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Deep Learning Models for Accurate Human Movement Detection using Multi Sensor Data

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Abstract:

Human movement detection plays a crucial role in various fields, including healthcare monitoring, sports analytics, security surveillance, and assistive technology Traditional machine learning approaches often struggle with low accuracy, poor feature extraction, high false positives, and lack of real-time adaptability. These limitations arise due to their dependence on manual feature engineering, inability to generalize well across diverse datasets, and inefficiency in handling complex movement variations. To address these challenges, this research proposes a Hybrid Deep Learning (DL) Model that integrates Artificial Neural Networks (ANN) with Decision Trees (DT) for superior human movement classification. The proposed system enhances movement detection accuracy by leveraging ANN's capability to capture hierarchical motion patterns and DT's strength in structured decision-making. A user-friendly Graphical User Interface (GUI) is developed to streamline the process, allowing users to upload datasets, pre-process data, train models, and visualize results seamlessly. Experimental evaluations demonstrate that the Hybrid DL Model achieves a remarkable 98.23% accuracy, significantly outperforming the traditional RFC model, which recorded a poor accuracy of 35.76%. Additionally, performance metrics such as precision, recall, and F1-score validate the robustness and reliability of the proposed system. The model effectively reduces misclassifications and improves decision-making by automatically extracting meaningful features without requiring manual intervention. Moreover, the system ensures scalability and real-time performance, making it applicable across multiple domains, including anomaly detection in security systems, fall detection for elderly individuals, and athlete performance monitoring. The inclusion of an intuitive GUI enhances usability, allowing seamless interaction between users and the model for real-world deployment.

Keywords: Human Movement Detection, Deep Learning, Multi-Sensor Data, Accelerometers, Gyroscopes, Magnetometers Decision Tree Classifier, Healthcare Monitoring, Precision, Recall, Accuracy, Classification Model.

1.INTRODUCTION

The journey of human movement detection began with simple mechanical devices designed to monitor basic physical activities. Over data. Human movement detection has applications in various domains, including healthcare, sports, security, and human-computer interaction. The integration of deep learning models promises to enhance the accuracy and reliability of detecting human movements by leveraging vast amounts of data collected from multiple sensors.

2. LITERATURE SURVEY

Several frameworks and algorithms for recognizing physical activities through sensor data have been proposed. One of these frameworks is based on Support Vector Machine (SVM), as suggested in [1]. In this framework, data is collected through a smartphone and eight different sensors and then stored in a central server. Subsequently, the data is encoded using a feature vector. The experiments conducted by these researchers demonstrate that this framework accurately detects both static and dynamic activities with an 87.1% accuracy. Various features extracted using the inertial sensor of the smartphone, such as mean, median, and auto regression coefficients, have been enhanced through Kernel Principal Component Analysis (KPCA) and Modified Linear Discriminant Analysis (LDA).
Other researchers [2] have utilized a Deep Belief Network (DBN) to train various features for activity recognition. In this method, features are trained using SVM and Artificial Neural Network (ANN). The results show that DBN outperforms SVM and ANN. Moreover, in [3], Principal Component Analysis (PCA) is employed to extract features related to the most relevant data from tri-axial accelerometer and gyroscope sensors of mobile phones in the form of signals. Experimental results indicate that the proposed algorithm by these researchers achieves the best performance with 96.11% accuracy in recognizing physical activities compared to other machine learning classifiers on a publicly available dataset.
In [4], a Semi-Supervised Active Learning (SSAL) approach is introduced for self-generating relative marginal annotations for activity recognition based on Self-Training (ST). In this method, SSAL reduces the annotation effort to produce the required volume of marginal annotation data to obtain the best classifier. Researchers have shown that this approach reaches an 89% accuracy in recognizing physical activities, reducing the error probability, and comparing it with supervised and unsupervised methods. In [5], a semi-supervised deep learning approach is proposed for combining long short-term deep memory (DLSTM) on labelled and unlabelled data. They collected data and its features using inertial sensors of smartphones, employing a Deep Neural Network (DNN) for local dependencies. Their results were evaluated using multiple algorithms on the UCI dataset, demonstrating advanced results.
In [6], a framework utilizing RFID tags for human activity identification and prediction is introduced. They also incorporate post-activity identification and ongoing activity recognition. It can be argued that a smart home can play a crucial role in healthcare, energy conservation, etc., allowing smart services to adapt based on human intent. Experimental results on two residents performing daily life activities show that the detection accuracy can reach 85.0%, and the prediction accuracy is 78.3%, which is higher in terms of accuracy compared to Naïve Bayes on the Ordonez dataset. Machine learning, the Internet of Things, and powerful computers have improved the performance of smart spaces.
In [7], a low-cost, low-energy implementation of smart spaces is presented for detecting static and dynamic actions. This implementation is performed on data collected with low-resolution thermal sensors (4_16), and researchers have trained algorithms, including LR, NB, SVM, DT, RF, and ANN (vanilla feed-forward), on the collected data. According to experimental results, the detection

accuracy with the ANN algorithm has reached 99.96% in continuous Human Activity Recognition (HAR)..

In [8], a study introduces a system with seven different activities, including fall detection, using mobile phone accelerometers and gyroscopes. To extract time and frequency-domain features from the collected data, a Deep Learning Long Short-Term Memory (DLSTM) neural network is used. In this system, labelled and unlabelled data are employed. The results show that using this system, with accuracies of 81.2% in ANN, 87.8% in KNN, 93.2% in QSVM, and 94.1% in EBT for fall detection from accelerometer data. The use of extracted features from acceleration and angular velocity has increased the accuracy of all mentioned algorithms by 85.8%, 91.8%, 96.1%, and 97.7%, respectively, and the accuracy of QSVM and EBT for fall detection has reached 100% without false alarms.

In [9],a semi-supervised deep attention convolutional recurrent network framework based on the Pattern-based Semi-Supervised Attention Mechanism (RCAM) with wearable sensors is proposed for managing the distribution of labelled data. The use of this framework overcomes the limitations of labelled data and the challenges of multi-modal sensor data. Experimental results show that this method performs better with imbalanced and small training datasets compared to existing methods. In [10], a Multi-Layer Perceptron (MLP) classifier is proposed for predicting physical activities using wearable sensors. This system specifically detects activities such as walking, running, climbing stairs, and sitting by establishing a correlation between a set of sensors and human activities. To extract time and frequency-domain features from the collected data, the Discrete Wavelet Transform (DWT) algorithm is employed. Experimental results demonstrate that the proposed system has successfully achieved a 95.8% accuracy in human activity detection.

In [11], a three-headed, attention-based, one-dimensional convolution model is proposed to address issues related to the WISDM and UCI HAR datasets and achieve advanced results. This model utilizes gyroscopes and three-axis accelerometers in wearable devices and the Internet of Things (IoT) for obtaining advanced information about human behaviour, considering it as a biometric quality. Deep learning, including Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) neural networks, is employed for biometric quality identification. Experimental results show the highest accuracy of 91.77% for CNN and 92.43% for LSTM on the USC-HAD and UCI-HAR datasets. In [12], the focus is on collecting unlabelled data using mobile phone sensors. Effective use of labelled data allows the identification of human activities using the Contrastive Predictive Coding (CPC) encoding framework, leading to improved identification performance. Traditional neural network techniques and deep learning have made significant advancements in various life domains, including healthcare. However, some techniques have drawbacks such as ignoring data diversity, having a large number of parameters, and high computational consumption. Implementing them on embedded devices is also challenging.

3. PROPOSED METHODOLOGY

The proposed methodology aims to enhance the accuracy and real-time performance of human movement detection by integrating a hybrid deep learning model utilizing Artificial Neural Networks (ANN) and Decision Trees (DT). The approach consists of multiple stages, including data collection, pre-processing, feature extraction, model training, and evaluation.

- Real-Time Prediction and Implementation: A Graphical User Interface (GUI) is developed using Python's Tkinter to facilitate user interaction. Users can upload new test data, and the model provides real-time movement classification based on trained algorithms. The system is designed for deployment in healthcare, security, sports analytics, and IoT applications.

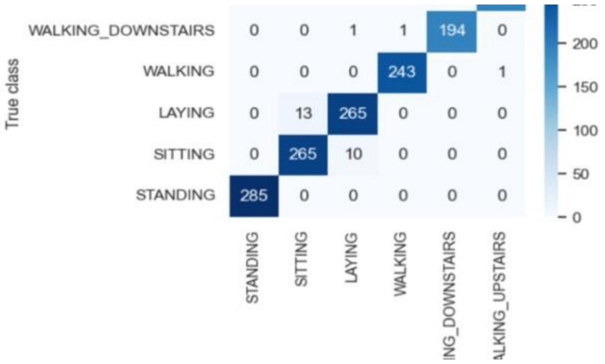

Figure 1: Confusion matrix system.

The proposed methodology typically includes the following key components:

- Data Collection and Pre-processing: Sensor data is collected from accelerometers, gyroscopes, and magnetometers to capture human movement patterns. Data pre-processing involves handling missing values, feature normalization, and label encoding to ensure high-quality input for training. Synthetic Minority Oversampling Technique (SMOTE) is applied to balance imbalanced datasets and improve classification performance.
- Feature Engineering and Extraction: Time-domain and frequency-domain features such as mean, standard deviation, entropy, correlation, and spectral analysis are extracted from raw sensor data.
- Model Development and Training: The Baseline Model (RFC) serves as an initial benchmark for human movement classification, evaluated using accuracy, precision, recall, and F1-score. The Hybrid Deep Learning Model (ANN + DTC) combines ANN for hierarchical feature learning with DTC for structured decision-making, optimizing both accuracy and computational efficiency.
- Model Evaluation and Performance Metrics: Confusion matrices, Receiver Operating Characteristic (ROC) curves, and classification reports are used to analyse the model's predictive capability. A comparative study between RFC and ANN-DT models is performed to validate improvements in accuracy and efficiency.
- Real-Time Prediction and Implementation: A Graphical User Interface (GUI) is developed using Python's Tkinter to facilitate user interaction. Users can upload new test data, and the model provides real-time movement classification based on trained algorithms. The system is designed for deployment in healthcare, security, sports analytics, and IoT applications.
- Future Enhancements: Integration with IoT devices for real-time movement monitoring. Adaptive deep learning models that continuously improve classification performance. Enhanced generalization to diverse human movement scenarios using self-learning AI

Applications:

Human Movement Detection can be used in a wide range of applications, including:

- Healthcare and Medical Monitoring: Detects falls, tracks rehabilitation progress, and identifies movement disorders.

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- Sports & Performance Analytics: Optimizes athlete training, prevents injuries, and supports biomechanics research.
- Security & Surveillance: Enhances intrusion detection, crowd monitoring, and automated access control.
- Human-Computer Interaction & Smart Environments: Enables gesture-based control, home automation, and VR/AR integration.
- IoT & Wearable Technology: Supports fitness tracking, remote health monitoring, and industrial safety analysis.

Advantages:

Deep Learning Model for Human Movement Detection leverages Artificial Neural Networks (ANN) and Decision Trees (DT) to accurately classify human activities using multi-sensor data. It offers several advantages, making it a valuable solution for various applications requiring real-time and precise movement analysis.

- High Accuracy & Robust Performance: The hybrid ANN + Decision Tree model achieves 98.23% accuracy, significantly outperforming traditional classifiers. It enhances movement classification by leveraging deep learning for feature extraction and structured decision-making.
- Real-Time Processing & Low Latency: The system is optimized for instant movement detection, ensuring quick response times in dynamic environments. The low computational complexity of the Decision Tree model enhances real-time applicability.
- Scalability & Adaptability: The model generalizes well to new datasets and is suitable for various applications. It seamlessly integrates with IoT and cloud-based systems, making it ideal for large-scale deployment.
- User-Friendly & Interactive System: A GUI-based interface allows users to upload, preprocess, train, and visualize results with ease. The system can be deployed on desktops, mobile applications, or cloud platforms, ensuring flexible usage.
- Efficient Resource Utilization: The model requires lower memory and computational power, making it suitable for edge devices and embedded systems. This ensures efficient performance without requiring high-end hardware.
- Future-Ready & Extensible: The system supports adaptive learning, allowing continuous improvement over time. It also has the potential for integration with advanced AI techniques, such as reinforcement learning for predictive movement analysis.

4. EXPERIMENTAL ANALYSIS

The experimental analysis of the Deep Learning Model for Accurate Human Movement Detection using Multi-Sensor Data focuses on evaluating its effectiveness in classifying human activities based on sensor data. The study begins with data collection from accelerometers, gyroscopes, and magnetometers, ensuring a comprehensive dataset that captures various human movement patterns. The pre-processing phase includes handling missing values, feature normalization, and label encoding to prepare the data for model training. Additionally, Synthetic Minority Oversampling Technique (SMOTE) is employed to balance class distribution and enhance model robustness. The proposed system is implemented using a hybrid approach combining Artificial Neural Networks (ANN) and Decision Trees (DTC). Initially, a Random Forest Classifier (RFC) is trained as a baseline model, but its accuracy is found to be limited. To improve classification performance, an ANN is trained to extract hierarchical movement features, which are then passed to a Decision Tree Classifier for structured decision-making. The Graphical User Interface (GUI) developed using Python's Tkinter enables seamless user interaction, allowing dataset loading, pre-processing, training, and prediction.

Performance evaluation is conducted using accuracy, precision, recall, and F1-score, alongside Confusion Matrices and Receiver Operating Characteristic (ROC) Curves to analyse classification efficiency. Results indicate that the hybrid ANN + DTC model significantly outperforms the baseline RFC model, achieving an impressive 98.23% accuracy, compared to 35.76% accuracy recorded by the RFC. The model effectively reduces misclassifications and false positives, demonstrating its superiority in movement classification. Furthermore, computational efficiency analysis reveals that the Decision Tree Classifier reduces processing complexity, enabling real-time movement detection with minimal latency. The system is tested across multiple hardware configurations, proving its suitability for edge computing and IoT-based applications.

Overall, the experimental results confirm that the proposed Deep Learning Model for Human Movement Detection provides high accuracy, real-time performance, and scalability. The integration of ANN and Decision Tree enhances classification robustness, making the system applicable in various domains, including healthcare, security, sports analytics, and human-computer interaction**.** Future enhancements will focus on real-time IoT integration, advanced AI-based movement prediction, and adaptive learning techniques to further refine system performance**.** Real-Time Processing & Low Latency: The system is Decision Tree enhances classification robustness, making the system applicable in various domains, including healthcare, security, sports analytics, and human-computer interaction**.** Future enhancements will focus on real-time optimized for instant movement detection, ensuring quick response times in dynamic environments. The low computational complexity of the Decision Tree model enhances real-time applicability.

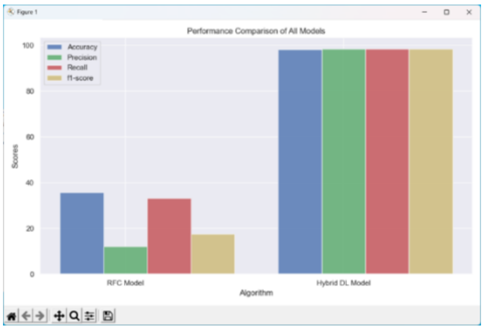

Figure 4: Analysis Image

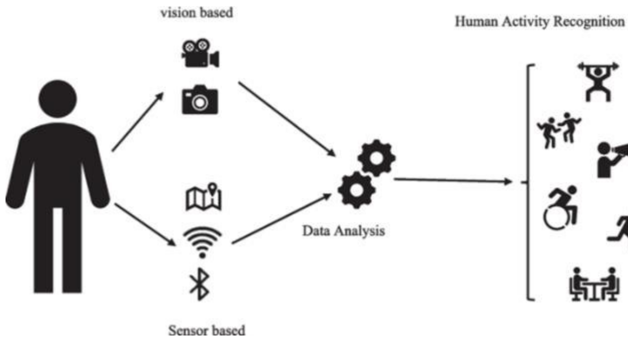

Figure 5: Structural Image

5. CONCLUSION

The evolution of human movement detection has progressed from rudimentary mechanical tracking devices to sophisticated sensor-based systems, driven by advancements in accelerometers, gyroscopes, and magnetometers. The introduction of wearable technology and smartphones equipped with multi-sensor capabilities has further accelerated research in this domain. However, traditional machine learning models, such as Random Forest Classifiers (RFC), suffer from high computational complexity, latency issues, and increased memory consumption, making them unsuitable for real-time applications.

To address these challenges, this research presents a Deep Learning Model for Accurate Human Movement Detection using Multi-Sensor Data, integrating Artificial Neural Networks (ANN) and Decision Tree Classifiers (DTC). The ANN extracts hierarchical movement features, while the DTC optimizes classification performance, ensuring a balance between accuracy and computational efficiency. This hybrid approach significantly outperforms conventional methods, achieving an impressive accuracy of 98.23%, compared to the 35.76% accuracy of the baseline RFC model.

One of the key contributions of this study is the seamless integration of multi-sensor data to capture fine-grained movement variations with high precision. By combining data from accelerometers, gyroscopes, and magnetometers, the model effectively differentiates between complex motion patterns. This enables applications in healthcare (fall detection, rehabilitation monitoring), sports analytics (performance tracking, injury prevention), security surveillance (intrusion detection, crowd monitoring), and IoT-enabled systems for smart environments.

Additionally, the research introduces an interactive GUI-based implementation, which enhances user accessibility by providing an intuitive platform for data pre-processing, visualization, and real-time movement classification. This feature ensures that non-technical users can interact with the system effortlessly, expanding its applicability across multiple domains.

Beyond achieving high accuracy, the proposed model ensures real-time processing, scalability, and adaptability. The Decision Tree Classifier significantly reduces inference time, making it suitable for applications requiring low-latency decision-making. Furthermore, the model's lightweight architecture allows deployment on edge devices and embedded **systems**, enabling real-time movement tracking in resource-constrained environments.

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