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A Smartphone Sensor Based Real-life Human Activity Recognition System using Deep Nets Method

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ABSTRACT-The proliferation of sensor devices in recent years has made Human Activity Recognition (HAR) a hotspot for academic interest. Smartphones with built-in sensors make it possible to employ such sensors for activity detection tasks like assisting the elderly with their everyday tasks. A plethora of high-tech sensors, such as global positioning systems (GPS), cameras, accelerometers, microphones, light sensors, and compass, are standard on these smartphones. Activity recognition is a promising field of study that might be used to provide consumers with flexible and efficient services. The purpose of our research is to evaluate a system that makes use of accelerometers, which are acceleration sensors that are built into smartphones. For the purpose of running the model and understanding six distinct human activities through supervised machine learning classification, twenty-six users' accelerometer data is collected while they go about their daily lives, including sitting, standing, lying down, walking, and climbing and descending stairs. Following the merging and aggregation of the sample data, supervised machine learning techniques were employed to generate prediction models from the instances. To get beyond the limitations of the lab, we used the Google Android platform and the Physics Toolbox Sensor Suite to gather this time series data. In this work, we take a look at how Machine Learning and Deep Nets have been used to address issues with human activity identification using smartphone sensors. Furthermore, we proved that data collected with lower frequencies can still serve their intended purpose. Our most basic Deep Nets model yielded a maximum accuracy of 95.71% for the male dataset and 94.62 % for the female dataset.

KEYWORDS-Accelerometer, Human Activity Recognition (HAR), Activities of Daily Life, Sensor, Smartphone Sensor, Deep Nets, WISDOM Dataset.

I. INTRODUCTION

Research in human activity recognition (HAR) has been steadily increasing in recent years, mostly driven by the use of cellphones in this field. Smartphones have recently become an integral component of people's daily lives. Smartphones allow us to record people's everyday activities. Two of the most common types of sensors are accelerometers and gyroscopes. Thanks to the built-in sensors included in cellphones, we are able to monitor the person's motion. Standing, walking, lying, sitting, going upstairs, and going downstairs are just a few of the common everyday behaviours that may be identified using this data [3]. In accordance with [4], there are three main types of sensors: those worn by the user (e.g., gyroscopes, accelerometers on bands, and smartphones), those attached to objects (e.g., RFID chips, accelerometers on cups, and Wi-Fi and Bluetooth) that record the motion of those objects, and finally, those embedded in the user's immediate environment (e.g., sound, door sensors, and Bluetooth) that reflect the user's interaction. [5]. The focus of this research is on the use of embedded sensors, such as gyroscopes and accelerometers, to identify human actions. These devices can measure acceleration (the rate of change of speed) in three dimensions, and smartwatches and smartphones can do the same. The use of smartphones for activity recognition has been the subject of much research. One reason to use smartphones for HAR action discrimination is because of their many useful features, such as their capacity to communicate, their portability, their computing power, the variety of embedded sensors they contain, and their ability to extract and combine context information from various real-world settings [6].We used data collected from both male and female volunteers, as well as data collected from a triaxial gyroscope and a 3-axis accelerometer on smartphones, for our study. We have developed an Android app that can retrieve the requested sensor data at a 1 Hz frequency. After the data gathering stage, we utilize the android app and are worried about getting inaccurate results because of software or hardware errors [7]. hence, we exclude any instances of missing data, extreme values, inconsistencies, and attempts at normalization. To further narrow down the necessary skills, we ran a procedure called principal component analysis, or PCA. We train it using a number of different Deep Nets models, such as SVMs, NBs, and LRs (Logistic Regression). Next, we document various actions such as walking, jogging, using the Deep Nets version, sitting, status, lying down, and on foot.

II. RELATED WORK

The sequence of sensor readings is in time, making Human Activity Recognition a time series issue. Unlike a 1D convolutional neural network (CNN) [9], T. LSTM [8] cells may detect correlations in time-dependent input without combining the timesteps. With the advent of "big data," LSTM [10] architecture has the potential to improve results in a number of untapped areas. Recent years have seen tremendous advancements in the area of HAR, but there is always need for improvement. Using a machine learning classification system, Gyllensten et al. [11] were able to distinguish between various actions such as walking, running, sitting, lying down, and cycling. Although the findings were typically excellent when tested in a controlled environment, the researchers found that the performance under real-world situations (i.e., with untrained data) was much worse. As we point out, one constraint is that sensors ideally ones that can be worn on the body could be used to monitor agents' movements in real time. Multiple sensors placed at strategically chosen points on the human body greatly improve the accuracy of activity classification, as demonstrated by Esfahani et al. [12]. Data collection and subsequent pooling for subject affiliation checks posed a significant challenge; a separate model would be required to recognize complicated behaviours, and the majority of untrained data would not be correctly categorized.Mi Zhangang [13] suggested a way to comprehend commands like "forward," "walk left," "proper," "up," "down," "soar," and "seat on a chair" utilizing a histogram of fundamental characters. Using data from accelerometer sensors, S. Dernbach et al. [14] followed ten people while they rode, walked, ran, sat, and stood. The sample frequency is 80 Hz, and the individual chooses the mobile for the sensor data series. The use of a multi-layer Perceptron yielded a 93% accuracy rate for this task. In addition to that, there are a plethora of other things to do, such as making coffee, drinking, going to the toilet, ironing, eating, cooking, applying cosmetics, combing hair and many more. Since reducing the computational cost of an operation increases its accuracy, accuracy of activities remains an unresolved issue in HAR-related work. A approach that considers the context and groups the five out of twenty actions to decrease computing complexity and error was developed by Liang Cao et al. [15] as a solution to this problem. Using logistic regression, K-nearest neighbor, and support vector machine (SVM), Li Fang et al. identified features from raw data. Logistic Regression had an average accuracy of 83.9%, KNN was 95.3% accurate, and SVM was 88.9% accurate. Up and down buses were the primary emphasis of the piece. For up bus, SVM achieved an accuracy of 89.5%, KNN 96.8%, and LR 89.7%; for downbus, SVM 84.2%, KNN 94.2%, and LR 81.9% [16]. Subjects wore two inertial sensor units on their wrists and ankles, and Yu-Liang Hsuetal. Collected a motion signal based on 10 everyday activities. For the purpose of processing raw data, nonparametric weighted feature extraction algorithms were employed to reduce the feature dimensions. The data was classified using a probabilistic neural network, which achieved an19ccuracyy rate of 90.5% [17].

III. MACHINE LEARNING

There has been a meteoric rise in the number of machine learning [18] applications that automate and solve issues across many different industries. This is mostly attributable to developments in processing power, advances in machine learning [19] methods, and the proliferation of accessible data. You can’t dispute the widespread usage of machine learning to address some of the most pressing issues in contemporary network administration and operation. Numerous Machine Learning surveys have been conducted for niche networking sectors or for specific network technologies. With the use of machine learning, data filtering and inference are now feasible. Beyond just gathering information, it involves putting that knowledge to use and improving it through time and experience [20]. Discovering and capitalising on latent patterns in “training” data is the fundamental objective of machine learning. Using the learned patterns, new data may be mapped to existing categories or classified.

A. Deep Nets

The use of artificial neural networks is the basis of deep learning, a subfield of machine learning. It has the ability to understand intricate data patterns and correlations. There is no requirement to explicitly code every single item in deep learning. Because of improvements in processing power and the availability of massive datasets, its popularity has been on the rise recently. The usage of deep neural networks, seen in figure 1, with several layers of linked nodes, is a defining feature of deep learning [21]. By sifting through data for hierarchical patterns and characteristics, these networks are able to learn complicated data representations. Without human intervention in the form of feature engineering, Deep Learning algorithms are able to learn and develop autonomously from data. Deep Learning models are able to learn from enormous datasets and scale to manage complicated and huge datasets.

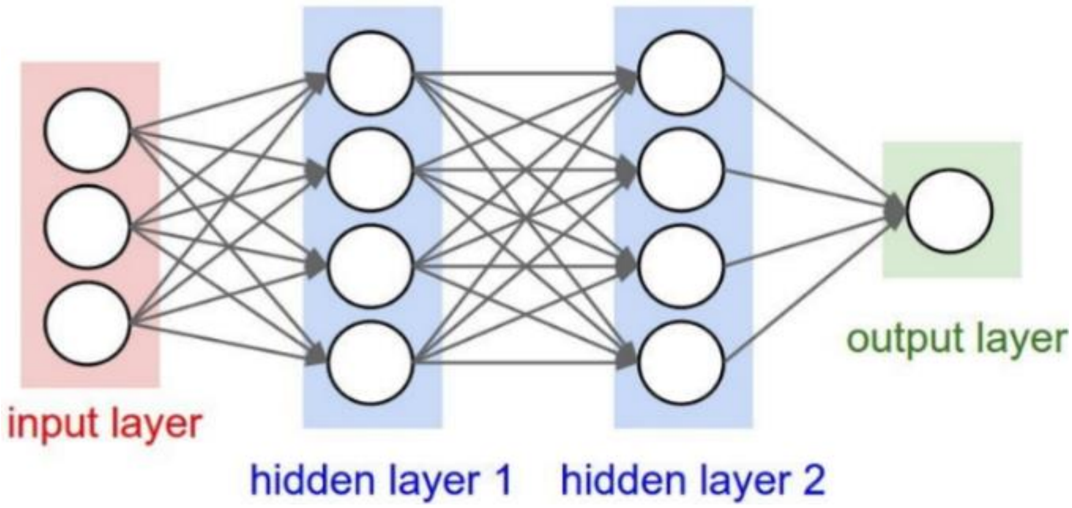

Figure 1: The Deep Nets

B. Support Vector Machine (SVM)

In order to differentiate between two sets of data, support vector machine classification uses features supplied by relevant data and a classifier that focuses on hidden data. Maximum range classification is the simplest form of support vector machine. The primary classification problem is often addressed by employing linearly separable training data for binary classification.

C. Random Forest

Both the classification and regression processes make use of a supervised learning method known as random forest. However, classification problems are its primary use. Having more trees in a forest makes it stronger, as is well known. In a similar vein, the random forest technique constructs decision trees from data samples, extracts [47] predictions from each tree, and finally finds the best choice by voting.

D. Decision Tree (DT)

The decision tree is a powerful supervised learning tool with many useful applications, including classification and regression. It makes a tree structure that looks like a flowchart, with each node representing an attribute test, each branch representing a test result, and each terminal node representing a class name. Repetition of attribute-based subset separation from the training data eventually leads to a stopping criterion, such as the maximum tree depth or the minimum number of samples required to separate a node. This is one of the strongest algorithms.

E. K- Nearest Neighbor (KNN)

To find the unknown data point, the Nearest Neighbor method zeroes in on the nearest neighbor whose value is known. Find the closest place as best you can. There are two methods for dismantling the Nearest Neighbor mechanism. When using closest neighbor classification algorithms, structure and function are seldom taken into account. A less approach is what K-NN [48] is called in the scheme. For every data point in the class description, the KNN method uses the NN for k to find out how many NN need to be verified. It is possible to classify NN methods as either KNN-dependent or KNN-less.

F. Naïve Bayes (NB)

Based on the Bayes theorem, the naïve Bayes classifier is a type of probabilistic classifier that assumes that each feature has an equal and independent impact on the target class [49]. Based on the premise that features do not interact with one another, the NB classifier uses each feature to determine the class membership of a sample in an equal and independent fashion. In addition to being computationally fast and easy to implement, the NB classifier performs admirably on large, high-dimensional datasets.

IV. PROPOSED APPROACH

A. Data Collection

Various methods for collecting information have been suggested. Various sensors included in smartphones and smartwatches were used to compile the dataset that uses HAR. A dataset was developed by Kwapisz et al. [22] using accelerometer data that was overseen by a member of the WISDOM team. For the “WISDM Smartphone and Smartwatch Activity and Biometrics Dataset,” researchers surveyed 51 people, giving them three minutes to complete 18 different activities. An individual’s dominant hand was adorned with a smart-watch, while their pocket was stocked with a smartphone.

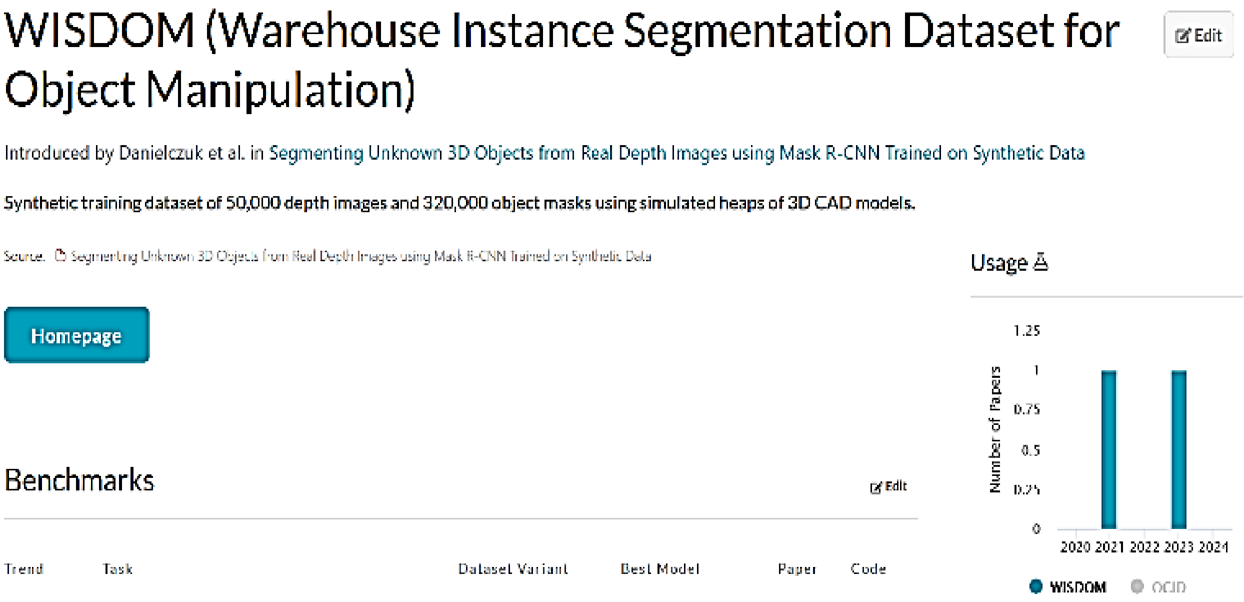

Figure 2: The WISDOM Dataset

Figure 2 shows a smartphone and wristwatch that were used to control the data collecting. Modelled using machine learning methods [23], the standard dataset for HAR utilizing smartphones was publicly available in 2012 and fully explained in 2013. Thirty adults, ranging in age from 19 to 48, had their smartphones worn around their waists to capture data from their gyroscopes and accelerometers in three dimensions [24]. Various standard datasets were subsequently used for modelling and implementation. Datasets obtained from the accelerometer and gyroscope sensors used in smartphones and smartwatches are made freely accessible for HAR in table 1.

B. Behaviours to be Identified

Impulsive and repetitive behaviours are the two main types of human behavior. Our study accounts for both impulsive and continuous measurements. In contrast to the stable actions of standing, sitting, laying down, and using the loo, we tried to use the impulsive motions of walking, jogging, typing, and writing. Everyone does these things all the time. The size or periodic structure of a job type is a good way to identify it. The periodicity of the oscillations distinguishes continuous motion from impulsive motion, which is characterized by a distinct sensor size.

a. Feature Selection and Pre-processing

With supervised learning, a plethora of candidate characteristics are introduced to more accurately represent the search domain. The problem is that a lot of these attributes are either limited in scope or are completely superfluous. The lowest feature size will drastically reduce the running duration of the learning algorithm and the learning technique. Since human behaviour may be both steady and impulsive, it is important to select sensor data qualities that distinguish between continuous and impulsive behaviours. We are worried that the use of an android app to gather data might lead to inaccurate results due to software or hardware issues. Consequently, we eliminate values that don't apply, extreme cases, and inconsistencies. Given that the three-axis gyroscope measures in radians per second and the three-axis accelerometer in metres per second squared, we developed a method to standardise the two databases. Informally called a "sample component analysis," Using the principal component analysis (PCA) method, features that are part of the actual collection of features may be identified, allowing one to either reduce the number of features or make selection trade-offs. As a result, we used principal component analysis (PCA) shown in figure 3 to our database and found that the three-axis gyroscope and triangle accelerometer both exhibit substantial changes when the original features are orthogonally transformed, or rotated.

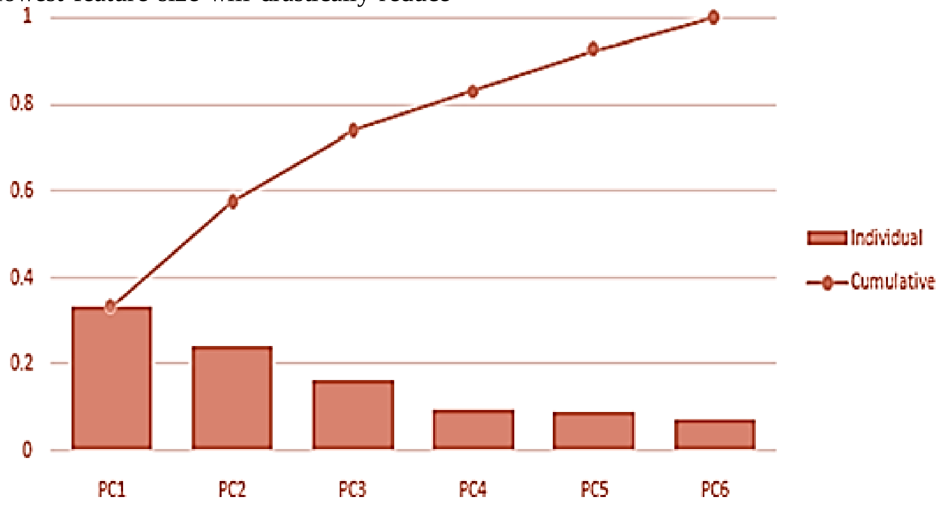

Figure 3: The Principal Components' Individual and Cumulative Variance

b. Applied Machine Learning Algorithms

A number of machine learning approaches are available for use in data classification. A distributed DNN requires at least two layers: an interface layer and an output layer. Each DNN has an interface layer that takes in signals, an output layer that chooses or predicts the input, and a hidden component that houses all of the processing power. The formal name for a DNS function that operates on a hidden layer is,

$$f: R^D \longrightarrow R^L \qquad (1)$$

The size of the input vector is denoted by D, the sizes of the output vector and function are given by x and L, respectively, in matrix notation.

$$f(x) = G(b^{(2)} + W^{(2)} (S(b^{(1)} + W^{(1)}x))) \qquad (2)$$

Where, weight matrices W (1) and W (2); bias vectors b(b(1) and b(2)); and activation functions G and S. The vector,

$$h(x) = \emptyset(x) = (s(b^{(1)} + W^{(1)}x))) \qquad (3)$$

In order to construct the cover layer, the weight matrix that links the input vectors to the buried layer is W(1) RD * D. The weights of the input partitions to the i-hidden partition are represented in each column of W(1). The logistic sigmoid, the hyperbolic tangent, and the nonlinear monotone product of Recertified Linear Units (ReLU) are common options for S in bivariate classification. In terms of mathematics, this activation function is defined as,

$$tanh(z) = (e^{(z)} - e^{(-z)}) / (e^{(z)} + e^{(-z)}) \qquad (4)$$

$$logit(z) = 1 / (1 + e^{-(z)}) \qquad (5)$$

$$ReLU(z) = max(0, z) \qquad (6)$$

Using fundamental functions is inevitable when expanding scalar functions to vectors and vectors. For example, the magnitude of the vector is the same for each member of the vector independently. The last vector of output,

$$O(x) = G(b^{(2)} + W^{(2)} h(x)) \quad (7)$$

The Bayes theorem proposes a naïve Bayes classifier, although the mining approach is considered better. The Bayes theorem states that it is possible for the event to happen once. Here is how the Bayes theorem is expressed mathematically.

$$P(A|B) = P(B|A)\, P(A) / P(B) \quad (8)$$

P(A) is the probability before event A in a given circumstance, and P(B) is the probability before event B in the same situation; both expressions together represent the likelihood of event A happening in that situation. the case, and P(A|B) shows that, under specific conditions, B will be performed. Regardless of the limitations of the classification issue, we may state that B is a data sample with an unknown class, and that P(A|B) indicates that hypothesis A is related to category C. One of the top classifiers, Random Forest, uses an ensemble learning strategy that maximises decision tree convergence. Decision trees, with its justification points serving as substitute predictor variables, were first proposed by a random forest. Decision trees that have trustworthy and practical impact. Subtrees that emerge from this process may show more dissonant development, but it's not always proportional to the amount of training they've received. We choose to build 100 decision trees in order to make the suggested categorization work as well as possible. A simple explanation of how to do the random forest operation is as follows.

- The available database is used to select swatches for dictatorships.
- The selected swatches are utilised to summarise the prediction findings, and the decision tree is started.
- Predicted results influence voting. There is a tallying of votes.

Support vector machine a.k.a. When it comes to classification, for every picture that falls into a certain category, a qualified hyperplane is compiled to help classify surrounding samples. After you've decided on a kernel and gamma and regularisation parameters, it's time to hit the SVM model. In this case, the gamma value helps denoising the SVM model, and merging the kernels determines how similar the opposing features are. Typically, SVM primarily adds binary classification, whereas kernels simplify linear classification. Our SVM model architecture yielded the highest performance results when we used the "rbf" kernel with a gamma value of 0.01.

Not only that, but a popular ranking algorithm known as KNN classifies fresh samples based on their predicted relationships using a database with data bits organised into distinct communities. Because it is non-parametric, it specifies the design's framework without making any assumptions on the data's distribution. Hence, it should be one of the main categorization possibilities when there is little to no prior information available. If k is greater than 0, KNN determines the interval k for future tests. At K=11, our model structure reaches its peak accuracy. In order to normalise the data, this method updates the value of each attribute.

$$Newx = Xmean - Oldx \quad (9)$$

The former value of the attribute is represented by Oldx, while the mean of the old value is denoted by Xmean. *The new value of the attribute is *Newx. As a result, the focus won't be on any one thing. The revised sample's normalised value is calculated using the given formula.

$$Normalized\ Xi = |Xi\text{-}Xmean| / St\ Deviation \quad (10)$$

This new sample included Xi. It lets you perform all the tasks in a new stage, which simplifies the differences. One can find the number of unique features by calculating the discrepancy between the frequencies of each attribute. Last but not least, KNN compares training data samples with new prediction data using a similarity metric. In order to train our network and assess its classification accuracy, we utilize 80% and 20% samples from our dataset, respectively. We apply DNA using the scikit-learning API, a machine learning framework. The classifier model made use of six hidden layers, where each layer had a different number of perceptron's 200 in the sixth layer, 300 in the fifth, and the same amount in the first three. The fourth layer had 300 perceptron's. One hundred layers make up a perceptron. Adding hidden layers to a DNN improves its accuracy; we found that six layers were enough to achieve excellent accuracy. Activation function "tanh" is the hyperbolic tangent function we use. As a solution, we use the "adam" classification approach, which is an optimizer based on stochastic gradients. We set the step size for updating the weights at 0.0001 so that the model can finish at the global maxima with a cap of 2000 iteration.

V. RESULTS ASSESSMENT

We use the given machine learning method to train 80% of our whole database and test 20% for both of them. The heat map showing the density neural network's performance on the male and female datasets displays this confusion matrix shown in figure 4.

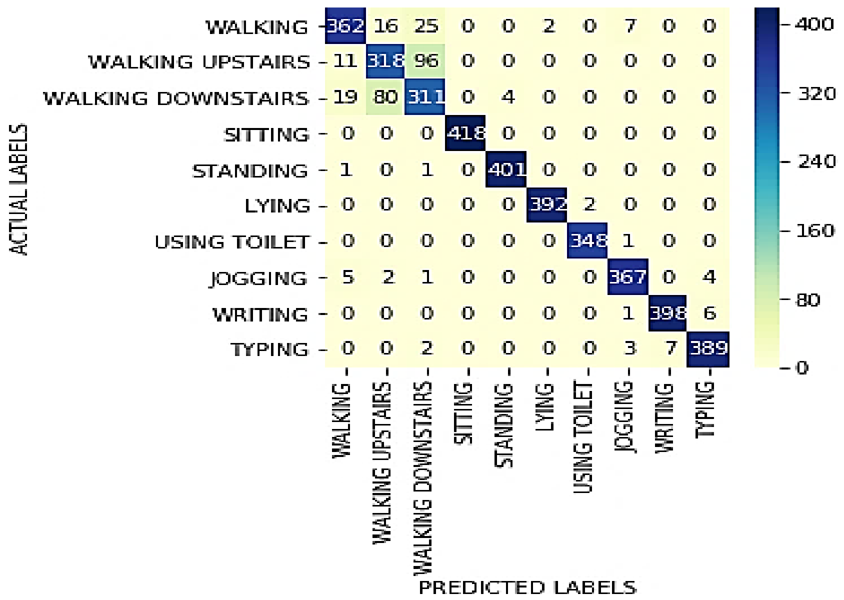

Figure 4: Deep Nets Performance on a WISDOM Dataset

In the instance of the male data set, it is evident from the confusion matrix that all events including sitting, standing, lying down, and using the restroom are accurately identified. Big misunderstandings are below. Out of the 514 cases of people walking down, 386 were correctly categorized, while the remaining 100 examples were up, 35 were walking, one was standing, and one was sitting on the toilet.

Table 1: Deep Nets Performance Estimation & other Classifier

	Female WISDOM Dataset Accuracy%	Male WISDOM Dataset Accuracy%
Support Vector Machine (SVM)	93.33	94.03
Decision Tree (DT)	89.71	89.93
Random Forest	93.81	94.22
Deep Nets	94.62	95.71
K- Nearest Neighbour (KNN)	93.61	94.18
Naive Bayes (NB)	86.68	86.88

Similar to this, practically all activities including jogging, writing, and typing are correctly categorized. Verify that every instance of sitting and laying has been accurately categorised using the female database. Only one instance involving the road was noted out of the 518 cases. The most common false beliefs regarding walking are as follows. Only 365 of the 495 cases 49 were pedestrians, 86 were above, and 4 were standing were accurately categorized.

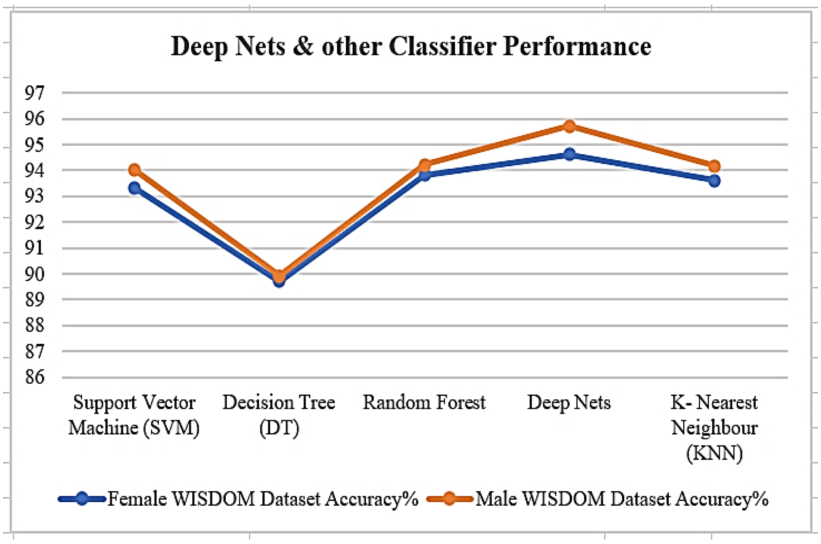

Figure 3: Deep Nets & other Classifier Performance Estimation

For SVM, we were able to get accuracy rates of 94.03% for the male dataset and 93.33% for the female dataset. 499 of the 502 cases in the male data set were correctly categorized, two were deemed to be of low grade, and one was found to be walking. The number of examples that were successfully categorised is represented by the confusion matrix's diagonal value. However, the female data set is appropriately classified, with 5 samples representing the understory and 2 samples representing runners, out of 482 samples of 475 stands. For both datasets, every instance of lying was correctly classified. For DT, the male dataset's accuracy was 89.93%, while the female dataset's accuracy was 89.71% shown in table 1. For the male data set, KNN's accuracy is 94.18%, while for the female data set, it is 93.61%. In the RF situation, we got the best accuracy for both men and women. For the male data set, it is 95.71%, while for the female data set, it is 94.62% shown in figure 4. The confusion matrix revealed that every case had been accurately categorized for sitting in the male database. The biggest falsehoods, however, are found on the higher and lower floors when one walks around. In the women's complex, all instances of sitting and using the restroom have the appropriate classification. For Naive Bayes (NB), we got the worst accuracy. For the male data set, it is 86.88%, while for the female data set, it is 86.66%. For male database, the biggest error was made while sprinting, walking, and walking upstairs and downstairs. The female database covers information about standing, walking up, walking down, and other types of movement. But all cases are divided correctly for jobs that are toilet-related.

VI. CONCLUSION

This study provides a thorough synopsis of the existing literature on HAR that makes use of inertial sensors in smartphones and smartwatches. We began with an overview of human activity, then moved on to detail the public dataset and the sensor modality that makes use of smartwatches and smartphones. Also covered in detail in this article are two approaches to activity recognition: the conventional one, which relies on shallow machine learning techniques, and the more modern one, which uses deep learning algorithms. In this paper, we tackle the problem of activity identification utilising three-axis and three-axis gyroscope sensors in smartphones. We found that out of all the rating systems, these ten random animal motions were the most accurate. In the last game, we saw that a lot of people were reading, using the lavatory and sending and receiving texts on their phones. Additionally, we proved that previous studies did not compare two separate datasets for males and females. This work helps to give a solid picture of the HAR domain when seen through the lens of inertial sensors found in smartphones and smartwatches. The data gathering method is more effective and robust at identifying human activities than other methods. In the future, we can incorporate more advanced recognition activities and expand our support for multi-sensor data.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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