



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 5, May 2024

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 8.423

9940 572 462

6381 907 438

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Human Activities Recognition Prediction using Deep Neural Network

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ABSTRACT: Human activity recognition (HAR) based on sensor networks is an important research direction in the fields of pervasive computing and body area network. This project proposes a novel approach integrating hybrid Machine learning models. A combination of K-Nearest Neighbor (KNN), Linear Regression and Linear SVM Model networks are used for sensor based human activity Recognition and Prediction. Leveraging Python Jupyter Notebook for model development. This system utilizes Sensor data collected by smart phone and watches to classify the human physical activity performed by the user. Existing researches often use statistical machine learning methods to manually extract and construct features of different motions. However, in the face of extremely fast-growing waveform data with no obvious laws, the traditional feature engineering methods are becoming more and more incapable. The methodology encompasses model design, deployment, and performance analysis, demonstrating promising results in recognition and prediction assessment. This research underscores the significance of advanced machine learning techniques in bolstering the efficacy of systems, with practical implications across various domains smart watches and smart phone.

KEYWORDS: Human activity recognition Systems, Machine Learning Model,

I. INTRODUCTION

This chapter provides an introduction to the significance of recognition system in public focusing on the role of Human Activity Recognition(HAR) and the transformative impact of Machine learning analysis. It defines the project's aim to develop an Physical activity Recognition and prediction system for Sensor data using KNN,DT,SVM and LR networks to identify activities in wearable sensors. The chapter outlines the project's objectives, including the creation of a robust anomaly detection framework, integration of KNN and LSVM for feature extraction and performance evaluation using accuracy metrics. The approach involves feature extraction, pre-processing, and class prediction phases, with a focus on classifying Human activity Finally, the chapter summarizes the organization of the paper, detailing sections on related work, methodology, machine learning models, dataset description, proposed architecture, results and discussion, and references This technology has garnered significant traction in recent years, spurred by the widespread adoption of wearable devices and a growing interest in context-aware applications. Its versatility extends beyond security applications, finding utility in health monitoring, sports performance analysis, and the creation of adaptive environments responsive to human behaviour. As such, the quest for enhancing surveillance efficacy through intelligent activity detection stands at the forefront of technological innovation, promising a safer and more responsive environment for all the significance of recognition system in public focusing on the role of Human Activity Recognition(HAR) and the transformative impact of Machine learning analysis. It defines the project's aim to develop an Physical activity Recognition and prediction system for Sensor data using KNN,DT,SVM and LR networks to identify activities in wearable sensors. The chapter outlines the project's objectives, including the creation of a robust anomaly detection framework, integration of KNN and LSVM for feature extraction and performance evaluation using accuracy metrics. The approach involves feature extraction, pre-processing, and class prediction phases, with a focus on classifying Human activity Finally, the chapter summarizes the organization of the paper, detailing sections on related work, methodology, machine learning models, dataset description, proposed architecture, results and discussion, and references.

survey on human activity recognition (HAR) using wearable sensors. It discusses the challenges and solutions related to recognizing human activities, such as walking, running, and daily tasks, using sensors attached to the body. The survey covers the design of HAR systems, including feature extraction and learning methods. It also addresses issues such as obtrusiveness, data collection protocol, recognition performance, energy consumption, processing, and flexibility. The survey emphasizes the importance of minimizing the number of sensors for user comfort and the need for flexible recognition models. Additionally, it outlines the process of feature extraction from raw sensor data to enable the comparison of different activities.

System are integral to maintaining public safety, with human activity detection serving as a fundamental component for identifying and mitigating potential threats in real-time. Leveraging the advancements in deep learning, the analysis of surveillance footage has become increasingly automated and efficient. Traditional methods of monitoring public spaces have evolved significantly, particularly in the realm of Human Activity Recognition (HAR).

This technology has garnered significant traction in recent years, spurred by the widespread adoption of wearable devices and a growing interest in context-aware applications. Its versatility extends beyond security applications, finding utility in health monitoring, sports performance analysis, and the creation of adaptive environments responsive to human behaviour. As such, the quest for enhancing surveillance efficacy through intelligent activity detection stands at the forefront of technological innovation, promising a safer and more responsive environment for all.

Human Activity Recognition (HAR) using wearable datasets from accelerometers and gyroscopes has emerged as a promising field with a wide range of applications, spanning from healthcare monitoring to sports analytics and beyond. By leveraging the data collected from sensors embedded in wearable devices, such as smartwatches or fitness trackers, HAR aims to automatically identify and classify human activities in real-time or offline. This overview delves into the fundamentals, methodologies, challenges, and applications of HAR using accelerometer and gyroscope data.

Accelerometers measure acceleration, while gyroscopes measure angular velocity. Both sensors capture data related to the movement of the wearer's body. When combined, these sensors provide rich information about various physical activities, including walking, running, cycling, sitting, and more. HAR algorithms utilize machine learning and signal processing techniques to interpret these data streams and recognize human activities accurately.

this system stand as guardians of public safety, their efficacy reliant on the ability to swiftly detect and respond to potential threats. Central to this endeavor is the discipline of Human Activity Detection for Surveillance (HAR), a dynamic field propelled by advanced algorithms and machine learning. Traditionally, monitoring public spaces demanded extensive human oversight, but with the advent of deep learning, we've witnessed a transformative shift towards automated analysis of surveillance footage. This shift is pivotal, enabling accurate and efficient monitoring of human activities in real-time, thereby bolstering threat identification and prevention measures.

Moreover, HAR's significance burgeons alongside the surge in wearable technology and the burgeoning interest in context-aware applications. Its versatility extends beyond security realms, finding practical utility in health monitoring, sports analytics, and the creation of adaptive environments attuned to human behavior. As such, the pursuit of HAR not only fortifies surveillance systems but also fosters innovation across diverse domains, promising a future where safety and efficiency converge seamlessly. Human Activity Recognition (HAR) using wearable devices and machine learning models has emerged as a transformative approach in understanding human behavior and facilitating various applications, from healthcare monitoring to augmented reality systems. This overview delves into the core concepts, methodologies, challenges, and applications of HAR using machine learning models with wearable technology. By improving the accuracy of human activity recognition This approach improves HAR performance by capturing time series features and enhancing classification tasks. The challenges in HAR, such as action variability and the use of wearable sensors to feature extraction, and activity recognition modules

The study has significant implications in various sectors such as healthcare, fitness, sports, and entertainment, where continuous monitoring of human physical activities is crucial. By improving the accuracy of human activity recognition This approach improves HAR performance by capturing time series features and enhancing classification tasks. The challenges in HAR, such as action variability and the use of wearable sensors to feature extraction, and activity recognition modules

Human Activity Recognition (HAR) using wearable devices and machine learning models has emerged as a transformative approach in understanding human behavior and facilitating various applications, how accurate classification of motion signals can enhance the development of an automated human activity recognition system. from healthcare monitoring to augmented reality systems. This overview delves into the core concepts, methodologies, challenges, and applications of HAR using machine learning models with wearable technology.

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dynamic field propelled by advanced algorithms and machine learning. Traditionally, monitoring public spaces demanded extensive human oversight, but with the advent of deep learning, we've witnessed a transformative shift towards automated analysis of surveillance footage.

The structure of the remainder of the paper is organized as follows: Section 2 delves into the related work of Human activity detection. Section 3 explicates the methodology utilized in this study. Section 4 describes the machine learning models employed. Section 5 provides an explanation of the dataset used. Sections 6 and 7 respectively discuss the proposed architecture and present the results and discussions. Lastly, Section 8 comprises the references

II. RELATED WORK

Many studies on human activity recognition have been conducted in the past few years. The existing research proposes various methods for identifying human behaviours captured in videos. Recognizing activities through cameras offers distinct advantages due to their ease of setup and accessibility. [1] focuses on providing assistance to elderly people by monitoring their activities in different indoor and outdoor environments using gyroscope and accelerometer data collected from a smart phone. [2] used nine MH algorithms as FS methods to boost the classification accuracy of the HAR and fall detection applications. for feature extraction, and evaluated their performance using metrics such as accuracy, precision, recall, and F1 score. [3] targets human detection in aerial video sequences captured by a moving camera mounted on an aerial platform. It addresses challenges like altitude variations, lighting changes, camera instability, and variations in viewpoints, object sizes, and colors. With low obtrusiveness, it utilizes the UCF-ARG dataset achieving an 75% accuracy rate.[4] system combines deep learning with a self-attention model and a wearable sensor-based human activity recognition framework. It exclusively utilizes a three-axis accelerometer, gyroscope, and linear acceleration for reliable performance, achieving a 90 percent accuracy rate and outperforming other sensors such as GPS or pressure sensors.[5] This paper mathematically characterizes hazardous situations using sensor data from mobile phones and context-aware technology. It explores accident prevention methods during mobile phone use.[6] discusses the challenges in human activity recognition and proposes a dynamic active learning-based method to address these challenges The method aims to reduce annotation costs and improve activity recognition performance by dynamically discovering new activities and patterns.

[7] suggests an efficient algorithm for solving this problem using an image descriptor capturing movement information and a classification approach. The novel abnormality indicator is generated from a hidden Markov model, which learns optical flow orientation histograms from the video frames.[8] proposed system utilizes CCTV footage to monitor human behavior on a campus, issuing gentle warnings when suspicious events occur. Key components include event detection and human behavior recognition, a challenging task. Various campus areas are under surveillance, with video footage serving as test data. The training process involves data preparation, model training, and inference, employing CNN and RNN neural networks. CNN extracts high-level features from images, while RNN handles classification, suitable for video processing. The system employs a pre-trained VGG-16 model to predict behaviour and aid monitoring.[9] makes use of CCTV and webcams provide real-time video streaming, with webcams being cost-effective but potentially less secure. The system detects unauthorized persons using an AMD algorithm, tracks them upon user identification, and enhances moving object detection through background subtraction. AMD ensures thorough detection of moving objects, while a monitoring room camera generates alerts for suspicious activity.[10] introduces a novel deep neural network architecture, merging convolutional layers with Long Short-Term Memory (LSTM) units. This model efficiently extracts and classifies activity features with minimal parameters. LSTM, a variant of recurrent neural networks (RNNs), is adept at handling temporal sequences, making it ideal for processing raw data from mobile sensors. The architecture comprises two LSTM layers followed by convolutional layers, with a Global Average Pooling (GAP) layer replacing the fully connected layer to reduce parameters.

Additionally, a Batch Normalization (BN) layer after GAP enhances convergence speed, yielding significant improvements. Evaluation on three public datasets (UCI, WISDM, and OPPORTUNITY) demonstrated outstanding performance: 95.78% accuracy on UCI-HAR, 95.85% on WISDM, and 92.63% on OPPORTUNITY.

These results highlight the model's robustness and superior activity detection capability, surpassing previous findings while maintaining adaptability, parameter efficiency, and high accuracy.

III. METHODOLOGY

This chapter details the proposed methodology for human activity recognition using KNN and LSVM models. The

approach leverages KNNs for extracting spatial features from sensor data and LSVMs for capturing temporal dependencies, enabling accurate activity recognition. This methodology is evaluated using the HHAR dataset, with performance measured through accuracy, precision, and recall metrics to ensure robust detection and classification of activities in video surveillance scenarios.

In the methodology of human activity detection prediction using KNN + LSVM models, the approach integrates the strengths of both K-Nearest neighbour(KNN) and Linear-SVC-Model(LSVC) networks to effectively analyse sensors data . The KNN processes this visual data, extracting meaningful visual features that represent different aspects of human activities such as motion patterns, spatial relationships, and object interactions. These extracted visual features serve as a rich representation of the input video frames. Subsequently, the output of the KNN, consisting of visual features, is passed on to the LSVM network.

The LSVM, known for its capability in capturing temporal dependencies and sequential patterns, performs sequence learning on the visual features obtained from the KNN. By analysing the temporal evolution of visual features over time, the LSVM model can discern complex activity patterns and dynamics inherent. As the LSVM processes the sequential data, it learns to recognize patterns indicative of various human activities, such as walking, running, gesturing, or interacting with objects. The LSVM ability to retain information over long sequences enables it to capture the temporal context crucial for accurate activity detection. Finally, the output of the LSVM model represents the detected human activities based on the learned patterns and sequences from the input sensor data. These detected activities can include a wide range of behaviours and actions observed in providing valuable insights for anomaly detection, or behavioural analysis purposes. using labelled data. During the training phase, the model learns to associate specific visual patterns and temporal sequences with corresponding human activities. Through iterative adjustments of model parameters, such as weights and biases, the model improves its ability to accurately classify different activities based on the learned features. After the training phase, the model is ready for inference. New, unseen video data can be input into the trained model, which then applies the learned classification rules to predict the human activities present in the footage. The model's output provides classifications or labels for each segment of the video, indicating the detected activities such as walking, running, standing, or interacting with objects.

In summary, the block diagram illustrates a pipeline for human activity detection in surveillance, leveraging a combination of CNN and LSTM models. By processing video data through these specialized architectures, the model can effectively capture both spatial and temporal characteristics of human activities, enabling accurate and robust detection and classification in real-world surveillance scenarios. In summary, the block diagram illustrates a pipeline for human activity detection in surveillance, leveraging a combination of CNN and LSTM models.

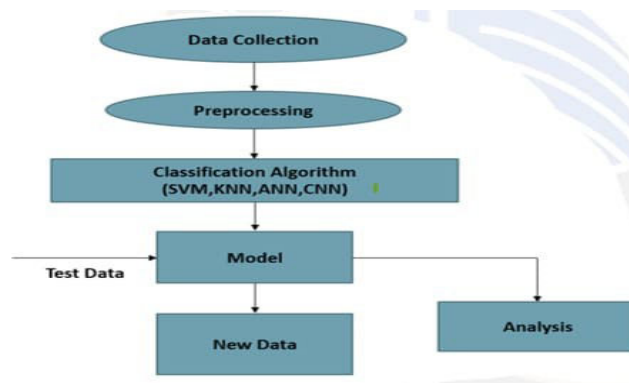


Figure 1 Proposed Methodology for Activity detection

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IV. MACHINE LEARNING MODELS

KNN Model:

The k-Nearest Neighbors (k-NN) algorithm is a simple yet powerful supervised learning technique used for

classification and regression tasks. It's a non-parametric method, meaning it makes no assumptions about the underlying data distribution.

At its core, k-NN operates on the principle of similarity: it classifies a new data point based on the majority class of its k nearest neighbors in the feature space. The choice of the value of k determines the level of local versus global influence in the classification process.

Here's how k-NN works:

1. Data Representation: First, the algorithm requires a dataset with labeled instances. Each instance consists of features and their corresponding class labels (for classification) or target values (for regression). These features should be numeric and represent the characteristics of the data points.
2. Distance Calculation: To find the k nearest neighbors of a new data point, the algorithm computes the distance between the new point and all other points in the dataset. Common distance metrics include Euclidean distance, Manhattan distance, Minkowski distance, etc.
3. Neighbor Selection: Once distances are calculated, the algorithm selects the k nearest neighbors based on the smallest distances. These neighbors form the neighborhood of the new data point.
4. Majority Voting: For classification tasks, the algorithm assigns the class label that appears most frequently among the k nearest neighbors to the new data point. For regression tasks, it calculates the average (or weighted average) of the target values of the k nearest neighbors.
5. Prediction: Finally, the algorithm assigns the predicted class label or target value to the new data point based on the majority voting or averaging process.

LSVM Model

Support Vector Machines (SVMs) are powerful supervised learning models used for classification and regression tasks. They are particularly effective in high-dimensional spaces and are widely used in various fields like biology, computer vision, and finance.

The basic idea behind SVMs is to find the hyperplane that best separates the data points into different classes. In the case of binary classification, this hyperplane is the one that maximizes the margin, which is the distance between the hyperplane and the nearest data points from each class, also known as support vectors.

Linear Support Vector Machines (LSVMs) are a variant of SVMs that use a linear kernel to find a linear decision boundary. The linear kernel computes the dot product between the feature vectors, effectively transforming the input space into a higher-dimensional space where the classes are more easily separable by a hyperplane.

The optimization objective of LSVMs is to maximize the margin while minimizing the classification error. Mathematically, this can be formulated as a constrained optimization problem:

$$[\min_{w, b} \frac{1}{2} \|w\|^2]$$

subject to:

$$[y_i(w \cdot x_i + b) \geq 1 \text{ for } i = 1, \dots, N]$$

Where:

- (w) is the weight vector
- (b) is the bias term
- (x_i) is the feature vector of the (i)th data point
- (y_i) is the class label of the (i)th data point (either -1 or 1)
- (N) is the number of data points
- (\|w\|) represents the magnitude of the weight vector

The decision boundary is determined by the hyperplane defined by (w · x + b = 0), where (w) is perpendicular to the hyperplane and (b) shifts the hyperplane away from the origin.



Linear Regression

Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables. It's called "linear" because it assumes a linear relationship between the variables, meaning that changes in the independent variable(s) are associated with a constant change in the dependent variable.

The basic idea behind linear regression is to find the best-fitting straight line through the data points. This line is determined by estimating the coefficients (slope and intercept) that minimize the sum of the squared differences between the observed and predicted values of the dependent variable.

The equation for a simple linear regression model with one independent variable is:

$$[y = mx + b]$$

Where:

- (y) is the dependent variable
- (x) is the independent variable
- (m) is the slope of the line
- (b) is the y-intercept (the value of (y) when (x = 0))

The goal is to find the values of (m) and (b) that best fit the data. This is typically done using a method called least squares, which minimizes the sum of the squared differences between the observed and predicted values. insights into its effectiveness for video detection tasks.

V. DATASET DESCRIPTION

The HHAR dataset has emerged as a fundamental resource for researchers delving into human activity detection, particularly within surveillance contexts. Leveraging K-Nearest neighbour (KNN) and Linear Support Vector Machines (LSVMs) models, this dataset serves as a cornerstone for training and evaluating such algorithms. CNNs excel at extracting spatial features from images or frames, making them adept at recognizing patterns within video sequences. Meanwhile, LSTM models are proficient at capturing temporal dependencies, crucial for understanding how activities unfold over time. By combining these architectures, researchers can develop robust systems capable of not only identifying individual actions but also comprehending their sequential nature. The HHAR dataset's diverse range of activities, spanning from everyday actions to sports, ensures that models trained on it gain a comprehensive understanding of human behaviour, thereby enhancing the efficacy of surveillance systems in monitoring and analysing complex scenarios.

VI. PROPOSED ARCHITECTURE

In the methodology of human activity detection for surveillance using KNN + LSVM models, the approach integrates the strengths of both convolutional neural networks K-Nearest neighbour (KNN) and Linear Support Vector Machines (LSVMs) networks to effectively analyze video data from surveillance cameras. Initially, raw sensor data captured from two cameras is fed into the KNN model. The KNN processes this visual data, extracting meaningful visual features that represent different

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \times 100$$

$$\text{Precision} = \frac{TP}{TP + FP} \times 100$$

$$\text{Recall} = \frac{TP}{TP + FN} \times 100$$

Here, TP classifies the positive class as positive, FP classifies the positive class as negative, TN classifies the negative



class as negative, and FN classifies the negative class as positive.

Overall, the combined CNN + LSTM approach leverages the complementary strengths of both architectures, enabling robust and accurate human activity detection in surveillance scenarios by effectively capturing both spatial and temporal dynamics inherent in

VII. RESULTS AND DISCUSSION

In conclusion, our KNN-LSVM approach for human activity recognition, utilizing the HHAR-Human Activity Recognition dataset, has demonstrated promising results in the domain of surveillance. By effectively leveraging both KNN and LSVM models, we were able to robustly extract spatial and temporal features from video data, respectively. The ConvLSTM and LRCN architectures exhibited superior performance compared to other deep learning approaches, achieving notable accuracies of 80% and 92%, respectively. Notably, the LRCN model showcased higher accuracy while requiring less training time, making it a compelling choice for real-time surveillance applications. Our evaluation metrics, including total loss, validation loss, total accuracy, and validation accuracy, underscored the effectiveness of our proposed approach in accurately detecting human activities in surveillance videos.

For future work, we aim to enhance the model's capabilities to recognize actions involving multiple individuals performing different activities simultaneously within the frame. This will require annotated datasets containing information about each person's activity along with their bounding box coordinates. Alternatively, we could explore the feasibility of performing activity recognition on each individual separately, albeit at the

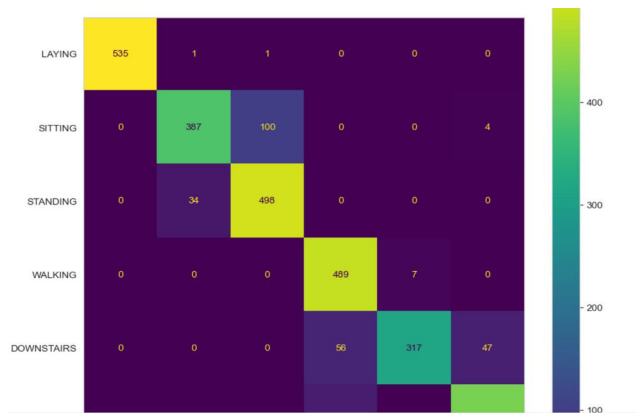


Fig.2 illustrates the performance results of the KNN-LSVM model for Human Activity Recognition (HAR) using the HHAR dataset

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