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Revolutionizing human activity recognition with prophet algorithm and deep learning

Jaykumar S. Dhage[1], Avinash K. Gulve[2]
[1]Department of Computer Science and Engineering, Dr. Babasaheb Ambedkar Marathwada University, Aurangabad, India
[2]Department of Computer Science and Application, Government College of Engineering, Aurangabad, India

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ABSTRACT

Various industries, such as healthcare and surveillance, depend heavily on the ability to recognize human activity. The "human activity recognition (HAR) using smartphones data set" can be found in the UCI online repository and includes accelerometer and gyroscope readings recorded during a variety of human activities. The accelerometer and gyroscope signals are also subjected to a band-pass filter to eliminate unwanted frequencies and background noise. This method effectively decreases the dimensionality of the feature space while improving the model's accuracy and efficiency. "Convolutional neural networks (CNNs)" and "long short-term memory (LSTM)" networks are combined to create pyramidal dilated convolutional memory network (PDCMN), which is the final proposal. Results from experiments demonstrate the effectiveness and reliability of the suggested method, demonstrating its potential for precise and effective HAR in actuality schemes.

Corresponding Author:

Avinash K. Gulve
Department of Computer Science and Application, Government College of Engineering
Aurangabad, India
Email: akgulve@gmail.com

1. INTRODUCTION

Today, human activity detection and recognition is a unique domain of research. Detecting individual activities now a day is very easy [1], [2]. Almost every person has owned a smart phone today [3]. A variety of sensors available in the smart phone makes it possible to detect the human activity in an accurate way [4], [5]. The components like accelerometer, gyroscope, microphone and camera available in the smart phone are useful to extract the required outcome for recognizing the activity [6], [7]. These devices are low cost and take less energy to work. Human activity recognition (HAR) has a vast scope as far as the applications are concerned, like healthcare, social networks, safety, detection of suspicious activities, transportation and surveillance systems [8], [9]. It is also used in recognizing the difference between the younger and older people activities [10], [11]. The artificial intelligence (AI) and IoT are helping HAR in a better way [12]. Because of these new components, the HAR is not only becoming more complex but also it is becoming the most interesting and open topic for the researchers [13]-[15]. The various machine learning (ML) approaches are used to extract the exact information and to reach at the conclusion [16]-[18].

In order to check the research in HAR, it is necessary to study the various approaches used in the past [19]-[21]. Muralidharan *et al.* [21] gives detailed information about the one-dimensional (1D) convolutional neural network (CNN) approach. The different ML approaches were implemented as a part of the HAR in this research work. 1D convolution approach proposed in the paper gives a validation accuracy of 96.13%. All the algorithms were implemented on the standard UCI dataset. The one-dimensional (1D) convolution approach is used with the data enhancement strategy after undergoing training, as suggested in article [22]. With this approach, the accuracy was increased and the factors like delay, computational complexity were reduced. Here, the numbers of false positive were also reduced. Kiranyaz *et al.* [23] has provided good information about CNN and its overall working. The authors have considered engineering applications with recent advancements. 1-D convolution is perfect to train and even with minimum computational complexity, it gives considerable accuracy in various applications. Three activity labels such as LAYING, SITTING, AND STANDING were considered from HAR dataset use by Minarno *et al.* [24]. They have implemented all the previously mentioned algorithms along with a new approach as a gradient boost. The logistic regression (LR) model, support vector machine (SVM), and linear kernel model have all been compared by the authors. The maximum accuracy reported by SVM with radial basis function (RBF) kernel model is 98.96%. Chen *et al.* [1] uses a graphics processing unit (GPU) framework. It employs a 1-D convolution to convert since the time domain to the frequency field. The dataset is Music-Net. It can perform spectrogram extraction. 34 spectrogram types with various parameters may be extracted in 2.8 hours. Zhang *et al.* [25] operated a typical 8-layer CNN, with batch normalization and dropout. By merging "two-layer graph convolutional network (GCN)", the "BDR-CNN-GCN" is created. Lee *et al.* [4] proposes a 1-D convolution for the classification of activities recognized by the model. In that model three activities namely run, walk, and still are implemented. The accuracy achieved with this algorithm is 92.71%. In the proposed work, apart from various ML algorithms such as LR, SVM, random forest (RF), decision tree (DT), neural network (NN), the deep learning approaches are also implemented. A new dataset is created with the help of an sensor app and then all the deep learning approaches are implemented. The prophet algorithms with the combination of TDL and long short-term memory (LSTM) are giving good results as compared to all other algorithms.

This study investigated the effectiveness of advanced deep learning algorithms for HAR using smartphone sensor data. While earlier studies have explored the impact of traditional ML techniques such as LR, SVM, DT, and RF on HAR, they have not explicitly addressed the potential of deep learning models to handle complex temporal patterns and large-scale datasets effectively. Furthermore, prior research often relied on limited datasets with constrained activity labels, lacking diversity and real-world applicability. This study aims to bridge these gaps by introducing robust deep learning models, TDL-LSTM and LSTM-TDL, trained on a comprehensive dataset with six activity labels, and evaluating their performance under real-world conditions.

We found that the proposed deep learning models, TDL-LSTM and LSTM-TDL, significantly outperformed traditional ML methods in HAR, achieving accuracies of 98.49% and 98.09%, respectively. The results indicated that these models effectively captured complex temporal patterns and subtle variations in the data. The TDL-LSTM model demonstrated a notably higher precision and recall for activities like "walking" and "standing" compared to other methods, suggesting its robustness in recognizing dynamic and static activities. These findings underscore the ability of deep learning architectures to process large-scale datasets and deliver superior performance in HAR tasks.

2. GENERAL ARCHITECTURE/PROCEDURE

Figure 1 shows the process flow for the HAR is given. To collect the data for the above flow, an app is developed. The data is collected from it. A smartphone Redmi Note 9 pro is used for the data collection. There are six labels available, and each person has a smartphone. Three-axial linear acceleration and three-axial angular velocity were recorded with the assistance of the built-in accelerometer and gyroscope. There are six activity labels. All the results are video-recorded to get the labels. The dataset formed through the experiment samples are split into two sets, where one set with 70% of samples is used as the training data and 30% as the test data. The preprocessing of sensor signals is done by applying filters. Then, they are sampled with sliding windows that overlap by 50% and last 2.56 seconds. Feature vectors are generated from each time window by calculating metrics across two domains: triaxial acceleration, which accounts for body acceleration, and triaxial angular velocity. This process yields a total of 561 attributes for analysis. The data is categorized into six specific activity labels: 0 represents laying, 1 corresponds to sitting, 2 indicates standing, 3 is for walking, 4 denotes walking downstairs, and 5 is for walking upstairs. Furthermore, each feature vector is tagged with an identifier to specify the subject.

Pre-processing: it purposes to raise the data's quality so that everyone can analyze it more effectively. In this research work, sliding window segmentation is used to break up the continuous sensor data into shorter time windows or chunks of a set length. Band-pass filter is used to filter the accelerometer and gyroscope signals to eliminate unwanted frequencies and noise. Min-max scaling is used to normalize the signals and place them within a predetermined range for consistent comparison and analysis. Band pass filter: it keeps the reduce extent band of frequencies by eliminate the very low frequency and very high frequency part. Edges are improved while noise is also diminished using band pass filtering.

Figure 1. Architectural diagram

Min max scaling: this simple normalization method yields the common numerical range of the scores $[0, 1]$ while also maintaining the original distribution shapes with the exception of a scaling factor. Let C stand for a group of raw match results out of a certain matcher. Then, c' represents the adjusted score of c. Assuming that $max(C)$ and $min(C)$ represent the utmost and minimum standards for the raw matching scores. The "normalized score" is then considered in (1).

$$c' = (c - min(C))/max(C) - min(C) \tag{1}$$

Due to its high susceptibility to outliers in the estimation data, this method is not robust. Due to the existence of outliers, the majority of the data is concentrated only within a smaller range.

Feature extraction: it helps to take out the best feature from those enormous data sets by pick and combining variables into traits. In this research work, statistical features, correlation analysis, and PSD are used to extract the features.

Statistical feature: the technique of clustering and evaluating data for the goal of determine originals and trends is known as statistical analysis. It is an approach for eradicate bias from data valuation by means of numerical review. This approach is profitable for assemblage research interpretations, set up statistical models, and planning investigations and research. In (2) and (3) designate the mathematical model of mean and standard deviation.

Mean,

$$\mu = \sum_{i=0}^{a-1} ipr(i) \tag{2}$$

Standard deviation,

$$\sigma_j = \sqrt{\frac{1}{A}\sum_{A}^{i=1} \left(P_{ji} - A_j\right)^2} \tag{3}$$

Minimum: the minimum number in our set of data is the data value that is less than or capable of all other values. If all of our data were arranged in increasing order of importance, the lowest number on our list would be it. The minimum value may occur more than once in the data set, but it is still a exceptional number by definition. There able be two minima since only one of these values can be greater than the other.

Maximum: the value that exceeds or is on a par with every other value in the set of data is considered to be its maximum value. If all of our data were arranged in ascending order, the highest number would be the last one listed. The greatest is a single number for a particular set of facts. For a data set, there is only one maximum, but this number may be repeated. There can never be two maxima since there would always be one value that is greater than the other.

Skewness: describes the unevenness or distortion present in a statistical distribution. This occurs when data points don't spread out symmetrically on either side of the median in what would typically be a bell-shaped curve. When the bell curve leans to one side-either left or right-it signals that the distribution is unbalanced. In (4) represents the mathematical equation of skewness.

$$\mu_3 = \sigma^{-3} \sum_{i=0}^{a-1} (i - \mu)^3 pr(i) \tag{4}$$

Kurtosis: is a measurement of the outlier nature of a real-valued random variable's probability distribution. In (5) represents the mathematical equation of kurtosis.

$$\mu_4 = \sigma^{-4} \sum_{i=0}^{a-1} (i - \mu)^4 pr(i) - 3 \tag{5}$$

Energy: is also referred to as the uniformity or angular second moment. In (6) represents the mathematical equation of energy.

$$E = \sum_{i=0}^{a-1} \quad [pr(i)]^2 \tag{6}$$

The method section given below outlines the systematic approach used to develop and evaluate advanced deep learning models for HAR. Data were collected using a smartphone application that recorded accelerometer and gyroscope readings during six predefined activities: laying, sitting, standing, walking, walking downstairs, and walking upstairs. Preprocessing included sliding window segmentation, band-pass filtering to remove noise, and min-max scaling for normalization, resulting in 561 feature attributes per window. Statistical feature extraction techniques, such as mean, standard deviation, skewness, and kurtosis, were applied to enhance data representation. Two deep learning models, TDL-LSTM and LSTM-TDL, were trained on a 70-30 train-test split using the Keras framework. Their performance was compared against traditional ML models using metrics like accuracy, precision, recall, and F1-score to validate their effectiveness.

3. PROPOSED METHOD

The proposed methodology of prophet algorithm is shown in Figure 2. For the data in the time range like stock prices and video frames, LSTM is the perfect approach. LSTM selectively remembers the patterns for long durations of time. It has both the options like, keeping the things in memory for short or long duration of time. It is an improvement over recurrent neural network (RNN). In LSTM, there are cell states with different dependencies. Here, they do not manipulate the entire information but they modify them slightly. LSTMs are essential in sequence classification because they can effectively learn patterns directly from raw time series data. This eliminates the need for manual feature engineering, allowing the model to perform well without relying on domain-specific expertise. It achieves equivalent speed and can quickly internalize a time series data format. To adopt each input before or after this LSTM layer, time distributed layer approach can be very useful. Keras provides a nice solution for the data where frame by frame activities, consecutive and sequential actions are available. It is named as “time distributed” layer. So, with this layer and with the LSTM, this model can provide very accurate results, provided that the fine synchronization is achieved.

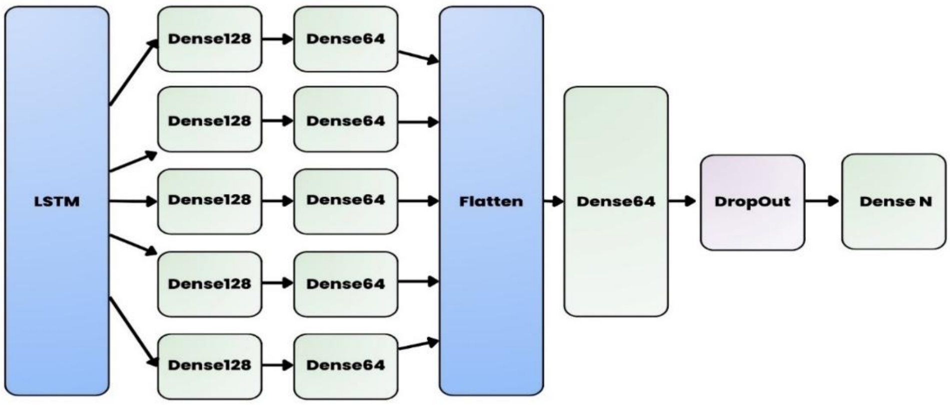

Figure 2. Prophet algorithm (LSTM-TDM/TDM-LSTM)

Time distributed layer work with several inputs. It produces one output per input to get the result in time. In HAR, it is required to check an object in motion. So, before detecting the movement, searching the object is more important. That is why, in this model, it needs to make convolutions before LSTM. Time distributed layer is very strong in the sense that, irrespective of its position with LSTM, the effect on the data will be same. Only one model can do the work. Keras is used to make movement prediction and recognition.

LSTM: RNN architectures with LSTM can handle sequential data with long-distance dependencies. LSTMs incorporate memory cells and specialized gating mechanisms, in contrast to conventional RNNs. As a result, the network can electively remember or forget information eventually, effectively capturing and preserving significant temporal patterns. These gates control the flow of information within the network.

LSTM has demonstrated success in a category of tasks, as well as speech recognition, language translation, and sentiment analysis, where it is essential to comprehend and model sequential data.

Fully connected layer: the dense layer, often referred to as the fully connected layer in NNs, plays a key role in the architecture. It forms a web of connections by linking each neuron in the current layer to every neuron in the previous layer, resulting in a fully interconnected structure. This design ensures that information flows seamlessly across the network, facilitating complex pattern recognition. SoftMax layer: the output of the fully connected layer is to be categorized by this layer.

CNN: deep neural networks with a known grid-like topology are known as CNNs. CNNs are designed for data with this type of topology. These networks use the convolution operation, as their name suggests. Due to their capacity to occupy the topology of illustrations, CNNs is widely used in image recognition. Then, as a result of its improvements with images, CNNs is used in other domains, such as hand gesture identification and HAR. The CNN architecture consists of multiple layers: input, convolution, pulling, output, and fully connected. Figure 3 depicts a CNN architecture consisting of an input layer, convolution, a pooling layer, two fully linked layers, and an output layer. The convolution layer generates feature maps from input data or output from the prior level by multiplying filters, input data, or output from the preceding layer element-by-element. Each feature map is subjected to a pooling layer after the convolution layer, which reduces the amount of CNN computation needed by downscaling the spatial size. All of the nodes in the fully connected layers are connected to every other node in the layer below, just like in FFNN. The output layer subsequently uses activation functions to get the outputs; “SoftMax” is a common activation function for classification problems. The weights in the fully connected layers and learnable filters in the convolutional layers are changed using optimization techniques like gradient descent and a backpropagation approach once the error has been calculated.

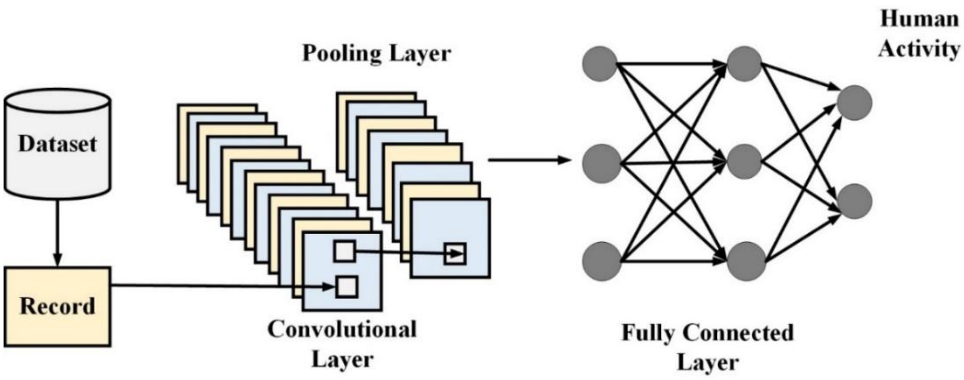

Figure 3. CNN architecture

The fundamental LSTM unit, which consists of a cell with an input, output, and forget gate, is shown in Figure 4. The concept of gating is used by LSTMs to address the exploding gradient problem. Each of the three gates can be thought of as a traditional artificial neuron, calculating an activation of a weighted sum of the “hidden state” g_(j-1) from the previous time step, any bias bi, and the current data k_j. Remembering values across unpredictable time periods is the cell's responsibility. The flow of values across the LSTM connections can be thought of as being controlled by the gates. At each time step, they determine which of the following operations the cell will perform. z_e is the weights connected to each multiplication at gate e in (7) to (12), and $tang$ are potential choices for activation functions. The input gate in Figure 4 regulates how much of a unfamiliar value flow into the cell during a write operation in (7).

$$e_j = \sigma\left(z_e\left[g_{j-1}, k_j\right] + bi_e\right) \tag{7}$$

Similar work is done by the forget gate, which regulates how much of the current cell value is retained while performing a reset:

$$l_j = \sigma\left(z_l\left[g_{j-1}, k_j\right] bi_l\right) \tag{8}$$

The potential memory cell is updated in a manner similar to (9).

$$\tilde{G}_j = tang\left(z_f\left[g_{j-1}, k_j\right] + bi_f\right) \quad (9)$$

And the inside long-term memory, also known as the further cell memory, is produced by combining these various internal values as (10).

$$h_j = l_j \circ f_j \circ \tilde{G}_j \quad (10)$$

As a result, the output gate generates the cell output to regulate the degree to which the value in the cell is used to work out the output activation, performing a read operation is expressed in (11).

$$h_j = \sigma\left(z_l\left[g_{j-1}, k_j\right] bi_h\right) \quad (11)$$

The hidden cell's output is eventually discovered and used to communicate with else cells in the deep network. A deep network with many units present has a lot of parameters because each gate has parameters for its weights and biases. Through network training, the weights of these associations are either knowledgeable or up-to-date. The mathematical model is shown in (12)

$$g_j = h_j \circ tang(f) \quad (12)$$

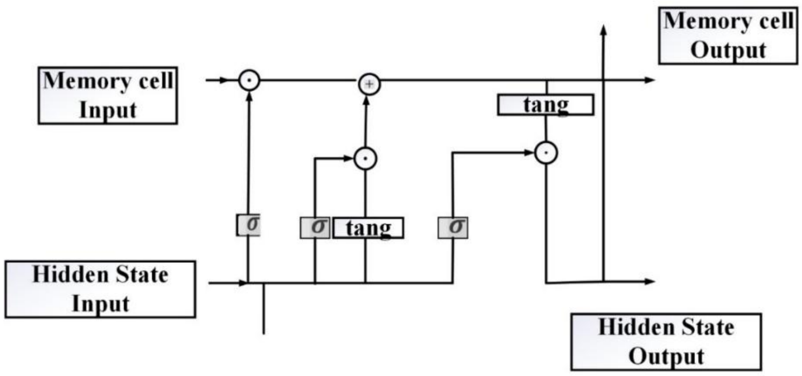

Figure 4. Architecture of LSTM

4. RESULTS AND DISCUSSION

The real time data set is created and named as sensor dataset. There are following activity labels used for the prediction and analysis. An app is developed to collect data from the people. 6 activity labels are: 0-laying, 1-sitting, 2-standing, 3-walking, 4-walking downstairs 5-walking upstairs.

The data set has a total 1,107 records. Here for the training purpose, 70% of data i.e. 774 records are used whereas 30% of data i.e. 333 records are used for the testing purpose. Figure 5 display the confusion matrix of different models. From Figure 5(a), it can be observed that the LR model gives least accurate results for “STANDING” label as compared to other 5 labels and the label “WALKING” gives the most accurate result. The accuracy is 97.39%. In Figure 5(b), it can be observed that the SVM model gives the least accurate results for “STANDING” label as compared to other 5 labels and the label “WALKING” gives the most accurate result. The accuracy is 97.79%. In Figure 5(c), it can be observed that the DT model gives the least accurate results for “WALKING DOWNSTAIRS” label as compared to other 5 labels and the label “WALKING” gives the most accurate result. The accuracy is 92.79%. In Figure 5(d), it can be observed that the RF model gives the least accurate results for “STANDING” label as compared to other 5 labels and the label “WALKING” gives the most accurate results. The accuracy is 96.19%. In Figure 5(e), it can be observed that the NN gives least accurate results for the “WALKING DOWNSTAIRS” label as compared to remaining 5 labels and the label “WALKING” gives the most accurate results. The accuracy is 97.69%. The other performance parameters precision, F1 score, and recall are also taken into consideration. As shown in Figure 5(f) and 5(g), when convolution is applied, the most accurate results are obtained. The convolution gives accuracy as 98.49% and LSTM with convolution given accuracy as 98.09%. All Figures are modified.

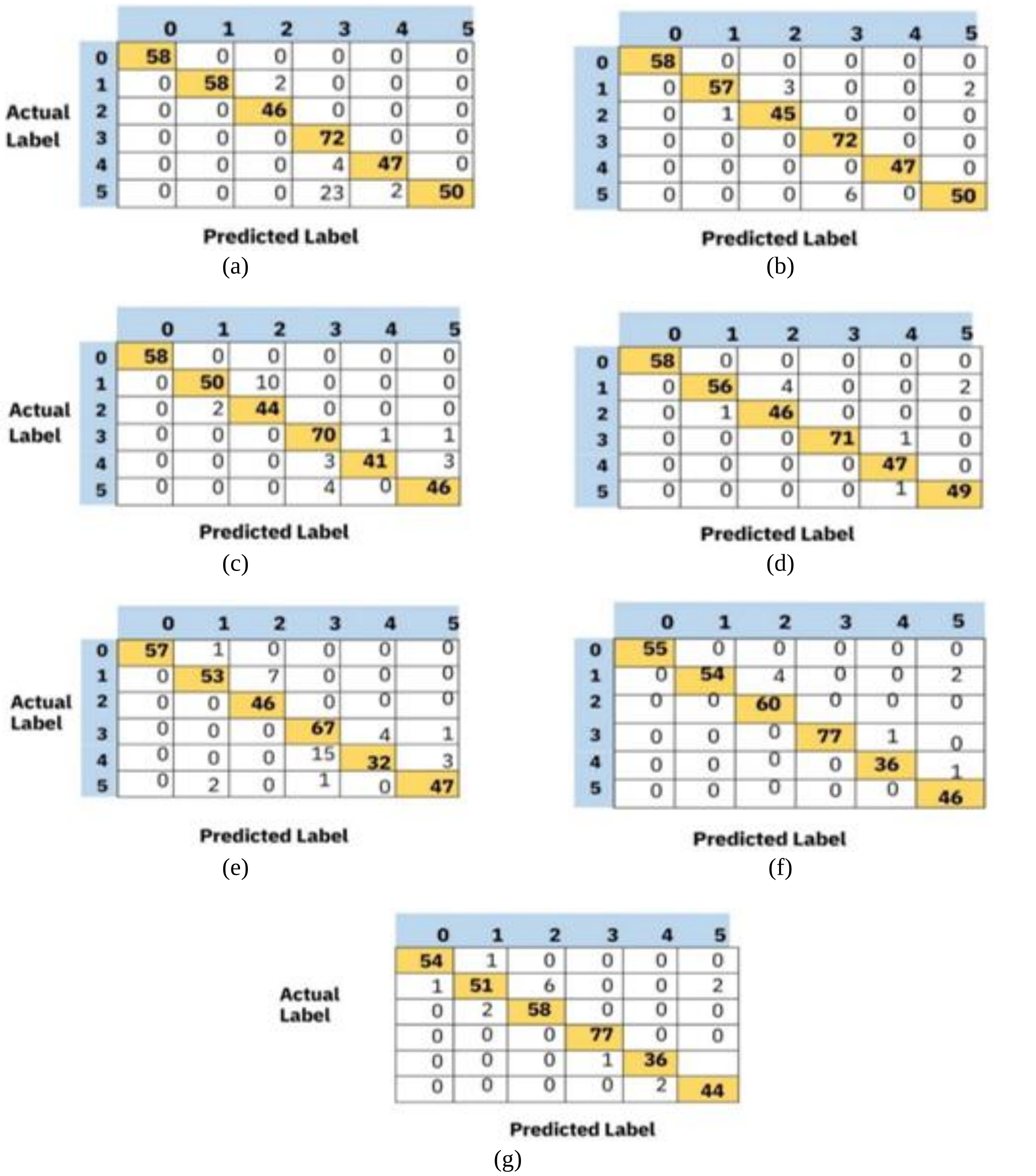

Figure 5. Confusion matrix of: (a) LR, (b) SVM, (c) DT, (d) RF, (e) NN, (f) TDL-LSTM, and (g) LSTM-TDL

The results in Table 1 make it clear that advanced deep learning techniques have a major impact on improving the accuracy of HAR. For example, the activity labeled “WALKING” has been predicted with top-notch accuracy, beating out older, more traditional methods. This shows just how powerful deep learning can be when it comes to working with complex datasets and accurately predicting activities. The overall model accuracy saw a noticeable jump to 98.49% and 98.09% with the latest deep learning models, which really underscores the potential these techniques have to elevate HAR systems.

Figure 6 shows the performance of various ML models in HAR, showing metrics such as Figure 6(a) accuracy, Figure 6(b) precision, Figure 6(c) recall, and Figure 6(d) F1 score. Advanced deep learning models-TDL-LSTM and LSTM-TDL-outperform traditional models like LR, SVM, DT, RF, and NN, with the highest accuracy of 98.49% and 98.09%, respectively. SVM and NN also perform well with accuracy around 97.79%, while DT and RF lag, especially in accuracy (92.79% and 96.69%, respectively). These results highlight the superior performance of deep learning approaches for HAR, particularly in handling complex data and delivering higher accuracy.

Table 1. Statistics of various algorithms

Sr. No.	Algorithm	Accuracy	Precision	Recall	F1 score
1	LR	97.39	0.956	0.94	0.94
2	SVM	97.79	0.96	0.95	0.95
3	DT	92.79	0.96	0.85	0.85
4	RF	96.19	0.92	0.91	0.91
5	NN	97.69	0.94	0.98	0.99
6	TDL-LSTM	98.49	0.95	0.95	0.96
7	LSTM-TDL	98.09	0.98	0.98	0.98

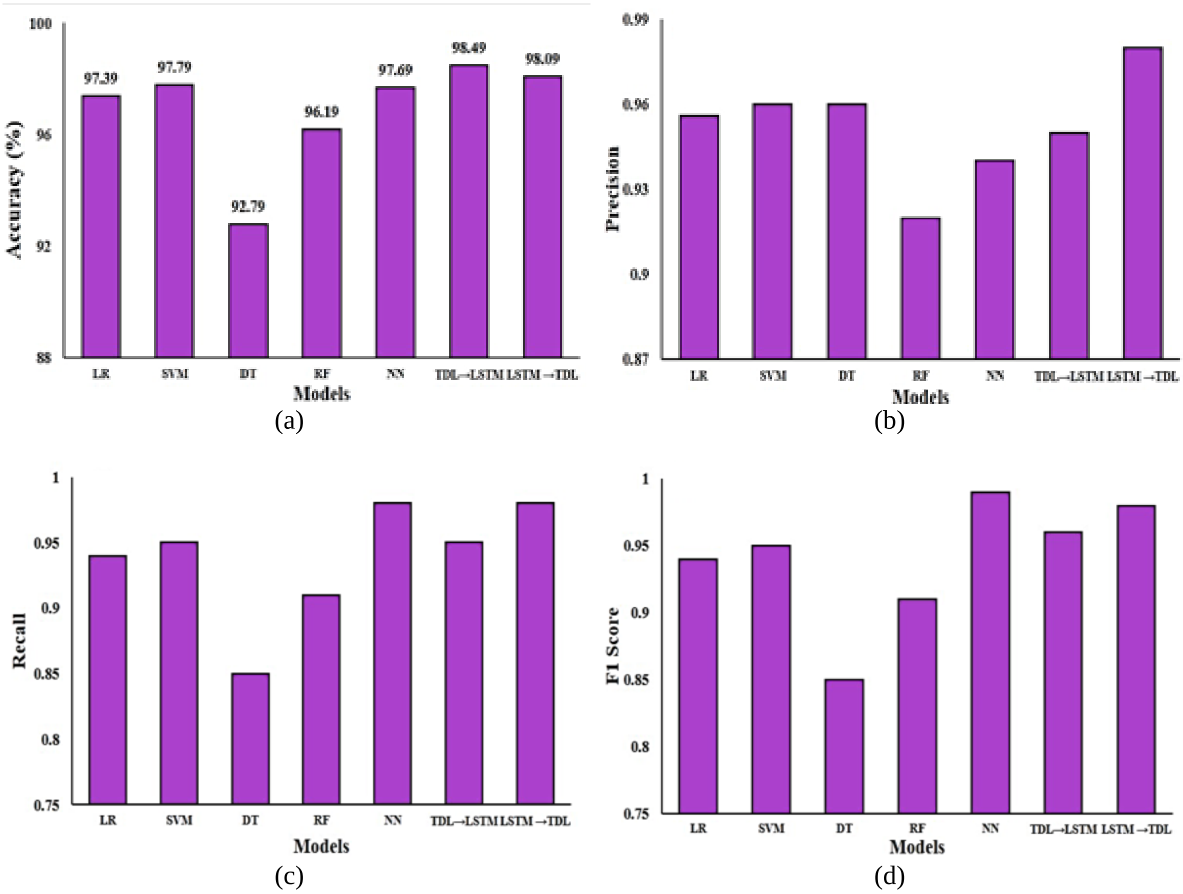

Figure 6. Graphical representation of: (a) accuracy, (b) precision, (c) recall, and (d) F1 score

Our study suggests that the proposed TDL-LSTM and LSTM-TDL models achieve higher accuracy in HAR compared to traditional ML models and earlier deep learning approaches. While Muralidharan *et al.* [21] reported a validation accuracy of 96.13% using a 1-D CNN, our models significantly outperform this with accuracy of 98.49%. Similarly, Kiranyaz *et al.* [23] highlighted the efficiency of 1-D CNNs in engineering applications with minimal computational complexity, yet their scope was limited to three activity labels. In contrast, our models were tested on a comprehensive dataset with six activity labels, demonstrating superior accuracy and robustness. Comparing with Minarno *et al.* [24], who achieved a maximum accuracy of 98.96% using SVM with an RBF kernel, our models provide comparable performance while addressing temporal dependencies more effectively through LSTM architecture. Additionally, unlike approaches by Zhang *et al.* [25] and Lee *et al.* [4], which focused on convolutional networks achieving accuracies of 92.71% and below, our models incorporate both convolution and recurrent layers, ensuring better capture of sequential data patterns. The results suggest that incorporating advanced deep learning architectures such as TDL-LSTM and LSTM-TDL may benefit HAR tasks by enhancing accuracy and reducing false positives without adversely impacting computational efficiency. These findings highlight the transformative potential of deep learning in advancing HAR beyond traditional approaches.

This study explored a comprehensive dataset with six activity labels using advanced deep learning models, TDL-LSTM and LSTM-TDL, achieving high accuracy and robust performance. However, further and in-depth studies may be needed to confirm the generalizability of these models, especially regarding their application in real-world environments with diverse sensor setups and varied population demographics. The dataset used, while extensive, was limited to controlled conditions and may not fully capture the complexities of natural activity patterns. Additionally, the computational efficiency of the proposed models in resource-constrained devices like smartphones needs further evaluation to ensure practical deployment.

5. CONCLUSION AND FUTURE WORK

Recent observations suggest that advanced deep learning models significantly enhance HAR accuracy. Our findings provide conclusive evidence that this improvement is driven by the effectiveness of algorithms like TDL-LSTM and LSTM-TDL, which achieve impressive accuracies of 98.49% and 98.09%, respectively, surpassing traditional ML methods. This advancement is attributed to the models' ability to handle large datasets and capture subtle patterns. The present work highlights opportunities for growth, including expanding datasets, incorporating varied activities and sensors, and adapting to real-world conditions to enhance accuracy and generalizability. Looking ahead, advancements in AI and ML could introduce novel architectures and algorithms, pushing HAR systems further and improving applications in healthcare, security, and smart homes. This study underscores the transformative role of deep learning in HAR and lays the groundwork for future innovation.

FUTURE WORK

Future research can build upon this study by focusing on expanding datasets to include more diverse activities, individuals, and real-world conditions, enhancing the generalizability and robustness of the models. Incorporating additional sensor types and exploring multi-modal approaches could further improve activity recognition performance. Additionally, investigating novel deep learning architectures or hybrid models might push the boundaries of accuracy and adaptability in HAR systems. Addressing challenges like real-time processing and computational efficiency will also be pivotal in broadening the practical applications of these systems across domains such as healthcare, security, and smart environments.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Jaykumar S. Dhage	✓	✓	✓	✓	✓	✓		✓	✓	✓				
Avinash K. Gulve	✓	✓				✓		✓	✓	✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no conflict of interest.

INFORMED CONSENT

Informed consent was obtained from all individual participants involved in the study.

ETHICAL APPROVAL

This study did not involve any experiments with human participants or animals, and therefore ethical approval was not required.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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BIOGRAPHIES OF AUTHORS

Mr. Jaykumar S. Dhage is a Research Scholar, from Dr. BAMU, Aurangabad. He has completed his Graduation and Post-Graduation, in computer science and engineering from Government Engineering College, Aurangabad. He has attended 40+ workshops and FDPs, with 15+ international and national conferences. He has published 10 papers in international journals with indexing Scopus, and Springer. He is having lifetime CSI membership. He is passionate about teaching programming languages such as C, C++, Java and Python. Currently, He is working as an Assistant Professor in JNEC, Aurangabad. He has received recognition for Infosys Campus Connect Program and SIH (Smart India Hackthon 2022) from the Director, MIT Aurangabad. He can be contacted at email: jaykumardhage2021@gmail.com.

Prof. Dr. Avinash K. Gulve has completed his Ph.D. from Dr. Babasaheb Ambedkar Marathwada University, Aurangabad year - 2016. He is working in Teaching from 1993. He has published 08 international papers in conference, 20+ international journal papers. He has attended 20+ training programs at various institutes. He has taught subjects like system programming, software testing, C, C++, DBMS, and Java. Currently he is working as an Associate Professor at MCA Department, Government College of Engineering, Aurangabad. He can be contacted at email: akgulve@gmail.com.