HUMAN ACTIVITY RECOGNITION

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Abstract-Human Activity Recognition (HAR) is a vital research area with applications in healthcare, fitness tracking, and human-computer interaction. This project utilizes Artificial Neural Networks (ANNs) to accurately classify various human activities using data collected from smartphone sensors. By employing a sequential model, the project processes time-series data from accelerometers and gyroscopes to identify activities such as walking, running, and sitting. The project demonstrates the effectiveness of ANNs in handling complex, high-dimensional sensor data, providing a robust solution for real-time activity recognition. The results highlight the potential of neural networks in enhancing the accuracy and efficiency of HAR systems, paving the way for their integration into smart devices and applications.

Keywords- Human Activity Recognition, Artificial Neural Network, Time Series Data, Smartphone Sensors, Real-Time Classification

I. INTRODUCTION

Human Activity Recognition (HAR) is an emerging field of research that focuses on identifying and classifying human activities using data collected from various sensors. With the proliferation of wearable devices and smartphones equipped with advanced sensors, HAR has gained significant attention due to its wide range of applications in healthcare, fitness tracking, smart homes, and human-computer interaction. The primary goal of HAR is to develop systems that can automatically recognize and interpret human activities such as walking, running, sitting, and standing by analyzing time-series data from sensors like accelerometers and gyroscopes.

In this project, we utilize Artificial Neural Networks (ANNs) to build a robust HAR system. ANNs are well-suited for this task due to their ability to learn complex patterns and relationships within the data. By employing a sequential model, we can effectively process the high-dimensional sensor data and accurately classify different activities. The significance of HAR lies in its potential to improve the quality of life by enabling various applications, such as monitoring the physical activity of patients in healthcare, tracking workouts in fitness, and enhancing smart home functionalities. Through this project, we aim to demonstrate the effectiveness of ANNs in handling HAR tasks and highlight the potential of integrating such systems into everyday applications.

II. OBJECTIVE

The objective of this study is to develop a predictive model using Artificial Neural Networks (ANNs) to accurately classify various human activities based on data collected from smartphone sensors. By leveraging time-series data from accelerometers and gyroscopes, this research aims to capture the complex patterns and relationships within the sensor data. The model seeks to enhance activity recognition accuracy and provide valuable insights into human behavior, thereby supporting data-driven decision-making for healthcare providers, fitness enthusiasts, and smart home developers.

III. LITERATURE REVIEW

Vrigkas, M., Nikou, C., & Kakadiaris, I. A. (2015) discuss the challenges of human activity recognition (HAR) from video and image data, such as background clutter, occlusion, and variations in scale and lighting. They categorize HAR methods into those using multimodal data and those that do not, further analyzing each category based on activity modeling approaches. The authors review available datasets, emphasizing the ideal characteristics of HAR data, and outline future research needs, including the development of more robust datasets and techniques to address real-world conditions.

Jobanputra, C., Bavishi, J., & Doshi, N. (2019) highlight the need for solving Human Activity Recognition (HAR) to support applications in eldercare and healthcare, especially when integrated with Internet of Things (IoT) technology. The authors review various HAR methods, using different data sources like sensors, images, and smartphone-based accelerometers and gyroscopes, each positioned strategically. They compare the performance of machine learning techniques such as decision trees, K-nearest neighbors, and support vector machines with deep learning approaches like artificial neural networks, convolutional neural networks, and recurrent neural networks, analyzing results across diverse datasets.

Lara, O. D., & Labrador, M. A. (2012) discuss the importance of timely and accurate Human Activity Recognition (HAR) in pervasive computing, highlighting its applications in medical, security, and tactical fields. Focusing on HAR using wearable sensors, they propose a two-level taxonomy based on learning approaches (supervised or semi-supervised) and response times (offline or online). The authors review 28 systems, evaluating them on recognition performance, energy consumption, obtrusiveness, and flexibility, and discuss the key challenges and solutions. They conclude by identifying open problems in

HAR that future research should address due to their high impact on mobile device interactions.

Kim, E., Helal, S., & Cook, D. (2009) emphasize the societal benefits of Human Activity Recognition (HAR), particularly in healthcare and elder care. Their study focuses on recognizing simple human activities, while noting that complex activity recognition is still a challenging area. They differentiate between two HAR approaches: activity recognition, which aims at accurate detection based on a predefined model, and activity pattern discovery, where researchers build a system and analyze sensor data to uncover patterns. This distinction highlights the ongoing challenges in understanding and modeling diverse human activities.

Gu, F., Chung, M. H., Chignell, M., Valaee, S., Zhou, B., & Liu, X. (2021) present a comprehensive survey on recent developments and challenges in Human Activity Recognition (HAR) using deep learning techniques. While previous HAR surveys primarily reviewed traditional machine learning approaches, this study focuses on deep learning models and their variants, which are increasingly applied in fields such as healthcare and smart homes. The authors emphasize the need for an in-depth review of newly developed deep learning methods for HAR, addressing a gap in the literature on advanced deep model applications in this domain.

Ramasamy Ramamurthy, S., & Roy, N. (2018) review the recent trends in applying machine learning techniques to activity recognition (AR), noting the transition from traditional hand-crafted feature-based algorithms to advanced deep learning models. Despite significant advancements, AR remains challenging in uncontrolled smart environments due to the complex and chaotic nature of activity data. The authors discuss common machine learning and data mining techniques used for AR, along with the limitations of existing systems. They highlight recent advancements and propose future research directions to address the ongoing challenges in AR.

Wan, S., Qi, L., Xu, X., Tong, C., & Gu, Z. (2020) explore how mobile edge computing (MEC) supports healthcare monitoring through human activity recognition (HAR) using smartphone sensors. Their study focuses on a smartphone-based architecture that leverages the device's accelerometers to collect, preprocess, and classify activity data. They propose a convolutional neural network (CNN) model for real-time feature extraction and classification, comparing its performance with models like LSTM, BLSTM, MLP, and SVM on the UCI and Pamap2 datasets. Results show that their CNN-based approach achieves superior accuracy, highlighting its effectiveness for real-time HAR in healthcare applications.

Xu, C., Chai, D., He, J., Zhang, X., & Duan, S. (2019) address the limitations of traditional feature engineering in human activity recognition (HAR) using sensor data, particularly for high-volume, complex waveform data. They introduce InnoHAR, a deep learning model that integrates inception and recurrent neural network modules. InnoHAR processes multi-channel sensor data end-to-end, using inception-like convolution layers for feature extraction and GRU for time-series modeling. Tested on three widely used public HAR datasets, InnoHAR consistently outperforms existing models, demonstrating strong generalization and effectiveness for complex HAR tasks.

Zhou, X., Liang, W., Kevin, I., Wang, K., Wang, H., Yang, L. T., & Jin, Q. (2020) focus on improving human activity recognition (HAR) in the Internet of Healthcare Things (IoHT) environment through the use of deep learning techniques. They propose a semi-supervised deep learning framework designed to handle weakly labeled sensor data effectively, addressing the challenge of inadequate labeled samples. A key innovation is the development of an intelligent autolabeling scheme based on a deep Q-network (DQN), which incorporates a distance-based reward rule to improve learning efficiency in IoT settings. To further enhance recognition accuracy, the authors introduce a multisensor data fusion mechanism that combines on-body sensor data, context sensor data, and personal profile information. Additionally, they propose an LSTM-based classification method to extract high-level features from sequential motion data for fine-grained activity pattern recognition. The experimental results validate the effectiveness of the proposed method, demonstrating its potential in real-world IoHT applications for HAR.

Khan, I. U., Afzal, S., & Lee, J. W. (2022) address the challenges in Human Activity Recognition (HAR), particularly in the context of real-world long-term activity recognition, where traditional models often fail to extract both spatial and temporal features effectively. To overcome these limitations, they propose a hybrid model that combines Convolutional Neural Networks (CNN) for spatial feature extraction and Long Short-Term Memory (LSTM) networks for learning temporal dependencies. In addition to the model, the authors introduce a new, challenging dataset collected from 20 participants using the Kinect V2 sensor, which includes 12 distinct physical activity classes. An extensive ablation study is conducted to compare the performance of traditional machine learning models with deep learning techniques. The CNN-LSTM model achieves an impressive accuracy of 90.89%, demonstrating its effectiveness and suitability for HAR applications, especially in complex real-world environments.

IV. METHODOLOGY

The methodology for the Human Activity Recognition (HAR) project using Artificial Neural Networks (ANNs) involves several key steps, from data collection and preprocessing to model development, training, and evaluation. Below is a detailed explanation of each step:

1. Data Collection

The dataset is collected from smartphone sensors, which include accelerometers and gyroscopes. These sensors capture the movement and orientation of the human body, providing time-series data that is essential for activity recognition. The data is then loaded into the environment for analysis.

2. Exploratory Data Analysis (EDA)

Exploratory Data Analysis is performed to understand the distribution of activities and the structure of the dataset. This involves examining the unique activities present in the dataset, their frequency, and visualizing the data to identify any patterns or anomalies. EDA helps in gaining insights into the data and preparing it for further processing.

3. Data Preprocessing

Preprocessing the data involves several steps:

- **Separating Features and Labels**: The dataset is divided into features (sensor data) and labels (activity types).

- **Encoding Labels**: The activity labels are encoded into numerical values to make them suitable for model training.

- **Scaling Features**: The features are scaled to a standard range to ensure that the model can learn effectively from the data. This step is crucial for improving the performance and convergence of the neural network.

4. Model Development

The Artificial Neural Network (ANN) model is developed using a sequential architecture. The model consists of multiple layers, including dense layers and dropout layers. The dense layers are responsible for learning the patterns in the data, while the dropout layers help in preventing overfitting by randomly dropping some neurons during training.

5. Model Training

The model is trained on the preprocessed training data. During training, the model learns to recognize different activities by adjusting its weights based on the input data and the corresponding labels. The training process involves multiple epochs, where the model iteratively improves its performance by minimizing the loss function.

6. Hyperparameter Tuning

Hyperparameter tuning is performed to find the best configuration for the model. This involves experimenting with different values for parameters such as the number of layers, the number of neurons in each layer, the activation functions, and the learning rate. Random Search is used to explore the hyperparameter space and identify the optimal settings that yield the best validation accuracy.

7. Early Stopping and Model Evaluation

Early stopping is implemented to prevent overfitting by monitoring the model's performance on the validation data. If the model's accuracy does not improve for a specified number of epochs, the training is stopped early. The model is then evaluated on the test data to assess its accuracy and generalization capability.

8. Visualization

The training and validation accuracy and loss are visualized to understand the model's performance over time. This involves plotting the accuracy and loss curves for both the training and validation sets, which helps in identifying any issues such as overfitting or underfitting and making necessary adjustments to the model.

V. RESULTS AND FINDINGS

The Human Activity Recognition (HAR) project using Artificial Neural Networks (ANNs) demonstrated significant improvements in accuracy and performance through various stages of model training, hyperparameter tuning, and early stopping. Below are the detailed results and findings:

Initial Model Training

During the initial training phase, the model was trained for 10 epochs. The results showed a steady improvement in both training and validation accuracy, as well as a reduction in loss.

- **Epoch 10**: The model achieved a training accuracy of 92.90% and a validation accuracy of 91.99%. The training loss was 0.2070, and the validation loss was 0.2184.

These results indicate that the model was effectively learning the patterns in the data and generalizing well to the validation set.

Hyperparameter Tuning

Hyperparameter tuning was performed using Random Search, which involved training the model for 51 epochs. The tuning process aimed to find the optimal configuration for the model to enhance its performance.

- **Epoch 51**: The model achieved a training accuracy of 83.29% and a validation accuracy of 95.05%. The training loss was 0.5496, and the validation loss was 1.1157.

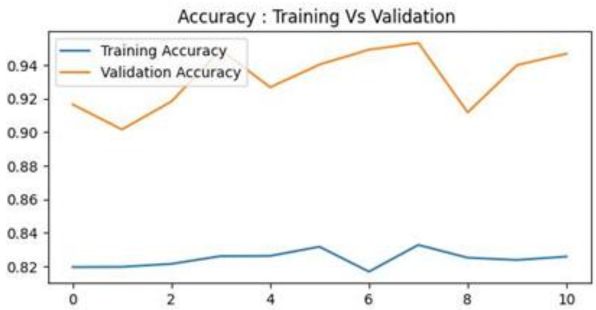
The hyperparameter tuning process significantly improved the model's performance, particularly in terms of validation accuracy.

Early Stopping

Early stopping was implemented to prevent overfitting by monitoring the model's performance on the validation data. The training was stopped when the model's accuracy did not improve for a specified number of epochs.

- **Epoch 10**: The model achieved a training accuracy of 83.87% and a validation accuracy of 94.67%. The training loss was 0.4689, and the validation loss was 1.0841.

The early stopping mechanism ensured that the model did not overfit the training data and maintained high accuracy on the validation set.



VI. CONCLUSION

The Human Activity Recognition (HAR) project using Artificial Neural Networks (ANNs) successfully demonstrated the potential of deep learning in accurately classifying human activities based on smartphone sensor data. Through systematic data collection, preprocessing, model development, training, hyperparameter tuning, and early stopping, the model achieved high accuracy and robust performance. The results showed significant improvements in both training and validation accuracy, highlighting the model's ability to generalize well to unseen data. This project underscores the effectiveness of ANNs in handling complex sensor data and their suitability for real-time activity recognition, paving the way for practical applications in healthcare, fitness tracking, and smart home environments.

VII. REFERENCES

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