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Anomalous Human Activity Detection Using SVM and Active Leaning Based Approach

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ABSTRACT: Real-time activity recognition using body sensor networks is an important and challenging task and it has many probable advantages. To capture human activity and analyze that data, these both activities are very essential in abnormal activity detection. To analyze data is crucial part for finding out actual facts behind human activity. Since it uses state transition table methodology for effectively discovering abnormal activity, recognize it and track it for old age people or kids from remote location. Here paper introduces an automated approach to activity tracking that identifies common activities that naturally occur in an individual's routine. Here it uses conventional SVM (Support Vector Machine). It is a binary classifier which is used to classify two classes of data.

So by considering these capabilities it can track the occurrence of regular actions to supervise functional health and to detect changes in human being's routine and everyday life. In this paper it describe our activity of data mining and tracking it in the field of image processing approach and validate our algorithms on data collected from remote sensors.

KEYWORDS: Human Activity, Classification, Multi-class SVM,Tele-health Care, State Transition, Smart Home Monitoring System, abnormal pattern recognition.

1. INTRODUCTION:

The understanding of context and human activities is a core component that supports and enables all kinds of context-aware. Proposed work developed a fully supervised learning methodology which recognition abnormal activity accurately with a minimal number of requests for ground-truth labels.

To recognize human activity even when there are no training data for a particular activity class. This methodology can generalize previously learned knowledge and extend its capability to recognize new activity classes. Like old aged people want to live an independent lifestyle, but at old age people become prone to different accidents, so living unaccompanied has high threat and is repeated.

Learning and recognizing human activities of daily living is very useful and essential to build smart home monitoring system [1] describe a fuzzy logic system for recognizing activities in home environment using a set of sensors: physiological sensors, microphones, infrared sensors, debit sensors and state-change sensors.

Hence, real –time processing of data is must for recognizing activity behaviour and predicting abnormal situations of the elderly. To deal with issues such as monitoring the daily activities, performance tracking of normal behaviour and wellbeing of elderly living alone a system which is non invasive, flexible, low cost and safe to use is designed and developed.

For recognizing the normal activities multi-class SVM is used here. As the data has many attributes SVM uses a kernel function for training, selected from all the various reputed kernel functions. Abnormal activities are detected by finding out all possible activities that can be performed from the current activity. To find out all possible activities, the data has to be classified using all classes, which requires high computational time. To reduce the computational time SVM uses transition table which help in avoiding unreachable states for classification.

The proposed approach is inspired by the following observations:

- Many human activities and perspective types share the same basic semantic parameters: For example, the parameters Sit, Run, Walk, Fall, Stand etc. these are common activity and can be observed in different scenes

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like having lunch, working at desk, talking on mobile etc activities. Therefore, the statistical model of parameters can potentially be transferred from one activity to another.

- The limits of supervised learning can be overcome by incorporating human knowledge: Rather than collecting sensor data and labels for every context, using nameable parameters allows humans to describe a context type without the process of sensor data collection. For example, one can easily associate the activity "office working" with the motion-related attributes such as "Sitting," "HandsOnTable," and sound-related attributes such as "PrinterSound," "KeyboardSound," and "Conversations."

Table 1.1: Different learning problems in abnormal human activity detection

Parameter	**Distinguished**	**Non-Distinguished**
Identified Parameter	**Pre-definedLearning**	**Active Learning**
Non Identified Parameter	**Non-definedLearning**	irregularity Detection, uncommon Class Discovery, Open Set Recognition

II. MOTIVATIONAL SCENARIO

- To proposes a novel scheme of representing human activities in form of a state transition table with the help of multi-class SVM
- The design, development, and implementation of a new framework for human activity recognition even when there are no training data for a particular activity class.
- The novel representation of human activities using bag-of-attributes models and attribute sequence models.
- The design and study of the semantic attribute sequence model, a new and general zero-shot learning model that is suitable for sequential data.
- The design of an active learning algorithm for activity recognition, which efficiently reinforce the recognition **accuracy** using minimal user feedback.
- The evaluation of the proposed framework on real-world experiments in two activity domains.
- The first results on zero-shot learning for human activity recognition.

III. RELATED WORK

1. Supervised Learning:

In the field of mobile, wearable, and pervasive computing, extensive research has been doneto recognize human activities (e.g. sitting, walking, running) [2, 3].In terms of the learning method, the majority of the research in this field used supervised learning approaches, including discriminative classifiers (e.g. Decision Trees, SVM) and generative models (e.g. Naive Bayes, Hidden Markov Model), where a classifier is trained on a large set of labelled examples of every target activity. There has also been prior study of representing high-level activities as a composite of simple actions, using a supervised layered dynamic Bayesian network. A widely acknowledged problem is that labelled examples are often time consuming and expensive to obtain [4, 5, 6].

2. Semi-Supervised and Transfer Learning

To lessen the reliance on labelled training data and to exploit the benefits of abundant unlabeled data, previous work has incorporated semi-supervised learning into activity or context recognition systems [7]. Semi-supervised learning approaches can improve the recognition accuracy by refining the decision boundary based on the distribution of the unlabeled data, or by assigning highly-confident estimated labels to the unlabeled data.

3. Active Learning

The idea of active learning algorithms is that a machine learning algorithm can performbetter with less training data if it is allowed to choose the data from which it learns [8].Active learning has been used to improve the

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accuracy of human activity recognition. It extend the previous work by integrating active learning in the framework for activity recognition, so that the system is able to recognize undefined activities.

4. Unsupervised Learning

Another related research direction is unsupervised learning. Unsupervised learning focuses on clustering or pattern discovery rather than classification [9]. In human activity understanding is divided into activity recognition and activity pattern discovery. The first category focuses on accurate detection of human activities based on a pre-defined or pre-trained activity model, while the second category focuses on finding unknown patterns directly from low-level sensor data.

The output of these approaches is a set of unnamed clusters which cannot be used for classification or recognition purposes. To perform recognition, labels are still needed to connect the discovered patterns to the actual classes.

5. Rule-Based Approach

There are also some rule-based approaches to activity recognition. In [11], Storf et al. proposed a multi-agent-based framework using rules and manual configurations written in the Extensible Markup Language (XML) format. The authors also used fuzzy reasoning ex. Detection of activity "preparing meal" involves a set of cases and rules, including the combination of usage stove, usage fridge, stay at kitchen counter, etc. with different weights for each case. Rule-based approaches may be hard to apply without much domain knowledge, or when the rules are not straightforward and thus have to be learned from data.

6. Zero-Shot Learning

The idea of zero-shot learning has recently been explored and has been shown to be useful for recognizing unseen new classes [12]. It presented one early study on the problem of zero-shot learning, where the goal is to learn a classifier that can predict new classes that were omitted from the training dataset.

Inspired by their work, our work extends the zero-shot learning framework to handle sequential data by modelling the sequence and structure of the attributes.

IV. IMPLEMENTATION

In this proposed system, a new learning framework for human abnormal activity recognition is proposed. The framework is designed based on the sequential human activities. It is also designed base on SVM, K-Means and Random Forest algorithm for improving accuracy and reducing time and space complexity where it gives confident about precession and recall value more than 90%.
You can see architectural diagram of Abnormal Activity detection at Home in fig 1.

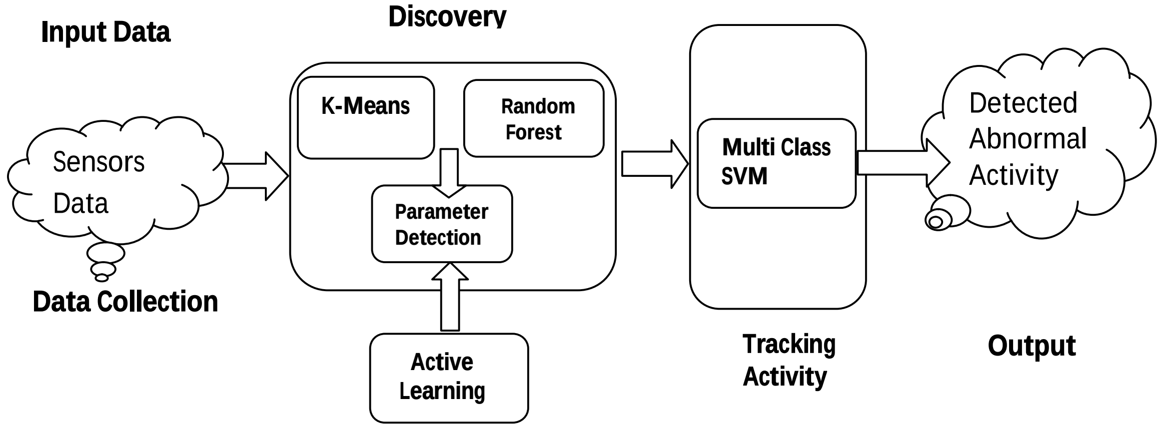

Fig1: Architectural diagram of Abnormal Activity detection

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Here it presents how abnormal activity detection takes place in the concept of smart home effectively on given input which is generated by remote sensors. The first step, it must consider is how to identify the everyday and repeatable activity which would be detectable by sensors or cameras that comprise our smart home concept.

Once it discover and categorize the activity and associate specific occurrences of the activity, we are keeping its appropriate entries in database. So it can build a model to recognize the activity and begin to analyze the occurrences of the existing as well as new activity. But how then it discovers new or run time activity which is not present in database? For that it uses Active directory concept which will detect Non-Distinguished learning concept at run time.

Here it is performing number of functionality on given input data such as filtering, normalization, multi class SVM, K-means and Random forest algorithm. Following Systems block diagram Fig 2 shows functionality of our system.

Input Data

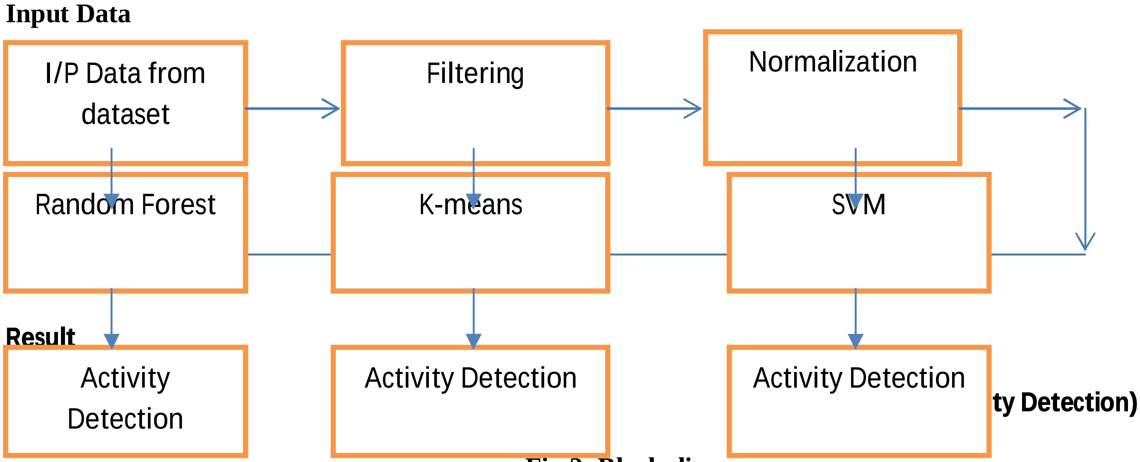

Fig 2: Block diagram

a. Input Data:

The sensed data is captured and collected, then continuously transmitted to the application which is present at hospital or any remote place for helping if any abnormal activity takes places know as a receiver. Captured data are continuously monitored and compared with different parameters, attributes and patterns.

b. Data tracking and discovering:

The Tracking, learning and recognition framework is not dependent of sensor data types or device types, so the source of sensor data is any kind of data. Selecting the right set of parameters or attribute is important for improving the recognition accuracy. Suppose persons intention to perform exercise activities, which may include warm up in which it include different sub activities are performed like lifting hands, sleeping, pitching, walking, and running. Each sub-activity can then be further broken down into fine-grained motions of limbs, joints, and muscles and on that basis it has been discovered appropriately.

The abnormal activities are stated using state transition table, which holds all possible states. The system is trained to classify the activities performed by the individuals and report the abnormalities. The system recognizes 9 different activities of an individual using multi-class SVM. The general architecture of the system is shown in Fig 1. The sliding window is used to split data into window of size N data for the system to recognize the activity. The sliding window reduces the flow rate and sends less data to the system to recognize the activity performed by the individual.

The proposed system uses seven features mean of each axis, standard deviation of each axis and velocity. These features help in reducing the noise in the dataset and influence in classifying the data with higher accuracy.

c. Multi Class SVM

In machine learning, support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. SVM helps in categorization since it is used for classification of images and its data. It gives significant search accuracy [12].

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Conventional SVM having problem of binary classifier since it uses series of SVM. Each SVM classifies data of single activity into single label. So for classifying multiple activities it uses multiple SVM in Series. But the problem is that it takes more time for computation due to more SVM. Therefore we are state transition table. This table stores all possible transitions from each state to other. The transition table is derived from the state transition diagram,

Final / Initial	Stand	Sit	Run	Walk	Fall
Stand	1	1	1	1	1
Sit	1	1	0	1	1
Run	1	0	1	1	1
Walk	1	1	1	1	1
Fall	1	1	0	0	1

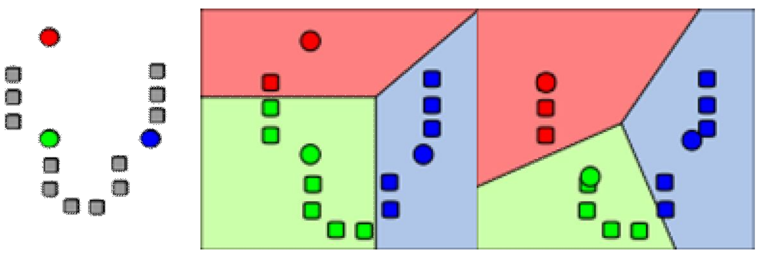
In SVM quadratic kernel function has high accuracy than other functions as number of attributes sample increases. The quadratic function is shown in following equation;

$$k(x,y) = 1 - \frac{\|x-y\|^2}{\|x-y\|^2 + c}$$

d. K-Means:

k-means is one of the simplest unsupervised learning algorithms that solve the well known clustering problem. It forms clusters of similar activity. It is used as a data mining which compares existing data of activity with run time old edge peoples activity for finding out abnormal activity and divide it in different cluster to recognize quickly. The procedure follows a simple and easy way to classify a given data set through a certain number of clusters.

It Calculate the distance between each data activity attribute and forms different activity cluster. It randomly selects '*c*' activities cluster centres.



1. *k*-means (*k*=3) are randomly generated within the data domain of humans activity .
2. *k* clusters are created by associating every observation with the nearest mean. The partitions here represent the Voronoi diagram generated by the means for classifying different activity in different cluster.
3. The centroid of each of the *k* clusters becomes the new mean.
4. Steps 2 and 3 are repeated until convergence has been reached.

e. Random Forest:

This class implements a Random Decision Forests classifier. Random Forests are an ensemble learning method that operates by building a number of decision trees at training time and outputting the class. The Random

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Forests algorithm is a good algorithm to use for complex classification tasks. It is using Classification Data structure to train the Random Forests classifier.

Since it uses K-Means and Random forest together to classify and discover abnormal activity effectively.

f. Abnormality Activity Detection

Abnormality Activity can be detected by categorizing the defined activities, Active directory activity which is not defined but it is normal activity and the undefined which is not normal that traces can be tagged as abnormal activity. The transition table used for multi class SVM selection, the same can be used for defining the normal activities. The transition table defines all possible states that can be performed by an individual. If any events occur out of the range of the transition table, the event is marked as abnormal. Fig3 shows Venn diagram of different activity at home.

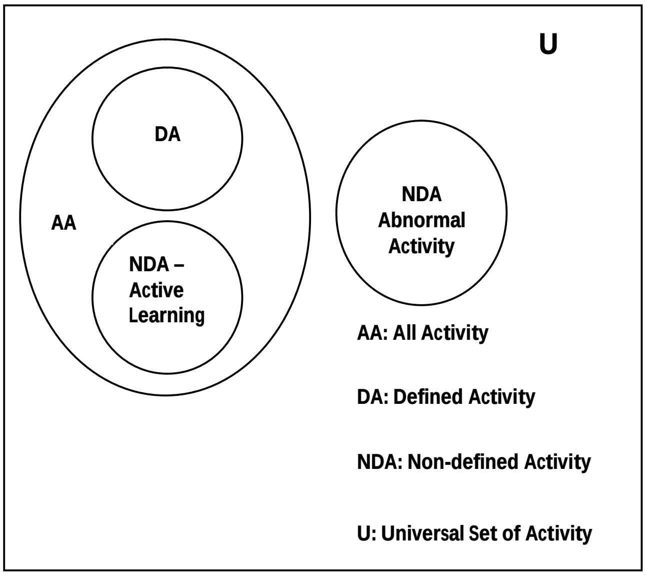

Fig 3: Venn Diagram of Humans Activity for detecting abnormalities.

V. CONCLUSION

Experimental results show that the proposed approach achieves 90% and above precision and recall in recognizing previously unseen, undefined new activities, and outperforms supervised learning where hundreds of labelled samples for the unseen activities are provided to the supervised to the developed tool as a Active learning. SVM classifier is built using various well known kernel functions which increase the accuracy of the system. The results extend and advance the state of the art in human activity recognition, and represent an important step towards bridging the gap between computers and humans.

REFERENCES

[1] H.Medjahed, D.Istrate, J.Bouny,and B.Dorizzi, “Human activities of daily living recognition using fuzzy logic for elderly home monitoring”, in proc. IEEE Int. Conf. Fuzzy Syst, aug 2009,pp.2001-2006.
[2] L. Bao and S. S. Intille. Activity recognition from user-annotated acceleration data.In Proceedings of The International Conference on Pervasive Computing, pages 1–17.Springer, 2004.
[3] U. Blanke and B. Schiele. Remember and transfer what you have learned – recognizingcomposite activities based on activity spotting. In International Symposium onWearable Computers, 2010.
[4] N. D. Lane, E. Miluzzo, H. Lu, D. Peebles, T. Choudhury, and A. T. Campbell.A survey of mobile phone sensing. IEEE Communications Magazine, 48:140–150,September 2010.
[5] H. Lu, J. Yang, Z. Liu, N. D. Lane, T. Choudhury, and A. T. Campbell. The jigsawcontinuous sensing engine for mobile phone applications. In Proceedings of The ACMConference on Embedded Networked Sensor Systems, SenSys ’10, pages 71–84, 2010.

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ISSN (Print) : 2320-9798

International Journal of Innovative Research in Computer and Communication Engineering

(An ISO 3297: 2007 Certified Organization)

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[6] M. Stikic, D. Larlus, S. Ebert, and B. Schiele. Weakly supervised recognition ofdaily life activities with wearable sensors. IEEE Transactions on Pattern Analysis andMachine Intelligence, 2011.
[7] B. Longstaff, S. Reddy, and D. Estrin. Improving activity classification for health applications on mobile devices using active and semi-supervised learning. In International Conference on Pervasive Computing Technologies for Healthcare, PervasiveHealth'10, pages 1–7, 2010.
[8] B. Settles. Active learning literature survey. In Computer Sciences Technical Report1648, University of Wisconsin–Madison, 2010.
[9] T. Huynh, M. Fritz, and B. Schiele. Discovery of activity patterns using topic models. In Proceedings of The International Conference on Ubiquitous Computing, UbiComp '08, pages 10–19, 2008.
[10] E. Kim, S. Helal, and D. Cook. Human activity recognition and pattern discovery.IEEE Pervasive Computing, 2010.
[11] H. Storf, M. Becker, and M. Riedl. Rule-based activity recognition framework: Challenges, technique and learning. In 3rd International Conference on Pervasive Computing Technologies for Healthcare, PervasiveHealth '09, pages 1–7, 2009.
[12] Adithyan Palaniappan, R. Bhargavi, V. Vaidehi "Abnormal Human Activity Recognition Using SVM Based Approach" ICRTIT-2012, IEEE.
[13] B. Hariharan, S. V. Vishwanathan, and M. Varma. Efficient max-margin multi-labelclassification with applications to zero-shot learning. Journal of Machine LearningResearch, 88(1-2):127–155, July 2012.
[14] M. Palatucci, D. Pomerleau, G. E. Hinton, and T. M. Mitchell. Zero-shot learning withsemantic output codes. In Proceedings of The Neural Information Processing Systems(NIPS), 2009.