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Machine Learning Based Efficient Human Activity Recognition System

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Abstract: Human actions pose a serious issue in many different fields. The intriguing potential in this area includes smart homes, assistive robotics, human-computer interfaces, and security upgrades, to name just a few. The cornerstone for the creation of potential applications in the areas of health, wellness, and sports is in particular activity recognition. Applications for Human Activity Recognition (HAR) are numerous due to its effect on wellbeing. The display of people presents a substantial challenge for the analysis of human behaviour through activities. The success of machine learning (ML) techniques in many applications stimulates their use in data analysis as they become more sophisticated. The routine collection and saving of data from Internet of Things (IoT) sensors, which is used to support decision-making, has also been made simpler by recent developments in advanced technology. Conversely, there is a crucial requirement to collect and organize patient data in electronic arrangement in the mainstream of the countries. The composed data will then be scrutinized for a diagnosis, a prediction, and probable therapies dependent on the patient's admissibility. The Wireless Sensor Data Mining (WISDM) Smartphone and Smart watch Activity and Biometrics Dataset is used in this study to forecast human activity. In this work, numerous human actions were used to train machine learning models. K-Nearest Neighbour (KNN), Naive Bayes (NB), and Support Vector Machine (SVM) methods are used to analyse with the novel model named, features-based fused SVM-KNN approach. The suggested model is superior to the other algorithms, according to the results.

Keywords: *Machine Learning, IoT Sensors, Human Activity Reorganization, SVM, KNN.*

1. Introduction

One of the furthermost significant areas of computer vision research today is human activity detection. It has various uses in daily routines and industry, including video surveillance, monitoring systems, virtual reality, and human-machine interaction. The difficulty in human activity detection is to accurately identify different behaviours in complex scenarios, to provide a high recognition rate, and to streamline implementation in real-time applications while consuming minimal processing power [1]. Thanks to developments in electronic and integrating technologies, smartphones of all kinds have become more prevalent and essential in our daily lives in recent years. The various sensing capabilities of today's smartphones, which are continually evolving, can identify a user's awareness of their surroundings and provide more specialised services. Because smartphones include so many sensors, it is conceivable to attain high-frequency and high-precision categorization signals in real-time [2]. The popularity of HAR using these felt data swiftly rises since these unprocessed data establish a connection between human activity and the sensors [3]. Compared to other smart devices, utilising cellphones to detect human movement has a number of benefits. There is no longer a need for extra devices that could be inconvenient and expensive for the candidate since practically everyone carries a smartphone today [4]. Second, the hand-held device features a range of built-in sensors that allow it to collect activity data from dissimilar perspectives. Third, the high-performance computing capabilities of smartphones have increased the recognition of complex and real-time online activities. Finally, due to their fundamental communication requirements, smart devices offer a greater range of potential applications [5].

The foremost objective of this paper is to develop an operative system that visually displays the prediction performance of ML approaches using an IoT sensors dataset for HAR. Additionally, it aims to develop a well-structured system that visually displays the prediction performance of various ML techniques using the

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proposed feature-based fused SVM-KNN approach. One of the furthermost imperative and thought-provoking challenges in computer vision is HAR. A few examples of potential applications include gaming, human-robot interaction, rehabilitation, sports, health monitoring, video surveillance, elder care, and robotics [6]. Humans engage in a variety of common and formal activities every day, including riding, housework, and viewing films. These activities all require a number of fundamental movements, such as standing, sitting, bending, running, and typing [7]. Designing a human-computer interaction system requires completing crucial tasks, one of which comprehends human activity. The required features may be extracted by the HAR module from the supplied signals [8]. The automated recognition of elderly people's actions is the primary goal of the proposed HAR system, which uses raw data from IoT wearable sensors [9].

Due to the significance of automated systems, computationally intelligent methodologies like Artificial Intelligence (AI) techniques, Machine Learning (ML), and Deep Learning (DL) are in demand for the classification of such processes [10] [11]. A variety of HAR ML techniques are examined in this study [12]. On the other hand, quick advancements in modern machinery have prepared it much simpler to regularly accumulate and store gigantic amounts of data that can be utilised to support important decisions [13]. The WISDM Smartphone and Smartwatch Activity and Biometrics Dataset is used in this study to forecast human activity. Building pre-trained ML models that can categorise a range of human behaviours is the aim of this research [14]. Walking, jogging, stair climbing, stair descending, sitting, standing, and lying down were all investigated as part of this study [15]. The architecture illustration for the suggested experimentation is publicized in figure 1.

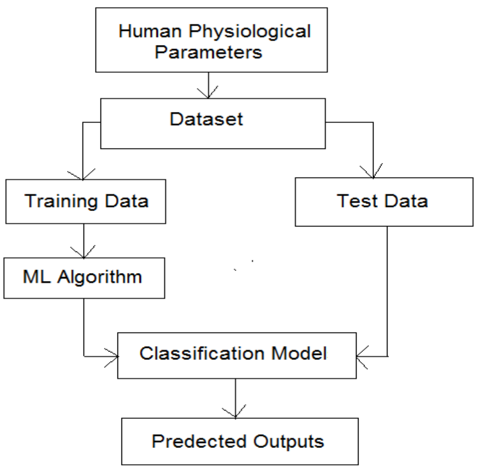

Fig.1. Proposed System Architecture

Therefore, the main unprejudiced of this work is to confirm how well the ML methods KNN, NB, and SVM perform when used with the suggested model for HAR. The performance of the model is affected by a variety of properties of ML in the suggested notion [16]. The remainder of the essay is organised as follows. The associated research articles in the HAR, ML, and IoT fields are included in Section 2. The proposed methodology is thoroughly explained in Section 3, and the results are shown and discussed in Section 4. Finally, section 5 offers a conclusion.

2. Related Works

The SVM model outperforms the other algorithms with a good percent accuracy in their examination by means of a smartphone sensor dataset from the UCI (University of California Irvine) Repository, according to a HAR model developed using machine learning techniques [17]. The SVM technique outperforms the competition in this instance, but the study's main drawback is that it requires a lot of time to train on large datasets [18]. The GSO-CCNN approach [21] is used to propose an ML and DL model for sophisticated cardiac disease prediction systems employing medical sensors for the IoT [19] and fog computing [20] (containing sensors to measure glucose level, respiration rate, temperature, oxygen level, EMG, EEG, and ECG). With high accuracy and improved resilience in identification, a system was developed for HAR using the WISDM dataset and the LSTM-Convolutional Neural Network (CNN) architecture; nevertheless, the full iteration requires more computational time and is challenging to extract the activity features [22]. With the help of CT-PCA (Principal Component Analysis), an unsupervised ML algorithm, and SVM (Statistical Vector Machine), an algorithm developed using the Online Independent Support Vector Machine (OISVM) [23], an Online Support Vector Machine (OSVM) technique that uses only a minor portion of a dataset and is impotent to achieve great accuracy for large datasets [24], a reliable human activity detection system was created using smartphone sensors.

With good percent accuracy and the advantage of feature selection, a Neighbourhood Component Analysis (NCA)-based SVM method for smartphone-based HAR with feature selection [25] and Dense Neural Network [26] was developed. This technique produces smaller models that are learned more quickly by taking into account only some of the characteristics. Unfortunately, since feature selection is often so time-consuming, the time-saving benefit of faster model training is lost [27]. The huge dataset is used to extract key properties for NCA implementation. This strategy lowers the operational expense. In order to identify the seven distinct human routines, grouping techniques including Random Forest (RF) [28] and KNN algorithms [29] were used. The results are summarised [30] after the actions are categorised using KNN and RF classifiers with varied neighbours. A range of systems, including Human Computer Interfaces (HCI), surveillance, patient monitoring, and other arrangements that encompass human-computer contact use HAR [31]. Applying K-means clustering, which includes pruning, and employing the frame2im function to extract the frames from videos in the form of images, increased HAR performance. It is suggested [34] to concentrate on CCTV footage and camera images in order to identify human activities using the CNN classifier and detect human postures using HAAR feature-based classifier. To capture and transmit motion data, as well as to identify real-time activities, multi-channel motion data gathered from a smartphone is restructured and turned into a virtual image with iOS application software [35]. Modern mobile phones have sensors built in that can discreetly detect daily living activities (ADLs). The different statistical and DL methods for the automated HAR are presented, and accelerometry data from a mobile phone used by the user was collected over a period of days in order to categorise ADL according to the degree of movement displayed into classes for the stationary, light ambulatory, intense ambulatory, and abnormal categories [36].

3. System Model

The dataset description opens this section. Human activity detection attempts to foretell a person's actions by using sensors and a trail of their past behaviour. The "WISDM Smartphone and Smartwatch Activity and Biometrics Dataset" includes 5418 participants who had to complete six tests in three minutes each. Every participant wore a Smartwatch on their dominant wrist and carried a smartphone in their pocket. A specially developed programme that operated on the Smartwatch and smartphone was in charge of data collection. Data was gathered using four sensors, including the accelerometer and gyroscope on the smartphone and Smartwatch. Every 50 ms, or at a rate of 20 Hz, sensor data were recorded. The watch in question is the LG G Watch, which runs Android Wear 1.5. Weka on Windows 10 and the UCI repository were used to get this dataset. This database contains 46 attributes [14]. These are the class designations for them:

- Walking
- Jogging
- Upstairs
- Downstairs
- Sitting
- Standing

3.1 Classification

The ML system is starting to play a significant role in many decision-making applications by classifying HAR into many groups depending on its characteristics. ML methods are frequently used to address issues in the healthcare industry. As a result of these ML technologies, medical decision support systems have been created. It examines how data is used by computers to learn. Research in machine learning (ML) is interdisciplinary and focuses on designing algorithms and how computers use these algorithms to learn. Taking in data from a feature dataset is all that learning entails. ML structures are often developed and put into usage in a way that permits an proficient system to use historical data to develop a solution to a diagnostic problem. Several learning algorithms, including supervised classification, unsupervised classification, and reinforcement learning, are accessible for the classification task. Classification is a unique supervised learning processes, where the target class is expected using the classification tool. This study uses supervised machine learning techniques to address the HAR classification as a common classification problem using IoT sensors [37]. With supervised learning produced from labelled samples in the training data set, the recommended system employs a number of supervised learning approaches. It helps learning models be trained effectively, enabling them to provide high classification accuracy. As a result, methodical processes and cautious algorithm selection for learning are needed [38].

Supervised Classification

One can predict the outcomes for unidentified data by using a mapping between a set of input variables X and a matching output Y that has been learned through supervised learning. The majority of practical machine learning methods use supervised learning. The procedures learn to estimate the outcome depending on the input, and all of the data is labelled. This study employs machine learning (ML) classification algorithms including KNN, NB, and SVM to demonstrate how each algorithm performs given a collection of features. The fused feature-based KNN-SVM model is compared to all these algorithms' performance.

3.1.1 K-Nearest Neighbor Algorithm

A supervised learning method known as KNN is used primarily for classification tasks. This strategy's core tenet is that it yields comparable outcomes for comparable training samples. It is intended to classify all or any samples and finds the input sample's closest value. Examine $X_i = \{x_1, x_2, \ldots, x_{iN}\}$ and $X_j = \{x_1, x_2, \ldots, x_{jN}\}$ the sample population as in eq. (1), so that the distance may be determined to determine how similar they are,

$$\mathrm{Dist}(X_i, X_i) = \sqrt{\sum_{m=1}^{N} (x_{im} - x_{jm})^2} \quad (1)$$

The equation above states the Euclidean distance, which compares how similar two pixel locations are. The pixels are consequently assigned to the group to which a large majority of them frequently belong. The KNN's K nearest neighbours count is K. The number of neighbours is the main deciding factor. K is often an odd number when there are two courses. When K=1, the process is known as the closest neighbour computation. This is the scenario that is the simplest to comprehend [39].

Algorithm: KNN classifier

Input: IoT sensor features

Output: Accuracy and Validity

Classify (X, Y, x)//X: Training data; Y: Class labels of X, x: Unknown sample, and the process in KNN model is shown in figure 2.

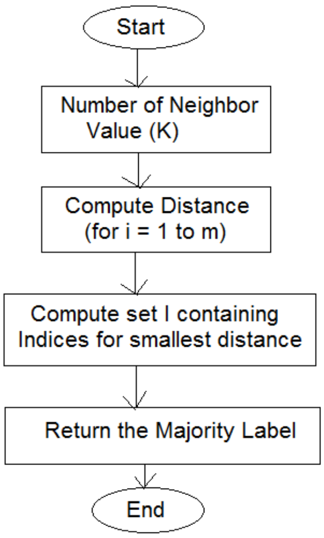

Fig.2. KNN Model

3.1.2 Naive Bayes Algorithm

An ML model called Naive Bayes is recommended even when working with data that contains millions of records because it can handle large amounts of data. With great results, it performs Natural Language Processing (NLP) tasks like sentiment analysis. The Naive Bayes theorem makes use of conditional probability. The conditional probability is the possibility that approximately will happen given that somewhat else has already happened. The conditional probability and our prior information can be used to compute the probability of an event.

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)} \quad (2)$$

Where,

P(A): The likelihood that hypothesis H is accurate. The prior probability is referred to as this.

P(B): Likelihood of the evidence.

P(A|B): The likelihood that the evidence supporting that theory is accurate.

P(B|A): The likelihood that the theory is correct, given the available data.

Naive Bayes is the name given to a classifier that uses the Bayes theorem. Membership probabilities are forecasted for each class, including the possibility that a certain class will include a specific quantity of data points. The likelihood is thought to be highest for the best-suited class. MAP is another name for Maximum A Posteriori.

- The MAP for a hypothesis is:

$$MAP\ (H) = \max P((H|E))$$

$$MAP\ (H) = \max P((H|E) * (P(H)) / P(E))$$

$$MAP\ (H) = \max(P(E|H) * P(H))$$

P (E), means probability evidence; that computes the outcome. P(E) elimination has no influence on the outcome.

Algorithm: NV classifier

Input: IoT sensor features

Output: Accuracy and Validity

3.1.3 Support Vector Machine Algorithm

It is a sort of supervised categorization that integrates the idea of decision planes. The support vector machine was developed as a learning tool to classify image qualities as positive or negative in challenges involving two groups of objects. It is effective at classifying data and has the ability to save the best attributes. Given that most situations are linearly divisible, another benefit of SVM is its robustness when there is a limited sample size [39]. SVM is a statistical technique for finding hyper planes in high-dimensional vector spaces. Assume that feature points are represented as (x, y) "tuples," where "xj" stands for the feature values and "yj" for the class. The equation below describes the multi-dimensional feature space for hyper plane.

$$b.x + b_0 = 0 \quad (3)$$

The following equation's function is calculated:

$$f(x^*) = b.x^* + b_0 \quad (4)$$

The objective in this scenario is to identify and establish the maximum-margin ideal hyperplane. The location of the hyperplane that results in the greatest difference between training points for the two classes is required by the SVM algorithm. It also criticises the complete space of points on the erroneous side of their margin if the two sides of the data overlap. This makes it simpler to accept a limited number of marginal misclassifications. Here, two new parameters, "" and "C," are added to permit violation. The definition of "maximize margin of “M"

$$\sum_{j=1}^{p} b_j^2 \qquad (5)$$

and

$$y_i(b.x + b_0) \geq \text{M}(1\ \text{i}),\ \ \text{i} = 1 \ldots \text{n} \qquad (6)$$

Where

$$\in \text{i} \geq 0,\ \sum_{i=1}^{n} \in \text{i} \leq \text{C}$$

Together, the parameters "C" regulate how much of each individual I is present, and they are commonly modified to go against the margin. SVM classifier is used for experimenting in this study.

Algorithm: SVM classifier

Input: IoT sensor features

Output: Accuracy and Validity

The model is shown in figure 3; this algorithm takes the optimised features as input, classifies them using the SVM with RBF kernel, and then specifies the hyperplane. The authenticity and accuracy of the results are then verified.

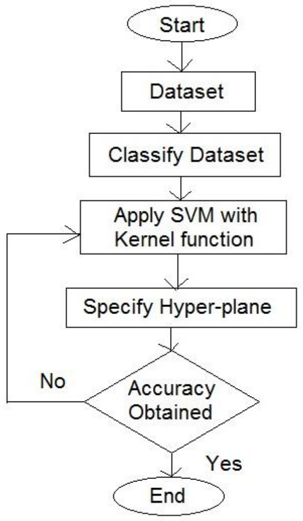

Fig.3. SVM Model

3.1.4 Features-based Fused SVM-KNN Algorithm

Each categorization method has its own set of benefits and drawbacks. In order to determine which approach provides the highest level of accuracy, the ensemble SVM-KNN algorithm is contrasted with the other algorithms. This paper introduces a new feature-based fused SVM and KNN classification algorithm. It is a classification model that extends KNN and SVM. This is a geometric classification method as well as a supervised learning strategy. All features are gathered by this classifier, which then divides them into groups based on how similar they are. The KNN algorithm is used to classify IoT sensor features in the feature extraction process.

In the suggested strategy as shown in figure 4, the distance between the test and training samples is determined using the K nearest neighbour method. The primary objective of KNN is to identify the query sample's neighbours before classifying it according to the majority class of its nearest neighbours. In the training and recognition of activities, the proposed fused classification approach can be employed efficiently for HAR analysis with low computational complexity. The KNN classification approach has a reduced processing complexity characteristic since it does not require the creation of a feature space. In the suggested hybrid technique KNN-SVM, the KNN algorithm is used as the first step in the classification process, and then the SVM method is used as the classification engine of this fused model in the second stage.

Algorithm: Proposed classifier

Input: IoT sensor features

Output: Accuracy and Validity

x – Training Feature;

y – Test Feature;

c – Class;

n – Number of classes

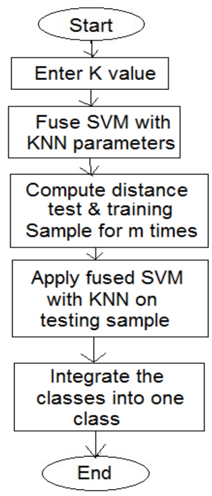

Fig.4. Fused SVM-KNN Model

4. Results and Discussions

4.1 Performance Measures Parameters

The training and testing processes make use of IoT sensor functionalities. 30 % data is provided for testing, and 70 % for evaluation. True Positive, False Positive, True Negative, False Negative, Precision, Recall, F1-Score, and classification accuracy are characteristics used to assess the numerous procedures [40]. The confusion matrix format is shown in figure 5.

True Positive (TP)	**False Negative (FN)**
False Positive (FP)	**True Negative (TN)**

Fig.5. Confusion Matrix Format

- Overall accuracy represents the percentage of correctly predicted outcomes. The equation below can be used to calculate it.

$$\text{Accuracy} = \frac{(TP+TN)}{(\text{TP+TN+FP+FN})} \quad (7)$$

- Precision measures the proportion of positive examples that are really anticipated to be positive.

$$\text{Precision} = \frac{\text{TP}}{\text{TP+TN}} \quad (8)$$

- Recall, also known as hit rate or sensitivity, gauges how well a classifier can identify successful cases.

$$\text{Recall} = \frac{\text{TN}}{\text{TP+TN}} \quad (9)$$

- The "Harmonic Mean" of recall with precision is the "F1 Score."

$$\text{F1\_Score} = \frac{(2 \times \text{Precision} \times \text{Recall})}{(\text{Precision} \times \text{Recall})} \quad (10)$$

Confusion matrix has been utilized in this research to describe how well the ML algorithms performed. It enables the visualization of an algorithm's execution. Additionally, it makes it simple to identify class-to-class inconsistency. Evaluation of different ML algorithms using evolution metrics are listed in table 1.

The suggested classifier outperforms the other classifiers in terms of classification performance, as seen in the table. Because it has a regularization parameter that prevents over-fitting, the SVM classifier has greater classification accuracy. For side HAR analysis, the performance metrics of the various classifiers are compared in the table above. When compared to other ML techniques, the suggested algorithm has the highest accuracy, as shown in figure 6.

Table.1. Evaluation of Different ML Algorithms using Evolution Metrics

ML Algorithms	Accuracy	Precision	Recall	F1-Score
KNN	89.24	88.50	89.18	88.56
NB	90.93	90.56	89.90	89.26
SVM	91.50	90.70	91.00	90.18
Proposed	93.20	92.34	92.59	90.69

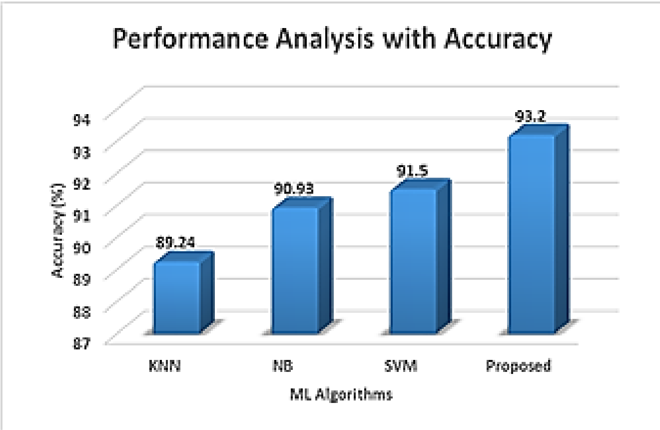

Fig.6. Comparative Analysis with Accuracy

Figure 7 shows the performance of Precision, Recall, and F1-Score, for all the ML models KNN, NB, SVM and fused SVM-KNN in which the proposed technique outperforms with the other algorithms. The proposed work achieved better classification accuracy due to the use of feature optimization technique.

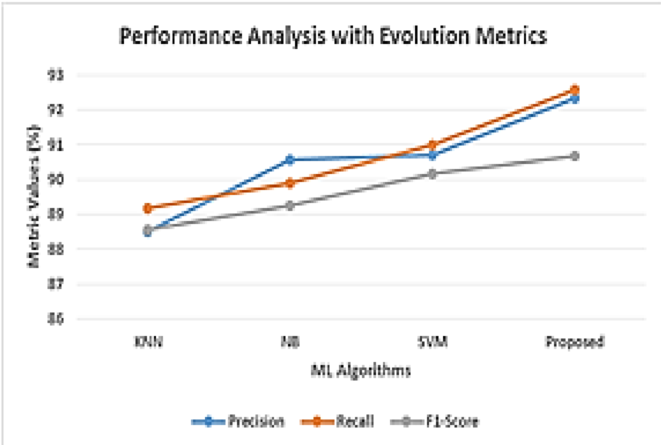

Fig.4. Comparative analysis with Precision, Recall and F1-Score

5. Conclusion

ML techniques are being used more and more in HAR systems. They have shown significant potential in improving their quality of life and preventing negative health-related consequences thanks to wearable sensor-based physiological monitoring. For senior adults who want to monitor their health, documenting daily exercise patterns may be helpful. A significant problem in the senior care system is the identification of human activities. With the advancement of sensor technology, individuals create long-run structures to monitor the health parameters using mountable devices. The above mentioned classification algorithms are implemented using python tool with IoT sensors dataset and the performance of the ML algorithms are compared. The proposed work has better classification accuracy due to the use of fused SVM-KNN technique.

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