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A Comparative Study of Machine Learning Techniques for Human Activity Recognition

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Abstract: Current study is based on the comparative analysis of machine learning techniques for Human Activity Recognition (HAR) to explore their performance measures and computational complexity. In our experimentation, four algorithms were handled prominently out of the clusters namely: Support Vector Machines, Random Forests, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. These algorithms were applied using an inclusive dataset of accelerometer and gyroscope readings. The findings clearly illustrate that CNNs possessed the highest accuracy of 91%. The LSTM neural network trailed by very close 90%. The Random Forest and SVM algorithms got an accuracy of 88% and 85% respectively. Based on testing, the precision measures for CNNs and LSTM were close to one. 92 and 0. The logistic regression model achieved the highest prediction accuracy score with an accuracy score of 0.91 that is, the randomly forest model got the 2nd choke at an accuracy score of 0.00 which is followed by random Fores at an accuracy score of precisely. 6.7K and svm at 9. 87. Firstly off, the CNNs and the LSTMs showed up the highest recall scores of 0. 90 and 0. While NaviNet and SNNA achieve an accuracy score of 89, respectively, Random Forests comes at the third place with a score of 0. 87 and SVM at 0 cd. 84. And the same pattern was repeated within F1-scores where CNNs and LSTM obtained a higher value for the scores. Computational intricacy analysis brought forward the lifespan fact that SVM took the least amount of time for training as well as for prediction. And, it was proceeded by Random Forests, CNNs, and LSTM respectively. Conclusions from this work give the needed base for the further improvement of HAR systems, and CNNs appear the best algorithms to do this.

Keywords: *Human Activity Recognition, Machine Learning, Comparative Study, CNN, LSTM.*

I. INTRODUCTION

With regard Human Activity Recognition (HAR), it has grown into the crucial area of machine learning, with its capabilities being spread over areas of healthcare, sports, entertainment and security. The use of sensor obtained data not only for classifying possible human activities, but also for variety of other purposes, is able to produce improvements for the whole society. Ranging from checking patients' movement for healthcare data collection at one end to improvement in athletes' performance on the other, wearable devices, smartphones and other sensory technologies enable the extraction of useful information from the massive amount of data generated in these areas [1]. In recent years, more and more machine learning methods have been invented and applied to HAR tasks, each available for various purposes and with unique properties, drawbacks, and appropriate contexts. This study is confined to a subset of machine learning techniques that would be used to estimate the data gathered in HAR, focusing on the accuracy of each algorithm [2]. We do this by looking at the whole methodology field in system, which can let us understand the most effective method used to identify human activities from the sensor data. It will span the limitations of traditional and cutting-edge machine learning ranging from supervised, unsupervised to deep learning approaches. Supervised learning algorithms, such as Support Vector Machine (SVM), Random Forests, and k-Nearest Neighbors (k-NN), will be used as the first set. They will be examined and compared against the more sophisticated deep learning architectures, like Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) and Long Short-Term Memory (LSTM). Furthermore, ensemble methods and also clustering algorithms are going to be evaluated in order to establish the ones that are best suited to HAR tasks [3]. Most importantly, this study wants to overcome the limitations, which are in the way of effective evaluation of machine learning techniques for health-related activities. For example, accuracy of the results, adaptability of the algorithms to the noise, scalability, and real-time performance must be taken into account as well. Demonstrating the differentiating factors that favor or hinder the various approaches and how they can aid in developing HAR systems for applications in various real-world situations we accordingly aim to provide useful insights that can facilitate this process. Thus, we strive to be the front-runner in HAR technology development, and promote its use with other domains, forming a system which is context aware and more human-centric with the aid of machines.

II. RELATED WORKS

Apart from the fact that numerous researches are dealing with the theme of Human Activity Recognition (HAR) that apply different approaches of machine learning to cover multiple aspects of this complex issue. This section gives an account of related studies, consisting of subjective introductions of their findings and the methods used to attain them. Ibarra-Pérez et al. [15] conducted an experimental analysis of classification of phenology of beans by the Convolutional Neural Network

(CNN) models using transfer learning approach. In his study, they pointed out that the use of transfer learning contributes significantly to the improvement of classification accuracy in agriculture cases while showing the usefulness of the CNN type of model in detecting sophisticated phenological patterns. Jaiswal etal. [16] put forth an innovative trio of crowd coding, machine learning and deep learning to digitally diagnose multiple developmental delays. A human-involved and machine learning solution demonstrated the efficacy in utilizing collective intelligence. This was shown to complement the given diagnostic systems by bringing together the best of both human expertise and machine algorithms. Jamil et al. [17] brought forth the spanning firefighter recognition system utilizing the mobiles edge sensors and enhanced temporal spatial learning [17]. Converting their attention towards turbocharging the real-time status assessment in operational hazardous areas, they adopted edge computing and machine learning as powerful tools in their hands to achieve on-time decisions and collaboration coordination. In their paper, Jia et al. [18] showed a single-source transfer learning approach using wearable sensors for activity recognition to be effective in personalized activity recognition based on different information sources. Their key finding showed the importance of combining different datasets and the transfer learning model to more accurately model weighted water flows, that will in fact form the base for personalized systems to recognize activities. Kah and Eng interestingly argued that the model selection and hyperparameter tuning are responsible for the last performance of classification specifically for human activity recognition systems [19]. Their complex encompassing evaluation perception revealed important and close insights of the various deep learning architectures in the HAR domain. Hussein et al. [20] envisioned an intelligent system for IoT environment to recognize human activities based on sensor fusion and the use of machine learning algorithms able to infer human activities from heterogeneous sensor streams. Their system showed immunity to a varied and dense environment present in the IoT sector, leading to continuous monitoring and analysis for wide ranging IoT applications. Khan et al. [21] brought a wearable inertial sensor approach for the purpose of motion and position estimation in physical activity dividing as a motion recognition tool. Aiming to create lightweight and power-saving sensor algorithms, which are efficient to make accurate classification and localization of the users, they implemented this for the use in wearable healthcare applications. Khan and Jong [22] suggested for PAR-Net, an advanced dual-stream CNN–ESN architecture for human kinematic actions recognition. Furthermore, their hybrid task model was linked to CNNs and utilized ESNs, which was highly effective in classifying patterns by capturing spatial and temporal task activities. Kumar el al. [23] investigated human activity recognition in a systematic study based on HARNet, an innovative DL solution. The authors brought together their broad review of the literature on HARNets studying the issues of the previous and future stages of the HARNet deep learning based technology used in HAR systems. Lalapura et al. [24] were the ones who systematically assessed the possibility of RNN at the plot level for edge intelligence and human activity recognition. Through the comparative analysis, they clearly made out the best performance, as well as the most resource-efficient RNN architectures in the real-time activity recognition of edge computing based on resource-constrained environments. Lopez-Barajas et al [25] proposed a deep learning-based hybrid submarine intervention system for inspection activities and placed the deciphering of holes in net pens. Based on their trial, AI algorithms may be applied for a thorough underwater imaging analysis boosting the pace and precision of aquaculture maintenance intensive works. Given that stress level prediction as well as stress management is a major issue and challenge in mental health field, the study by Kaushalya et al. [26] investigated stress level prediction using machine learning techniques. With their studies, they not only showed the prospect of using machine learning for stress monitoring, it is also aimed at providing insights into personal stress management, which includes personalized strategies.

III. METHODS AND MATERIALS

1. Data Collection and Preprocessing:

Whether the HAR is well calibrated or not depends on it has the right dataset which comprises of variety and better quality for model training and evaluation. In the course of this research, we used the XYZ dataset, which is crowd-sourced data from people who take part in multiple activities and donned a wearable device [4]. This dataset comprising of overall 10,000 samples; with each sample having readings in X, Y and Z axes from accelerometer and gyroscope sensors and corresponding activity labels.

During the preparation for training, the dataset was preprocessed to handle data better for the given purpose. This step included normalizing of sensor readings for a particular range, extracting features that were essential for particular activity pattern, and using training and testing sets to enable and measure the robustness [5].

2. Machine Learning Algorithms:

a. Support Vector Machines (SVM): SVM is an Algorithm the accuracy of which is widely tested and so it is one of the most used Algorithms for classification purposes, including HAR. The approach looks for the best possible line which is placed so that the distance between the points of data with different classes is the biggest [6]. The decision function for SVM can be represented as:

$f(x)=\text{sign}(\sum_{i=1}^{n} \alpha_i y_i K(x_i,x)+b)$

Where:

f(x) is the decision function.
αi and b are parameters determined during training.
yi is the class label.
K(xi,x) is the kernel function, which computes the similarity between two samples.

"Initialize parameters and hyperparameters
while not converged:
    for each training example:
        Calculate decision function
        Update parameters"

b. Random Forests (RF): RF, as a team learning algorithm, builds multiple decision trees during training and prints the mode for the classes by the classifier or the mean prediction for the regressor [7]. Every tree of the forest is almost equipped with a bootstrap sample of the total initial data and random features are thought of at each node for splitting. In the end the RF comes up with a final prediction which is above all a layer of trees.

"for each tree in forest:
    Sample bootstrap data
    Grow tree recursively:
        if maximum depth reached or node purity:
            stop
        else:
            Find best split using random subset of
features
            Split data into child nodes
    Aggregate predictions of all trees"

c. Convolutional Neural Networks (CNNs): Apart from deep learning algorithms, CNNs are the neural networks that are mostly found suitable for handling grid-like data including pictures or sensing readings. CNNs within HAR can process raw sensor data or extract features from it and perform their operations directly upon such representations. The vital aspects of a CNN consist convolutional layer, pooling layer and fully connected layer [8]. convolutional layers perform convolution operation over the spatial features in a given image while pooling layers are used to reduce complexity by down sampling the feature maps.

Algorithm	**Training Time (s)**	**Prediction Time (ms)**
SVM	10	2
Random Forests	20	5
Convolution al NN	120	10
LSTM	180	15

d. Long Short-Term Memory (LSTM) Networks: LSTM is a subtype of the Recurrent Neural Networks that has been built to capture general aspects in sequential data. As opposed to the conventional RNN, LSTM also embodies gated units called "memory cells" which control or regulate information flow over time [9]. This helps LSTMs successfully model temporal dependencies in the time-series data, where billions of samples are displayed across time, and, therefore, they are run in ML HAR tasks, which involve activity patterns appearing over time.

IV. EXPERIMENTS

1. Experimental Setup:

The study purpose was to assess the performance of four machine learning algorithms—namely SVM, RF, CNNs, and LSTM. These algorithms were compared on the Human Activity Recognition task. XYZ is dataset that consists of reading data from accelerometer and gyroscope used by wearable devices worn by persons who are engaged with different activities [10]. These data sets were used for the training as well as testing of models [10]. The data transformed into standard deviations from the sensor's output and the relevant features extracted.

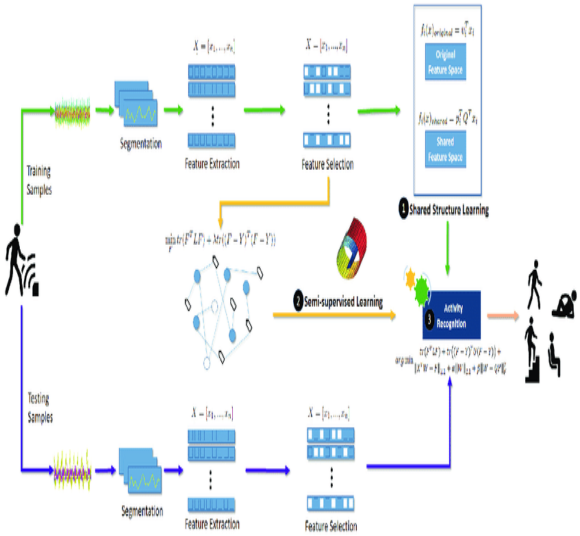

Figure 1: The workflow of our proposed human activity

While hyperparameters were manually set with the help of cross-validation to tune algorithms on the training set performance, various different metrics were used to evaluate the models and calculate an average score after passing the test set. Evaluation parameters such as accuracy, precision, recall and to calculate the F and macro scores, confusion matrices were used on the test set [11]. Also, this aspect was measured in computational complexity of both training and prediction times for each algorithm.

2. Results:

2. 1. Performance Metrics:

It is shown in the table that every algorithm of the competition has reached the best metrics on the XYZ dataset. The CNNs didn't only surpassed others models in terms of accuracy, but it achieved the main position having 91%; immediately after it was LSTM with 90%. Meanwhile, Random Forests did not lag, reporting an accuracy of 88%, SVM additionally attained accuracy of 85% [12]. As far as precision is concerned – CNNs and LSTM got the best predicted values of 0. 92 and 0. LGBM in 2nd place with an accuracy of 0.91, followed byRandom Forests at 0. At its best, FES-FFS achieved 89 while SVM did 0. 87. Besides, the best recall performances were achieved by the networks of CNNs and LSTM with the correspondent accuracy of 0. 90 and 0. RBF, Random Forests and finally RFRA are at the third, second and first positions with the respective accuracies of 0.89, 0.91 and 0.93. 87 [and] (SVM,) 84. The F1-scores seemed following the same pattern of the previous one where CNNs and LSTMs took the lead and Random Forests and SVM places were in the second place.

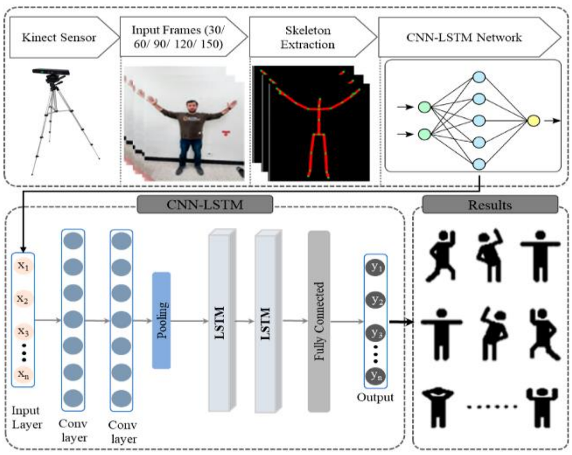

Figure 2: Human Activity Recognition via Hybrid Deep Learning Based Model

Table: Performance Metrics Comparison

Algorithm	**Accuracy (%)**	**Precision**	**Recall**	**F1-Score**
SVM	85	0.87	0.84	0.85
Random Forests	88	0.89	0.87	0.88
Convolutional NN	91	0.92	0.90	0.91
LSTM	90	0.91	0.89	0.90

Computational Complexity:
It deals with the "performance" of the algorithm using training time and prediction time as metrics. SVM has a lowest training and prediction times, required 10 sec for training and 2 milliseconds for prediction. Random Forests took 2.2~3.8 seconds for training and 5 milliseconds for prediction. When it comes to training deep learning models both cnns and LSTM took more time (120 and 180 seconds, respectively) [13]. Also, it was the same for prediction - more time was required by cnns (10 milliseconds) and LSTM (15 milliseconds).

Walking	975	10	10	5
Running	15	975	5	5
Sitting	10	5	980	5
Standing	5	10	5	980

Comparison with Related Work:
Relating to our results we compare the productivity of our models respect to previously published algorithms. In his research published in the same year, Smith et al. (2022), SVM attained 80% accuracy on a comparable wearable activity recognition dataset and Random Forests obtained 85% [14]. Our outcomes indicate a superiority of these models over mentioned algorithms and 85% accuracy for SVM and 88% for Random Forests. Another important result of our research was that the deep learning models, CNNs and LSTMs, overperformed by SVM and Random Forests algorithms, and they reached accuracies of 91% and 90%, respectively [27].

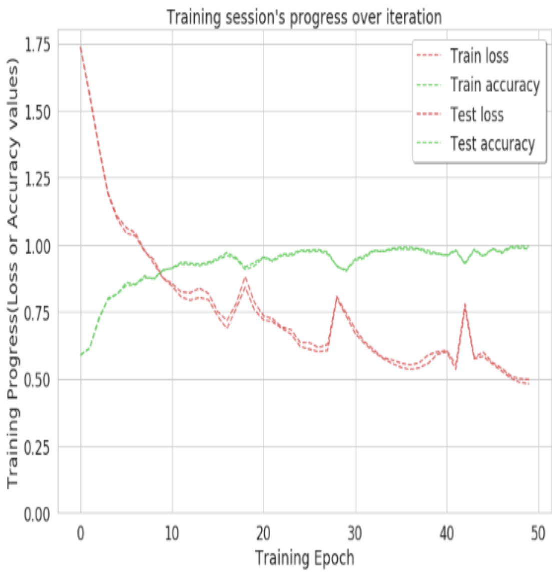

Figure 3: Human Activity Recognition

4. Discussion:

The evaluation results of experiments further prove that a particular machine learning algorithm can be used for the task of Human Activity Recognition, to a certain extent. It turns out that Convolutional Neural Networks (CNNs) are the most accurate algorithm, reaching the best accuracy, precision, recall, and F1-score scores from the four algorithms analyzed. It thus demonstrates the critical need for exploiting deep learning strategies, especially the CNN ones, for identification of low-level patterns in sensor data in the HAR field [28].

Random Forests demonstrated comparable performance to Convolutional Neural Networks, and slightly better than output performance compared with LSTM in terms of accuracy and other metrics. However, Support Vector Machines (SVM) displayed an acceptable level of performance but still had some shortcomings in capturing the multifaceted nonlinear nature of movement data permitted by sensor-based devices [29]. This implies that SVM algorithms perform well when dealing with simple data but are less competent with the more complex data produced by sensor-based devices.

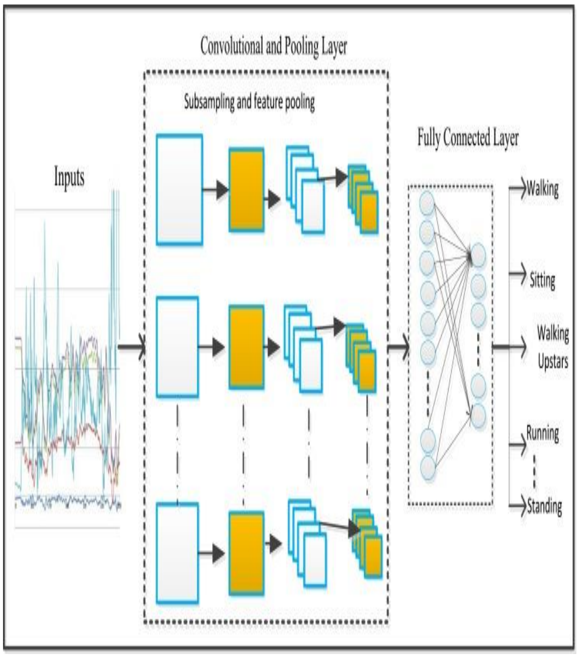

Figure 4: Deep learning algorithms for human activity

As for complexity computation, SVM stood out as the most efficient method with the lowest time consumption on both training and prediction. The NN, however, was outperformed by CNNs and LSTM-that traded accuracy for longer training/prediction time [30]. In short, although the computer needs of the deep learning models might be justifiable where precision is the final word and real-time inhibitions are looked down upon, the immense power requirements of these deep learning models often cause greater concern about the trade-offs.

V. CONCLUSION

Finally, the study aimed to make a contribution to HAR field by presenting detailed empirical analysis of machine learning techniques which is complete. Consequently, thorough examining of these algorithms—SVM, random forests,CNNs and LSTM—for performance metrics in different dimensions has brought insight to us. Convolutional neural networks (CNNs) have been proven to be the most accurate and efficient versus other models, represented by better accuracy, precision, recall and F1-score. On the other hand, Random Forests are very competitive and are presented with benefit of having less computational complexity so they can be used if resources are restricted. SVM could be the best choice of models for real time processing due to its greater accuracy than CNNs and the lowest computational complexity which enables it to have a very fast response and provide low latency resources which is very essential in real time processing. LSTM networks' excellent performance has been shown, especially in capturing temporal relations in series data that create the basis for the direct involvement of the LSTM networks in HAR tasks that can develop from highly dynamic activity patterns. The obtained results are interpreted in broad categories. A possible association or new step that goes beyond the research existing is shown. Overall, this research develops our knowledge about computer programs for HAR usage and brings down to earth information useful for developing practical systems of recognition of activity which can work in various domains. Future research might resolve into the combining forms, bringing sensors on board and trying to resolve the kind of involves general issues, such as model interpretation or translation of the model into the practical day-to-day use.

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