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Human Action Recognition Using Deep Learning and Nonparametric Model With Some Exchanges in Karl Popper's Viewpoint and Kuhn's Paradigm: A Literature Review From Perspective of Philosophy of Science

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Abstract

Human skeletal detection and human gesture recognition are interesting subjects that have been investigated during the past three decades. Single-RGB, RGB-D camera, and Initial Measurement Unit (IMU) are some of the sensors for recording human motion data. Numerous methods for gesture recognition and classification have been reviewed in this survey. The classification is divided into nonparametric models and deep learning models, which afterwards will be compared in terms of accuracy and running time, respectively. The feature extractions are separated based on features processed from the sensor data, including skeleton-based features, depth image-based features, and hybrid features. A comparison of accuracy values will be offered based on the model and its attributes. In addition, we present an interchange of perspectives on deep learning and nonparametric models based on Karl Popper's perspective and Kuhn's paradigm in the study of the philosophy of science. By substituting the falsification principle for induction, Popper attempts to refute the traditional empiricist perspective of the scientific method. From the philosophy of science's perspective, the study on human action recognition is in the normal science phase according to Kuhn's paradigm and is corroborated in accordance with Popper's theory.

Keywords: human action recognition; nonparametric model; deep learning model; Karl Popper; Kuhn's Paradigm; philosophy of science
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1. Introduction

Throughout the history of human understanding, philosophy and science have always related to one another. Philosophy and science are intertwined in their pursuit of truth fragments. The aim of science is to describe, whereas the task of philosophy is to interpret the phenomena of the universe or the truth in mind, whereas the truth of science is derived from experiences and observations. Before doing a survey of human gesture recognition using deep learning and nonparametric models, its ontology, epistemology, and axiology must be understood. The etymology of ontology comes from the Greek language. Ontology derives from the Greek terms "ontos," which means "being," and "logos," which means "science, teachings, or beliefs." Ontology, in terms of terminology, is the branch of science that explores the true nature and essence of things. Epistemology is the branch of philosophy that examines in depth how to get accurate information. Axiology is a branch of research that explores the philosophical nature of values. [1]

Ontology classifications can be defined by their textual definitions, a set of properties, and a logical definition composed of several formulas [2]. We first should establish the ontology for human action recognition in semantic space. According to Ziaeefard [3], human action recognition can be differentiated using semantic space characteristics. As depicted in Fig. 1, the semantic space is separated into body parts (pose and poselets), qualities, linked objects, human-object interactions, and the context of the location. Using a similar method to the human ability to distinguish

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in semantic space, a machine can learn to recognize human activities from a given image sequences.

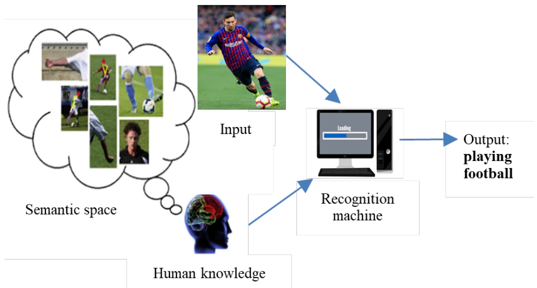


Fig. 1. Semantic space: playing football recognition [3]. Pose (certain parts of body pose of football player), poselet (right hand lifted, left hand straight down), attributes (head looking down), related objects (ball, interaction left foot with ball), context of place (ball field).

In a nutshell, epistemology is the study of how to obtain knowledge. There are some methods to obtain knowledge, i.e., literature review, survey, and interview [4]. For example, in a survey, we can use the Likert scale as a survey instrument and use certain scales in questionnaires. To obtain a good survey, we use reliability and validity tests to measure the acceptance indicator [5]. The knowledge that we want to obtain as well as our study goal, i.e., how to implement a human action recognition algorithm for machine learning by using a vision sensor, We use some parameters as a performance index to compare between nonparametric models and deep learning models, such as accuracy and running time. To get accuracy, we use a confusion matrix as shown in Table 1.

Table 1: Confusion Matrix

		Prediction	
		Class 1	Class 2
Observation	Class 1	TP	FN
	Class 2	FP	TN

where True positive (TP) is positive observations and positive predicting results, False negative (FN) is positive observations and negative predicting results, True negative (TN) is negative observation results and negative predicting results, and False positive (FP) is negative observations and positive predicting results. The accuracy can be calculated as shown in Eq. (1).

$$\text{Accuracy} = \frac{TP+TN}{TP+FN+FP+TN} \quad (1)$$

Running time depends on the specifications of the hardware used (GPU/processor), the algorithm in the model is built, and the framework of model used. There is a trade-off between accuracy and the amount of time it takes to compute. For example, if you want more accuracy, it will take longer to compute, but if you want less accuracy, it will take less time. Vision sensors, such as the RGB-D sensor, are used for the recognition of human movements, facial recognition, the introduction of human interactions [3], and 3D reconstruction. The RGB-D sensors for example are Kinect, Asus Xtion, and Intel RealSense. These sensors have the capability to capture imagery and are subsequently processed for detection and recognition purposes. There are open-source benchmark datasets for human pose estimation using RGB-D sensor to carry out performance tests of learning models such as MSR Action3D[1] [6], UTKinect-Action3D[2] [7], MSRDaily-Activity3D[3] [8], UTD-MHAD[4] [9], SBU Kinect Interaction[5] [10], NTU RGB+D[6] [11], and PKU-MMD[7] [12].

Axiology is about the value of research that can be used to solve real problems in our society. The implementation of human action recognition has a wide range of applications, such as surveillance cameras (or video surveillance), elderly care, virtual reality, and human-machine interactions [3]. Our approach in terms of axiology is to build a learning and control system for human motion recognition in general. Examples of human motion are Indonesian traditional dancing and traditional martial arts such as pencak silat.

Online recognition, occlusion, variations in camera capture angle, computational time, and biometric changes present a major difficulty in human action recognition. Online recognition is the ability to recognize changes and classify movements instantaneously (in limited time intervals) of video sequences continuously. Occlusion, where an affected part of the body also causes the detection process to become more difficult [13]. Variations in camera capture angles and biometric changes, such as variations in body size, appearance, shape, and sensor-to-subject distance, will impact the algorithm's performance. Time computation is also a factor in influencing an algorithm's performance.

A human action recognition model will be divided into two models, i.e., a nonparametric model [14] and a deep learning model. In nonparametric models, a mathematical model is used to classify a set of statistical data where the data of variables tested in the hypothesis model did not follow a certain probability distribution. Furthermore, the feature extraction results of the next feature are processed and modeled mathematically with certain classification methods in order to obtain the desired human action recognition. While on a deep learning model, feature extraction can be built automatically from deep learning architecture design learning to be subsequently used in motion recognition processes. Examples of classifier methods on nonparametric models are random forest (RF), k-Nearest Neighbor (kNN), Support Vector Machine

[1] research.microsoft.com/en-us/um/people/zliu/actionrecorsrc
[2] cvrc.ece.utexas.edu/KinectDatasets/HOJ3D.html
[3] research.microsoft.com/en-us/um/people/zliu/actionrecorsrc
[4] personal.utdallas.edu/~kehtar/UTD-MHAD.html
[5] github.com/xrenaa/SBU_Kinect_dataset_process
[6] rose1.ntu.edu.sg/datasets/actionrecognition.asp
[7] www.icst.pku.edu.cn/struct/Projects/PKUMMD.html

(SVM), Extreme Learning Machine (ELM), Hidden Markov model (HMM), graph, and template matching. Meanwhile, the examples for the classifier method on deep learning models are the convolution neural network (CNN), the recurrent neural network (RNN), and CNN + LSTM (long short-term memory).

Karl Popper established one of the most popular falsification methods in the philosophy of science. The viewpoint of Karl Popper is a useful beginning point for falsifying suggested theories or hypotheses. Popper produced a comprehensive critique of historicism, holism, and their associated ideas [15]. For the research to be corroborated, every observation, experiment, and method employed must be falsified by others (methods, experiments, or observations). If the proposed theory or hypothesis can withstand a process of falsification, then the theory or observation is supported or strengthened. The idea or hypothesis is provisionally accepted so long as no other theory or scientific observation refutes it [16]. To find a novelty in every field of study, one might begin by examining historical science and its paradigm. As demonstrated in Fig. 2, Kuhn divides the structure of scientific revolutions into four paradigms: pre-science, normal science, anomaly and the development of scientific discoveries, and crisis and the emergence of scientific ideas [17].

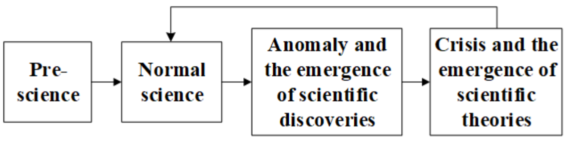


Fig. 2. The structure of scientific revolutions by Thomas Kuhn [17].

2. Human Action Recognition Features

The extraction of features from the sensor readings of RGB or RGB-D cameras can be categorized as skeleton-based, depth image-based, or hybrid [18]. Table 2 represents the accuracy of human action recognition, while Table 3 depicts the survey-related processing or computation time for skeletal detection. The study of human action recognition is in the normal science phase according to Kuhn's paradigm, including the scientific practice of reasoning, observing, and experimenting within a well-established paradigm or explanatory framework. Recent research in human action recognition employs skeletal estimation, depth-image estimation, and hybrid features as shown in Table 2.

2.1. Depth Image-based Features

The features of the depth image can be extracted using the depth motion map (DMM). For depth sequences with a number of N-frames, DMM can be obtained through Eq. (2) as follows.

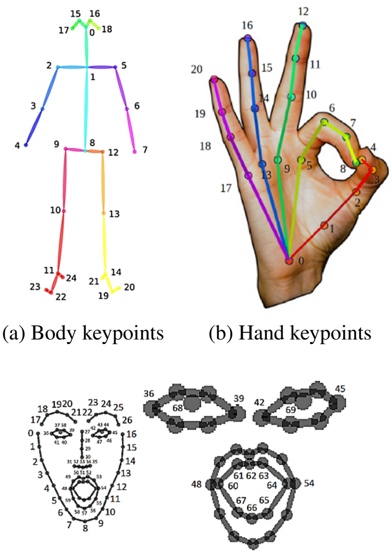
$$DMM_{\{f,s,t\}} = \sum_{i=1}^{N-1} \left| \mathrm{map}^{i+1}_{\{f,s,t\}} - \mathrm{map}^{i}_{\{f,s,t\}} \right| \qquad (2)$$

Fig. 3. Openpose for skeleton readings in single subjects and two subjects, for example, pencak silat motions.

where i represents the frame index, f, s, and t represent orthogonal projection 2D-mapping to the front, side, and top sides, respectively. From the DMM computing results, the next step is to implement human action recognition using histograms of oriented gradients (HoG) [19]. Additionally, the approach of principal component analysis (PCA) can be used to minimize the dimensionality of these features.

2.2. Skeleton-based Features

The skeleton-based method employs CNN or RNN based on the adopted deep learning structure to determine the coordinate position of the joint skeleton using a single-RGB sensor. VNect (Mehta et al. [20]) and OpenPose are open source pretrained models for human pose estimation (Ze Chao et al. [21]). Fig. 3 illustrates a joint skeleton reading application utilizing OpenPose, with a single subject and many subjects. OpenPose has the ability to read Part Affinity Field (PAF) skeletons and a number of human objects. OpenPose divides the body's posture into 25 joints, and it can be used for face and hand readings, as one can see in Fig. 4.



(a) Body keypoints (b) Hand keypoints

(c) Face keypoints

Fig. 4. OpenPose for reading the joint skeleton position for the body (top left), hand (top right), and face (bottom) [21]

Table 2: Survey on Human Action Recognition Literature Using the RGB-D Sensor With Corresponding Datasets

Dataset: MSR Action3D

Features	Nonparametric Model				Deep Learning Model			
	Ref.	Year	Classifier	Acc. (%)	Ref.	Year	Classifier	Acc. (%)
	Wang et al. [22]	2014	Actionlet Ensemble	86	Veeriah et al. [23]	2015	RNN	92.03
	Chaaraoui et al. [24]	2014	SVM	92.46	Du et al. [25]	2015	RNN	94.49
	Theodorakopoulos et al. [26]	2014	kNN	93.61	Núñez et al. [27]	2018	CNN+LSTM	96
	Koniusz et al. [28]	2016	SVM	93.96	Lee et al. [29]	2017	LSTM	97.22
Skeleton-based	Liu et al. [30]	2016	Matching	94.4				
	Guo et al. [31]	2018	SVM	95.24				
	Liu et al. [32]	2018	SVM	95.6				
	Qiao et al. [33]	2017	SVM	95.9				
	Chen et al. [34]	2016	Graph	96.1				
	Jia et al. [35]	2013	SVM	89.3	Wang et al. [36]	2015	CNN	94.58
	Devanne et al. [37]	2015	kNN	92.1	Wang et al. [38]	2016	CNN	100
Depth image-based	Yang et al. [39]	2014	SVM	93.9				
	Liu et al. [40]	2016	SVM	94.28				
	Chen et al. [41]	2017	ELM	96.7				
	Liu et al. [42]	2018	SVM	97.64				
	Wang et al. [22]	2014	SVM	88.2	Liu et al. [43]	2016	CNN	84.07
	Ji et al. [44]	2018	SVM	90.8	Kamel et al. [45]	2018	CNN	94.51
	Jalal et al. [46]	2017	HMM	93.3	Shi et al. [47]	2017	RNN	94.9
Hybrid features	Kong et al. [48]	2016	SVM	93.99				
	Zhu et al. [8]	2013	RF	94.3				
	Ohn-Bar et al. [49]	2013	SVM	94.84				
	Shahroudy et al. [50]	2016	SVM	98.2				

Dataset: UTKinect-Action3D

Features	Nonparametric Model				Deep Learning Model			
	Ref.	Year	Classifier	Acc. (%)	Ref.	Year	Classifier	Acc. (%)
	Theodorakopoulos et al. [26]	2014	kNN	90.95	Rahmani et al. [51]	2017	LSTM	95.96
	Wang et al. [52]	2016	Matching	93.47	Lee et al. [29]	2017	LSTM	96.67
	Chen et al. [34]	2016	Graph	95.96	Liu et al. [53]	2016	LSTM	97
Skeleton-based	Vemulapalli et al. [54]	2014	SVM	97.08	Núñez et al. [27]	2018	CNN+LSTM	99
	Guo et al. [31]	2018	SVM	97.85	Liu et al. [55]	2018	LSTM	99
	Koniusz et al. [28]	2016	SVM	98.2				
	Liu et al. [42]	2018	SVM	86	Liu et al. [43]	2016	CNN	82

Depth image-based	Slama et al. [56]	2014	PDF	95.25	Wang et al. [38]	2016	CNN	90.91
					Wang et al. [36]	2015	CNN	91.92
Hybrid features	Raman et al. [57]	2016	HMM	87.9	Liu et al. [43]	2016	CNN	96
	Zhu et al. [8]	2013	RF	91.9				
	Liu et al. [58]	2015	HC-RF	92				
	Zhang et al. [59]	2016	SVM	94.9				
Dataset: MSRDailyActivity3D								
Features	Nonparametric Model				Deep Learning Model			
	Ref.	Year	Classifier	Acc. (%)	Ref.	Year	Classifier	Acc. (%)
Skeleton-based	Zanfir et al. [60]	2013	kNN	73.8	Núñez et al. [27]	2018	CNN+LSTM	63.1
	Qiao et al. [33]	2017	SVM	75				
	Cai et al. [61]	2016	MIL	78.52				
	Liu et al. [42]	2018	SVM	91				
Depth image-based	Oreifej et al. [62]	2013	SVM	80	Wang et al. [36]	2015	CNN	78.12
	Yang et al. [39]	2014	SVM	86.25	Wang et al. [38]	2016	CNN	85
	Jia et al. [35]	2016	SVM	80.63	Luo et al. [63]	2017	CNN+LSTM	86.9
	Chen et al. [41]	2017	ELM	89	Shinde et al. [64]	2018	YOLO	88.358
Hybrid features	Kong et al. [48]	2016	SVM	73.21				
	Ji et al. [44]	2018	SVM	81.3				
	Zhang et al. [59]	2016	SVM	86				
	Kong et al. [65]	2016	DRRL	87.5				
	Shahroudy et al. [50]	2016	SVM	91.25				
	Althloothi et al. [66]	2014	SVM	93.1				
	Jalal et al. [46]	2017	HMM	94.1				

Table 3: Time Computation Parameter (Note: mAP (%) is mean Average Precision)

Vision Sensor	Ref.	Year	Methods	Model	mAP (%)	Time Computation	Framework	Hardware	Output
single-RGB camera	Newell et al. [67]	2016	stacked hourglass	Deep learning: CNN	87.4	75 ms	-	Nvidia TITAN X	body joint (single-person)
single-RGB camera	Mehta et al. [20]	2017	VNect	Deep learning: CNN	76.6	CNN 18 ms, skeleton fitting 7–10 ms, pre-processing and filtering 5 ms (total 33 ms)	Caffe	6-core Xeon CPU 3.8 GHz, Titan GPU	Body joint (multi-person)
single-RGB camera	Zhe Cao et al. [21]	2017	OpenPose: PAF	Deep learning: multistage-CNN	85.6	22 fps - 36 ms (body + foot)	Cuda 8	Nvidia GTX 1080 Ti	Body, fingers, and face (multi-person)
Kinect v2 + FIR camera	Nishi et al. [68]	2017	VICON	Fully convolutional network (FCN)	87.5	50 fps	-	1 GForce GTX Titan X; 2 Nvidia Titan X	body joint
Kinect v2	Vasileiadis et al. [69]	2019	PAF	3D-CNN	87.3	360 ms (0.36 s per frame or 2.8 fps)	Chainer	NVIDIA GTX 970 GPU	body joint
single-RGB camera	Luvizon et al. [70]	2019	Soft-argmax	Deep learning: CNN	90.8	29.3 fps	Tensorflow	NVIDIA GPU K20	body joint

Table 4: Dimension Complexity of Computing Process

Methods	Computation
BMLD[1]-GMM[2]	$\mathcal{O}(J \times K_h D^2)$
LDA[3] + HMM	$\mathcal{O}(K_h MP + P^3) + \mathcal{O}(N_h H^2)$
PCA[4] + NBNN[5]	$\mathcal{O}(m^3 + m^2 r) +$ $\mathcal{O}(r \times n_c \times n_d + log(n_c + n_d))$
SVM[6]	$\mathcal{O}(r^3)$
PCA + STOP[7]	$\mathcal{O}(m^3 + m^2 r) + \mathcal{O}(n_c \times r)$
PCA + CRC[8]	$\mathcal{O}(m^3 + m^2 r) + \mathcal{O}(n_c \times r)$

Notes:
[1]BMLD: bi-gram maximum likelihood decoding
[2]GMM: Gaussian mixture model
[3]LDA: linier discriminant analysis
[4]PCA: principal component analysis
[5]NBNN: Naive Bayes nearest neighbour
[6]SVM: support vector machine
[7]STOP: space-time occupancy patterns
[8]CRC: collaborative representation based classification

2.3. *Hybrid Features*

Using the fusion principle, one can utilize some features as hybrid features. The collaborative representation classifier (CRC) is one application approach for fusion principles [71]. In addition to the RGB-D sensor for the DMM depth image and skeleton feature, inertial characteristics are also incorporated. Chen et al. [19] combine the DMM, skeleton, and inertia parameters of fusion sensors in online movement recognition. Dimensional complexity using L_2-regularized CRC method is $\mathcal{O}(m^3 + m^2 r) + \mathcal{O}(n_c \times r)$, as shown in Table 4. In detail, the computation time for all steps are (2.0 ± 0.4) ms/frame for projected map generation, (3.3 ± 0.6) ms/frame for DMM process, (2.5 ± 1.2) ms/sequence of motion for PCA process, and (1.8 ± 0.5) ms/sequence of motion for human action recognition process.

3. Classifier Methods for Human Action Recognition

The classifier methods for human movement recognition are generally categorized into nonparametric model models and deep learning models. Some of the classifier methods related to these two models can be seen in Fig. 5. In deep learning models, the CNN-based movement recognition process generally focuses on the position processing or the trajectory of the joint skeleton in an image, which is then processed with CNN for its classification.

Li et al. [72] use a joint distance map (JDM) of one or several joint skeletons converted into color variations to obtain temporal information. Mehta et al. [20] introduce the online method for the 3D skeletal pose by using single-RGB cameras. The 2D pose is taken from a joint position without using the depth image method and converted into a 3D pose with the skeleton fitting process. Pham et al. [73] use a 3D joint

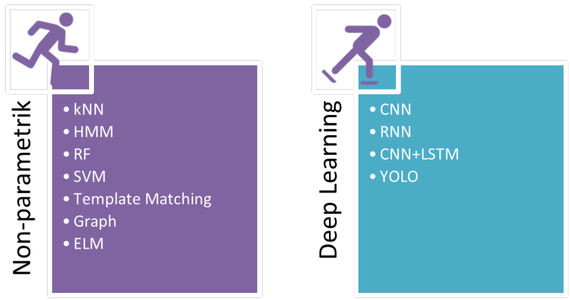


Fig. 5. Some classifier methods for human action recognition.

skeleton coordinate and divide each skeleton into five parts, where each joint is combined in the order of the physical form of the body, which adopts the evolution of 3D spatio-temporal motions. Ze Chao et al. [21] use the CNN + PAF multi-stage architecture to improve the detection performance of multiple subjects with the OpenPose application, as shown in Fig. 6. The network is categorized into two parts: the top predicts confidence maps, while the bottom predicts affinity fields, where **F** denotes feature maps, ρ^t and ϕ^t are the CNNs for inference at Stage t.

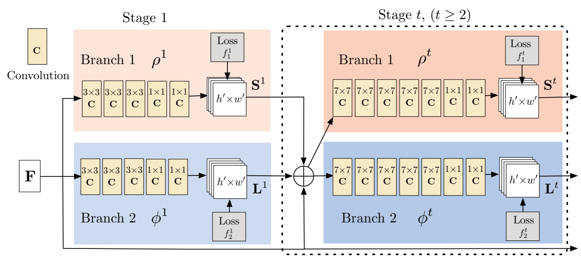
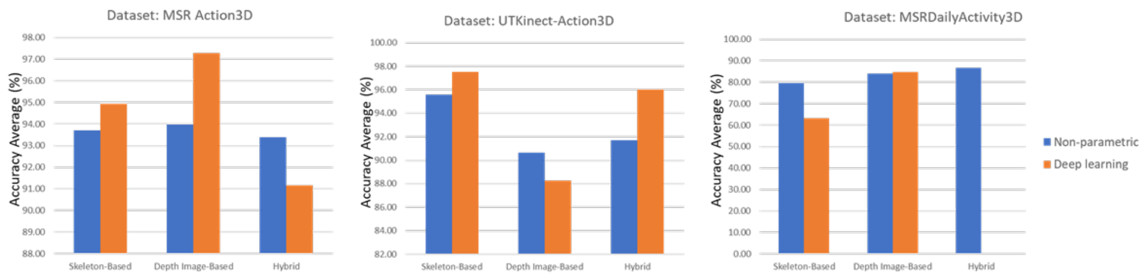


Fig. 6. Two-branch multi-stage CNN+PAF using OpenPose [21]. The first stage is to predict the PAF, $\mathbf{L}^t$, and the second stage is to predict the level of confidence map, $\mathbf{S}^t$.

4. Discussions

We obtain a comparison of accuracy for human action recognition using three different datasets as shown in Fig. 7 from data processing on Table 2. Nonparametric models have an average accuracy 90% while deep learning models have an average accuracy about 89.1%. Although deep learning has become popular recently, nonparametric models still have a better performance index in terms of average accuracy for human action recognition. A Deep learning model has been used as a skeleton detection model, which has better time processing and is suitable for online recognition. For example, the OpenPose algorithm approximately has a computation time of 36 ms (22 fps) using Nvidia GTX 1080 Ti which is considered fast enough for online recognition as shown in Fig. 3.

From Popper's viewpoint, to accommodate the falsification process, we propose a flowchart for the falsifying step with scientific observation or experiment as shown in Fig. 8. We put falsification process as well as



(a) MSR Action3D dataset (b) UTKinect-Action 3D dataset (c) MSRDailyActivity3D dataset

Fig. 7. The accuracy comparison for nonparametric models and deep learning models using benchmark datasets: (a) MSR Action3D dataset, (b) UTKinect-Action 3D dataset, and (c) MSRDailyActivity3D dataset.

evaluating process on the same step. Kuhn's paradigm of the scientific revolution, human action recognition is now in the stage of normal science. The method that is used for classification now is the machine learning method that has been developed in 19th of century with minor modifications in the algorithm, particularly in deep learning models. There is still no emergence of new scientific discoveries and theories yet. Human action recognition using nonparametric and deep learning models deserves additional research into more challenging problems such as occlusion, shading, unusual activities, viewpoint variation, camera motion, background clutter, and execution rate [74].

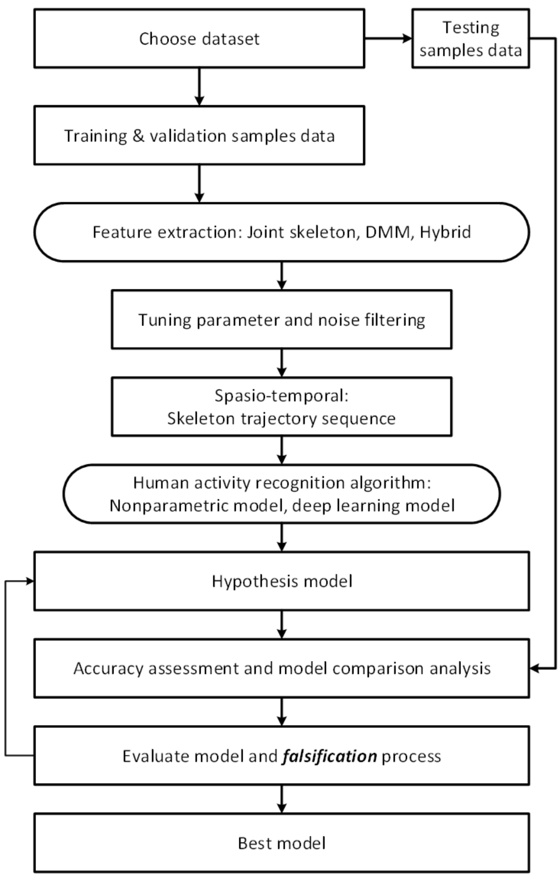


Fig. 8. Searching method for the best learning model of human action recognition with added Popper's falsification.

5. Conclusion

This paper reviews human action recognition, incorporating some philosophy of science approaches. Deep learning and nonparametric approaches have been studied in order to determine the state of the art in human action recognition using different types of features such as depth-image based features, skeleton-based features, and hybrid features. From the philosophy of science's perspective, the study of human action recognition is in the normal science phase according to Kuhn's paradigm, including the scientific practice of reasoning, observing, and experimenting within a well-established paradigm or explanatory framework as shown in the literature study in Table 2. In accordance with Popper's theory, the human action recognition study is corroborated by the usage of a methodology to falsify a method through the performance of evaluation metrics. Although the deep learning is more favorable nowadays, the evaluation performance findings indicate that deep learning and nonparametric methods yield equivalent outcomes.

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