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A comparative study on various Machine Learning Techniques for Human Activity Recognition and Fall Detection

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ABSTRACT

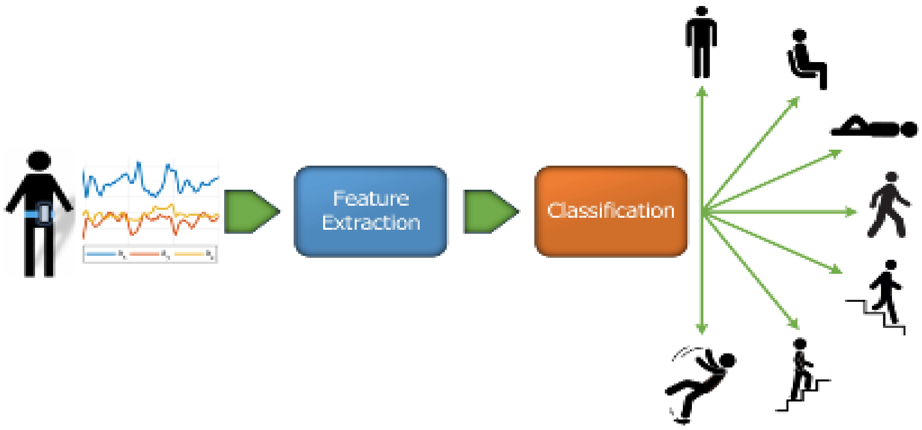
Falling is one of the most serious drawbacks prevailing among the elderly people as well as physically challenged people. It has impressed the researchers in the field of behavioural analysis for healthcare applications. The recent technologies like IoT, sensors placements, wearable devices and so on were contributed to improve the performance of the fall detection systems. To bridge the gap in the mobile technologies, this paper is an extensive survey of fall detection using machine learning algorithms. Initially, we present the scope of the vision based algorithms in brief. The recent techniques are surveyed from the aspects of performance achieved and the limitation. Finally, a comparative study is done to find the issues pertaining in this field. The issues like feature selection, theories of collected data, scope of sensors, privacy and supervised and unsupervised machine learning have to be addressed with the scope of the mobile technologies. Though the researchers have achieved steady progress, this research area still confronts the real-time issues.

Keywords: Fall detection, Feature selection, Machine learning techniques, Mobile Technologies, Wearable devices.

INTRODUCTION

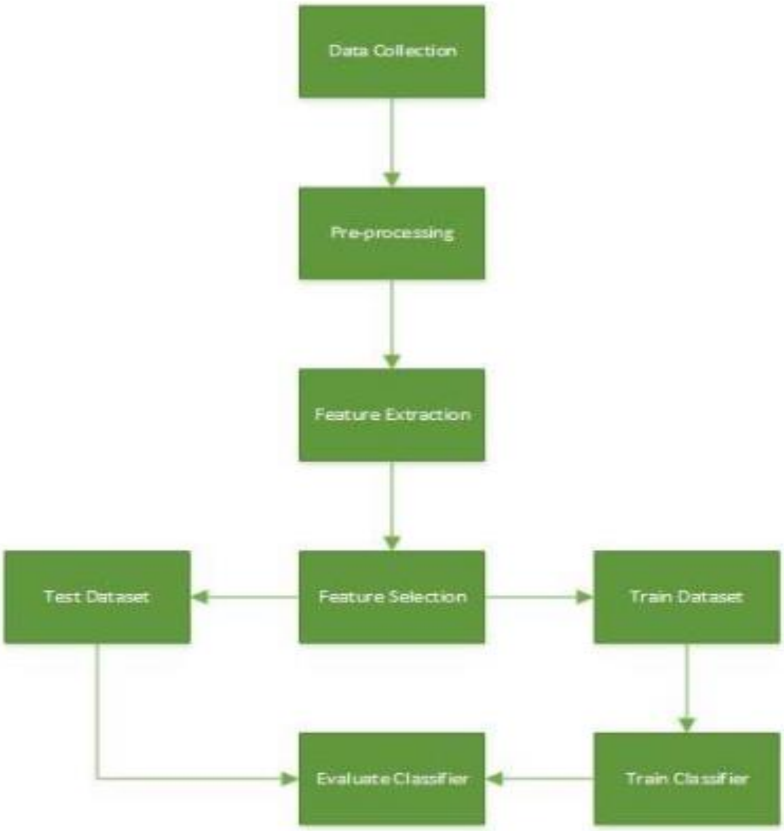
The recent developments made in the Information & Communication Technologies (ICT) have renovated with numerous benefits on real-time applications. In specific to, the advancements of the medical field has increased the life expectancy rate of the elderly people. This trend made remarkable changes in the healthcare policies of elderly people with the objective of leading an active and independent life. It is also observed that the lack of physical activity is one of the causes of global mortality (Chelli and Pätzold, 2019). In line with that, the falls and the emergency are the two major accidents which seek immediate medical attention in the case of elderly people. The fall prediction at an earlier phase has influenced the growth of medical technologies as well as declined the life expectancy rate among elderly people. Therefore, the research on discovering the Activities of Daily Living (ADLs) (Micucci et al., 2017; Sao, 2017) which is known as Human Activities (HA) has become a fascinating research area. Behavior Recognition is one of the promising fields of this research area which predicts the ADLs by understanding more about the behaviors of humans. The activity of the human is deduced by means of sensor devices. The data patterns are attributed from the sensor data which is projected into the set of known human activity. Along with the fall detection, the recognition of the human activities is most required for the applications areas of transport, fitness, military and ambulation. By means of a camera assisted data collection process, the data are collected and analyzed over longer time periods. From the generated signals, the information about activity acceleration, orientation and other movements are computed. These are combined with the machine learning techniques by exploring the pattern recognition process.

Figure 1 Framework of Activity Recognition (Chelli and Pätzold, 2019).



Vision based human behaviour recognition (Rasheed et al., 2015; Martínez-Villaseñor et al., 2018; Tsinganos and Skodras, 2018) deals to provide solutions for the physical inability issue based on observing their past behaviours. The main motivating factor is, the provided solutions must be robust rather than accurate (Hassan et al., 2018). Fall detection technologies are invented on the basis of the Human Action Recognition (HAR) module (Li et al., 2014). It detects the falls by analyzing the estimated pose of a human. It has helped to reduce the fall risk rate and also secured the life expectancy rate. Motion analysis (Li et al., 2019) is the prime idea to detect the falls at an untimely phase. The pose of a human is explored to cover up the tasks such as tracking the person, classifying the activities, interpreting the carried activities and so on. These are addressed by the identifications of objects from the captured images. It is efficiently handled by the image processing techniques that extract the relevant task oriented features by the set of human actions. Further, the obtained actions are then classified using Machine learning techniques (Vallabh et al., 2016).

Figure 2 Framework of the machine learning classifier (Li et al., 2019).



The rest of the paper is structured as follows: Section II describes related work; Section III presents the Comparative Study on recent techniques; Section IV presents the Research Challenges pertaining in this field and finally, Conclusion is given in Section V.

RELATED WORK

This section presents the reviews of existing studies from the aspects of objective used, techniques used, achieved performance and the limitation. In Yacchirema et al. (2019), the machine learning approach was designed to detect the falls with the aim of yielding highest accuracy. It was analyzed on 8 types of falling postures which has given 96.26% accuracy. However, the computational costs of quadratic and polynomial based kernels are not focussed. Fall detection for people supporting the physically disabled persons by accessing the synthetic data (Hsieh et al., 2016). It was designed to provoke the workers by giving an alarm. Though it sends an emergency alarm but the verification of false positive and true negative alarms is not studied. Pertaining to it, a comparative study on fall detection of all machine learning algorithms (Leier et al., 2018) was studied. Feature selection process was focussed to build efficient training data. It was analyzed over the video frames which has given 93.46% SVM; 91.29% Naive Bayes and 92.24% NN. Here, the image segmentation has to be addressed more from the distorted background images. In (Zerrouki et al., 2016), a 2D skeleton data was explored using supervised machine learning. With use of k-NN, naive Bayes and the SVM, the motion features at 2D position were collected, analyzed and compared. While collecting the skeletal data, the imbalance of data on different poses has brought computational time challenges.

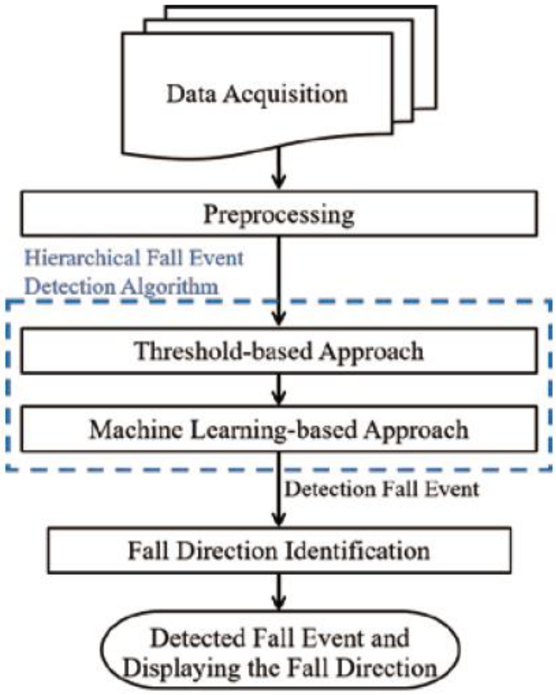
The placement of multiple sensors on the ADLs were analyzed using ensemble learning (Ghazal et al., 2019) which has improved to 94.87% recognition accuracy. The data collected via accelerometer did not perform well in the arm position. In Gjoreski et al. (2020), the movement decomposition and the SVM classifier were studied to recognize the fall detection. The data collected from the wrist wearable devices. The system has achieved 99% accuracy with the highest data dimensionality and node failures issues. Fall detection from the video clip data was studied by de Quadros et al. (2018) that explored the efficiency of extreme learning machines. It classified the data by optimized features. Here, the particle swarm optimization was used to select the relevant features for classification purposes. It was explored on the six types of actions and the achieved performance is 86.73% accuracy. In video clips, the frames are analyzed which have the capability to throw serious dimensionality problems, while detecting the objects. The chance of fake alarms increased during the running and walking position of daily activities (Ma et al., 2014) which was resolved by the statistical based machine learning approach. Initially, the statistical information such as max, min, avg and mean of different poses was collected. This was then fed into the Weka learning model under 10-cross fold validation. It was efficient on the short data analysis process. It is not suitable for real-time captured data.

An intelligent IoT based ambient network (Yin et al., 2015) was focussed to improve the fall recognition process. Along with the sensor based measurement data, the biological and physiological profile were also used for analytic purposes. Based on the categorization of risks, the fall positions were classified. In some cases, the flexibility and continuity of data reduces the accuracy rate. In Anupama et al. (2018), a comprehensive review was done to detect the falls based on the monitoring services. Decision tree was used to categorize the data. Based on the data arrangements, the threshold values were matched with the estimated pose values and then, the classification was done. Dynamic activities and the network link connectivity are not focussed in this study. Impact given by the failed sensor nodes has affected the performance of the detection accuracy, which was focussed by Vallabh and Malekian (2018) on analyzing the dynamic activities. With the help of ANOVA, the feature selection process was modulated. Relied upon the threshold value of the selected features, the mobile data was acquired to do the detection process. Due to the evolution of different mobile subjects, the dynamic movement analysis brings trade-off in the false positives.

In Santoyo-Ramón et al. (2018), the prevention model was suggested using machine learning techniques for six forms of ADLs. Here, an incessant assessment was made to verify the monitoring systems for all events. The high accuracy fall event detection algorithm and fall direction identification were explored to prevent the falls at an untimely phase. System has achieved above 90% performance. Based on the ground truth data, the prevention strategies were incorporated, however, the distorted signals may affect the performance of the data acquisition process. A survey was conducted to inquire about the facts of fall detection systems (Hsieh et al., 2018). It has stated that the challenges exist in the feature selection process, privacy and the design of prediction models. Similar study was done by Xu et al.

(2018), in which the data collected from the elderly people using a 3-axial accelerometer. Due to the power restriction in sensors, the efficiency of the detection model was reduced. Therefore, the distorted signals were modulated and then the universal features were collected. It has achieved a sensitivity rate of 99.73% at 40Hz sampling frequency. It has reduced the false alarm rate, however, the learning criteria increases as the sampling frequency increases

Figure 3 The functional diagram of the proposed fall monitoring system (Hsieh et al., 2018).



The deployment of ML techniques with the heuristics searching approaches was discussed by Nguyen et al. (2017) using Microsoft Kinect v2. It was explored on the video tagging based ML methods. Initially, the skeletal data was collected and then organized into a set of instructions. With the help of adaptive boosting trigger models, the fall objects were detected with the accuracy of 95.42%. Relied upon the training samples, the accuracy will be yielded and thus, here it was designed by confidence factors. In Souza et al. (2020), the fall detection algorithm was imposed on the public health data in Brazil. Here, inertial sensors were used to monitor and capture the data. Different ML classifiers were executed on the captured fall states by trained sensor data. It has reduced the false positives rate and also increased the detection accuracy. While detecting the falls using object recognition models, image segmentation (Rodrigues et al., 2018) plays a crucial role in enhancing the detection rate. The segmentation process was improved by two studies, namely, Fixed-size Non-overlapping Sliding Window (FNSW) and Fixed-size Overlapping Sliding Window (FOSW). By adjusting the window rate, the detection accuracy was increased to 25% than k-NN and SVM.

Table 1 Comparison study in terms of accuracy, specificity and sensitivity; F_s = 40Hz (Nguyen et al., 2017)

Method	Specificity (%)	Sensitivity (%)	Accuracy (%)
Proposed (KNN – based)	97.89	97.06	97.54
Proposed (MLP – based)	99.62	98.26	99.05
Proposed (SVM – based)	97.70	99.73	98.55
Mezghani (SVM – based)	94.44	99.60	96.60
Abdelhedi (Threshold – based)	82.85	54.14	70.87

In Putra and Vesilo (2017), the cause of unintentional falls has reduced the life expectancy rate, which was modulated by wearable sensors and the ML using signal processing techniques. It was explored in SisFall datasets which has achieved 97% F1 Score. Feature extraction process was improved by Giuffrida et al. (2019) for accelerometer based data. Noise filtering models were explored on extracting the features and then classified via Support Vector Machines (SVM). It has reduced the false alarm rate by increasing the efficiency of data capturing modules. Similar to this, in Chen et al. (2016), the critical falls was studied by improvising the segmentation approaches and the window sizes. SVM classifier has yielded better performance than the k-NN and Naive Bayes at window size 0.5s. Acute post-fall intervention (Liu et al., 2019) is one of the critical fall states which were improved by mStroke. In order to ensure the reliability of the fall recognition models via mobile phone based data application process, the use of ML algorithms were compared. It has stated the scope of sensor placements and the analysis of universal features. In Harris et al. (2016), the smart wristband was optimized to detect the falls using modified k-means algorithms; Perceptron Neural Networks & CNN algorithms. With the use of 9-axis inertial sensor units, CNN has effectively optimized the collected data than the PNN and CNN. Owing to this, in Zheng et al. (2019), the Doppler frequency was modulated for classification purposes. The path gain network was devised to improve the falls states from static and dynamic motions.

COMPARATIVE STUDY

This section presents the reviews of existing studies from the aspects of objective used, techniques used, achieved performance and the limitation.

Table 2 Reviews and comparative study

Ref. No.	Technique used	Achieved results	Dataset used	Limitation
Chelli and Pätzold (2019)	Class Incremental Extreme Machine Learning (CIELM) was employed to detect the falls based	Batch learning time was significantly reduced. It has improved the	Mobile phone based data collection module	Though it has reduced the computational time, the execution time

	on the labeled activities. Here, the samples are trained to the ELM which has detected the class of falls, even without the use of previous training data. Here, data was collected from the mobile phone activities.	stability of learning models.		was increased, even for minimum weights of labeled samples.
Zhao et al. (2014)	Class Incremental Random Forests (CIRF) was employed to detect the new activity based on the experiences given by the past activities. Then, an axis theorem was used to construct a better decision tree. Each tree was split by following the Gini Index value. Each learning phase was incremented by the Gini Index value of existing learning models.	It has efficiently detected new classes by increasing the learning rate 20%. The accuracy of testing data was found to be 93.78% which was 5.68% greater than the CIELMs.	It was explored in 3 datasets, namely, UCI DSADS dataset, OPPORTUNITY dataset and HARUSDS dataset.	Computational costs of the training data is not studied. The hidden node problem in the decision tree is also not studied.
Hu et al. (2018)	Artificial Neural Networks (ANN) was employed to detect the abnormalities of the human poses. In order to increase the detection accuracy, the layer based	It has discussed the scope of ANN in the different fields of the data collection process.	Surveyed papers from 2016 to 2018.	The scope of decision making from the sensors measurements have to be focussed.

	architectures were followed up to identify the classes.			
Casilari-Pérez and García-Lagos (2019)	This study was aimed to reduce the computational loads by incorporating the light weight feature extraction process using Lifting Wavelet Transform (LWT). Then, the extracted features were fed into the SVM classifier which identified the falls based on the daily activities.	By the use of a lightweight feature extraction process, the RMSE was reduced with the highest detection accuracy rate of 98.31% and the sensitivity rate of 97.14%.	Haar and Biorthogonal 2.2 wavelets	Computational costs are not explained in terms of time and frequency domain features.
Liang and Usaha (2017)	ANN was employed to detect the falls for the elderly people as well as muscular dystrophy patients. With the help of accelerometers, the signals of the motion were captured and then employed for building neural classifiers.	It has reduced the signals errors by adjusting synaptic weights according to the learning rate.	Wearable devices were embedded into the body part of humans.	Rate of false positivity is high.
Purushothaman et al. (2018)	With the use of a sensitive floor sensor made out of a piezoelectric material and the machine learning approach, the fall detection was studied. Here, a supervised random	It has achieved 94.4% of true positive rate and the 2.4% of false positive rate.	It was analyzed on 742 events of 3710 instances.	In the case of feature reduction analysis, the fitting rate of the algorithm will be bounced, if it applies to the large scale

	forest algorithm was used for aggregating and classifying the classes.			datasets.
Minvielle et al. (2017)	Bayesian; k-nearest neighbor algorithms and kernel based ELM were used to detect the falls.	It was analyzed under k-cross validation models. At k=5, the rate of f-measure was 1.8% for k-nearest neighbor algorithm & 6.6% for Naive Bayes algorithm.	Events of fall detection.	False positive rate is higher, when the k-value changes.
Altay and Ulas (2019)	Supervised machine learning model was incorporated to detect the falls. Feature selection plays a vital role in this study. The selected features performed based on the accelerated data.	The different combinations of features such as (Mean,std,var, kurt, skew, pca); (Mean, std, skew, pca) ; (std, var, kurt, skew, pca) & so on were analyzed. All combinations have yielded above 93.50% of accuracy.	FARSEEING fall repository which has 900 samples data.	False rejection rate becomes high when the combinational features go beyond the threshold levels. Data imbalance issue is not focussed.
Aktay and Efe (2019)	Kernel based ELM was compared with the bayesian and k-nearest neighbor algorithm. Expert system was instantiated for better decision	Compared to the bayesian and k-nearest neighbor algorithm, the kernel based ELM has achieved better accuracy of	MTw Software Development Kit was used to collect the data.	Class distribution between fall and non-fall states will be collided due to the poor decision

	making process	0.8786 with reduced 0.1344 sensitivity rate		making models.
Wang et al. (2019)	Detecting the new falls using ANN, as a tool. It has been employed to improve the testing accuracy rate from the captured signals.	Out of 381 falls, 375 falls data was detected with sensitivity of 0.984%.	With the help of the accelerometer ADXL345, the data was acquired.	It is carried in small-scale data and thus, the ability of hidden layers is not utilized properly.
Pierleoni et al. (2015)	With the use of android-low cost smartphones, SVM classifiers were employed to process the signals.	It has achieved 99.3% of sensitivity and 96% of specificity.	Sensor based data was collected and preserved in multithreading models.	If the distance of the sensor node varies beyond the threshold value, then the monitoring services are also suspended.
Zurbuchen et al. (2020)	All machine learning algorithms were combined with the ensemble learning, in order to prove the detecting efficiency of each algorithm.	Compared to k-NN, SVM, DT , RF, the Gradient Boosting (GB) achieved 98.06% sensitivity and 98.70% accuracy.	Wearable sensors were used for data collection purposes. Sisfall dataset was employed here.	Iteration steps are limited on each algorithm , which will be inducing a longer waiting time in post-processing results.
Leu et al. (2017)	Motion classification was done by decision tree algorithms. Falling events differ on the age factors. Thus, it is required to detect the falls with common factors. Therefore,	It was experimented over three brands of mobile phones, namely, iPhone 4, iPhone 5 and iPhone 6. Compared to the walking and	Data collected from the wearable sensors via mobile phones.	The data is not collected and analyzed on the dynamic motions,which limits the scalability of the systems.

	the motions are defined and then trained for classification using machine learning systems.	standing up position, the sitting down and running position was perfectly classified by all three mobile brands.		
Chelli and Pätzold (2018)	Recognition of falls in daily activities using machine learning algorithms. Based on the acceleration signals, features are trained and then classified using quadratic based SVM classifiers.	It has achieved 93.2% of accuracy which was better than ANNs.	Data collected from the wearable sensors.	The correlation values on selected features helped to recognize the falls. It is practically not suitable due to high computational costs.
Toda and Shinomiya (2019)	The combination of IoT sensors was employed with the machine learning algorithms. It was analyzed over different feature subset selection processes.	Depending on the process of the embedded tags, the ML classifier detected the falls. It has preserved the memory space as well as yielded highest computational spaces.	Passive RFID sensor tags were used to collect the data.	It purely depends on the RSSI values, which gives unstable values for running and standing activities.

CHALLENGES AND ISSUES IN HUMAN ACTIVITY RECOGNITION AND FALL DETECTION (HARFD)

From the above conducted reviews, the challenges pertaining in this field are summarized as follows:

Feature selection

In general, the fall will be defined from the pose of the human. It is further detected by the features of the human pose. In order to build efficient training data, the selection of features plays a vital role in the detection process. It supplies knowledge to the designing classifier. Prior algorithms such as threshold-based, shape-based and rule-based are presented to select the relevant features. However the selection of relevant features remains to be a challenging task. Based on the application requirements, the trained features behave inappropriately in another environment. Therefore, an optimized feature selection has to be addressed in terms of searching space.

Theories of collected data

Mostly the detection/ prevention algorithms are applied on the simulated datasets. To deal with the real-time data, the coordination between the sensor placements and the algorithms are the core process. It helps to reduce the false alarm and false positive rate. However, depending on the constraints, the dependent variable of the class gets diverted.

Scope of sensors

The review has stated that the use of the accelerometer was more profound than the gyroscope, magnetometer and barometer. Wearable devices are embedded with these general types of sensors. The dealing of acquired signals from these sensors has also impacted the detection algorithms. The differentiation between normal and distorted signals is the complex tasks over signal processing techniques. Sampling rates of the signals with respect to time factors have also judged the scope of classifiers.

Data Privacy

In the angle of the user's end, privacy plays an important role in fall detection algorithms. Vision based algorithms are employed for detecting the falls by image (or) skeletal data. Since the information is being collected from the mobile assisted technologies, the chances of data threats are high. Therefore, the need for security algorithms has to be addressed.

Supervised & Unsupervised machine learning algorithms

Irrespective of the forms of machine learning algorithms, Detection accuracy is the major key findings of the ML algorithms. An increased accuracy value is obtained by improving the error rate. False positive rate is defined as the process of correctly detecting the class of falls. The strategies applied over ML algorithms are the improvement of error criteria, which most algorithms fail to support with low computational costs.

CONCLUSION

Fall detection is the initial step to preserve the elderly people from any serious threats. The aim of the fall detection algorithm is to prevent (or) detect the people falling at an untimely phase. However, the chance of getting injured cannot be ignored. The study of detecting the falls of elderly people in the healthcare sectors becoming a hot research topic due to the wide scope of application requirements. In recent times, the growth of wireless technologies has taken the real-time applications into another level. This paper is a comprehensive survey of fall detection using machine learning algorithms for mobile-assisted technologies. The survey is carried out from the angle of three key points, viz,

a) Sensors and its upgradation: Mostly depth camera, Kinect 2 sensors that support Wi-Fi technologies have been employed to collect the data.
b) Upgradation in algorithms: The scope of Machine learning is widely employed however, the feature extraction process has to be renovated according to the learning criteria.
c) Performance of the detection system: Many algorithms have proved the efficiency by yielding the highest accuracy rate, but, it is practically not feasible.

Owing to these key points, the challenges presented in this environment is presented in a fine-grained way i.e.
a) Feature selection
b) Theories of collected data
c) Scope of sensors
d) Privacy
e) Supervised and unsupervised machine learning.

Even though several challenges are imbibed in this system, the core challenges and issues which require promising solutions are explored.

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