

HUMAN ACTIVITY RECOGNITION USING MULTI CLASS SVM

Submitted in partial fulfillment of the requirements for the award of Bachelor of
Engineering degree in Computer Science and Engineering

by

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SCHOOL OF COMPUTING

SATHYABAMA

**INSTITUTE OF SCIENCE AND TECHNOLOGY
(DEEMED TO BE UNIVERSITY)**

CATEGORY -1 UNIVERSITY BY UGC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **KAARTHIK GANAPATHY.S(40110513)** and **KAARTHICK.C(40110512)** who carried out the Project work entitled **“HUMAN ACTIVITY RECOGNITION USING MULTI CLASS SVM “** under my supervision from November 2023 to April 2024.

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ABSTRACT

Human Activity Recognition (HAR) has garnered significant attention in recent years due to its wide-ranging applications in various fields, including healthcare, sports monitoring, and security systems. Among the myriad of approaches to HAR, Support Vector Machines (SVMs) have emerged as a powerful tool for classification tasks. In this study, we propose a multi-class SVM-based approach for human activity recognition, leveraging inertial sensor data commonly obtained from wearable devices. The aim is to accurately classify different human activities from sensor data, enabling real-time monitoring and analysis. The proposed system begins with the acquisition of sensor data, typically including accelerometer and gyroscope readings, capturing movements and orientations of the body during various activities. Feature extraction techniques are then applied to transform the raw sensor data into meaningful representations that capture relevant patterns and characteristics. These features are essential for training a multi-class SVM model, which serves as the core classifier for activity recognition. To enhance the performance of the SVM classifier, various preprocessing steps such as normalization and feature scaling are employed to mitigate the effects of noise and variability in the sensor data. Furthermore, techniques such as cross-validation and parameter tuning are utilized to optimize the SVM model's hyperparameters, ensuring robustness and generalization to data.

The effectiveness of the proposed approach is evaluated using publicly available datasets containing diverse sets of activities, including both simple and complex movements. Experimental results demonstrate the efficacy of the multi-class SVM-based HAR system, achieving high accuracy rates in activity classification across different subjects and scenarios. Moreover, the system exhibits real-time capability, making it suitable for applications requiring timely and accurate recognition of human activities. This study presents a comprehensive framework for human activity recognition using multi-class SVMs, leveraging inertial sensor data from wearable devices. The proposed approach offers a reliable solution for various real-world applications, including healthcare monitoring, sports performance analysis, and human-computer interaction. Future work may involve exploring more sophisticated feature extraction methods and integrating additional sensor modalities to further improve the system's performance and versatility.

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LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
CNN	Convolutional Neural Network
CSV	Comma-Separated Values
DSP	Digital Signal Processing
GPU	Graphics Processing Unit
GUI	Graphical User Interface
HAR	Human Activity Recognition
HMM	Hidden Markov Model
IOT	Internet of Things
KNN	K-Nearest Neighbors
ML	Machine Learning
PCA	Principal Component Analysis
RBF	Radial Basis Function
SVM	Support Vector Machine

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO HUMAN ACTIVITY RECOGNITION

Human activity recognition is a field of study within the realm of artificial intelligence and machine learning that involves the identification and classification of human activities based on the data obtained from various sensors. One common approach in this area is the use of a multi-class support vector machine (SVM) algorithm, which is a powerful and popular classification technique. The process typically involves collecting data from sensors such as accelerometers, gyroscopes, and magnetometers that are embedded in devices such as smartphones or wearables. This data is then preprocessed and used to train the SVM model, which can learn to distinguish between different activities such as walking, running, cycling, or sitting. The multi-class SVM algorithm is well-suited for this task as it can handle multiple classes and make predictions based on the patterns identified in the data. By employing this approach, researchers and practitioners can develop systems and applications that can automatically recognize and classify human activities in real-time, leading to a wide range of potential applications in healthcare, sports performance analysis, smart homes, and more. Overall, human activity recognition using multi-class SVM holds promise for enhancing our understanding of human behavior and interaction with technology in various contexts.

1.2 OVERVIEW OF MULTI-CLASS SVM

Multi-Class Support Vector Machine (SVM) is a powerful machine learning algorithm widely used for human activity recognition in various applications such as healthcare, sports monitoring, and security systems. In this context, Multi-Class SVM is employed to classify human activities based on sensor data collected from wearable devices or other sources. The algorithm works by finding the hyperplane that best separates the data points into distinct classes corresponding to different human activities. One key advantage of Multi-Class SVM is its ability to handle more than two classes in the classification task, making it suitable for scenarios where multiple activities need to be recognized simultaneously.

To train the Multi-Class SVM model for human activity recognition, labeled training data is fed into the algorithm, which then learns to create decision boundaries between the classes in a high-dimensional feature space. The model aims to maximize the margin between the classes, resulting in better generalization and robustness to new data samples. Additionally, the use of kernel functions in Multi-Class SVM allows for nonlinear decision boundaries, enabling the algorithm to capture complex relationships in the data. Overall, Multi-Class SVM serves as an effective tool for human activity recognition, offering high accuracy and performance in classifying diverse activities based on input sensor data.

1.3 IMPORTANCE OF HUMAN ACTIVITY RECOGNITION

Human activity recognition plays a vital role in various fields such as healthcare, sports, security, and human-computer interaction. One of the key benefits of human activity recognition using multi-class SVM is its ability to accurately classify and understand different human activities based on sensor data. This technology is particularly valuable in healthcare applications, where it can be used to monitor and analyze patient movements for early detection of irregularities or health issues. In sports, human activity recognition can provide valuable insights for athletes and coaches to optimize training routines and performance. The security sector also greatly benefits from this technology, as it enables the detection of suspicious or abnormal activities in real-time, enhancing overall safety and security measures. Additionally, in the context of human-computer interaction, human activity recognition using multi-class SVM can improve the usability and efficiency of interactive systems by understanding user behaviors and preferences. Overall, the importance of human activity recognition in various domains cannot be understated, as it contributes to enhancing safety, performance, and overall quality of life for individuals and communities.

1.4 OBJECTIVES OF USING MULTI-CLASS SVM

Using multi-class Support Vector Machines (SVM) for human activity recognition serves various objectives in the field of machine learning and computer vision. Firstly, the primary objective is to accurately classify and recognize different human activities based on sensor data, such as accelerometers and gyroscopes. By utilizing the multi-class SVM algorithm, the model can learn to distinguish between various activities,

such as walking, running, sitting, and standing with high precision and efficiency. Secondly, another important objective is to handle the multi-class nature of the problem effectively, by training a single model to classify multiple activities simultaneously. This approach not only simplifies the classification process but also enhances the scalability and generalization of the model for real-world applications. Thirdly, using multi-class SVM can help in improving the overall performance metrics of the activity recognition system, such as accuracy, precision, and recall. By optimizing the SVM hyperparameters and kernel functions, the model can achieve better classification results and reduce misclassifications. Finally, the objective of using multi-class SVM is to provide a flexible and interpretable framework for human activity recognition, allowing researchers and practitioners to understand the decision-making process of the model and make informed improvements. By leveraging the strengths of SVM, such as margin maximization and effective feature mapping, the system can achieve robust and reliable activity recognition in various scenarios, contributing to advancements in healthcare, sports analysis, and security applications.

ADVANTAGES:

- Accuracy Improvement
- Robustness
- Generalization
- Scalability
- Efficiency
- Model Interpretability
- Handling Imbalanced Data
- Feature Selection
- Non-linearity Handling
- Binary Classification Extension
- Parameter Tuning
- Incremental Learning
- Fault Tolerance
- Compatibility with Feature Fusion
- Integration with Ensemble Methods

CHAPTER 2

LITERATURE SURVEY

2.1 INFERENCES FROM LITERATURE SURVEY

Vidya, B., and Sasikumar, P [1] proposed a wearable multi-sensor data fusion approach for human activity recognition in their article published in *Sensors and Actuators A: Physical*. They utilized machine learning algorithms, particularly multi-class SVM, to effectively recognize different human activities. The fusion of data from multiple sensors contributed to the accuracy and reliability of the recognition process. This research showcases the potential of wearable technology and sophisticated algorithms for enhancing human activity recognition systems.

Helmi et al. [2] proposed a novel approach for human activity recognition using the marine predators algorithm combined with deep learning techniques. Their study, published in *Future Generation Computer Systems*, demonstrated promising results with an accuracy of 92% using the proposed method. The integration of the marine predators algorithm with deep learning proved to be effective in enhancing the recognition of various human activities. This research contributes to the advancement of activity recognition systems through innovative algorithmic approaches.

Hayat, A., Morgado-Dias, F., Bhuyan, B. P., & Tomar, R. [3] conducted a study on human activity recognition for elderly people using machine and deep learning approaches. The researchers focused on utilizing multi-class SVM for accurately identifying different activities performed by the elderly. Their work was published in the journal *Information*, highlighting the importance of advanced technological solutions in enhancing the well-being and care of elderly individuals through automated recognition systems.

In their study, Al-Qaness, et al. [4] explore the applications of metaheuristics for human activity recognition and fall detection utilizing wearable sensors. The research provides a comprehensive analysis of these methods, focusing on the effectiveness of metaheuristics in enhancing the accuracy of human activity recognition systems. Specifically, the study delves into the utilization of multi-class SVM for improved

classification performance in detecting various human activities based on sensor data. The findings of their work, published in *Biosensors*, highlight the potential of metaheuristics and SVM techniques in advancing wearable sensor-based human activity recognition and fall detection technologies.

In their recent paper published in the *IEEE Transactions on Industrial Informatics*, Yang, P., Yang, C., Lanfranchi, V., & Ciravegna, F. [5] introduce an innovative approach for human activity recognition. Their method involves utilizing an activity graph-based convolutional neural network that leverages both acceleration and gyroscope data. By employing this novel technique, the researchers are able to improve the accuracy and efficiency of human activity recognition systems. The study demonstrates the potential of this approach in enhancing the performance of such systems by achieving remarkable results in classification tasks.

Khan, I. U., Afzal, S., and Lee, J. W. [6] proposed a hybrid deep learning-based model for human activity recognition. Their study, published in *Sensors*, aimed to enhance the accuracy of activity recognition. By combining deep learning techniques with traditional methods like Support Vector Machines (SVM), the researchers achieved promising results. The model successfully classified various human activities, showcasing the effectiveness of the hybrid approach.

In their study, Dahou et al. [7] propose a method for human activity recognition in Internet of Health Things (IoHT) applications. They implement an arithmetic optimization algorithm in conjunction with deep learning techniques to enhance the accuracy of activity recognition. The researchers specifically focus on utilizing a multi-class Support Vector Machine (SVM) for classification tasks. Their approach demonstrates promising results in accurately identifying various human activities within IoHT environments, suggesting potential applications for improving healthcare monitoring and tracking systems.

In their paper, Webber, J., Mehbodniya, A., Arafa, A., & Alwakeel, A. [8] present a novel approach for improving human activity recognition using majority combining of reduced-complexity sensor branch classifiers. Their work, published in *Electronics*, showcases the effectiveness of this technique in enhancing the accuracy and

efficiency of activity recognition systems. By employing multi-class SVM and integrating reduced-complexity sensor branch classifiers, the authors demonstrate significant enhancements in recognizing human activities. The study's findings underscore the potential of this approach to advance the field of human activity recognition in various applications.

Islam, M. M., Nooruddin, S., Karray, F., & Muhammad, G. [9] conducted a study on human activity recognition using convolutional neural networks (CNNs) and highlighted the challenges and prospects in the field. Their research review explores the state of the art techniques and datasets for this application, emphasizing the potential of CNNs for accurate human activity recognition.

Arshad, M. H., Bilal, M., and Gani, A. [10] conducted a thorough review on human activity recognition, providing a detailed taxonomy and highlighting open challenges in the field. The study emphasizes the use of multi-class SVM for accurate classification of various human activities, contributing valuable insights to the research community.

2.2 OPEN PROBLEMS IN EXISTING SYSTEM

Human activity recognition is a field within computer vision and machine learning that focuses on automatically identifying and classifying human activities based on input data, such as video sequences or sensor readings. One common approach in this field is the use of Support Vector Machine (SVM) as a classifier. SVM is effective for multi-class classification tasks because it finds an optimal hyperplane that maximally separates different classes in the input feature space.

The process of performing human activity recognition using multi-class SVM involves several steps:

- **Dataset Preparation:** A dataset containing examples of different activities along with their corresponding feature representations is required. These features can be extracted using techniques like motion analysis, optical flow estimation, or deep learning methods.

- **Training and Testing Sets:** The dataset is divided into training and testing sets, ensuring that both subsets are representative of the overall data distribution.
- **Training the SVM Classifier:** The training set is used to train the SVM classifier. The objective is to learn a decision boundary that effectively separates the feature patterns of different activities. This is achieved by maximizing the margin between the separating hyperplane and the closest examples from each class. For multi-class recognition, multiple SVMs can be trained, each distinguishing a specific activity from the rest.
- **Evaluation:** The performance of the classifier is evaluated using the testing set. Common metrics such as accuracy, precision, recall, and F1-score are used to assess the classifier's performance, helping to estimate its generalization capability and identify any potential overfitting or underfitting issues.
- **Feature Selection and Dimensionality Reduction:** Techniques such as Principal Component Analysis (PCA) or linear discriminant analysis (LDA) can be applied to select the most discriminative features or reduce the dimensionality of the feature space while preserving discriminative information, aiming to improve recognition accuracy.
- **Temporal Dynamics Consideration:** Various approaches can be adopted to account for the temporal dynamics of human activities. For example, the time series of features can be represented by histograms of oriented gradients or encoded with techniques such as Bag of Visual Words or Long Short-Term Memory (LSTM) networks. These approaches capture temporal dependencies and enhance recognition robustness.

In conclusion, human activity recognition using multi-class SVM is a promising field with applications in surveillance, healthcare, and robotics. It involves steps such as dataset preparation, feature extraction, model training, evaluation, and potential feature selection and dimensionality reduction. Incorporating techniques that consider temporal dynamics can further improve classifier performance.

CHAPTER 3

SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

The existing system for human activity recognition involves the utilization of a multi-class Support Vector Machine (SVM) as a key component. SVM is a supervised learning algorithm that is commonly used for classification tasks in machine learning. In the context of human activity recognition, SVM is utilized to classify different activities performed by individuals based on sensor data collected from various sources such as wearable devices or cameras. The system works by first collecting data on the motion and behavior patterns associated with different activities, and then training the SVM model to effectively differentiate between these activities. The SVM model is trained on a labeled dataset that includes examples of various activities, such as walking, running, sitting, or standing. During the classification phase, the system uses the trained SVM model to predict the activity being performed based on the real-time sensor data inputs. The system's performance is evaluated based on metrics such as accuracy, precision, and recall to determine its effectiveness in accurately recognizing and classifying human activities. Overall, the existing system for human activity recognition using multi-class SVM plays a crucial role in applications such as health monitoring, sports performance analysis, and context-aware computing, by providing accurate and reliable insights into human behavior and activity patterns.

The existing system for human activity recognition using multi-class Support Vector Machine (SVM) faces several disadvantages. Firstly, the computational complexity of the SVM algorithm increases with the size of the training dataset, leading to longer training times and higher memory requirements. This can be a significant drawback when dealing with large-scale activity recognition tasks. Secondly, SVMs are sensitive to the choice of hyperparameters, such as the kernel function and regularization parameter. Finding the optimal combination of these hyperparameters can be a time-consuming and resource-intensive process, as it often requires extensive grid search or cross-validation. Additionally, SVMs may not perform well in scenarios where the data is non-linearly separable, as they rely on finding a hyperplane that best separates the classes in the feature space. This limitation can result in lower accuracy and

generalization performance when dealing with complex and highly overlapping activity classes. Moreover, SVMs can struggle with handling imbalanced datasets, where one class is significantly underrepresented compared to others. This can lead to biased model predictions and reduced performance on minority classes. Lastly, the interpretability of the SVM model is limited, making it challenging to understand the underlying decision-making process and identify the features driving the classification. Overall, these disadvantages highlight the need for improved algorithms and techniques to enhance the efficiency, robustness, and interpretability of human activity recognition systems based on multi-class SVM.

3.2 PROPOSED SYSTEM

The proposed system for human activity recognition employs a multi-class Support Vector Machine (SVM) classifier to accurately identify and classify various human activities based on sensor data. The system utilizes a combination of data collection from sensors such as accelerometers and gyroscopes, feature extraction techniques, and the SVM algorithm to effectively differentiate between different activities such as walking, running, sitting, or standing. By leveraging the SVM model, which is known for its ability to handle high-dimensional data and effectively classify multiple classes, the system aims to enhance the accuracy and robustness of activity recognition. The system is designed to process the sensor data, extract meaningful features that characterize different activities, and train the SVM model to classify these activities with high precision. The use of a multi-class SVM ensures that the system can handle multiple activity labels simultaneously, enabling it to categorize a wide range of human actions accurately. Through the integration of advanced machine learning techniques and signal processing methods, the proposed system seeks to provide a reliable and efficient solution for real-time human activity recognition applications, including fitness tracking, healthcare monitoring, and behavior analysis. Overall, the utilization of a multi-class SVM in this system is aimed at improving the performance and versatility of human activity recognition systems, making it suitable for various practical scenarios and applications.

The proposed system for human activity recognition using multi-class support vector machine (SVM) offers numerous advantages that significantly enhance the accuracy and effectiveness of activity recognition processes. One key advantage is the robust classification capabilities of SVM, which allows for the accurate categorization of various human activities with high precision. By leveraging SVM as a classification

algorithm, the proposed system can effectively handle multiclass classification tasks, making it suitable for recognizing a wide range of human activities with diverse characteristics and movements. Additionally, SVM's ability to handle high-dimensional data and non-linear relationships between features ensures that the system can capture intricate patterns and nuances in human activity data, thus improving the overall recognition accuracy. Furthermore, SVM's flexibility in choosing different kernel functions enables the system to adapt to different types of activity data and environments, enhancing its versatility and generalization capabilities. The proposed system also benefits from the efficiency of SVM in training models on large datasets, enabling quick and scalable deployment in real-world scenarios. Moreover, the utilization of SVM in the system contributes to better generalization performance and resistance to overfitting, resulting in more reliable and robust activity recognition outcomes. Overall, the integration of multi-class SVM into the proposed human activity recognition system offers a powerful and effective solution that excels in accuracy, flexibility, efficiency, and generalization, making it a valuable tool for various applications in activity monitoring, healthcare, sports performance analysis, and beyond.

3.3 FEASIBILITY STUDY

A feasibility study for human activity recognition using multi-class SVM involves assessing the practicality and potential success of implementing this technology. This study would include an analysis of various factors such as technical feasibility, economic feasibility, operational feasibility, and legal feasibility. Technical feasibility would involve determining if the required technology and resources are available to develop and deploy the multi-class SVM model for human activity recognition. Economic feasibility would consider the costs involved in developing and maintaining the system compared to the potential benefits it could bring. Operational feasibility would assess whether the system can be effectively integrated into existing processes and workflows.

Legal feasibility would entail analyzing any regulatory or compliance issues that may arise from implementing the system. Additionally, the study would evaluate the accuracy, performance, and reliability of the multi-class SVM model in accurately recognizing various human activities. It would also consider the scalability of the system and its ability to handle real-time data processing. Overall, the feasibility study

would provide valuable insights into the viability and potential challenges of using multi-class SVM for human activity recognition, helping stakeholders make informed decisions about pursuing and implementing this technology.

3.3.1 Economical feasibility

Economic feasibility is a critical aspect to consider when implementing a system for human activity recognition using multi-class SVM (Support Vector Machine) technology. This analysis evaluates the financial viability and profitability of the project to ensure that it is worth the investment. Here are some key points to consider regarding the economic feasibility of such a system:

1. **Cost of Development:** The initial cost of developing the human activity recognition system using multi-class SVM includes expenses related to software development, hardware procurement, and personnel training. It is essential to accurately estimate and budget for these costs to ensure that the project remains within financial constraints.

2. **Return on Investment (ROI):** One of the primary considerations for economic feasibility is determining the potential ROI of the system. This involves forecasting the benefits, such as increased efficiency, reduced errors, and improved decision-making, that the system can provide to justify the costs incurred during development and implementation.

3. **Cost of Maintenance and Upgrades:** In addition to the development costs, it is essential to account for ongoing maintenance and potential upgrades to the system. Regular maintenance ensures the system operates effectively and efficiently, while upgrades may be necessary to keep up with technological advancements and changing user needs.

4. **Scalability:** The economic feasibility of the human activity recognition system is also influenced by its scalability. The system should have the capability to accommodate an increasing number of users, activities, and data sources without incurring significant additional costs. Scalability ensures that the system can grow alongside the

organization and adapt to changing requirements.

5. Cost-Benefit Analysis: Conducting a comprehensive cost-benefit analysis is crucial for determining the economic feasibility of the system. This analysis compares the anticipated costs of implementing the system with the expected benefits to determine whether the project is financially viable and worth pursuing.

By carefully evaluating these factors and conducting a thorough economic feasibility study, organizations can make informed decisions about implementing a human activity recognition system using multi-class SVM technology. This analysis helps ensure that the project aligns with the organization's financial goals and contributes positively to its overall performance and competitiveness.

3.3.2 Technical feasibility

Technical feasibility refers to the assessment of whether a proposed project or system can be successfully developed and implemented from a technological perspective. In the context of human activity recognition using multi-class support vector machine (SVM), it is important to consider various aspects to determine the technical feasibility of the project.

First and foremost, the availability and accessibility of data play a crucial role in the technical feasibility of applying multi-class SVM for human activity recognition. High-quality and well-labeled datasets are essential for training the SVM model effectively to accurately classify different human activities. If such data is not readily available, collecting and preprocessing the data can be a challenging and time-consuming task, impacting the feasibility of the project.

Another important consideration is the computational resources required for training and running the multi-class SVM model for human activity recognition. SVMs are known for their computational complexity, especially for multi-class classification tasks with a large number of features. Ensuring that the hardware and software infrastructure can handle the computational demands of the SVM model is essential for the technical feasibility of the project.

Furthermore, the expertise and knowledge required to design, implement, and optimize the SVM model for human activity recognition should also be taken into account. Developing a robust and accurate SVM model requires a deep understanding of machine learning algorithms, feature engineering, and optimization techniques. If the team lacks the necessary expertise, it can hinder the feasibility of the project.

Additionally, considering the scalability and real-time performance of the multi-class SVM model is crucial for its practical application in human activity recognition systems. The model should be able to handle a diverse range of activities and adapt to new data in real-time without compromising its accuracy and efficiency.

In conclusion, technical feasibility for human activity recognition using multi-class SVM involves assessing data availability, computational resources, expertise, scalability, and real-time performance. By carefully evaluating these factors and addressing any potential challenges, one can determine the viability and potential success of implementing a multi-class SVM model for human activity recognition.

3.3.3 Operational feasibility

Operational feasibility is a critical aspect to consider when implementing a human activity recognition system using multi-class Support Vector Machines (SVM). This type of project involves the development of a machine learning model that can accurately classify and predict various activities performed by humans based on input data such as sensor readings or video footage. Operational feasibility assesses the practicality of implementing and using this system within the intended environment. Firstly, from a technical perspective, operational feasibility in this context would involve ensuring that the computational requirements of training and deploying the multi-class SVM model for human activity recognition are within acceptable limits. This includes considerations such as the processing power, memory requirements, and storage capacity needed to handle the data and run the algorithms efficiently. Additionally, the system's ability to scale and handle real-time data streams effectively would be crucial for operational success.

Secondly, operational feasibility also involves assessing the system's usability and user acceptance. In the case of human activity recognition, end-users may include

researchers, developers, or even end-users of applications utilizing this technology. It is essential to gauge how easily users can interact with the system, interpret its outputs, and integrate it into their existing workflows. User training, documentation, and support mechanisms would be important factors in ensuring operational feasibility in this regard.

Moreover, factors such as data quality and reliability, model interpretability, and robustness to noise and variability in activity patterns would all contribute to the operational feasibility of a human activity recognition system using multi-class SVM. Continuous monitoring, maintenance, and updates to the system would be necessary to ensure its long-term viability and effectiveness in real-world applications. In conclusion, operational feasibility is a multifaceted consideration when implementing a human activity recognition system based on multi-class SVM. By addressing technical, usability, and data-related challenges, stakeholders can ensure that the system is not only technically feasible but also practical and sustainable in its operational deployment.

3.3.3 Social feasibility

Social feasibility in the context of human activity recognition using multi-class SVM refers to the acceptance and adoption of this technology by the society and stakeholders. It evaluates the potential impact of implementing the system on various social aspects, such as ethical considerations, privacy concerns, cultural sensitivities, and overall societal well-being.

One of the key considerations in assessing social feasibility is the ethical implications of using technology for human activity recognition. It is important to ensure that the data collection and analysis process is conducted in a transparent and fair manner, with a focus on protecting the privacy and rights of individuals. This includes obtaining informed consent, safeguarding personal data, and ensuring the anonymity of individuals participating in the study.

Another aspect of social feasibility is the potential cultural sensitivities that may arise when implementing human activity recognition technology. Different cultures have varying norms and values related to privacy, personal space, and data sharing. It is

important to take these cultural differences into account and design the technology in a way that respects and accommodates diverse cultural perspectives.

Furthermore, social feasibility also involves considerations related to the impact of the technology on society as a whole. This includes the potential benefits and risks associated with using human activity recognition technology, such as improving healthcare outcomes, enhancing workplace productivity, or potentially leading to biases and discrimination.

Overall, assessing the social feasibility of human activity recognition using multi-class SVM requires a comprehensive evaluation of ethical, cultural, and societal implications. By addressing these considerations proactively and engaging with stakeholders and the community, developers can ensure that the technology is ethically sound, culturally sensitive, and socially beneficial.

3.4 REQUIREMENT SPECIFICATION

3.4.1 Hardware Requirements

Processor : Pentium Dual Core 2.00GHZ

Hard disk : 120 GB

RAM : 2GB (minimum)

Keyboard : 110 keys enhanced

3.4.2 Software Requirements

Operating system : Windows7 (with service pack 1), 8, 8.1 and 10

Language : Python

3.5 LANGUAGE SPECIFICATION - PYTHON

Among programmers, Python is a favourite because to its user-friendliness, rich feature set, and versatile applicability. Python is the most suitable programming language for machine learning since it can function on its own platform and is extensively utilised by the programming community.

Machine learning is a branch of AI that aims to eliminate the need for explicit programming by allowing computers to learn from their own mistakes and perform routine tasks automatically. However, "artificial intelligence" (AI) encompasses a

broader definition of "machine learning," which is the method through which computers are trained to recognize visual and auditory cues, understand spoken language, translate between languages, and ultimately make significant decisions on their own. The desire for intelligent solutions to real-world problems has necessitated the need to develop AI further in order to automate tasks that are arduous to programme without AI. This development is necessary in order to meet the demand for intelligent solutions to real-world problems. Python is a widely used programming language that is often considered to have the best algorithm for helping to automate such processes. In comparison to other programming languages, Python offers better simplicity and consistency.

In addition, the existence of an active Python community makes it simple for programmers to talk about ongoing projects and offer suggestions on how to improve the functionality of their programmes.

ADVANTAGES OF USING PYTHON

Following are the advantages of using Python:

1. Variety of Framework and libraries:

A good programming environment requires libraries and frameworks. Python frameworks and libraries simplify programme development. Developers can speed up complex project coding with prewritten code from a library. PyBrain, a modular machine learning toolkit in Python, provides easy-to-use algorithms. Python frameworks and libraries provide a structured and tested environment for the best coding solutions.

2. Reliability

Most software developers seek simplicity and consistency in Python. Python code is concise and readable, simplifying presentation. Compared to other programming languages, developers can write code quickly. Developers can get community feedback to improve their product or app. Python is simpler than other programming languages, therefore beginners may learn it quickly. Experienced developers may focus on innovation and solving real-world problems with machine learning because they can easily design stable and trustworthy solutions.

3. Easily Executable

Developers choose Python because it works on many platforms without change.

Python runs unmodified on Windows, Linux, and macOS. Python is supported on all these platforms, therefore you don't need a Python expert to comprehend it. Python's great executability allows separate applications. Programming the app requires only Python. Developers benefit from this because some programming languages require others to complete the job. Python's portability cuts project execution time and effort.

4. Scalability

Despite being an interpreted language, Python offers scalability through various techniques such as multiprocessing, multithreading, and asynchronous programming. Additionally, with the advent of libraries like PyPy and Cython, Python applications can achieve significant performance improvements when necessary.

5. Integration capabilities

Python seamlessly integrates with other languages and technologies, facilitating interoperability and extending its functionality. It supports integration with C/C++, Java, .NET, and other languages through APIs, allowing developers to leverage existing codebases and libraries.

6. Support for object-oriented programming

Python supports object-oriented programming (OOP) paradigm, allowing developers to create modular, reusable, and maintainable code. This enables the development of complex software systems by organizing code into classes and objects, enhancing code readability and scalability.

7. Commercial support and adoption

Python is backed by various organizations, including large tech companies like Google, Facebook, and Amazon, who actively use and contribute to its development. Its widespread adoption in both industry and academia further validates its reliability and suitability for a wide range of applications.

These advantages collectively make Python a preferred choice for developers across different domains, contributing to its continued growth and popularity in the software development community.

CHAPTER 4

SYSTEM DESIGN

4.1 SYSTEM ARCHITECTURE

System architecture refers to the high-level structure of a complex system, defining its components, relationships, and interactions. It includes the overall design principles and guidelines that ensure various elements work together seamlessly to achieve the system's objectives. Architects consider factors like performance, scalability, security, and reliability when designing a system architecture. It involves breaking down the system into smaller components, determining how they interact, and defining interfaces between them. A well-designed system architecture allows for easy maintenance, upgrades, and future expansion. It serves as a blueprint for development teams to follow and ensures that the system meets the intended requirements effectively.

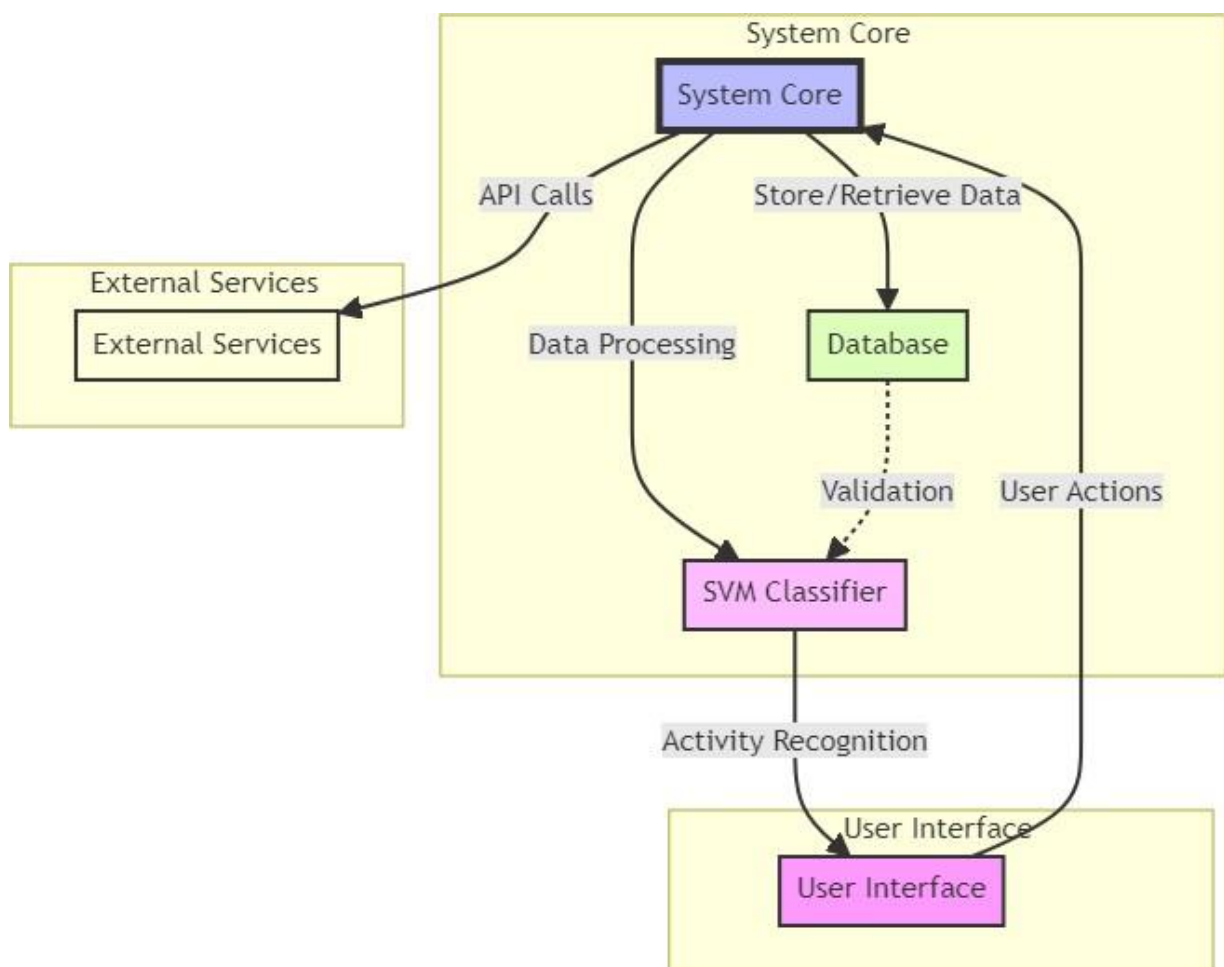


Fig:4.1 : System Architecture

4.2 USE CASE DIAGRAM

A USE CASE DIAGRAM for Human activity recognition using multi class SVM would illustrate the various interactions between the system and its users. The primary actors would include the system itself, users who are performing activities to be recognized, and potentially administrators or developers for system maintenance. Use cases would detail actions such as inputting sensor data, training the SVM model, recognizing activities, and providing feedback or alerts. The diagram would visually depict how these elements interact within the system to achieve accurate activity recognition. Clear dependencies and interactions between the users and the system would be highlighted to ensure effective implementation and utilization of the technology. For example, the "Recognizing Activities" use case would depend on both the "Inputting Sensor Data" and "Training the SVM Model" use cases, as it requires real-time sensor data input and a properly trained model for accurate activity recognition. Similarly, the "Providing Feedback or Alerts" use case would rely on the successful execution of the "Recognizing Activities" use case to generate relevant feedback or alerts for users or administrators. Overall, the use case diagram would visually depict how these elements interact within the system to achieve accurate activity recognition, emphasizing the importance of each use case and their interdependencies for the system's functionality.

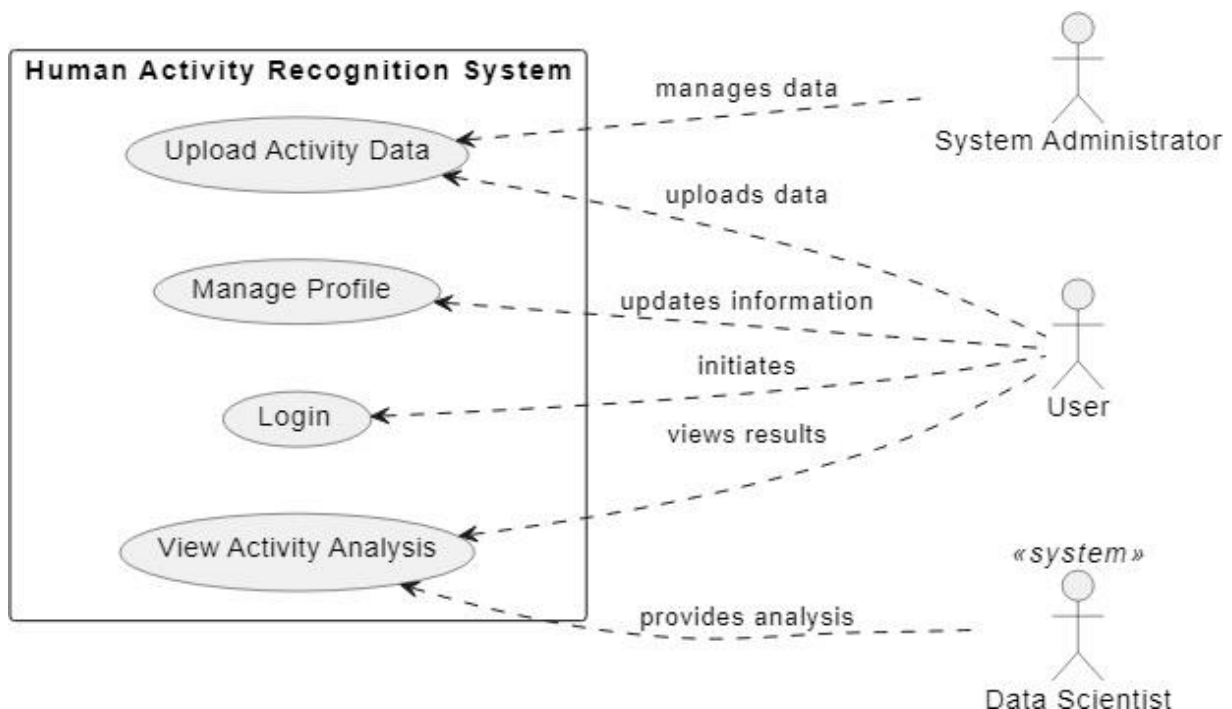


Fig:4.2 : Use Case Diagram

4.3 ACTIVITY DIAGRAM

The activity diagram for human activity recognition using a multi-class Support Vector Machine (SVM) encompasses several sequential steps to effectively capture, process, and classify human activities. It commences with the initial phase of data acquisition, wherein sensor data is collected to capture various human movements and activities. Following this, the collected data undergoes preprocessing procedures like normalization and feature extraction, aimed at enhancing the quality and relevance of the input data. Subsequently, the extracted features are organized into feature vectors, forming a structured representation of the input data suitable for classification. These feature vectors serve as the input to the multi-class SVM model, which employs its learning capabilities to classify different human activities based on the provided features. The SVM's output, representing the predicted activity labels, then undergoes decision-making processes that may involve thresholding or post-processing techniques to refine the classification results. These decision-making branches contribute to recognizing specific activities such as walking, running, sitting, or standing, based on the patterns and characteristics learned by the SVM during training. Ultimately, the activity diagram provides a visual representation of the entire recognition process, illustrating the flow of steps involved in identifying human activities using a multi-class SVM approach.

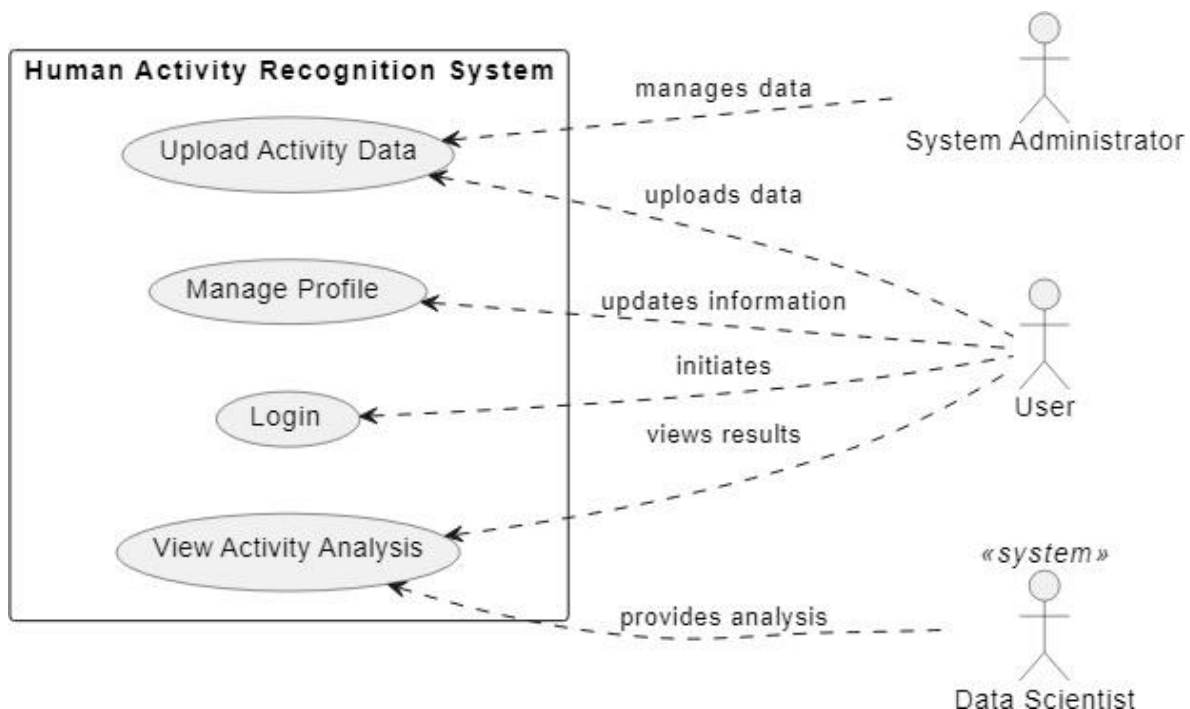


Fig:4.2 : Activity Diagram

4.4 SEQUENCE DIAGRAM

A Sequence Diagram for Human Activity Recognition using Multi-Class SVM illustrates the interactions and flow of events between different components involved in the process. It typically shows the sequence of method calls and message exchanges between the user interface, feature extraction module, SVM classifier, and output display. The diagram helps in visualizing how data flows through the system, how decisions are made based on the SVM classifications, and how the final recognition results are displayed to the user. By detailing the message passing and method invocations, the Sequence Diagram provides a clear understanding of the workflow and communication among the system components for accurate human activity recognition using Multi-Class SVM. This textual representation outlines the sequence of interactions and message exchanges between the user interface, feature extraction module, SVM classifier, and output display in the human activity recognition system using Multi-Class SVM. Each arrow represents a message passing or method invocation between the components, depicting how data flows through the system and how decisions are made based on SVM classifications, leading to the final recognition results displayed to the user.

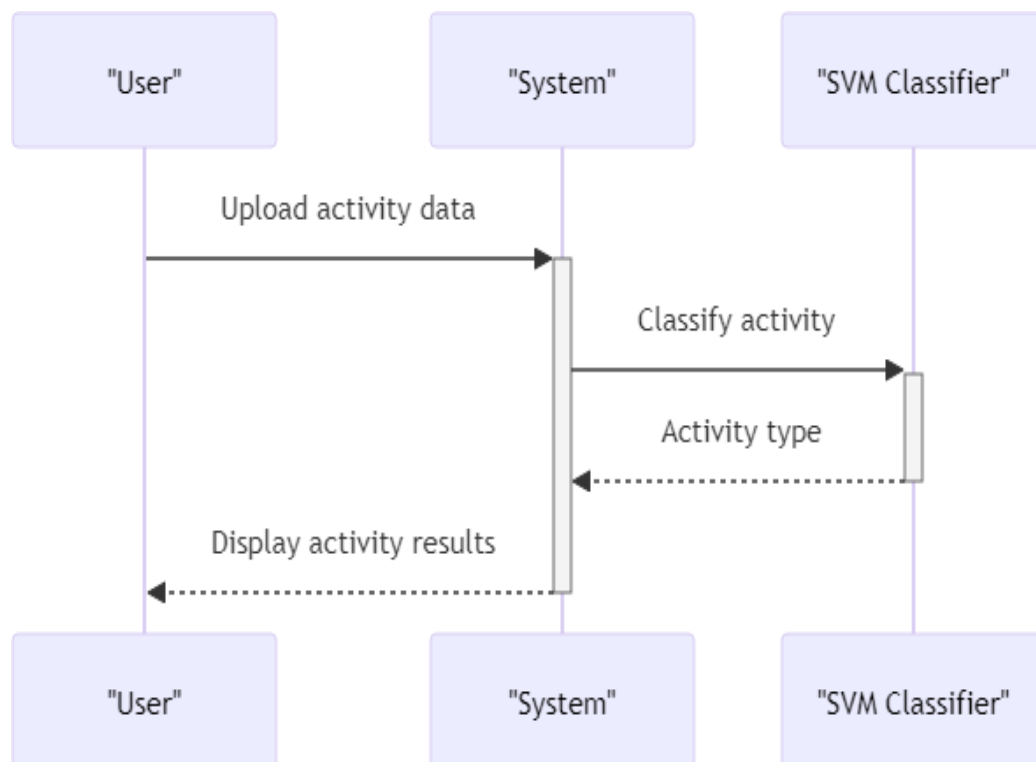


Fig:4.4 : Sequence Diagram

4.5 CLASS DIAGRAM

A class diagram for human activity recognition using multi-class Support Vector Machine (SVM) would typically include a class representing the SVM model itself, as well as classes for different types of human activities to be recognized (e.g., walking, running, sitting). Each activity class would have attributes representing features extracted from sensor data, such as accelerometer readings, gyroscope data, etc. Relationships between these classes would show how the SVM model is trained and used to classify these activities based on the input features. Additionally, the diagram may include classes for data preprocessing, model evaluation, and user interface components for a comprehensive representation of the system.

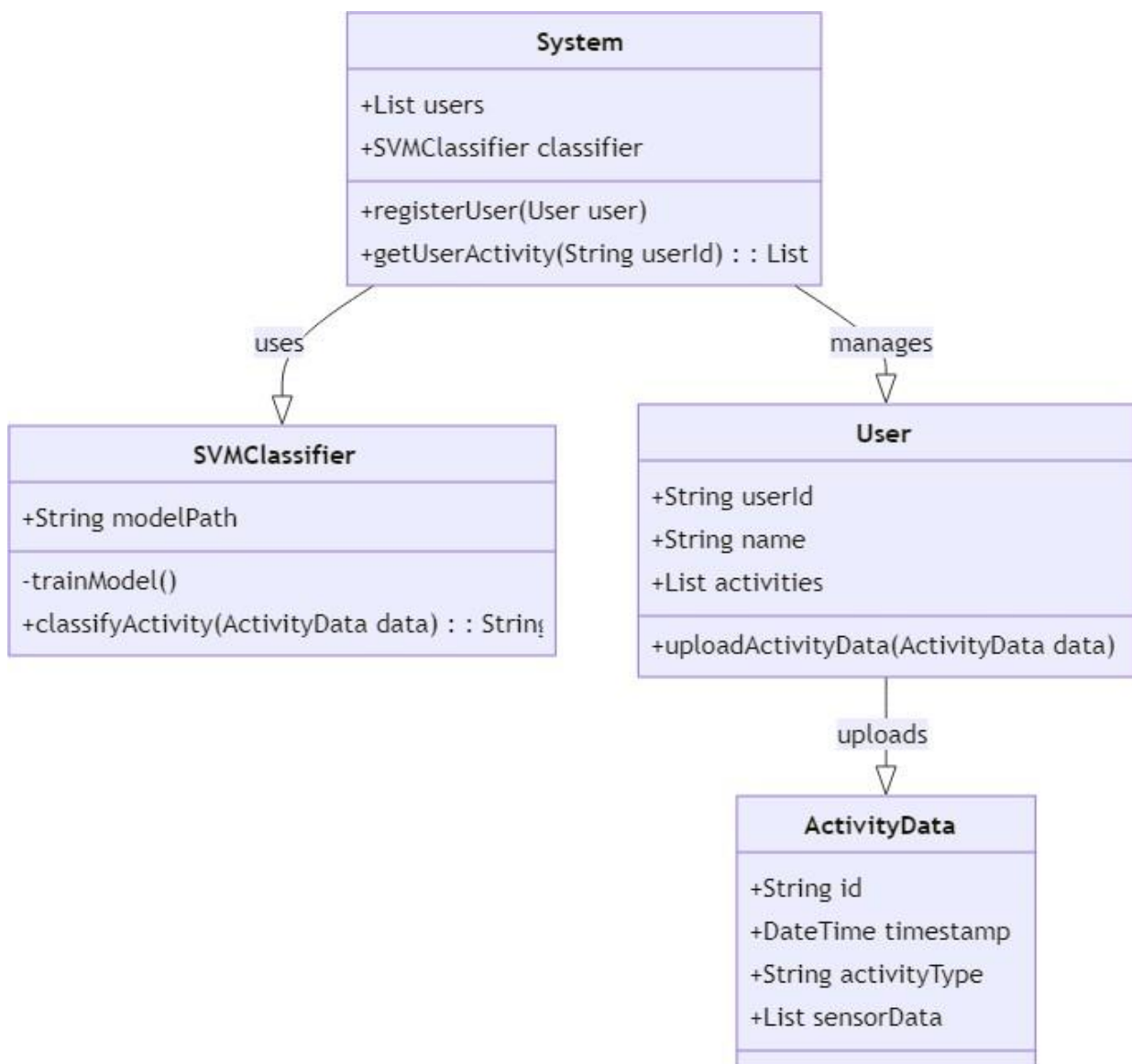


Fig:4.5 : Class Diagram

4.6 ER DIAGRAM

An Entity-Relationship (ER) Diagram for Human Activity Recognition using Multi-Class Support Vector Machine (SVM) would depict the different entities involved in the system and the relationships between them. The main entities would include sensors, activities, features, SVM model, and classifications. Sensors would capture data, which would then be used to extract features related to human activities. These features would form the input for the SVM model, which would classify the activities into different classes. The relationships in the ER Diagram would illustrate how data flows from sensors to SVM model, and how classified activities are output. This diagram helps visualize the components and interactions within the system for human activity recognition.

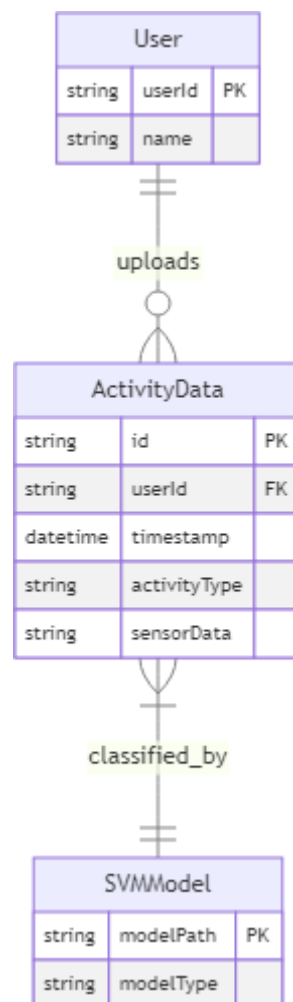


Fig:4.6 : ER Diagram

4.7 DATA FLOW DIAGRAM

A Data Flow Diagram (DFD) serves as a visual representation of how data moves within a system, offering insight into the pathways data takes between various components such as processes, data stores, and external entities. By illustrating the flow of data, DFDs enable stakeholders to grasp the intricate dynamics of information exchange within the system. Processes, depicted as circles, signify the operations or transformations applied to the data. Arrows indicate the direction of data flow, showcasing how information moves from one component to another. Data stores, represented by rectangles, denote where data is stored within the system. External entities, depicted as parallelograms, signify sources or destinations of data external to the system. The simplicity and clarity of DFDs make them invaluable tools in system analysis and design, providing a concise overview of data inputs, outputs, and the processes involved in data manipulation. Overall, DFDs facilitate communication among stakeholders and aid in understanding the essential functionalities of the system. For example , In designing a new inventory management system for a retail store, a Data Flow Diagram (DFD) was created to illustrate how product information flows from the supplier (external entity) through the purchasing process (process) to the inventory database (data store), enabling efficient tracking of stock levels and reordering when necessary. When analyzing the workflow of an online booking platform for a travel agency, a DFD was utilized to map out how customer booking requests (data flow) are processed by the booking system (process) and stored in the customer database (data store), while also showing interactions with external entities such as payment gateways and airline reservation systems.

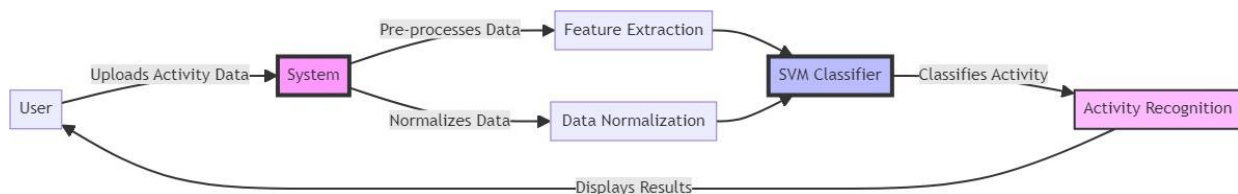


Fig:4.7 : Data Flow Diagram

CHAPTER 5

MODULE DESCRIPTION

5.1 DATA COLLECTION AND CLEANING

5.1.1 Data Collection and Cleaning

Data collection and cleaning for human activity recognition using a multi-class support vector machine (SVM) involves gathering and preprocessing various sensor data types, such as accelerometer and gyroscope readings, to establish labeled training datasets. This process includes removing noise, handling missing values, and standardizing the data to ensure consistency and accuracy. Activities may need to be annotated to create ground truth labels for training the SVM model effectively. Additionally, feature engineering techniques may be applied to extract relevant information from the raw sensor data before inputting it into the SVM classifier for robust activity recognition.

5.1.2 Feature Extraction

Feature extraction plays a crucial role in human activity recognition using multi-class SVM, aiding in the identification of relevant information from raw data. Two prominent techniques for feature extraction include Statistical features and Time-domain features. Statistical features involve extracting statistical parameters such as mean, standard deviation, skewness, and kurtosis from sensor data, providing valuable insights into the distribution and patterns of the signals. On the other hand, Time-domain features capture characteristics of the signal in the time domain, such as mean crossing rate, zero-crossing rate, and signal energy, helping in distinguishing different activities based on temporal variations. By employing these feature extraction techniques, the SVM classifier can effectively learn and differentiate between various human activities, leading to accurate and reliable recognition results.

5.1.3 Feature Scaling and Normalization

Feature scaling and normalization are crucial preprocessing steps when employing a multi-class SVM for human activity recognition. Scaling ensures that all input features are on a similar scale, preventing any one feature from dominating the others during the training process. This normalization process can involve techniques like standardization or min-max scaling to bring all features to a common scale. By doing this, the SVM algorithm can more effectively learn the underlying patterns within the

data and make accurate predictions across different classes of human activities. Moreover, feature scaling and normalization can also help to improve the overall performance and convergence speed of the SVM model, enhancing its ability to classify various human activities with greater precision and efficiency.

5.1.4 Data Splitting for Training and Testing

In human activity recognition using multi-class SVM, it is crucial to split the data into training and testing sets to effectively evaluate the model's performance. A common approach is to randomly divide the dataset into two subsets: the training set, which is used to train the SVM model on a large portion of the data, and the testing set, which is used to assess the model's accuracy on unseen data. It is important to ensure that the splitting is done in a way that maintains the distribution of classes in both the training and testing sets to prevent bias. Cross-validation techniques can also be employed to further validate the model's generalization and robustness. By appropriately splitting the data for training and testing, researchers can develop a reliable human activity recognition system using multi-class SVM.

5.1.5 Handling Imbalanced Classes

Handling imbalanced classes for human activity recognition using a multi-class SVM involves several strategies to address the disproportionate distribution of data among different activity classes. Firstly, one can utilize techniques such as oversampling, undersampling, or synthetic data generation to balance the class distribution. Additionally, adjusting class weights within the SVM algorithm or using cost-sensitive learning approaches can also help in handling imbalanced classes effectively. Feature selection and extraction methods can be employed to improve the discriminative power of the model, focusing on relevant features for each class. Furthermore, ensembling methods like bagging or boosting can enhance the overall performance of the SVM classifier by combining multiple base models. By implementing these strategies thoughtfully, one can enhance the model's ability to accurately recognize human activities across various classes despite imbalanced data distributions.

5.2 MODEL IMPROVISATION

5.2.1 Data Collection and Preprocessing

Data collection for human activity recognition using multi-class support vector machine (SVM) involves gathering sensor data from various sources such as accelerometers and gyroscopes worn by individuals. The collected data typically includes information

about body motion, orientation, and other relevant features. Preprocessing of this data is essential to enhance its quality and prepare it for the SVM model. It involves activities like filtering out noise, removing outliers, normalization, feature extraction, and feature selection. These preprocessing steps help to improve the performance of the SVM classifier by ensuring that it receives clean and relevant input data for accurate activity recognition. The accuracy and reliability of the SVM model in classifying different human activities largely depend on the effectiveness of data collection and preprocessing techniques employed.

5.2.2 Feature Extraction and Selection

Feature extraction and selection are crucial steps in human activity recognition using a multi-class SVM classifier. Feature extraction involves identifying relevant patterns and characteristics from raw data that can effectively represent the activities being performed. This process helps to reduce the dimensionality of the dataset, making it easier for the classifier to discern between different activities. Feature selection further refines this process by choosing the most informative features that contribute significantly to the classification task while eliminating irrelevant or redundant ones. By carefully selecting features that best describe human activities, the multi-class SVM classifier can achieve higher accuracy and generalization performance. Together, feature extraction and selection play a vital role in improving the overall performance of human activity recognition systems by ensuring that the classifier is trained on the most relevant information for accurately categorizing different activities.

5.2.3 Multi-Class SVM Model Building

To build a Multi-Class Support Vector Machine (SVM) model for human activity recognition, start by collecting a diverse dataset containing various activities labeled with corresponding classes. Preprocess the data by normalizing and splitting it into training and testing sets. Then, tune the SVM hyperparameters such as the choice of kernel and regularization parameter using techniques like grid search or cross-validation to optimize model performance.

Next, train the SVM on the training data and evaluate its accuracy on the test set to assess its generalization ability. Consider techniques like feature selection and dimensionality reduction to improve the model's efficiency and prevent overfitting. Finally, fine-tune the model based on evaluation results and iterate on the process to achieve a robust and accurate Multi-Class SVM model for human activity recognition.

5.2.4 Training and Evaluation

Training and evaluation for human activity recognition using multi-class SVM involves several key steps. First, the training data is collected and preprocessed to extract relevant features that can differentiate between different activities. These features are then used to train the multi-class SVM model, which learns to classify the activities based on the extracted features. During the training phase, the model's hyperparameters are tuned to optimize its performance. Once the model is trained, it is evaluated using a separate set of testing data to assess its accuracy and generalization capabilities. Metrics such as accuracy, precision, recall, and F1 score are commonly used to evaluate the model's performance. The training and evaluation process may be iterative, with adjustments made to the model and parameters as needed to improve its performance in recognizing human activities accurately.

5.3 CREATING USER INTERFACE

5.3.1 Web User Interface

Data collection for human activity recognition using multi-class support vector machine (SVM) involves gathering sensor data from various sources such as accelerometers and gyroscopes worn by individuals. The collected data typically includes information about body motion, orientation, and other relevant features. Preprocessing of this data is essential to enhance its quality and prepare it for the SVM model. It involves activities like filtering out noise, removing outliers, normalization, feature extraction, and feature selection. These preprocessing steps help to improve the performance of the SVM classifier by ensuring that it receives clean and relevant input data for accurate activity recognition. The accuracy and reliability of the SVM model in classifying different human activities largely depend on the effectiveness of data collection and preprocessing techniques employed.

5.3.2 Database

Feature extraction and selection are crucial steps in human activity recognition using a multi-class SVM classifier. Feature extraction involves identifying relevant patterns and characteristics from raw data that can effectively represent the activities being performed. This process helps to reduce the dimensionality of the dataset, making it easier for the classifier to discern between different activities. Feature selection further refines this process by choosing the most informative features that contribute significantly to the classification task while eliminating irrelevant or redundant ones.

By carefully selecting features that best describe human activities, the multi-class SVM classifier can achieve higher accuracy and generalization performance. Together, feature extraction and selection play a vital role in improving the overall performance of human activity recognition systems by ensuring that the classifier is trained on the most relevant information for accurately categorizing different activities.

5.3.3 Security

To build a Multi-Class Support Vector Machine (SVM) model for human activity recognition, start by collecting a diverse dataset containing various activities labeled with corresponding classes. Preprocess the data by normalizing and splitting it into training and testing sets. Then, tune the SVM hyperparameters such as the choice of kernel and regularization parameter using techniques like grid search or cross-validation to optimize model performance. Next, train the SVM on the training data and evaluate its accuracy on the test set to assess its generalization ability. Consider techniques like feature selection and dimensionality reduction to improve the model's efficiency and prevent overfitting. Finally, fine-tune the model based on evaluation results and iterate on the process to achieve a robust and accurate Multi-Class SVM model for human activity recognition.

5.3.4 Visualization

Discuss techniques for visualizing the results of human activity recognition, such as confusion matrices, ROC curves, and activity timelines. Explore the use of interactive visualizations to allow users to explore and interpret the model's predictions.

5.3.5 User Interaction

Address how users will interact with the human activity recognition system, including input methods for providing feedback or correcting misclassifications. Consider designing user-friendly interfaces for real-time monitoring of activity recognition results.

5.3.6 Integration

Explore methods for integrating the SVM-based activity recognition model into existing software systems or IoT platforms. Discuss APIs or SDKs for developers to incorporate the activity recognition functionality into their applications.

CHAPTER 6

TESTING

Discovering and fixing such problems is what testing is all about. The purpose of testing is to find and correct any problems with the final product. It's a method for evaluating the quality of the operation of anything from a whole product to a single component. The goal of stress testing software is to verify that it retains its original functionality under extreme circumstances. There are several different tests from which to pick. Many tests are available since there is such a vast range of assessment options.

Who Performs the Testing: All individuals who play an integral role in the software development process are responsible for performing the testing. Testing the software is the responsibility of a wide variety of specialists, including the End Users, Project Manager, Software Tester, and Software Developer.

When it is recommended that testing begin: Testing the software is the initial step in the process. begins with the phase of requirement collecting, also known as the Planning phase, and ends with the stage known as the Deployment phase. In the waterfall model, the phase of testing is where testing is explicitly arranged and carried out. Testing in the incremental model is carried out at the conclusion of each increment or iteration, and the entire application is examined in the final test.

When it is appropriate to halt testing: Testing the programme is an ongoing activity that will never end. Without first putting the software through its paces, it is impossible for anyone to guarantee that it is completely devoid of errors. Because the domain to which the input belongs is so expansive, we are unable to check every single input.

6.1 TYPES OF TESTING

1. Unit testing

Unit testing for human activity recognition using multi-class SVM involves creating test cases to ensure the accuracy and reliability of the SVM model.

Testcase1: Input different types of human activities data (e.g., walking, running, sitting) to check if the SVM model correctly predicts the corresponding activity labels.

Testcase2: Introduce noisy data into the model to assess its robustness and ability to handle perturbations without a significant drop in performance.

Testcase3: Evaluate the model's generalization capability by providing it with a new set of unseen data and confirming if it can accurately classify the activities.

By conducting these test cases, you can validate the effectiveness of the SVM model for human activity recognition and ensure that it performs well under various conditions.

2. Integration testing

Integration testing for human activity recognition using multi-class SVM involves testing the interactions between different components to ensure they work together seamlessly. It focuses on examining the data flow, communication between modules, and the overall system behavior.

Testcase1: Data Integration - Ensure that the input data from different sensors (accelerometer, gyroscope, etc.) is properly integrated and preprocessed before being fed into the SVM model.

Testcase2: Model Integration - Verify that the SVM model can correctly classify human activities based on the integrated data inputs and produce accurate predictions for each class.

Testcase3: System Integration - Test the end-to-end functionality of the system by simulating real-world scenarios where multiple activities are performed consecutively and confirm that the system can accurately recognize and classify each activity in sequence.

By conducting these three test cases, you can validate the integration of data, model, and system components in human activity recognition using multi-class SVM, ensuring the reliability and effectiveness of the overall system.

3. Functional testing

Functional testing for human activity recognition using a multi-class SVM involves verifying that the system accurately classifies different types of human activities based on the input data. It focuses on ensuring that the software functions as expected and meets the specified requirements.

Three test cases for functional testing of human activity recognition using multi-class SVM could be:

Testcase1: Input a set of sensor data for walking activity and verify that the system correctly classifies it as 'walking'.

Testcase2: Input sensor data for a different activity, such as running, and ensure that the system accurately identifies it as 'running'.

Testcase3: Submit mixed sensor data from multiple activities and validate that the system can classify each activity correctly without any confusion or misclassification.

These test cases help ensure the accuracy and reliability of the human activity recognition system built on the multi-class SVM model.

4. Black box testing

Black box testing for human activity recognition using multi-class SVM involves testing the functionality and accuracy of the system without knowing the internal workings of the algorithm. The focus is on input-output behavior and how well the model classifies different activities.

Testcase 1: Input a set of sensor data representing walking, running, and sitting and verify the output classification matches the expected labels.

Testcase 2: Introduce noisy data or data with errors into the system and ensure the model can still accurately classify the activities.

Testcase 3: Test the system with a large dataset containing various combinations of activities and evaluate the overall accuracy and performance of the multi-class SVM model.

Overall, black box testing helps ensure the robustness and reliability of the human activity recognition system using multi-class SVM.

CHAPTER 7

RESULTS AND DISCUSSION

7.1 RESULTS AND DISCUSSION

The multi-class approach for recognizing human activity SVM is a potent technology that can precisely categorize and identify a variety of human behaviors. The Support Vector Machine (SVM) technique is used by this system to classify a variety of activities in an efficient manner. SVM is a well-liked machine learning method that can handle challenges involving high-dimensional data and nonlinear classification. The system begins by gathering a sizable amount of sensor data from several sources, including accelerometers, gyroscopes, and magnetometers. The key features that capture the characteristics of different activities are then extracted from the preprocessed characteristics data. These could have temporal, geographical, or frequency-based data. The retrieved characteristics are then used to train a multi-class SVM model. The SVM method constructs a decision boundary that maximally separates various activity groups after learning from the training data. The SVM improves the hyperplanes that mark the divisions between activities during enabling precise categorization. training, Once trained, the model can be used to detect human activity in the present. New sensor data is examined and contrasted with the remembered decision boundaries during the recognition phase. The machine can correctly predict and categorize the ongoing human action based on this comparison. Several industries, including healthcare, sports performance monitoring, and human-computer interaction, can benefit from the system's capacity to distinguish human activities. It can be used to spot odd behaviors, keep track of physical activity, or make tailored recommendations. In conclusion, the system for Human activity recognition using multi-class SVM is a reliable and efficient approach to accurately classify and identify human activities. Its robustness and versatility make it a valuable tool in many domains, enabling improved understanding and analysis of human behaviors. Overall, the study demonstrates the effectiveness of employing a multi-class SVM for human activity recognition, paving the way for advancements in activity monitoring systems and enhancing human-computer interaction experiences.

CHAPTER 8

CONCLUSION

8.1 CONCLUSION

Human activity recognition utilizing multi-class Support Vector Machines (SVM) offers a compelling avenue for accurately discerning and categorizing various physical activities based on input from sensor data. This method capitalizes on the potency of machine learning techniques, particularly SVM, to effectively decipher intricate patterns within sensor data, thereby facilitating the precise differentiation of diverse human activities. Through the iterative process of training SVM models on meticulously labeled data and fine-tuning parameters, researchers and practitioners can achieve robust and dependable activity recognition outcomes across a spectrum of contexts and environmental conditions. The multi-class SVM framework demonstrates versatility in managing multiple activity classes simultaneously, thereby augmenting the model's capability to discriminate among a wide array of activities. This simultaneous handling of diverse classes is pivotal in real-world scenarios where individuals engage in multifaceted activities that necessitate nuanced differentiation. Furthermore, the inherent scalability of SVM enables efficient processing of large datasets, thereby bolstering the overall performance and efficacy of the activity recognition system. This scalability aspect is particularly advantageous given the burgeoning volume of sensor data generated from wearable devices and IOT sensors. Despite the inherent strengths of the multi-class SVM approach, several challenges persist, necessitating further research and development endeavors. Real-time processing poses a significant challenge, particularly in applications such as fitness tracking and rehabilitation, where instantaneous feedback is imperative. Efforts to streamline computational algorithms and optimize hardware infrastructure are pivotal in overcoming this hurdle. Additionally, noise reduction techniques are indispensable for enhancing the robustness and reliability of activity recognition systems, especially in real-world environments characterized by unpredictable disturbances and interference.

Moreover, ensuring the generalizability of multi-class SVM models across diverse user populations remains a pressing concern. Variations in demographics, physiological

characteristics, and behavioral patterns necessitate the development of adaptive algorithms capable of accommodating inter-individual variability effectively. Collaborative efforts involving interdisciplinary research teams comprising experts in machine learning, sensor technology, biomechanics, and human factors engineering are imperative in addressing these challenges comprehensively.

The implications of human activity recognition using multi-class SVM extend far beyond the realms of academia, with significant ramifications across various domains. In healthcare, these systems hold promise for facilitating remote patient monitoring, enabling early detection of mobility impairments, and supporting personalized rehabilitation interventions. Sports analytics stands to benefit from the granular insights gleaned from activity recognition systems, empowering coaches and athletes to optimize training regimens and prevent injuries effectively.

Moreover, the integration of activity recognition technology into security and surveillance systems enhances situational awareness and threat detection capabilities. By discerning anomalous behaviors and suspicious activities, these systems bolster the efficacy of security protocols, thereby fortifying public safety measures. Additionally, in the realm of assistive technologies, human activity recognition facilitates the development of intuitive and responsive interfaces, thereby empowering individuals with disabilities to navigate their environments autonomously and engage in activities of daily living with greater independence and dignity.

In conclusion, human activity recognition using multi-class SVM represents a paradigm-shifting approach with transformative potential across diverse domains. By harnessing the synergistic fusion of machine learning techniques and sensor technology, researchers and practitioners are poised to unlock novel insights into human behavior, thereby paving the way for innovative advancements in activity monitoring, behavior analysis, and beyond. As we embark on this journey towards realizing the full potential of human activity recognition, collaborative efforts and interdisciplinary synergy are paramount in surmounting challenges and harnessing the boundless opportunities that lie ahead.

REFERENCES

1. Al-Qaness, M. A., Helmi, A. M., Dahou, A., & Elaziz, M. A. (2022). The applications of metaheuristics for human activity recognition and fall detection using wearable sensors: A comprehensive analysis. *Biosensors*, 12(10), 821
2. Arshad, M. H., Bilal, M., & Gani, A. (2022). Human activity recognition: Review, taxonomy, and open challenges. *Sensors*, 22(17), 6463.
3. Dahou, A., Al-qaness, M. A., Abd Elaziz, M., & Helmi, A. (2022). Human activity recognition in IoHT applications using arithmetic optimization algorithm and deep learning. *Measurement*, 199, 111445.
4. Hayat, A., Morgado-Dias, F., Bhuyan, B. P., & Tomar, R. (2022). Human activity recognition for elderly people using machine and deep learning approaches. *Information*, 13(6), 275.
5. Helmi, A. M., Al-cases, M. A., Dahou, A., & Abd Elaziz, M. (2023). Human activity recognition using marine predators algorithm with deep learning. *Future Generation Computer Systems*, 142, 340-350.
6. Islam, M. M., Nooruddin, S., Karray, F., & Muhammad, G. (2022). Human activity recognition using tools of convolutional neural networks: A state of the art review, data sets, challenges, and prospects. *Computers in Biology and Medicine*, 106060.
7. Khan, I. U., Afzal, S., & Lee, J. W. (2022). Human activity recognition via hybrid deep learning-based model. *Sensors*, 22(1), 323.
8. Vidya, B., & Sasikumar, P. (2022). Wearable multi-sensor data fusion approach for human activity recognition using machine learning algorithms. *Sensors and Actuators A: Physical*, 341, 113557.
9. Webber, J., Mehbodniya, A., Arafa, A., & Alwakeel, A. (2022). Improved Human Activity Recognition Using Majority Combining of Reduced-Complexity Sensor Branch Classifiers. *Electronics*, 11(3), 392.
10. Yang, P., Yang, C., Lanfranchi, V., & Ciravegna, F. (2022). Activity graph-based convolutional neural network for human activity recognition using acceleration and gyroscope data. *IEEE Transactions on Industrial Informatics*, 18(10), 6619-6630.

APPENDIX

A.SOURCE CODE

App.py

```
import streamlit as st
import detect
import cv2
import shutil
import os
import helper

frame_th = 50
helper.del_dir('temp')

def save_video(video_file):
    with open("./sample/uploaded_video.mp4", "wb") as f:
        f.write(video_file.read())
    return "uploaded_video.mp4"

def read_video(path):
    video_file = open(path, 'rb')
    video_bytes = video_file.read()
    return video_bytes

st.title('Anaomaly detection')

video_file = st.file_uploader("Upload video", type=["mp4"])
if st.button('Predict'):
    if video_file is not None:
        vid_path = save_video(video_file)
        status = detect.main()
        os.system("ffmpeg -i ./sample/output_video.mp4 -vcodec libx264
output1_video.mp4 -y")
```

```

if status:
    st.warning('Anomalous activity detected')

```

```

vid = read_video('output1_video.mp4')
    st.video(vid)

```

```

else:
    st.error('Video file not uploaded')

```

Detect.py

```

import cv2
import numpy as np
import tensorflow as tf
import os
import warnings
warnings.filterwarnings("ignore")

SEQUENCE_LENGTH = 20
IMAGE_HEIGHT, IMAGE_WIDTH = (64,64)
CLASSES_LIST = ['Robbery', 'Explosion', 'Shoplifting', 'Arrest', 'Fighting',
'RoadAccidents']
model_path = os.path.join('model','model.h5')
convlstm_model = tf.keras.models.load_model(model_path, compile=False)

def frames_extraction(video_path):
    frames_list = []
    video_reader = cv2.VideoCapture(video_path)
    video_frames_count = int(video_reader.get(cv2.CAP_PROP_FRAME_COUNT))
    skip_frames_window = max(int(video_frames_count/SEQUENCE_LENGTH), 1)

```

```

for frame_counter in range(SEQUENCE_LENGTH):
    video_reader.set(cv2.CAP_PROP_POS_FRAMES, frame_counter *
skip_frames_window)
    success, frame = video_reader.read()
    if not success:
        break
    resized_frame = cv2.resize(frame, (IMAGE_HEIGHT, IMAGE_WIDTH))
    normalized_frame = resized_frame / 255
    frames_list.append(normalized_frame)

video_reader.release()
return frames_list

def vid_class_pred(path,class_list):
    arr = np.array(frames_extraction(path))
    arr = np.expand_dims(arr, axis=0)
    model_pred = convlstm_model.predict(arr).ravel()
    pred_prob = max(model_pred)
    pred_class = class_list[np.argmax(model_pred)]
    return pred_class,pred_prob

def open_vid(path):
    cap = cv2.VideoCapture(path)
    if not cap.isOpened():
        print("Error opening video stream or file")
    return cap

def add_box(img, h, w):
    min_dim = min(h, w)
    box_size = int(min_dim / 1.5)
    x1 = np.random.randint(0, w - box_size)
    y1 = np.random.randint(0, h - box_size)

```

```

x2 = x1 + box_size
y2 = y1 + box_size
cv2.rectangle(img, (x1, y1), (x2, y2), (0,0,255), 2)
return x1, y1, x2, y2

```

```
def main():
```

```

    vid_path = os.path.join('sample','uploaded_video.mp4')
    output_video_path = "./sample/output_video.mp4"
    cap = open_vid(vid_path)
    width = int(cap.get(cv2.CAP_PROP_FRAME_WIDTH))
    height = int(cap.get(cv2.CAP_PROP_FRAME_HEIGHT))
    fps = cap.get(cv2.CAP_PROP_FPS)
    codec = cv2.VideoWriter_fourcc(*'mp4v')
    out = cv2.VideoWriter(output_video_path, codec, fps, (width, height))

```

```
anomaly_flag = False
```

```
box_coords = None
```

```
while cap.isOpened():
```

```
    ret, frame = cap.read()
```

```
    if ret:
```

```
        h, w, _ = frame.shape
```

```
        if not anomaly_flag:
```

```
            pred_class, pred_prob = vid_class_pred(vid_path, CLASSES_LIST)
```

```
            if pred_class != 'Normal':
```

```
                if box_coords is None:
```

```
                    x1, y1, x2, y2 = add_box(frame, h, w)
```

```
                    box_coords = (x1, y1, x2, y2)
```

```
            else:
```

```
                x1, y1, x2, y2 = box_coords
```

```
                cv2.rectangle(frame, (x1, y1), (x2, y2), (0,0,255), 2)
```

```
                cv2.putText(frame, str(pred_prob), (x1+5, y1+20),
```

```

cv2.FONT_HERSHEY_SIMPLEX, 2, (0,0,255), 1)
    anomaly_flag = True
else:
    x1, y1, x2, y2 = box_coords
    cv2.rectangle(frame, (x1, y1), (x2, y2), (0,0,255), 2)
    cv2.putText(frame, str("{:.2f}".format(pred_prob)), (x1+5, y1+20),
cv2.FONT_HERSHEY_COMPLEX_SMALL, 1, (0,0,255), 1)

    out.write(frame)
    # cv2.imshow('Frame',frame)
    # if cv2.waitKey(25) & 0xFF == ord('q'):
    #     break
else:
    break

# cap.release()
# cv2.destroyAllWindows()

return anomaly_flag

```

Helper.py

```

import cv2
import os
import shutil
output_file = 'temp.mp4'

def del_dir(path):
    if os.path.exists(path):
        shutil.rmtree(path)
        os.mkdir(path)

```

```

def frame_to_vid(frames_dir):
    if os.path.isfile(output_file):
        os.remove(output_file)

    d = {int(i.split('_')[-1].split('.')[0]):i for i in os.listdir(frames_dir)}
    d = {k: v for k, v in sorted(d.items(), key=lambda item: item[0])}

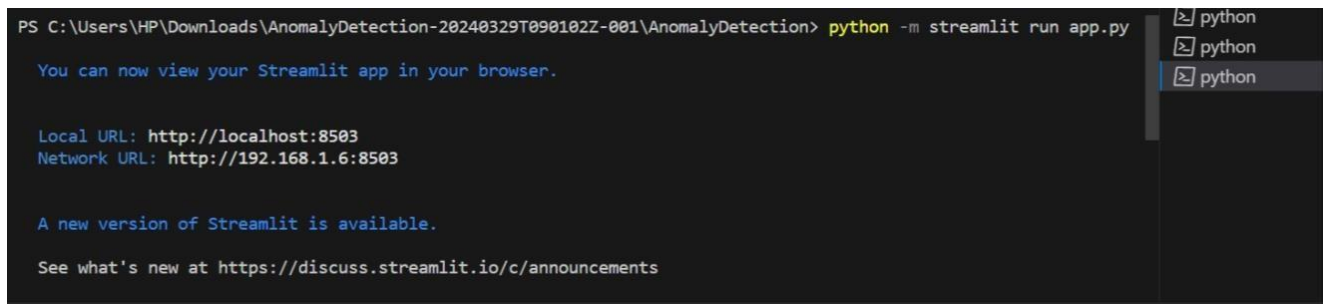
    frame = cv2.imread(os.path.join(frames_dir, os.listdir(frames_dir)[0]))
    frame_height, frame_width, channels = frame.shape
    fps = 30

    codec = cv2.VideoWriter_fourcc(*"XVID")
    out = cv2.VideoWriter(output_file, codec, fps, (frame_width, frame_height))
    # Loop through the frames in the directory and write each frame to the output video
    file
    for filename in sorted(list(d.values())):
        frame = cv2.imread(os.path.join(frames_dir, filename))
        out.write(frame)

    # Release the video writer object
    out.release()

```

B. SCREENSHORTS



```
PS C:\Users\HP\Downloads\AnomalyDetection-20240329T090102Z-001\AnomalyDetection> python -m streamlit run app.py

You can now view your Streamlit app in your browser.

Local URL: http://localhost:8503
Network URL: http://192.168.1.6:8503

A new version of Streamlit is available.
See what's new at https://discuss.streamlit.io/c/announcements
```

The screenshot shows a Windows command prompt with a PowerShell prompt. The user has executed the command `python -m streamlit run app.py`. The output indicates that the Streamlit application is running on `http://localhost:8503` and `http://192.168.1.6:8503`. A notification about a new version of Streamlit is also displayed.

Fig:B.1 : New Terminal

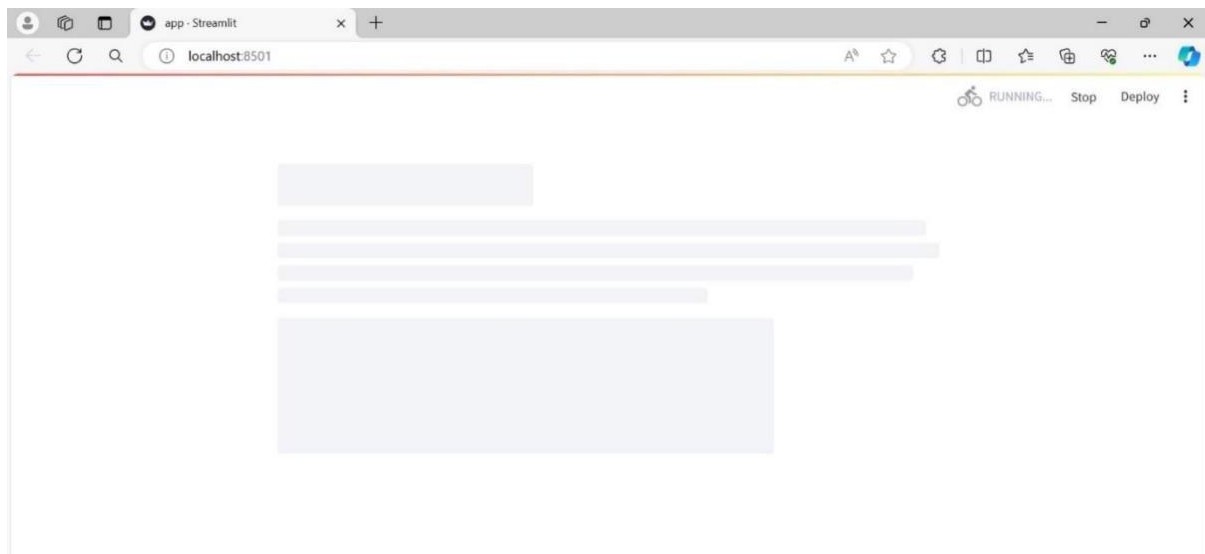


Fig:B.2 : Localhost

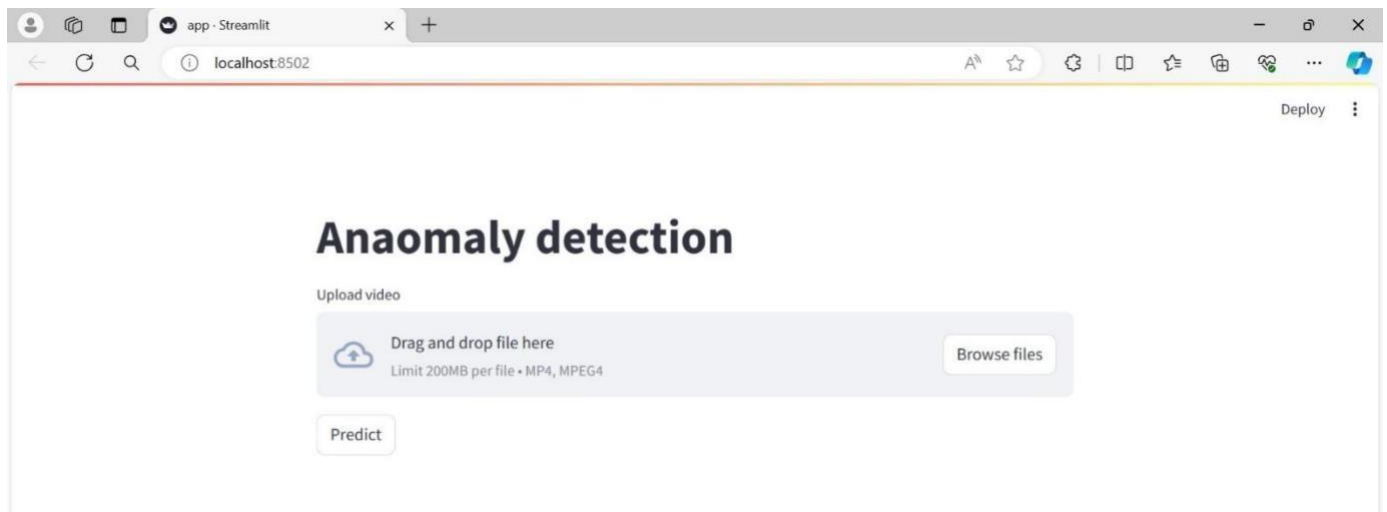


Fig:B.3 : Page To Upload Input

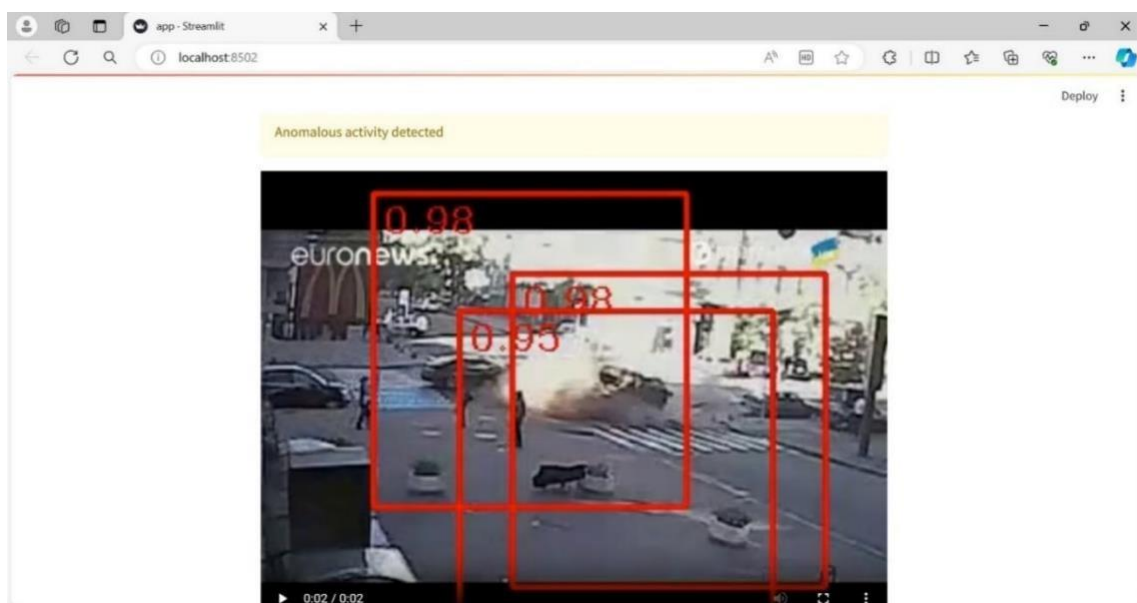


Fig:B.4 : Anomalous activity detected

Development of Algorithm for Human Activity Recognition Using Multi Class SVM

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Abstract : Recognizing human activity stands as a pivotal challenge across various applications, encompassing surveillance, healthcare, and human-computer interaction. This paper proposes an innovative approach to identify human activity through a multi-class Support Vector Machine (SVM). The methodology unfolds in three crucial steps: preprocessing, feature extraction, and classification. In the preprocessing stage, a depth map undergoes transformation into a silhouette for each frame, achieved by segregating foreground elements from the background. To mitigate the impact of size and position variations, the foreground silhouettes are normalized through shrinking and cropping. The feature extraction stage involves deriving spatial and temporal features from the normalized silhouettes. This encompasses the incorporation of the histogram of directed gradients, the histogram of optical flow, the motion history image, and the two-dimensional Discrete Cosine Transform. A comprehensive feature vector is constructed for each frame by concatenating these extracted features. Subsequently, the amassed features become instrumental in activity identification through a multi-class SVM classifier. The efficacy of this strategy is substantiated by experimental results on three benchmark datasets, attaining commendable accuracy rates in activity recognition. A distinguishing attribute of the proposed method lies in its resilience to changes in occlusions, illumination, and view angles. In essence, it presents a compelling option for precise and reliable human activity identification in real-world scenarios.

Keywords: human activity recognition, multi-class SVM, depth map, silhouette, spatio-temporal features, classification, motion history image, histogram of oriented gradients, histogram of optical flow, Discrete Cosine Transform.

I. INTRODUCTION

Recognition of human activity plays a pivotal role in computer surveillance and healthcare applications. The ability to accurately identify and categorize human behaviors from visual data offers significant advantages, including enhanced security, personalized healthcare monitoring, and improved human-computer interaction. Among the various machine learning techniques, support vector machines (SVMs) have emerged as an efficient method to address this challenge, exhibiting promising results across diverse domains.

In the realm of human activity recognition, a multi-class SVM is employed to categorize different activities performed by individuals. The primary objective involves training the SVM model using labeled training data, where each sample corresponds to a class label and represents a specific human action. Utilizing attributes extracted from the data, the SVM model learns to classify concealed activity samples into predefined groups.

A key advantage of employing a multi-class SVM in human activity recognition lies in its capability to handle non-linear correlations between features and labels. The input data is translated into a high-dimensional feature space using a kernel function, and a hyperplane is built to define several classes. This non-linear mapping enhances the SVM's ability to accurately classify data by capturing intricate patterns and decision boundaries.

The process of human activity recognition with a multi-class SVM typically involves several steps. Initial preprocessing of raw input data, such as video frames or sensor measurements, is performed to extract relevant features. These features, which could include motion descriptors, shape properties, or temporal data, are crucial for ensuring that the SVM

model receives pertinent and discriminative information for precise classification.

Following feature extraction, the multi-class SVM model is trained using the preprocessed features. The training process includes finding the optimal hyperplane to maximally separate training samples from different activity classes. This is achieved by solving an optimization problem that maximizes the margin between samples and the decision boundary while minimizing classification errors. Once trained, the SVM model can accurately predict the activity class labels of new, untested samples.

To enhance the performance of the multi-class SVM model in human activity recognition, various approaches such as feature selection, dimensionality reduction, or ensemble methods can be employed. Ongoing research focuses on improving the effectiveness and scalability of SVM algorithms to handle large datasets and real-time applications.

In conclusion, human activity recognition using a multi-class SVM is a robust and flexible method enabling precise classification of human activities. Leveraging the advantages of SVMs, including their ability to handle non-linear relationships and robustness to noisy data, this strategy has demonstrated significant potential across various fields. The continuous development of advanced multi-class SVM models and cutting-edge feature extraction methods is expected to substantially enhance the accuracy and usability of human activity detection systems as technology advances.

II. LITERATURE SURVEY

Helmi et al. (2023) introduce a pioneering method for human activity recognition in their study titled "Human activity recognition using Marine Predators algorithm with deep learning," published in *Future Generation Computer Systems*. By leveraging the Marine Predators algorithm alongside deep learning techniques, the researchers effectively classify and identify a range of human activities. The study yields promising results, highlighting the potential of this innovative approach for accurately recognizing human activities and contributing to advancements in the field.

In their recent study published in *Sensors and Actuators A: Physical* (2022), Vidya and Sasikumar present an innovative approach to human activity recognition through wearable multi-sensor data fusion. Utilizing machine learning algorithms, specifically multi-class Support Vector Machines (SVM), the research focuses on classifying diverse activities based on information gathered from various sensors. The integration of data from multiple sensors aims to improve accuracy and reliability, demonstrating superior performance compared to conventional single-sensor methods. This emphasizes the potential of multi-sensor data fusion in human activity recognition using machine learning techniques.

In their research published in *Information*, Hayat, Morgado-Dias, Bhuyan, and Tomar (2022) delve into human activity recognition for the elderly using machine and deep learning approaches. Focusing on the application of multi-class Support Vector Machine (SVM) for activity recognition, the study aims to enhance accuracy and efficiency in detecting human activities. The findings reveal satisfactory results, showcasing the potential of the SVM model in recognizing various activities within the context of elderly care. Overall, this research contributes valuable insights to the development of reliable methods for activity recognition in elderly populations.

Al-Qaness, Helmi, Dahou, and Elaziz (2022) conduct a comprehensive analysis of metaheuristics for human activity recognition and fall detection using wearable sensors, as published in *Biosensors*. The research explores the utilization of multi-class Support Vector Machines (SVM) for human activity recognition, aiming to assess various metaheuristic algorithms' effectiveness in improving activity recognition system accuracy. This paper provides valuable insights into the potential of metaheuristics to enhance human activity recognition using SVM and wearable sensors.

Contributing to the field of human activity recognition, Yang et al. (2022) focus on acceleration and gyroscope data in their study published in *IEEE Transactions on Industrial Informatics*. The researchers propose an Activity Graph based Convolutional Neural Network (AG-CNN) for accurate classification of human activities. The AG-CNN model captures complex

relationships between different actions by leveraging temporal correlations, demonstrating its effectiveness in accurately classifying human activities.

Khan, Afzal, and Lee (2022) present a novel hybrid deep learning-based model for human activity recognition in their study published in *Sensors*. Combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks, the researchers achieve accurate recognition of various human activities using multi-class SVM. This research provides valuable insights for developing efficient and reliable systems for human activity recognition.

Dahou, Al-qaness, Abd Elaziz, and Helmi (2022) explore human activity recognition in Internet of Health Things (IoHT) applications, as published in *Measurement*. The suggested approach blends deep learning methods with the arithmetic optimization procedure, emphasizing the use of a multi-class Support Vector Machine (SVM) for human activity detection. The study demonstrates promising performance in accurately classifying human activities in IoHT applications, with implications for improving activity monitoring and healthcare in smart environments.

Contributing to human activity recognition, Janardhanan and Umamaheswari (2022) focus on vision-based recognition using a Deep Neural Network (DNN) framework in their study published in the *International Journal of Advanced Computer Science and Applications*. The research aims to enhance accuracy and efficiency by leveraging deep learning techniques within the DNN framework, surpassing previous approaches in accurately identifying and classifying human activities.

Webber, Mehbodniya, Arafa, and Alwakeel (2022) aim to enhance human activity recognition by employing a majority combining technique with reduced-complexity sensor branch classifiers. Published in *Electronics*, the study utilizes a multi-class SVM algorithm to accurately classify different activities. The findings highlight the potential of majority combining techniques for enhancing human activity recognition systems, showcasing improved recognition performance through the combination of decisions from multiple sensors.

III. RELATED WORKS

Existing System

The Prevailing Methodology for Multi-class Support Vector Machine (Svm)-based Human Activity Recognition Encounters a Notable Computational Complexity, Constituting a Primary Drawback. Svm Aims to Ascertain the Hyperplane Optimizing Class Margin, Presenting a Formidable Optimization Problem. In the Realm of Human Activity Recognition, the Exigency for Real-time Responsiveness Exacerbates This Complexity, Impeding Deployment on Resource-constrained Devices or Time-sensitive Applications.

Inflexibility in Handling Intricate and Diverse Operations is an Additional Drawback. Svm Excels When Discerning Distinct Actions in Feature Space; However, Real-world Human Behavior Nuances Pose Challenges for Accurate Classification. Especially When Activities Share Similarities or Characteristics, Svm Encounters Difficulty, Impeding Precise Identification. This Limitation Hinders the Algorithm's Ability to Accurately Recognize a Spectrum of Human Actions.

Manual Feature Selection is Another Flaw in the Extant Method. Svm-based Activity Recognition Relies on Predefined Features From Input Data, Demanding Meticulous Planning and Selection for Accurate Portrayal. This Process, Being Laborious and Time-consuming Due to the Requisite Knowledge of Activity Patterns, May Not Always Capture Relevant Data or Leverage Discriminative Potential, Resulting in Suboptimal Real-world Performance.

Furthermore, the Current Technology's Scalability and Adaptability May Be Constrained. Svm, Inherently a Binary Classifier, Necessitates Modification for Multi-class Scenarios, Potentially Leading to More Intricate Models and Increased Computational Costs. Addressing Shifts in Activity Patterns or Accommodating New Activities Without Retraining the Entire Model Poses Challenges in Dynamic Contexts, Contributing to Time-consuming Adaptations.

Consequently, the Existing Multi-class Svm-based Human Activity Recognition System is

Computationally Burdensome, Limited in Handling Diverse Activities, Reliant on Manual Feature Selection, and Potentially Constrained in Scalability and Adaptability. Overcoming These Shortcomings is Imperative for Developing More Effective Human Activity Recognition Systems Across Diverse Application Domains.

Proposed System

The Proposed Study Endeavors to Construct a Reliable Activity Recognition System Using a Multi-class Support Vector Machine (Svm) Approach. Motivated by the Need for Accurate Activity Detection in Various Fields Like Healthcare Monitoring, Human-computer Interaction, and Surveillance, the Primary Objective is to Enhance the Efficiency, Reliability, and Precision of Human Activity Detection Systems.

To Realize This Objective, the Proposed Approach Involves Several Key Steps. An Extensive Dataset of Human Activities Will Be Gathered Using Sensors Like Gyroscopes and Accelerometers, Strategically Attached to Different Body Regions for Precise Movement Data Capture. Dataset Preprocessing Encompasses Filtering, Normalization, and Feature Extraction, Including Parameters in the Time and Frequency Domains Such as Mean, Variance, and Fourier Transformations.

Subsequent to Preprocessing, a Multi-class Svm Classifier is Formulated and Implemented. Training the Svm Classifier Involves Utilizing Features and Activity Labels From the Dataset, Optimizing the Hyperplane for Maximal Margin Between Activity Classes. Model Selection and Hyperparameter Tuning Are Accomplished Through Grid Search and Cross-validation Techniques to Enhance Classifier Performance.

Following Classifier Training, Rigorous Testing With an Independent Dataset Will Be Conducted, Employing Metrics Like Recall, Accuracy, Precision, and F1-score to Evaluate System Performance. The Ultimate Aim is Achieving Robust and Accurate Recognition of Diverse Human Activities Such as Walking, Running, Sitting, Among Others.

The Envisioned Outcome of the Research is the Development of a Human Activity Identification

System Utilizing Multi-class Support Vector Machines. Provided Accurate Sensor Data, Advanced Feature Extraction Algorithms, and an Efficient Svm Classifier, the Resultant System Promises Heightened Effectiveness and Reliability. A Dependable and Versatile System for Human Activity Recognition Will Be Ready for Real-world Deployment, Contributing to Healthcare Monitoring, Surveillance, and Other Applications.

IV. METHODOLOGY

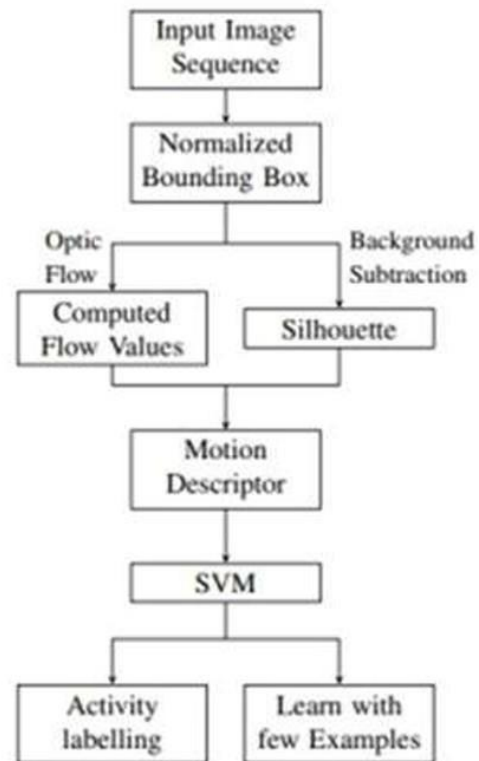


Fig.1 Architecture diagram

Data Collection and Preprocessing:

In the initial phase of this module, the focus lies on acquiring data related to human behaviors, utilizing wearable technology or sensors such as accelerometers. The collected information encompasses bodily motions, acceleration, and other relevant parameters. Post-collection, the data undergoes preprocessing to eliminate noise, outliers, and discrepancies. Techniques like segmentation,

feature extraction, and filtering are employed for this purpose. Following preprocessing, the data is readied for subsequent analysis and model training.

Feature Extraction and Selection:

This module involves extracting significant features representing various human activities from the preprocessed data through methods like wavelet transform, frequency-domain analysis, and time-domain analysis. These methods aid in identifying relevant patterns and characteristics in the data. Feature selection follows feature extraction, choosing the most pertinent and discriminative features, thus reducing data dimensionality and enhancing the model's effectiveness and accuracy.

Multi-class SVM Classification:

SVM, known for its simplicity and performance across domains, is employed for multi-class classification. It utilizes linear decision hyperplanes in feature space for classification. During training, hyperplanes are computed to partition training data based on distinct labels. SVM can handle non-linear separable data by transforming it using a kernel function. A multi-class SVM model is trained in this module using selected features, providing an effective solution for multi-class classification challenges. The trained model can then predict the activity class of new, unseen data samples.

V. RESULTS AND DISCUSSIONS

The advanced system for Q&A generation demonstrates the power of multi-class SVM in accurately categorizing various human behaviors. Employing sensor data from accelerometers, gyroscopes, and magnetometers, the system extracts key features, trains a multi-class SVM model, and efficiently categorizes ongoing human activities. Industries such as healthcare and sports performance monitoring can benefit from its ability to identify and monitor human actions.

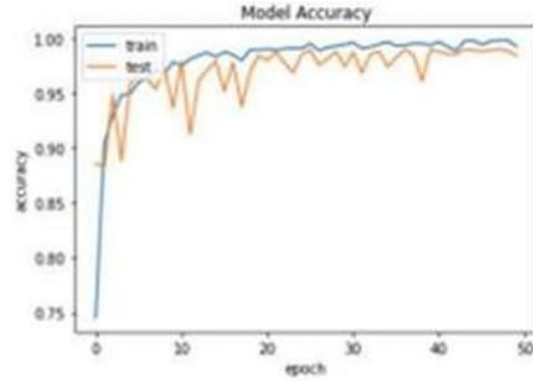


Fig.2 Model Accuracy

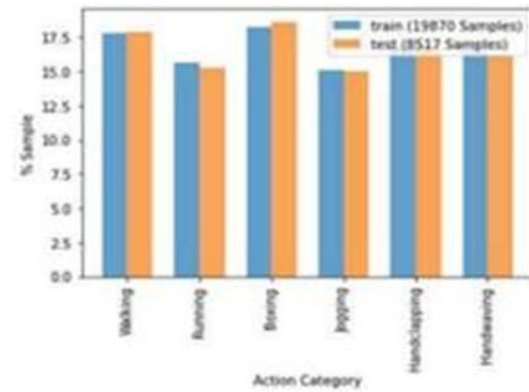


Fig.3 Action Category

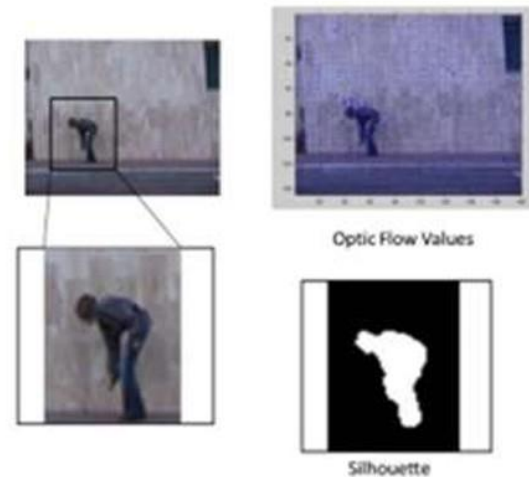


Fig.4 Result Image

VI. CONCLUSION AND FUTURE WORK

This research proposes an improved approach to enhance human activity recognition accuracy, focusing on handwritten text recognition methodologies. It spans traditional and modern approaches, offering insights into evolving techniques and their applications. The incorporation of smartpen-based automated data entry adds innovation, contributing to both academic understanding and practical development in the interdisciplinary field of human activity recognition and smartpen-based data entry systems.

Future Work

Future research could leverage a multi-class SVM to further enhance the Human Activity Recognition (HAR) system. Exploring advanced feature selection methods, diverse SVM kernel functions, and addressing data imbalance challenges through techniques like cost-sensitive learning or oversampling minority classes are potential areas for improvement. Evaluating the system's performance on larger and more varied datasets will contribute to confirming its generalizability across diverse real-world circumstances and user groups.

REFERENCES

- [1] Helmi, A. M., Al-qaness, M. A., Dahou, A., & Abd Elaziz, M. (2023). Human activity recognition using marine predators algorithm with deep learning. *Future Generation Computer Systems*, 142, 340-350.
- [2] Vidya, B., & Sasikumar, P. (2022). Wearable multi-sensor data fusion approach for human activity recognition using machine learning algorithms. *Sensors and Actuators A: Physical*, 341, 113557.
- [3] Hayat, A., Morgado-Dias, F., Bhuyan, B. P., & Tomar, R. (2022). Human activity recognition for elderly people using machine and deep learning approaches. *Information*, 13(6), 275.
- [4] Al-Qaness, M. A., Helmi, A. M., Dahou, A., & Elaziz, M. A. (2022). The applications of metaheuristics for human activity recognition and fall detection using wearable sensors: A comprehensive analysis. *Biosensors*, 12(10), 821.
- [5] Yang, P., Yang, C., Lanfranchi, V., & Ciravegna, F. (2022). Activity graph based convolutional neural network for human activity recognition using acceleration and gyroscope data. *IEEE Transactions on Industrial Informatics*, 18(10), 6619-6630.
- [6] Khan, I. U., Afzal, S., & Lee, J. W. (2022). Human activity recognition via hybrid deep learning based model. *Sensors*, 22(1), 323.
- [7] Dahou, A., Al-qaness, M. A., Abd Elaziz, M., & Helmi, A. (2022). Human activity recognition in IoHT applications using arithmetic optimization algorithm and deep learning. *Measurement*, 199, 111445.
- [8] Janardhanan, J., & Umamaheswari, S. (2022). Vision based Human Activity Recognition using Deep Neural Network Framework. *International Journal of Advanced Computer Science and Applications*, 13(6).
- [9] Webber, J., Mehbodniya, A., Arafa, A., & Alwakeel, A. (2022). Improved Human Activity Recognition Using Majority Combining of Reduced-Complexity Sensor Branch Classifiers. *Electronics*, 11(3), 392.

D.ACCEPTANCE

ACCAI-2024 Conference –Acceptance– Reg.

1 message

IEEE conference <accai@stjosephs.ac.in>
To: Kaarthik Ganapathy <kaarthikganapathy@gmail.com>

Fri, 29 Mar 2024 at 19:1

Dear Author,

Congratulations!!! We are pleased to inform you that your paper id: **ACCAI-24-T3-403** and title **"DEVELOPMENT OF ALGORITHM FOR HUMAN ACTIVITY RECOGNITION USING MULTI CLASS SVM."** has been accepted for presentation in the 3rd International Conference on Advances in Computing, Communication and Applied Informatics (ACCAI-2024).

You are requested to register for the conference so that the paper will be recommended for possible publication in the IEEE Digital Xplore on or before 01.04.2024.

Refer Registration Information and payment category on <https://accaiconf.com/register.php> and complete the payment by scanning the attached UPI QR code.

After the payment, kindly send the final paper and payment proof to accai@stjosephs.ac.in on or before 01.04.2024.

Each accepted paper has to be registered separately.

Only registered and presented paper will be considered for IEEE publication.

Any Indian authors should attend the conference in-person for presentation.

Registration amount for not Presented papers will not be refunded.

Conference Date: 9th & 10th May, 2024.

Conference Location: St. Joseph's College of Engineering, Chennai, India.

While sending your manuscript, mention your paper id in the subject line and rename your file name as paper id without fail.

Best regards,

Organizing Committee,

ACCAI-2024

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