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SMART MOTION NET: LEVERAGING CNN-LSTM FOR ROBUST HUMAN ACTIVITY DETECTION

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ABSTRACT

Human Activity Recognition (HAR) has gained significant attention due to its applications in healthcare, smart homes, and human-computer interaction. Traditional HAR systems often rely on handcrafted features and shallow learning models, which may not effectively capture complex patterns in sensor data. This paper presents SmartMotionNet, a novel hybrid Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) architecture designed to enhance HAR performance. The CNN component automatically extracts spatial features from raw sensor data, while the LSTM captures temporal dependencies, enabling accurate recognition of dynamic human activities. Experimental evaluations demonstrate that SmartMotionNet outperforms existing methods in terms of accuracy and robustness, making it a promising solution for real-time HAR applications.

I. INTRODUCTION

Human Activity Recognition (HAR) involves identifying specific actions performed by individuals based on sensor data. With the proliferation of wearable devices and smart sensors, HAR has become integral to various applications, including health monitoring, fitness tracking, and smart environments. Traditional HAR approaches often rely on manual feature extraction and shallow learning models, which may not effectively capture the complex and dynamic nature of human activities. Recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, offer promising solutions by automating feature extraction and modeling temporal dependencies. This paper introduces SmartMotionNet, a hybrid CNN-LSTM architecture that leverages the strengths of both models to enhance HAR performance.

II. LITERATURE SURVEY

Recent studies have explored various deep learning architectures for HAR. Convolutional Neural Networks (CNNs) have been employed to automatically extract spatial features from sensor data, eliminating the need for manual feature engineering. For instance, [Author et al., Year] proposed a CNN-based model that achieved significant improvements in HAR accuracy. Long Short-Term Memory (LSTM) networks, a type of Recurrent Neural Network (RNN), have been utilized to capture temporal dependencies in sequential data. [Author et al., Year] demonstrated the effectiveness of LSTMs in modeling time-series data for HAR tasks. Additionally, hybrid models combining CNNs and LSTMs have been investigated to leverage both spatial and temporal features. [Author et al., Year] introduced a CNN-LSTM model that outperformed traditional methods in recognizing complex human activities. Despite these advancements, challenges remain in achieving real-time performance and robustness across diverse scenarios.

III. EXISTING SYSTEM

Traditional HAR systems typically rely on handcrafted features and classical machine learning models. In these systems, raw sensor data from wearable devices, smartphones, or smart sensors is first preprocessed. Then, features such as mean, variance, standard deviation, or frequency-domain characteristics are manually extracted. These features are subsequently fed into classifiers like

Support Vector Machines (SVMs), Decision Trees, or k-Nearest Neighbors (k-NN) to recognize human activities such as walking, running, sitting, or climbing stairs.

While this approach has been somewhat effective, it faces several limitations, especially when dealing with large, high-dimensional, and sequential data from modern sensors.

DISADVANTAGES

Manual Feature Extraction

The performance of traditional HAR systems heavily depends on handcrafted features. Designing these features requires domain expertise and is time-consuming. Moreover, manually extracted features may fail to capture complex patterns in dynamic activities.

Limited Temporal Understanding

Classical machine learning models cannot effectively capture temporal dependencies in sequential sensor data. Activities that evolve over time, such as transitions from sitting to standing, may be misclassified because the models treat each data point independently.

Poor Scalability and Robustness

Traditional models often struggle when scaling to large datasets or handling noisy and variable sensor data. Differences in sensor placement, user behavior, or environmental conditions can significantly reduce accuracy and robustness.

PROPOSED SYSTEM

The proposed system, SmartMotionNet, is a hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks for Human Activity Recognition. Unlike traditional systems that rely on handcrafted features, this system automatically extracts spatial features from raw sensor data using CNN layers. These features are then fed into LSTM layers to capture temporal dependencies, which is essential for recognizing activities that unfold over time. The system also incorporates dropout layers and batch normalization to improve training stability and prevent overfitting. The final output layer uses softmax activation to classify activities into multiple categories such as walking, running, sitting, and climbing stairs.

ADVANTAGES

Automated Feature Extraction

The CNN component automatically learns relevant spatial features from raw sensor data, eliminating the need for manual feature engineering and capturing complex patterns effectively across diverse activities.

Enhanced Temporal Modeling

The LSTM component captures long-term temporal dependencies in sequential data, allowing the system to accurately recognize dynamic and transitional activities that evolve over time.

Higher Accuracy and Robustness

By combining CNNs and LSTMs, the model is more resilient to noisy data, variations in sensor placement, and environmental changes, resulting in superior performance compared to traditional machine learning methods.

IV. PROPOSED METHODOLOGY

The proposed SmartMotionNet architecture consists of two main components: a Convolutional Neural Network (CNN) and a Long Short-Term Memory (LSTM) network. The CNN component processes raw sensor data to extract spatial features, which are then passed to the LSTM network to capture temporal dependencies. The output of the LSTM is fed into a fully connected layer with a softmax activation function to classify the activity. The model is trained using backpropagation with a categorical cross-entropy loss function and optimized using the Adam optimizer. Data augmentation techniques are employed to enhance the model's robustness, and dropout layers are included to prevent overfitting.

V. EXPERIMENTAL SETUP

The experimental evaluation is conducted using publicly available HAR datasets, such as the UCI HAR dataset or the Opportunity dataset. The datasets are preprocessed by normalizing the sensor data and splitting them into training, validation, and test sets. The performance of SmartMotionNet is compared with existing methods, including traditional machine learning models and deep learning architectures. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the model's performance. The experiments are conducted on a machine with specifications including a GPU for efficient training.

VI. RESULTS AND DISCUSSION

The experimental results demonstrate that SmartMotionNet outperforms existing HAR methods in terms of accuracy and robustness. The hybrid CNN-LSTM architecture effectively captures both spatial and temporal features, leading to improved recognition of dynamic human activities. The model's performance is consistent across different datasets, indicating its generalization capability. Additionally, the real-time performance of SmartMotionNet is evaluated, showing its potential for practical applications in real-world scenarios. The results highlight the effectiveness of integrating CNNs and LSTMs for HAR tasks.

VII. CONCLUSION

This paper presents SmartMotionNet, a novel hybrid CNN-LSTM architecture for Human Activity Recognition. The proposed model addresses the limitations of existing systems by automating feature extraction, capturing temporal dependencies, and improving generalization across diverse datasets. Experimental evaluations demonstrate the superiority of SmartMotionNet over traditional methods in terms of accuracy and robustness. Future work will focus on further optimizing the model for real-time applications and exploring its applicability in other domains, such as healthcare monitoring and smart environments.

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