER LIMB MOVEMENTS

Abnormal arm, hand, and finger movements and gestures caused by diseases are also widely studied in the literature. Several papers studied upper limb motor symptoms such as tremors, rigidity, and slow movements of PD, HD, and AD patients. In [114], a gesture-based control of home automation is developed. Image data are acquired using cameras and wearable devices to merge contextual sources with the gesture pendant. The system is designed to accomplish two tasks: gesture recognition using an HMM model and tremor detection using Fast Fourier Transform (FFT). The presented system is evaluated using simulated data and reached 95% and 97% accuracy in gesture identification and tremor detection, respectively. Paper [115] evaluates the viability of utilizing accelerometer data to predict the severity of PD patients' symptoms and motor difficulties. 12 participants had uniaxial accelerometer sensors attached to their upper and lower limbs to obtain data. Signal filtration and segmentation were done to prepare data for classification by the SVM model. It was found that the margin of error was 1.8%. Study [116] investigates how involuntary movement complexity can be utilized to distinguish PD treatment states. For data collection, subjects are directed to stand with their arms extended for 60 seconds while a magnetic motion tracker with nine sensor recording tools. Signals are prepared using sample entropy, multi-scale sample entropy, and statistical analysis, while MLP is employed for classification.

The best-achieved recognition rate is 100% using slope features. Work [117] presents a non-invasive method for capturing and assessing hand-related fine motor abilities. In total, 13 patients, 8 of whom suffered from PD, were studied using a depth sensor. Background segmentation, and region of interest (ROI), followed by binary segmentation within ROI, are used to identify and track palms. A combination of SVM with RBF which can optimize kernel parameters, was used for analysis. This method yielded a highly precise detection rate. Paper [118] describes an approach for estimating future gestures from a sequence of hand motions using a deep neural network. Using a capacitance sensor, a dataset including

120 behaviors was obtained from 9 participants. Attention-based GRU model was used to extract temporal information and estimate gestures. The accuracy of this model was 99.6%, which is comparable to other comparable models.

In [114], a gesture-based home automation control is developed, which can also be used for hand tremor detection. Image data are acquired using cameras and wearable devices to merge contextual sources with the gesture pendant. The system is designed to accomplish two tasks: gesture recognition using an HMM model and tremor detection using FFT. The presented system is evaluated using simulated data and reached 95% and 97% accuracy in gesture identification and tremor detection, respectively. Paper [119] proposes a smartphone-based method to measure upper limb tremors in PD patients. Smartphones are utilized to gather data from 45 patients, both with and without PD. The study examines two types of motions: postural hand tremor and rest hand tremor. The random forest bootstrap aggregation of 500 trees is used for feature selection.

Moreover, since the user data is susceptible to overfitting, an out-of-bag error estimate is used to overcome that. Paper [120] assessed bradykinesia using ML algorithms. Movement Disorders Society-Sponsored Revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS) was the basis for the study. A sample of 25 people with PD had their motion data recorded utilizing orientation sensors. The recorded signals were filtered to eliminate noise and drift. Spline interpolation was also employed for signal fitting, while statistical measures and a forward-selection wrapper were used for feature extraction and selection. The classification was performed using SVM in LOOCV and yielded 41.5%, 40%, and 52% for the finger-tapping, diadochokinesis, and toe-tapping classes.

Study [121] investigates the Leap Motion Controller for objective motor dysfunction evaluation in PD patients. Using a board sensor, motion data is obtained for 28 subjects performing predefined exercises. A collection of MATLAB methods, including MathWorks, MA, Natick, and the USA, are used to extract features. In addition, the Peak finder technique measures the number of movements each workout, while power spectral density is employed to estimate movement power. Multiple ML classification techniques are utilized, including NN, SVM, LR, and K-means. The SVM model produces the highest performance, with an accuracy of 85.71%, a sensitivity of 83.5%, and a specificity of 87.7%. The Praxis test is a gesture-based diagnostic test accepted as diagnostically indicative of cortical pathologies such as AD. Using the Praxis test, paper [122] examines the feasibility of using static and dynamic upper-body gestures in a medical context to automate test processes. Video data for 60 people, including 29 gestures, are recorded in their workplace. A tree structure is utilized to represent skeletal data, which is then smoothed to reduce jitter. Preprocessing procedures comprise normalized joint positions, hand segmentation, and PCA. CNN is utilized in the classification step to recognize hand motions, while LSTM is used to aggregate temporal information. An average accuracy of 90% is achieved using the framework.

The authors of [123] suggest an assessment scale for HD patients to reduce evaluator inconsistencies and provide a more accurate scale. The study is based on collecting accelerometer data for 92 subjects, including healthy and HD patients. A low-pass filter is utilized to filter out noise to prepare the collected data, while Wavelet Packet Decomposition (WPD) is employed to extract features. The classification is accomplished using an ensemble classifier and compared to a linear regression model. This model achieved impressive classification results with a sensitivity of 97.7%, specificity of 100%, and accuracy of 98.8%. Report [124] diagnoses PD utilizing the kinematic characteristics of hand motions. Using the Leap Motion sensor, 32 participants are subjected to data collection. The study covers diagnosing three types of movements finger tapping, hand pronation-supination, and hand opening-closing. Maximum and lowest points were determined using parameters such as opening-closing speed and amplitude to extract features. Classification is performed using the KNN, SVM, DT, and RF models, with RF attaining the highest accuracy of 98.4% by merging all classes. Study [55] presents an interpretable visual system (PD-Net) for quantitatively assessing motor performance. Short video data was collected for 149 people, comprising 509 videos; this was augmented with data from two other datasets: Panoptic Hand [125] and FreiHand [126]. The framework is separated into three stages: OpenPose was used to identify hand keypoints, and Frequency filtering, peak detection, and wave segmentation were used for pattern analysis. The classification was completed using LR, SVM, extreme gradient boosting (XGB), and RF. An overall accuracy of 87.6% is obtained using the RF model. Review [56] provides an in-depth analysis of existing computational approaches used in the whole neurodegenerative spectrum, namely for AD, PD, HD, ALS, and MSA. It proposes a taxonomy of the specific clinical features and existing computational methods and provides a detailed analysis of the various modalities and decision systems employed for each disease. The paper also identifies and presents the sleep disorders present in various diseases and represent an important asset for onset detection, as well as overviews the existing data set resources and evaluation metrics. Finally, it identifies current remaining open challenges and discusses future perspectives.

Upper limb movement abnormalities originating from other diseases have also been analyzed with the help of machine-learning methods and algorithms. The authors of [127] developed an EMG gesture recognition framework to aid the elderly and others with physical impairments. Using the Biopac device, the authors recorded EMG signals from three patients doing 4 different hand movements. During preprocessing, EMG signals are preprocessed using a Butterworth bandpass filter, segmented, and transformed using the Wavelet approach. Regarding feature extraction, different statistical measures are applied. ANN was trained for the recognition process and achieved a classification rate of 88.4%. A multiple-tracking method is proposed by [128] to identify qualitative limb movement. Enhanced local connectivity constraint-based identification for small weak markers is employed in neonate limb videos. NB and KNN models are used to monitor the market movements on limbs using the discovered markers. Lastly, for anomaly identification, a window-averaged noteworthy is employed. The proposed method shows potential for monitoring the mobility of infant limbs, which assists in disease diagnosis.

Paper [129] compares several machine learning algorithms for gait pattern recognition in motor disorders using discriminant features extracted from gait dynamics. The work also highlights procedures that improve gait recognition performance. The literature analysis shows that kernel PCA and genetic algorithms are efficient at reducing dimensional features due to their ability to process nonlinear data and converge to the global optimum. Comparative analysis of machine learning performance demonstrates that the SVM model exhibits higher accuracy and proper generalization for new instances. Research [130] utilizes machine learning to recognize and categorize allergic rhinitis motions. Raw sensor data was acquired from 103 individuals with active allergic rhinitis. Data is then subjected to feature engineering and signal processing methods. PCA is used to enhance machine learning model performance, whereas Grid Search and Randomized Search improve recognition accuracy by hyperparameter tuning. The classifier accurately detected 15 allergic rhinitis gestures in a complicated range of head movements with a 93% accuracy rate. In [131], an approach based on ML is suggested for identifying gestures made by neuromuscular patients. Surface electromyogram (sEMG) signals data is used from UC2018 DualMyo [132] and UCI datasets. During data preparation, domain time-frequency and fractal dimension features are retrieved, followed by selecting features using soft ensemble approaches, such as t-tests, entropy, and wrapper feature reduction. The SVM classifier is utilized for gesture recognition and obtained 98%.

Paper [133] suggests a framework for detecting upper limb motions for stroke patients. The proposed architecture integrates digital signal processing, namely the discrete wavelet transforms, with the augmented probabilistic neural network (APNN). SEMG data from the NINAPro database [134] is utilized for model evaluation. The suggested technique is compared to SVM, KNN, and probabilistic neural networks (PNN), where the EPNN model obtained the highest accuracy of 75.5%. Research [134] investigates ML algorithms for Carpel Tunnel Syndrome (CTS) severity classification. A dataset of 1037 CTS subjects was used for the training process. Data preparation includes applying manual feature selection, collinearity testing, normalizing, and one-hot encoding. Random upsampling and Synthetic Minority Over-sampling Technique (SMOTE) are applied to address imbalance difficulties in multi-class classification. ML models, including XGB, KNN, and RF, are used for assessment. The XGB model has the highest accuracy, with 76.6%. Paper [135] develops a gesture detection system to aid paralyzed patients in conveying basic requirements and urgent alerts. Using accelerometer sensors and an Arduino microcontroller, data is collected from patients. To preprocess the data, motion data cleansing and transformation are performed. To perform gesture recognition on the obtained dataset, the KNN model is implemented, and a recognition rate of 97% is attained.

G. ABNORMAL LOWER LIMB MOVEMENTS

The PD-related abnormal lower limb movements have been studied in the following papers. Study [136] develops a pattern recognition approach for diagnosing PD during standardized gait tests. The methodology includes the obtained EMG data from 10 healthy and PD patients. EMG continuous signals are segmented and statistically analyzed to extract features, which are then passed to the forward features selection method. Through feature selection, kurtosis and mean frequency are the best features, with kurtosis suggesting a significant difference. Paper [57] examines relevant studies for identifying PD motor symptoms using machine learning. Four specific motor symptoms of Parkinson's disease are highlighted, including dyskinesia, bradykinesia, and freezing of gait. Work [137] suggests employing gait Vertical Ground Reaction Force (VGRF) collected by foot sensors to determine the severity of Parkinson's disease automatically. A two-channel model integrating LSTM and CNN is designed to identify the spatiotemporal patterns underlying the gait data. The suggested model is tested on a PhysioNet database [138] consisting of three datasets [139], [140], [141] and is compared to NB, KNN, LR, RF, DT, SVM, and GBDT. However, the integration of CNN and LSTM obtained accuracies of over 98%.

In [142], the Weighted Random Forest (LWRF) regression model is proposed to predict PD symptoms using Hoehn and Yahr (H&Y) and Universal Parkinson Disease Rating Scale (UPDRS) scale. Ground Reaction Force (GRF) values are received as input and passed FFT to extract time-domain features. Compared to KNN, RF, DT, and LR, the suggested model obtained 99% accuracy and 99.5% specificity. Paper [143] suggests using a 2D video to assess PD patients' gait. During the timed-up-and-go (TUG) test, 16 PD patients and 15 healthy subjects were observed. Simultaneously, a pressure sensor was employed to analyze gait. The OpenPose model is used for joint detection, followed by the intra-class correlation coefficient (ICC) for statistical video and sensor data comparison. As a result, gait parameters collected by video tracking in the validation tests have intraclass correlation coefficients of more than 0.9, which indicates reasonable agreement with values determined using GAITRite. Paper [144] evaluates bradykinesia in PD patients using an SVM model. A dataset for 12 PD patients is collected using a waist-mounted triaxial accelerometer. The gathered signals were filtered and passed to SVM for classification, where an accuracy of 91.8% was achieved. In addition, the severity was identified and evaluated with less than 10% error using the UPDRS.

The study of gait disorders is another topic for AI researchers. Study [145] compares the performance of PCA-based unsupervised feature extraction algorithms with those based on time-domain and statistical features. This work examines three supervised feature extraction: frequency-based feature extraction, manual time-domain, and statistical feature extraction. Experiments conducted on the DAPHNet dataset [146] indicate that using the DT model with unsupervised features achieves 79.09% for the F1-measure. Similarly, paper [147] utilizes wearable accelerometer data to recognize gait disorders using ML. Wearable triaxial accelerometers are used to collect data on 51 participants. The obtained data are statistically analyzed using Pearson's correlation coefficient and PCA. It is found experimentally that the SVM classifier achieves an accuracy of 88%, outperforming the KNN, DT, and NB methods. Report [129] reviews machine-learning techniques used for gait pattern detection in motor diseases. Based on its ability to analyze nonlinear data, kernel PCA and evolutionary algorithms are found to be effective in feature dimensionality reduction. Moreover, the SVM model performs better than other machine learning algorithms regarding the accuracy and correct generalization for new data. The study finds that SVMs may provide a fast and reliable method for assessing the subject's clinical state.

Research [148] builds a system for detecting gait-related health issues. The proposed model uses a DNN-based approach to predict a patient's 3D body posture using video records that follow 8 markers. The encoder and decoder modules of an hourglass network are used for time series construction, followed by a multi-view fusion approach is used to the time series. As a final module, DNN is utilized for classification and attained an accuracy of 71%. Paper [149] proposes a multi-sensor fusion system to detect gait disturbance patterns and fall detection. Motion data are collected using a multisensory system. Zero-point correction, Kalman filtering, and analog-to-digital (AtD) conversion are applied for preprocessing. As part of a two-stage activity identification system, a PNN is used to identify falls during regular activities, and an ensemble classifier comprised of SVM, RBFs, and KNN is used to identify gait disturbance patterns. Experimentally, the proposed fusion approach improves detection accuracy to 99.37% and enables quicker fall detection compared to single-sensor systems (around 205 milliseconds).

Research [150] studies the ability of radar to distinguish between several types of human-aided and uncontrolled motion using deep learning. This study includes 127 distinct predefined features, including 13 physical features, 3 cepstral coefficients, 10 DCT coefficients, and 101 LPC coefficients. Compared to a multi-class voting SVM classifier trained on 127 pre-defined features, a deep autoencoder structure is employed for feature extraction and classification. The time-frequency distribution of the received signal is represented by a short-time Fourier transform (STFT) or spectrogram. Auto-encoder structure achieved 89% accurate classification, a 17% increase obtained by voting SVM. Paper [151] compares 2D parameters calculated using a typical marker-based technique with a pipeline with fewer markers. A stereophotogrammetric system recorded the body motions of 10 chronic stroke patients. For preparation purposes, key-point detection and homograph transformation are used for preprocessing. A statistical parametric mapping (SPM) technique is used to study elevation angles, and ResNet-50 is applied to extract features after proper fine-tuning. The results show no significant differences between a set of specified parameters calculated using the standard and markerless approaches. Study [152] proposes a system that integrates artificial intelligence technology with certain sectors of the Korean medical area of rehabilitation. The goal is to stop bedsores in patients lying down following surgery by turning them over and observing their range of motion in the arms and legs. To detect and track joints, OpenPose and AlphaPose are used for joint tracking. On the MPII Human Pose dataset, MobileNet obtained a degree of provision of 95% and an angular inaccuracy of fewer than 5 degrees, making it suitable for recovery confirmation.

In [153], a multi-step classification strategy is developed to address the challenge of dealing with unbalanced medical data. The authors utilize sEMG data from 22 different patients [154]. By partitioning the sEMG signal into different frequency bands, eleven discrete wavelet transform (DWT)-based features are extracted. Oversampling is also used to deal with the imbalance issue. This strategy is evaluated using six models: Gradient Booster, Classification and Regression Trees (CART), Bagging, Extra Tree (ET), and RF. ET performs best, with 93.1% accuracy and an F1 of 85.3%. Paper [155] aims to employ sEMG from leg muscles to predict hip and knee angles for human walking. Physiological and correlation analyses are utilized to select and evaluate two sEMG signals from seven muscles during walking, which are filtered and normalized. Fuzzy Wavelet Neural Network (FWNN) is developed as an intention recognition model and merged with Zeroing Neural Network (ZNN) to reduce prediction errors. The result indicates that the FWNN-ZNN model can more effectively assess human motion intention, resulting in an R2 value of 99.94%.

III. FINDINGS

While the previous section describes the major goals and main results of the reviewed papers, this section provides detailed insights into the analyzed health conditions, the investigated patients' activities and abnormal body actions, the used datasets, the applied data preprocessing techniques, the implemented methodology and the achieved results that are obtained in the reviewed papers. The findings are organized in separate tables according to the body parts. The acronyms used are listed in Table S1.

TABLE 1. Abnormal body poses and movements.

Cite	Studied Condition	Body Language	Data	Methodology	Results
[71]	Movement detection - ICU patients	Getting out of bed, getting into bed, getting out of a chair, getting into a chair	Video data including 4 behaviors with 563 videos	Wall-mounted depth sensors for 3D volumetric for data collection, data augmentation, and simulation for preprocessing, ResNet for visual features extraction, LSTM for temporal structure reasoning, YOLOv2 for predicting spatial locations	Specificity: 89.2% Recall: 87.2% Accuracy: 68.8%
[67]	Daily movement detection - elderly people	Sitting down, taking medicine, falling, hands waving, eating, clapping, phone conversation, walking, exercising, standing up, cleaning, picking an object, reading an article, pointing to an object, single-hand waving	Video data from MSRAction3D [156], online self-annotated dataset [157], and MSRDailyActivity3D [158]	Background denoising and segmentation for preprocessing, multi-features approach for feature extraction, vector quantization algorithm for features concatenation and conversion, code matrix and symbol representation for feature selection, HMM for active region selection	Accuracy with online self-annotated dataset: 71.6%, MSRDailyActivity3D: 92.2%, MSRAction3D: 93.1
[69]	Movement tracking - pressure ulcer patients	Supine, supine hands on the body, supine-folded leg, supine-crossed leg, right yearner, right fetus, left yearner, left fetus	Pressure image data for 20 subjects	Pressure Sensing Mat for data collection, Symmetric Gaussian, closing and bridging techniques, and bounding box for data normalization, linear filtering for posture signature extraction, KNN for binary pattern matching	Accuracy: 97.1% Precision: 96.4% Recall: 97.13% F1: 96.73%
[72]	Motion monitoring - in-bed patients	Random horizontal positions, fixed horizontal positions, rotation of joints, body stretching, simulated seizures	Motion data from Multimodal Dataset [159]	Hashing for preprocessing, 3D KNN follows the hashing-based model for information retrieval for pose estimation, CNN model for both extracting features and pose estimation	Best MAE Position: 8 Orientation: 19.29
[75]	Motion-based depression detection - depressed patients	Upper/lower parts of the left and right arms, head, upper and lower parts of the left and right legs	Video data for 48 subjects, including 60 videos	Analog cameras for data collection, the mixture of parts (MoPS) for body detection, relative Parts Movement (RPM) for body parts detection, Space-Time Interest Points (STIP) for body motion analysis, and SVM for the detection	Accuracy: 97.2% F1: 97%
[64]	Daily activity recognition - healthy, elderly people, and patients	Ascending stairs, descending stairs, jumping, walking with a load, walking, bending, kneeling, lying, sitting, squatting, standing, standing-to-bend, kneeling-to-stand, lying-to-sit, sitting-to-lie, sitting-to-stand, standing-to-kneel, standing-to-sit, bending- to-stand	Video and motion data, including 20 behaviors, and SPHERE Challenge Dataset [160]	Triaxial accelerometer information for feature representation, OpenNI framework for features extraction. Models for activity recognition: a non-linear model including RF and SVM, L1-regularized LR	SVM Accuracy: 65.08%
[51]	Abnormal activity detection - psychiatric patients	Entrance and exit from the room, fighting, sleeping, talking, breaking out	Video data, including 6 behaviors	Surveillance cameras for data collection, background segmentation, foreground blob detection, blob tracking, blob analysis for preprocessing, and hard decision rules for recognition.	Accuracy: 85%
[79]	Posture assessment – PD patients	Motor symptoms including bradykinesia, rigidity, tremor, posture instability, gait disorders	Video data for 35 subjects, including 125 videos	Features embeddings for features representation, Uniform Manifold Approximation and Projection (UMAP) for dimensionality, ensemble model for assessments using ResNet, ST-GCNs, and HCNs	F1: 78%
[70]	Tremor monitoring, freezing of gait, and fall detection - PD patients	Falling, tremors, freezing of gait episodes, standing to sit, sitting, standing	Video data for 7 subjects, including 12 behaviors	Microsoft Kinect for data collection, a rule-based method using (x,y)-coordinates for monitoring and detection	Accuracy: Fall detection: 99% Tremor monitoring: 91% Freezing of gait detection: 92%
[53]	Tremor assessment - PD patients	Sitting in a chair with their hands on their lap, lying on the bed, supination of the upper limbs, parallel to the floor, walking freely without help, taking and retaining objects, and finger to the nose	Motion data for 23 subjects, including 5 behaviors	Wearable sensors for data collection, low-pass finite-impulse-response for signal preprocessing, window technique for features extraction, best-first search algorithm for features selection, HMM model for classification	Accuracy: 87% Recall: 84.5% Specificity: 84.5%
[76]	Gait detection - PD patients	The slowness of movements, tremors, muscle stiffness, posture alteration, freezing of gait	Motion data for 21 subjects	Triaxial sensors for data collection, spectral window stacking for data representation, stochastically quadrupled strategy for data augmentation, a spectral technique for features representation, CNN model for classification	Accuracy: 89% Recall: 91.9% Specificity: 89.5% GM: 90.6%
[80]	Parkinsonian movements detection - PD patients	Move forward, take a seat, and then stand up, pronation/supination, fold a towel, tighten the bolt after attaching the nut, tighten the nut after attaching it to the anchor bolt, transfer books from one bookcase to another, fill a glass with water, relaxed arms, place some water in a glass, tapping the surface with the fingertips, tapping index and thumb while bending elbows, with the index finger, touch the nose, standing with the arm out in front, standing with your arms crossed in front of the chest and the palms facing in, place the arms at the sides, palms facing outward	Motion Data for 83 subjects, including 15 behaviors, 670 samples per each	Hands wearable sensors for data collection, high-pass filtering for preprocessing, statistical methods and rolling window for features extraction, PCA, Factor analysis, independent component analysis, and Multidimensional scaling for dimensionality reduction For detection: random forests, logistic regression, SVM	Accuracy: 67%
[77]	Automatic quantification of myoclonic jerks - patients with myoclonus epilepsy	Head movement in flexion-extension and side-to-side rotation, trunk flexion when sitting, finger-to-nose movement, finger on the nose, both arms forward with palms down and then wrists extended, heel-to-toe shin	Video data for 10 subjects, including 9 behaviors	OpenPose for human keypoint detection, automatic myoclonus rating scale (AMRS) for points scoring and measuring smoothness, spearman's technique for correlation testing, log dimensionless jerk for evaluating velocity spikes during the movement	R2: 0.88 p-value: 0.001
[78]	Posture detection - psychologically distressed	Head, face, hand, arm, leg, foot fidgeting (fidgeting of hand to hand, hand to arm, hand	Video data for 35 subjects, including 9 behaviors	Multi-modal Deep Denoising Auto-Encoders, Gaussian Mixture Model (GMM), Improved Fisher	Best Accuracy with LR: 83.38%

TABLE 1. *(Continued.)* **Abnormal body poses and movements.**

	people	to the leg, hand to face, hand free, both legs on the floor, leg on the other leg, fidgeting with crossed hands, single hand fidgeting, leg only, head only, face, arm only, feet)		Vector Encoding for feature representations, RF for feature selection, MLP & LR for classification.	
[83]	Depression analysis - depressed and bi-polar patients	Upper body expressions and gestures, head movements, and facial dynamics	Video data for 60 subjects	Viola-Jones object detector for face analysis, histograms of gradients and flow for upper body analysis, histogram of head movements for face movement analysis, SVM for classification	F1: 80% Accuracy: 76.7%
[82]	Pain detection - patients with chronic lower back pain	One leg stand, sitting still, reach forward, sit to stand, stand to sit, bend and walk	Video and motion data from Emo-Pain Dataset [161]	Feature vectors for representing data. Two models: RF for pain detection, Two-Stage Classification using KNN and HMM for pain detection	Best Mean Accuracy with RF: 48.26 %
[81]	Gestures detection - patients with muscle and joint pains	Body poses	Video data for 10 subjects, including 7 behaviors, with 50 samples each	Feature vectors for representing data. For gestures recognition: Optimized Neural Network with Levenberg-Marquardt, SVM, KNN	Best Accuracy Optimized NN: 91.9%
[73]	Lower back joint load prediction - patients with musculoskeletal disorders	Body poses	Video and motion data for 12 subjects	Video down-sampling and normalization for preprocessing, motion capture model for joint 3D annotation, hourglass network for 2D and 3D poses estimation	Force absolute errors: 9.06 ± 7.60 N·m/4.85 ± 4.85 N.
[68]	Fall detection - elderly people	Forward lying (fall forward from standing and use of hands to dampen fall), front knees lying (fall forward from standing: first impact on knees), sideward lying (fall sideward from standing: bending legs), back-sitting chair (fall backward while trying to sit on a chair)	Motion data for 8 subjects, including 64 behaviors, and from MobiAct [162]	Wearable sensors (MetaMotionR) for data collection, scaling, normalization, data sampling for preprocessing, ReliefF algorithm for features selection, LSTM for fall detection	Precision: 96% Recall: 96% Accuracy: 95.8%
[61]	Fall detection - patients and elderly people	Walk, fall, walk and fall, walk and run	Motion and sound data for 2 subjects, including 3 behaviors	Wearable sensors for data collection, Fourier Transform (STFT) for signal diagnosing and detection, SVM for classifying sounds and movements, Kalman filtering kernel for smoothing falls consecutive occurrences	Accuracy: 98.2%
[63]	Fall detection - elderly people	Falling, lying, standing, walking, sitting, sitting, and lying	Video data for 3 subjects, including 45 behaviors	Smart infrared motion capture for data collection, Kalman filtering for noise smoothing, reference attributes, body attributes, and angle attributes for body description, eight ML algorithms are compared, including SVM, KNN, RF, Bagging, AdaBoost M1, RIPPER Decision Rules, NB, and C4.5	Best Accuracy SVM: 97.7%
[65]	Fall detection - patients	A simple walk, simple walk and fall, simple walk and run	Motion data for 2 subjects, including 3 behaviors	Wearable sensors for data collection, SVM model for detection, context-aware server for patients' video transmission	Accuracy: 96.72%
[62]	Posture detection - elderly people	Standing, sitting, bending/squatting, side lying, and lying	Video data including 5 behaviors, with 30 samples each	Camera for data collection, background subtraction approach for segmentation, projection histograms for features extraction, hybrid KNN model with evidence accumulation technique for the detection, bounding box angle test for invalid detection angle test	Accuracy: 95.57%
[66]	Pose recognition and fall detection - elderly people	Standing, sitting, falling	Video data for 10 subjects, including 3 behaviors, with 60 samples each	Pyroelectric infrared sensor for data collection, the L1 norm for data normalization, linear programming, and orthogonal matching pursuit for sparse approximation	Accuracy: 100%
[50]	Upper body pose estimation - hospital patients	Poses of the head, hands, elbows, shoulders	Video data for 3 subjects, including 4 behaviors, with 3119066 frames	Microsoft Kinect V2 for data collection, Light Normalization and cropping for preprocessing, CNN with Kalman filter with noise parameters for joint position estimation	Best Accuracy observed case: 96.8% Average Accuracy: 91.93%
[84]	Infant abnormal movements - cerebral palsy	Body poses and movements	Video data from the MINI-RGBD dataset, including 12 sequences [85]	OpenPose for extracting 2D poses, Histogram of Oriented Gradients (HOG) for features extraction, Histogram of Joint Orientation 2D (HOJO2D), and Histogram of Joint Displacement 2D (HOJD2D) for features representation. Models for classification: KNN, LDA, and ensemble learning.	Best Accuracy in Ensemble: 91.6%

IV. DISCUSSIONS: ANALYSIS OF ABNORMALITIES, DATA, AND METHODOLOGY

From initially collected 180 AI research and review papers that mention different activities of people with health conditions, diseases, pains, and their relationships to patients' body motions and postures, we selected 83 papers that clearly discussed the abnormal activities and the *causational relationships* of diseases and pains to *abnormal body actions*. The reviews (in Section II) and the detailed findings (in Section III) are categorized following the hierarchical order: body parts, health conditions, and body language. Section II briefly describes the major problems studied in the papers and the results obtained from the main research methods applied in these papers. The tables in Section III provide more details on the health conditions, abnormal activities, abnormal body actions, datasets, methodology, methods, algorithms, and results that are extracted from the studies given in the research papers. The following two subsections provide

TABLE 2. Abnormal head poses and movements.

Cite	Studied Condition	Body Language	Data	Methodology	Results
[52]	Head movement recognition - otoneurologic patients	Head shaking (head repetitive left and right turning)	Motion data for 44 subjects	Syntactic method to recognize eye movement. Models for recognition: Decision Tree, SVM, Naïve Bayesian, Kohonen networks, Neural Networks	Best Accuracy DT: 89.8%
[88]	Abnormal head movement classification - patients	Flopping head movements	Image data from Normal Abnormal Head Movement Dataset (NAHM), including 9112 images	Normalization and image resize for preprocessing, Multi-Task Cascaded Convolutional Networks for feature extraction, and CNN for movement classification.	Accuracy: 98.31%
[87]	Computer vision syndrome detection - patients with eye diseases	Head movement: more than five movements within a time threshold, eye blinking rate: more or fewer than 2-3 blinks per second, close eye duration	Video data	OpenCV for head frames extraction and eye localization, image segmentation for preprocessing, Haar-cascade algorithm for detection	Accuracy: 99.95%

further insights into these findings and mine different statistical and relational properties using data analysis techniques. To thoroughly study the findings, we first construct the dataset ("~/ai-dataset.csv" in Table S1) based on the tables in Section III. This dataset consists of 80 rows where each row represents a specific health condition concerning abnormal activities or abnormal body actions, and 28 columns that provide all the information related to diseases, pains, expressible body parts, abnormal activities, abnormal body actions, data types, datasets, data preprocessing techniques, feature extraction and selection procedures, methodology, methods, algorithms, performance evaluation metrics, results, which are extracted from the reviewed papers.

We use descriptive and exploratory data analysis methods, i.e., univariate, bivariate, and multivariate analysis techniques, to establish the statistical and relational properties of all features in the dataset. First, we analyze the "medical" features of the dataset, i.e., the diseases, pains, and other conditions together with abnormal activities and body actions caused by these health conditions. Next, we examine the "AI" features, i.e., the datasets, data preprocessing techniques, feature engineering procedures, methods, performance evaluation metrics, and results. Lastly, we investigate the methodologies grouping them into "similarity clusters" to identify more powerful and reliable methodologies for detecting, recognizing, and analyzing abnormal activities and body actions of people with health conditions. We should also mention that the current analysis is subjective to the information provided in the reviewed papers, which still needs to be more complete. However, the used approaches and developed analysis methods and techniques in the research are applicable and scalable to any extent.

A. STATISTICAL PROPERTIES OF MEDICAL FEATURES

First, we can observe the distribution of the selected 83 AI papers for review in the following figure (Figure 3), which shows that the intensive studies of abnormal activities and abnormal body actions of patients using AI techniques started in 2013.

Since our main objective is to analyze abnormal activities and body actions based on the expressible body parts where these abnormalities happen, we begin our analysis by identifying the papers' distribution accordingly. The distribution of the papers studying the patients' abnormal activities and abnormal body actions caused by diseases and pains in each body part is depicted in Table 7.

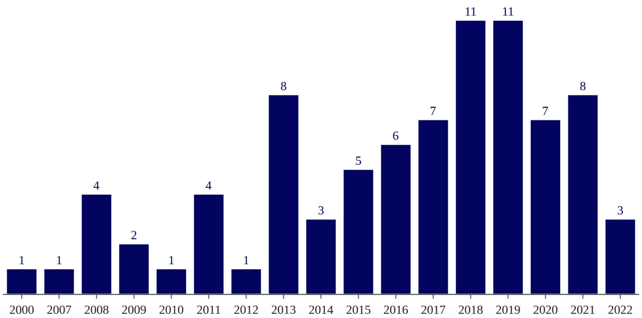

FIGURE 3. The Distribution of the reviewed papers according to the years of publications.

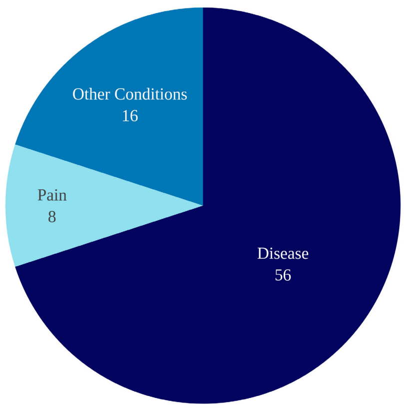

FIGURE 4. The case apportions of the reviewed papers.

One can notice that the number of papers reviewed (**83**) differs from the total (**80**) in Table 8 because the table includes only research papers.

Figure 4 demonstrates the apportions of these papers according to the cases, i.e., diseases, pains, and other health conditions considered in the papers. Most research papers (70%) center on the machine learning tasks on abnormal body actions resulting from diseases, while a smaller percentage (20%) tackles abnormal activities of people with health conditions such as elderliness, immobility, and disability. A few papers (10%) also analyze pain-caused abnormality problems.

Moreover, Figure 5 gives a more detailed illustration of the distributions of the papers according to the body parts, including the proportions of diseases, pains, and other health conditions.

Here, we can see that the effect of diseases is observed in all expressible body parts, pain is spotted mostly on the face,

TABLE 3. Abnormal facial expressions.

Cite	Studied Condition	Body Language	Data	Methodology	Results
[95]	Emotions detection - autism patients	Facial expressions for neutral, anger, sadness, disgust, fear, and happiness	Eye movement data for 21 subjects	Fixation map for vertical fixation position, Gaussian mask for emotion estimation error	Autism class Accuracy: 90% Normal class Accuracy: 92%
[93]	Facial-expression recognition - patients	Facial expressions for happiness, sadness, anger, anxiety, and neutral	Video data for 100 subjects, including 4 emotional states, JAFFE Dataset [163], and CK dataset [164]	Bandlet transform for geometrical image representation, Dividing bandlet results into blocks, Histogram, Kruskal-Wallis for feature selection, GMM, and SVM for recognition	Accuracy: 99.95%
[91]	Facial expression analysis - depressed patients	Facial expressions for neutral, sadness, disgust, fear, surprise, anger, happiness	Video data from the FACES dataset [165]	AdaBoost algorithm with Haar features for face detection, AAM for landmark detection PCA for dimensionality reduction, Normalization for preprocessing, SVM for facial expression classification	Accuracy: 82.0%
[100]	Face expression detection - traumatic brain injury patients	Facial expressions for neutral, happiness, anger, sadness, surprise, and fatigue	Video data with 539 video sequences	Viola-Jones (VJ) method for face detection, supervised decent method for landmark alignment, CNN and LSTM for detection	AUC: 75.26%
[97]	Automatic facial expression analysis - depressed patients	Face expressions for contempt, attenuation of happiness, disgust, attenuation of sadness	Video data from Spectrum dataset [166]	Facial Action Coding System (FACS) for manual coding, AAM for face landmark and automatic coding, Localized Gabor features for features, PCA for dimensionality reduction, SVM model for classification	Best F1: 77.3%
[103]	Automatic pain detection - patients with shoulder pain	Pain expressions	Image data from the UNBC-McMaster dataset [101]	Grayscale conversion for preprocessing, iterative shape alignment using Generalized Procrustes Analysis (GPA) and texture warping for facial region extraction, Gabor filtering for feature extraction, PCA for feature compression, SVM for classification	Accuracy per frame level: 82.43% Accuracy per image level: 95.5%
[105]	Automatic pain detection - children	Brow lower, cheek raiser, lid tightener, nose wrinkle, upper lip raiser, lip corner puller, lip stretcher, eyes closed	Video data for 143 subjects with 598 samples	iMotions software for automated facial action unit detection, FACS AU coder for manual facial action unit detection, Statistical measures and PCA for dimensionality reduction, NN model for detection	AUC: 72%
[92]	Automated facial action coding - neuropsychiatric patients	Face expressions of happiness, sadness, anger, fear, and disgust	Video data for 8 subjects, including 5 emotional states	Active Shape Model (ASM) for face landmarks detection and tracking, Similarity transformations for geometric features extraction, Gabor wavelet filter for calculating texture features, Gabor responses in each Regions-of-Interests for dimensionality reduction, Gentle Adaboost model for classification	Highest flatness: 83.36% Highest inappropriateness: 67.25%
[99]	Depression early detection - depressed patients	Face expressions for neutral, sadness, disgust, fear, surprise, anger, and happiness	Video data for 52 subjects, including 7 emotional states	Viola-Jones detector for face key-point tracking, person-specific AAM for features extraction, and SVM for recognition.	Accuracy: 78.85 % Precision: 77.75% Recall: 80.77% F1: 79.2% Specificity: 76.92%
[54]	Apathy detection - AD patients	Apathetic facial expressions	Eye gaze data for 48 subjects with 3840 samples	Visual attention scanning technology for data collection, RNN for extracting visual features representation, and eye movement detection	AUC: 81.4%
[106]	Pain facial expression classification - patients with shoulder pain	Face expressions of anger, contempt, disgust, fear, happiness, sadness, surprise	Image data from the UNBC-McMaster dataset [101]	GPA for landmark alignment, data under-sampling for data balancing, labels standardization, VGG-16 for facial features extraction, LSTM for temporal features extraction	Accuracy: 97.2%
[102]	Pain detection - patients with shoulder pain	Facial pain expressions	Image data from the UNBC-McMaster dataset [101]	Viola-Jones object detection model for face tracking, pyramid histogram, and local binary pattern for features extraction. Models for detection: SVM, DT, RF, KNN	Best Accuracy KNN: 96%
[101]	Pain detection - patients with shoulder pain	Facial pain expressions	Image data for 129 subjects with 200 videos and 48,398 frames	AAM for face landmarks tracking and features extraction, SVM for detection	ROC: 83.9%.
[104]	A patient state recognition system	Normal, pain, tensed facial expressions	Speech and video data 100 subjects, 30 samples per each	Bandpass filter for speech features extraction, local ternary patterns and multi-directional features for video features extraction, GMM for recognition	Accuracy: 99.4%

TABLE 4. Abnormal eye movements.

Cite	Studied Condition	Body Language	Data	Methodology	Results
[111]	Eye-tracking - AD patients	Eye fixation, pro-saccade, and smooth pursuit	Eye movement data for 57 subjects	Infrared video eye tracker for data collection, Visual and Object Space Perception battery for shape detection, HMM for features extraction and eye tracking, logistic regression for classification	Accuracy: 95%
[109]	Eye movement analysis - AD patients	Eye fixations	Eye movement for 20 subjects	Linear mixed-effect model for eye gaze analysis	
[108]	Eye tracking - dyslexia patients	Eye fixations	Eye movement data for 97 subjects, with 1135 readings	Tobii 1750 eye tracker for data collection, SVM for binary classification	Accuracy: 80.18%
[110]	Eye-tracking - obsessive-compulsive disorder	Eye fixations	Video data for 85 subjects	iView X Eye-tracking Device for eye movement tracking, eye patterns for fixation interpretation, linear regressions for tracking	
[113]	Eye movement analysis – PD patients	Vertical eye movements	Eye movement data for 54 subjects	EEG and VEOG for data collection, VEOG filtering for preprocessing, and Statistical analysis for feature selection. ML models for analysis: DT, KNN, SVM	Off-class Accuracy: 69.10% On-class Accuracy: 87.27%
[107]	Fixational eye movements analysis - macular disease patients	Eye fixations	Video data for 30 subjects	Rodenstock scanning laser ophthalmoscope for data collection, cross-correlation procedure for movement fixational extraction, bivariate contour ellipse area for quantifying fixation stability, multiple regression for analysis	Multiple R2 0.901 Adjusted R2 0.889

and other health conditions are investigated in relation to the body (as a whole) and limbs.

Figure 6 represents the distribution of each disease, pain, and health condition considered in the reviewed papers. The figure reveals that the reviewed papers highly concentrate on studying a few diseases, pains, and other conditions, such as Parkinson's disease, neurological disorders, musculoskeletal disorders, health conditions involving elderly people, and shoulder pain. Parkinson's disease has been under the special target of AI research, i.e., the 29% of the reviewed papers have studied abnormal activities and body actions caused by Parkinson's disease. The concentrated application of machine learning studies in the reviewed papers on neurodegenerative conditions such as Parkinson's, Alzheimer's and

TABLE 5. Abnormal upper limb poses and movements.

Cite	Studied Condition	Body Language	Data	Methodology	Results
[130]	Gesture recognition - allergic rhinitis patients	Touching the nose, the eyes, and the ears with fingers and hands	Motion data for 103 subjects, including 970 gestures with 18 behaviors	Wearable sensors for data collection, energy filtering, normalization, segmentation, and quantization for preprocessing standardization method for feature scaling, and PCA for dimensionality reduction. Models for recognition: KNN, SVM, RF, and DT	Best Accuracy with SVM: 93%
[135]	Gesture recognition - paralysis patients	Bending finger(s)	Motion data, including 4 gestures	Arduino with an accelerometer for data collection, data cleaning, transformation, and reduction for preprocessing, KNN for classification	Accuracy: 97%
[127]	Gesture recognition - disabled and elderly people	Hand left, right, up, and down movements	EMG signal data for 3 subjects, including 4 gestures	Butterworth bandpass filter for noise removal, wavelet technique for denoising signal segmentation, EMG levels decomposition for signal transformation, statistical measures for features extraction, ANN for gesture recognition	Accuracy: 88.4%
[122]	Gesture recognition - cognitive patients and elderly people	Hand and finger gestures	Video data for 60 subjects, including 29 gestures	Tree structure for representing skeleton, data smoothing for reducing jitter, normalized joint positions, hands segmentation, PCA for preprocessing, CNN for recognizing hands gestures, LSTM for aggregating temporal features	Avg. Accuracy: 90%
[55]	Gesture recognition - PD patients	Finger tapping, hand movement, pronation-supination movement	Video data for 149 subjects, including 509 videos, datasets from Panoptic Hand [125] and FreiHand [126]	OpenPose for hand key points detection, frequency filtering, peak detection, and wave segmentation for pattern analysis, LR, SVM, XGB, and RF for classification	Accuracy: 87.6%.
[118]	Gesture estimation - PD patients	Finger flexion, wrist flexion, wrist extension, ulnar deviation, radial deviation, supination, and pronation	Motion data for 9 subjects, including 78724 gesture sequences with 12 behaviors	Wearable sensors for data collection, concentric contraction activation for wrist flexion preprocessing, attention-based GRU model, MLP, SVM, KNN, RF for temporal information extraction and gestures estimation	Accuracy: 99.6% Recall: 96% Specificity: 97%
[121]	Leap motion evaluation - PD patients	Pronation and supination of the forearms, opening and closing of the hands, thumb-forefinger tapping, hand postural tremor	Motion data for 28 subjects	Leap Motion Controller for data collection, MathWorks, MA, Natick, and USA off-the-shelf algorithms for features extraction, peak finder algorithm for movement count, power spectral density for power estimation, NN, SVM, LR, and K-Means for motion evaluation	SVM: Accuracy: 85.71% Recall: 83.5% Specificity: 87.5%
[124]	Disease detection - PD patients	Finger tapping, hand pronation and supination, hand opening and closing movements	Motion data for 32 subjects, including 128 instances	Leap Motion Controller for data collection, maximum and minimum points are calculated for features extraction, KNN, SVM, DT, and RF for classification	Accuracy per class FT: 95.3%, OC: 90.6% PS: 93.8% All classes: 98.4%
[114]	Medical monitoring – patients with pathological tremors	Hand tremors	Image data, including 4506 images	Pendant camera for data collection, HMM for gesture recognition, FFT for tremor detection	Accuracy: Gesture rec: 95% Tremor det.: 97%
[120]	Diagnosis and monitoring - PD patients	Finger flexion and extension, wrist pronation and supination, toe-tapping	Motion data for 25 subjects	Wearable sensors for data collection, signal filtering to eliminate noise and drift, spline interpolation for signal fitting, statistical measures for features extraction, and forward-selection wrapper for features selection. PCA for dimensionality reduction, SVM for classification	Avg. error Finger Tapping: 15% Diadochokinesis: 9.3% Toe Tapping: 18.2%
[119]	Tremors assessment - PD patients	Postural tremor of the hands, rest hand tremor	Motion data for 45 subjects	Smartphone sensors for data collection, out-of-bag for feature selection, NB, LR, SVM, AdaBoost, C4.5, BagDT for assessment	BagDT AUC: 0.9435 Recall: 82% Specificity: 90%
[116]	Levodopa-induced dyskinesias detection - PD patients	Hand postural tremors	Motion data for 29 subjects	Magnetic motion tracker for data collection, Sample entropy, multi-scale sample entropy, statistical analysis for preprocessing, MLP for classification	Accuracy: 100%
[115]	Monitoring motor fluctuations - PD patients	Finger to the nose, finger tapping, opening and closing of the hands, heel tapping, quiet sitting, pronation, and supination movements of the forearms	Motion data for 12 subjects	Wearable sensors for data collection, signal filtration and segmentation for preprocessing, SVM for classification	Error: 1.8%
[117]	Hands movement analysis - PD patients	Finger taps, opening and closing the hands, pronation, and supination movements of the hands	Video data for 13 subjects	Microsoft 3D camera sensor based on Time of Flight for data collection, background segmentation for palm detection, ROI for palm tracking, binary segmentation within ROI for palm center discrimination, statistical measures for features extraction, SVM with RBF for classification	Accuracy: 100%
[133]	Upper limb movement classification - stroke patients	Hand and finger movements	sEMG data from the NINAPro database [167]	DWT for time-frequency features extraction, Models for classification: SVM, KNN, PNN, and EPNN	Avg Accuracy: 75.5%
[128]	Assessment of spontaneous limb movements - neonates	Limbs movement with abrupt	Video data	Local connectivity constraints for eliminating extra noise and comparing patterns, SIFT for detecting candidate points, NB and KNN for classification	
[123]	Automated assessment of movement impairment - HD patients	Hand movements	Accelerometer data for 92 subjects	GENEactiv accelerometers for data collection, low-pass filter for noise filtering, WPD for features extraction, Ensemble for classification including NB, majority voting, and DT	Accuracy: 98.8% Specificity: 100% Sensitivity: 97.7%

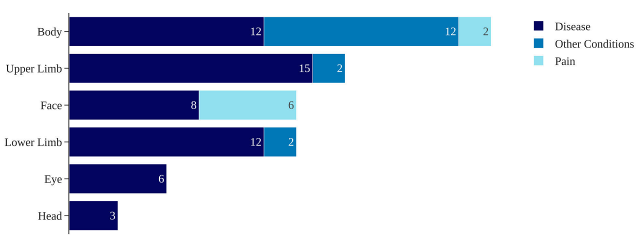

FIGURE 5. The distribution of the studies according to the body parts.

neurological diseases, and musculoskeletal disorders can be rationalized from medical and artificial intelligence perspectives. Such diseases and disorders often lead to involuntary and uncontrolled body movements and postures, including tremors, rigidity, balance problems, gait freezing, bradykinesia, and abnormal facial expressions, which are outward manifestations of the underlying diseases. As such, these observable symptoms enable the identification, recognition, and analysis of the abnormal bodily actions induced by these diseases using machine (deep) learning techniques without significant exertion.

Looking at it from another angle, we can notice that the surveyed literature also reveals a distribution of the most frequently researched unusual behaviors and abnormal body actions in connection with health conditions (see, Figure 7).

TABLE 6. Abnormal lower limb movements.

Cite	Studied Condition	Body Language	Data	Methodology	Results
[148]	Automatic health problem detection - patients with gait disorders	Gait disorders of PD, stroke, and orthopedic patients	Video data for 95 patients	Hourglass network for time series generation, multiview fusion for time series, DNN for classification	Avg. Accuracy: 71%
[143]	Quantitative gait analysis - PD patients	Walking, turning a round, sit-to-stand, stand-to-sit	Video data for 31 patients, including 62 samples	Digital cameras for data collection, OpenPose for joint detection, ICC for statistical comparison of video with sensor data	Intraclass correlation coefficiency > 0.9
[149]	Activity detection - patients with gait disorders	Vertical fall, fall to left, fall to the right, fall frontward, fall backward, dragging gait, forward gait, normal gait	Motion data with 10 behaviors	Multisensor fusion system for data collection, zero-point correction, Kalman filtering, AtD conversion for preprocessing, PNN for detecting regular falls, and ensemble classifier comprised of SVM, RBFs, and KNN is gait disturbance patterns detection.	Recall: 99.37% Specificity: 100%
[151]	Marker-less gait analysis - stroke survivors	Walking	Video data for 10 subjects	Infrared and RGB cameras for data collection, 2D key-points detection and homography transformation for preprocessing, SPM for elevation angles analysis, ResNet-50 for features extraction	
[152]	Prevention of bedsores and leg rehabilitation - disabled patients and elderly people	Lying down, turning the body in both directions while lying down, sitting on the bed	Image data from the MPII Human Pose dataset [168]	OpenPose and AlphaPose for joint tracking, MobileNet	Provision: 95% Angular inaccuracy < 5
[150]	Unaided gait recognition - patients with neuromuscular diseases	Walking, limping, walking using a cane, walking using a walker, walking using crutches with one leg bent at the knee, jogging, creeping, crawling, falling from an upright position, falling from a chair, quickly sitting down using a wheelchair	Motion data 10 subjects including 864 measurements with 12 behaviors	STFT for data representation, deep autoencoder, and SVM for classification	Accuracy: 88.94 % Precision: 89% Recall: 89%
[137]	Gait detection and severity rating - PD patients	Walking	Motion data from PhysioNet [138]	Data reshape and Normalization for preprocessing, models for recognition: NB, KNN, LR, RF, DT, SVM, GBDT, CNN, and LSTM	Best Accuracy: CNN + LSTM: 98.88%
[147]	Freezing of gait recognition - PD patients	Walking	Motion data for 51 subjects	Wearable triaxial accelerometers for data collection, Pearson's correlation coefficient for statistical analysis, and PCA for dimensionality reduction. Models for recognition: SVM, KNN, DT, and NB	SVM Accuracy: 89.14 % Recall: 88.52% Specificity: 88.77%
[136]	Gait recognition - PD patients	Walking, heel-toe tapping, foot rotation, seesaw (plantar flexion and dorsiflexion of both feet)	EMG data for 10 subjects	EMG sensors for data collection, automatic segmentation for continuous signals, statistical measures for features extraction, forward feature selection SVM for classification	Recall: 90% Specificity: 90%
[145]	Detection and recognition of gait freezing - PD patients	Walking forward and backward, turning	Motion data from the DAPHNet dataset [146]	Approaches for features extraction: Frequency-based feature extraction, and manual time-domain and statistical feature extraction, PCA, DT for classification	Recall: 77.7% Specificity: 87.56% F1: 79.09%
[142]	Gait analysis - PD patients	Walking	Motion data from PhysioNet [138]	GRF sensors for data collection, FFT for extracting time-domain features, LWRF, KNN, SVR, DT, and RF for classification	Accuracy: 99.0% Recall: 97.8% Specificity: 99.5%
[144]	Estimating bradykinesia severity- PD patients	Walking slow, short steps, walking with assistance, walking hesitation, walking with difficulty	Motion data for 12 subjects	9x2 wearable device sensor for data collection, signal filtering, SVM for classification	Accuracy: 91.81% Recall: 92.52% Specificity: 89.07%
[155]	Lower limb continuous estimation - stroke patients	Walking	sEMG data for one subject	Gyroscope sensor for data collection, signal filtering and normalization for preprocessing, FWNN, and ZNN for estimation	R2: 0.9994
[153]	Knee abnormality detection - people with knee disorders	Walking	sEMG data for 22 subjects from [154]	Wavelet denoising for noise removal Signals segmentation, Normalization, and Oversampling for preprocessing Statistical measures for features extraction. Models for classification: ID3, Gradient Booster, CART, Bagging, ET, and RF	Accuracy: 93.1% F1: 85.3%

TABLE 7. The distribution of the research papers studied the abnormal activities and causational relationships of diseases and pains to body language.

	body	head	face	eyes	u/limb	l/limb	total
d/p	26	3	14	6	17	14	80

* u/limb = "upper limb," l/limb = "lower limb," d/p = "disease/pain"

Here, it is observable that the most frequently researched abnormal activities include "walking," "sitting," "standing," "lying," and "falling," along with abnormal hand, finger, and arm gestures. Additionally, facial expressions such as "sadness," "happiness," and "disgust" have been extensively studied.

By contrasting Figures 6 and 7, we can infer the cause-and-effect relationships between the most extensively studied health conditions and the most commonly researched abnormal behaviors and activities. In other words, these frequently occurring anomalies are indicative of symptoms and signs of the most examined diseases and other health problems. To gain a broader and deeper understanding of how diseases, pains, and other health issues correlate with abnormal behaviors and body language, it is essential that we accurately scrutinize each study and pinpoint all potential connections of this nature. The information displayed in the second and third columns of Tables 1-7, and the assembled dataset (Table S1), is the output of such meticulous efforts. Tables 8-

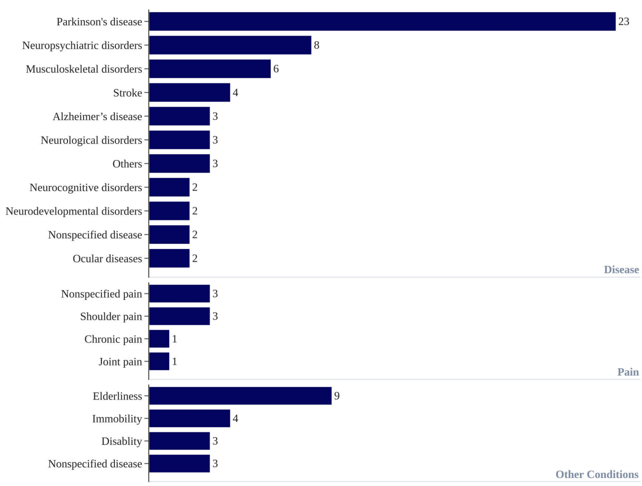

FIGURE 6. The distribution of diseases, pains, and other health conditions.

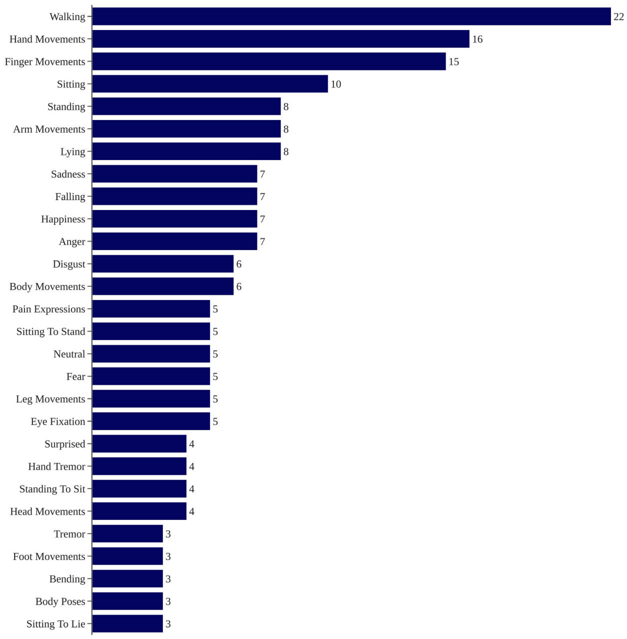

FIGURE 7. The distribution of the examined abnormal activities and body actions studied in a minimum of three papers.

TABLE 8. The list of the diseases along with the correlated abnormal body actions and activities.

Disease	Abnormal activities and body actions
Allergic rhinitis	finger movements, hand movements
Alzheimer's disease	eye fixation, pro-saccade, smooth pursuit, apathy
Musculoskeletal disorders	body poses, arm movements, finger movements, leg movements, head movements, crawling, creeping, falling, jogging, limping, sitting, sitting to lie, standing to lie, walking
Neurocognitive disorders	hand movements, finger movements
Neurodevelopmental disorders	facial expressions for anger, disgust, fear, happiness, sadness, neutral, and eye fixation
Neurological disorders	body poses, body movements, leg movements, arm movements, eye fixation
Neuropsychiatric disorders	facial expressions for anger, attenuation of happiness, attenuation of sadness, contempt, disgust, fear, happiness, neutral, sadness, surprise, and body movements, head movements, arm movements, hand movements, leg movements, foot movements, lying
Nonspecified disease	facial expressions for anger, excitement, happiness, neutral, sadness, and head flopping
Ocular diseases	eye fixation, eye blinking, head movements
Otoneurologic disease	head shaking
Parkinson's disease	arm movements, eye movements, falling, finger movements, foot movements, gait disorders, gait freezing, hand movements, hand tremor, unstable postures, lying, rigidity, sitting, sitting to stand, standing, standing to sit, tremor, turning, walking, bradykinesia
Stroke	finger movements, hand movements, walking, arm movements
Traumatic brain injury	facial expressions for anger, fatigue, happiness, sadness, surprise, neutral

10 summarize the concise lists of individual diseases, pains, and other health conditions along with the associated abnormal body actions and activities they induce.

TABLE 9. The list of the pains along with the correlated abnormal body actions and activities.

Pain	Abnormal activities and body actions
Chronic pain	bending, sitting, sitting to stand, standing to sit, walking, standing
Joint pain	body poses
Nonspecified pains	pain expressions, tense
Shoulder pain	facial expressions for contempt, disgust, fear, happiness, sadness, surprise, anger, and pain expressions

TABLE 10. The list of the other health conditions along with the correlated abnormal body actions and activities.

Condition	Abnormal activities and body actions
Disability	falling, hand tremors, walking, hand movements
Elderliness	bending, bending to stand, body movements, falling, finger movements, hand movements, hand tremor, jumping, kneeling, kneeling to stand, lying, lying on the side, lying to sit, sitting, sitting to lie, sitting to stand, squatting, standing, standing to bend, standing to kneel, standing to kneel and kneeling to lie forward, standing to lie forward, standing to lie on the side, standing to sit and sitting to lie backward, standing to sitting, walking, walking and falling, walking and running, sitting
Immobility	body movements, hand movements, leg movements, lying, sitting, sitting to stand, standing to lie, standing to sit, lying to stand
Nonspecified diseases	elbow poses, falling, hand poses, head poses, running, shoulder poses, walking, walking and falling, walking and running, walking

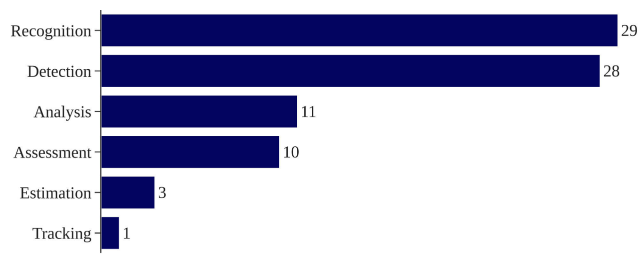

FIGURE 8. The categorization of machine learning tasks as studied in the reviewed articles.

B. STATISTICAL PROPERTIES OF AI FEATURES

This subsection comprehensively examines the statistical characteristics of AI-driven information within the reviewed papers. Specifically, it involves exploratory and descriptive analyses pertaining to various aspects such as data types, datasets, data preprocessing techniques, feature engineering procedures, methods employed for detection, recognition, and other machine learning tasks, as well as the evaluation of performance.

Firstly, it is important to note that the studies that have been reviewed primarily focus on machine learning tasks, including the detection, recognition, analysis, and evaluation of abnormal activities and abnormal bodily movements in patients with various health conditions, as shown in Figure 8.

Figure 9 demonstrates that the studies utilize various data types such as videos, images, audio, motion, EMG, and sEMG signals. This assortment of data is collected using a range of sensors, as indicated in Figure 10.

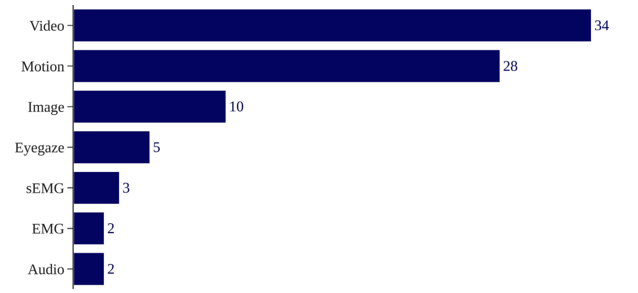

FIGURE 9. **The distribution of the data types used in the studied tasks.**

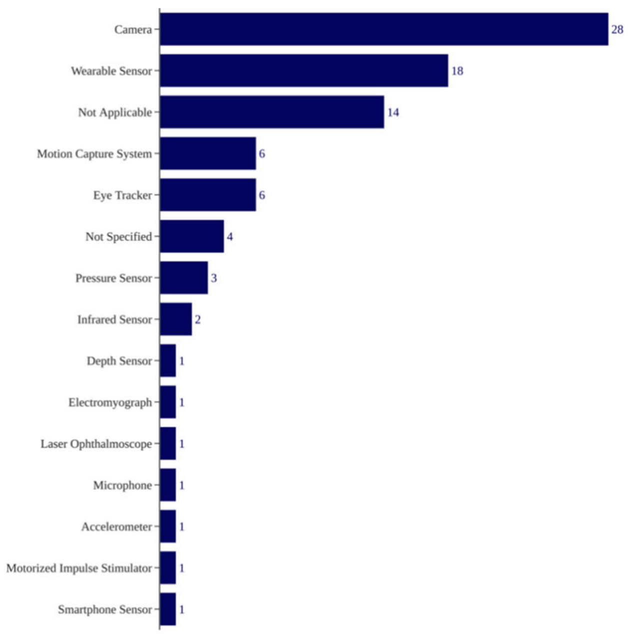

FIGURE 10. **The distribution of the devices used for data collection.**

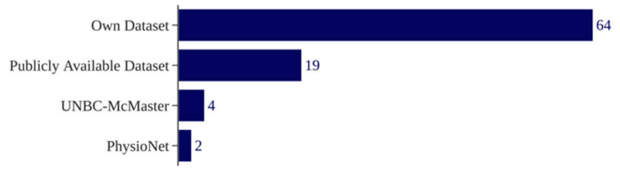

FIGURE 11. **The distribution of the datasets used in the reviewed papers.**

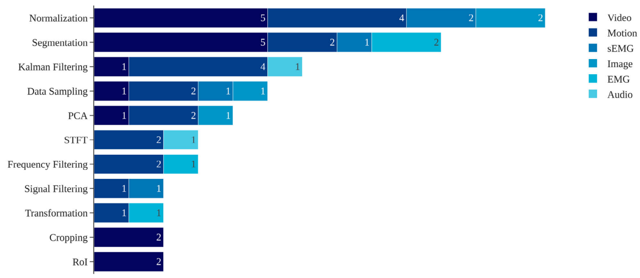

FIGURE 12. **The data preprocessing techniques exploited in a minimum of two papers.**

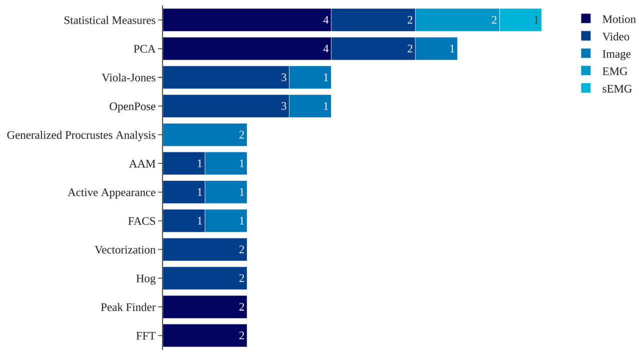

FIGURE 13. **The feature engineering strategies utilized in a minimum of two papers.**

The utilization of datasets varies across the studies examined in our review, as illustrated in Figure 11. Among the total number of studies scrutinized, 64 produced their own datasets, while 19 employed either publicly accessible datasets or datasets that they made available to the public under a specific name. Four studies utilized the UNBC-McMaster dataset, created to support and simplify research on pain, particularly regarding facial expressions. Furthermore, two studies used PhysioNet, an extensive collection of well-characterized digital recordings of physiological signals, time series, and related data designed for use by the biomedical research community. These results emphasize the significance of considering the origin of the dataset when carrying out research, as it can influence the precision and dependability of the results obtained. Additionally, the availability and accessibility of public datasets can advance the progress of research in the AI-powered healthcare domain.

Though the research in the reviewed papers mainly aims to solve a few machine learning tasks (Figure 8) and use the data of a few types (Figure 9), the papers use a relatively larger number of data preprocessing techniques and feature engineering methods to transform raw data to the input data for the considered models. Figures 12 and 13 illustrate the variety of these techniques and methods used in at least two papers. It is important to highlight that various data preprocessing techniques such as normalization, segmentation, Kalman filtering, Principal Component Analysis, and sampling are used universally across different data types. On the other hand, methods such as cropping and defining regions of interest are mostly employed for video data. Although statistical methods and Principal Component Analysis are the most prevalent techniques for feature engineering in the data preparation phase, the use of vectorization and Histogram of Oriented Gradients is specific to motion data. Similarly, Fast Fourier Transform and peak finding techniques are exclusively employed with video data. The complete lists of data preprocessing and feature engineering techniques can be found in Tables S2 and S3.

The papers under review also highlight the wide range of machine learning, deep learning, and other AI-based techniques and algorithms employed for detection, recognition, and evaluation tasks. Figure 14 provides a visual representation of the distribution of these techniques and algorithms in relation to the problems addressed in these papers. Notably, relatively simple models such as SVM,

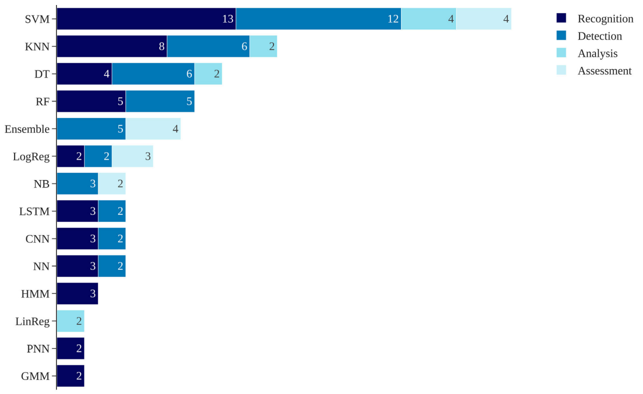

FIGURE 14. The distribution of the methods in relation with machine learning tasks, which are utilized in at least two papers.

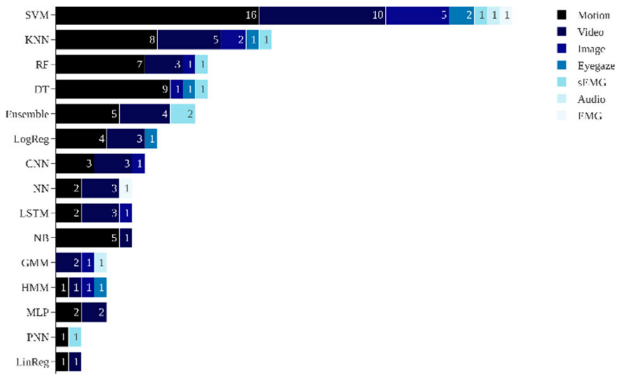

FIGURE 15. The distribution of the methods in connection with the data types, which are utilized in at least two papers.

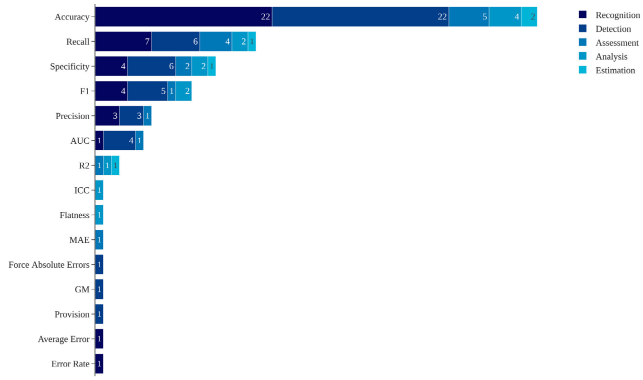

FIGURE 16. The distribution of the evaluation metrics used in the machine learning tasks.

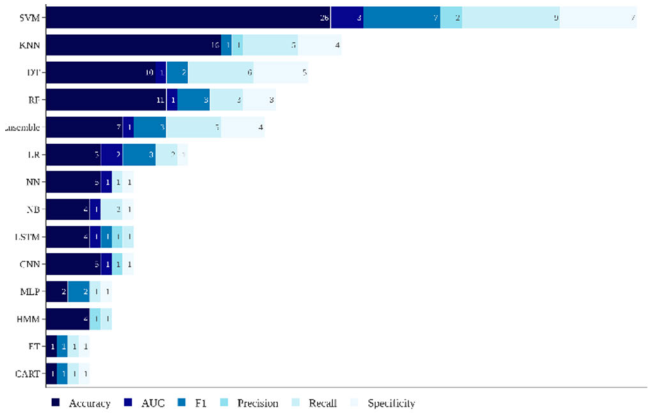

FIGURE 17. The evaluation metrics employed in the most frequently used machine learning models.

KNN, and DTs are more commonly used than complex deep-learning approaches.

Two factors can explain this phenomenon. First, the studies conducted so far have widely utilized non-visual data such as motion, EMG, and sEMG data. Second, despite the primary data for the models being visual data (videos and images), the data preprocessing and feature engineering techniques simplified them into a format that could be more efficiently processed using basic machine learning methods. While less complex than deep learning methods, this approach yielded better performance results that were either on par with or exceeded those of the more complex methods. Figure 15 illustrates the distribution of methods and algorithms in ratio to the data types, providing evidence for this assertion. The complete list of algorithms and methods used in the reviewed papers can be found in Table S4.

The performance of the implemented models for the tasks mentioned in the papers has been evaluated using the standard evaluation metrics, mostly with accuracy, though recall, specificity, and F1-score are also used in many papers. In Figure 16, the distribution of evaluation metrics is shown based on the tasks addressed by the models used in the studies. The figure reveals that most studies solely relied on accuracy as their evaluation metric. However, using accuracy alone can be problematic since it needs to account for important factors such as class imbalance, false positives, and false negatives. While a few studies incorporated other metrics like recall (20), specificity (15), and F1-score (12), the number of studies using these metrics is significantly lower compared to the accuracy metric (55). As a result, studies may consider incorporating metrics such as recall, specificity, and F1-score to provide a more comprehensive understanding of how well their models are performing. This could lead to more robust and accurate evaluations of ML models, which, in turn, may promote greater trust in the model's results.

Figure 17 provides a clear visual overview of the prevailing trends in performance evaluation for abnormal body language analysis algorithms. It shows that accuracy is the most commonly used metric across almost all algorithms, reflecting its importance as a basic performance measure in this field. Among the algorithms, SVMs are the most frequently evaluated across all metrics, suggesting their popularity.

The figure also reveals a notable imbalance in using different evaluation metrics, with accuracy being utilized far more frequently than other measures like AUC, precision, recall, and F1 score. This tendency could be attributed to several factors. Firstly, accuracy is a straightforward and intuitive measure of an algorithm's performance, as it simply represents the proportion of total correct predictions. This makes it an appealing choice for researchers when they wish to convey their findings in a manner that is easily understandable to a broad audience, including those who may need to be more experts in ML. However, other metrics might be more appropriate depending on the problem's specific nature. Precision, recall, and F1 score are particularly relevant for problems where the classes are imbalanced or when the cost of different types of errors (false positives versus false negatives) is not the same. For instance, in a body language analysis task where false positives (incorrectly predicting a certain body language gesture when it did not occur) are much more costly than false negatives (failing to predict a gesture when it did occur), precision (which focuses on the proportion of true positives among all positive predictions) would be a more relevant measure. The underutilization of these metrics suggests that many studies in body language analysis using ML focus on overall accuracy at the expense of considering the specific costs and implications of different types of errors. This might indicate an area where the methodological rigor of this field could be improved. In addition, certain metrics may be less commonly used with specific algorithms due to the characteristics of those algorithms. For instance, precision is less commonly used to evaluate HMMs, CNNs, and LSTMs. These algorithms are often used for sequence prediction tasks, where measures based on individual predictions, like precision, might be less relevant compared to other metrics that consider the sequence structure. Overall, these observations suggest that while accuracy is a crucial basic measure, a more balanced use of different evaluation metrics could provide a more nuanced understanding of an algorithm's performance in body language analysis tasks, taking into account the specific nature of the task and the characteristics of the algorithm being used.

Finally, the complete relationships of all parts of the studies, i.e., data collection sensors, data types, data, data preprocessing techniques, feature engineering procedures, models, and algorithms, as well as the performance evaluation metrics, are shown in the "research flow network" (Figure 18) that clusters all the elements of the flow based on the methodologies used. Different elements of the methodologies' steps are represented with different colors. The thickness of a node corresponding to a methodology step and the edges from this node to other nodes demonstrate the ratio of the step's usage in all reviewed studies. From this flow network, we can identify more reliable methodologies for different machine learning tasks involving abnormal activities and abnormal body actions of patients.

Wearable sensors, RGB cameras, motion capture systems, and eye trackers are among the most utilized data collection methods for studies that constructed their own datasets. Subsequently, motion, video, image, and eye gaze data are the most generated and utilized for data preprocessing. Regarding motion data, various data preprocessing and feature engineering techniques are employed. For instance, normalization and filtering as part of data preprocessing and finding peaks and FFT for extracting motion features. Segmentation and normalization are among the frequently utilized preprocessing techniques for video and image data – as they are similar in nature. Most studies opt to utilize statistical measures for extracting features from motion, video, and image data.

Moreover, key points extraction is primarily used by video and image data. Some studies do not perform any data preprocessing or feature extraction and directly apply machine learning algorithms to the data. SVM was by far the most frequently used algorithm for recognition, detection, assessment, and analysis. Moreover, tree-based algorithms, such as RFs and DTs, were employed alongside SVMs – due to their higher degree of explainability. It is evident from our findings; machine learning algorithms have significantly higher adoption as compared to deep learning algorithms – this could be due to the small, generated dataset, the task at hand being less complex, a need for smaller models, or the unavailability of computational resources or technical knowledge in the field of deep learning to utilize the algorithms effectively. Few studies do not use any evaluation metrics as they were concerned with data analysis.

Nevertheless, accuracy, specificity, recall, and F1-score are the most used evaluation metrics to assess the performance of the trained models. Accuracy had the highest adoption compared to the other metrics; however, it is important to note that accuracy may be misleading in cases where the dataset is imbalanced. Hence, adopting other performance metrics such as F1-score, Cohen's kappa, and ROC-AUC is more appropriate.

Figures 19-21 present the unique methodological steps for image, video, and motion data types, showing the complete process for each. Starting from data collection, the edges are depicted as the pale shade of lavender, which is then linked to the data types in a soft shade of mint green. The data does not always go through data preprocessing (a light shade of yellow-green) and can link directly to either feature engineering (a warm shade of peach) or methods & algorithms (a bright shade of coral). Lastly, the task (a soft shade of pink) links to the evaluation metrics used (a light shade of grey). For clarity, we focus on specific data types and their relationships with the steps in the methodology. The flow network diagram for the image data type is shown in Figure 19. We can observe a series of adopted data preprocessing techniques such as PCA, normalization, and data sampling. However, there are cases where the data is directly utilized for training. Distinct feature engineering techniques are applied to the preprocessed image data, which indicates the diverse sets of techniques that can be adopted depending on the task. SVM and KNN are the most adopted for detection and recognition.

Figure 20 shows the methodologies for the video data type. Most studies used RGB cameras to create datasets. Data sampling, segmentation, filtering, and normalization are the frequently utilized techniques for improving data quality. Some studies extracted key points from data without applying any preprocessing techniques. Statistical measures, dimensionality reduction, and Viola-Jones are common for feature extraction and selection. Our findings indicate the diverse set of preprocessing, feature selection, and extraction techniques

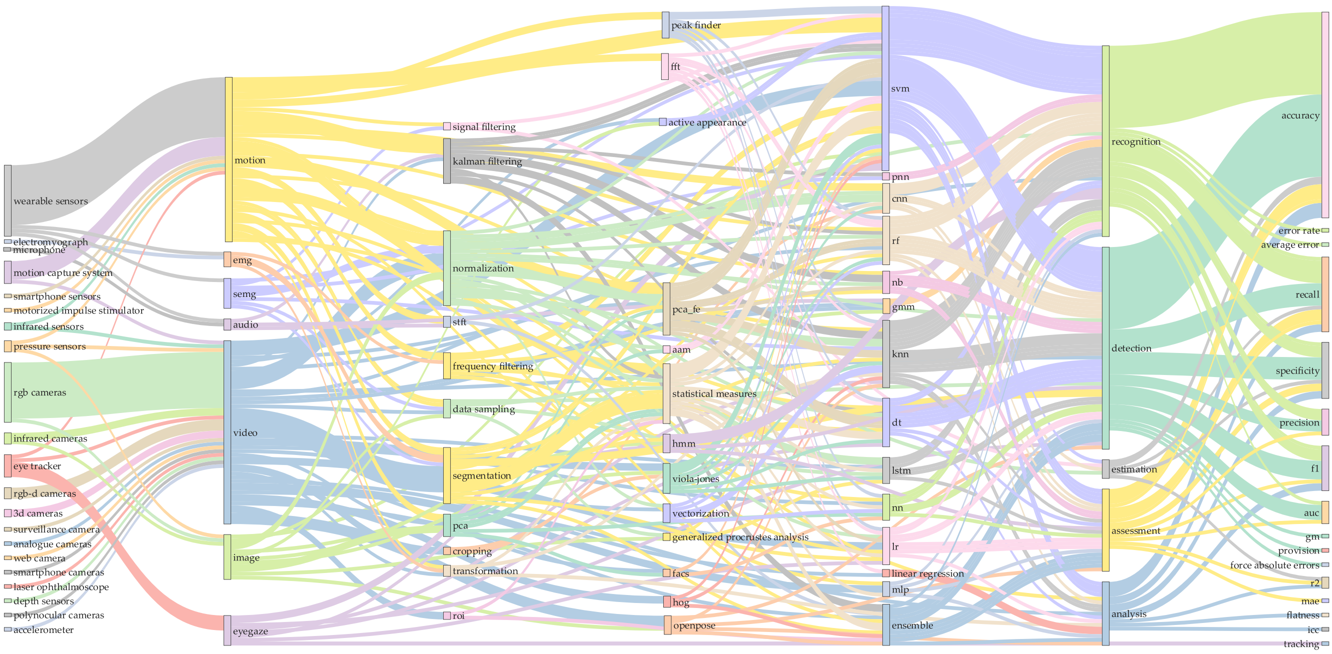

FIGURE 18. A Sankey diagram that illustrates the research flow network based on different methodology steps. The diagram uses lines (or links) of varying thicknesses to indicate the magnitude and direction of the flows between the different categories. The bars (or nodes) from left to right are labeled as follows: data collection, data type, data preprocessing, feature engineering, techniques and algorithms, task, and evaluation metrics (the interactive chart can be accessed via https://bit.ly/sankey-figure).

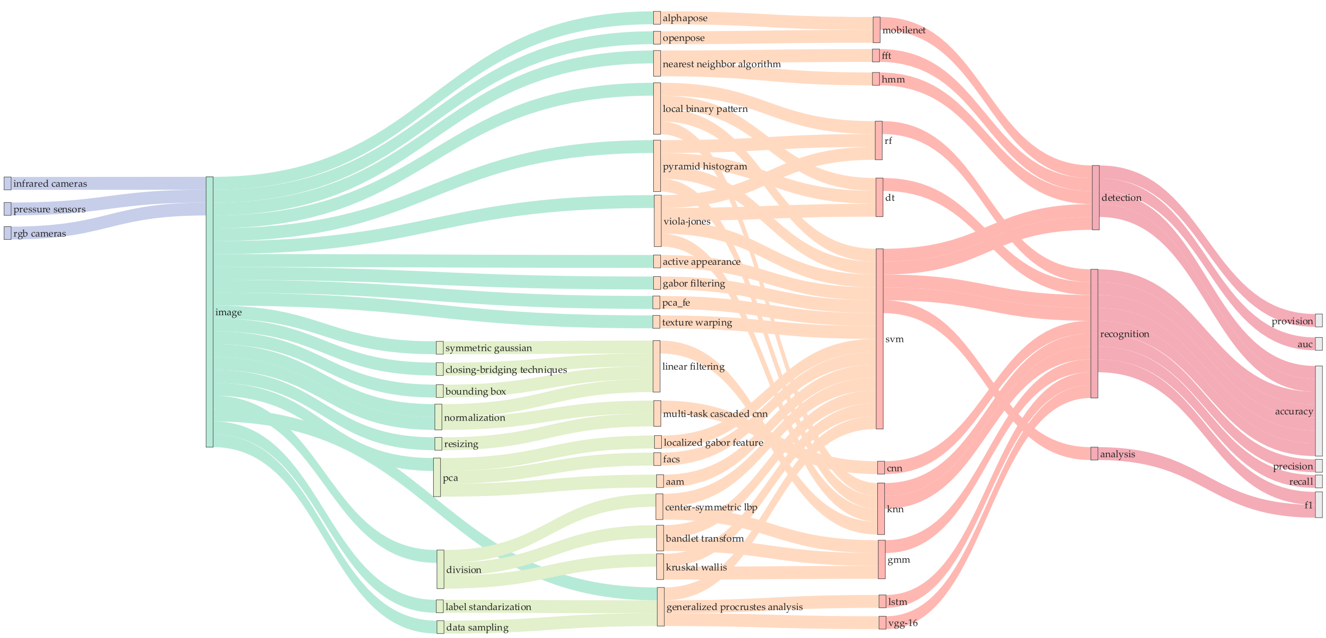

FIGURE 19. A Sankey chart that illustrates a clearer research flow network for the image data type. The nodes and links are color-coded based on the different methodology steps: data collection (a light shade of blue-purple), data type (pale green-blue), data preprocessing (a light shade of yellow-green), feature engineering (a warm shade of peach), techniques and algorithms (a bright shade of coral), tasks (a soft shade of pink), and evaluation metrics (a light shade of gray). Three methods of data collection were used to generate image data. The studies conducted little data cleaning, as PCA and normalization were among the frequently utilized techniques for data preprocessing. Various feature engineering techniques, such as Viola-Jones, pyramid histogram, and local binary pattern, were employed. SVMs, in particular, were the most adopted technique for recognition tasks (the interactive chart can be accessed via https://bit.ly/sankey-for-image).

adopted across the different studies for video data types. As a result, no predominant techniques are utilized for studying video data types. Surprisingly, only DT was not used on video data. Deep learning methods (e.g., LSTM, ResNet, and CNN) had more adoption for video data as compared to other data types.

Figure 21 illustrates the methodologies applied to motion data. Sensors and motion capture systems were the primary

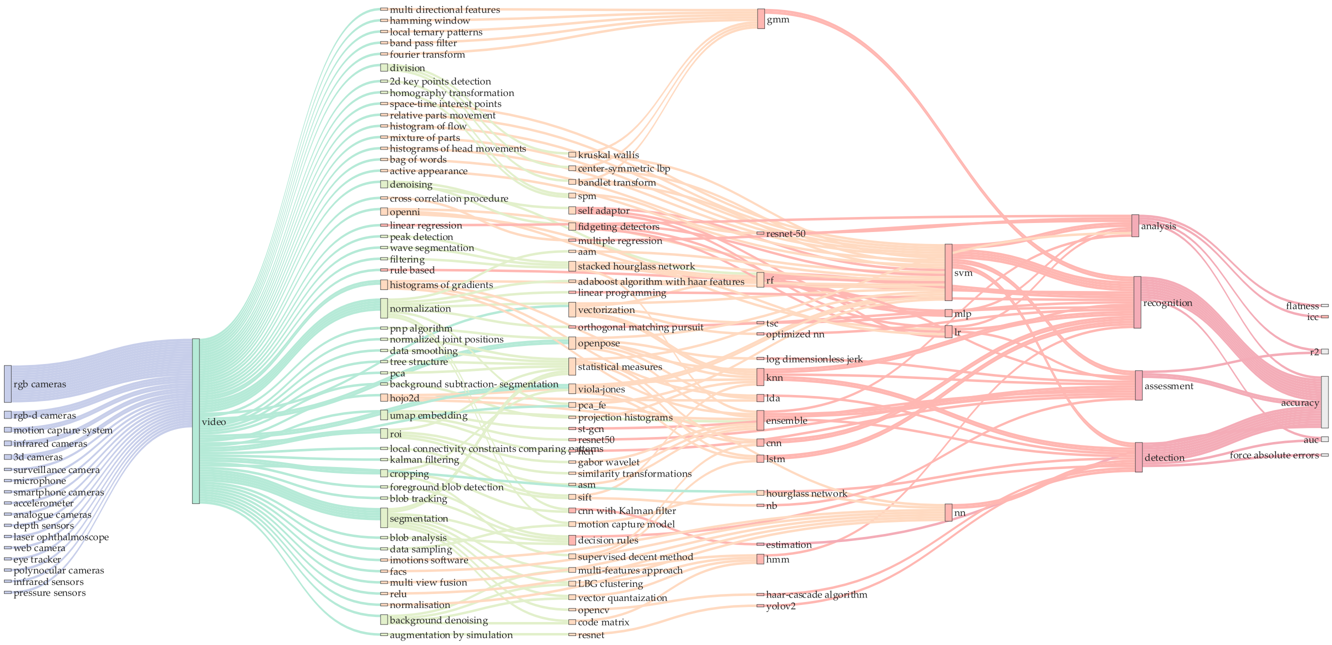

FIGURE 20. A Sankey chart that presents a clear research flow network for the video data type. The nodes and links are color-coded based on the different methodology steps such as data collection (a light shade of blue-purple), data type (pale green-blue), data preprocessing (a light shade of yellow-green), feature engineering (warm shade of peach), techniques and algorithms (bright shade of coral), tasks (soft shade of pink), and evaluation metrics (a light shade of gray). A diverse set of data collection methods were used, including cameras of different types such as RGB, RGB-D, infrared, and 3D cameras. Normalization, segmentation, and filtering were frequently employed for data preprocessing, while statistical measures, dimensionality reduction, and Viola-Jones were frequently utilized for feature engineering. The chart shows that a diverse set of techniques were employed for video data, with a higher adoption rate of DL techniques compared to image data (the interactive chart can be accessed via https://bit.ly/sankey-for-video).

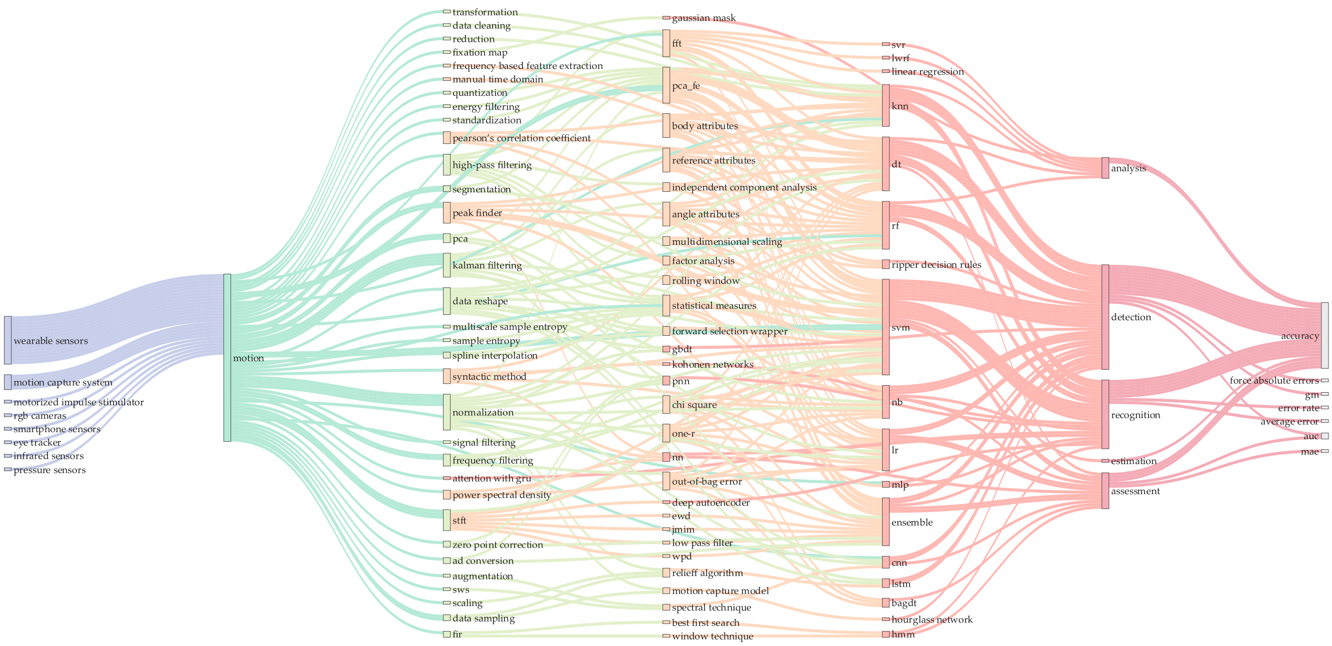

FIGURE 21. A Sankey chart that presents a clear research flow network for the motion data type. The nodes and links are color-coded based on the different methodology steps: data collection (a light shade of blue-purple), data type (pale green-blue), data preprocessing (a light shade of yellow-green), feature engineering (a warm shade of peach), techniques and algorithms (a bright shade of coral), tasks (a soft shade of pink), and evaluation metrics (a light shade of gray). Most studies utilized wearable sensors and motion capture systems to generate motion data. Normalization, Kalman filtering, dimensionality reduction, and STFT were frequently adopted as preprocessing techniques. Finding peaks, statistical measures, and PCA were frequently used for feature engineering. While SVMs were the most commonly adopted classification technique, ensemble techniques had a higher adoption rate (the interactive chart can be accessed via https://bit.ly/sankey-for-motion).

methods of data collection. Kalman filtering, normalization, dimensionality reduction, and STFT were the frequently used techniques for data preprocessing on motion data. As for feature engineering, finding peaks, statistical measures, and correlation analysis had higher adoption. Similarly, with other data types, SVM was the go-to algorithm for detection, recognition, and assessment, using accuracy as the evaluation metric.

V. CONCLUSION

The paper reviewed and analyzed 83 AI papers (out of 180 collected ones) that investigated machine learning tasks such as detection, recognition, and assessment of abnormal activities of people with some health conditions and abnormal body actions (i.e., postures, movements, gestures, and expressions) caused by some diseases and pains. Section II (the ''review'' phase) identified the correlations of diseases, pains, and other health conditions with abnormal activities and body actions and associated machine learning problems with abnormality analysis and acquired outcomes. Section III (the ''summarization'' phase) provided essential information, including details about data, research framework components such as data preprocessing and feature engineering techniques, machine learning methods, performance evaluation metrics, and results in the tables, which formed the foundation for subsequent data analysis. In both sections, the findings were organized with respect to the body parts where the abnormalities happened.

Before thoroughly analyzing the review findings, we constructed the dataset based on the tables in Section III. Each row of this dataset represented a unique research paper. Its columns provided all the information related to both ''medical'' features such as diseases, pains, expressible body parts, abnormal activities, abnormal body actions, and abnormality patterns, and ''AI'' features such as data types, data collections devices, datasets, data preprocessing techniques, feature extraction and selection procedures, methodologies, methods, algorithms, performance evaluation metrics, and results, which were extracted from the papers. Representing the mined information as the dataset enabled us to carry out descriptive and exploratory analyses of the findings. These investigations considered in Section IV offered comprehensive insights into all medical and AI characteristics and their interconnections found in the reviewed articles.

The analysis established several important facts on health conditions, abnormal body actions, and their interconnections in the first part of the section. We identified that neurodegenerative diseases, musculoskeletal disorders, and health issues associated with the senior population are the most studied health conditions (Figure 6), together with abnormal activities related to walking, sitting, standing, falling, and abnormal upper and lower limb movements (Figure 7). Moreover, this subsection provided detailed lists of the cause-and-effect relationships between diseases, pain, and other health conditions, with all considered abnormal body actions that are mined from the reviewed articles (Tables 8-10).

The second part of the section laid down all important facts related to individual stages of the implemented machine learning frameworks and diverse interconnections between the stages. Firstly, the data analysis approach assisted us in categorizing machine learning tasks considered in the papers (Figure 9) and determining the varieties of the data employed (Figure 10), the data gathering devices deployed (Figure 11) as well as the datasets utilized for executing machine learning models (Figure 12). The initial stages of the research methodologies, i.e., data preprocessing and feature engineering techniques, were fully extracted from the reviewed papers (Tables S2 and S3). More importantly, the study identified that normalization, segmentation, Kalmar filtering, PCA, and data sampling were the most universal data preprocessing techniques (Figure 12). At the same time, statistical measures and PCA were the most prevalent methods for feature engineering (Figure 13). It was also determined that relatively simple models such as SVM, KNN, and DT-based models were predominantly utilized across the investigated machine learning tasks, even in processing intricate data types such as videos and images, rather than complicated deep learning models (Figures 14 and 15). The analysis revealed that the standard performance evaluation metrics, including accuracy, recall, specify, and F1-score, were extensively employed in most studies. Furthermore, it was noted that most studies primarily depended on the accuracy metric alone (Figure 16). From the ''algorithmic'' perspective, it was once again confirmed that these evaluation metrics were integral to all ML models (Figure 17).

After analyzing individual stages and pairwise relations in the utilized research methodologies, our analysis focused on determining the most reliable methodologies for specific machine learning tasks by constructing a ''methodology flow network,'' which described the whole problem-solving processes in the reviewed papers by categorizing the steps of methodologies into ''similarity clusters.'' (Figure 18). To provide a clearer depiction of the methodology flow network and obtain more reliable data preprocessing and feature engineering techniques, methods, and algorithms, as well as performance evaluation metrics in machine learning pipelines, we examined sub-flow networks based on predominantly utilized data types such as images (Figure 19), videos (Figure 20) and motion data (Figure 21).

To summarize, we can firmly assert that our data-driven analysis carried out contributes significantly to understanding the causational associations of health conditions with abnormal behaviors or body actions. Moreover, it aids in identifying effective strategies for addressing machine learning problems related to abnormal activities and body movements. Consequently, we can develop trustworthy AI-powered intelligent systems that accurately analyze and monitor patients' health conditions, which can be employed in two slightly distinct tasks. Firstly, machine (deep) learning systems that detect, recognize, and assess abnormal activities of people with health conditions and patients' body language can clearly identify body abnormalities caused by a specific disease or pain and precisely analyze any changes in the physical and psychological conditions of the patients. Secondly, sophisticated systems equipped with comprehensive knowledge of all diseases and pains causing specific abnormal body actions can enhance the automatic diagnosing proficiencies of healthcare systems utilizing patients' body abnormalities as external signs and symptoms of diseases and pains.

As previously stated, the current analysis is reliant on the information provided in the papers we have reviewed. A lack of adequate information may cause significant downsides in developing the most robust, reliable, and efficient AI-powered research frameworks for analyzing abnormal activities of people with health conditions and patients' abnormal body language, which, in its turn, adversely impacts the quality of the healthcare integrated intelligent systems that are built upon these frameworks.

One of the core challenges in AI-based studies centered around analyzing patients' abnormal body language is the lack of robust domain (healthcare and medical) knowledge about all possible abnormal movements, postures, gestures, and expressions caused by diseases and pains. The standard approach for examining abnormalities in AI studies is to select certain but not exhaustive abnormal body actions based on some criteria. Starting with such selections, albeit all-inclusive, a sufficient amount of data is collected, potent data preprocessing and feature engineering techniques are utilized, powerful machine (deep) methods and algorithms are applied, and high-performance results are achieved, but the outcomes are still constrained by the selected scope. From an AI perspective, the acquired results are consistent and robust, yet, through a healthcare lens, they remain still incomplete due to the limited domain knowledge employed in the AI studies. Consequently, such AI research-based intelligent systems have limitations: they are unable to detect all disease-caused abnormal actions happening in different parts of the body, subtly distinguish abnormality patterns, and as a result, precisely analyze the external signs and symptoms of diseases and pains.

An approach to overcoming such limitations present in AI studies is to conduct a comprehensive review and analysis of domain research articles focused on investigating the causational relationships of diseases and pains with patients' abnormal body language. These researches carried out by healthcare and medical experts have identified possible abnormal movements, postures, gestures, and expressions happening in various body parts as consequences of diseases and pains. Since these outcomes have been driven through rigorous patient assessments in reliable clinal or laboratory settings, they provide strong support for considering the established abnormal body actions as the causational effect of the corresponding diseases. Consequently, AI researchers can more comprehensive and accurate lists of possibly all abnormal bodily movements caused by diseases and pains in a cost-effective and efficient manner. The data collected and synthetically generated (for training purposes) in accordance with these abnormalities result in developing more accurate, trustworthy and complete machine learning models for analyzing and monitoring healthcare patients through their body language. Thus, our next paper aims to review and analyze healthcare and medical research papers from an artificial intelligence perspective to identify the strong causational relationships of diseases and pains with abnormal movements and postures happening in all expressible parts of the body.

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