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MULTI-SENSOR BASED PHYSICAL ACTIVITY RECOGNITON AND CLASSIFICATION USING MACHINE LEARNING TECHNIQUES

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ABSTRACT

The increasing popularity of wearable devices like smart watches, smart phones, and wristbands has generated a need to analyze user patterns and activity relationships. This study utilizes the MHHBA Physical Activity Monitoring dataset, consisting of data from 12 different physical activities performed by 10 subjects wearing 3 inertial measurement units and a heart rate monitor. The dataset is invaluable for activity recognition, intensity estimation, and the development of algorithms for data processing, segmentation, feature extraction, and classification. To enhance accessibility, the original data has been transformed and merging all the datasets into a comprehensive CSV file. Leveraging this enriched dataset, we apply machine learning techniques to accurately predict the specific activity a user is engaged in. We employ the K-Nearest Neighbors (KNN) algorithm, Random Forest algorithm, Robust Scalar to standardize the features and Grid Search CV for best neighbors.

1. INTRODUCTION

Everybody's health can be improved by engaging in regular physical activity, regardless of age; children under five or seniors over 65. Engaging in several health advantages of physical activity have been demonstrated, such as lowering the risk of non-communicable diseases and greatly enhancing an individual's health and well-being. Physical activity, whether at a moderate or high intensity, is beneficial to health. Those who are not physically active have a 20–30% greater death risk compared to individuals who are physically active, and their risk of dying from non-communicable diseases is also increased [1].Roughly 6% of fatalities globally are attributed to physical inactivity, making it one of the primary causes of mortality [17]. The World Health Organization (WHO) therefore recommends engaging in physical activity for people of all ages, with recommendations for the duration the level of physical exertion based on age group [1]. It has been observed that physical activity lowers the risk of obesity, hypertension, diabetes, and heart disease, and fractures while improving bone health, mental fitness, and muscle and cardiopulmonary fitness. The risks of non-communicable diseases can be considerably reduced by encouraging healthy living and physical activity. It's the best treatment for obesity as well [3]. One of the main chronic illnesses is obesity, which also raises the risk of much significant comorbidity, including depression, type 2 diabetes, sleep apnea, hypertension, and so on. In order to determine which activity classification method works best on a balanced dataset, the study analyzes a number of machine learning approaches. In order to identify the machine learning methods that are most appropriate, the suggested work evaluates the performance of a selection of cutting-edge algorithms with varying training splits and degrees of imbalance. Any skeletal muscle-driven movement that involves the use of energy is referred to as physical exercise. It includes all actions, regardless of intensity, carried out day or night.

Types of Activity:

Structured exercise: Scheduled exercises designed to increase physical fitness (e.g., jogging, weightlifting, swimming).

Unstructured activity: Coincidental movement incorporated into everyday tasks (e.g., housekeeping, gardening, walking to work).

Activities of daily living (ADLs): Physically demanding actions that are necessary for everyday living (e.g., clothing, bathing, eating).

Health Benefits: Maintaining general health and wellbeing depends on engaging in regular physical activity. Lower the risk of some malignancies, heart disease, stroke, and type 2 diabetes, among other chronic illnesses. Enhance mental well-being by lessening anxiety and depressive symptoms. Make muscles and bones stronger. Promote weight control through calorie burning and muscle growth. Boost vitality and enhance the caliber of your sleep.

Various Intensity Levels: Depending on how intense the exercise is, it might be classified as follows:

• Light: Requires little effort on the part of the body, such housework or casual walking.

Like vigorous walking or riding, moderate activity causes discernible increases in heart rate and breathing. During vigorous exercises such as jogging or walking uphill, it becomes challenging to have a conversation.

What is Physical Activity Recognition?

Researchers in the field of Physical Activity Recognition (PAR) are working to create methods that can use data gathered from multiple sensors to automatically determine the precise physical activity a person is performing. For many fitness trackers and wearable device applications, it is an essential component.

What is Physical Activity Classification?

Using information gathered via wearable technology or other sensors, physical activity (PA) classification is the process of automatically classifying the kind of physical activity that individual is performing. Physical Activity Recognition (PAR) technology relies heavily on this feature. Many different fields can benefit from the use of Physical Activity Recognition (PAR) technology. Following is an outline of some major domains in which PAR is having a noteworthy influence:

Health and Fitness:

Fitness Trackers and Wearable Devices: The majority of fitness trackers and wearable technology are powered by PAR. They can use it to precisely monitor a variety of exercises, such as cycling, swimming, walking, and running, and even distinguish between different types of exercises (like lunges and squats). Users can track their calorie consumption, activity intensity, and duration with the usage of this data.

Personalized Health Monitoring: Sedentary behavior can be detected by health monitoring equipment using PAR. By encouraging the user to be more active and leading a healthier lifestyle, it can then set off notifications or alarms. In order to provide individualized rehabilitation programs or early identification of possible health problems, PAR-based technologies can also be utilized for activity monitoring in patients with certain illnesses.

Sports Training: REAL-TIME feedback on technique and movement is made possible for athletes via PAR. In order to maximize training regimens, reduce the risk of injury, and enhance performance, this can be very helpful. An athlete's technique can be improved for better outcomes by using PAR-based systems, which can assess complicated movements unique to various sports.

Safety and Security:

Fall Detection: Fall detection devices, particularly for older or vulnerable populations, heavily depend on PAR. Parametric activity recognition (PAR) might possibly save lives by detecting abrupt changes in movement patterns, such as a precipitous drop in movement or extended cessation of movement.

Entertainment and Gaming:

Virtual Reality (VR) and Augmented Reality (AR): In VR/AR environments, PAR can facilitate organic user interaction. It creates a more immersive and captivating experience by enabling users to physically control virtual items. In the virtual world, for example, PAR can convert motion such as sprinting or walking in place.

Motion-Controlled Games: Use of PAR to track user movements for game play is possible with gaming consoles and mobile games. This creates opportunities for creative game design where getting 'moving' becomes essential to the experience.

Other Applications:

Workplace Ergonomics: Employers can utilize PAR to track employees' posture and levels of physical activity. Utilizing this information can help evaluate ergonomics and offer suggestions for better workstation layout or encouraging breaks for physical exercise.

Smart Homes and Ambient Assisted Living: Automating chores depending on user activity is possible with the integration of PAR into smart homes. For instance, a person entering a room may trigger the lights to switch on, or the thermostat may change its setting in response to the amount of activity within. Furthermore, senior citizens' activities can be observed and assistance can be given as required in assisted living settings using PAR.

Ultimately, the way we track and analyze physical activity could be completely transformed by PAR technology. Beyond just measuring fitness, its uses have led to improvements in a number of other fields, including entertainment, safety, and health.

It is anticipated that PAR will grow ever more advanced and broadly applicable as machine learning algorithms and sensor technology advance. PAR can further improve user experiences in a variety of industries with increased accuracy and the capacity to recognize a wider range of actions.

1.1 OBJECTIVE OF PROJECT

Through the use of multi-sensor data from wearable devices, this research seeks to monitor and detect user behaviors and physical activity. The goal of the research is to use the MHHBA Physical Activity Monitoring dataset to develop and implement machine learning techniques for accurate activity prediction. The primary goal is to improve physical well-being by increasing our understanding of user activity patterns and relationships. For activity categorization on balanced datasets, the study also examines various training splits and data imbalance levels to find the optimal machine learning methods.

1.2 SCOPE OF THE PROJECT

Due to its utilization of wearable technology and the growing demand for thorough user activity research, this idea has a lot of potential. The broad MHHBA Physical Activity Monitoring dataset is utilized to create a strong foundation for machine learning applications by offering a range of data points for accurate predictions. Creating and categorizing algorithms is made simpler by converting raw data into a readable CSV format, which also enhances accessibility. The project's objective is to explore various machine learning techniques in order to increase the possibility for wearable-based activity monitoring to be broadly accepted and to improve health and well-being.

2.1 PROBLEM STATEMENT

Because sensor data is complicated and high-dimensional, established methods in the field of multi-sensor-based action monitoring and detection frequently have difficulty correctly recognizing and classifying activities. Several obstacles face current approaches, such as those that use logistic regression and hybrid descriptors:

Excessive Dimensionality: Sensor data is frequently exaggerated, becoming it costly to analyze computationally and vulnerable to over fitting. The performance of the model is affected by the difficult task of selecting the most pertinent characteristics from a broad variety of descriptors.

Model Generalization: Although it has its uses, logistic regression might not adequately represent the non-linear correlations in the data, which could result in less than ideal performance on tasks involving action detection.

Tuning of Parameters: The hyper parameters of logistic regression can have a significant impact on its effectiveness, necessitating a great deal of fine tuning to obtain good outcomes.

2.2 Existing System

Through the use of conventional data fusion techniques, the current system focuses on Physical Activity Recognition and Measure (PARM) in controlled conditions. To improve detection accuracy and identify different forms of physical activity, these methods process data from wearable sensors and ambient sensors. In open, dynamic IoT contexts, however, their application is restricted. New obstacles for PARM research have been brought about by the development of IoT technology, which has made it possible to connect affordable wearable's and Smartphone apps. How traditional data fusion techniques may effectively leverage IoT technologies to meet these difficulties is not well understood by the current system. Consequently, investigating IoT-based PA data gathering models is necessary for PARM applications.

Disadvantages of Existing System

- The process of acquiring data can be disrupted and proper recognition of physical activity may be hampered if any component of the infrastructure malfunctions or problems.
- To successfully adopt an IoT-based PA Data Acquisition model, it is imperative to ensure the implementation of strong security measures and address privacy concerns.

2.3 Proposed System

This work presents a system based on the MHHBA Physical Activity Monitoring dataset that uses machine learning techniques to predict the particular activity a user is involved in. The dataset includes information from ten people who participated in twelve distinct physical activities while donning wristbands and smart watches. In order to improve accessibility, we have converted the source data and combined all of the datasets into a single, large CSV file. The basis of our activity prediction engine is this enriched dataset. We use algorithms called K-Nearest Neighbors (KNN) & Random Forest, which categorize activities according to how similar they are to examples that have been tagged.

Advantages of Proposed System

- It can minimize computational complexity and enhance efficiency by removing elements that are unnecessary or redundant, improving the model's performance and accuracy in forecasting physical activity.
- This is especially helpful in anticipating physical activity because there can be a complex and non-linear relationship between many predictors and activity levels.

3. RELATED WORKS

F. Merrouche and N. Baha, et al, There are significant concerns for older adults living alone. The biggest danger to their life is falls. In order to support older adults' safe and independent living, a novel vision-based fall detection technique is presented in this work. To differentiate between fall and normal activity, the suggested technique makes use of motion data and shape deformation. This study primarily contributes by proposing a novel descriptor based on silhouette deformation and a new image sequence representation that captures the transition between various postures, which is discriminant information for action categorization. Two cutting-edge datasets (the SDU fall and the UR fall dataset) are used for the experimental results, and the results are compared. The collected findings demonstrate how well the suggested technique performs in distinguishing between fall incidents and typical activities. With the SDU autumn dataset, the accuracy reached is up to 98.41%, while with the URFall dataset, it is up to 95.45%.

Xiaolu Cheng, et al One of the most important topics in international public health nowadays is the prevalence of obesity. One of the main contributing factors to the obesity pandemic has been identified as physical exercise. This research aims to investigate the correlation between weight status and physical activity levels. Additionally, it will evaluate the efficacy and prognostic value of several widely used machine learning and conventional statistical techniques.

S. An, Y. Li, and U. Ogras, Human posture estimation (HPE), the capacity to estimate 3D human body position and movement, opens up a wide range of applications for home-based health monitoring, including remote rehabilitation training. A number of potential remedies utilizing sensors have surfaced, including wearable inertial sensors, millimeter-wave (mm Wave) radars, depth sensors, and RGB cameras. Few datasets utilize various modalities and concentrate on home-based health monitoring, despite prior efforts to create datasets and benchmarks for HPE. In order to close the gap, we introduce mRI, a multi-modal dataset for 3D human posture estimation using mm Wave, RGB-D, and inertial sensors. Our collection of more than 160k synchronized frames from 20 participants engaging in rehabilitation exercises meets the action detection and HPE requirements. With our dataset, we conduct thorough trials and identify the strength of each. More importantly, we expect that mRI will make it easier to use home-based health monitoring. We also anticipate that it will spur research in the areas of posture estimation, multi-modal learning, and action understanding.

J. X. Chen, Emotional binary categorization was carried out in both valence and arousal dimensions in studies using the DEAP dataset. Deep CNN models were compared with shallow machine learning models, such as Bagging tree (BT), Support Vector Machine (SVM), Linear Discriminate Analysis (LDA), and Bayesian Linear Discriminate Analysis (BLDA). The outcomes demonstrated that deep CNN models performed better since they don't require human feature engineering. Using combined temporal and frequency characteristics, they were able to attain a recognition performance that was 3.29% higher in the arousal dimension and 3.58% higher overall when compared to the top standard BT classifier.

F. Heidarivincheh, We present the problem of action completion moment detection: determining the point at which an action is deemed to have successfully accomplished its objective. The suggested joint classification-regression recurrent model predicts completion from a given frame and then combines contributions at the frame level to identify the completion moment at the sequence level. A recurrent voting node is presented here, which uses either regression or classification to forecast the relative position of the completion moment within the frame. Additionally, the technique can identify incompleteness. In addition to identifying successful ball catches, the approach may also identify whether the ball is safely caught. We assess the technique using sixteen actions spanning daily and sports-related activities from three public datasets. The completion moment is detected within one second in 89% of all sequences studied, according to the results, when integrating contributions from frames before and after the completion moment.

4. METHODOLOGY OF PROJECT

To implement the project, a dependable system for real-time activity prediction must be created using the high-level Python web framework Django. We will develop an intuitive user interface that will allow users to submit data from wearable devices for instantaneous analysis, facilitating seamless interaction with the machine learning models. Robust Scalar, K-Nearest Neighbors (KNN) method, and Random Forest algorithm will be incorporated into the backend for feature standardization. Data processing, segmentation, and feature extraction will be handled by the Django framework for efficient model training and prediction. The ultimate goal is to promote a healthier way of life by providing an intuitive internet application that lets users track and learn more about their physical activity.

MODULES:

There are 5 modules in this section to understand the working of the project. The following are the modules in this project.

- Collection of Datasets,
- Analysis of Datasets,
- Preprocessing of Data,
- Model Selection,
- Model Evaluation.

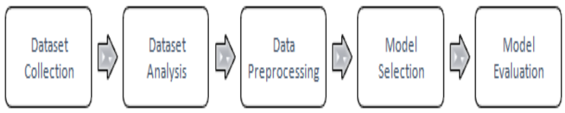


Figure: 1 Modules

Data Collection: Obtaining the dataset needed for training and testing the multi-sensor action detection system is the primary task of the project's first phase. Sensor data from a range of physical activities, such as acceleration and gyroscope readings, is included in the collection. In particular, the dataset has 12,15,745 items with 13 columns that include sensor readings (alx, ary, arz, grx, gry, and grz), subject information, and activity labels (Activity).

Dataset Analysis Using the Pandas library, the dataset is loaded. The file, "dataset.csv," includes sensor data with several properties including gyroscope (glx, gly, glz), acceleration (alx, aly, and alz), and others. df.shape and df.info() have been used to analyze the dataset in order to determine its structure and look for any missing values.

Data Preprocessing: Data cleaning involves handling features like "subject" that are judged superfluous and eliminating them from the dataset. To ensure balanced representation, resembling is utilized to limit one of the activity categories to 40,000 observations. removing data points for each feature that are outside of the 98% confidence zone in order to handle duplicate entries and outliers. To enhance model performance, the data is scaled using scikit-learn's Robust Scalar. The dataset is separated into attributes (X) and target labels (Y) for easy comprehension after the activities have been labeled.

Model Selection: To identify activities based on the preprocessed sensor data, the KNN algorithm is used. To determine the ideal number of neighbors (neighbors) for the KNN classifier, a grid search is conducted. The dataset is used to train a Random Forest Classifier, which increases the accuracy of action recognition even further. Both the scaled and unsealed data sets are used to assess the model. We applied these techniques after obtaining accuracy results on the train set of 91.509% & 99.99% without Robust Scalar and 93.835% & 99.99% with Robust Scalar

Splitting the dataset:

Split the dataset into train and test. 80% train data and 20% test data.

Model Evaluation:

Models are assessed using metrics such as accuracy, precision, recall, F1 score, and sensitivity. Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a .pkl file using a library like pickle. Make sure you have pickle installed in your environment. Next, let's import the module and dump the model into.pkl file. The best KNN & Random Forest models are saved as a .pkl files for UI detection.

Saving the Trained Model:

Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a .h5.

5. ALGORITHM USED IN PROJECT

- **KNN & Random Forest with Robust Scalar &Grid Search CV**

We propose an approach that classifies activities using the Random Forest and K-nearest neighbors (KNN) algorithms. Activity classification is greatly enhanced by the KNN approach, which considers the "k" nearest neighbors in the feature space. To ensure that the algorithm is resilient against outliers and to improve its efficiency, we scale features using resilient Scalar. To systematically tune the hyper parameters and determine the optimal combination to increase the accuracy of the activity prediction, we utilize Grid Search CV. The Random Forest technique provides a dependable and accurate model for activity prediction by building an ensemble of decision trees.

K-Nearest Neighbors (KNN): Activities are categorized by this method by comparing sensor data to the training data's closest labeled activities. It uses the "k" closest neighbors into account while predicting.

Step 1: Select the number K of neighbours
Step 2: Calculate the distance

$$\sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$$

Figure: 2 Euclidean Distance

Step 3: Take the KNN – K nearest neighbors based on the calculated distance.
Step 4: Among these K neighbors, count the number of points belonging to each category.
Step 5: Assign the new point to the category most prevalent among these K neighbors.
Step 6: Our model is ready.

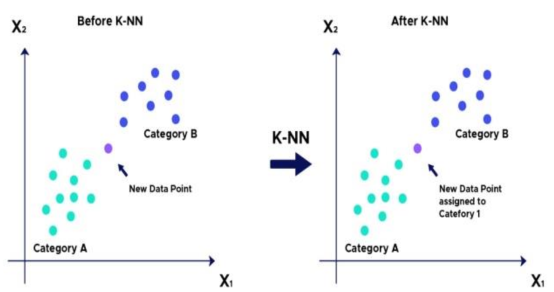


Figure: 3 K-Nearest Neighbors

Random Forest: Multiple decision trees are combined into one ensemble technique called the Random Forest algorithm. A randomized subset of the characteristics and data are used to train each tree. The method operates in multiple stages. Initially, it chooses a random selection of features and a bootstrap sample of data to train a decision tree. To produce a collection of decision trees, this process is carried out several times. Predictions are created for each new data point by running it through each decision tree. For classification tasks, the final prediction is determined by the majority vote of the trees; for regression tasks, it is determined by averaging the forecasts. Accuracy and robustness are improved with this method.

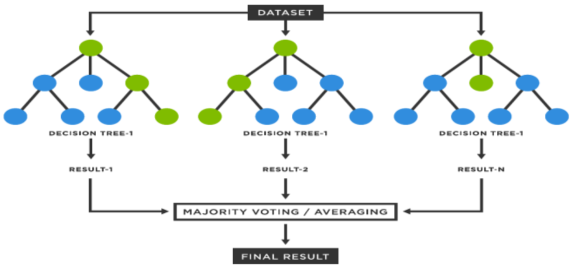


Figure: 4
Random Forest

6. DATA FLOW DIAGRAM

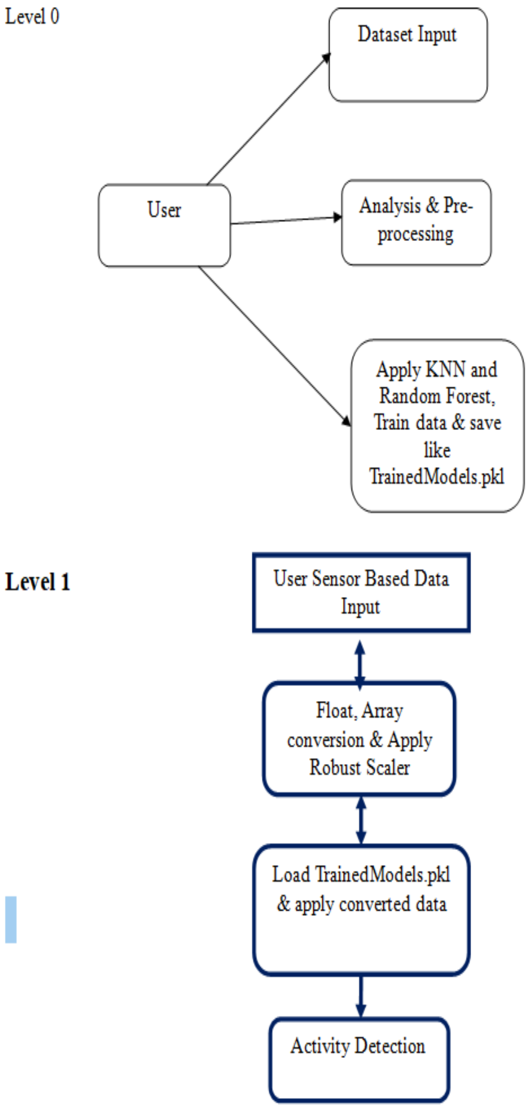
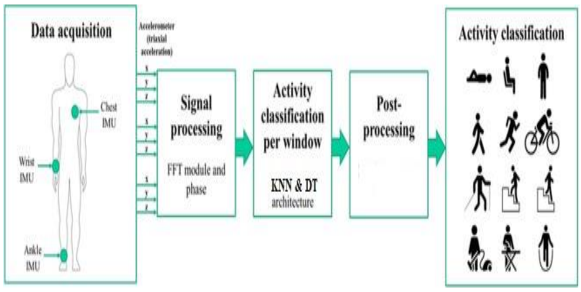


Figure: 5 Data Flow Diagram

7. SYSTEM ARCHITECTURE



System Architecture Of Project

8. RESULTS

Figure: 6 Home Page

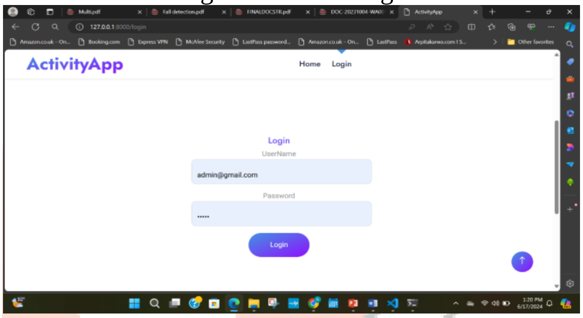


Figure: 7 Login Page

Figure: 8 Abstract Page

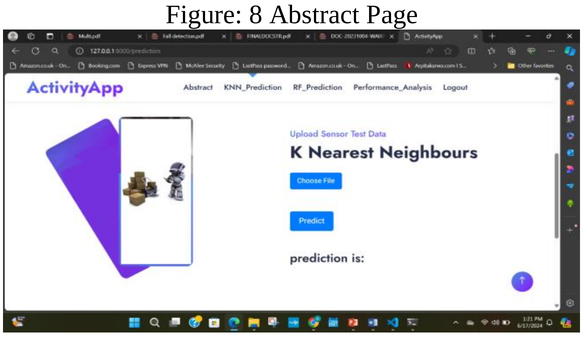


Figure: 9 KNN Classifier Page

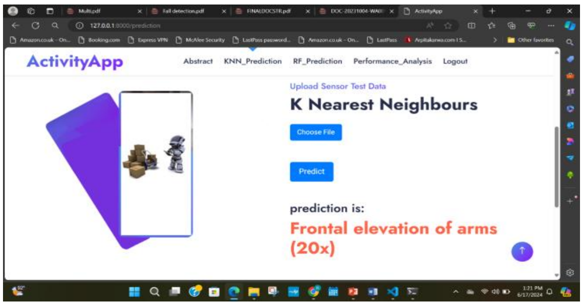


Figure: 10 KNN classifier Page with an activity predicted

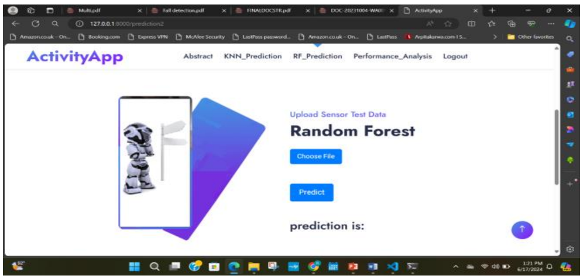


Figure: 11 RF Classifier Page

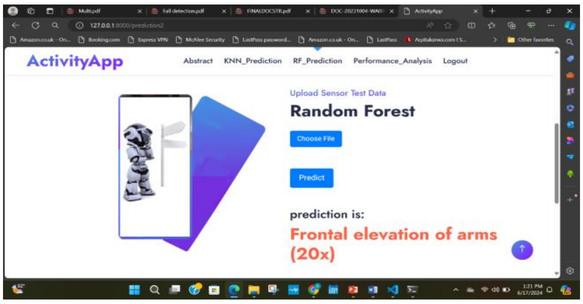


Figure: 12 RF Classifier with an activity predicted

9. FUTURE ENHANCEMENT

Need to investigate new features and sophisticated modeling methods in the future, especially in the field of Human Activity Recognition (HAR). Could explore deep learning approaches, concentrating on managing large-scale datasets to improve the system's performance in various real-world situations. The suggested Multi-Sensor Data-Based Action Recognition system will continue to evolve and get better as a result of the search for novel features and models.

10. CONCLUSION

In the present study, the suggested Multi-Sensor Data-Based Action Recognition system shows good activity detection in the current investigation. In particular, it concentrated on the identification of activities by applying robust scaling approaches and K-Nearest Neighbours (KNN) and Random Forest classifiers. The technology demonstrates flexibility in its application, finding use in a variety of domains including emergency rooms, virtual gaming, and healthcare. Through the Feature extraction using ML techniques extraction, carried out was a thorough study of sensor data that included gyroscope and acceleration values. After characteristics relevant to sensor data were extracted, We employed RF and KNN classification in the subsequent assessment shown with highest learning accuracies of 93.83% and 99.99%.To validate the robustness of the system, rigorous UI testing was conducted using Django methodologies, by taking a file or input values it can efficiently detects activities.

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