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IMPLEMENTATION AND ANALYSIS OF MODIFIED MOTION DETECTION ALOGRITHM FOR MONITORING OF EXERCISE EXECUTED

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ABSTRACT
Physical exercises are extremely helpful for personal wellbeing, but they may also be harmful and even risky if done incorrectly. When there is no adequate instruction and input to match the workouts to the right motions, errors in exercise occur. Deep learning has achieved considerable performance and precision in image recognition and classification in the computer vision area. As a result, technique for detecting correct exercise posture is built in this research work. The accuracy model is used in conjunction with the classification of right and incorrect postures using the MATLAB tool. The approach of motion detection is a significant part of computer vision technology. Its aim is to incorporate real-time tracking, real-time video recording, and object detection in the target region, as well as to store data that users are involved in as a foundation for exercise. This research paper highlights on how to execute motion detection on real-time video in an optimal manner. The standard motion detection algorithm is modified by implementing the statistical model of image recognition, and the enhanced motion detection algorithm is introduced in the framework.

Keywords: Motion detection; Background estimation, Pose estimator, image initialization

INTRODUCTION
Physical activity plays a significant role in maintaining physical health among human. They are classified into four categories based on their cumulative impact on the human body. Flexible workouts include physiotherapy and stretching exercises as well as aerobic exercises like walking. The anaerobic activities like weight training, physical conditioning, and power exercises [1]. Physical fitness is described as any scheduled, organized physical exercise that aims to enhance one or more aspects of physical health [2]. However, various research indicates that exercise benefits neuroplasticity and the brain's capacity to self-repair [3]. Exercise is often treated as thefoundation of treatment management of any injury. Exercises like shoulder presses, squats, and deadlifts are good for health and safety, but they can also be risky if done wrong. The intense loads used in above exercises may trigger serious muscle or ligament injury.

Many people involve in a daily workouts routine, but they do not retain correct shape (pose) [4]. This may occur because of shortage of formal training via classes or a personal trainer, as well as muscle exhaustion or applying heavy load. This research aims that people do workouts in the proper posture and study provides correct and incorrect workout data sets to determine a correct posture that would be helpful for rapid body growth.

Detection of motion of an object from a sequence of a moving frame can be done using “background subtraction” when the camera is at a stationary position. This method works on the principle of building a prototype of the static site that is ‘objects with no motion’ called “background”. Then the background is compared with every setof sequences to differentiate regions of the motions in moving frames called as “Foreground” that is ‘moving objects’ in the frame. Motion Detection for any physical exercise is achieved through numerous actions: Firstly, construct a robust, adaptive background model that contract with quick adjustments, enduring changes in the scene, and object obstructions. This model is applied to get foreground pixels utilizing the background subtractionmethod. Afterward, object detection and noise cleaning are utilized, monitored through human modeling to identify, and monitor exercises. Used Techniques are following:

- Human Model
- Surveillance
- Motion Analysis
- Image Processing
- Tracking
- Motion Detection

It is also well accepted that daily exercise improves both physical and psychological health. Furthermore, the incidence of obesity and other chronic disorders, such as asthma, diabetes, or Alzheimer's disease, is minimized, and physically active individuals have a higher standard of life as well as an elevated mental and cognitive sense of well-being [5]. Body weight workouts are done by utilizing just the athlete's own body weight without the use of any mechanical reinforcement [6]. Initially, they were performed as part of school activities or special forces exercises. They are now often used in conjunction with endurance and free weight exercise, such as in CrossFit or obstacle races. The prevalence of exercise among athletes, as well as the pervasiveness of mobile devices, are explanations for the large number of current fitness applications.

The reasons are often incorrect execution of exercise is the lack of a warm-up, or incorrect placement of individual extremities. For example, after identifying potentially unsafe faulty positions, the user should be alertedand advised as to which detail of the exercise was done incorrectly. As a result, casualties caused by unsupervisedexercises could be dramatically decreased, and ineffective or suboptimal exercises may be prevented. In general, posture is characterized as the comparative arrangement of body parts in relative to the physical condition, for example lying down, sitting, or standing [7].

Right posture entails a straight away spine that retains the spine's natural curve in the human body[8]. Correct posture decreases stress on the user through maintaining the muscles and skeleton in alignment. In all places, involving standing, lying down, and sitting, this relaxed musculoskeletal condition supports the body's supporting mechanisms and avoids injury or progressive deformation. Furthermore, proper posture requires that the body not be angled upward, backward, left, or right [9]. As a result, the significance of proper stance should be stressed, and keeping proper sitting position is particularly crucial since the pressure on the back is larger in a sitting posture compare with standing or lying down posture, while some variations can exist [10]. Working with a machine necessitates keeping a sitting pose for an extended period, making it extraordinarily challenging to retain proper posture [11]. People's postures appear to shift due to behaviors, for example slouching and crossing their knees, and they keep a poor pose despite their awareness of wrong posture and capability to provide proper posture. If incorrect postures happen to a routine at a young age, people can conform and find them relaxed, which can put pressure on the pelvis, spine, tendons, joints, muscles, bones, and discs, leading to weakness and deformation [12].

Thus, improper exercises like unnecessary machine usage, the use of desks and chairs that are not the right height, a deficiency of health care education, a lack of exercise, holding large school bags, and unhealthy postures while learning or seeing television impact the shape of muscles, distort the body, and induce irregular growth, making it impossible to maintain correct posture [13]. Improper pose has several detrimental impacts on the back. For example, Joint imbalance restricts the mobility of tendons and joints, making regular exercise and movement impossible and the incorrect pose may also result in pain [14]. Furthermore, such a stance suggests an incomplete interaction between body components, induces inefficient equilibrium due to tension on the body's supporting systems, and inhibits proper functioning of the body's structures. This can lead to cosmetic issues as well as discomfort and physical disability [15]. As a result, correct posture is critical for preserving body equilibrium, proper alignment of supportive tissues, and good body functioning; therefore, to conclude that correct posture is a requirement for a balanced existence is not an exaggeration[16]. However, there are not sufficiently standardized services for posture adjustment open to the general population. This research work describes the recognition of moving objects in image classifications of the moving video of the physical exercise.

Motion Detection

Motion detection technique is used in this research for detection of correct or incorrect posture in physical exercise among the human body which reduce the chance of having incorrect posture and injuries. Motion detection is the method of considering an image frame involving a moving body to image processing methods thatallow motion tracking. Using background segmentation or differential methods, involving the moving features of the images are removed through disposal the motionless sections of the images to isolate the moving component. Machine learning and Computer vision approaches have eliminated the need for motion recognition. Using hardware tracking systems in a managed setting to a state-of-the-art algorithm that merely allows a sensor to trackand analyses motion.

Pose Estimator

To mark RGB images for pose estimation using DCNN. After experimenting with a variety of cutting-edge pose estimators, apply the pre-trained setup, open Pose for pose recognition. Open Pose uses component affinity fields, which are vectors that encode the location and orientation of limbs, to implement a novel method to pose estimation. The model is made up of a multi-stage Convolutional Neural Network with binary branches, one for learning the trust mapping of a main point on a picture and the other for learning component affinity fields [17]. Open Pose is reliable and effective, as well as scalable to many persons without increasing run-time.

Background Image Initialization

There are many methods for obtaining an initial background image; however, the time average approach cannot deal with image background issues. Since the method of taking the median from continuous multi frame can easily and reliably solve this problem. As a result, the median method is used for background initialization.

Background Update

For the background model to respond best to light transitions, it is important to refresh the background in real- time to correctly remove the moving entity. The camera is attached; the background model will stay reasonably steady in a long-time span.

Extraction of Moving Object

The dynamic threshold approach is ideal for removing moving objects by utilizing dynamically modified threshold values due to the lighting variations of the two pictures. The influence of light changes has been efficiently suppressed by this method as shown in Figure1.

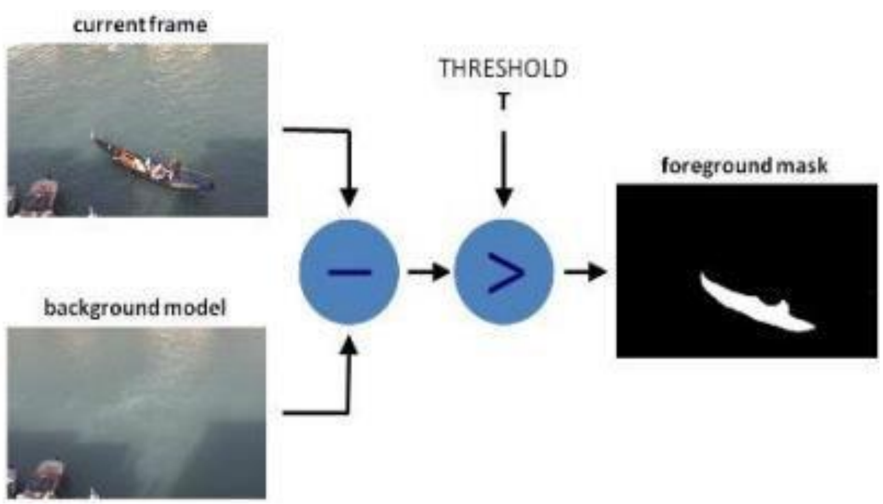

Figure 1: Background Subtraction [19]

REVIEW OF LITERATURE

Haas et.al [20] have suggested a home-centered physiotherapy technique centered on the Kinect. They created a device that uses a Kinect camera to monitor the motions of human extremities, enabling an individual to perform workout movements prescribed by a physiotherapist. They used the Cosine rule to calculate the extremity lengths and angle between the necessary joints to determine the correctness of the motions in a specific exercise.

Fitlinxx [21] is a touch screen interface that is intended to be used on weightlifting equipment in a gym. The user must first log into the machine before beginning any exercise. The machine then calculates the number of repetitions the user makes. However, this computer must be installed on any system in order to detect machine exercises. As a result, the method is costly since the computers must be outfitted with the device in order to monitor the exercises.

Slama et al [22] suggest modelling an occurrence as a dynamical structure with an observability matrix described as an aspect of a Grassmann manifold and developing a new behavior recognition learning algorithm centered on a vector representation formed by integrating local coordinates in tangent spaces related through various groups.

Zhou et al. [23] suggest a method for studying a pose lexicon composed of semantic poses identified through textual data and their corresponding visual poses determined through visual attributes, accompanied by determining the maximal translation likelihood of a series of semantic poses provided a stream of visual pose candidates for action identification.

Yiyang et.al [24] uses photographs from a fisheye camera taken every 30 seconds to calculate forecast horizons of 1, 2, and 3 minutes. The technique employs a Support Vector Machine (SVM) for direct sky irradiance, followed by an optical flow algorithm to map the passage of clouds and obtain the occlusion to the light. The irradiance is then forecast using an analytical algorithm. The authors preprocessed the picture by flattening it, which may result in data loss and, as a result, a reduction in accuracy. Furthermore, the sparse optical flow technique is used for movement analysis, which measures the corners but does not account for cloud deformation specifically.

To solve this challenge, M. Mazoor et.al [25] stated a Linear SVM based approach, and the Scale Invariant Transform Function (SIFT) algorithm was used to obtain elements and introduce local interest points. The bag of terms model is used for grouping.

Dong et al [26] stated a classification system centered on forward view images of automobiles that would use a semi-supervised convolutional neural network. Dong et al. produced a BIT-data set containing of 9850 high-resolution images of the cars' front views. The machines work at 96.1 percent efficiency during the day and 89.4 percent efficiency during the night.

Denis Kleyko, et.al [27] have been compared with various deep learning motion detection algorithms. The processing of data included 3074 tests. The classification was performed through logistics regression, neural networks and vector support systems.

Zell et al [28] take a fascinating approach to analyzing human motions in which the body is described as a mass-spring mechanism and the stresses and torques that flow across the joints of the body are calculated. They discovered that through utilizing activity parameters and expert input, they can simplify physical research by analyzing the angles and distances between joint main points and give important feedback to users without requiring a complete physical simulation.

Nweke et.al [29] suggest deep learning-based smartphone and wearable sensor-centered human behavior recognition. (MWSHAR) is a moniker for a group of people who Feature isolation increases the procedure's functionality while reducing running time and complexity. Nonetheless, with today's multimodal and comprehensive sensor data input, immediate identification of human behavior is dependent on handcraftedfeatures incapable of handling complicated functions. Furthermore, through combining wearable sensors orsmartphone and deep learning methods for feature learning, it provides variety, higher generalization, and solves problems in human differentiation. The aim of this research is to compile comprehensive outlines of deep learning methods for detecting human activity using cell phones and other readily accessible sensors.

For real-time behavior categorization, Ravi et al [30] suggested a deep learning-based function (FL-DLA). Theuse of this collective framework helps to address a few of the drawbacks of deep learning methods that include node computation. Spectral-domain preprocessing is used to enhance the recommended form of in-node computation in real-time before the data is moved to the deep learning context. The classification accuracy of our proposed deep learning approach is evaluated in the lab and on real-world data sets utilizing state approaches. Their outcomes determine the efficacy and effectiveness of a variety of methods including the two approaches employed in their optimized pipeline across a variety of human activities.

Ma and Pang [31] used sports medical evidence to train the Convolutional Neural Network Algorithm (CNNA). This article starts with an improved CNN deep learning approach for ensuring accurate diagnosis and risk assessment of sports-related diseases. It employs a self-modified algorithm, which is augmented through self-coding tensor convolution. The Neural Network model aids in the study of multidimensional sport medicine results. Finally, this paper suggests a cloud-based hardware-on-the-loop modelling paradigm for developing a smart medical data network for sports medicine. Experiments show that this approach provides technological guidance and references for applying an accurate cloud-based fusion framework. With the massive increase in input, the conventional deep learning algorithm is slow and unavoidable in athletics health data mining.

Hannink et al [32] proposed using a (DCNN) to map stride comprehensive inertial sensor data to stride duration. Because of its distinction from the stride concept, the proposed solution is not subject to the technique limitations that limit the usage of state-dual integration approaches. Furthermore, the precision of the benchmark dataset may be increased. A more precise motive stride duration measurement may provide new insights into neural development disorders or early signals. Because of the stage statement's freedom, previously unknown diseases may now be investigated in mobile gait analysis by retraining and the execution of the suggested method. As a result, the dataset used for testing can capture the problem's most important uncertainty. Any application to a population other than those used for training could result in a lack of model validity.

Table 1: Various techniques used for motion detection

Author	**Technique used**	**outcomes**
Haas et.al[20]	Kinect camera to monitor the motions of human extremities	An individual to perform workout movements prescribed by a physiotherapist. They used the Cosine rule to calculate the extremity lengths and angle.
Fitlinxx [21]	Touch screen interface that is intended to be used on weightlifting equipment in a gym	The machine then calculates the number of repetitions the user makes. However, this computer must be installed on any system in order to detect machine exercises.
Slama et al [22]	Dynamical system with an observability matrix described as an aspect of a Grassmann manifold	Developing a new action recognition learning algorithm based on a vector representation generated by integrating local coordinates in tangent spaces associated with various classes.
Yiyang et.al [24]	Uses photographs from a fisheye camera	Result in data loss and, as a result, a reduction in accuracy
M. Mazoor et.al [25]	Linear SVM based approach,	Used to obtain elements and introduce local interest points
Dong et al [26]	Semi-supervised convolutional neural network	Dong et al. produced a BIT- data set containing of 9850 high-resolution images of front views.

Denis Kleyko, et.al [27]	Deep learning motion detection algorithms	The classification was performed through logistics regression, neural networks and vector support systems.
Zell et.al [28]	Fascinating approach to analyzing human motions	Analyzing the angles and distances between joint main points and give important feedbackto users without requiring a complete physical simulation.
Nweke et.al [29]	Deep learning-based smartphone and wearable sensor-centered	The aim of this research is to compile comprehensive summaries of deep learning methods for detecting human activity using cell phones and other readily accessible sensors.
Ravi et al [30]	Deep learning-based function (FL-DLA).	Their outcomes determine the efficacy and effectiveness of a variety of methods including the two approaches employed in their optimized pipeline across a variety of human activities.
Ma and Pang [31]	Sports medical evidence using the Convolutional Neural Network Algorithm (CNNA).	This approach provides technological guidance and references for applying an accurate cloud-based fusion framework
Hannink et.al [32]	Using Deep convolutional neural network	The dataset used for testing can capture the problem's most important uncertainty

BACKGROUND STUDY

Over the past few years, computer-based work and analysis have become the primary selection for everyone. Motion detection algorithms for image processing can be especially useful for any physical exercise monitoring over computer applications. This research work describes the recognition of changing objects in image sequences of the moving video of the physical exercise. Moving entity identification in an image series is a critical low-levelactivity for various computer vision systems, for example video control, traffic management, and sign language identification. Context subtraction is a technique that is commonly used while the camera is stationary. The basic idea behind these approaches is to create a representation of the static scene known as backdrop, and then evaluate any frame of the series to this context to distinguish the areas of irregular motion known as foreground.

PROBLEM FORMULATION

A pretrained real-time method named Open Pose to detect human body key points in videos for the pose estimation component. (For more information on Open- Pose and our rationale for selecting this method, see Technical Approach.) This model works right out of the box, making it easy to set up for users of program. Using Open Pose helps us to use state-of-the-art pose estimating algorithms for our challenge when focusing on the real assessment of exercise posture. Depending on the algorithm, there is an evaluation of pose marker in variousways: for heuristic algorithms, supply in each video for assessment, while for ML algorithms, estimation is done by dividing the video dataset into train and test sets and reporting effects on the test set. The aim of this study is todevelop a system for detecting incorrect body movements during resistance training and providing input. The architecture is created with the MATLAB platform, which allows it to create applications and run mathematical algorithms.

RESEARCH OBJECTIVES

1. To access the knowledge, practice and concerns related to motion detection.
2. Identification of correct or incorrect posture of executed exercise.
3. Transformation of absolute differential image to Gray Image.
4. To identify the barriers in Evaluation and Assessment of Detection Algorithms.

5. To show the simulation of the research study to represent the effectiveness of the research with validation points.

RESEARCH METHODOLOGY

In the dataset healthy adult subject having experience of performing the physical exercises without any previous surgery were recruited to maintain the dataset of human exercises on activity recognition chain using on-body inertial sensors. ARC (Activity Recognition Chain) as a universal-function structure for constructing and assessing activity recognition systems.

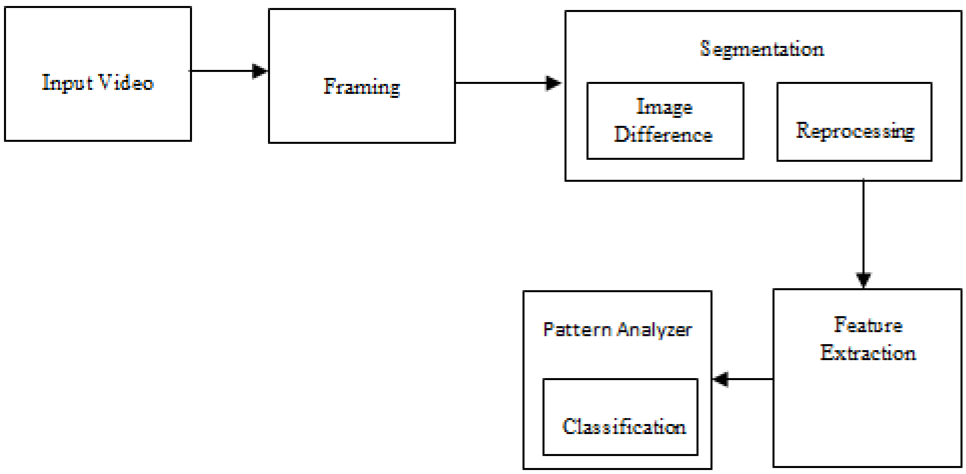

Figure 2: Computational flow of activity recognition chain

The behavior classification system is represented in Fig 1 and follows the activity identification chain (ARC) structure suggested by [33]. Following is a brief overview of how each stage of the ARC was designed and evaluated.

- **Input Video**

The real-time camera carries the input video and that can be taken from predefined data set.

- **Framing**

In the framing section, there is a need to translate the input video to the frame using any tool. A mixture of frames is called a video. Each video has several frames, so frames are taking by using that value.

- **Segmentation**

It is primarily the deciding action for every image processing program. This protocol recognizes the area of the picture generated by the application. Segmentation is handled via classification of all these ROIs (Region of interests) through the nearby region. After classifying the ROI background subtraction can be done.

a. Current And background image

The first frame (image) is named background image after translating video to frames, and other than the initial image is an existing image. These images are not identical at the time of moving video detection object. And at the time of non-moving object identification, these latest images are often similar.

$$\Delta t = \lambda \frac{1}{(M \times N)} \sum_{i=0}^{N-1} \sum_{j=0}^{M-1} |F(i,j) - B(i,j)| \quad (1)$$

Then,

$$Dif\_frm(x,y) = 1 \ |Fk(x,y) - Bk - 1(x,y)| > t + \Delta t \quad (2)$$

BACKGROUND SUBTRACTION

This implies that effectively subtract the current image and the background image, and every time the current image is changed, the background image is fixed. Through this technique, one can easily detect the moving object.

If the output is 0 that implies no moving. And If the output is 1 that implies moving object detected.

In background estimation, the recursive approximation temporal median was suggested to estimate the background. The significance of this approach lies in the robustness of the non-linearity offered in comparison with the linear recursive average and the exceptionally low cost of the computation. This research analyzes some of the operator's interesting properties, implements the principle of ∑-∆ estimation, and uses it to get a nearby adaptive motion detection. For every pixel of the series that offers a pixel-level decision framework, the ∑-∆ filteris introduced and applied to calculate two directives of sequential statistics.

∑-∆ Background estimation

It is the input sequence for - estimation, and Bt is the approximate history. The sign function sgn is specified as sgn(a) = 1 if and is less than zero, sgn(a) = 1 if an is greater than zero, and sgn(a) = 0 if an is equal to zero. So, at each frame, the approximation is actually incremented by one if it is less than the sample or decremented through one if it is greater. If It is a distinct random signal, the combination of the number of indexes s t such that Is Bt and the number of indexes s t such that Is > Bt converges to one in the mean. As a result, Bt approximates It's median. However, in addition to detecting changes in time-varying signals, this filter has some intriguing properties. Certainly, viewing this history calculation as a simulation of a time-varying analogue signal's digital conversion utilizing - modulation (A/D conversion utilizing just contrast and elementary increment/decrement, thus the term - filter). Since the accuracy of the - modulation is restricted to signals with absolute time derivatives less than unity, the modulation error is proportional to the signal's variance intensity, which corresponds to a motion probability estimate of the pixels here. The absolute discrepancy between It and Bt is then used as our firstdifferential estimate: the difference t in specified point 2. This filter is often applied to calculate the time-variance of the pixels, which represents their motion movement measure and is applied to determine if the pixel is more likely to be ‘‘moving" or ‘‘stationary."

Reprocessing

The difference image obtained includes the motion region as the complexity of the background, and it also contains a considerable volume of noise. However, Noise ought to be eliminated.

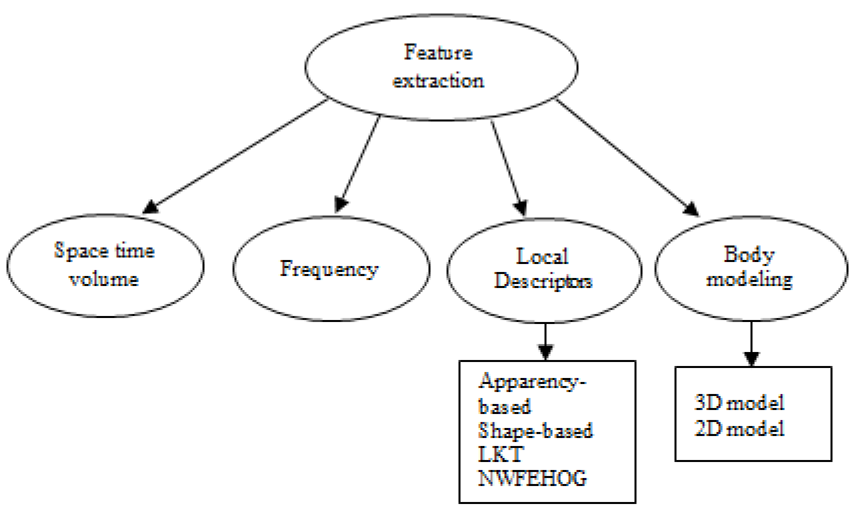

Figure 3: Feature Extraction Categories

Feature Extraction

The fourth stage of the proposed method extracts and represents characteristics of segmented structures for example structure, silhouette, colors, and movements in the form of features. As shown in Figure 3, the features can be divided into four categories: space-time detail, frequency transform, local descriptors, and body modelling.Figure 3: Feature Extraction Categories. The space-time information is first measured. The image features of the space-time volume (STV) are generated by concatenating the consecutive silhouettes of artefacts along the time axis. The derived 3D XYT volume will catch the consistency of human activity (along x-y spatial coordinates andtime). Frequency domain data may be used in comparison to the spatial-temporal domain view. More explicitly, the discrete Fourier transform (DFT), which has long been used to explain the geometric structure of objects. STVand DFT are global features that consider the whole scene. As a result, certain local descriptors are taken into account. Local descriptors such as scale-invariant function transform (SIFT) and histogram of directed gradient (HOG) capture picture patch characteristics. They are preferably invariant to context clutters, appearance, and occlusions, and in certain situations even rotation and size.

Pattern Analyzer

"Patterns may be a physical item, concept of a physical items, or ideas about an abstract collection." Analysis describes something you saw or perceived. That is the method by which an unexplained entity is classified and passed on a label. Two pattern detection functions are categorization and clustering used to recognize image medical research. The classifiers may also be classified as parametric and non-parametric approaches in general. Parametric assumes that the class-compatible type of distribution of the given characteristics are well defined, andthe non-parametric system contains limited hypotheses as far as the shape of distribution is concerned. Parametric classifiers that evaluate parameters such as variance and mean by assuming a distribution of data for that provided. Which may determine the form of the moving object by using the context subtraction method (if the background picture and current image change). No moving target is detected otherwise (if there is no variation in the background image and current image).

Working Steps:

1. In this paper one video file first taken as input, then using "n number of frames" to convert the video to "n number of frames". Save the frames in any format with the correct format and naming.
2. Image resizing is used in frame separation.
3. In the first frame of the film, the background picture is considered other than the first one considers the new picture (say as the previous image). and the background picture is unchanged, but based on iteration and video, the current image is different. The output is in the form of differential images through subtracting the background image from the current image. Then transformation of any current image from RGB to Greyscale before background subtraction.
4. For this divergence image applied thresholding and dynamic thresholding by taking an example:

   Thresholding, Difference image > 35=1 otherwise 0

   For dynamic thresholding, Difference image >100=1. Otherwise, 0
5. After background subtraction, the current image is updated.
6. Tracking of objects using morphological functions is done. If the background image and the current image are analogous, meaning that no moving object detected or moving Object detected. For, more than a single object different outbox for various colours is used.

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Implementation Results

Input 1:

Figure 4: Input of result 1

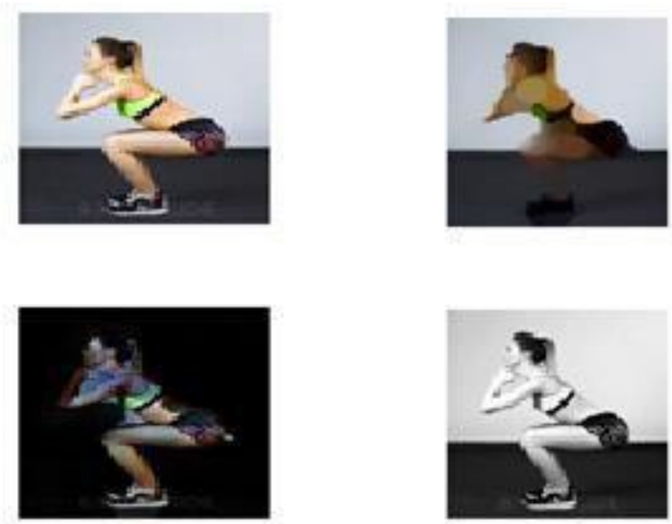

Figure 5: Image enhancement stages of result 1

The simulation result of input 1 comprises of:

1. Confusion matrix

0.9333	0.0667
0.2333	0.7667

matrix [1]

2. Inertial sensor coordinates of exercise posture of input 1 are given below

Table 2: Inertial Sensors coordinates of input 1

X coordinates	Y coordinates
-0.6122	0.7630

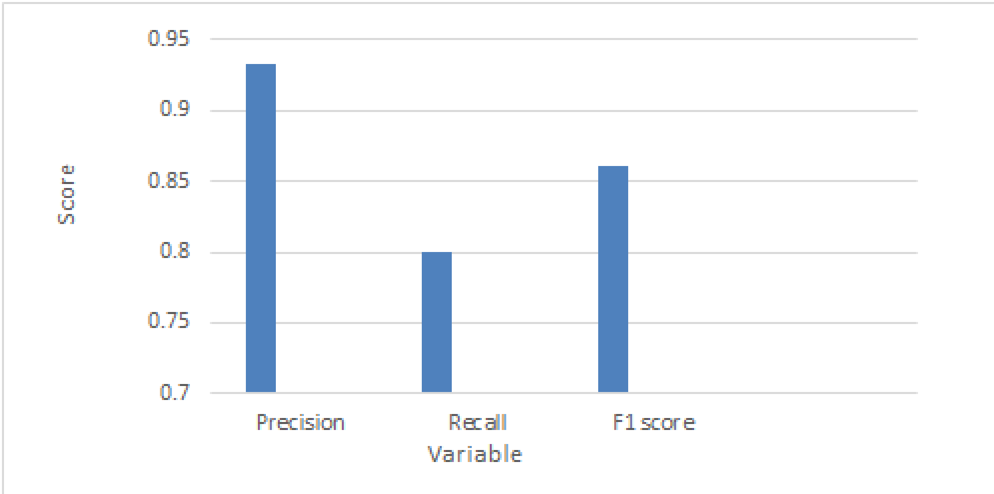

Figure 6: Simulation Result of input 1

```
>> main
Inertial Sensors coordinates are
   -0.6122      0.7630


confMat =

    0.9333      0.0667
    0.2333      0.7667


ans =

    'loaded image is of a correct_posture '

 Accuracy is = 85 %
 Precision is = 93.3333 %
 Recall is = 80 %
 Fscore is = 86.1538 %
```

Figure 7: provides better insight on precision, recall and F1 score.

3. Using confusion matrix, the accuracy of given model is 85%. F1 score, Precision and Recall provides better insight into the posture detection as shown in above graph of figure 7.

Input 2:

Figure 8: Input of result 2

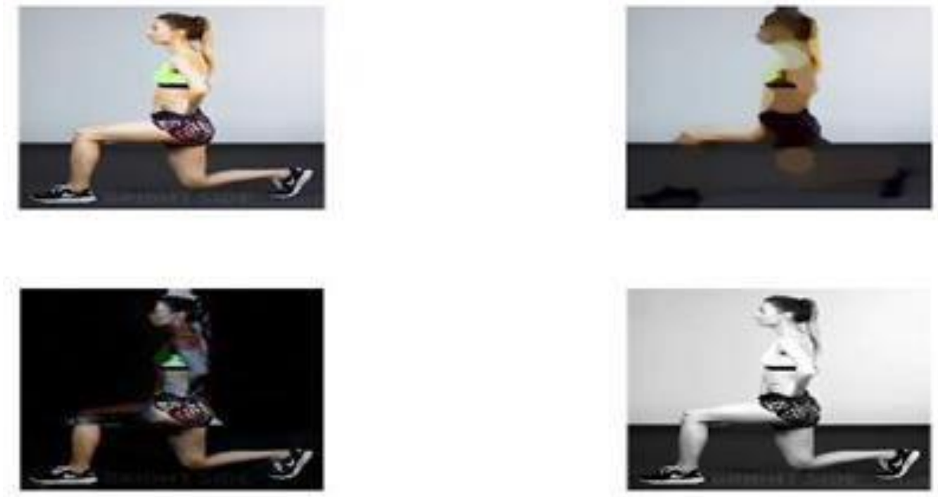

Figure 9: Image enhancement stages of result 2

```
>> main
Inertial Sensors coordinates are
   -0.2259   -0.6977


confMat =

    0.6833    0.3167
    0.0667    0.9333


ans =

    'loaded image is of a correct_posture '

 Accuracy is = 80.8333 %
 Precision is = 68.3333 %
 Recall is = 91.1111 %
 Fscore is = 78.0952 %
```

Figure 10: Simulation Result of input 2

The simulation result of input 2 comprises of:

1. Confusion matrix

0.6833	0.3167
0.0667	0.9333

matrix [2]

2. Inertial sensor coordinates of exercise posture of input 2 are given below:

Table 3: Inertial Sensors coordinates

X coordinates	Y coordinates
-0.2259	-0.6977

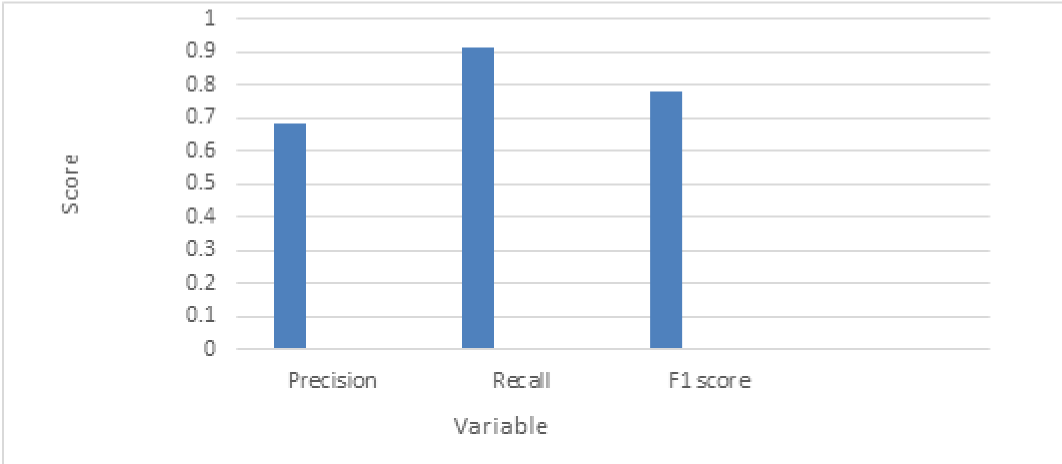

Figure 11: Provides better insight on precision, recall and F1 score

3. Using confusion matrix, the accuracy of given model is 80%. F1 score, Precision and Recall provides better insight into the posture detection as shown in above graph of figure 11.

Input 3:

Figure 12: Input of result 3

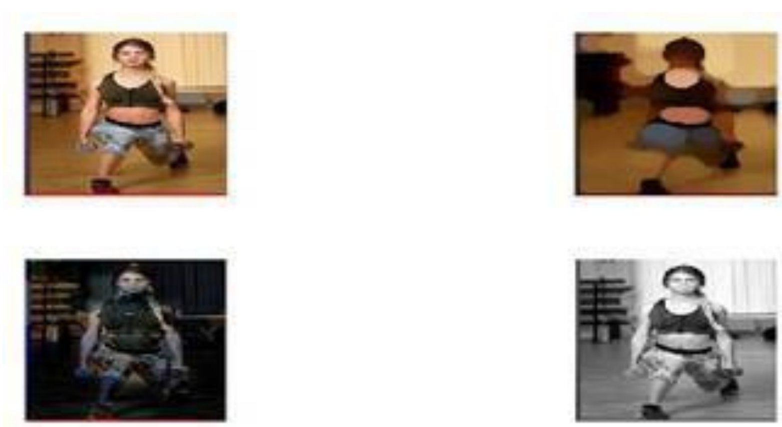

Figure 13: Image enhancement stages of result 3

```
>> main
Inertial Sensors coordinates are
    0.5551    0.4714


confMat =

    0.5167    0.4833
    0.2333    0.7667


ans =

    'loaded image is of a incorrect_posture '

 Accuracy is = 64.1667 %
 Precision is = 51.6667 %
 Recall is = 68.8889 %
 Fscore is = 59.0476 %
```

Figure 14: Simulation Result of input 3

The simulation result of input 3 comprises of:

1. Confusion matrix

0.5167 0.4833
0.2333 0.7667 matrix [3]

2. Inertial sensor coordinates of exercise posture of input 3 are given below:

Table 4: Inertial Sensors coordinates

X coordinates	Y coordinates
0.5551	0.4714

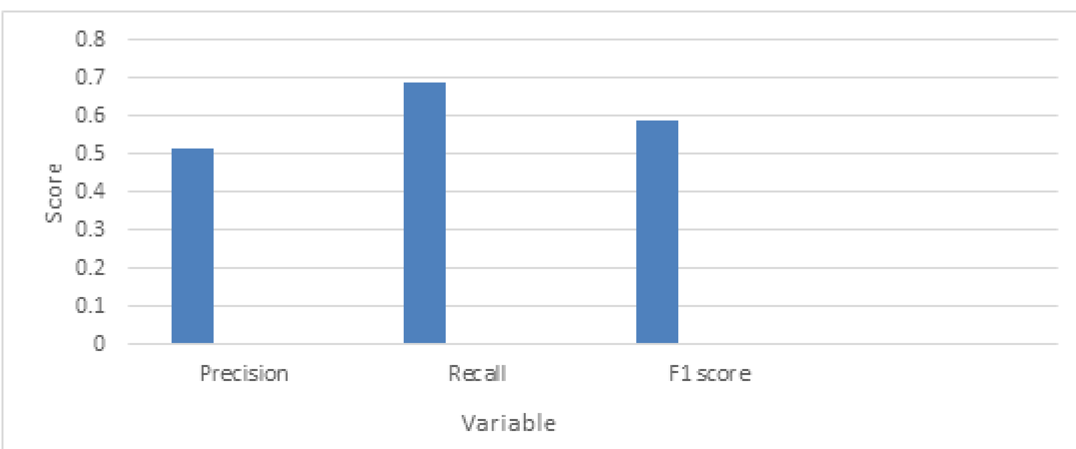

Figure 15: Provides better insight on precision, recall and F1 score

3. Using confusion matrix, the accuracy of given model is 64.1667%. F1 score, Precision and Recall provides better insight into the posture detection as shown in above graph of figure 15.

Input 4:

Figure 16: Input of result 4

Figure 17: Image enhancement stages of result 4

```
>> main
Inertial Sensors coordinates are
   -0.5809    0.0904


confMat =

    0.8500    0.1500
    0.2333    0.7667


ans =

    'loaded image is of a incorrect_posture '

 Accuracy is = 80.8333 %
 Precision is = 85 %
 Recall is = 78.4615 %
 Fscore is = 81.6 %
>>
```

Figure 18: Simulation Result of input 4

The simulation result of input 4 comprises of :

1. Confusion matrix

0.8500	0.1500
0.2333	0.7667

matrix [4]

2. Inertial sensor coordinates of exercise posture of input 4 are given below:

Table 5: Inertial Sensors coordinates

X coordinates	Y coordinates
-0.5809	0.0904

3. Using confusion matrix, the accuracy of given model is 80.8333%. F1 score, Precision and Recall provides better insight into the posture detection as shown in above graph of figure 19.

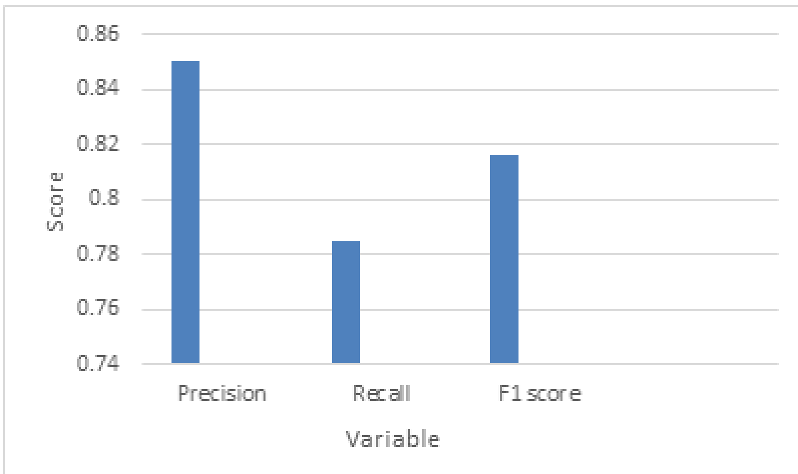

Figure 19: provides better insight on precision, recall and F1 score

CONCLUSION AND FUTURE SCOPE

In this paper, a video surveillance and detection method were successfully established. This method primarily offers an effective mechanism for monitoring and is intended to be extremely useful to any individual or agency. As a result, a motion detection system in a video format was completed and effectively introduced. For each exercise, the correct technique was implemented using the relevant coordinates of the inertial sensor to detect the proper posture. In this research performance matrices are generated for each input frame for calculating the accuracy of the model. Methodology deals with Machine learning algorithms to automatically assess posture correctness using only named input images. The future scope of the research study could be as follows: the due course of time as started to understand the minute details of work, significantly realized this research work would be enormously crucial in the upcoming future.

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