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RECOGNIZING HUMAN ACTIVITY USING MACHINE LEARNING

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Abstract : Recognizing human activity aims to infer a person's actions from a set of observations captured by several sensors. Data acquisition, processing and inference on edge devices add a complexity factor to the task, as they involve a trade-off between hardware efficiency and performance. We present a prototype of a wearable device that identifies a person's activity: walking, running or staying still. The system consists of a Texas Instruments MSP-EXP430G2ET launchpad, connected to a BOOSTXL-SENSORS boosterpack with a BMI160 accelerometer. The designed prototype can take acceleration measurements, process them and either transmit them to a computer or classify the activity in the microcontroller. Additionally, our system has LEDs to display coloured signals according to the inferred activity in real-time. The classification algorithm is based on the calculation of statistical features (mean, standard deviation, maximum and minimum) for each accelerometer axis, the application of a dimensionality reduction algorithm (LDA, Linear Discriminant Analysis) and an SVM (Support Vector) Human Activity Recognition is a dynamic field of research and logical improvement in which different models have been proposed utilizing diverse strategies for recognizable proof and categorization of activities using Machine Learning. The features of picture or video information set are extracted utilizing distinctive kinetic models related with spatial feature leaning. Numerous deep layer trained models have been successfully utilized in this field to reach the basic objective of this model which is recognition and categorization of action taking place. These activities include day to day exercises like running, jogging, eating, sitting, etc. There can be numerous sorts of activities in totally different fields like healthcare, childcare, security or work security. Human Activity Recognition contains an exceptionally noteworthy part in completely different areas like human computer interaction, video surveillance framework, robotics, daily monitoring, wildlife observation, etc.With the use of distinctive datasets like UCF-101, HMDB-51, Hollywood2, Sports- 1M and training them this task of recognition of activity can be proficiently done. The execution of Convolutional Neural Network (CNN) model for image recognition with the help of OpenCV helps in effective working of this model. Such application of distinctive datasets on activity recognition model has made a difference in simple categorization of activity based on it's nature whether normal or anomalous and suspicious. According to the identified nature a caution is sent through server to the authority concerning the happening of odd movement taking place at real time. Due to such application of this model numerous harmful activities can be dodged or at slightest negative results of such activities can be minimized.

Keywords— Human Activity Recognition; Machine Learning; Convolutional Neural Network; OpenCV; video surveillance;

I. INTRODUCTION

With fast improvements within the field of activity recognition and proposition of numerous new models based on scientific and innovative improvements monstrous progress in this field can be seen and observed. The improvement in deep learning and OpenCV with highly trained datasets have opened a new entryway of opportunities for upcoming research in this field. Such progress can lead to authentic and valuable application of such models in this digitally prepared world for the well- being of all living creatures. The use of modern and advanced technology in this field by different researchers and engineers have resulted in various applications of these models. Due to such highly trained models the activities taking place at real time can be observed in exceptionally viable and ideal way. Anomalous or suspicious activities can be treated with convenient strategies guaranteeing peace and concordance within the society of living beings. This can be also very useful in making a smart home environment as well as smart healthcare service with the assistance of regular monitoring. Numerous security issues can be handled carefully and the harm to be caused can be minimized. Such successful application of these models in day-to-day life can also guarantee the psychological wellbeing of individuals without concerns of the harm due to such activities. The human activity recognition model can be actualized with the use of camera module which captures the crude information that serves as an input to the recognition system. By making distinctive outlines of such input information categorization of activity is done after feature extraction. Such activity is then identified as normal or suspicious and quick alert is sent to the authority.

I. RESEARCH METHODOLOGY

In this paper, a machine learning-based yoga pose estimation methodology presented in algorithm 1 is proposed to detect correct yoga poses and provide feedback to improve the yoga posture. The proposed approach has been done on NVIDIA DGX V-100 and consists of three main steps:

(1)**Feature extraction**: videos or images are given as input to the model, and frames are extracted at regular intervals from videos and sent to Keras multiperson pose estimation to extract key points. From these key points, 12 joint vectors are calculated. For all these 12 joints, angles between the *x*-axis and joints are found, respectively

.(2)**Classification**: these angles are sent to the classification model to classify the pose among 6 yoga poses. These angles are compared with an array of 12 angles of the classified pose. This array contains average angles of 12 joints from the dataset.

(3)**Feedback generation**: the differences are calculated, respectively, for every angle, and suggestions are revealed for every angle. Based on the sign of difference, whether to rotate joints in clockwise or anticlockwise direction is given as feedback output.

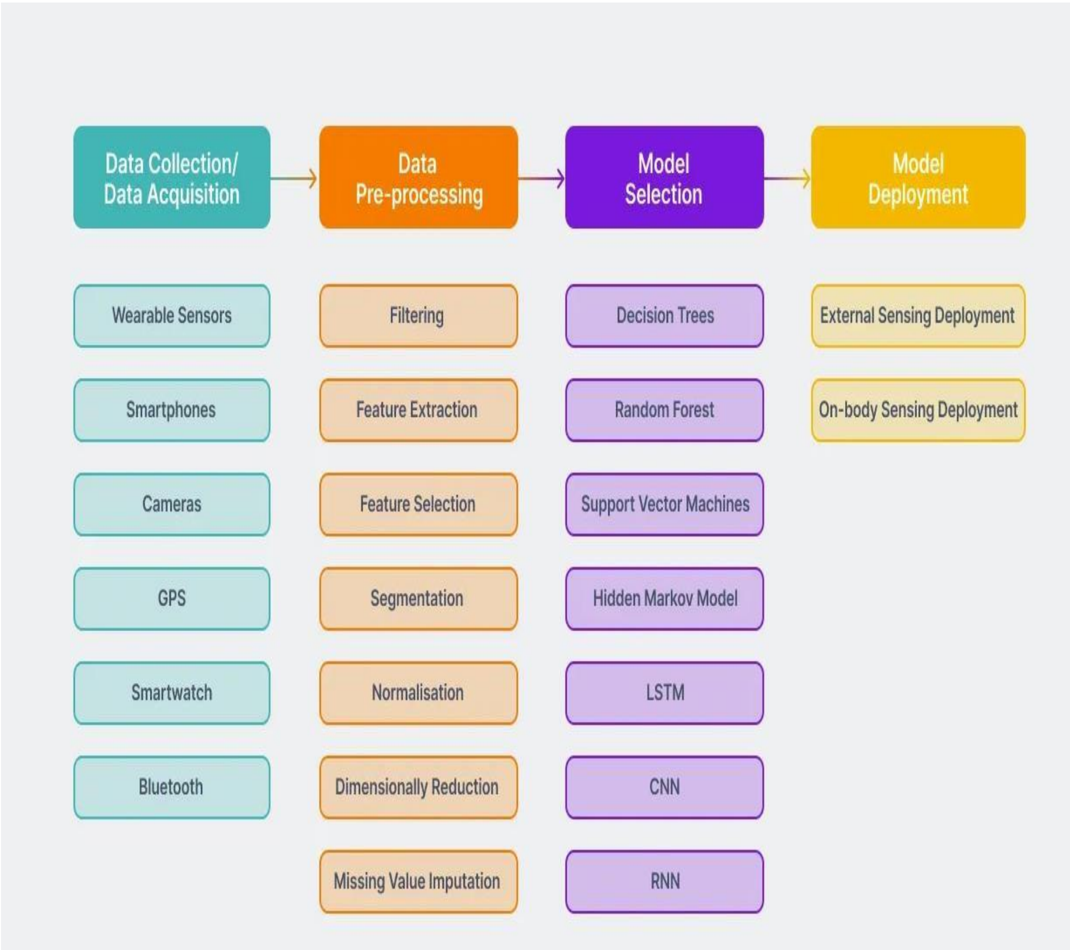


Fig:1

1. Data collection

The data for HAR is usually acquired by sensors attached to or worn by the user. Standard HAR sensors include accelerometers, gyroscopes, magnetometers, and GPS sensors.

Accelerometers can detect changes in movement and direction and quantify velocity across three axes (x, y, and z). Magnetometers can sense magnetic fields and order, whereas gyroscopes can measure rotations and angular velocity. GPS sensors are capable of helping track a user's whereabouts and movements, although they are less typically employed for HAR because of their substantial electricity consumption and limited indoor precision. Sensor data is often captured as time-series data, for each sample reflecting sensor measurements at a specific point in time (e.g., every second).

2. Data pre-processing

Data preprocessing is an essential stage in Human Activity Recognition (HAR) since it cleans, transforms, and prepares raw sensor data for future analysis and modeling. Some standard preparation processes include:

1. **Filtering**: Filtering is a signal processing technique for removing noise and undesirable signals from raw sensor data. Depending on the frequency range of the signs of interest, typical filters used during HAR include low-pass filters, high-pass filters, and band-pass filters for noise suppression and image enhancement.
2. **Feature extraction**: The features used are determined by the type of action and the sensor modality. Accelerometer data, for example, can be used to extract features such as mean, standard deviation, and frequency-domain properties, such as Fourier transformation and wavelet transformation parameters.

3. **Feature selection:** The process of selecting features is used to minimize the feature space's degree of dimensionality and increase the precision and effectiveness of activity identification algorithms. This entails deciding on the most relevant characteristics based on their exclusionary ability, association with activity labeling, and redundancies with other features.

4. **Segmentation**: To extract the temporal aspects of the activities, segmentation requires separating the sensor information into more compact segments or windows. The size and overlap of the window are determined by the duration and intensity of the activity being watched. After that, the segmented data is used to compute the characteristics of each window.

5. **Normalization**: Normalization is the process of scaling features to have a neutral mean and variance of 1 to guarantee that they are similar across sensors and participants.

6. **Dimensionality reduction**: Principal component analysis (PCA) and t-distributed stochastic neighbor embedding (t-SNE) are dimensionality reduction techniques that have the potential to minimize the feature space's degree of dimensionality and removeredundant or irrelevant features.

7. **Missing Value Imputation**: Imputation is about filling in incomplete sensor data. The incompletion may happen due to device malfunction or data transmission faults. Simple imputation approaches can be utilized for missing values, including mean or median interpolation.Data preparation is a crucial stage in HAR since it affects the precision and dependability of activity identification models.

3. Model selection

Several machine learning algorithms may be used to recognize human activities. The choice should depend on data complexity, available resources, and performance criteria. Here are some popular HAR machine learning models:

Decision trees: Decision tree algorithms are straightforward models that deal with non-linear interactions among features and labels. They can be used for *classification tasks* in Human Activity Recognition based on sensor data such as accelerometers or gyroscope readings. Decision trees are easy to interpret and can handle

1. both continuous and categorical data, making them useful for gaining insights into the most important features of a given classification task. However, they may suffer from *overfitting* and fall short in scenarios where the input data is highly complex or noisy.

2. **Random forest**: Random forests are decision tree ensembles that can manage noisy and high-dimensional data. They resist overfitting and can deal with missing values. On the other hand, random forests may take more computational resources than decision trees and might need to perform better on tiny datasets.

3. **Support Vector Machines**: SVMs are robust models that deal with nonlinear and lineardata. They can deal with high-dimensional data while being less susceptible to overfitting. However, they may need careful hyperparameter tweaking and can be computationally costly with massive datasets.

4. **Hidden Markov Models**: HMM is a statistical model used in HAR to recognize sequential patterns in sensor input. HMMs are very useful for time-series data and may be effective for complex activities with several steps.

5. **Convolutional Neural Networks (CNNs):** *CNNs* are *deep learning* algorithms well-suited for picture and time-series data, such as gyroscope and accelerometer data. These algorithms can efficiently handle hierarchical features from raw data and manage complex data patterns but may need more computation power than other models and are prone to overfitting.

4. Model deployment

Human Activity Recognition (HAR) systems are deployed using one of two methods:

1. **External sensing deployment:** In this method, external sensors (including cameras or motion detectors) are placed in the surroundings to collect information on human activities. A HAR model running on a different computing machine processes the sensor data. This method is excellent for monitoring actions in public places or when the person being tracked cannot wear a gadget.

1. **On-body sensing deployment:** Here, the sensors (such as a wrist-wear accelerometer) are worn by the person being observed to capture information about human activities. A HAR model, possibly locally on the smartwatch or a distant computing system, processes the sensor data. This method effectively monitors performance in private locations or when the person being monitored can wear a gadget.

Initially, the image of a yoga practitioner performing an asana was captured by a camera and fed separately to the four deep learning architectures, which then estimate the pose performed by the practitioner by comparing it with the pretrained model. If it does not match any of the five asanas, an error was shown.

Twenty practitioners in the age group of 18–60 years performing different postures in real time were captured and fed separately to the proposed architectures, and a comparison of the estimated accuracy was done.

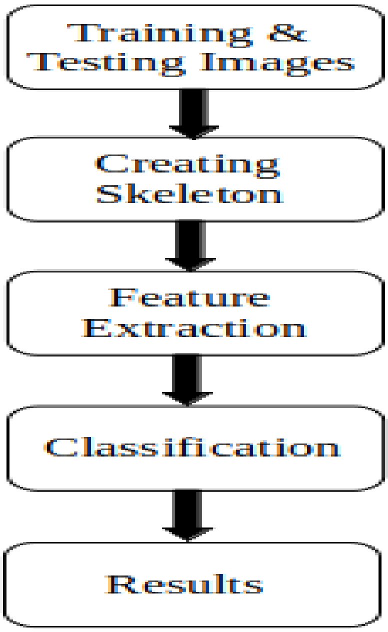


Fig 2

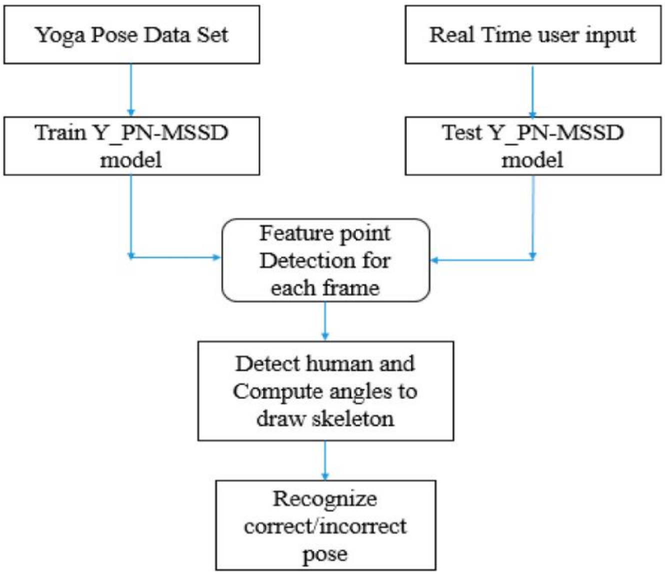
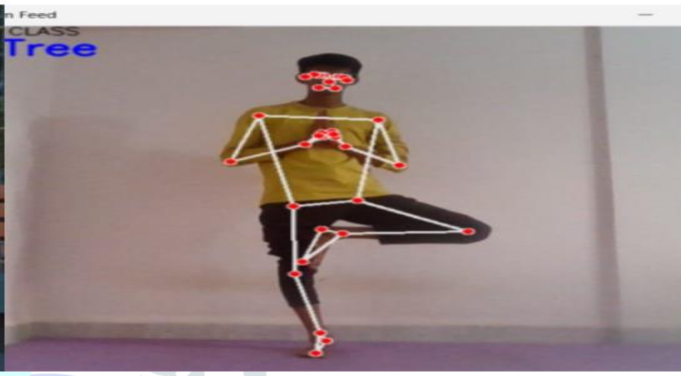


Fig.3

Pose estimation for Human activity postures was done using different proposed techniques. The results of pose estimation were shown for each of the three activity for all the four architectures used. For simplicity, the images of the same individual were shown (after taking consent) for all estimations and comparisons. The five yoga poses considered for posture estimation are as follows:



IV. RESULTS AND DISCUSSION

Our system successfully detects the human activity and make predictions accordingly we worked on human activity which are yoga pose, running , health care, exercises , sports etc. Our model gives 100% accuracy so from that we say our system does an excellent job. It display the name of yoga , exercises , Sports and the probability range from 0 and 1. If the probability is 1 or near to 1 then it predicts the right yoga pose, exercise. If the probability is near 0 or 0 then the system prediction is false. This helps the user to do yoga , running, sitting, sports correctly. We made a desktop application it is user-friendly. To take benefit of our system user needs to successfully register and log in. Here are some snaps of real-time Human activity recognized.

II. FUTURE SCOPE

Human Activity Recognition can benefit various applications in fields like smart home monitoring, healthcare services, security surveillance, childcare etc. In future this application can be updated by using object activity recognition in which activities performed by objects can also be tracked and analyzed. Application of integrated large datasets can be done to identify the activity taking place as slower rate of time. Even very subtle or minute variations should be recognized by the system. The data of actor performing the anomalous activity can be stored and identification of actor can be done if not caught in the first place. Activities that are of reoccurring manner should be stored to save time and space during recognition process. Implementation of such model can also be done in Government authority section. Much more developments for improvisation in accuracy and dealing with issues related to optical identity and background clutter of image can be done.

III. CONCLUSION

The time-distributed CNN layer discovers patterns between key points in one frame and also the SVM reviews in the latest frames for the memory of previous frames, the results build the system even a lot of strong by minimizing the error because of false key point detection. Because the frames of Yoga pictures are sequential. We tend to plan a Yoga identification system using a conventional RGB camera. The dataset is collected using an HD 1080p Logitech digital camera for fifteen people (ten males and 5 females) and created publicly available. The machine learning-based framework eliminates the options giving the addition of the latest asanas by simply preparing the model with new data. We tend to apply the time-distributed CNN layer to detect patterns between key points during a single frame and the LSTM to study the patterns found within the recent frames. Using LSTM for the memory of previous frames and polling for denoising, the results build the system even more strong by minimizing the error because of false key point detection. Since the frames of a Yoga video are sequential. The same approach can be used for posture recognition in varied tasks likes, sports, healthcare, and image classification.

VI. REFERENCES

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