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Deep Learning for Human Activity Recognition using on-Node Sensors

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Abstract: ***Due to advancement in technology, availability of resources and by increased utilization of on node sensors enormous amount of data is obtained. There is a necessity of analyzing and classifying this physiological information by efficient and effective approaches such as deep learning and artificial intelligence. Human Activity Recognition (HAR) is assuming a dominant role in sports, security, anti-crime, healthcare and also in environmental applications like wildlife observation etc. Most techniques work well for processing offline instead of real- time processing. There are few approaches which provide maximum accuracy for real time processing of large-scale data, one of the compromising approaches is deep learning. Limitation of resources is one of the causes to restrict the usage of deep learning for low power devices which can be worn on our body. Deep learning implementations are known to produce precise results for different computing systems.We suggest a deep learning approach in this paper which integrates features and data learned from inertial sensors with complementary knowledge obtained from a collection of shallow features which generates the possibility of performing real time activity classification accurately. Eliminating the obstructions caused by using deep learning methods for real-time analysis is the aim of this integrated design. Before passing the data into the deep learning framework, we perform spectral analysis to optimize the planned methodology for on-node computation. The accuracy obtained by combined approach is tested by utilizing datasets obtained from laboratory and real world controlled and uncontrolled environment. Our outcomes demonstrate the legitimacy of the methodology on various human action datasets, beating different techniques, including the two strategies utilized inside our consolidated pipeline. We additionally exhibit that our integrated design's classification times are reliable with on node real-time analysis criteria on smart phones and wearable technology.***

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I. INTRODUCTION

One of the components of machine learning involving algorithms impressed by the assembly and performance of human brain is Deep learning. In a broad range of applications, it is proven that the performance obtained by using deep learning is more when compared to other traditional approaches [1] [2] [3] [4].

A.Introduction to Human Activity Recognition (HAR)

HAR is the process involving identifying and predicting different movements of a person which depend on the time-series obtained from inertial sensors. Recognition can be done by exploiting the data recovered from different sources, for example, ecological [7] or body-worn sensors. Motion sensors on various body parts including the chest, waist, wrist, and thighs are used in a few methodologies which are accomplishing great characterization results. When the sensors are attached to humans, data is collected from these sensors and analyzed by making use of various advanced learning techniques to perform activity recognition and build different models. Applications ranging from security applications and support for logistics to location-based services can be found. In healthcare, in case of neurodegenerative diseases such as Parkinson's disease there is a possibility of using activity recognition to detect symptoms which are used for evaluating the person's condition [8]. This is also used for patients who are in rehabilitation centers for evaluating the recovery process [11].Smart phones are raising new research open doors for human-focused applications where the client is a rich wellspring of context data and the phone is the first-hand detecting device. Most recent gadgets accompany implanted implicit sensors, for example, microphones, accelerometers, dual cameras and gyroscopes. A productive alternate solution for HAR is the utilization of smart phones with in-built inertial sensors. At present, health monitoring devices such as fit bits, Apple watches, Microsoft bands and other smart phone apps and wearable sensors are used to collect data continuously. These gadgets contain sensors which are capable of anticipating or sensing the external environment, have prudent resources which are used to process and transfer the data, sensors may be worn on the body, carried in purse or pocket or home installation may be done. HAR can be used to interpret this physiological data substantially. The current commercial devices can only provide some information such as step count and cadence.

Current advanced methodologies like Deep learning are capable of extracting discriminating features which give rise to the scope of performing real time classification. Therefore, we have to combine features of wearable devices and the deep learning methods to achieve the ability to perform complex analysis.

B. Introduction to Feature Extraction and Data Analytics

Data Analytics is the study of investigating raw data to make inferences about that information. This is used in Science and Technology to confirm or invalidate existing models or hypotheses. Analyzing features and giving a conclusion about them is part of Data Analytics.For a long time, AI and activity recognition techn ologies have focussed on design and use of "shallow" featur es focused on activities conducted, for sensor-based identific ation of human movement. Study of time series uses shallow features such as statistical parameters to evaluate time series information and excerpt purposeful statistics and essential characteristics from the data. Highlights, for example, mean, Fourier changes, and images, are ordinarily extricated from portions of information and afterwards trained utilizing classification techniques. In any case, these strategies are as yet constrained to the specific classification undertakings that they were intended for. Deep Learnt Features are extricated automatically as opposed to being handmade, which allows the usage of these techniques for obtaining productive outcomes[5].In the Body Sensor Networks domain, feature extraction is becoming progressively significant [7] as sensors can create enormous amounts of information, which makes handcrafting a difficult task. The current commercial devices can only provide some information such as step count and cadence. Current advanced methodologies like Deep learning are able to extract discriminating features which give rise to the scope of performing real time classification. Therefore, we have to combine features of wearable devices and the deep learning methods to achieve the ability to perform complex analysis.

C. Introduction to Fastest Fourier Transform in the West

One of the software libraries readily available for the computation of Discrete Fourier Transform (DFT) is Fastest Fourier Transform in the West. This library is not confined to a particular machine or a particular problem. It uses a planner which is a program which applies the algorithms by checking the hardware of the device so that maximum efficiency is obtained. Every problem is considered as a loop with multi-dimensional DFTs. Recursion is followed on multi-dimensional loops. The problem is divided into smaller and simpler ones and solved recursively by the code generated by special purpose compilers. There are no limitations of length of subsets, rank of multidimensional transforms and capable of supporting DFTs for vectors consisting of three components [9].

D. Introduction to the Torch Framework

Torch Framework consists of software libraries in which most of the machine learning algorithms are implemented.
The general process is:

- Production of datasets
- Trainer to input information and to collect output and parameter optimizations to improve performance.

Models and algorithms such as AdaBoost, K- Nearest Neighbors (KNN), Baye's classifiers, Gaussian models, multilayer perceptrons, Support Vector Machines (SVM) and Markov models are implemented [10].

II. RELATED WORK

The main challenge faced for time series analysis while designing classification method is to select particular features for systematization [12], [13]. In some applications frequency related data and in others statistical parameters are used for classification of activity performed. Different techniques such as support vector machines and decision trees [14] are trained to perform segregation tasks by using "shallow features". Statistical parameters, symbolic representation [17], basis transform coding [6] are some of the "shallow features" that are capable of describing time series data. A method has been proposed which combines many classification methods to increase the accuracy and performance of the device.

Using methods such as Deep Belief Networks (DBN), Convolutional Neural Networks (CNN), Restricted Boltzmann Machines (RBM) and other deep learning methodologies, information regarding the features can be gained from the data captured by different inertial sensors [2]-[3]. Models consisting of many layers should be used in order to discover changes in orientation of sensors, placement of sensors etc. An attempt to classify data using RBMs and DBNs with multiple hidden layers has been made by Alsheikh *et al.* [4]. Hence, combination of advanced Deep learning and Hidden Markov Model (HMM) with three thousand neuron layers is finally used.

A. Some of the limitations of existing approaches

- No generalization: if some of the activities performed on a daily basis are not present in the dataset of the model then the accuracy is dropped. Also difference in the placement of sensor can cause confusion as the axes of the sensors may change.
- Not suitable for low resource consumption: Time and frequency related statistics are collected without any optimizations before the activity analysis.
- Requires generation of features that are hand-crafted.

The factors such as high computational power, thousands of neuron layers, huge amounts of data, bulkiness of used machines makes it unsuitable for devices which work on less power, which are mobile and which should be capable of performing real time classification. Deep learning methods for wearable and mobile devices uses spectrogram representation of the data obtained by inertial sensors. However, the results obtained in [1] might not subjugate the precision and accuracy which is provided by using shallow features. This might be because of less complexity of the design, limitation of resources in case of shallow features.
We have to exploit the recent advances in machine learning, in order to reduce above mentioned limitations. Therefore, instead of using only shallow features or deep learnt features we combine both of them to make the technology suitable for low power devices such as wearable devices.

III. METHODS

The features obtained for Human Activity Recognition are of three types:

- Hand-crafted features
- Frequency transformation features
- Deep features.

A. Feature Extraction and Classification by shallow features or Handcrafted features

Some researchers have proved that rather than using the handcrafted features known as shallow features individually, various learning algorithms can be aggregated in order to obtain greater classification accuracy. This accuracy is more but when compared to recent advanced machine learning algorithms, the performance might be less. For example, Zainudin et al. [13] and Catal et al. [15] combined decision trees, calculated relapse, regression and multilayer perceptron for HAR. Their outcomes demonstrate that combined learnings can significantly enhance the process of action classification.

B. Feature Extraction and classification by Deep Learning

The time series data gathered from the accelerometer and gy roscope is transmitted straight to the deep learning system, i n a conventional deep learning method for
the identification of human activity. This system involves implicit associations between pairs of input signals, such relations are usually ignored.
In fact, a variety of layers are built one on the other to constr uct set of features by trying to capture all potential signal per mutations with more nodes. Nonlinear transformation is performed by every single layer in the hidden framework on the outcome of its previous layer. Then the data collected as features are represented in a specified order which is from low level to high level. Non linearity isolates layers, and without them each layer will gather into one linear function and this will be same as a single layer network. Then the process of training and testing is done and the results are obtained.
The different deep learning frameworks which are available for HAR are

a) CNN template for accelerometer and gyrometric information, where each accelerometer data axis is fed through separate convolution layers, pooling layers, then concatenated prior to being analyzed by fully connected hidden layers.

b) DIVIDE AND CONQUER BASED CNN where behaviors are divided into two categories which are Static and dynamic. Activities requiring motion are known as dynamic and activities where the object is stationary are called static, the model segregates based on the two main classes.

c) RECURRENT NEURAL NETWORKS which figures out how to delineate window of sensor information to an action, where the perceptions in the information grouping are perused each in turn, where each time step may involve at least one factors. It predicts an action for each time step of sensor information, which are then combined so as to anticipate a movement for the window.

C. Classification by combining Shallow features and Deep Learning

Wong *et al*. [1], proved that deep learning features might be less discriminative than shallow features in some cases. Some of the possible reasons for this might be usage of deep learning methods consisting less neuron layers, as they cannot fully identify the characteristics for classification and another reason might be that deep learning features are completely dependent on data collected, therefore, if the data sets are not prepared correctly (i.e., change in sensor's location, amplitude, sampling rate) the accuracy and performance obtained will be further reduced. In these sequences of event, shallow features prove to be more effective. Consequently, we believe that information collected form shallow features and deep learning approaches are complementary which can perhaps be jointly used for classification in HAR.

In the proposed framework we mainly use combination of these features.

The process of combining these shallow and deep learnt features is done using three steps as demonstrated in Fig. 1. Obtaining data from inertial sensors is the fundamental step. The two main inertial sensors are Accelerometer and Gyroscope. The second step is extracting information to form segments which are to be utilized along process A and process B, where deep learnt features and shallow features are estimated and parallelly calculated. Then in the third step both the features are combined to form fully connected layers which are finally reduced to form soft-max layer which gives the potential outcome with maximum probability. The illustrative representation of the proposed model is given below.

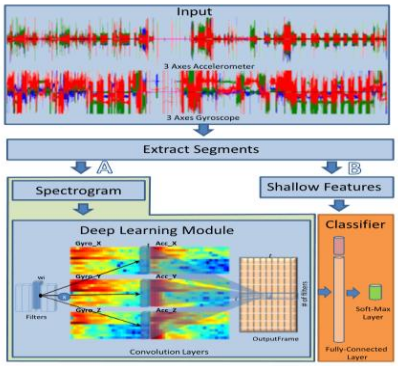

Fig. 1. Illustrative work of proposed strategy :Input data is collected from the inertial sensors, shallow and learnt features are separately extracted and combined by fully connected layer.

a) INPUT

Over the last decade several inertial sensor approaches have been put forward that address most of the limitations. Advancement in micro-electro-mechanical sensors, durability, reliability and orientation estimation algorithms are gradually leading to increase in the usage of inertial sensors in motion capture applications. These sensors are based on inertia and other measuring principles. The two main inertial sensors are accelerometers and gyroscopes. Accelerometers are electromechanical gadgets capable of measuring static and dynamic forces of acceleration. Gyroscope is used for measurement of orientation and its rate of change.

Deployment of sensors can be done in two ways.

1) In multi-sensor packages like Body Sensor Networks and triaxial accelerometers.
2) Paired with alternative sensors like accelerometers, gyroscopes, blood pressure and temperature sensors.

In the first approach of using only accelerometers, the number of body sensors and their placement was becoming an obtrusive defect. Gyroscopes are also used individually, but when paired with accelerometers as in second approach, the activity recognition performance obtained is enhanced. One of the HAR frameworks for utilizing biaxial accelerometers and machine learning classifiers for acknowledgment of 20 exercises of day to day living, has been proposed. The performance accuracy is nearly 84%, depending on the activities to be classified. The Frequency of gravitational forces is assumed to be low, nearly 0.3 Hz.

b) SEGMENT EXTRACTION

After collection of input signals, segments containing 'n' samples are extracted using a window which is applied individually to axis of 3 axes accelerometer and 3 axes gyroscope. Segments of 4 to 10s are used in Human Activity Recognition [4]. If we increase the length of segments, it results in a better recognition accuracy but it also increases the response time which is not suitable for performing real time activity analysis as the boundary between different activities becomes less specified. Therefore, the number of segments we use depends on the application, whether we are using it in mobile application or in wearable devices.

c) DEEP LEARNING MODULE AND SPECTROGRAM

Along the process A in Fig. 1, we use a spectrogram representation of the inertial data.This is important if interpretable characteristics are to b e extracted which captures intensity differences between the closest inertial points. The representation of spectrogram shows the changes in signal amplitude and sampling rate, as the sensor keeps moving. Spectrogram represents a signal as a function of frequency and time which is the magnitude of Short Time Fourier Transform. A long signal is broken into small parts, and then we separately compute Fourier transform and then we compute the magnitude which results in formation of spectrogram. The individual signals are represented as

$$\mathrm{STFT}\{x[n]\}(m,\omega) = X(m,\omega) = \sum_{n=-\infty}^{\infty} x[n]\omega[n-m]e^{-j\omega n}$$

Here, *x[n]* is the signal and *w[n]* is the window. The total magnitude is given by

$$\mathrm{spectrogram}\{x(n)\}(m,\omega) = |X(m,\omega)|^2.$$

We obtain a matrix of the form st x sf where st is the time-localized points and sf represents frequencies.

Algorithm1: Proposed Algorithm

Input:

x-Acc, y-Acc, z-Acc	Raw Triaxial Acceleration information
x-Gyr, y-Gyr, z-Gyr	Raw Triaxial Gyroscopic information
kw	ID Convolution Kernel Size
sf	Number of frequency points in Spectrogram
st	Number of time-localized points in Spectrogram
dw	Step of the convolution
wp	Number of Filters
n	Number of samples in each segment

Output:

Result label

1: Segment Extraction
2: a[1], a[2], a[3] <- segm(x-Acc,n), segm(y-Acc,n), segm(z-Acc,n);
3: g[1], g[2], g[3] <- segm(x-Gyr,n), segm(y-Gyr,n), segm(z-Gyr,n);
4: Extract Shallow Features
5: s <- **Extract_shallow_Features (a[1], a[2], a[3], g[1], g[2], g[3]);**
6: Extract Learnt Features
7: S_a[1], S_a[2], S_a[3] <-Spectrogram(a[1]), Spectrogram(a[2]), Spectrogram(a[3]);
8: S_g[1], S_g[2], S_g[3] <-Spectrogram(g[1]), Spectrogram(g[2]), Spectrogram(g[3]);
9: for i=1 to wp:
10: **for** t=1 to sf:
11: **for** z=1 to 3:
12: $o[t][i] \mathrel{+}= \sum_{j=1}^{st}\sum_{k=1}^{kw} w[i][j][k] * S\_g[z][j][dw*(t-1)+k];$
13: $o[t+sf][i] \mathrel{+}= \sum_{j=1}^{st}\sum_{k=1}^{kw} w[i][j][k] * S\_a[z][j][dw*(t-1)+k];$
14: **end for**
15: **end for**
16: end for
17: Combine Features
18: Cb <-**Combine (s,o);**
19: Classification
20: Fc <-**Fully_connected(cb);**
21: Result <-**Soft max(fc);**

Fig. 2. Proposed Algorithm for our approach

The activities which involve more and different movement of the sensors produce higher spectrogram values, then the activities which have repetitive activities like walking and running. After the spectrogram is computed, we send it as an input to our deep learning module where hierarchies of characteristics are used to perform on-node classification. Spectrograms for different activities as shown in Fig.2.

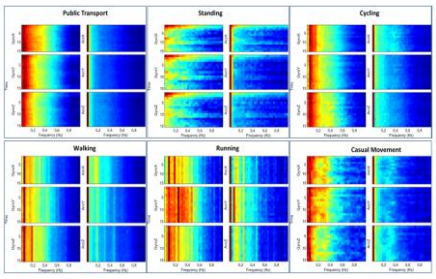

Fig. 3. Examples of spectrograms obtained as different patterns for class recognition and extraction of features.

But our design is built in such a way that it overcomes the issues of regular deep learning framework, so that it is suitable for devices which require less power. In this method, we only use a few hidden layers to obtain the outcome and to cut down the computation charges. The spectral data along different axes are fed into 1-D Convolutional kernels and using the same principle that is followed in CNN [16]. Each activity has different set of frequencies, so the sum of local 1-D convolutions over the predetermined input is performed for each individual frequency. Spectrogram of different sensors is grouped along column wise and spectrogram of x, y, z axes are grouped along the rows. Calculation of the weighted sum is done by the formula represented below.

$$o[t][i] = \sum_{j=1}^{st}\sum_{k=1}^{kw} w[i][j][k] * \mathbf{input}[j][dw*(t-1)+k]$$

Therefore, we obtain the output layer o[t][i]. Here, w[i] represent the filters which are applied on the spectrogram vertically.

As we compute the convolution of different axes with different layers, we combine them at last without any discrimination to maintain the properties. So, each filter applied along each axis share same weights for making the computation easier.

d) SHALLOW FEATURES

In Fig. 1 shallow features are utilized along the process B. These include various statistical parameters like mean, median and variance. We take six input segments 3 axes information of accelerometer and gyroscope. A final vector is obtained as output which consists of 102 features

TABLE I
SHALLOW FEATURES EXTRACTED FROM PROPOSED APPROACH

Input Data	Features
Raw signal	Interquartile Range, Amplitude, Kurtosis, Root Mean Square, Variance, Standard Deviation, Mean-cross, Zero-cross, Mean, Median, Mode Skewness
First Derivate	Root Mean Square, Variance, Mean Standard Deviation

IV. CLASSIFICATION

After shallow and deep learning features are separately computed they are merged together, primarily to form a fully connected layer and then a soft max layer. In deep learning, the term logits layer is prominently utilized for the last neuron layer of neural system for distinguishing task which produces raw expectation esteems as real numbers going from [-infinity, +infinity]. As shown in lines 20 and 21 of Fig.1, Soft-max method transforms numbers otherwise known as logits into probabilities that aggregate to one. Soft max method yields a vector that shows probability distribution of potential results.

V. TRAINING PROCESS

70% of the data collected is used for training the model. The model is trained by using deep neural networks. For renewal of the weights of various layers we use the error values which are obtained from the target values and obtained values. Stochastic gradient descent (SGD) is employed to decrease the different abnormalities in the results. To improvise the training procedure, we use three different approaches:

Weight decay

It is a technique used to regularize the overfitting of hidden layers. If there is no further update, according to the weight update rule, the weights are exponentially decreased to zero.

Momentum

It is a component used for stimulating Stochastic gradient descent (SGD). It assembles a velocity vector in the direction where there is constant decline in the objective during iterations.

Dropout

It is a process which combines different neural networks architectures in an efficient way and also prevents overfitting. In each iteration of training process, one node is dropped along with its connections and which node is to be dropped is random and determined by the probability of the retaining node. Generalization value is depreciated by training the neural network without dropouts.

VI. EXPERIMENTAL RESULTS

A. Datasets

For evaluating our model, we use data obtained from real world based on five public datasets which uses tenfold cross validation. This data has been collected from ten subjects with their smart phones through applications which are built for this purpose. This dataset is independent of the placement of smart phone. Table 2 shows the datasets, their descriptions and statistics. The final dataset has different sampling rates and amplitude range as the sensors vary from one phone to other.

TABLE II
SYNOPSIS OF HUMAN ACTIVITY DATASETS

Dataset	Description	# of classes	Subjects	Samples	Sampling Rate
Active-Miles	Daily activities collected in uncontrolled environment	7	10	4,390,726	50-200 Hz
WISDM v1.1	Daily activities collected in a laboratory	6	29	1,098,207	20 Hz
WISDM v2.0	Daily activities collected in uncontrolled environment	6	563	2,980,765	20 Hz
Daphnet FoG	Freezing of gait in Parkinson's patients	2	10	1,917,887	64 Hz
Skoda	Manipulative gestures performed in a car	10	1	701,440	98 Hz

B. Parameters Optimizations

An optimization process is performed on the final model and a few parameters are evaluated to find best results of the following.

- Size of convolutional kernels
- Probability of retaining the node during dropout
- Total number of filters in each convolutional layer
- Total number of convolutional layers.

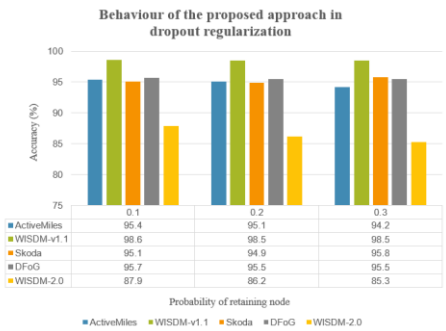

Fig. 4. Behaviour obtained by increasing the probability of retaining a node

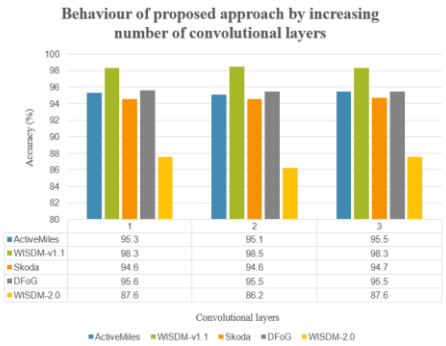

Fig. 5. Behavior obtained by increasing number of Convolutional levels

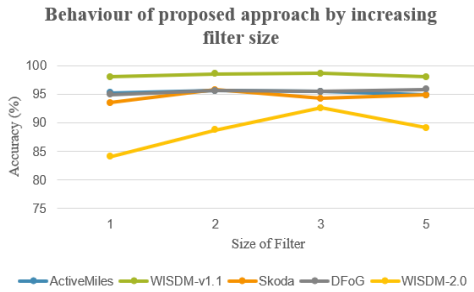

Fig. 6. Behavior obtained by increasing the size of filters.

Fig. 4, 5 and 6 show the behavior of the proposed framework. Presence of more classes causes great variability, which reduces the performance of the framework by escalating the likelihood of reserving the node at the time of dropout. Therefore, we opt for less classes and high probability to obtain better results as shown in Fig. 4

From Fig. 5, We infer that increasing the levels does not cause any substantial improvement, so we conclude that few levels are enough to completely know about the learnt and shallow features.

Fig. 6, shows that most favourable filter size can be 2 or 3 depending on the complexity of the dataset. The optimal experimental values are 80 neuron nodes and 32 filters in every individual convolution layer. The filter size is obscurely dependent on number of filters, so modifications can be made if there are limitations of resources.

C. Implementation

The fundamental purpose of the proposed framework is to perform human activity recognition on low power devices by combining deep learnt features with shallow features. This proposed framework is implemented on different low power platforms. It is trained on 2x Intel Xeon E5-2680v2 CPU, 64GB DDR3 RAM and then exported to different platforms.

Fig. 7(a): Main view of the application ActiveMiles. (b): The percentage of various activities performed in a day. (c): Histogram representation of METS.

TABLE III
COMPARISION OF PROPOSED MODEL WITH EXISTING METHODS IN DIFFERENT DATASET

Approach	Shallow Features	Deep Features	ActiveMiles Accuracy(%)	WISDM v1.1 Accuracy(%)	WISDM v2.0 Accuracy(%)	Skoda Accuracy(%)	Daphnet FoG Accuracy(%)
Shallow-features	Yes	No	95.0	97.4	92.5	95.9	95.8
Catal *et al.*	Yes	No	91.7	94.3	89.8	86.9	94.8
Alsheikh *et al.*	No	Yes	84.5	98.2	82.9	89.4	91.5
Ravi *et al.*	No	Yes	95.1	98.2	88.5	91.7	95.7
Ours	Yes	Yes	95.7	98.6	92.7	95.3	95.8

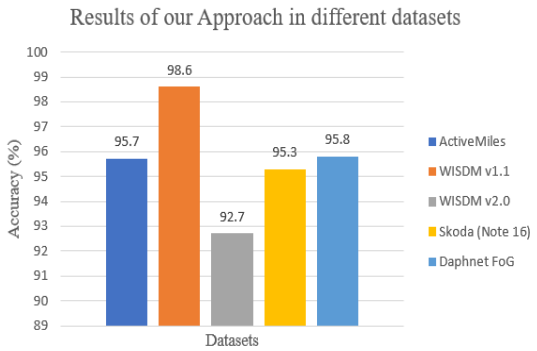

Fig. 8.Accuracy values of the combined approach

Mobile application "Active-Miles" uses the proposed framework for activity recognition. This app provides information on calories burnt, percentage of activities performed and also provides assessment of a biological parameter METS that expresses standard physical activity levels. To demonstrate on-node activity recognition, the proposed framework is implemented on Intel Edison. To implement deep learning model and extracting spectrogram we make use of FFTW3 library [9] and Torch Framework [10].

D. Classification Results

To illustrate the quality and accuracy of our model, we compared different approaches of Human Activity Recognition (HAR) in table III. The first approach is based solely on the shallow features that correlate with our combined pipeline system A. [1],[4] are purely dependent on deep learnt features which coincides with process B of our combined pipeline. From the above statistics, it is clear that by using only shallow features we obtain only 4 to 4.2% greater accuracy than deep learning approaches and also accuracy of deep learning approaches is only 0.1 to 0.8% greater than our model applied to Active-Miles app. Therefore, by combining statistical parameters as shallow features and deep learning features, we overcome the drawbacks and exploit the generalizable solution.

Precision

The extent of positive descriptions of data which are really correct. It is a measure of positive predictive statistics.

$$Precision = \frac{true\ positives}{true\ positives + false\ positives}$$

Recall

The extent of genuine positives which are recognized correctly. It is a measure of sensitivity.

$$Recall = \frac{true\ positives}{true\ positives + false\ negatives}$$

TABLE IV
PRECISION AND RECALL VALUES IN ALL DATASETS

WISDM v1.1						
	Walking	Jogging	Sitting	Standing	Upstairs	Downstairs
Prec. (%)	99.37	99.64	97.85	98.15	95.52	94.44
Recall (%)	99.37	99.40	98.56	97.25	95.13	95.90

WISDM v2.0						
	Walking	Jogging	Stairs	Sitting	Standing	Lying Down
Prec. (%)	97.17	98.01	85.00	87.32	82.05	88.65
Recall (%)	97.19	97.73	76.98	89.28	82.11	85.80

Skoda					
	Write on notepad	Open Hood	Close Hood	Check Gaps Front door	Open Left Front door
Prec. (%)	96.67	97.78	89.47	91.15	100.00
Recall (%)	91.34	97.78	94.44	92.79	100.00

	Close Left Front door	Close both Left door	Check trunk gaps	Open and Close trunk	Check Steering wheel
Prec. (%)	88.89	92.86	98.78	100.00	93.55
Recall (%)	80.00	94.20	97.59	98.04	100.00

Daphnet FoG		
	No Freeze	Freeze
Prec. (%)	97.40	67.89
Recall (%)	98.15	59.92

The precision and recall values for different classes or probable outcomes by using the proposed model are demonstrated in table IV. For most of the classes the recall is above 85%. Daphnet FoG is used to detect events of freezing of gait. Therefore, it consists two classes freeze and no freeze. The capability to achieve real time performance of our proposed model on a smart phone or wearable low power devices is tested and it depends on the computational time required for the classification. The computational time is calculated for Intel Edison, Samsung Galaxy and LG Nexus 5 smart phone by exporting the proposed framework onto the above devices. 53.8, 125.2 and 198.8ms are the obtained results. The computational cost is also low which further increases the efficiency to perform real time activity classification.

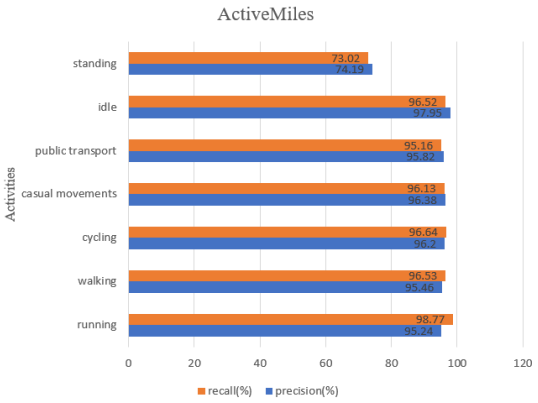

Fig. 9. Recall and Precision values of ActiveMiles application based on our approach

VII. CONCLUSION

The model suggested would resolve the abnormalities produced by individual usage of shallow features and learnt features when real time estimation is required. The model is capable of generalizing a range of datasets collected inan uncontrolled environment in the real world. The classification accuracy obtained is more, the computational cost is less and efficiency is more even when resource limitation exists. This shows that proposed algorithm is convenient for on-node HAR in real-time applications.

REFERENCES

1. D. Ravi, C. Wong, B. Lo, and G.-Z. Yang, "Deep learning for human activity recognition: A resource efficient implementation on low-power devices," in Proc. 2016 IEEE 13th Int. Conf. Wearable Implantable Body Sensor Netw., Jun. 2016, pp. 71–76.
2. M. Zeng et al., "Convolutional neural networks for human activity recognition using mobile sensors," in Proc. 2014 6th Int. Conf. Mobile Comput., Appl. Services, Nov. 2014, pp. 197–205. [Online]. Available: http://dx.doi.org/10.4108/icst.mobicase.2014.257786
3. Y. Chen and Y. Xue, "A deep learning approach to human activity recognition based on single accelerometer," in Proc. 2015 IEEE Int. Conf. Syst., Man, Cybern., Oct. 2015, pp. 1488–1492. [Online]. Available:
4. http://dx.doi.org/10.1109/smc.2015.263
5. M. A. Alsheikh, A. Selim, D. Niyato, L. Doyle, S. Lin, and H.-P. Tan, "Deep activity recognition models with triaxial accelerometers," Nov. 2015. [Online]. Available: http://arxiv.org/abs/1511.04664
6. M. Zeng, L. T. Nguyen, B. Yu, O. J. Mengshoel, J. Zhu, P. Wu, and J. Zhang, "Convolutional Neural Networks for human activity recognition using mobile sensors," in Mobile Computing, Applications and Services (MobiCASE), 2014 6th International Conference on. IEEE, Nov. 2014, pp. 197–205.
7. T. Huynh and B. Schiele, "Analyzing features for activity recognition," in Proc. 2005 Joint Conf. Smart Objects Ambient Intell.: Innovative ContextAware Services: Usages Technol., 2005, pp. 159–163. [Online]. Available: http://dx.doi.org/10.1145/1107548.1107591
8. G.-Z. Yang, Body Sensor Networks, 2nd ed. New York, NY, USA:
9. Springer, 2014.
10. P. Angeles, M. Mace, M. Admiraal, E. Burdet, N. Pavese, and R. Vaidyanathan, A Wearable Automated System to Quantify Parkinsonian Symptoms Enabling Closed Loop Deep Brain Stimulation. Cham, Switzerland: Springer, 2016, pp. 8–19. [Online]. Available: http://dx.doi.org/10.1007/978-3-319-40379-3_2
11. LM. Frigo and S. G. Johnson, "The design and implementation of fftw3," Proc. IEEE, vol. 93, no. 2, pp. 216–231, Feb. 2005.
12. F.R. Collobert, S. Bengio, and J. Mariethoz, "Torch: A modular machine´ learning software library," IDIAP, Martigny, Switzerland, Tech. Rep. EPFL-REPORT-82802, 2002.
13. K.-H. Chen, P.-C. Chen, K.-C. Liu, and C.-T. Chan, "Wearable sensor-based rehabilitation exercise assessment for knee osteoarthritis," Sensors, vol. 15, no. 2, pp. 4193–4211, 2015. [Online]. Available: http://www.mdpi.com/1424-8220/15/2/4193
14. M.Shoaib,S.Bosch,O.D.Incel,H.Scholten,andP.J.Havinga,
15. "AsurveyofonlineactivityrecognitionusingmobilephonesSensors",vol.15,no.1, pp. 2059–2085, 2015. [Online]. Available: http://www.mdpi.com/14248220/15/1/2059
16. M. N. S. Zainudin, M. N. Sulaiman, N. Mustapha, and T. Perumal, "Activity recognition based on accelerometer sensor using combinational classifiers," in Open Systems (ICOS), 2015 IEEE Confernece on. IEEE, Aug. 2015, pp. 68–73.
17. K. H. Walse, R. V. Dharaskar, and V. M. Thakare, "A study of human activity recognition using AdaBoost classifiers on WISDM dataset," Inst. Integrative Omics Appl. Biotechnol. J., vol. 7, no. 2, pp. 68–76, Jan. 2016.
18. C. Catal, S. Tufekci, E. Pirmit, and G. Kocabag, "On the use of ensemble of classifiers for accelerometer-based activity recognition," Appl. Soft Comput., vol. 37, pp. 1018–1022, Dec. 2015. [Online]. Available: http://dx.doi.org/10.1016/j.asoc.2015.01.025
19. Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," Proc. IEEE, vol. 86, no. 11, pp. 2278– 2324, Nov. 1998.
20. J.Lin,E.Keogh, S.Lonardi, and B.Chiu, "A symbolic representation of time serie, with implications for streaming algorithms," in Proc. 8th ACM SIGMOD Workshop Res. Issue Data Mining Knowl. Discovery, 2003, pp. 2-11[online].

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