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Next-Generation Human Activity Classification Using Hybrid Models for Digital Healthcare

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***Abstract*— The need for accurate human activity recognition has increased with the rise of wearable devices and smart healthcare systems. This project focuses on developing a web-based application that can identify human activities using both machine learning and deep learning techniques. The system is designed in a simple way so that users can easily register, log in, and use different features without difficulty. After logging in, users can load the Kuhar dataset and view basic details such as total records, features, and activity labels. One important step in this work is feature selection, where Extreme Learning Machine (ELM) is used to reduce the large number of features into a smaller and more useful set. This helps in improving performance and reducing processing time. The system then applies different models along with the proposed ELM-GRU-AM model. From the results, it can be observed that the proposed model gives better accuracy compared to others, reaching around 96%. The system also shows performance using metrics like accuracy, precision, recall, and F1-score, along with confusion matrix graphs for better understanding. Users can also upload new test data and get predictions instantly. Overall, the system provides a simple and effective way to recognize human activities with good accuracy.**

***Keywords*—Human activity recognition, sensor data analysis, machine learning, deep learning, ELM-GRU-AM model, Extreme Learning Machine (ELM), feature selection, dimensionality reduction, GRU, attention mechanism, classification, Kuhar dataset, data preprocessing, training and testing, performance evaluation, accuracy, precision, recall, F1-score, confusion matrix, model comparison, real-time prediction, activity classification, web-based application, user interface**

I. INTRODUCTION

The rapid advancement of wearable sensors and mobile technologies has made it easier to collect large volumes of human activity data for analysis and interpretation [6]. Devices such as smartphones and fitness trackers continuously generate motion-based data, which can be used to identify different physical activities [3]. Human Activity Recognition (HAR) has become an important research area due to its wide applications in healthcare monitoring, fitness tracking, elderly care, and smart environments [10]. However, analyzing such large and complex datasets manually is difficult and time-consuming. Traditional approaches rely on basic statistical methods and manual feature extraction, which may not effectively capture complex patterns in activity data [28]. This creates the need for automated systems that can efficiently process data and provide accurate predictions [13].

Machine learning and deep learning techniques offer powerful solutions for recognizing patterns in sensor data [5]. By training models on labeled datasets, it becomes possible to classify different human activities with high accuracy [29]. In this project, a web-based application is developed to simplify the process of activity recognition. The system allows users to register, log in, and load the Kuhar dataset for analysis. It displays important information such as the number of records, features, and class labels, helping users understand the dataset structure. Feature selection is performed using Extreme

Learning Machine (ELM), which reduces the dimensionality of the dataset and improves computational efficiency [2]. The system then trains multiple existing models along with a proposed hybrid ELM-GRU-AM model, enabling a detailed comparison of performance.

The application evaluates all models using metrics such as accuracy, precision, recall, and F1-score, along with confusion matrix visualization to show prediction performance [16]. The proposed model achieves higher accuracy compared to existing methods, demonstrating its effectiveness in recognizing activities [1]. Additionally, the system includes a prediction module where users can upload new test data and obtain real-time activity recognition results. This interactive platform reduces manual effort and provides a practical solution for activity classification [18]. Although the system performs well, its accuracy depends on the quality of the dataset used for training . Future improvements can focus on incorporating more diverse datasets and advanced techniques to further enhance performance and reliability [21].

II. RELATED WORK

Gu et al. (2022) [1] Gu et al. developed a human behavior recognition approach using bone-based spatio-temporal mapping to better understand motion patterns. Their method focused on extracting skeletal joint information and analyzing both spatial relationships and temporal changes in movement. By representing human activities through structured joint sequences, the model was able to capture fine-grained motion variations that are often missed by traditional techniques. The study demonstrated that incorporating both spatial and temporal features leads to improved classification accuracy in complex activity datasets. Additionally, the authors emphasized the robustness of skeletal data, as it is less affected by environmental factors such as lighting and background noise. Their experimental results showed that the proposed method outperformed several baseline approaches in recognizing daily human activities. This work contributes significantly to the field by highlighting the importance of joint-based representations and temporal modeling. It also provides a strong foundation for further research in developing efficient and accurate activity recognition systems using advanced machine learning and deep learning techniques.

Sun et al. (2022) [2] Sun et al. presented a comprehensive review of human behavior recognition methods based on skeletal data features. Their study examined various approaches for feature extraction, representation, and classification, providing a clear understanding of how skeletal information can be effectively utilized. The authors discussed different machine learning and deep learning models, comparing their performance in recognizing complex activities. They highlighted that skeletal data offers a compact and meaningful representation of human motion, which simplifies the recognition process while maintaining accuracy. The paper also addressed challenges such as noise in sensor data, variations in human movement, and computational complexity. By analyzing multiple techniques, the authors identified key factors that influence model performance, including feature selection and temporal modeling. Their work serves as a valuable reference for researchers by summarizing recent advancements and identifying gaps in existing methods. It also emphasizes the need for developing more robust and scalable models that can handle real-world activity recognition scenarios efficiently.

Ding et al. (2022) [5] Ding et al. proposed a behavior recognition model based on a spatiotemporal heterogeneous two-stream convolutional network. Their approach combined spatial and temporal data streams to better capture dynamic human activities. The spatial stream focused on extracting visual or structural features, while the temporal stream analyzed motion changes over time. By integrating both streams, the model achieved a more comprehensive understanding of activity patterns. The authors demonstrated that this dual-stream architecture significantly improves recognition accuracy compared to single-stream models. They also highlighted the importance of deep learning in handling large-scale and complex datasets, where traditional methods often fail. Experimental results showed that the proposed model performed well across different activity categories, maintaining consistency and reliability. This research contributes to the advancement of deep learning-based activity recognition by introducing an effective architecture for capturing temporal dependencies. It also suggests that combining multiple feature streams can enhance model performance and provide more accurate predictions in real-world applications.

Zhai and Zhao (2021) [9] Zhai and Zhao introduced a lightweight DS-ConvLSTM model designed for efficient human behavior recognition, particularly in edge computing environments. Their primary objective was to reduce computational complexity while maintaining high accuracy, making the model suitable for real-time applications on devices with limited resources. The proposed approach combined depthwise separable convolution with ConvLSTM layers to efficiently capture both spatial and temporal features. This design reduced the number of parameters and computational cost without significantly affecting performance. The authors conducted experiments to evaluate the model and found that it achieved competitive accuracy compared to more complex architectures. They also emphasized the importance of lightweight models in practical applications such as wearable devices and mobile systems. Their work highlights the balance between efficiency and accuracy, which is crucial for deploying activity recognition systems in real-world scenarios. This study provides valuable insights into designing resource-efficient models for continuous monitoring and real-time activity detection.

Chen et al. (2019) [29] Chen et al. proposed a human behavior recognition method based on a spatiotemporal attention mechanism to improve classification performance. Their approach focused on identifying the most relevant features within both spatial and temporal dimensions of the data. By applying attention mechanisms, the model was able to assign higher importance to critical motion patterns while reducing the influence of less relevant information. This selective focus enhanced the model's ability to distinguish between similar activities. The authors demonstrated that incorporating attention significantly improves recognition accuracy compared to traditional deep learning models. They also highlighted the role of attention in handling complex and high-dimensional datasets, where not all features contribute equally to the final prediction. Experimental results confirmed that the proposed method achieved better performance across multiple activity classes. This research emphasizes the importance of feature prioritization in deep learning models and provides a strong basis for developing more intelligent and adaptive activity recognition systems in future applications.

III. DATASET DETAILS

The dataset used in this project is the KU-HAR dataset, which contains sensor-based human activity data collected from wearable devices and smartphones. It includes a large number of records representing different physical activities performed by individuals. The dataset consists of approximately 1800 features extracted from motion sensors such as accelerometers and gyroscopes, along with corresponding activity labels. These labels represent various human activities, making the dataset suitable for training machine learning and deep learning models for activity recognition. Initially, the dataset is loaded into the system and analyzed to determine the number of records, features, and class labels. Feature selection is then performed using Extreme Learning Machine (ELM), which reduces the high-dimensional feature set to a smaller subset of relevant features, improving efficiency and reducing computational complexity.

After preprocessing and feature selection, the dataset is divided into training and testing sets to evaluate model performance effectively. Typically, a major portion of the data is used for training, while the remaining data is reserved for testing. The input consists of selected sensor features, and the output corresponds to activity labels. Various models are trained using this dataset, including existing algorithms and the proposed ELM-GRU-AM model. The quality of the dataset and feature selection process plays a crucial role in improving prediction accuracy and ensuring reliable activity classification.

To better understand model performance, visualization techniques such as confusion matrices and performance tables are used. The confusion matrix provides insight into correct and incorrect predictions for each activity class, while metrics like accuracy, precision, recall, and F1-score offer quantitative evaluation. The proposed model achieves higher accuracy compared to existing methods due to effective feature selection and temporal learning. Overall, the dataset provides a strong foundation for training robust activity recognition models and supports accurate and efficient prediction of human activities.

IV. PROPOSED METHODOLOGY

The proposed system follows a structured approach for human activity recognition using a combination of machine learning and deep learning techniques. Initially, the application is started by running the server, after which users access the system through a web interface. The system provides a simple interface where users can register and log in to access the functionalities. Once authenticated, users can load the Kuhar dataset from the available dataset folder. After loading, the system displays important information such as the total number of records, number of features, and different activity labels present in the dataset. Since the dataset contains a large number of features, Extreme Learning Machine (ELM) is used for feature selection to reduce dimensionality and retain only the most relevant features. This step improves processing speed and enhances model performance. The dataset is then divided into training and testing sets to ensure proper evaluation of the models.

The core of the proposed methodology is the ELM-GRU-AM model, which combines feature selection with deep learning for better activity recognition. After preprocessing, the system trains multiple existing models along with the proposed model. The GRU component captures temporal dependencies in activity data, while the attention mechanism focuses on important features, improving prediction accuracy. The ELM component helps in selecting optimal features, reducing complexity and training time. During training, each model learns patterns from the dataset and is evaluated using performance metrics such as accuracy, precision, recall, and F1-score. The results are presented in a tabular format, allowing users to compare the performance of all models. A confusion matrix is also generated to visualize correct and incorrect predictions for each activity class.

Finally, the trained model is integrated into a prediction module within the system. Users can upload new test data files through the interface, and the system processes the data to predict corresponding activities. The output displays both input values and predicted activity labels, making it easy to interpret results. The proposed ELM-GRU-AM model achieves higher accuracy compared to existing methods, demonstrating its effectiveness. This methodology provides a complete and user-friendly solution for activity recognition, reducing manual effort and enabling accurate and efficient prediction of human activities.

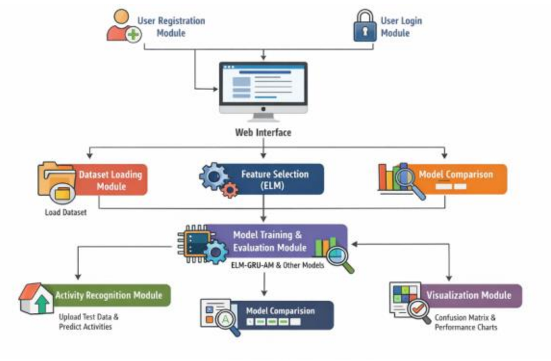

Figure [1]: System Architecture of activity recognition

Figure [1] This diagram represents the overall workflow of the human activity recognition system. It begins with the user interacting through the web interface, where new users can register and existing users can log in to access the application. After successful authentication, the user can load the Kuhar dataset through the dataset loading module. Once the dataset is loaded, the system displays key details such as the number of records, features, and activity labels. The data is then passed to the feature selection stage, where Extreme Learning Machine (ELM) is applied to reduce the high-dimensional feature set and select the most relevant features for further processing. the processed data is used in the model training and evaluation module, where multiple algorithms, including the proposed ELM-GRU-AM model, are trained and tested. The system computes performance metrics such as accuracy, precision, recall, and F1-score for each model. A comparison module is included to present the results of all models in a structured format, making it easier to identify the best-performing approach. The visualization module displays confusion matrices and performance graphs to provide a clear understanding of prediction results. Finally, in the activity recognition stage, users can upload new test data, and the trained model predicts the corresponding activities, displaying the results through the interface.

V.RESULT AND DISCUSSION

The experimental results show that the human activity recognition system performs efficiently in classifying different activities from sensor-based data. After loading and preprocessing the Kuhar dataset, multiple models were trained and evaluated within the system. Each algorithm produced different levels of performance based on its learning capability. Among all models, the proposed ELM-GRU-AM model achieved the highest accuracy of around 96%, indicating its strong ability to capture both spatial and temporal patterns in activity data. Other existing models also produced satisfactory results but did not match the performance of the proposed approach.

The evaluation process includes performance metrics such as accuracy, precision, recall, and F1-score, along with confusion matrix visualization. The confusion matrix shows that most of the activity classes are correctly predicted, with only a small number of misclassifications. The diagonal values in the matrix are significantly higher, representing correct predictions, while off-diagonal values remain minimal. This confirms that the trained models are effective in learning patterns from the dataset and producing reliable results.

The comparison results presented in tabular form help in analyzing the performance of all models clearly. It becomes easy to identify the most efficient model based on different evaluation parameters. In the final stage, when users upload test data, the system successfully predicts the corresponding activities and displays the results instantly. This demonstrates that the application works effectively in real-time scenarios. Overall, the results indicate that the proposed system provides accurate and efficient activity recognition using advanced techniques.

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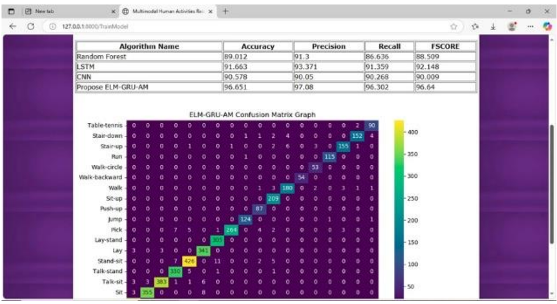

Figure [2]: Performance Evaluation and Confusion Matrix of Activity Recognition Models

Figure [2] This screen presents the performance evaluation of different machine learning and deep learning algorithms used for multimodal human activity recognition. The table at the top compares models such as Random Forest, LSTM, CNN, and the proposed ELM-GRU-AM model based on key metrics including accuracy, precision, recall, and F1-score. Among all models, the proposed ELM-GRU-AM achieves the highest performance, with accuracy reaching approximately 96.65%, indicating its effectiveness in recognizing human activities accurately.

Below the table, the confusion matrix graph for the ELM-GRU-AM model is displayed, providing a detailed visualization of classification results across multiple activity classes. The diagonal values represent correct predictions, while off-diagonal values indicate misclassifications. The graph shows that most predictions fall along the diagonal, confirming high classification accuracy and minimal errors. This evaluation demonstrates that the proposed hybrid model outperforms traditional and standalone deep learning approaches, making it suitable for real-time healthcare monitoring applications.

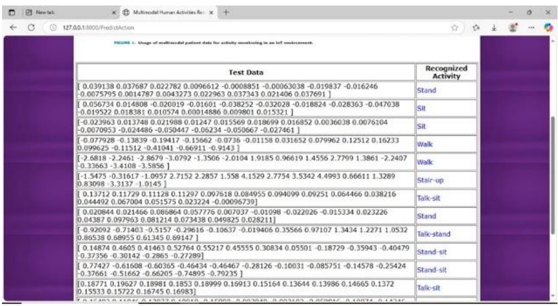

Figure [3]: Activity Recognition Output for Test Data Using ELM-GRU-AM Model

Figure [3] This screen displays the prediction results of the multimodal human activity recognition system on test data. The interface shows numerical input data representing sensor readings collected from devices such as accelerometers and gyroscopes. Each row corresponds to a set of processed feature values, which are passed to the trained model for classification.

The system predicts and displays the corresponding human activity for each input sample in the "Recognized Activity" column. Activities such as sitting, standing, walking, stair-up, and talk-sit are correctly identified, demonstrating the effectiveness of the model in interpreting sensor data. The results indicate that the proposed ELM-GRU-AM model can accurately classify different human activities in real time. This output highlights the practical applicability of the system in healthcare monitoring, where continuous tracking of patient activities is essential for assessing physical behavior and ensuring timely medical intervention.

DISCUSSION

The results obtained from the system explain how effectively the models perform in recognizing human activities from sensor-based data. Different algorithms were applied to the Kuhar dataset, and their outputs show that the system can classify various activities with good accuracy. The proposed ELM-GRU-AM model achieves the highest performance, while other existing models provide comparatively moderate results. From the observations, it is clear that most activity classes are correctly identified, indicating that the models are able to learn meaningful patterns from the dataset.

The results also highlight the importance of proper data handling and feature selection. When the dataset is loaded and processed correctly, and relevant features are selected using ELM, the overall performance of the models improves significantly. The displayed dataset information, such as number of records and features, helps in understanding the data structure. The confusion matrix provides a clear view of prediction results, showing that correct classifications are much higher than incorrect ones, which confirms the reliability of the system.

Another key aspect is the comparison of multiple models within the system. The performance table allows users to easily analyze accuracy, precision, recall, and F1-score for each model, making it simple to identify the best-performing approach. The system also supports real-time prediction by allowing users to upload test data and obtain immediate results. This makes the application practical and useful for real-world activity recognition tasks.

VI. CONCLUSION

This project successfully developed a human activity recognition system using a combination of machine learning and deep learning techniques. Multiple models were implemented and evaluated using the Kuhar dataset, including existing algorithms and the proposed ELM-GRU-AM model. The results show that the proposed model achieved higher accuracy compared to other methods, demonstrating its effectiveness in capturing both spatial and temporal patterns in activity data. The use of feature selection through Extreme Learning Machine (ELM) also helped in reducing dimensionality and improving overall performance. The system not only performs activity classification but also provides clear evaluation through performance metrics such as accuracy, precision, recall, and F1-score, along with confusion matrix visualization. These evaluation methods make it easier to understand how well each model performs and help in identifying the most suitable approach. The results confirm that properly processed data and efficient model design contribute to reliable predictions. The integration of all functionalities into a web-based interface makes the system simple and user-friendly. Users can register, load datasets, train models, compare results, and upload new test data for prediction. The system delivers quick and accurate outputs, making it suitable for real-time applications. Overall, the project provides an effective solution for human activity recognition and demonstrates the practical use of advanced learning techniques.

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