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Human Activity recognition using machine learning

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Human activity recognition is a broad field of study concerned with identifying the specific movement or action of a person based on sensor data. It can improve people's well-being by automatically assessing and summarizing their daily activities. In this study an automatic detection of nine different human activities from body sensor data was developed. The human activity data was collected from 30 between the age of 12 and 55 to provide data. from those 17 participants were male and 13 participants were female. Participants completed nine activities (sitting, standing, walking, running, upstairs, downstairs, sit-up, jumping and cycling) while wearing an I-phone eight plus in the pocket. Records from 18 individuals used for training, 6 participants data was used for validation and the remaining 6 participants records were used for testing. The human activity data is captured by via phone's integrated acceleration and gyroscope sensors. Hence a total of nine-dimensional data (triaxial accelerometer data (linear acceleration and body acceleration) and triaxial gyroscope data) was acquired using these two sensors. In all case the sample rate used to capture the data was 50Hz. In this study both classical machine learning and deep learning methods were exported. In classical techniques four machine learning classifiers (SVM, KNN, logistic regression and decision tree) have been used to categorize the data. For this to work 18 set of features were carefully computed. Three deep learning models (CNN, LSTM and hybrid CNN-LSTM) have been also trained in the accurate detection of human activity classification.

Keywords: human activity recognition, classical machine learning, deep learning.

1. Introduction

Human activity recognition is concerned with identifying the specific movement or action of a person based on sensor data [1]. It has gained much attention in the current decade due to the wide range of application [2]. It provides an estimation of the energy consumption during everyday life this help to balance the number of calories consumed from food and beverage with the number of calories the body used for activity and this used to prevent overweight and obesity. Worldwide over 2.8 million people dying each year as a result of being overweight or obese in 2021 [3]. When a person's body mass index is over 25 is consider as overweight and over 30 is obese. Worldwide 1.9 billion adults are overweight and 650 million obese [4]. Once considered the problem of the developed nation, the problem is slowly creeping into developing countries too. For instance, in Ethiopia, according to a recent Ethiopian study, the prevalence of central obesity was estimated to be 37.31% at the national level [5]. according to world cancer research international study by year 2025 170 million adults worldwide may have a body mass index of over 35kg/m2 [6].

According to CDC's study people, who are overweight or obese compared to those with healthy weight, are at increased risk for many series diseases and health conditions [7]. These include causes for death (mortality), high blood pressure, high LDL (low density lipoproteins) cholesterol, low HDL (high density lipoproteins) cholesterol or high levels of triglycerides, type 2 diabetes, coronary heart disease, stroke, gallbladder disease, osteoarthritis (a breakdown of cartilage and bone with in joint), sleep apnea and breathing problems, many types of cancer, mental illness such as clinical depression, anxiety and other mental disorder, body pain and difficulty with physical functioning [8][9].

Researchers have linked rising obesity rates to globalization processes, which they believe contributes to obesity by flooding low-income countries markets with cheap but obesogenic foods [10]. Sedentary behavior and physical inactivity are also significant risk factors for obesity [11]. As the management expert peter Drucker once famously said, "if you can't measure it, you can't manage it.", properly measuring daily human activity will give a valuable information about the wellbeing of the person and hence giving a constant reminder for a potential life style and behavior change that could reduce the risk of developing chronic illnesses.

Activity recognition is closely associated with health, as it provides information about physical activity performed by a person. Regular physical activity is essential for maintaining good health, as it helps to prevent and manage a wide range of chronic diseases. Therefore, by accurately recognizing and tracking physical activities individuals can gain insights into the patterns of physical activity, set goals for increasing or maintaining physical activity levels, and monitor progress towards achieving these goals. Human activity detection can help promote an active society by encouraging people to engage in physical activity and adopt healthier lifestyles. It also motivates people to increase their physical activity levels by setting goals, tracking progress, and providing feedback.

Overall, human activity detection is a valuable tool for promoting health and wellbeing, increasing productivity, and improving quality of life. By accurately detecting and tracking physical activity, we can better understand human behavior and make informed decisions to improve our lives.

The human activity recognition in this study proposes a process of automatically identifying and classifying different physical activities performed by a person, such as sitting, standing, walking, running, upstairs, downstairs, jumping, sit up and cycling. It involves using sensors from a standard mobile phone, such as accelerometers and gyroscopes to collect data about the movements.

2. Related Works

In this section, recent literature (2013-2022) is reviewed. The reviewed paper where strategically selected. The selected literature encompasses studies that have utilized machine learning and deep learning approaches for human activity recognition. These approaches have gained significant attention in recent years due to their ability to effectively capture and analyze complex patterns in activity data. By reviewing the literature, we aim to gain insights into the advancements made in human activity recognition techniques and the corresponding sensor types used in these studies. Human activity recognition based on wearable sensors have a problem of many sensors are attached to a subject and can't move comfortably because of many wire connections, as well as it is expensive in terms of energy consumption and device configuration. Instead of focusing on wearable sensor based, numerous studies incorporated video sensor technologies like RGB cameras to monitor and recognize human activity. This may be a problem of difficulty in recognition due to low light environment or darkness [12][13]. To avoid the problem of difficulty in recognition due to low light environment or darkness some researcher used Kinect camera. This camera also has a problem of so sensitive to sunlight and not suitable for outdoor application [14]. To overcome these problems easily available smart phone embedded accelerometer and gyroscope sensors are preferred.

2.1. *Classical machine learning*

Classical machine learning algorithms have been widely used in Activity Recognition due to their ability to learn from data and make predictions on new instances. Muralidharan K. et al. [15] illustrate by using accelerometer and gyroscope sensors which classify 6 human activities sitting, standing, climbing up, down the stairs case, walking and laying down by using classical machine learning classifiers logistic regression, linear and kernel SVM, decision tree and random forest achieved accuracy results of kernel SVM 96.57%, linear SVM 96.6%, logistic regression 95.4%, random forest 91% and decision tree 85.5%.

In other study, Sandeep Kumar Polu et al. [16] investigated the recognition of five human activities, namely laying, sitting, standing, upstairs, and downstairs, using accelerometer data and two machine learning classifiers, namely Random Forest and modified Random Forest. The researchers implemented an online activity recognition framework on the Android platform and evaluated the performance of the classifiers. The results indicated that the modified Random Forest classifier achieved 93% accuracy in recognizing the human activities.

2.2. *Deep Learning*

Although machine learning algorithms that require hand-crafted feature extraction are explainable, they often have limited generalization abilities and may experience issues with parameter non-convergence and network instability. As a result, researchers and domain experts are motivated to explore human activity recognition using deep learning approaches.

Sarbagya Ratna Shakya et al. [17] conducted a study on human activity recognition using an accelerometer sensor attached to a mobile device worn around the waist region. They explored various machine learning classifiers, including K-nearest neighbor (KNN), Random Forest, and Decision tree, as well as deep learning models such as convolutional neural network (CNN) and recurrent neural network (RNN). The results of their experiments indicated that the KNN classifier achieved the highest accuracy of 91%, followed by RNN with 81.7% accuracy. Notably, the CNN model outperformed all other methods, achieving the highest accuracy rate of 92.2% in human activity recognition.

Imran Ullah Khan et al. [18] proposed a hybrid model for activity recognition by combining convolutional neural network (CNN) and long short-term memory (LSTM). The CNN is employed for extracting spatial features, while the LSTM network is utilized to capture temporal information. The dataset used in their study was collected from twenty participants using a Kinect sensor. The research findings showed that the hybrid CNN-LSTM model achieved the best performance in activity recognition. However, it is worth noting that the model utilized a Kinect sensor, which is sensitive to sunlight and not suitable for outdoor applications.**Summary**

In this study, the focus is on end-to-end machine learning algorithms by addressing the gaps identified in the literature by using accelerometer and gyroscope sensors, which are readily available and can be easily embedded in smartphones. These sensors provide raw data that can be processed and analyzed using classical machine learning classifiers and deep learning models. By evaluating the performance of these algorithms, including the hybrid CNN-LSTM model, the study aims to assess their effectiveness in accurately recognizing human activities. These studies demonstrate that the use of classical machine learning algorithms Various sensors such as smartphones and smartwatches are utilized to collect data, and feature extraction techniques including time-domain, frequency-domain, and wavelet-based features are commonly employed. SVMs, decision trees, KNN, and random forests are the most commonly used classifiers. In this thesis, we investigated KNN, SVM, Decision Tree, and Logistic Regression classifiers using 18 features extracted from our in-house dataset collected using a smartphone placed in a pocket. The literature reviewed in this study highlights the potential of deep learning models in accurately recognizing human activities using various sensors and feature extraction techniques. These studies have demonstrated that deep learning models outperform traditional machine learning algorithms in terms of accuracy and robustness. However, it is important to consider the specific characteristics of the dataset and the complexity of the activities being recognized, as these factors can influence the performance of the models. One of the key advantages of deep learning models is their ability to handle time-series data, which is crucial for human activity recognition as it involves capturing both spatial and temporal information. Deep learning models, such as the hybrid CNN-LSTM model, have shown promising results in capturing the temporal dynamics of human activities. additional literature reviewed are available in main paper.

3. Research Method

This section provides information about the research method to develop a human activity recognition (HAR) system. It has two major parts: In the first part explainable machine learning approaches (classical machine learning) for HAR has been studied in depth. The second part investigated the use of Deep learning methods in human activity recognition. To train, validate and test our proposed models, 9 human activities from 30 volunteers have been collected each lasting over five minutes in duration. The proposed methods were also evaluated on an existing public dataset as a sanity check. Figure 1 shows the detailed block diagram of all the steps involved in this study. In depth description of each block is presented in the following section.

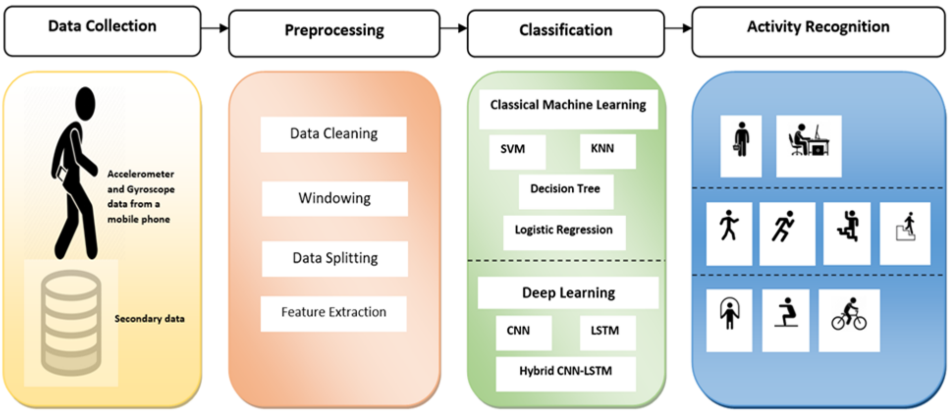

Fig. 1. Detailed block Diagram

3.1. *Selection of Activities*

Human physical activities are diverse and can be classified into various categories [19]. In order to better understand the effects of these activities on human health and well-being, in this study they are broadly categorized into three groups: postural, walking behavior, and sports activities. Postural activities include standing and sitting are associated with different levels of muscle activation and energy expenditure. For instance, standing requires more muscle activation than sitting, and thus results in a higher energy expenditure. Walking behavior encompasses normal walking, running, ascending stairs, and descending stairs, and is known to have significant cardiovascular and metabolic benefits. Sports activities, such as rope jumping, sit-ups, and cycling, involve high levels of physical exertion and can contribute to improvements in strength, endurance, and overall fitness.

In selecting the nine activities, we have considered their prevalence in a typical urban Ethiopian lifestyle, and their potential impact on health and well-being. These selected activities include standing, sitting, normal walking, running, ascending stairs, descending stairs, sit-up, rope jumping, and cycling. By automatically detecting and examining the duration of these activities, we can gain a better understanding of how daily physical activity can contribute to overall health and well-being in Ethiopian urban population.

3.2. *Data Collection*

The effectiveness of Machine Learning (ML) heavily relies on the quality and quantity of data available for algorithm training. It is precisely the availability of abundant data and the ease of collecting and processing it that has made ML so popular in recent years. To develop and evaluate ML algorithms, two types of datasets are used: public datasets and collected datasets.

Fig. 2. Logical flow of the data collection process showcasing a volunteer participant with corresponding accelerometer and gyroscope data

Public Dataset

Open-source datasets provide a cost-effective and efficient solution for acquiring data to train and validate machine learning models. The main purpose of utilizing these datasets is to ensure the reliability and credibility of the proposed algorithm while enabling comparisons with other approaches. For this study, a dataset appropriate to our research objectives was chosen. One such dataset, accessible through open-source [20], includes data collected from 30 volunteers aged between 19 and 48. The volunteers wore a Samsung Galaxy S II smartphone on their waist while performing six activities, including walking, walking upstairs, walking downstairs, sitting, standing, and laying. The smartphone's embedded accelerometer and gyroscope captured 3-axial linear acceleration and 3-axial angular velocity at a constant rate of 50Hz, and the data was manually labeled using video recordings. The dataset was randomly divided into training and test sets, with 70% of volunteers used for generating the training data and 30% for the test data. For each record, tri-axial acceleration from the accelerometer and gyroscope and a 561-feature vector with time and frequency domain variables were obtained, including total acceleration and estimated body acceleration.

Collected Data

The use of public datasets, while rich and detailed, may not always align with our specific research goals. This limitation is exemplified by the inability to obtain data that covers all nine identified human physical activities. Therefore, collecting our own dataset becomes necessary. For this research, human activity data was collected (total of 1,679,819 rows) from 30 volunteers between the ages of 12 and 55 who agreed orally to participate after being informed about the data collection process and objectives. Of the participants, 17 were male and 13 were female. The participants performed nine activities (sitting, standing, walking, running, walking upstairs, walking downstairs, sit-up, rope jumping, and cycling) while carrying an iPhone 8 plus in their pocket, a logical placement for daily mobile phone use. Eighteen individuals' records were used for training (1,036,510 rows), six for validation (329417 rows), and six for testing (313892 rows). The phone's integrated acceleration and gyroscope sensors captured the data, resulting in nine-dimensional data comprising triaxial accelerometer data (linear and body acceleration) and triaxial gyroscope data. All data was captured at a sample rate of 50Hz.

3.3. *Preprocessing*

In human activity recognition systems, data preprocessing plays a crucial role in the data mining process by manipulating and enhancing the data before it is utilized [21]. This initial step involves primarily cleaning the data, applying windowing techniques and data splitting. During the data cleaning step, various operations are performed, such as dropping null values, converting the data type of the Z-axis column to float, excluding rows with zero elapsed seconds, and sorting the data in ascending order based on the subject. These operations ensure the data is in a suitable format for further analysis.

Raw time series data obtained from human activity recognition often poses challenges for standard classification algorithms due to its temporal structure and inherent noise [22]. To address these issues, windowing techniques are employed.

Selecting an appropriate window size is critical to accurately capture the motion patterns present in the data. An excessively large window size results in fewer data points for training, potentially leading to information loss, while an excessively small window size may fail to capture the motion patterns effectively. Literature suggests that a window size of five seconds is optimal for capturing most activities [23]. This optimal window size has been validated in this thesis by comparing it with window sizes of 75 and 120 observations, which represent smaller and larger window sizes, respectively. The performance of the activity recognition system was found to be affected by these variations in window size. Therefore, a window size of five seconds, corresponding to 100 observations, was adopted for this thesis to ensure accurate motion capture and analysis.

Prior to designing new features, it is essential to split the data into training, testing, and validation sets using the Pareto principle, also known as the 80-20 rule, which states that "80% of output (outcomes) result from 20% of all input (causes)" [24]. This data splitting process ensures that the model is trained on a representative subset of the data and evaluated on independent subsets [25].

In this study, the data was split based on the participants' IDs. Specifically, out of the total participants, the first 18 participants were allocated for the training set, six participants were assigned to the validation set, and the remaining six participants were used for the test set. This partitioning strategy ensures that the model is trained on a significant portion of the available data while maintaining distinct subsets for validation and testing.

Every signal in time domain is made up of many sinusoids of different frequency this make difficult for analysis. therefore, time domain signal changed in to frequency domain to solve much easier by fast Fourier transform (FFT).

3.4. *Feature Extraction*

In human activity recognition using classical machine learning algorithms, the selection of appropriate features plays a critical role in accurately detecting and classifying activities [26]. Numerous features have been proposed in the literature that demonstrate the ability to capture the characteristics of the activities of interest [27]. In this study, we have chosen to extract 18 features for the purpose of feature engineering in classical machine learning.

The selected 18 features encompass various statistical and signal-based measures that have proven effective in capturing relevant information about the activities [28]. These features include Mean, Standard deviation, Average absolute deviation, maximum value, minimum value, Range, Median, Median absolute deviation, Interquartile range, Positive value count, Negative value count, Number of values above mean, Number of peaks, Skewness, Kurtosis, Energy, Signal magnitude area, and Average resultant acceleration over the window.

Each of these features contributes unique insights into the characteristics of the activities and provides valuable information for the subsequent classification process. By considering a diverse range of features, we aim to capture both the temporal and statistical aspects of the activity data, enabling the machine learning algorithms to make accurate predictions and classifications.

3.5. *Classification*

In this study, utilized four classical machine learning classifiers to analyze the data: Support vector machine (SVM), K-nearest neighbor (KNN), logistic regression, and decision tree and experimented with three prominent deep learning models: convolutional neural network (CNN), long short-term memory (LSTM), and a hybrid CNN-LSTM model.

4. Results and Discussion

This chapter provides a comprehensive presentation and discussion of the results from all the proposed techniques for automatic human activity recognition. The proposed methodology was evaluated on both a publicly available dataset and a dataset specifically collected for the purpose of this thesis. The chapter starts by presenting the results of classical machine learning algorithms on the public dataset, followed by an examination of the performance of activity detection in the collected dataset. Additionally, detailed presentations and discussions of the results from each deep learning algorithm are also included.

Table 1. performance evaluation of four classical machine learning algorithms on open-source data [Note: pre. = precision, Rec= recall, F1= F1-score]

Activities	SVM			KNN			LR			DT		
	Pre.	Rec.	F1	Pre.	Rec.	F1	Pre.	Rec.	F1	Pre.	Rec.	F1
walking	0.96	0.99	0.98	0.83	0.99	0.90	0.95	0.99	0.97	0.80	0.89	0.84
upstairs	0.97	0.96	0.97	0.90	0.91	0.91	0.96	0.94	0.95	0.79	0.75	0.77
downstairs	0.99	0.97	0.98	0.98	0.75	0.85	0.99	0.96	0.97	0.88	0.82	0.84
sitting	0.97	0.89	0.93	0.92	0.76	0.83	0.96	0.88	0.92	0.84	0.77	0.80
standing	0.91	0.98	0.94	0.81	0.94	0.87	0.90	0.97	0.93	0.80	0.87	0.83
laying	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Average accuracy	0.97			0.91			0.96			0.85		

Based on the investigation on Table1, SVM and LR emerged as the top-performing algorithms for accurately identifying the six human activities. Notably, the experimental results for the open-source dataset indicate that the SVM model achieved the highest accuracy of 96.6%, while the Decision Tree (DT) model had the lowest accuracy at 85%. It is important to note that no hyperparameter optimization was performed in this experiment, and the train-test split adhered precisely to

Table 2. Performance evaluation of four classical machine learning algorithms on our collected local data set [Note: pre. = precision, Rec= recall, F1= F1-score]

Activities	*SVM*			*KNN*			*LR*			*DT*		
	Pre.	*Rec.*	*F1*	*Pre.*	*Rec.*	*F1*	*Pre.*	*Rec.*	*F1*	*Pre.*	*Rec.*	*F1*
Sitting	*0.99*	*0.99*	*0.99*	*0.96*	*0.97*	*0.96*	*0.99*	*0.99*	*0.99*	*0.98*	*0.98*	*0.98*
Standing	*0.98*	*0.97*	*0.98*	*0.96*	*0.96*	*0.96*	*0.98*	*0.97*	*0.97*	*0.97*	*0.96*	*0.97*
Walking	*0.75*	*0.77*	*0.76*	*0.47*	*0.68*	*0.55*	*0.52*	*0.90*	*0.66*	*0.54*	*0.58*	*0.56*
Upstairs	*0.74*	*0.78*	*0.76*	*0.58*	*0.40*	*0.47*	*0.78*	*0.29*	*0.43*	*0.37*	*0.61*	*0.46*
Downstairs	*0.73*	*0.63*	*0.67*	*0.42*	*0.30*	*0.35*	*0.75*	*0.44*	*0.56*	*0.40*	*0.36*	*0.38*
Running	*0.91*	*0.87*	*0.89*	*0.90*	*0.87*	*0.88*	*0.91*	*0.97*	*0.94*	*0.89*	*0.52*	*0.66*
Sit-up	*0.68*	*0.74*	*0.71*	*0.82*	*0.49*	*0.61*	*0.98*	*0.59*	*0.74*	*0.82*	*0.69*	*0.75*
Jumping	*0.69*	*0.87*	*0.77*	*0.68*	*0.59*	*0.63*	*0.98*	*0.66*	*0.79*	*0.43*	*0.74*	*0.54*
Cycling	*0.69*	*0.82*	*0.75*	*0.60*	*0.68*	*0.64*	*0.82*	*0.94*	*0.87*	*0.68*	*0.75*	*0.71*
Average Accuracy	*0.89*			*0.81*			*0.87*			*0.79*		

the dataset owners' recommendations. Considering the average detection accuracy of the classical machine learning classifiers on the open-source dataset, we have determined that the SVM, LR, DT and KNN models will be selected for further use in our local dataset.

Based on the findings presented in Table 2, the proposed system demonstrated accurate identification of human activities such as standing or sitting. This outcome is expected since the features extracted from sitting and standing data provide distinct information. However, distinguishing exercises like sit-ups, jumping, and cycling, as well as differentiating between walking upstairs, downstairs, and normal walking, posed a significant challenge. The SVM technique achieved the highest average detection accuracy, reaching 89%. In comparison, KNN yielded a lower result of 81%. These results indicate that there is still room for improvement in the system's performance.

The provided results in Table 4, 3 showcase the performance of various deep learning models on the open-source dataset. Among these models, the hybrid CNN-LSTM achieved the highest accuracy of 92.6%, while the CNN model recorded the lowest accuracy at 90.8%. It is worth noting that, contrary to the expectations set by existing literature, the deep learning algorithms did not perform as well as classical machine learning algorithms in accurately classifying the six human activities in this open-source dataset. It is important to consider that no hyperparameter optimization was conducted, which could potentially explain the subpar performance of these techniques. However, achieving an overall accuracy of over 90% in a multiclass challenge using data from just a single sensor is still remarkably high. As a result, all three of these algorithms will undergo further investigation for the detection of human activities in our local dataset.

To enhance performance, the hyperparameters were carefully optimized for each algorithm. For the CNN, parameters such as the number of convolutional layers,

Table 3. Performance evaluation of three deep learning algorithms on open-source data [Note: pre. = precision, Rec= recall, F1= F1-score]

Activities	CNN			LSTM			CNN-LSTM		
	Pre.	Rec.	F1	Pre.	Rec.	F1	Pre.	Rec.	F1
Walking	0.99	0.97	0.98	0.99	0.92	0.95	0.99	0.97	0.98
Upstairs	0.90	0.81	0.85	0.86	0.76	0.81	0.98	0.99	0.99
Downstairs	0.88	0.90	0.89	0.84	0.88	0.86	1.00	0.94	0.97
Sitting	0.97	0.89	0.93	0.94	0.92	0.93	0.78	0.88	0.83
Standing	0.92	0.91	0.92	0.88	1	0.94	0.92	0.77	0.83
Laying	0.81	0.95	0.88	0.86	0.90	0.88	0.89	0.99	0.94
Average Accuracy	0.91			0.91			0.93		

Table 4. Performance evaluation of three deep learning algorithms on collected local data [Note: pre. = precision, Rec= recall, F1= F1-score]

Activities	CNN			LSTM			CNN-LSTM		
	Pre.	Rec.	F1	Pre.	Rec.	F1	Pre.	Rec.	F1
Sitting	0.85	0.97	0.88	0.85	0.98	0.91	0.99	0.96	0.97
Standing	1	0.98	0.99	0.99	0.97	0.98	1.00	0.98	0.99
Walking	0.81	0.97	0.88	0.94	0.88	0.91	0.89	0.95	0.92
Upstairs	0.77	0.54	0.64	0.91	0.63	0.75	0.95	0.63	0.76
Downstairs	0.88	0.50	0.64	0.79	0.87	0.83	0.89	0.70	0.79
Running	0.69	0.85	0.76	0.73	0.89	0.80	0.83	0.85	0.84
Sit-up	0.73	0.90	0.81	0.76	0.90	0.83	0.68	0.92	0.78
Jumping	0.99	0.96	0.97	0.99	0.86	0.92	0.99	0.97	0.98
Cycling	0.89	0.87	0.88	0.70	0.87	0.77	0.91	0.87	0.89
Average Accuracy	0.92			0.91			0.94		

dropout rate, batch size, and number of epochs were fine-tuned. Similarly, for the LSTM, hyperparameters such as the number of LSTM layers, number of LSTM units, dropout rate, learning rate, batch size, and number of epochs were optimized. As for the hybrid CNN-LSTM, a combination of the aforementioned hyperparameters from both CNN and LSTM was optimized. Based on table 4 hybrid CNN-LSTM model has the highest performance.

5. Conclusion

The main goal of this paper was to develop a comprehensive automatic human activity detection method that can detect nine different activities from mobile phone integrated sensor data. Using the phone's built-in accelerometer and gyroscope sensors placed inside pocket which is easy and comfortable to use with nine human activities sitting, standing, walking, walking upstairs, walking downstairs, running, sit-up, jumping and cycling data was collected from 30 volunteers between the ages of 12 and 55 by preprocessing this data and using 4 classical machine learning classifiers and 3 deep learning models human activities are recognized effectively with high F1score and recall, very near precision and confusion matrix. and the other aim was to compile human activity dataset from different public datasets. in this work open-source data with six activities sitting, standing, walking, walking upstairs, walking downstairs and laying was used and it occurred accuracy of SVM 97%, LR 96%, KNN 91%, DT 85% from classical machine learning classifiers and deep learning models with accuracy of LSTM 91%, CNN 91% and hybrid CNN-LSTM 93% and other performance measuring parameter very near precision, high F1score, high recall value and confusion matrix effectively done. The study also assessed to collect local data to develop and evaluate the performance of the proposed algorithm. this objective also meets with highest performance accuracy of 94% when classifying using CNN-LSTM model the proposed method resulted in higher accuracy, f1 score and confusion matrix and also, with another model's accuracy of CNN 92%, LSTM 91%, SVM 89%, LR 87%, KNN 81% and DT 79% effectively done with high recall and f1-score, very near precision and confusion matrix. when compare classical and deep learning algorithms for human activity recognition. the performance of the deep learning-based model is better than machine learning-based algorithms and when compare the performance with in deep learning algorithm hybrid CNN-LSTM model has highest performance since human activity recognition data is time-series data that includes spatial and temporal information which required a robust model with the ability to learn both information. The spatial information is from CNN model and the temporal information is from LSTM model based on this hybrid CNN-LSTM model is the best human activity detection tool. This indicates that with a simplified approach, multiple human activities can be reasonably detected. By analyzing these activities, one can promote to increase their physical activity levels, promote health and wellbeing, increasing productivity, and improving quality of life for the subjects.

Limitation of the study and Future Work

In this study thirty participants were used to provide data due to limitation of resource. This limited the size of data set that need to be collected for classification. Although the data were collected from participants who residing in Addis Ababa. Collecting data from people with different life style, geographic area and increasing number of participants will make the data more representative and might improve the performance of the proposed models. In this study the data was captured in particular day this limited to represent the aggregated potential of participants to do activities.by regularly measuring activities for some specific time could the data more representative to represent the potential of particular person to do activities. And also, in this work only nine human activities were considered by increasing more activities will make more effective. By preparing such normative data, it may be possible to improve model performance and human activity recognition.

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