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Decoding Human Behavior: Human Activities Recognition using Machine Learning Approach

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***Abstract*— The study of Human Activity Detection (HAD) has become a challenging topic, especially when technology such as Internet of Things (IoT) is introduced, allowing for a wide range of applications in the field of healthcare and elderly care. This study looks at new methods developed in HAD, such as sensor-based, mobile devices and visual data processing. The paper points out the potential uses of HAD, from simple to complex behaviors, powered by video frames, wearable sensors and accelerometers. HAD can be integrated with promise in medical diagnostics, surveillance and real-time activity detection. The research goal is to identify and classify human activities based on the NTU-RGB-D dataset, which is used to collect 3D skeletal data. More detailed analysis can be done if a subset of acts is considered, e.g., drinking, picking up, applauding, and saluting. The proposed system emphasizes to develop a machine learning model for activity prediction with high accuracy by implementing Logistic Regression Algorithm. This paper highlights the role, subset selection, algorithm integration and experimental setting of the skeletal-joints dataset from the NTU-RGB-D dataset. The Logistic Regression Algorithm is effective and with decision tree majority voting amazing accuracy is achieved. Logistic Regression is shown to be better through comparative evaluations. The effectiveness of the study verifies its feasibility to understand and predict human behavior.**

***Keywords*— Human Activity Detection (HAD), Modern Techniques, Decision Tree, Logistic Regression, Human Behaviors.**

I. INTRODUCTION

The development of new methodologies and technologies to overcome the barrier of human-computer interaction is gaining a growing interest. Hand gestures have become a key motivator in hand gesture research, not only for their representation, but also for the algorithms used to recognize them [3]. Extensive efforts have been devoted to the detection of human activities in both images and videos [4-7].The analysis of human actions has garnered significant attention due to its applicability in various domains, including visual surveillance, video retrieval, human-computer interaction, and sports training[8-12].

Extensive research endeavors have been documented in the realm of hu-man activity recognition, spanning a wide array of applications, encompassing but not limited to: detecting abnormal home activities [13], tracking tennis [14], deciphering human gestures [15], under-standing sports activities [16], studying human interactions [17], monitoring pedestrian traffic [18], decoding simple actions [19–22], and addressing healthcare-related applications [23–25].

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Human Activity Detection (HAD) is now a challenging yet important problem to solve. Its applica-tions are endless, especially in health and aged care, thanks to the integration of technologies such as the Internet of Things (IoT). There are a variety of ways to implement HAD, such as sensor-based, mobile, and visual data analysis. This paper explores in detail a detailed literature review of cutting-edge techniques in the field of HAD, providing a brief overview of each technique.

All these techniques are tested on different sets of data, derived from the different types of tools that are used to collect data. Sensors, images, accelerometers, gyros-copes and other sensors all over dif-ferent locations. The results of each approach are then discussed in a systematic way and compared with the methodology used and the type of data set used. This paper not only covers classical ma-chine learning methods, but it also explores the world of deep learning methods. It is possible to identify human activities ranging from simple ones, such as jogging, sitting, sleeping, standing and more, to more complex ones, such as showering, cooking and driving, using methodologies known as HAD. These activities can be understood by integrating all of the data sources, such as video frames, still images, wearable sensors, and accelerometers. The possibilities of HAD include medi-cal diagnostics, where the potential is great to monitor individuals in-depth, especially the elderly population. Furthermore, integration can help lower crime rates by improving surveillance, and the development of intelligent environments based on real-time activity recognition. One key aspect of HAD is related to driving behavior, which not only helps to promote safe driving methods, but also impacts the capabilities of military operations detection. The overall goal is to elaborate the de-tection and identification of human activities. To this end, the study uses the NTU-RGB-D dataset, which contains 60 human activities captured using depth sensors, providing 3-dimensional skeleton data with the coordinates of 25 body joints for each frame. This information can then be used to train and implement algorithms to predict human activities, which is the basis of the rich dataset. For the purpose of simplifying the scope of the task, the study chooses to narrow its focus to a subset of activities.

II. Related Work

This deep neural network is additionally connected with contextual information, both global and local, to enhance the model's performance in accurately recognising the human behaviours in real-world scenes. The proposed method is superior to the baseline methods and demonstrates better performance on the Collective Activities Dataset, demonstrating the potential of context-based deep learning algorithm for activity recognition [26]. This study uses a deep network architecture, which includes bidirectional long short-term memory (LSTM) cells with residual connections, to improve the recognition of human activity using wearable sensors. The bidirectional connections capture temporal relationships and the residual connections alleviate the gradient vanishing problem. This method leads to significant accuracy gains, and is superior to previous methods for recognition rates on datasets such as the Opportunity dataset and UCI dataset [27]. The use of Dynamic Vision Sensors (DVS) is investigated in human activity recogni-tion. Dynamic Vision Sensors (DVS) operate by measuring changes in the pixel values rather than taking full frames of images. Because of this capability, they are highly suitable for power-efficient wearable devices. The study introduced motion maps generated from DVS video slices and combined them with Motion Boundary Histogram (MBH) features for activity recognition[28].Another important study by Rana Mostafa and MayadaHadhood presented a detailed review of modern human activity recognition techniques using wearable sensors. Their research evaluated several approaches on well-known datasets such as MHealth, USCHAD, UTDMHAD, WISDM, WHARF, and OPPORTUNITY[29].The author focused on recognizing human activities from skeleton pose sequences, mainly in the area of human-robot interaction. Their work compared different classification methods in machine learning [30].The authors introduced the NTU RGB+D dataset to address the growing demand for large-scale datasets in deep learning.Their research demonstrated that deep learning models, especially LSTM networks, can effec-tively utilize this dataset for accurate human activity analysis and recognition.The study underscores the importance of data-driven learning frameworks when substantial data quantities are available [31]. Hu-man activity recognition: A review - Michalis Vrigkas, ChristophorosNikou, Ioannis A. Kakadiaris . This comprehensive review highlights the challenges in human activity recognition and presents a taxonomy for categorizing techniques. The study delves into various multimodal and unimodal approaches, discuss-ing advancements in data representation, feature extraction, and classification methodologies. Moreover, it emphasizes the ongoing tasks in controling issues like occlusion, model generalization, and annotation [32]. For use in health care applications, a deep learning-based approach is proposed that can identify distinct activities as well as short-duration, infrequent transitions between two different activities [33]. Time analysis in human activity recognition: This article improves the accuracy of activity recognition systems for long windows. To

accomplish this, the article evaluates different techniques for combining sub-window information within a window. The study uses a state-of-the-art convolutional neural network (CNN) based system for human activity recognition. The CNN's convolutional layers are utilized to ex-tract features from signal spectra while fully connected layers are used to classify activities within each window [34].
An innovative method that uses ensemble learning of multiple convolutional neural network (CNN) models to recognize human behavior. Using the publically accessible dataset, three distinct CNN models are trained, and several ensembles of the models are produced. The combined accuracy of the first two models is 94% [35]. With regard to fall detection and motion recognition utilizing acceleration data, the research explicitly attempts to close this gap. The dataset, UniMiB-SHAR, which has a history in the HAR field, to guarantee repeatability employed. Using raw temporal input, better results achieved in fall detection (98.71% vs. 99.82%) and activity recognition (88.5% vs. 98%) than the most current work on this dataset, making this paper really contemporary [36]. An architecture for a deep neural network pro-posed that uses a self-attention mechanism to learn and pick key time points while simultaneously captur-ing the spatiotemporal properties of many sensors time-series data. Through the use of a mix of recurrent and convolution networks, the use of the suggestedstrategy on six obtainable datasets, demonstrating that the self-attention mechanism provided a notable boost inperformance over deep networks are shown. It is demonstrated that, for the examined datasets, the suggested model was best for earlier cutting-edge tech-niques in terms of statistical significance [37]. Various ways have been implemented over the years. Sev-eral methods are available for identifying different activities, like whether the participant is running, walking, dancing, jogging, or falling. For each strategy, multiple methodologies and datasets are used[38].Because the data represents a multivariate classification problem. The dataset was input into the modules of machine learning classification techniques., and the accuracy of each model was calculat-ed[39].To cover the gap with real-time, the dataset was acquired utilizing the sensors of many persons' smartphones, with practically complete choice. In this method, a comparison of the previous outcomes and the current ones is shown. To accomplish this, many machine learning algorithms commonly adopted in HAR were applied in pursuit of the optimal algorithm-hyperparameter combination. HAR is a critical field of research, with the goal of identifying and categorizing human actions from data. The data input to these models is primarily derived from various sources such as movies or image sequences acquired by a range of devices such as surveillance cameras, cellphones, or specialist recording equipment[40,42].There have been numerous advances that have resulted in incorporated sensing technologies, including sensors, the cloud, and the Internet of Things. Sensors are low-cost electronic devices that may be cleverly incor-porated into movable equipment, hence HAR-related research use sensors[41].Gestures are fundamental hand gestures made with various parts of the body to convey certain messages. Humans conduct relative-ly simple actions that involve a series of motions. Understanding various levels of human actions forms the base for constructing advanced HAR systems. Most of the HAR-related experiments use sen-sors[43].This study is primarily concerned with determining the most effective strategy to developing the HAR framework for older individuals. This study uses both machine learning and deep learning method-ologies, to determine which is more appropriate[44].
In conclusion, the surveyed literature showcases the evolution of human activity recognition through the integration of deep learning, sensor technologies, and innovative data representations.The objective is to deeply study human behavior and develop an intelligent system that can learn from the given dataset and accurately predict different human activities. To achieve this, it is important to first understand the dataset thoroughly and identify a suitable machine learning technique that can effectively recognize and classify human actions.

III. METHODOLOGY

A. Data Acquisition

The "NTU-RGB+D" dataset and its extended version "NTU-RGB+D 120" make an important contribu-tion to the computer vision and recognizing human actions. The dataset is meticu-lously curated to enable advanced research of human activity analysis. The basic "NTU-RGB+D" dataset consists of a collection of 56,880 sample videos, which represents a wide range of human actions in 60 different action classes. These action classes represent a wide range of human action and be-haviors. This dataset contains a col-lection of videos, each of which are rich mixings of various data modalities, such as RGB videos, 3D skeletal data, depth mapping sequences, and infrared (IR) videos. The multimodal approach gives a com-plete overview of the actions carried out, which lets for a more complex understanding of human activity. The "NTU-RGB+D 120" dataset has been extended from the "NTU-RGB+D" dataset, further highlighting the potential of the dataset. This longer set contains 57,600 video samples, for a total of 114,480 samples in 120 different action classes. This expansion expands the range of actions that can be covered and also adds to the details that the data set can capture with regard to human movement. The data comprises the components of the dataset are recorded by Kinect cameras, which are known for their capacity to obtain detailed data related to human movements. An inherent part of the data set, the depth maps and IR videos have a resolution of 512 x 424 pixels, which provides high-quality spatial representation of actions. The videos on the other hand have a resolution of 1920 x 1080 pixels, giving them a more colorful and realis-tic look of the actions being captured.

B. System Architecture

The architecture of the proposed system is given in the Fig. 1. Dataset called "NTU-RGB-D" used and extract the four features from each of the 36 samples. The data prepared with feature extraction of rele-vant features that best characterize each human activity with filtering and obtaining the necessary data from the dataset.

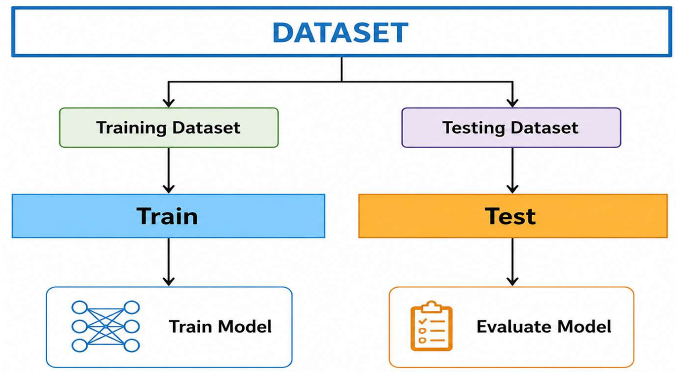

Fig. 1. Architecture for the proposed system

The code implements the Logistic Regression Algorithm to train and test a model for the following four activity classes: Drinking, Pick up, Clapping, and Salute. These activities are divided into 80 percent training and 20percent testing subsets from the total dataset. Specifically, each of the 30 samples per ac-tivity is utilized for training. The dataset comprises a total of 120 samples. The primary goal is to con-struct a precise predictive model using the Logistic Regression Algorithm. Once trained, the Logistic Re-gression model will be able to recognize human activities based on the input features. Comparison with Other Algorithms: The proposed system will not only rely on the Logistic Regression Algorithm but also conduct a thorough comparison with other classification algorithms. Prominent methods: Decision Trees, Support Vector Machines, and Neural Networks, will be applied to discern how the Logistic Regression Algorithm differentiates in terms of accuracy, efficiency, and generalization capabilities. Every one of these files has the name"SxxxCxxxPxxxRxxxAxxx.skeleton," where "S" stands for "Setup," "C" for "Camera," "P" for "Performer," "R" for "Replication," and "A" for "Action". And the samples are contin-uously numbered from 1 to 3 using the code "xxx". Each such file contains a record of the specifics of human action and joints.

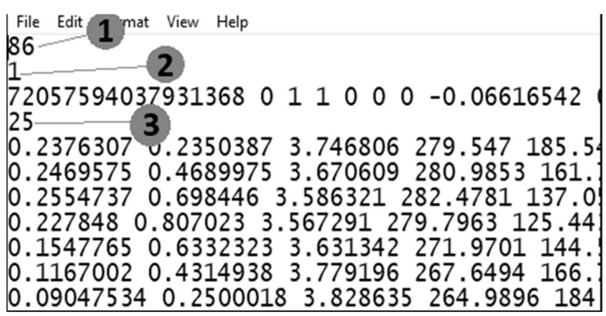

Fig. 2. 3-D Skeleton file of human actions and joints for the dataset

From the fig. 2 the following observations are found:

- The very first line indicates number of frames of the action have been captured. There are 86 frames in the model.
- The second line describes how many actors are involved in the sequence. There is just one actor listed in the sequence.

- The third line describes the human actor's 25 joints, which are consistent throughout the action.
- The values of each joint in the very first frame is gathered in the 25 lines. The first three numbers rep-resent the joint's location in 3-D space, expressed in 3-D coordinates.

IV. Discussion

The model of the Activities found gives with all the values of the skeleton-joints, number of frames x 25(skeletal-joints) x 3-D((X, Y, Z) coordinate of the each skeletal-joints and the column-Y contains action ID or activity ID for the fetched data.
The model's training and testing using the Logistic Regression Algorithm are performed for the ac-tions of Drinking, pick up, Clapping, and Salute of four classes, each of which represents 80% and 20% of the total dataset, respectively. Train each of the 30 samples for each activity. There are a total of 120 samples in the dataset. To create a precise model for prediction, the Logistic Regression Algorithm was employed.
A skeletal file was manually input into the classification model to execute predictions. Upon receiv-ing the skeletal file as input, the system extracted essential features for prediction. Subsequently, a se-quence of skeletons was generated for each frame, and the outcomes were displayed alongside the corre-sponding class accuracy. The skeletons from each frame in the skeleton file were plotted to visually rep-resent and recreate the human actions recorded in the dataset. This helped in clearly understanding and analyzing the movements and activities performed. Logistic Regression was employed as the primary classification algorithm, but a few other classifiers were tried to compare their performance with Logistic Regression. The prediction accuracy and overall efficiency of the four classifiers: MLP Classifier, Deci-sion Tree Classifier, Linear Regression, and K-Neighbors Classifier were compared.

V. Results

The primary objective of this research was to thoroughly study human actions and develop a predictive system that could learn and predict human behavior. A successful execution of this objective necessitated a meticulous understanding of the dataset as well as the identification and deployment of an effective machine learning (ML) algorithm.
The implemented system demonstrated its efficacy, by employing a decision tree majority voting ap-proach for classification and prediction, we achieved notable accuracy levels. Our extensive experimenta-tion revealed that the Logistic Regression (LR) algorithm emerged as the most effective ML algorithm for our specific purpose. Utilizing an 80-20 split for training and testing data, the Logistic Regression model achieved commendable accuracy scores, showcasing the viability of the "sag" solver approach for initial-izing the algorithm.

A. Logistic Regression

Numerous data mining and machine learning approaches for classification of data involve logistic re-gression. LR covers multi-class and provides likelihoods. However, LR was used to address the classifi-cation issue in several imbalanced and multi-class datasets. LR may be mathematically expressed as.

$$P = 1/(1 + e^{(\beta 0+\beta 1x1+\cdots+\beta nxn)} (1)$$

where in (1) P is the probability of the event occurring, β0,β1,…,βn are the coefficients of the model, and x1,…,xn are the predictor variables.
The provided Table 1 listed each classifier's recall, precision, F1 score, and recognition accuracy. To tackle the recognition problem, we choose for LR. LR outperformed other classifiers, achieving 76.73% F1 score, 78.42% recall, and 80.31% accuracy. In the proposed research, the choice of LR is not only determined by accuracy; we also considered four different metrics as part of the classifier selection criteria. Additionally, the validity and consistency of the results are demonstrated by the evaluation results of the MLP, Linear Regression, Decision Classifier, and K-Neighbors Classifier, which all utilize our suggested method of selection.

TABLE I: PERFORMANCE OF ALGORITHMS FOR THE DATASET

Algorithm	F1 Score (%)	Recall (%)	Precision (%)	Accuracy (%}
Logistic Regression	76.73	78.42	80.31	77.27
MLP Classifier	31.82	33.41	31.32	32.72
Linear Regression	50.41	50.33	51.22	51.66
Decision Tree Classifier	44.21	44.62	44.71	45.56
K-Neighbours Classifier	61.54	60.32	62.35	62.45

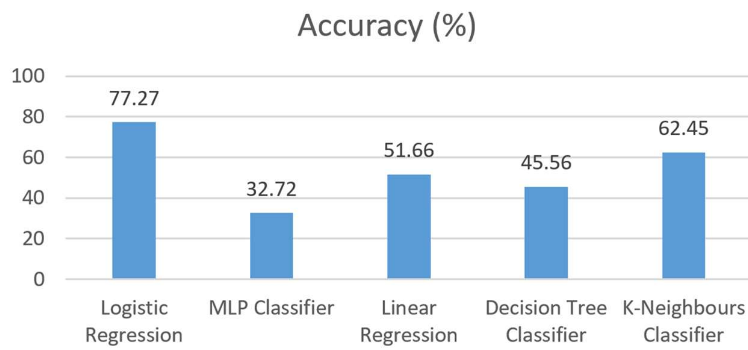

Fig. 3 Comparison between the classifier for the dataset.

An analysis of the performance of various ML algorithms yielded valuable insights given in table 1. Based on the graphical representation given in Fig 3, it becomes evident that Decision Tree Algorithms and the MLP Classifier exhibited comparatively lower effectiveness within the context of this paper. Conversely, the K-Neighbors Classifier displayed superior performance in comparison to linear regression methods. In particular, Logistic Regression (LR) was the most remarkable among the classifiers, reflect-ing its capability in dealing with the complexities of predicting human behavior.

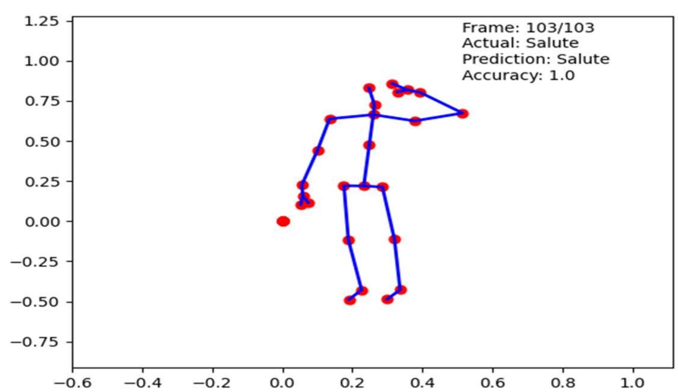

Fig. 4 Plotting frames of action for the activity salute

When the prediction code is run, an output window will appear, showing plots of the ske-letal joint configuration for each frame, as well as real-time predictions. The use of plots is required to provide a visual representation of the body's movement and limb articulation while doing the activity. After manu-ally typing in a skeleton file, the resulting graphic displays the projected and observed behaviors, as shown in Figure 4.

VI. Conclusion and Future Work

During the past few decades, human activity recognition technology has developed to a fast-growing research field that is attracting a lot of attention and research efforts from researchers around the world. In recent years, the emergence of low-cost RGB-D (range,back-light, and depth) sensors has dramatically changed the situation, making the detection of human activity both more accessible and more reliable than ever before. There is, however, one interesting finding: in the majority of the research, attention has been paid to the identification of temporary acts, and much of it has overlooked the context of the entire opera-tions. The proposed approach is based on a trained classifier with logistic regression (LR) algorithm for decoding learnt behaviors. After intensive experimentation on the NTU-RGB-D dataset, with 4 behav-iours, each of 30 samples, our technique proved to be extremely accurate in predicting the results. Through comparative studies, with various algorithms, for benchmarking, the effectiveness of our ap-proach was shown. With other methods, our methodology displayed higher prediction accuracy, highlight-ing its potential for dealing with the intricacies of human activity recognition.

This Paper proposes a new step towards human activity recognition. Research to date has provided valua-ble insight and positive outcomes, but the future offers great potential for expansion and refinement. The incorporation of real-time detection, a more thorough understanding of human ac-tions, and tackling out-standing issues will all contribute to the field's further progress. With the advancement of technology and research, the possibilities of predicting and understanding human actions are limitless.

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