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Overview of feature learning approach of Human Activity Recognition Using Wearable Sensors and Machine Learning in sports domain

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ABSTRACT
As shown aging population structure, it caused variations in physical or mental deterioration, could influence individuals' personal satisfaction, result in injuries, emotional well-being or the lack of physical activity. Sensor-based human activity recognition (HAR) is one of the most encouraging assistive advances to help more seasoned individuals' day to day existence, which has enabled colossal potential in human-focused applications. Current studies in HAR focus on the machine learning approaches for classifying human daily activities, but this survey wishes to provide a more wide-ranging introduction for newcomers and scholars to HAR for their fitness and health care section. We initially present the condition of-workmanship sensor modalities in HAR. We look more into the methods associated with each progression of wearable sensor modularity focused HAR as far as sensors, exercises, information pre-handling, highlight feature learning and classification, including regular methodology that is conventional approaches. We focus on wearable sensor base HAR (WSHAR) for their activities classification like running, waking, cardioetc. We also definite the survey of some dataset related to HAR.Proposed one algorithm for data pre-processing task.

Keywords: Human Activity Recognition (HAR), Activity of Daily Living (ADL), Machine Learning (ML), Classification, wearable, sensor, smart watch, fitness, athletes.

I. INTRODUCTION

The most recent 20 years have seen steadily expanding research action in the field of human movement acknowledgment[1]. Human Activity Recognition (HAR) is inspiring task in ML/DL. Researcher's gaveprimeimportance on activity recognition from picture - Images and videos.Furtherthey centers their focus around human's day to day existence and conduct by utilizing wearable and encompassing sensors.

Healthcare and sports are one such foundation that is leveraging this standard of data collection and performing analytics that is informative to healthcare and sports athletes [2]. This analysis and prediction work improves the one's life and performance of athletes. Such investigation allows the viewers in the area of medical services and sports to augment their profits either commercially or personally at a singular level [2].

Identifying everyone's daily activities, outcomes and performance of athletes and its relation to general wellness isproducing a lot of interest in the research community [2].

The utilization of accelerometers and gyroscopes in wearable gadgets, for example, smart-watches and cell phones are currently broadly acknowledged for observing actual work of athletes and also improving health of normal people [3][4].

The improvement made in Human Activity Recognition during the earlier few decades encourages researchers to increase the recognition performance and practicality of HAR under more truthful settings in diverse methods. Also better to know the future planning.

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Human Activity Recognition (HAR) follow five steps process:

a. Selecting and arranging appropriate sensors to a human body or the climate to follow human exercises, activities and behaviour.
b. Gathering data or information from deployed sensors dependent on explicit task later pre-process that noisy data.
c. After pre-handling step extract treasured feature from the sensor information for later classification.
d. Using appropriate ML algorithm for interactivities working out on classification models.
e. Generate pre-performance report by using testing and learning model that is generated after interactivities.
f. after interactivities and classification, produce pre-performance report by using testing and learning model

Each and every five step of procedure involves a lot of algorithms, technologies and methods to use [5].

HAR Sensor Category:

As far as the sensors conveyed in HAR, it is very well may be extensively arranged into three classifications: that is

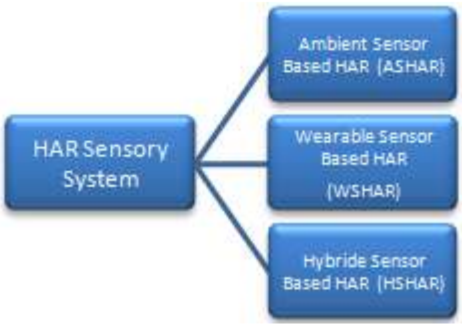

Fig.1 HAR Sensor System

The ambient sensor-based HAR (ASHAR)

This type of sensor extracts human actions from the sensors that are permanently embedded in the environment or attached to some definite stuffs, they are building floor, door, etc.., this sensors can include light sensor, RFID, PIR, temperature, pressure sensor, flow sensors, etc. the movement of flexibility of this type of sensor is less because of no on-body sensors are used, it works in a narrow range where the sensors are deployed. This type of ambient sensors may neglect to work in certain circumstances when the user doesn't contact the object that surrounding with ambient sensors or doesn't enter the working space of a sensor introduced in the environment[6][7][8][9][10]. (Debes et al., 2016; Liu, Yu, & Cang, 2018; Mehr, Polat, & Cetin, 2016; Tunca et al., 2014; Zhang et al., 2017)

The wearable sensor-based HAR (WSHAR)

The substitute to ASHAR with static sensor deployment is WSHAR, which identifies human actions by mining and processing the informative data from wearable devices using ML algorithms.Wearer is moving so WSHAR can work in a comparatively large area. Currently, smart wrist watches, smart glasses, wrist bands, smart wearable jewellery, smart electronic garments, patches for skin, t-shirt, GPS Shoes and so on specifically-designed devices are the mainstream products attached wearable technologies in HAR(Adaskevicius, 2014; Filippoupolitis, Oliff, Takand, & Loukas, 2017; Hassan, Uddin, Mohamed, & Almogren, 2018) [11][12][13].To improving the result of performance of WSHARinstead of one sensor on body parts various sensors on several body parts can benefit (Chernbumroong, Cang, & Yu, 2014; Gao, Bourke, & Nelson, 2014; Laudanski, Brouwer, & Li, 2015) [14][15][16].However, multiple sensors with several body parts can points to greater cost as compared to one sensor on body part. WSHAR system has some limitations also that may define less accurate recognition for certain action of activities(Chernbumroong, Cang, Atkins, & Yu, 2013) [17]. To improve the performance of HAR we can combine the sensors that can capture rich information about human actions but that can leads to complexity of HAR system as compared to single sensor type.

WSHAR catches more attention due to its lesser cost, portability, light weight, flexibility in day-to-day use and satisfied performance(Diethe Twomey, Kull, Flach, & Craddock, 2017; Roy, Misra, & Cook, 2016) [18][19].and it has empowered massive applications in assisted living, such as sports assessment, gait analysis, daily activity analysis, fall detection, performance prediction etc.

The hybrid sensory-based HAR (HSHAR)

This type of sensor supports multiple sensors with same and multiple body parts. It also needs data fusion and sensing synchronization from different sensor modalities.It could raise the price and difficulty of a HAR system linked with a solitary sensor modality.

From above observedthis survey gives priority on the wearable sensor-based HAR.We analysed the techniques attached with every steps of WSHAR for Sensors, activities and actions, data

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pre-processing, feature learning, classification and prediction. The classification according to sensor category and the location of sensors is defined in the table 1.

As per our research direction we are going to continue with the WSHAR.

1. Wearable sensor-based HAR (WSHAR):

1.1. Overview:

To monitor continuous daily activities of human use some wearable sensors like smart wrist watches, smart glasses, wrist bands, smart wearable jewellery, smart electronic garments, patches for skin, t-shirt, GPS Shoes and so on. (Adaskevicius, 2014; Filippoupolitis, Oliff, Takand, & Loukas, 2017; Hassan, Uddin, Mohamed, & Almo- gren, 2018) [11][12][13].

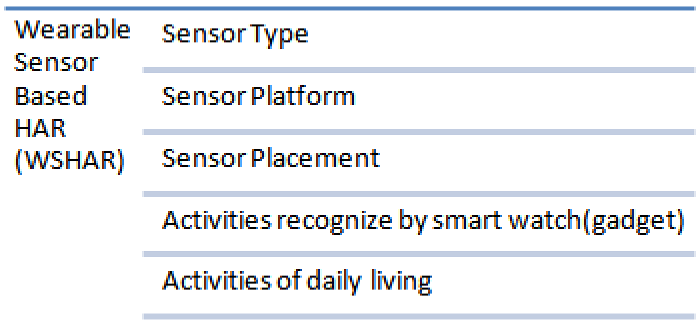

Fig. 2 WSHAR-Wearable sensor-based HAR

Table 1 Summary of Sensor Category in HAR System

Sensor Category	Description	Sensors	Sensor Placement	Advantages	Disadvantages	References
ASHAR	Recognize daily human activities from sensors that are embedded with environment	Camera, light sensor, reed switch sensor, RFID, PIR, temperature, flow sensor, pressure sensor, etc.	Ceiling, In room	Camera gives direct information, provide important information.	It is very expensive, privacy issue, limited information and working space, need sensor.	Laudanski, Brouwer, and Li (2015) Sztyler, Stucken-schmidt, and Petrich (2017)[16][20]
WSHAR	Recognize human activities from wearable sensors.	Accelerometer, gyroscope, max and min heart rate, cadence, pace, etc., built in a smart -phone, band, watch, garment, jewellery or other devices	One to One, One to Multi, Multi to One, Multi to Multi	It is low cost devises, capture motion related data like accelerometer, flexibly worn on body	No contextual information, noise data collection	(Phillips et al., 2017) (Jalal, Kamal, & Kim, 2017) (Luo et al., 2017) (Tunca et al., 2014) (Mehr, Polat, & Cetin, 2016)[21][22][9][8]
HSHAR	Combining ASHAR and WSHAR for	Blend of vision and accelerometers,	Wrist, rooms, pant pockets	Capture rich information and use the	Difficult system structureand	(Hayashi, Nishida, Kitaoka, &

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	human activity reorganization	combination of passive infrared (PIR) sensors and accelerometers, and so on		strengths of different sensor modalities	higher price, data blending and synchronization	Takeda, 2015) (Diethe et al., 2017) (Nakamura et al., 2010)[23][18][24]

Sensor location mentions to where the sensors are located on body parts and how the sensors are involved to those locations, which is a difficult in the wearable sensor-based HAR (WSHAR).(Anwary, Yu, & Vassallo, 2018; Chamroukhi, Mohammed, Trabelsi, Oukhellou, & Amirat, 2013; Moncada-Torres, Leuenberger, Gonzenbach, Luft, & Gassert, 2014; Vepakomma, De, Das, & Bhansali, 2015)[25][26][27][28].

Position sensors are gadgets that can recognize the sense the movement of an object or decide its general position estimated from a set up reference point. Movement sensors identify the development of an object and can be utilized to trigger activity. For example foot or leg involved motion capture by a foot-mounted accelerometer.
Situation of sensor might fluctuate along various applications.

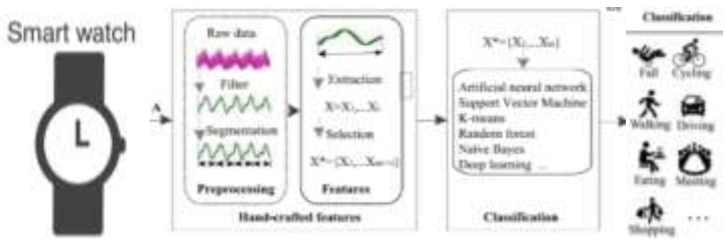

Fig. 3 WSHAR Procedure

1.2. Wearable Sensors

1.2.1. **Sensor type:** Here we discover the wearable sensors used in Health care. Wearable sensors are diverse from industrial sensors, that planned to see some specific task of requirement like small in size, low power consumption, high accuracy, higher density etc. this type of sensory are small and compact in size so they are easy to fitted on user's body parts. It can include inertial physical health sensors, camera, environmental sensors, microphone, etc. below fig 4 define the sensor category with their types that are used for sensing some data for analysis purpose.

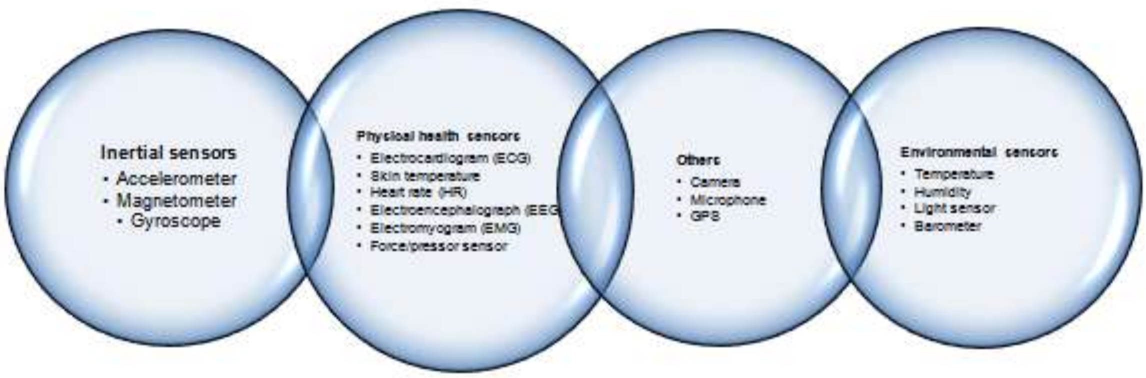

Fig. 4 Sensor type

Table 2 Offerings the most usually used wearable sensors in HAR for health care and sports athletes. Among them, movement based inertial sensors have been all around applied in WSHAR, like accelerometer, gyroscope.(Chernbumroong, Cang, & Yu, 2014; Gjoreski & Gams, 2011b; Hassan, Uddin, Mohamed, & Almogren, 2018) [14][30][13].

Wearable sensor type	**Pros**	**Cons**
Inertial Sensor	conveying rich motion movement data, little size, simple to utilize, and so on	limitation of Battery life
Environmental Sensor	Conveying rich essential information identified with exercises, can be used for varieties of purpose for heatlh condition detection.	Unfit to acquire enormous scope application because of the issues of size,accuracy, cost, and so on.
Physical Health Sensor	Conveying data related to exercises.	Generally utilized with inertial sensors and delivering noise signals.
Other	Corresponding data withdifferent sensors	Security concerns, complex algorithm applied, and so forth

Along with a wearer's movement or body postures the perceptions differ sensitively, in this manner conveying rich movement caused data. (Kwapisz, Weiss, & Moore, 2011) [31]

Use accelerometers information to detect physical activities, like walking, Running - jogging, swimming, cardio, cycling etc.

Internal sensor Use an accelerometer, a gyroscope and a magnetometer for recognition of one's activity. This kind of sensor suffers from some restrictions like battery power, low frequency of signal consumption.

For environmental sensor light sensor, barometer, temperature sensors, can be frequently found in human activity recognition.

Physical Health Sensor that used with internal sensor for recognition of physical activity. Multi-sensor platform also used for HAR that define more accuracy in result other than single sensor.

1.2.2. **Sensor platform:**In WSHAR, the sensors are usuallyconsolidated into one stage conveyed by clients or person when they perform exercises. To reduce the obtrusiveness during use, for that we can use sensor devices like smart phone, smart watch or band, smart cloths etc.

In present smart phones come with a variety of sensors like accelerometers and gyroscopes.People use their smart phone for every task and they keep it with them.To recognize a wide range of daily activities using smarts phone we use some application like strava or some phone are have their default application to track user motions or activity (Guo et al., 2016; Hassan, Uddin, Mohamed, & Almogren, 2018; Kwon, Kang, & Bae, 2014; Reddy et al., 2010; Sun Zhang, Li, Guo, & Li, 2010) [32][13][33][34][35].

Moreover phones are come with memory and battery that's why we can save activity of user and take improvement steps for poor performance as well as use that data for health improvement and doesn't require other hardware.The main problem with smartphone is location to carry the phone like pocket, some belt, or on hand. Carrying a smartphone on body constantly probably won't be appropriate for regular use when the phone carrier performs daily activities at home.

Smart-watches are planned with incorporated sensors that enable an association with a PC or a telephone. Some of the example related to smart watches for tracking human activity are shown in (Chernbumroong, Cang, & Yu, 2014; Filippoupolitis, Oliff, Takand, & Loukas, 2017; Mortazavi et al., 2014; Vepakomma, De, Das, & Bhansali, 2015)[14][12][28]

Gradually smart watch is mounted on wrist. With a moderately standard and fixed body area, wearing a smart watch is more helpful and less prominent for a person contrasted with conveying a cell phone constantly. Smart watch is better option for sports or athletic person and for health purpose for patient. So that point of view smart watch is improvedselection as compared with smart phone but both share the similar difficulty - sensor inside both the device are static and that sensors are not for a particular definite task.

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Smart clothes can embed more sensors, specifically physical sensors, to reach more data. Due to easy and simple wearing it is comfortable to user. They are regularly found in long haul observing applications (Adaskevicius, 2014)[11].

For example, Smart shirts and t-shirt are designed to monitor and exact cardiac, respiratory, rest and other day by day activities and exercises, which integrate pulse and ECG sensors (Hexoshin 2018)**[36].**

Lorussi et al. (2016) cultivate a smart textile platform that contain smart sensing gloves, shirt, trousers, T-shirt, knee sensors, shoes for the assessment of patients and observehealth and performance of athlete. This type of cloth is used for babies also to track babies sleep, body position, breathing movement etc (Mimobaby 2018)**[37]**. Typically this type of smart clothes wears tightly to ensure the quality and accuracy of output. Because smart clothes need to touched with body part of skin.

Loose wearing of clothes defines low accuracy result.

A special device called an IMU that is inertial measurement unit that processes and report craft's velocity and orientation, by means of a grouping of a gyroscope, an accelerometer, a magnetometer and occasionally together with a barometer. Single or more groupings of the IMU sensors are repeatedly active to identify human activities using different applications, that shows better satisfied performance outcome. (Bulling, Blanke, & Schiele, 2014; Georgi, Amma, & Schultz, 2015; Montalto et al., 2015; Su, Tong, & Ji, 2014).[38][39][40][41]

A device that built for specific purposes in HAR research that is known as Specifically-designed platforms, in which instruments or sensors are combined for specific task only. Burns et al. (2010)[42] designUsing multiple compound sensor units design a flexible sensing device. Their device comprises the abilities of kinematic sensing, physiological sensing, ambient sensing and external hardware integration.

Uddin, Salem, Nam, and Nadeem, (2015)[43] define a framework with a wrist-worn 9-axis- sensor device. They validate the probability of the device based on hands washing and drinking. This type of specific designed task sensor requires cost in hardware and research period. All this defined sensor platform or gadgets is mentioned in below table that is table 3.

Table 3 WSHAR Sensor platforms (gadgets).

Platform	Strengths	Weaknesses	Picture	References
Smartphones	Ubiquitous, equipped with a variety of sensors, battery and memory	Limited placing locations on body, arbitrary orientations in pockets, etc.		Sun et al. (2010) Guo et al. (2016) Hassan, Uddin, Mohamed, and Almogren (2018)[35][32][13]
Smartwatches	Integrated sensors, a relatively standard and fixed body location	Limited sensor types for different applications		Vepakomma, De, Das, and Bhansali (2015) Chernbumroong, Cang, and Yu, (2014) Uslu, Dursunoglu, Altun, and Baydere, (2013) [28][14][44]
Smart clothes	More sensors embedded, long term monitoring, the relative movement between the body parts and the sensors, etc.	Usually needed to wear tightly to ensure the quality contact of the sensors with the skin or other body parts		Adaskevicius (2014) Hexoshin (2018) Lorussi et al. (2016) [11][36 - not][45]
Inertial measurement unit (IMU)	A fixed combination of sensors, small, low power, can also provide the attitude angles of the device, etc.	Time-consuming alignment and calibration, etc.		Georgi, Amma, and Schultz (2015) Su, Tong, and Ji (2014) Anwary, Yu, and Vassallo (2017)[39][41][46]

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Specifically-designed devices	The sensors precisely required for a exact task or a common research purpose in HAR	An extra cost in hardware and research period		Wang et al. (2018) Uddin, Salem, Nam, and Nadeem (2015) Cook, Gargiulo, Lehmann, and Hamilton (2015) [47][43][48]

1.2.3. Sensor placement

Location of sensor denotesto the body locations where the sensors are located and how the sensors are involved to those places, this one is a main research problem in WSHAR. Some of the sensor location with their activity is define in the table 4. Also the table 5 is used to show the place where we can use wearable sensor to collect the data.

Table 4 Sensor placement and their recognise activity.

Sensor location Accelerometer	Recognise Activity	References
a foot-mounted accelerometer orthe foot or leg involved motion	It recognise gait, step, distance or energy consumption detection	Anwary, Yu, & Vassallo, 2018; Chamroukhi, Mohammed, Trabelsi, Oukhellou, & Amirat, 2013; Moncada-Torres, Leuenberger, Gonzenbach, Luft, & Gassert, 2014; Vepakomma, De, Das, & Bhansali, 2015.[25][26][27][28]
The wrist-worn sensors	It recognise normal activities, such as ironing, brushing teeth and cooking	Chernbumroong, Cang, Atkins, & Yu, 2013; Mannini & Sabatini, 2010.[17][49]
The thigh-located sensors	It can sensitive to the leg-involved activities, like jogging, riding, walking, running, etc.	Moncada-Torres et al., 2014; Ronao & Cho, 2015; Wu, Dasgupta, Ramirez, Peterson, & Norman, 2012. [27][50][51]

Table 5 Body locations of wearable

Sensor body location	References
Hand	Kundu, Mazumder, Lenka, & Bhaumik, 2017. [52]
Arm	Bulling, Blanke, & Schiele, 201.[38]
Wrist	Pavey, Gilson, Gomersall, Clark, & Trost, 2017.[53]
Chest	Gao, Bourke, & Nelson, 2014.[54]
Pocket	Kwon, Kang, & Bae, 2014.[33]
Feet	Anwary, Yu, & Vassallo, 2018.[25]
Shank	Bahrepour, Meratnia, Taghikhaki, & Havinga, 2011.[55]
Head	He & Bai, 2014.[56]
Vest	Bourke, Van de Ven, Chaya, OLaighin, & Nelson, 2008.[57]
Trunk	Bahrepour, Meratnia, Taghikhaki, & Havinga, 2011.[55]
Thigh	Banos et al., 2013.[58]
Belt	Capela, Lemaire, & Baddour, 2015.[59]
Ankle	Suto, Oniga, Lung, & Orha, 2017.[60]
Waist	Barreto, Oliveira, Sousa, Cardoso, & Duarte, 2014.[61]
Leg	Wang et al., 2013.[62]
Hip	Banos et al., 2013.[58]
Pelvic	Ravi, Dandekar, Mysore, & Littman, 2005.[63]
Back	He & Bai, 2014.[56]
Abdomen	Zheng, Wong, Guan, & Trost, 2013.[64]
Neck	Fontana et al., 2015.[65]
Ear	Pansiot, Stoyanov, McIlwraith, Lo, & Yang, 2007.[66]
Knee	Atallah, Lo, King, & Yang, 2010.[67]

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Table 6 WSHAR categorize in terms of sensors location.

One to one	In this type, sensor position may change with the body location and type of activity from the head to feet, But fixes on one body part.	Suto, Oniga, Lung, and Orha (2017) Examine the effectiveness of the popular ML approaches based on a right-ankle-mounted accelerometer, and their outcomes recommend that only one sensor is not suitable for everyday activity recognition [60].
One to multi	For human activity recognition one to one sensor provides inadequate information so that investigator place one sensor to several body parts with the aim to get rich and valuable information for future analysis.	One position-aware HAR system that placing seven accelerometers in diverse body locations to overcome the problem of one to one type that is develop by Sztyler, Stuckenschmidt, and Petrich (2017).[20]
Multi to one	In this type, two or more sensors placed on single body part with the aim to gather varioussource of information so here device accuracy is also measure.	A novel framework for HAR proposed by Vepakomma, De, Das, and Bhansali (2015). They use a wrist- worn device with several sensors Inside, including accelerometer, gyroscope, barometric pressure, humidity, etc. These multi-modal sensor data from the wrist-worn sensors provide rich information for recognizing complex in-home activities [28].
Many to many	In this type, multiple sensors that used with multiple body location to overcome the result of above three types, this type is expected to accomplish better performance in WSHAR.	For activity classification Chernbumroong, Cang, and Yu (2014) present a practical home-based Human Activity Recognition which use several types of sensors on multiple body location. They use seven sensors (i.e., the altimeter, accelerometer, heart rate monitor, barometer, gyroscope, light and the temperature sensor) for activity classification [14].

1.3. Activities recognize by smart watch(gadget)

Smart gadgets recorded activates are listed in bellow figure, that define this type of main and sub activitieswere record by smart watch.

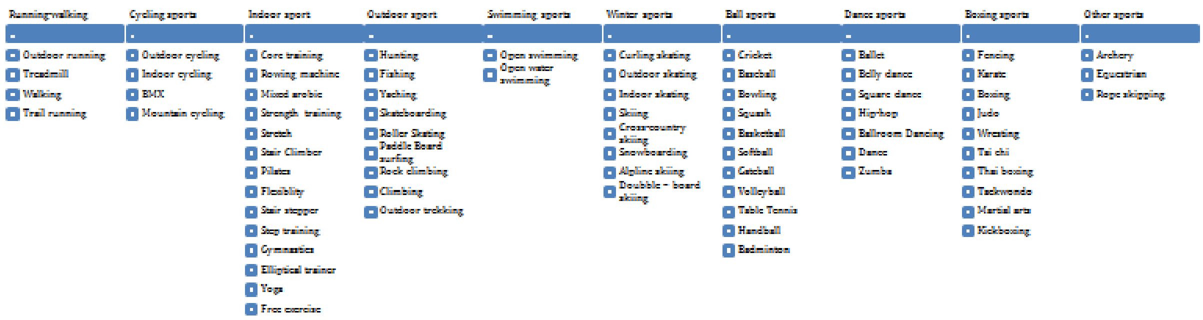

Fig. 5Activities Recorded by smart watch.

1.4. **Activities of daily living:** HAR is a widespread research exploration field of AI-ML. Most investigations in Human Activity Recognition emphasis around indoor exercises or activity of daily life (ADL) in assisted existing applications(Anwary, Yu, & Vassallo,

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2017; Hannink et al., 2017; Jung et al., 2015) [46][68][69]. HAR activities can be usually grouped in three levels according to their interval and difficulty: transition activities, basic activities, and complex activities.

Transition activities are the temporal patterns among activities, for example stand-to-sit, sit-to-lie, push-ups, bicep curls and so on (Mortazavi et al., 2014; Reyes-Ortiz, Oneto, Sama, Parra, & Anguita, 2016)[70][71]. The recognition of this type of activities is generally seen in fitness or rehabilitation-related applications (Farah, Bad-dour, & Lemaire, 2019; Masse, Gonzenbach, Paraschiv-Ionescu, Luft, & Aminian, 2016)[72][73], furthermore, which can also be used to identify complex or basic activities.

The another type of activity that is basic activities, that are the activities which have a longer period than transition actions, such as running, walking, lying, cooking, stairs using, etc. (Hassan, Uddin, Mohamed, & Almogren, 2018, Lorussi et al., 2016, Wang et al., 2018)[13][45][47].

The last type that is Complex activities, are in the form of serial, interweaved or concurrent patterns of transition or basic activities, for example relaxing, coffee time, smoking, talking and so on (Liu et al., 2016, Shoaib et al., 2016)[74][75].

The various levels of activities or exercises and day by day schedule can assist reveal with people's every day context and wellbeing conditions. The recognition of ADL is expected to understand, keep up with and help the day to day routine of the observed. Below three tables show the diverse types of activities that is Transition, basic and complex among them we focus on Basic type of activity.

Table 7 Transition Activity

Application	**Activity**	**References**
Fitness	Bicep curls, crunches, push ups, jumping jacks, shoulder lateral raises	(Mortazavi et al., 2014) [70]
Rehabilitation	Loading response, push-off, swing, terminal swing	(Farah, Baddour, & Lemaire, 2019) [72]
Fitness	Hammer-curl with dumbbell, push-ups, etc.	(Um, Babakeshizadeh, & Kulic, 2016) [76]
Gait analysis	Gait	(Hannink et al., 2017) [68]
Dietary intake	Bite, drink, utensiling, etc.	(Ramos-Garcia & Hoover, 2013) [77]
Physiatric rehabilitation	Joint dynamics, posture, head position	(Hermanis et al., 2016) [78]

Table 8 Basic Activity

Application	**Activity**	**References**
ADL	Brush, exercise, eat, iron, read, lie, wipe, falls, watch TV, etc.	(Wang et al., 2018) [47]
ADL and Falls	Walking, sitting, falls.	(Rasheed et al., 2015) [79]
ADL and heart failure	Standing, walking, ascending/descending stairs, heart failure, etc.	Zheng, Liu, Chen, Ge. and Zhao (2014) [80]
Assessment of stroke patients	Handshake, shoulder touch, etc.	(Yu, Xiong, Guo, & Wang, 2016) [81]
Fall detection	Walking, sit down, stepping up/down, running, falling, etc.	(Jung et al., 2015) [69]
ADL	Sitting, walking, stand-to-sit, sit-to-lie, etc.	(Hassan, Uddin, Mohamed, & Almogren, 2018) [13]

Table 9 Complex Activity

Application	**Activity**	**References**
ADL	Relaxing, coffee time, early morning, clean up, sandwich time	(Liu et al., 2016) [74]

ADL	Walk, jog, bike, write, coffee, smoke, eat, etc.	(Shoaib et al., 2016) [75]
ADL and fitness	Sit, walk, row, jump, cycling, exercise, coffee time, etc.	(Liu et al., 2016) [74]

The advancement of a HAR framework normally follows a normalized grouping of activities including the utilization of sensor designing, information examination and AI-ML methods. The sequence of process is known as Activity Recognition Chain (ARC).

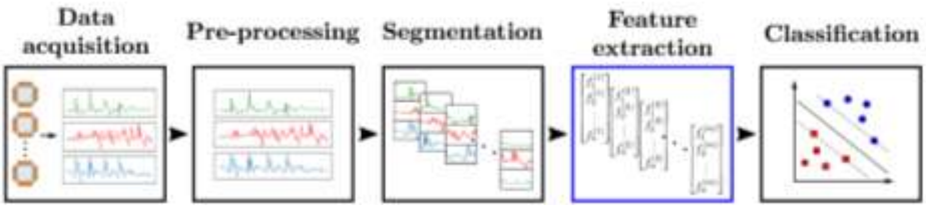

Fig.6Activity Recognition Chain (ARC).

1.5. **Source (row) data pre-processing:**Before we go through the primary data pre-processing step let's have a look of accelerometer data that we are going to collect from smart phone and watch.

The smart phone and watch come with an accelerometer and gyroscopes from that the accelerometer also known as G sensor (motion sensor), it is a device that allows you to measures and analyse linear and angular accelerometer. The operation principle of an accelerometer is simple it measures the acceleration force in g and take measurements in one, two and three plans. Currently most common accelerometer are 3-axis ones, which are designed as a system of three separate accelerometer. Each of which measures the acceleration in a different direction in X, Y and Z planes.

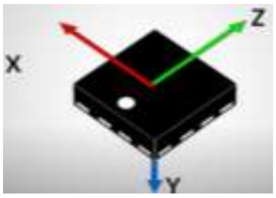

Fig.7 3-axis accelerometer

Assuming that 3-axis accelerometer is positioned so that the x-axis sensor points left, the Y axis sensor points downwards, and the Z axis sensor is directed forward.There are three types of accelerometer that is MEMS, PIEZOELECTRIC and PIEZORESISTIVE among them MEMS is most probably used in smart watch.MEMS(Micro-Electro-Mechanical system) is a type of capacitive accelerometer is the cheapest and the smallest among the three. This is made of components between 1 to 100 micrometre.

The pre-handling of the gathered source information in Fig. 2 can include filtering or separating (noise elimination), nominalization, and separation or segmentation, etc. and so forth this part just discussions about information sifting and division.

1.5.1. **Filtering (binning)**

In human activity recognition, first we have to filter the source sensor signals to eliminate a few undesirable parts from a signal, since crude sensor information may be polluted by electronic noise or other arte-realities. Before the time series are split into time windows for feature extraction filtering is apply to remove the unwanted noise from data use 3 types of filters.

Table 10 types of filters for removing unwanted noise.

Filter Name	**Use of filter**	**References**
Low pass	This type of filter are used to smooth or remove the outliers	(Kalantarian, Alshurafa, Le, & Sarrafzadeh, 2015) and (Nam & Park, 2013) [82][83]

Median pass	Median filter usually eliminate big spikes.	(Hu, Chen, Wang, & Chen, 2014) [84]
High pass	High pass filter remove low frequency information.	(Machado et al., 2015) [85]

To remove noise from the acceleration signal as of research better to apply the median and low-pass Butterworth filter (Hassan, Uddin, Mohamed, & Almogren, 2018) [13].

1.5.2. Windowing segmentation

The data that collected from wearable sensors that are known as time series data in the form of seconds or minutes which is relatively long period compared with the sensors' examining rate (mostly varying from 20 Hz to 100 Hz).

For simply fining the later learning, time series are repeatedly segmented into definite time windows. For the simplicity of implementation sliding window is the greatest current segmentation approach. It partitions the time series into fixed size windows. Different window sizes are employed in WSHAR that is define in bellow table.

Table 11 sliding window size

Window size	**Reference**
0.08 s	(Berchtold, Budde, Schmidtke, & Beigl, 2010) [86]
0.1 s	(Murao & Terada, 2014) [87]
0.2 s	(Zhang & Sawchuk, 2012) [88]
0.5 s	Chavarriaga, Bayati, & Millán, 2013 [89]
1 s	Bulling, Blanke, & Schiele, 2014 [38]
1.6 s	(Suto, Oniga, & Sitar, 2016 [90]
2 s	Laudanski, Brouwer, & Li, 2015 [16]
2.56 s	Hassan, Uddin, Mo- hamed, & Almogren, 2018 [13]
3.88 s	Chernbumroong, Cang, & Yu, 2014 [14]
4 s	Wang et al., 2013d [62]
5 s	Machado et al., 2015[85]
6.7 s	Bao & Intille, 2004 [91]
8.53 s	Guo, He, & Gao, 2012 [92]
9 s	Kalantarian, Alshurafa, Le, & Sarrafzadeh, 2015 [82]
10 s	Catal, Tufekci, Pirmit, & Kocabag, 2015 [93]
12.8 s	Wang et al., 2018 [47]
30 s	Liu et al., 2012 [94]

In table 30 s window is define but even bigger size of window is also considered.Typically, a window covers more than a few seconds time interval. A small-size window permit into consideration quicker feature extraction in later advances yet may not cover an adequate number of circles of one action. A huge size window can cover more circles of one action and contain the data from more than one action; this may delay recognition. A few researchers decide the window size by utilizing experimental qualities or referring to other comparable examinations; lengths of the information to track down the ideal size of window. (Hu, Chen, Wang, & Chen, 2014) [84] Conclude that the length of the window should fulfil two conditions:

1) No less than one pattern of the exercises is genuinely remembered for one window and it is demonstrated that a window of a few seconds can adequately catch circles of exercises like strolling, running, utilizing steps, and so forth;
2) The size should be set to 2^n subsequently being handily utilized in the Fast Fourier Transform (FFT) calculation in one window. Thusly, a few examinations which use recurrence area highlights set the examples in a single window

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as 2^n in each section (Bayat, Pomplun, & Tran, 2014, Guo, He,& Gao, 2012, Wang et al., 2018) [95][92][47].

We really want to consider the sampling rate of sensors when discussing the quantity of samples in a single window since the sample number is determined by both the window size and the sampling rate. A wide scope of inspecting rates is investigated in WSHAR, shifting from 1hz, 5hz, 6hz, and up to 800hz. Usually, greater examining (sampling) rates can get more data subtleties however combined with higher energy necessities and higher noise impact; lower examining rates save significant energy yet may preclude specific pertinent data, in this manner lower precision or accuracy. Though the high inspecting rate might assist with expanding the acknowledgment precision, it likewise prompts a few overlay expansions in computing load. Consequently, they recommend 20 Hz to be the fitting inspecting rate for the wearable framework utilizing multiple sensors.

While applying window divisions called segmentation, the cross-over means overlap between two following windows is typically taken on to diminish data misfortune at the edges of the window. The most frequently used over-lap rate is 50% (Davis et al., 2016, Kwon, Kang, & Bae, 2014, Laudanski, Brouwer, & Li, 2015) [96][33][16].

1.6. Feature learning approaches for classification

This approach can be done using two ways that is ML and automatic learning feature DL the comparison is shown in Table 9.

In general, there are some feature learning methods related to ML, selected in our relative study. We check seven diverse feature crafting approaches covering most of the recent state-of-the-art ones in HAR:

Feature learning approaches for classification	Hand-crafted features (HC)
	Multi-Layer-Perceptron (MLP)
	Convolutional Neural Network (CNN)
	Long Short-Term Memory network (LSTM)
	Hybrid model featuring CNN and LSTM layers
	Autoencoder (AE)
	Codebook approach (CB)

Hand-crafted features (HC): This features are the measures calculated from every single window segmentation in a time domain or frequency domain, which are measured to capture the valuable representation of the data for distinguishing individual-different activities in HAR, such as mean, median and principal frequency (Hassan, Uddin, Mohamed, & Almogren, 2018, Suto, Oniga, & Sitar, 2016) [13][97]. Instead of manual feature crafting method this method creates a starting point in our relative study. This feature have accomplishedexcessive success in HAR applications (Hassan, Uddin, Mohamed, & Almogren, 2018, Li et al., 2009) [13][98].
The key benefit of utilizing hand-crafted features is that the elements (Features) are computationally lightweight to execute particularly in universal gadgets or device (Morales & Akopian, 2017) [99].

Multi-Layer-Perceptron (MLP): The most fundamental type of ANN highlighting featuring completely associated layers. The highlights features learned by this model are gotten in a managed supervised manner.The MLP results are utilized as baseline for automatic supervised feature crafting.

Convolutional Neural Network (CNN):A class of ANN featuring convolutional layers which comprise neurons performing convolution items on little fixes of the input map of the layer, subsequently extricating highlights features or deep extracted features conveying data about local design patterns. Apart from image processing, NLP, audio recognition, CNNs newly started to be used for time series-processing in sensor-based HAR processing. Deep learning can automatically learn features from raw sensor data with fewer human efforts, which enhances parameters layer-by-layer (Wang et al., 2017) [100].

Long Short-Term Memory network (LSTM): One of the best and boundless variations of Recurrent Neural Networks which component layers containing LSTM cells, ready to store data

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information after some time in an interior memory. LSTM networks are utilized to catch transient conditions in broadened application fields like automatic translation [101], image captioning [102] or video-based activity recognition [103].

Hybrid model featuring CNN and LSTM layers: Exploiting the high measured quality of ANN-based designs, past investigations in sensor-based HAR announced that hybrid architectures models can extract feature that carryinghighlighteddata about short and long term time conditions, and yield best preferred performances over CNNs or LSTM network[104].

Autoencoder (AE):A class of ANNs prepared in a completely unsupervised manner to get familiar with a condensed representation which leads to the most accurate reproduction of its input data on its output layer. The outcome gained by this approach is used as a starting point for unsupervised feature learning.

Codebook approach (CB): An unsupervised feature learning technique constructed on the determination of "representative" subsequences—mentioned to as codewords—of the signals utilized for the learning.The group of codewords (codebook) is then used to extract histogram- based features based with respect to similitudes between processed data-information and codewords. Codebook-based strategies can be viewed as one-layer CNN, as codewords are learned in a comparative solo manner to convolutional parts. They were utilized in past works for time series classification [105]or HAR [106].
From the above listed feature learning approach for classification we continue our study with the Handicraft feature (HC).

Table 12 Comparison of hand-crafted feature and automatically learned features.

Feature type	Advantages	Disadvantages	References
Hand-crafted Features	The physical meanings of the features	Domain Space information required	[107]
	Are easy to understand and implement. Extraction is effective and simple to convey	Sensor-type explicit	
	For many HAR problems it works very well and efficiently	Further features or element selection needed	
Automatically learned features	No Domain Space information required	So many computing resources required	
	From the crude data automatic features learning applied	Parameters are hard to regulate	
	Features are more robust and general.	The learned features are fewer interpretable	

1.6.1. Hand-crafted features

In the crude information space, the particular worth at a particular time instant of an example (for example the perusing of 30 ◦C from a temperature sensor) doesn't convey adequate data to portray an action that the perusing starts from. Besides, when we think about two exercises as far as two given time windows, it is almost unthinkable that double time series (i.e., sectioned-segmented windows) cover indistinguishable signals even the two windows address a similar movement performed by a similar person.As needs be, quantitative and useful informative variables can be calculated based on each widow from crude sensor information; these are hand-created features. Consequently, hand-created features are intricately intended for comparing and separating various exercises activities. A wide scope of hand-created highlights have been investigated to further develop HAR execution (Attal et al., 2015, Sani, Massie,

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Wiratunga, & Cooper, 2017, Wang et al., 2016, Wang et al., 2018, Wu et al., 2012)[108][109][110][47][51]. We classify the hand-crafted feature elements as the accompanying kinds, i.e., time-domain features, frequency-domain features, and other hybrid features.

Time-domain features: Time- domain features are those elements got straightforwardly from a window of sensor information and are commonly statistical measures. They have been seriously examined in various applications and ended up being viable and valuable for HAR. These features depend on a complete and natural comprehending of how a particular movement or stance will create a bunch of discriminative highlights from estimated sensor signals.For illustration, static and dynamic exercises should create different signal qualities. Take the acceleration increase signal for instance, the signal magnitude area (SMA) determined by the accelerationmagnitude summed over three axes within each and every window has been seen as particularly successful to recognize static exercises from dynamic activities, like sitting and strolling.(Machado et al., 2015) [85]and (Hassan, Uddin, Mohamed, & Almogren, 2018) [13] use SMA and additional features to expand the recognition accuracy of dynamic activities. Additionally Studies show that Standard deviation (Std) is useful to accomplish reliably high precision in separate exercises like walking, standing, and stairs using (Laudanski, Brouwer, & Li, 2015) [16].Certain additional well-applied time-domain features are median, skewness, zero crossing rate, autoregressive coefficient (AR),variance, peak-to-peak and so on.

Frequency-domain features: Are the features or highlights which are represented to define the periodicity of signals. To produce frequency-domain features, a window of the sensor data information should initially be applied a transformation function, for example Fast Fourier Trans- form (FFT), Discrete Wavelet Transform (DWT), or Discrete Cosine Transform (DCT). The result of FFT giving is a bunch of premise coefficients which address the amplitudes of the recurrence components of the signal and the conveyance of the signal energy. Examples of frequency-domain features based on of FFT incorporate spectral energy (Hassan, Uddin, Mohamed, & Almogren, 2018) [13], entropy (Hassan, Uddin, Mohamed, & Almogren, 2018) [13], dominant frequency (Y(Suto, Oniga, & Sitar, 2016, Wang et al., 2018)) [97][47].These FFT-determined features are stated for to be valuable to progress the recognition performance execution in the previously mentioned applications. (Ayachi et al., 2016) [111] show the high effectiveness of DWT in their recognizing and dividing or segmenting work for older individuals' everyday living exercises in view of numerous body-worn inertial sensors. (Alickovic, Kevric, & Subasi, 2018) [112] propose one more automatic seizure detection and expectation prediction model in view of EEG measurements. They take on wavelet packet decomposition – WPD, DWT and empirical mode decomposition - EMD as feature extractors, and the WPD outperform the other two methods. (He & Jin, 2009) [113] create a HAR system based on DCT-extracted features from acceleration data; their investigational outcomes achieve the accuracy of 97.51%. Most time-domain and frequency-domain features are created since a separate channel (axis) of a sensor; for example mean and dominant frequency.

It is very easy to understand and implement the hand-crafted features. In table 10 we conclude key hand-crafted features effectively exploited in diverse HAR applications. This can stretch robust signs for HAR related tasks.

Table 13-a: Typical hand-crafted features used in HAR - Time-domain features

Feature title	**Description**	**Formula (if possible)**	**References**
Mean	The average value of the signal over the window	$\mu = \frac{1}{T}\sum_{i=1}^{T} S_i$	Margarito et al., 2016 [114]
Root Mean Square (Rms)	The quadratic mean value of the signal over the window	$\sqrt{\frac{1}{T}\sum_{i=1}^{T} S_i{}^2}$	Sani, Massie, Wiratunga, & Cooper, 2017 [109]
Peak-to-peak amplitude (Ptp)	The difference between the maximum and the minimum value over a window	$max = \{S_1, S_2, \dots S_T\} - min\,\{S_1, S_2, \dots S_T\}$	Machado et al., 2015 [85]
Zero crossing rate (Czr)	Rates of time signal crossing the zero value,		Machado et al., 2015 [85]

	normalized by the window length		
Mean crossing rate (Cmr)	Rates of time signal crossing the mean value, normalized by the window length		Banos et al., 2014 [115]
Signal magnitude area (SMA)	The acceleration magnitude summed over three axes within each window normalized by the window length	$\frac{1}{T}(\sum_{i=1}^{T}\lvert a_x(t)\rvert + \sum_{i=1}^{T}\lvert a_y(t)\rvert + \sum_{i=1}^{T}\lvert a_z(t)\rvert)$	Hassan, Uddin, Mohamed, & Almogren, 2018 [13]
Average of peak frequency (Apf)	The average number of signal peak appearances in each window		Janidarmian, Roshan Fekr, Radecka, & Zilic, 2017 [116]
Log-energy	Log of energy	$\sum_{i=1}^{T} log(S_i{}^2)$	Sani, Massie, Wiratunga, & Cooper, 2017 [109]
Movement Intensity (MI)	Mean of the total acceleration vector over the window	$\frac{1}{T}\sum_{i=1}^{T}\sqrt{a_{xi}{}^2 + a_{yi}{}^2 + a_{zi}{}^2}$	Chernbumroong, Cang, & Yu, 2014 [14]
Variance of MI (VI)	The variance of Movement Intensity over the window	$AI = \frac{1}{T}(\sum_{i=1}^{T} MI(i) - AI)^2$	Zhang & Sawchuk, 2011 [117]
Averaged derivatives (Ader)	The mean value of the first order derivatives of the signal over the window	$\frac{1}{T}\sum_{i=2}^{T}\frac{s_i - s_i - 1}{2}$	Zhang & Sawchuk, 2011 [117]
Crest factor (Cftor)	The ratio of peak values to the effective value over the window	$\frac{0.5(S_{max} - S_{min})}{RMS}$	Y (Wang et al., 2016) [110]
Percentiles	10th, 25th, 50th, 75th, 90th		King et al., 2017 [118]
Interquartile range (Interq)	Difference between the 75th and 25th percentile		King et al., 2017 [118]
Autocorrelation (Autoc)	The correlation between values of the process at different times	$\frac{\sum_{i=1}^{T-1}(S_i - \mu)(S_{i+1} - \mu)}{\sum_{i=1}^{T}(S_i - \mu)^2}$	Machado et al., 2015 [85]
Pairwise correlation (Corrcoef)	The ratio of the covariance and the product of the standard deviations between each pair of axes	$Corr_{XY} = \frac{\sum_{i=1}^{T}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{T}(x_i - \bar{X})}\sqrt{\sum_{i=1}^{T}(y_i - \bar{y})}}$	Janidarmian, Roshan Fekr, Radecka, & Zilic, 2017 [116]
Standard deviation (Std)	Measure of the spreads of the signal over the window	$\sigma = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(S_i - \mu)^2}$	Laudanski, Brouwer, & Li, 2015 [16]
Coefficient of variation (C v)	The ratio of the standard deviation to the mean	$\frac{\sigma}{\mu}$	Janidarmian, Roshan Fekr, Radecka, & Zilic, 2017 [116]
Kurtosis	The degree of peakedness of the signal probability distribution	$\frac{\frac{1}{T}\sum_{i=1}^{T}(S_i - \mu)^4}{(\frac{1}{T}\sum_{i=1}^{T}(S_i - \mu)^2)^3} - 3$	Sztyler, Stuckenschmidt, & Petrich, 2017 [20]
Skewness	The degree of asymmetry of the sensor signal probability distribution	$\frac{\frac{1}{T}\sum_{i=1}^{T}(S_i - \mu)^3}{(\frac{1}{T}\sum_{i=1}^{T}(S_i - \mu)^2)^{\frac{3}{2}}}$	Zhang & Sawchuk, 2011 [117]
Max	The largest value in a set of data	$\max\{s_1, s_2, \ldots s_T\}$	Hassan, Uddin, Mohamed, & Almogren, 2018 [13]

Min	The smallest value in a set of data	$\min\{S_1, S_2, \ldots S_T\}$	Chernbumroong, Cang, Atkins, & Yu, 2013 [17]
Median	The middle number in a group of ordering numbers	$\text{median}(S_i)$	Murao et al. , 2014 [87]
Mode	The number that appears the most often within a set of numbers	$\text{mode}(S_i)$	Chernbumroong, Cang, & Yu, 2014 [14]
Variance	The average of the squared differences from the Mean	$\frac{1}{T}\sum_{i=1}^{T}(S_i - \mu)^2$	Mortazavi et al., 2014 [70]
Autoregressive coefficient(AR)	Coefficients of an IIR filter, α_i	$X(n) = \sum_{i=1}^{P} \alpha_i\, s(n-p) + e(n)$	Hassan, Uddin, Mohamed, & Almogren, 2018 [13]
Median absolute deviation(MAD)	The median of the absolute deviations from the data's median	$\text{median}_i \cdot (\lvert S_i - \text{median}_j(S_j)\rvert)$	Suto, Oniga, & Sitar, 2016 [97]

Table 13-bTypical hand-crafted features used in HAR - Frequency-domain features

Feature title	**Description**	**Formula (if possible)**	**References**
Dominant frequency (Domifq)	The frequency corresponding to the maximum of the squared discrete FFT component magnitude of the signal from each sensor axis		Suto, Oniga, & Sitar, 2016 [97]
Spectral energy (SpecEgy)	The sum of the squared discrete FFT component magnitude of the signal from each sensor axis, normalized by the window length	$\frac{\sum_{i=1}^{\lvert\omega\rvert}\lvert x_i\rvert^2}{\lvert\omega\rvert}$	Hassan, Uddin, Mohamed, & Almogren, 2018 [13]
Spectral entropy (SpecEnt)	Measure of the distribution of frequency components, normalized by the window size	$\sum_{i=1}^{T/2}[p(i) \cdot \lg(p(i))]$	Hassan, Uddin, Mohamed, & Almogren, 2018 [13]
The spectral centroid frequency (SCF)	The estimate of the "centre of mass "of the spectrum		Sani, Massie, Wiratunga, & Cooper, 2017 [109]

1.7. Feature dimensionality reduction and feature selection:

More features convey better data information, which is gainful for further developing classification performance execution. Feature dimension, particularly for the hand-crafted features, extracted from the time, frequency or hybrid domains, develops very high in maximum HAR work.The early set of highlights can be repetitive or too enormous to even think about being manipulated; this could cause greater calculation cost, little learning efficiency and over-fitting on concealed information. To improve further developing generalization and interpretability Suitable element dimensionality reduction and feature selection can be applied in this regard to enable more precise and quicker learning.

1.7.1. **Feature dimensionality reduction:**Like Prominent Component Analysis – PCA, Autoencoder (Wang, 2016) [110], Kennel PCA-kPCA (Hassan, Uddin, Mohamed, & Almogren, 2018) [13], Sparse filtering (Ngiam et al., 2011) [119] and so on, Feature dimensionality reduction is one of the two methods for resolving the above defined issues, which remakes features to swap the original features elements by creating linear or nonlinear blends of the contribution to a unsupervised way (He & Jin, 2009) [113].

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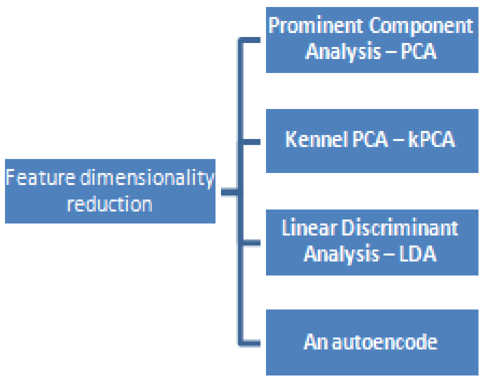


Prominent Component Analysis - PCA: Is one of the notable dimensionality reduction strategies. The essential thought of PCA is to observe the ideal projection that straightly changes the original elements into another feature component space in the variance sense (Yang et al., 2012). The factors, which are positioned by their variance (from biggest to most reduced) in the new feature space, are called principal components. The principal components that donate to very great variance are preserved.

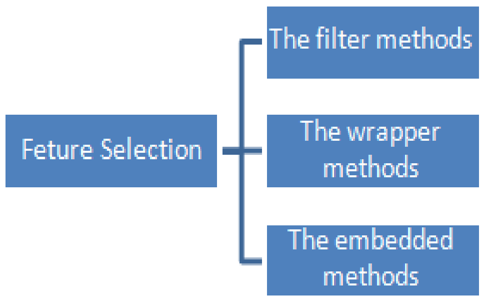
Kennel PCA – kPCA:Through a kernel function kPCA followed by a usual PCA (Wu, Wang, & Liu, 2007) [120]., It observes the ideal nonlinear change of information, which maps the input feature information highlights into a higher-layered feature component space (e.g., radial basis function (RBF) kernel); PCA family are great at looking for the best delegate information projection. However, it may not function admirably since PCA doesn't think about any distinction in classes.

Linear Discriminant Analysis – LDA: It projects the original features into another space of minor dimension by expanding the between-class distinguishableness while distinguishableness their inside class inconstancy (Uray et al., 2007) [121]. Kernel LDA (kLDA) is the nonlinear addition of LDA, which accomplishes LDA in the feature pace mapped by a nonlinear kernel function (Schölkopf, Smola, & Müller, 1998) [122].

An autoencode: It organization can get familiar with a lower-layered representation of information by limiting the mean squared mistake between the info and the result (preferably, the information and the outcomes are equivalent) (Van Der Maaten, Postma, and Van sanctum Herik, 2009) [123]. It contains two parts that is encoder, and decoder. The purpose of encoder is to compress the original input data information into a low-dimensional demonstration and the decoder are used for to rebuild the original input data based on the low-dimension demonstrationproduced by the encoder. It is commonly used for to reduce the data dimension.

These years, the autoencoder and its extensions exhibit a auspicious capacity to gain significant features from information for action recognition (Chen et al., 2017, Chikhaoui & Gouineau, 2017, Gu, Flórez-Revuelta, Monekosso, & Remagnino, 2015) [124][125][126].

1.7.2. **Feature selection (FS):** This techniques, differs from the dimensionality reduction methods (for example PCA), select a subgroup from a feature group lacking varying the original demonstration of the features (Guyon & Elisseeff, 2003) [127]. Consequently, the chosen features preserve the original semantics of the original features.An efficient feature selection can removeunnecessary features, streamline the model building, deliver the benefit of interpretability and improve generation performance.A varied variability of FS technologies have been planned and applied in HAR. FS can be categorized into three groups i.e., filter, wrapper and embedded.



The filter methods: It is Feature Selection algorithms which filter out unrelated features by calculating the significance of a feature to the output by some standards, such as correlation, distance, information, consistency, similarity and statistical measures (Dessì& Pes, 2015, Gheid & Challal, 2016)[128][129]. This method first ranks the original features based on its criteria, then chooses the features with greater rankings. These methods are independent of some classifiers, thereby being more efficient. Some example of filter methods are Correlation-based Feature Selection (CFS) (Hemalatha & Vaidehi, 2013) [130], Relief (Gupta & Dallas, 2014) [131], Mutual information (MI)-based feature selection methods (Cang & Yu, 2012) [132], Canonical Correlation Analysis (CCA) (Kaya, Eyben, Salah, & Schuller, 2014) [133], etc.

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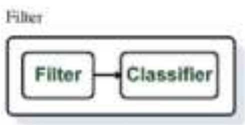
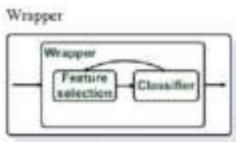
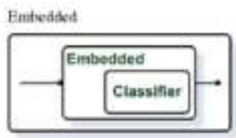
The wrapper methods: This method select a subset of elements with the most segregating properties by utilizing specific classifiers to assess the quality of a candidate feature, for example SVM (Bolón-Canedo, Sánchez-Maroño, & Alonso-Betanzos, 2013) [134] and neural networks (NNs) (Kabir, Islam, & Murase, 2010) [135].
Process of typical wrapper method
1) Find a subset of features;
2) Performance of the predefined classifier can be assessing by chosen feature set;
3) The cycle rehashes until when the assessed precision of adding any component is not exactly the assessed exactness of the list of feature capabilities previously chosen
This method offer the accurate result by features dependency. This method is rarely used because it is computationally expensive since performance assessments through a classifier are usually done by cross-validation (Wang et al., 2005) [136].

The embedded methods: This method will quite often exploit the merits of filter and wrapper techniques by coordinating component feature choice into model learning (Li et al., 2017) [137].This can be carried out by regularization methods which present extra requirements (highlight coefficients) into the improvement (limiting fitting blunders) simultaneously.The greatest broadly used embedded methods are Lasso (Li et al., 2017) [137] and Ridge regression (Liu, Peng, Liu, & Huang, 2015) [138].Sparse representation is other feature selection method (Liu et al., 2016, Subrahmanya & Shin, 2010) [74][139].

There is no thorough limit between feature dimensionality reduction and feature component selection; research keeps on supporting the case that there is certifiably not a "best method"for all job (Gui et al., 2017) [140].

Table 14: Feature selection techniques - Bolón-Canedo, V., Sánchez-Maroño, N., & Alonso-Betanzos, A. (2013) [134]

	Filter method	**Wrapper method**	**Embedded method**
Working			
Information	Generic set of methods which do not incorporate a specific machine learning algorithm.	Evaluation on a specific machine learning algorithm to find optimal features.	Embeds (fix) feature during model building process. Feature selection is done by observing each iteration of model training phase.
Speed	Much faster	Slower	Medium
Over-fitting	Avoids Over-fitting	Prone to Over-fitting	Less prone to Over-fitting
Performance	Sometimes may fail to select best feature	Better performance	Good Performance
Example	Correlation, chi-square test, ANOVA, Information gain etc.	Forward selection, Backward elimination, Stepwise selection etc.	Lasso, Elastic Net, Ridge Regression etc.
Advantage	• Classifier independence • Computation cost is less • Working Faster • Good generalization ability	• collaboration with the classifier • feature dependencies capture	• collaboration with the classifier • other than wrapper method the computation cost is less • feature dependencies is capture
Disadvantage	No collaboration with the classifier	• Computationally expensive • Risk of over-fitting • Selection is dependent on classifier	selection is based on Classifier

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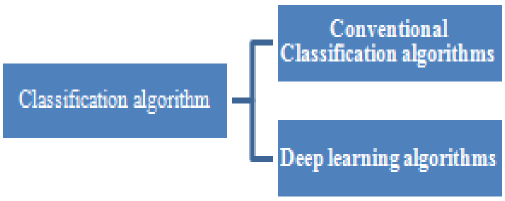
Classification algorithms:

Classification process should be done to recognize human activities. The job of classification is to interpret the input features and give a prediction of the observations (the movement, activity, and exercise) (Alpaydin, 2014) [141].As far as classification algorithms utilized for HAR, present techniques can be well-ordered into two kinds: 1) conventional classification algorithms and 2) deep learning algorithms. The first technique attempt to build a wide-ranging depiction of the input with a probabilistic model such as a Bayesian network or model the mapping from inputs (features) to outputs (activity labels) such as SVM (Chen et al., 2012). The representation is started from the raw data, deep learning algorithms are the represented using multiple layers (LeCun, Bengio, & Hinton, 2015) [142]. Research follow the machine learning approach so follow conventional classification algorithms.



Conventional classification algorithms:

The derivative features from the raw sensor data are then served to diverse classification algorithms for models building to organize or classify data (such as, the activities under consideration for HAR). These kinds of classification algorithm are usually considered into two types: supervised and unsupervised. Supervised algorithms deal with labelled data and unsupervised algorithms consisting of unlabelled input data. Usage of supervised algorithms is to working out datasets to build models and check datasets to validate the models. Some of the algorithm that support supervised techniques that is Support Vector Machines - SVMs (Mehrang et al., 2017) [143], Artificial Neural Network - ANN (Khan, Tufail, Khattak, & Laine, 2014) [144], Naïve Bayes - NB (Mortazavi et al., 2014) [70], Decision trees - DT (Mortazavi et al., 2014) [70], k-Nearest Neighbours - kNN (Adaskevicius, 2014) [11], Multiplayer Perceptron - MLP (Bayat, Pom-plun,& Tran, 2014)[95], Random forest - RF (Pavey et al., 2017) [53], etc.

(Mehrang et al., 2017) [143] explore activity monitoring using a single wrist-worn device that is prepared through an optical heart rate sensor and a triaxial accelerometer. They cover their dataset by variability of home-specific activities like standing, sitting, household, and stationary cycling that is done through 20 male members for that they apply SVM and RF algorithm for classification work. Results of leave-one-subject-out cross-validation show 89.2% and 85.6% average accuracies from RF and SVM, respectively.

(Janidarmian, Roshan Fekr, Radecka, & Zilic, 2017) [116]To find the greatest predictive model for varied human exercise or activities Conduct a widespread comparison among 293 dissimilar classifiers, such as DT, SVM, kNN, NB, etc., author also take care of definite factors, for example position of sensor on body, cloth, body shape and accidental misplacements, hinder building a solid model for diverse activities. First they create a whole dataset that focusing on acceleration data and do a widespread feature extraction on data. For feature dimensionality reduction PCA is applied. The averaged accuracy achieves 96.44 ±1.62% with k- fold cross-validation and 79.92% ±9.68% with subject-independent cross-validation. Experimentationoutcomesshow that kNN and its collectivetechniquesdisplay stale results over diverse situations, followed by ANN and SVM

Some of the dataset review used with HAR and ADL type of research are define in the below table.

Table 15-a: Review on Data set

Sr. no.	Paper name	Author name	Year of publication	DataSet	Reference
1	Introducing a New Benchmarked Dataset for Activity Monitoring	Attila Reiss, Didier Stricker	2012	PAMAP2(Physical Activity Monitoring for Aging People)	(Reiss & Stricker, 2012) [145]
2	Energy	Davide Anguita,	2013	SBHAR	(Anguita, Ghio,

	Efficient Smartphone-Based Activity Recognition using Fixed-Point Arithmetic	Alessandro Ghio, Luca Oneto, Xavier Parra, Jorge L. Reyes-Ortiz			Oneto, Parra, & Reyes-Ortiz, 2013) [146]
3	Transition-Aware Human Activity Recognition Using Smartphones	Jorge-L.Reyes-Ortiz, LucaOneto , AlbertSamà, XavierParra, DavideAnguita	2016	SBHAR	[71]
4	mHealthDroid: A Novel Framework for Agile Development of Mobile Health Applications	Oresti Banos, Rafael Garcia, Juan A. Holgado-Terriza, Miguel Damas, Hector Pomares, Ignacio Rojas, Alejandro Saez, and Claudia Villalonga	2014	mHealth	(Banos et al., 2014)[147]
5	Activity Recognition using Cell Phone Accelerometer s	Jennifer R. Kwapisz, Gary M. Weiss, Samuel A. Moore	2011	WISDM	(Kwapisz, Weiss, & Moore, 2011) [31]
6	Feature extraction for robust physical activity recognition	Jiadong Zhu, Rubén San-Segundo and José M. Pardo	2017	REALDISP	(Baños et al., 2012)[148]
7	The MobiAct Dataset: Recognition of Activities of Daily Living using Smartphones	George Vavoulas, Charikleia Chatzaki, Thodoris Malliotakis, Matthew Pediaditis and Manolis Tsiknakis/	2016	Mobi- Act	(Vavoulas et al., 2016) [149]
8	The Opportunity challenge: A benchmark database for on-body sensor-based activity recognition	Ricardo Chavarriaga, Hesam Sagha, Alberto Calatroni, Sundara Tejaswi Digumarti, Gerhard Tröster, José del R. Millán, Daniel Roggen	2013	OPPORTUNITY	(Chavarriaga et al., 2013)[89]
9	A Comparative Study of Feature Selection Approaches for Human	Fatima Amjad , Muhammad Hassan Khan, Muhammad Adeel Nisar, Muhammad Shahid Farid and Marcin Grzegorzek	2021	CogAge dataset	(Amjad, F et al., 2021)[150]

	Activity Recognition Using Multimodal Sensory Data				
10	Applying machine learning to predict future adherence to physical activity programs	Mo Zhou, Yoshimi Fukuoka, Ken Goldberg, Eric Vittinghoff and Anil Aswani	2019	Mobile Phone-Based Physical Activity Education program (mPED)	[151]
11	Daily Activity Recognition sing Wearable Sensors in Machine Learnin and Feature Selection	Abeer A. Badaw, Ahmad Al-Kabbany, and Heba Shaban1	2021	Human Gait Database (HuGaDB)	[152]
12	Enhanced Human Activity Recognition Based on Smartphone Sensor Data Using Hybrid Feature Selection Model	Nadeem Ahmed, Jahir Ibna Rafiq and Md Rashedul Islam	2020	Human Activity Recognition Using Smartphones Data Set	[153]

Detail related to Dataset

Table 15-bSummary on review on Data set

Dataset name	Description
PAMAP2	Which comprises daily activities (sitting, watching TV, jogging, etc.) collected from 9 elderly subjects with three inertial sensors and heart rate placed on ankle, chest, and dominant arm; Dataset publicly available on: http://www.pamap.org/demo.html.
SBHAR	Which is originally created for six different human activities using a waist- mounted smartphone from 30 subjects and is updated to include six more postural transitions
mHealth	Which covers 12 daily activities for health monitoring using three inertial sensors and ECG sensor;
WISDM	Which is a dataset collected from 29 users with single accelerometer embedded in a mobile phone, including sitting, jogging, standing, working, etc.;
REALDISP	Which is produced in gradual sensor displacement conditions, including 33 fitness activities recorded by nine wearable IMUs on different body parts from 17 subjects
Mobi-Act	Which comprises data of nine different types of ADLs from 50 subjects and four different types of falls from 44 subjects using the smartphone-based accelerometer, gyroscope and orientation sensors located in a

	trousers' pocket;
OPPORTUNITY	Which comprises a set of basic and complex activities collected from four subjects in an environment with both ambient and wearable sensors
CogAge dataset	It contains 9700 instances of 61 different atomic activities obtained from 8 subjects. afterwards it comprises set of six subject and seven activities (Brushing teeth, Cleaning room, Handling medications, Preparing food, Styling hair, Using telephone, Washing hands) - smartwatch and glasses
mPED	Data of 210 community dwelling physically inactive women, age 25 to 69 yearsThe trial consisted of a 3-week run-in period, a 3-month intervention period using the app, accelerometer, andbrief counselling to increase physical activity, and a 6- month maintenance period using accelerometer (and theapp) to maintain activity.
HuGaDB	The signals from an accelerometer, a gyroscope, and an Electromyography (EMG) sensors areacquired from the thigh, shin, and foot of the right and left legs. Given that three placements are used for each type of sensor, this results in the acquisition of a total of fifty-four signals. The data wasgathered from 18 healthy, young, adult participants.
Human Activity Recognition Using Smartphones Data Set	Built from the recordings of 30 subjects performing activities of daily living (ADL) while carrying a waist-mounted smartphone with embedded inertial sensors.

Data set from UCI Machine Learning Repository

Table 16 Description of dataset of kaggel

WISDM Smartphone and Smartwatch Activity and Biometrics Dataset	Contains accelerometer and gyroscope time-series sensor data collected from a smartphone and smartwatch as 51 test subjects perform 18 activities for 3 minutes each [154].
Heterogeneity Activity Recognition Data Set	Activity recognition data set - The Heterogeneity Dataset for Human Activity Recognition from Smartphone and Smartwatch sensors consists of two datasets devised to investigate sensor heterogeneities' impacts on human activity recognition algorithms. The dataset contains the readings of two motion sensors commonly found in smartphones. Reading were recorded while users executed activities scripted in no specific order carrying smartwatches and smartphones. Activities: 'Biking', 'Sitting', 'Standing', 'Walking', 'Stair Up' and 'Stair down'. Sensors: Sensors: Two embedded sensors, i.e., Accelerometer and Gyroscope, sampled at the highest frequency the respective device allows. Devices: 4 smartwatches (2 LG watches, 2 Samsung Galaxy Gears) 8 smartphones (2 Samsung Galaxy S3 mini, 2 Samsung Galaxy S3, 2 LG Nexus 4, 2 Samsung Galaxy S+) Recordings: 9 users

Our dataset description:

As we seen earlier from that we are going to take care of running trainings, consuming the information that they provide to examine, interpret and extract some final assumptions.

The data we are going to work with has been obtained from a database that gathers all the activities from smart watch with combination of GPS and a heart rate sensor: Garmin smart watch. By using smart phone or web, Garmin Connect (https://connect.garmin.com/) is the tool for tracking, analyzing and sharing health and fitness activities recorded by your paired Garmin device.

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The period of time of our activities is from 2017 to 2022. Total 15 users are participated for this dataset and 15000 data are collected from them. During all this time the combined workouts activities are like running, Indoor Running, Cardio, Treadmill Running or trail Running, Walking, Pool Swimming, Cycling, Strength Training, Open Water Swimming, whitewater Kayaking/Rafting, mountain Biking, pilates exercise - Pilates is a low impact exercise comprising controlled movements that enhance your balance, core strength, mobility, flexibility, and even mood…

From the above listed activities we are focusing on running activities that are perform on road. The most common parameters of running sessions are Activity type, Date, Distance, Calories, Time, Avg HR, Max HR, Avg Run Cadence, Max Run Cadence, Avg Pace, Best Pace, Elev Gain, Elev Loss, Avg Stride Length, Min Temp, Best Lap Time, Number of Laps, Min Elevation, Max Elevation.

This dataset we are going to consider as testing dataset and for training dataset more users are participated for data collection.

Proposed algorithm for data pre-processing:

Step1: Import all required libraries.
Step2: For 1 to n (users) do
Take one by one user data file in .csv format.
Print data from file
Check user information by filename.info
Now add one column on 1st index position named it with 'user' that stores unique user id as numeric type that defines separate user's records.
End for
Step3: append one by one user record and make one data frame.
Step4: Print records from file and analyse the data.
Step5: Check shape and size of test dataset.
Step6: generate .csv file from all appended record.
Step7: Check for null value specifically on distance column (feature), if null value is present then replace it with '0' in test dataset otherwise continues with next step.
Step8: Check for '--', '0.00' and ', 'coma separated value like - 1,033' type of value in the distance column (feature) in the dataset, If this type of value is present in the test dataset then replace it with 0.
Step 8: After replacing the value check the data type of each columns (features) of dataset and focus on the distance column.
Step 9: check data type of distance column
If (distance is of float type)
Then leave it
Else
If (Distance is of object type)
Then that distance column data type is cast it with float type.
Step 10: Sort the data and fetch the records that have distance >=5.00 km.
Step11: focus on activity type that is categorical value so we need to convert it in numeric type for that make unique activity type with value and convert data type object as integer.
Step 12: Now working on a Time feature it is in the format of 'HH:MM:SS' as object data type, we can't work on that so we need split it by lambda function and separate all the feature as different column as 'HH', 'MM' and 'SS' as data type integer.

Step 14: In the next step we focus on Date feature with 'YYYY-MM-DD HH:MM:SS' so we need to separate the date from starting time for that we need to split it by lambda function and make 'DD', 'MM', 'YYYY' as a different column as integer type.
Step 15: End of the algorithm

II. CONCLUSION

This era, Sensor-based HAR structure has been accomplishing constant progress. Every sensor modality has its own strengths and weakness. ASHAR - Ambient senor-based HAR deals ambient context, but it generally deliver limited data-information about the human activity. WSHAR - Wearable sensor-based HAR is more bendable for long-period use and can deliver rich set of motion data information, however, which habitually suffer the difficulties, like arbitrary signal affected by the sensors worn on specific body parts. The HSHAR - hybrid sensory HAR which blending ambient and wearable sensor modalities can deliver richer set or complementary data information from diverse sensors. Nevertheless, a mixture of diverse sensor modalities can also include the difficulties, such as accumulative the difficulty of the system and costs, effective data synthesis between diverse sensor modalities. The conversation above is also potted in Table 1.This paper centres a focus on the WSHAR - wearable sensor modality formeasuring athletic performance, prediction of performance and health care, counting the sensors used in HAR, the sensor placement on different body portions, the most mutual seen sensor platforms in HAR, activities well-defined in this arena, data segmentation, feature learning, classification, etc.Separating effective elements or features for recognizing exercises or activities is a critical and challenging task. For the component learning, we study both the usually utilized Hand-craftedfeatures and automatically learned features, but we highlights the Hand-crafted features for WSHAR.We discuss Feature dimensionality reduction and feature selection approach related to data processing and focus on supervised ML techniques for classification approach. Proposed the algorithm related to pre-processing task.

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