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HUMAN ACTIVITY DETECTION BASED UPON CNN WITH PRUNING AND EDGE DETECTION

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Abstract: Human activity detection is basic requirements especially within smart environments like smart homes. The primary requirement of smart environment is energy conservation. To achieve this, first target to detect the human activities accurately using neural network-based approach. This paper presents a unique combination of CNN with pruning and edge detection mechanism to accurately detect human activities. The entire process of human activity detection is portioned into set of phases. In the first phase, data acquisition is performed. The CNN with pruning and edge detection utilised KDH dataset derived from Kaggle. In the second phase, pre-processing to eliminate the noise from the image frames. In the third phase, edge detection and feature extraction were ensured. In the last phase classification is performed. The result of the human activity detection mechanism is expressed in the form of classification accuracy. High classification accuracy of over 95% was observed.

***Index Terms* - Human Activity, CNN, Pruning, Feature extraction, Classification accuracy.**

I. INTRODUCTION

Human activity detection using the machine learning mechanism offers advantages. To accomplish these wearable devices were employed. Wearable devices contain sensors to monitor the activities performed by the user. Li et Al. in 2018 [1] discussed the detection of human activity using wearable sensors. Wearable sensors detect the activities and record them onto the dataset. The dataset was then analysed using the machine learning based approach. LSTM based mechanism yield accurate results but was slow for larger datasets. The result of the detection was expressed in the form of classification accuracy. Khelalef et. Al. in 2019 [2] provide the mechanism of human activity detection by the use of deep learning. The deep learning approach requires large dataset. Feature extraction from such approaches was slow but accurate. [3], [4]To avoid complexity, entire process of extracting features was portioned into layers. In the initial phase, dataset was presented to the input layer, the processing layer extract the features and output layer classify the result. Overall classification accuracy will be high in case pre-processing was successfully performed. The overall process of detection of human activity is given in the figure 1.

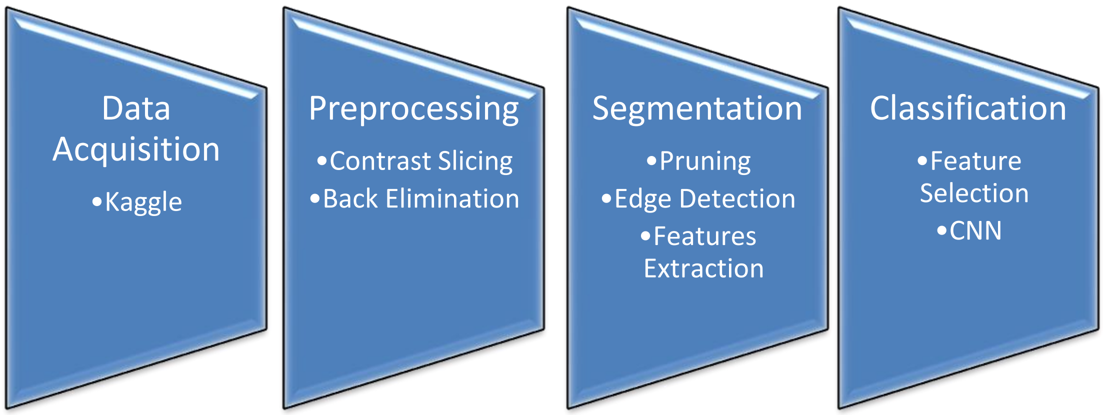

Figure 1: Process of human activity detection

The rest of the paper is organised as under section 2 gives the literature survey of the techniques used for human activity detection, section 3 gives the problems discovered from the literature, section 4 gives the proposed mechanism, section 5 gives the performance analysis, section 6 gives the conclusion.

II. Literature Survey

This section presents the mechanisms that are used to detect the human activities. The result obtained from these techniques also presented within this section.

Oukrich et al. in 2018 [5] detects human activity based on ontology based mechanism. This mechanism was strictly based on fuzzy logic and mechanism of human activities detected with pre-training model. The hold out ratio of 0.1 was used. The result was obtained using classification accuracy of 95%. Marinho et. Al. in 2017 [6] discussed the fake profile detection mechanism using machine learning mechanism. The layered based approach is followed for the detection of human activities. The classification accuracy of over 90% was achieved using this mechanism. Bharathi in 2020 [7] detects the human activities from the Kaggle dataset using deep and machine learning mechanism. Both the mechanism was used since machine learning operates on smaller datasets and deep learning perform operation on larger datasets. The result of the approach was presented in the form of classification accuracy. Xu et al. in 2018 [8] presented the convolution neural network based mechanism for the detection of human activities. The human activity detection mechanism follows set of steps including pre-processing, segmentation, and classification. The classification phase produces the classification accuracy of 94%. The mechanism ensures the better detection of movement from dataset. Sun et. Al in 2018 [3] proposed machine learning and deep neural network based mechanism for the detection of human activity. The activity recognition resulted in better detection of human activity in terms classification accuracy. Sharma et. Al in 2019 [9] uses LSTM network for the human activity detection. Pre-processing mechanism employed remove the noise if any from the dataset. After removing the noise from the dataset, segmentation and classification through LSTM was used. The result of the approach was presented through classification accuracy that was in the range of 92%

III. Problem definition

The approach discussed in [9], [10] [11], [12][13], [14] extract the features from the image based or text-based dataset. However, in case video dataset was presented all the described techniques leads to lower classification accuracy or may not operate at all. This means image frame extraction mechanism is missing in existing system. In addition, edge detection was not used within the existing techniques to determine the activities within the dataset. The extracted problems were listed as under

- Image frame extraction from the video dataset was missing.
- Classification accuracy calculated though CNN without edge detection and pruning was low
- Pre-trained model was not used hence detection and classification was slow.

IV. Methodology of work

The proposed mechanism was based upon the CNN with pruning and edge detection. The dataset used was extracted from KDH dataset. First, image frames were extracted from the video-based dataset. After extraction of image frames, noise from the image frames will be eliminated using pruning and edge detection. After the noise from the image was removed, feature extraction and selection take place. The model for this is known as convolution neural network. The process of feature extraction and selection takes place through iterative approach. The methodology of the proposed work is given in the figure 2.

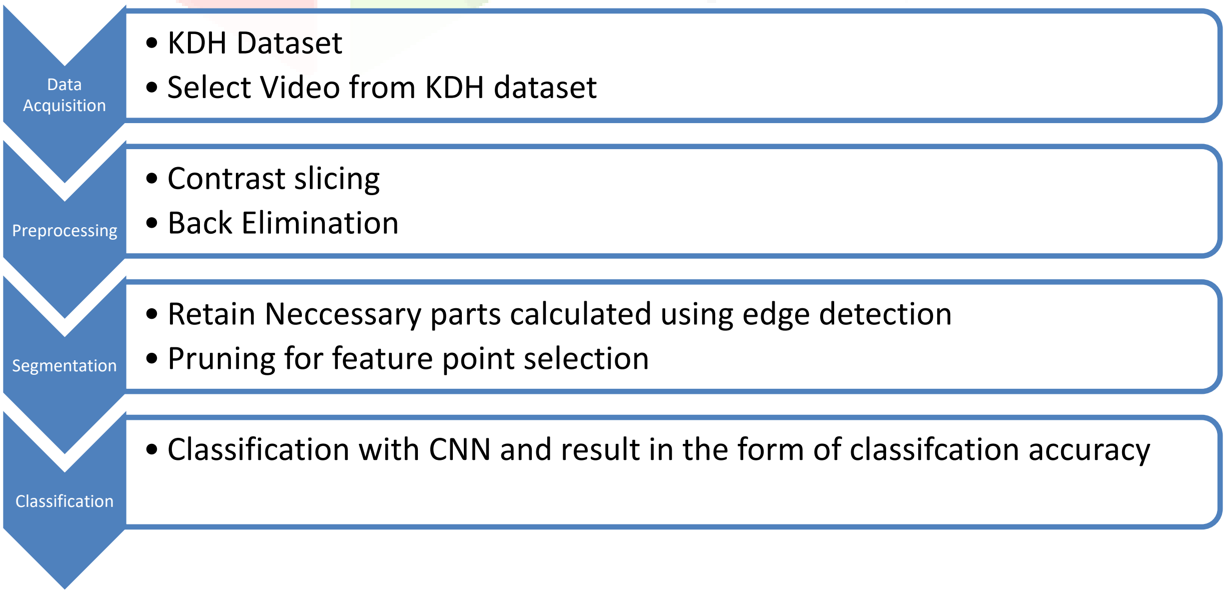

Figure 2: Proposed methodology

The overall mechanism of detection human activity will be possible only if comparison is performed with the pre-trained model. The pre-trained model used for the detection mechanism ensure quick and reliable result. The algorithm for the detection process is given as under

Algorithm Human_Activity_Detection

- KDH data acquisition
- Video to image frame conversion

$Image_i$=Video2image($KDH\_Dataset_i$)

- Pre-processing

Perform Contrast slicing $Image_i$=Red_Component(Image)*2
$Image_i$=Green_Component(Image)*2
$Image_i$=Blue_Component(Image)*2
Back Elimination: $Image_i$=255-$Background_i$

- Segmentation\\ Retaining the image components if weight factors are higher than threshold. The process is known as edge detection and feature point selection

If($Weight_i$>Threshold)
$Image_i$=$Image_i$+$Image_{i+1}$
End of if

- Classification

Compare the features extracted with pre-trained model for result prediction.

V. Performance analysis and result

The result of the proposed mechanism is presented in the form of classification accuracy, detection rate, specificity, and sensitivity. The performance analysis is given in table 1.

Table 1: Classification accuracy result

Activity Detected with KDH dataset	Classification accuracy (Without edge detection and pruning) in %	Classification accuracy with edge detection and pruning in %
Cycling	80	92
Running	82	93
Swimming	85	94

The plot to clearly visualise the result is given in the figure 3. Clearly the result from KDH dataset when Swimming is performed is higher as compared to Cycling and Running.

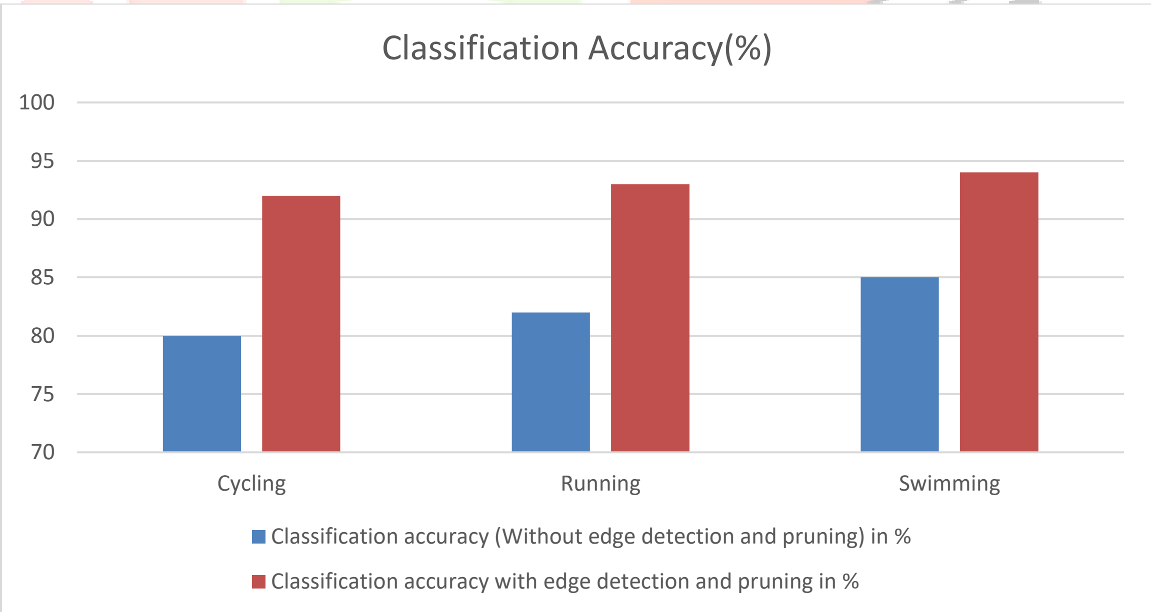

Figure 3: Classification Accuracy comparison

Activity Detected with KDH dataset	**Specificity (Without edge detection and pruning) in %**	**Sensitivity (Without edge detection and pruning) in %**	**Specificity with edge detection and pruning in %**	**Sensitivity with edge detection and pruning in %**
Cycling	62	70	70	84
Running	65	71	75	85
Swimming	70	72	79	89

The detection rate is another significant attribute determining the worth of CNN with edge detection and pruning based mechanism. The Detection rate was also improved using this mechanism. The result obtained with discussed approach is given in table 2.

Table 2: Recognition rate

Activity Detected with KDH dataset	**Recognition Rate (Without edge detection and pruning) in %**	**Recognition Rate with edge detection and pruning in %**
Cycling	69	90
Running	69	91
Swimming	72	92

The visualization of result for the detection of human activity is presented in the figure 4.

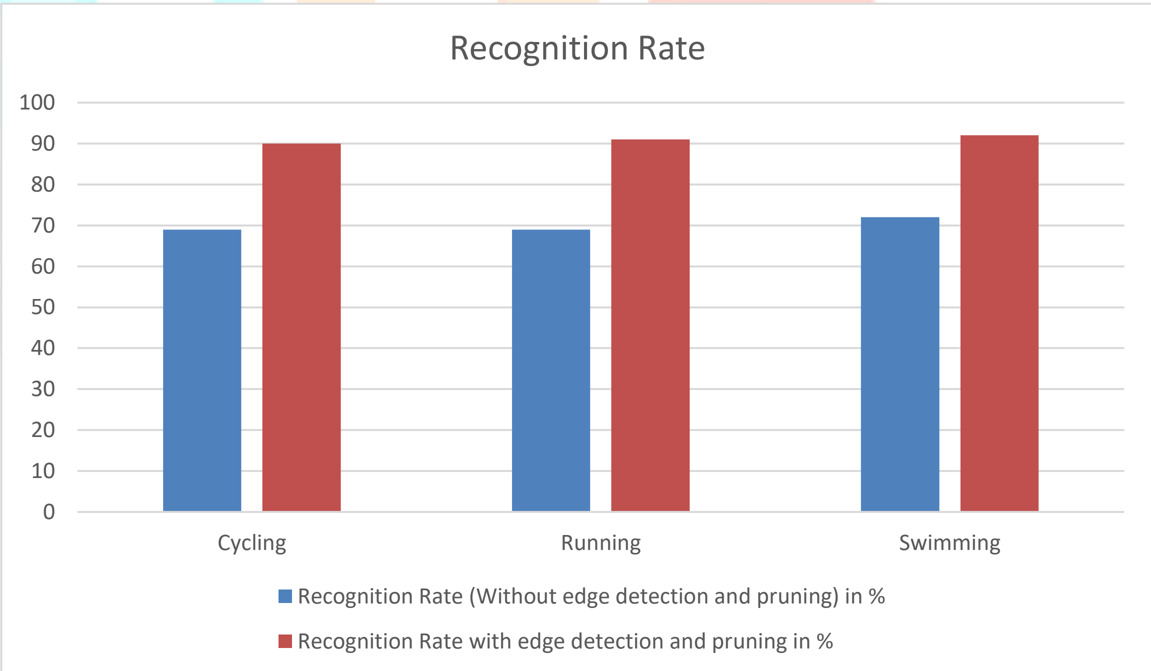

Figure 4: Recognition rate with existing and proposed mechanism

The recognition rate is improved by the margin of 16% approximately. The mechanism clearly shows improvement over existing CNN based mechanism. The last comparison of result is in the form of specificity and sensitivity. Both parameters enhance the classification accuracy. The result of specificity and sensitivity is given in table 3

Table 3: Specificity and sensitivity with proposed and existing work

The plot for the tale 3 is given in figure 5.

Figure 4: Specificity and sensitivity for the proposed and existing mechanism

The specificity and sensitivity obtained from the edge detection and pruning based CNN is much better as compared to existing approach proving worth of study.

VI. Conclusion and future scope

The approach used for the detection of human activities in the proposed work is CNN with pruning and edge detection. The dataset was derived from Kaggle named KDH dataset. The followed approach first converts the video-based dataset into image frames and after that it list the image frames for pre-processing. Within pre-processing contrast slicing and back elimination is performed. In the segmentation-based mechanism edge detection and elimination of unnecessary image area was performed. At the end, pre-trained model of CNN was used for performing classification. Overall, the result in terms of classification accuracy, recognition rate, specificity and sensitivity were improved by significant margin.

The proposed model was implemented on small scale dataset and in future, large dataset can be tested upon the proposed model.

VII. References

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