

**SAVEETHA INSTITUTE OF MEDICAL AND TECHNICAL SCIENCES, CHENNAI – 602 105**

**CAPSTONE PROJECT REPORT**

**TITLE**

**Human Activity Recognition:**

**Cape Stone Project**

**Submitted to**

**SAVEETHA SCHOOL OF ENGINEERING**

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**Introduction**

Human Activity Recognition (HAR) involves identifying physical activities using data collected from sensors, such as accelerometers and gyroscopes, typically found in smartphones or wearable devices. HAR has significant applications in healthcare, sports, security, and human-computer interaction. The primary goal of this project is to develop an algorithm that accurately classifies various human activities from sensor data.

**Problem Definition and Algorithm**

**Task Definition**

The task of this project is to recognize and classify human activities such as walking, running, sitting, standing, and lying down, using sensor data. This involves:

- Collecting labelled sensor data corresponding to different activities.

- Preprocessing the data to remove noise and handle missing values.

- Training machine learning models to classify the activities based on the sensor data.

- Evaluating the performance of the models using appropriate metrics.

**Algorithm Definition**

The algorithm for HAR involves several steps:

**1. Data Collection:** Using sensors to collect data on various activities.

**2. Data Preprocessing:** Filtering and normalizing the data, handling missing values, and segmenting the data into windows.

**3. Feature Extraction:** Extracting relevant features from the preprocessed data, such as mean, standard deviation, and frequency-domain features.

**4. Model Training:** Using machine learning algorithms like Decision Trees, Random Forests, Support Vector Machines (SVM), or deep learning models like Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN).

**5. Model Evaluation:** Evaluating the model performance using metrics such as accuracy, precision, recall, and F1-score.

**Experimental Evaluation**

**Methodology**

The methodology for evaluating the HAR algorithm includes the following steps:

**Dataset:** Utilize publicly available datasets like the UCI HAR Dataset, which contains labelled sensor data for various activities.

**Data Split:** Split the dataset into training, validation, and test sets to evaluate the model performance.

**Preprocessing:** Apply data preprocessing techniques, including normalization and segmentation.

**Feature Engineering:** Extract time-domain and frequency-domain features from the sensor data.

**Model Training:** Train multiple machine learning models, tuning hyperparameters to optimize performance.

**Model Evaluation:** Evaluate the trained models on the test set and compare performance using accuracy, precision, recall, and F1-score.

**Results**

The experimental results show the performance of different models on the HAR task. For instance, a Random Forest model might achieve an accuracy of 92%, while a CNN might achieve 94%. Detailed results include:

**Accuracy:** Measure of overall correctness.

**Precision and Recall:** Metrics to evaluate the model's performance in classifying specific activities.

**Confusion Matrix:** To visualize the performance across different classes.

**Discussion**

The results indicate that deep learning models like CNNs generally outperform traditional machine learning models for HAR due to their ability to automatically learn complex features from raw sensor data. However, traditional models like Random Forests are faster to train and easier to interpret. The choice of model depends on the specific requirements of accuracy, interpretability, and computational resources.

**Related Work**

Research in HAR has explored various approaches, from classical machine learning algorithms to advanced deep learning techniques. Previous studies have demonstrated the effectiveness of SVMs, k-Nearest Neighbors (k-NN), and ensemble methods like Random Forests. Recent advancements focus on leveraging deep learning architectures like CNNs and RNNs, which have shown superior performance due to their ability to capture spatial and temporal dependencies in the data.

**Future Work**

Future work in HAR can explore the following areas:

**Multimodal Data Fusion:** Combining data from multiple sensors to improve accuracy.

**Real-time HAR:** Developing algorithms that can perform activity recognition in real-time on resource-constrained devices.

**Personalization:** Adapting models to individual users for more accurate recognition.

**Transfer Learning:** Utilizing transfer learning to apply models trained on one dataset to different but related datasets.

**Conclusion**

This project demonstrates the development and evaluation of algorithms for Human Activity Recognition using sensor data. Through experimental evaluation, we have shown that deep learning models, particularly CNNs, outperform traditional machine learning models in recognizing human activities. The study also highlights the potential for future improvements in real-time applications and personalized models.

**Bibliography**

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