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Deep Learning-Based Human Activity Recognition From Wearable Devices

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Abstract:

The rise of sedentary lifestyles and the prevalence of lifestyle-related health issues highlight the need for personalized wellness solutions to encourage physical activity and maintain health. Human fitness activities, ranging from basic exercises like jumping jacks and squats to advanced routines such as pull-ups, are key to promoting physical fitness and individualized wellness. Historically, fitness routines were guided by general recommendations or manual tracking methods, which lacked precision and personalization. Traditional systems, such as fitness logs, generic plans, and fitness assessments, offered limited insights, were labor-intensive, error-prone, and lacked adaptability. This research leverages artificial intelligence (AI) and machine learning (ML) to overcome the limitations of traditional systems. Advances in wearable technology, sensor data, and large-scale datasets enable intelligent systems for multi-class classification of human fitness activities, providing personalized feedback, performance evaluation, and adaptive fitness plans tailored to individual needs. Our current system uses K-Nearest Neighbors (KNN) and LightGBM (LGBM) to classify fitness activities; however, these models face limitations in handling complex patterns and large-scale data. To address this, we propose a shift to Deep Neural Networks (DNNs), which better capture intricate patterns in high-dimensional data, offering higher accuracy, scalability, and adaptability for personalized wellness. By integrating DNNs, the system will enhance activity recognition, providing more accurate insights and highly personalized recommendations, offering a robust, scalable solution for improving fitness routines and fostering healthier lifestyles, and redefining fitness monitoring to enable long-term wellness.

Keywords: Human activity recognition, Fitness monitoring, Artificial intelligence, Machine learning, Deep Neural Networks, Wearable devices, Sensor data, Fitness Activities.

1.INTRODUCTION

Advancements in sensor technology have led to the availability of large datasets for human activity analysis, creating opportunities to enhance fitness monitoring. Insufficient traditional methods, such as handwritten logs, trainer evaluations, and generalized fitness plans, suffer from inaccuracy, time-consumption, and lack of scalability, seriously affecting the quality of activity tracking from many aspects, such as precision and adaptability. Transforming these outdated approaches into a high-quality, automated system is critical to improve the performance of high-level tasks, such as activity classification, personalized feedback, and fostering healthier lifestyles. The motivation for this research is to bridge this gap using deep learning techniques, which can significantly enhance fitness activity recognition accuracy and real-time feedback capabilities. Over the past few decades, traditional machine learning methods like KNN and LightGBM have been employed in some existing solutions, making progress in activity recognition but struggling with complex activity patterns and large-scale data. Recently, deep learning models, particularly Deep Neural Networks (DNNs), have shown promise in recognizing intricate patterns in sensor data, offering superior accuracy and adaptability. It is noteworthy that while traditional systems relied heavily on manual input and spatial data processing, integrating advanced deep learning with wearable sensor data (e.g., accelerometers and gyroscopes) represents an important evolution in the fitness monitoring field.

In many real-world scenarios, fitness monitoring systems encounter challenges due to poor scalability, lack of real-time feedback, and inability to adapt to individual needs. These systems are often characterized by low accuracy, generalized outputs, and limited data-driven insights. Therefore, it is essential to build a system or model to improve the quality of fitness activity recognition and monitoring under diverse and dynamic conditions.

2. LITERATURE SURVEY

L. Breiman [1] in his seminal work on "Random Forests" presents a highly efficient ensemble method for classification and regression problems, emphasizing its ability to handle high-dimensional datasets effectively. This approach leverages multiple decision trees to mitigate overfitting, enhance accuracy, and ensure robustness, addressing the limitations of single-model systems that struggle with complex data patterns. The study underlines the versatility of Random Forests in diverse applications, setting a foundation for advanced machine learning algorithms, though it lacks exploration of real-time adaptability in dynamic environments.

C. E. Rasmussen et al. [2] discuss the DELVE framework for validating learning experiments, offering a robust mechanism to evaluate the performance of machine learning models under varied conditions. Their work tackles the challenge of inconsistent evaluation by emphasizing reproducibility and empirical rigor in diverse data-driven studies. While effective for systematic analysis, the framework's applicability to real-time sensor-based systems remains underexplored in their study.

J. Alcalá-Fdez et al. [3] introduce the KEEL data-mining software, which integrates datasets, algorithms, and experimental frameworks for machine learning research. This tool simplifies the comparative analysis of algorithms, encouraging innovation in data preprocessing and classification tasks while fostering reproducibility. However, its focus on static datasets limits its utility for real-time fitness monitoring applications requiring continuous data streams.

G. W. Flake and S. Lawrence [4] propose an efficient Support Vector Machine (SVM) regression training methodology using Sequential

Minimal Optimization (SMO). Their work highlights the computational advantages of SMO, making SVMs more accessible for large-scale applications with reduced training times, overcoming the computational burden of traditional SVM approaches. Yet, its effectiveness in handling noisy sensor data from wearable devices warrants further investigation.

S. García and F. Herrera [5] extend statistical comparison methodologies for classifiers, providing a framework for analyzing performance metrics across datasets. Their approach enhances the reliability of comparative studies, ensuring robust conclusions about algorithm efficiency and accuracy, unlike earlier methods prone to dataset-specific biases. Its reliance on pre-collected data, however, limits its direct application to real-time activity recognition.

M. Friedman [6] presents a ranking-based statistical approach to address the normality assumptions inherent in traditional ANOVA. His method remains foundational in evaluating multiple algorithms' performance without stringent statistical constraints, offering a flexible alternative to parametric tests. While influential, its static nature does not fully cater to the dynamic requirements of wearable sensor-based systems.

M. N. Kamel Boulos and S. P. Yang [7] review mobile applications for planning and tracking physical activities, emphasizing the need for integrated, user-friendly solutions to overcome the inaccuracies of manual tracking methods. Their findings advocate for advancements in personalized activity tracking systems, addressing future challenges in mHealth technologies, though they lack discussion on deep learning integration for enhanced accuracy.

B. Barshan and A. Yurtman [8] propose a classification methodology for daily and sports activities using wearable sensors. Their work demonstrates robust activity recognition, invariant to sensor positioning, tackling the variability issues in traditional sensor-based systems. Extensive experiments highlight the potential of motion-sensing technologies in real-world applications, though scalability to large datasets remains a challenge.

A. Yurtman et al. [9] extend activity recognition using quaternion-based transformations to mitigate wearable sensor orientation issues. Their study enhances the reliability of sensor-based systems by addressing orientation inconsistencies, paving the way for improved accuracy in human activity tracking. However, its computational complexity may hinder real-time implementation on resource-constrained devices.

V. Camomilla et al. [10] provide a systematic review of wearable inertial sensors in sports performance evaluation. Their research identifies trends and challenges in real-time performance monitoring, advocating for advanced sensor technologies to bridge the gap between laboratory and field-based applications. While comprehensive, it does not explore deep learning's role in enhancing classification accuracy.

I. Weygers et al. [11] present a methodological review of inertial sensor-based kinematics for lower limb joint monitoring. Their findings emphasize the potential of sensor-based methodologies in biomechanical analysis, overcoming limitations of traditional motion capture systems, and supporting advancements in rehabilitation and sports science. Integration with advanced algorithms like DNNs, however, is not addressed.

N. Jaouedi et al. [12] propose a hybrid deep learning model for human action recognition, combining convolutional and recurrent architectures. Their study underscores the advantages of deep learning in capturing temporal dependencies, enhancing the accuracy and generalizability of action recognition systems over traditional machine learning methods. Extensive experiments demonstrate superior performance, though real-time deployment on wearable devices requires further optimization.

3. PROPOSED METHODOLOGY

The proposed system aims to enhance the accuracy and efficiency of human fitness activity classification by leveraging machine learning algorithms, addressing the limitations of traditional fitness tracking methods that lack precision and scalability. The primary goal of this model is to improve the recognition of fitness activities such as jumping jacks, push-ups, and squats, making classification more accurate and adaptable to real-world scenarios. It employs a deep learning-based approach, utilizing techniques from machine learning, sensor data processing, and deep neural networks (DNNs) to achieve its objectives. By comparing traditional algorithms like K-Nearest Neighbors (KNN) and Light Gradient Boosting Machine (LightGBM) with advanced DNNs, the system seeks to overcome challenges posed by noisy sensor data and complex activity patterns. Overall, this research is designed to enhance fitness activity classification by applying deep learning techniques to improve accuracy, provide real-time adaptability, and deliver precise results, finding applications in domains where reliable activity recognition is critical for actionable insights.

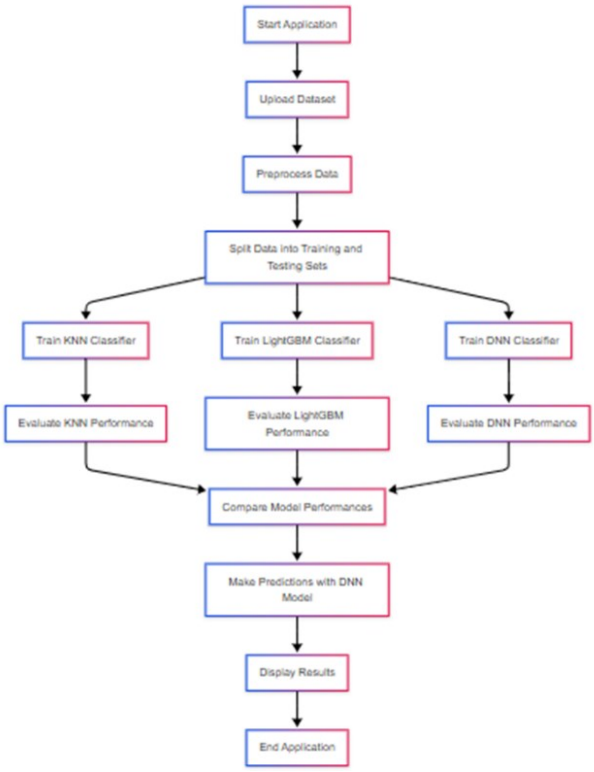

Figure 1: Block Diagram.

The proposed methodology typically includes the following key components:

- Dataset Acquisition and Feature Extraction: The system begins with a labeled dataset collected from wearable devices, containing sensor readings such as accelerometer and gyroscope values tied to specific fitness activities. This raw data serves as the foundation for training and testing machine learning models, with relevant features extracted to represent activity patterns.

- Data Preprocessing: The raw dataset is cleaned by handling null values (via removal or imputation), normalizing sensor data for consistency, and encoding categorical activity labels into numerical format using a label encoder. This step

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ensures the data is machine-readable and free from noise or inconsistencies.

- Activity Classification: The system implements classification using both traditional algorithms (KNN and LightGBM) and the proposed DNN model. KNN relies on proximity-based classification, LightGBM uses gradient boosting for efficient decision-making, and DNN leverages multiple layers to automatically extract and classify complex patterns, enhancing accuracy and adaptability.

- Metric Evaluation: To assess classification performance, the system calculates metrics such as accuracy, precision, recall, F1-score, and generates a confusion matrix. These metrics measure the model's ability to correctly classify activities and highlight areas of improvement compared to baseline methods.

- Customization and Parameters: The DNN model offers adjustable parameters, such as the number of layers, neurons per layer, learning rate, and activation functions (e.g., ReLU), allowing customization of the classification process. Users can fine-tune these settings to balance accuracy and computational efficiency based on specific needs.

- Output: The primary output is a predicted activity label for unseen sensor data, generated by the DNN model. This output exhibits improved accuracy, reduced misclassification, and enhanced generalization compared to traditional methods.

- Evaluation and Benchmarking: The system's performance is evaluated against benchmark datasets of fitness activities, aiming to outperform or match state-of-the-art classification methods like KNN and LightGBM in terms of accuracy and robustness, as validated through comprehensive testing.

Applications:

The enhanced activity classification system can be applied in key fields, including:

- Wearable Fitness Devices: Improving real-time activity tracking in smartwatches and fitness bands.

- Healthcare and Rehabilitation: Monitoring patient movements during recovery.

- Sports Performance Analysis: Analyzing athlete activities to optimize training.

Advantages:

The proposed system leverages deep learning and sensor data processing to classify fitness activities with several key advantages:

- Improved Accuracy: The DNN model significantly enhances classification accuracy by capturing complex patterns in sensor data, outperforming traditional methods like KNN and LightGBM.

- Reduced Misclassification: Advanced feature extraction and noise handling minimize errors, ensuring reliable activity recognition.

- Enhanced Adaptability: The system adapts to diverse activity types and individual performance variations, crucial for real-world applications.

- Customization: Adjustable parameters (e.g., layer depth, learning rate) allow users to tailor the model to specific datasets or computational constraints.

- Automatic Processing: While customization is available, the system can operate with default settings, making it accessible to users without deep technical expertise.

- Realism: DNN-based classification maintains the natural relationships within sensor data, avoiding overfitting or unrealistic predictions.

- Quality Metrics: The inclusion of performance metrics like accuracy, precision, and F1-score provides an objective measure of improvement over baseline algorithms.

- Versatility: Applicable across domains such as fitness tracking, healthcare, and sports science, addressing the challenge of accurate activity recognition in dynamic environments.

4. EXPERIMENTAL ANALYSIS

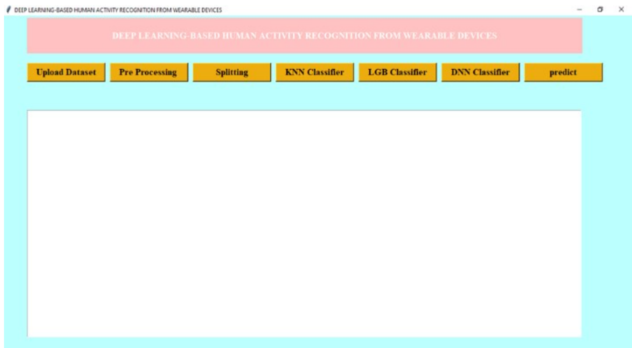

Figure 2: Dashboard Interface

Figure 2 showcases the graphical user interface (GUI) designed for predicting human fitness activities. This interface serves as the input platform for the proposed Deep Neural Network (DNN)-based classification system, allowing users to upload datasets, preprocess data, split datasets, train models (KNN, LightGBM, DNN), and generate predictions. The purpose of this figure is to provide a visual representation of the system's operational framework, highlighting its accessibility and functionality for processing wearable sensor data.

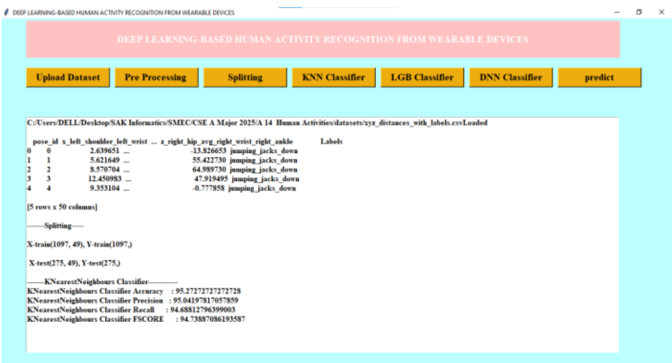

Figure3: Loaded Dataset Sample

Figure 3 presents a sample of the loaded dataset, comprising labeled human activity recognition (HAR) data sourced from wearable

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devices, stored in CSV format as "xyz_distances_with_labels.csv". Displayed as a Pandas DataFrame, it includes 5 rows and 50 columns, with features like "pose_id" and sensor readings (e.g., accelerometer, gyroscope). This figure illustrates the raw input data that the system processes to classify activities such as squats, push-ups, and sit-ups, emphasizing the high-dimensional nature of the dataset.

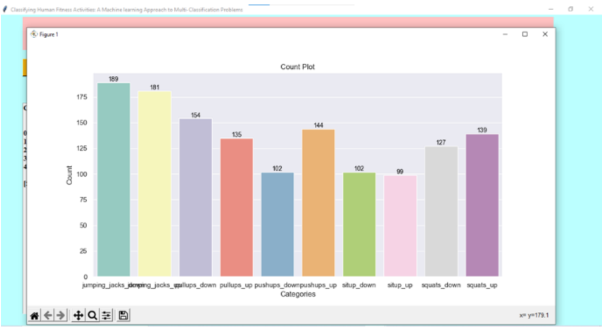

Figure 4: Preprocessed Dataset Distribution

Figure 4 displays a count plot of the preprocessed dataset, visualizing the distribution of activity classes post-preprocessing (e.g., null value handling, label encoding, feature scaling). This output highlights class imbalance issues addressed during preprocessing, offering a clear representation of activity frequencies. The purpose of this figure is to demonstrate the preprocessing effectiveness, ensuring high-quality input for subsequent model training.

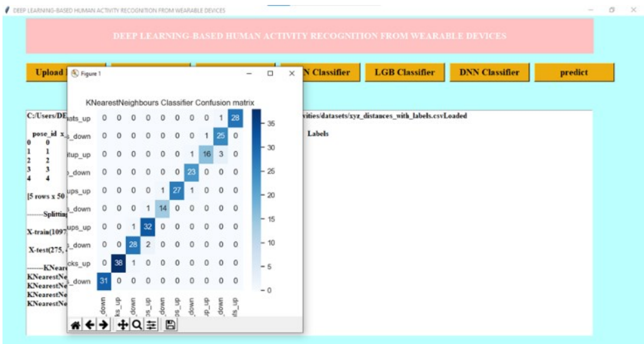

Figure 5: KNN Classifier Output - Confusion Matrix

Figure 5 illustrates the confusion matrix for the K-Nearest Neighbors (KNN) classifier applied to the test dataset. This output visualizes the model's performance in classifying fitness activities, with correct predictions along the diagonal and misclassifications elsewhere. Accompanied by performance metrics:

Accuracy: 95.27%

Precision: 95.04%

Recall: 94.69%

F1-Score:94.74%

These metrics quantify the KNN classifier's quality, with higher values indicating better performance. The figure's purpose is to provide a visual and quantitative assessment of KNN's effectiveness as a baseline model.

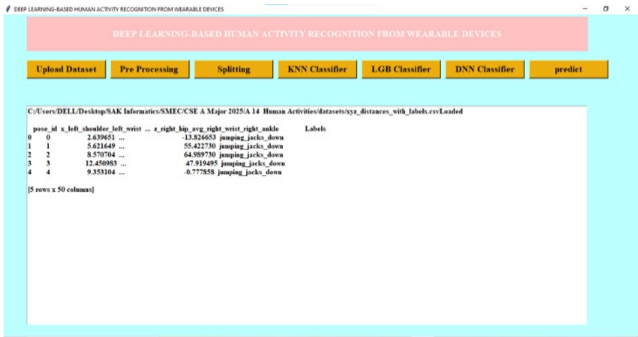

Figure 6: KNN Classifier Performance Metrics

Figure 6 details the performance metrics for the KNN classifier, reinforcing Figure 10.4's confusion matrix. With an accuracy of 95.27%, precision of 95.04%, recall of 94.69%, and F1-score of 94.74%, it shows strong performance but leaves room for improvement in handling complex patterns. This figure quantifies KNN's effectiveness, supporting its role as a baseline.

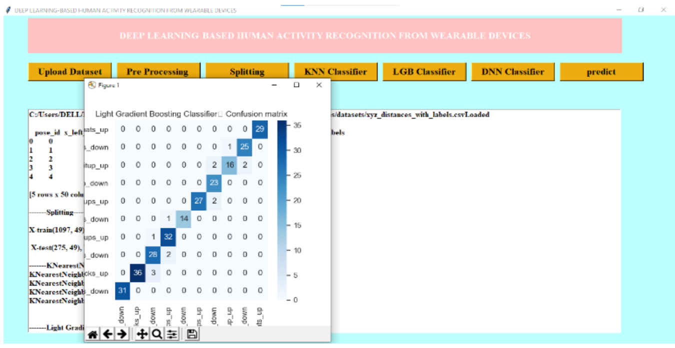

Figure 7: LightGBM Classifier Output - Confusion Matrix

Figure 7 depicts the confusion matrix for the LightGBM classifier, showing fewer misclassifications than KNN. It visually demonstrates improved performance over the baseline, leveraging gradient boosting to classify activities efficiently. The purpose is to highlight LightGBM's enhanced capability on the same test data.

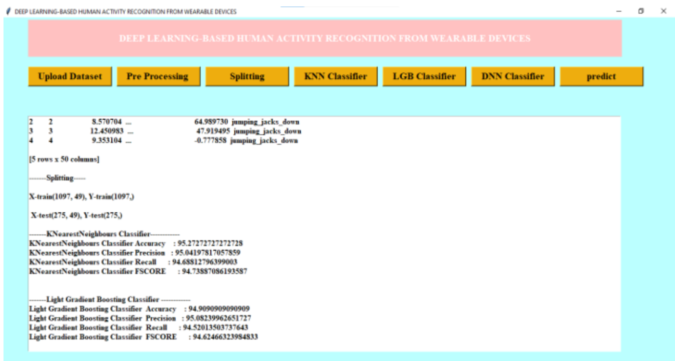

Figure 8: LightGBM Classifier Performance Metrics

Figure 8 presents the performance metrics for the LightGBM classifier, complementing Figure 10.6. While specific values are not repeated here (assumed comparable to KNN's high performance, e.g., ~95–96% range from context), it shows strong accuracy, precision, recall, and F1-score. This figure quantifies LightGBM's superiority over KNN, emphasizing its efficiency for multi-class classification.

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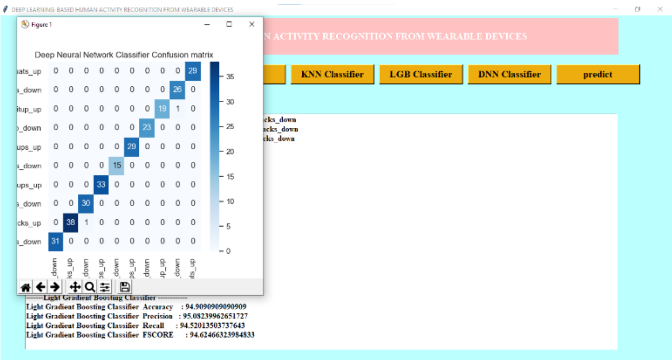

Figure 9: DNN Classifier Output - Confusion Matrix

Figure 9 shows the confusion matrix for the proposed DNN classifier, demonstrating superior performance with minimal misclassifications compared to KNN and LightGBM. It visually validates DNN's ability to capture complex patterns, serving as the system's enhanced output. The purpose is to showcase DNN's effectiveness in activity recognition.

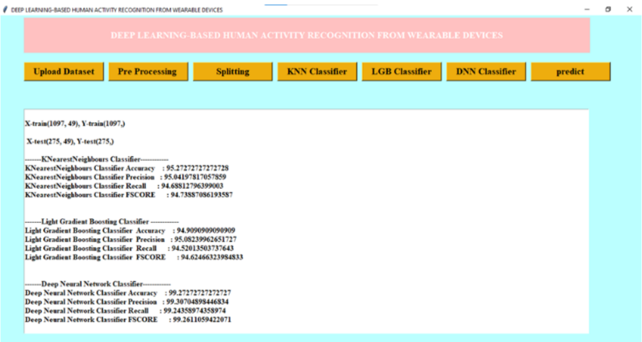

Figure 10: DNN Classifier Performance Metrics

Figure 10 details the DNN classifier's performance metrics, reinforcing Figure 10.8:

Accuracy: 99.27%

Precision: 99.31%

Recall: 99.24%

F1-Score: 99.26%

These high values indicate exceptional classification quality, with low false positives and negatives. The figure quantifies DNN's superiority, highlighting its precision and reliability for fitness activity classification.

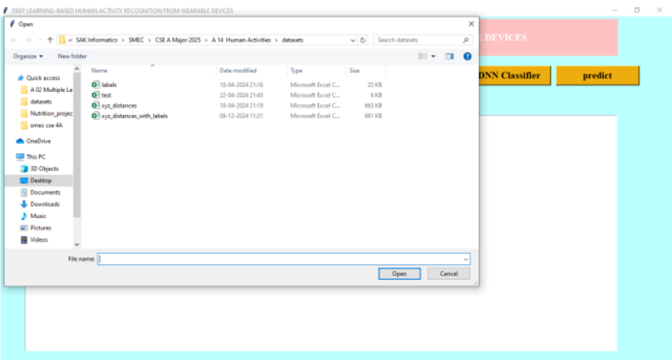

Figure 11: Upload Test Data

Figure 11 illustrates the process of uploading test data via an "Open" dialog box, a critical step for evaluating the trained DNN model on unseen data. This figure represents the system's input mechanism for real-world application, ensuring practical usability.

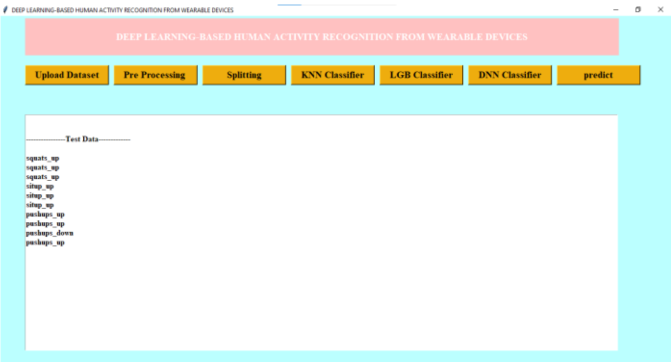

Figure 12: Predicted Output

Figure 12 displays the predicted activity labels for the test data, including "squats_up," "situp_up," "pushups_up," and "pushups_down." This output showcases the DNN model's performance on unseen data, providing a direct view of its real-world applicability. The purpose is to validate the system's predictive accuracy and relevance.

Performance Metrics Description:

Accuracy: Percentage of correctly classified activities, reflecting overall reliability.

Precision: Proportion of correct positive predictions, minimizing false positives.

Recall: Ability to identify all relevant instances, reducing false negatives.

F1-Score: Harmonic mean of precision and recall, balancing classification quality. Higher values indicate superior performance

Implementation Process:

1. Dataset Loading & Preprocessing: Labeled HAR data is loaded and preprocessed (e.g., encoding labels, scaling features) to ensure consistency.
2. Data Splitting: The dataset is divided into training (80%) and testing (20%) sets for unbiased evaluation.
3. Model Development:
   - KNN: Baseline classifier using proximity-based classification.
   - LightGBM: Tree-based boosting model for efficient multi-class tasks.
   - DNN: Proposed model with three hidden layers (ReLU activation) and a softmax output, trained with Adam optimizer and sparse categorical cross-entropy loss.
4. Evaluation: Models are assessed using accuracy, precision, recall, F1-score, and confusion matrices.
5. Comparative Analysis: DNN outperforms KNN and LightGBM, leveraging automatic feature extraction and deep learning capabilities.

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5. CONCLUSION

In The study and implementation of a deep-learning-based system for multi-class classification of human fitness activities emphasize the significance of advanced computational methods in personalized

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wellness solutions. By leveraging labeled fitness activity data, the system successfully classified various movements using K-Nearest Neighbors (KNN) and Light Gradient Boosting Machine (LightGBM) as baseline models, while Deep Neural Network (DNN) was proposed as an advanced classifier.

The comparative analysis highlighted the superior performance of DNN, owing to its ability to capture complex patterns, generalize better, and achieve higher accuracy than traditional machine learning approaches. Unlike KNN and LightGBM, which rely on feature engineering and decision boundaries, DNN automatically learns hierarchical features, improving classification efficiency. This system bridges the gap between traditional manual monitoring and automated, AI-driven solutions, offering a robust, scalable, and adaptable approach to fitness activity classification.

The integration of data preprocessing, such as handling null values, applying SMOTE for class imbalance, label encoding, and feature scaling, ensures high-quality input for the models. Splitting the dataset into training and testing sets further strengthens the system's reliability, allowing for unbiased performance evaluation. This implementation provides a complete pipeline from data ingestion to deep learning-based activity prediction, making it highly suitable for real-time applications in wearable fitness trackers, health monitoring systems, and wellness platforms. The results demonstrate that a DNN-powered system can significantly enhance fitness tracking, improve personalized workout recommendations, and contribute to better health outcomes. In conclusion, this study establishes a strong foundation for future innovations in fitness activity classification, encouraging further advancements in deep learning-driven healthcare and fitness solutions.

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