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Vision-based human activity recognition using CNN

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ABSTRACT

Human Activity Recognition (HAR) is a commonly discussed topic in computer vision. HAR implementations include representations such as health care and contact between the human and computer systems. When the imaging technology progresses and the camera system improves, there is a relentless proliferation of innovative approaches for HAR. Human activity recognition is an important component in many creative and human-behavior driven programs. The ability to recognize various human activities enables the developing of intelligent control system. Usually the task of Identification of Human activities is mapped to the classification task of images representing person's actions. This Project used for human activities' classification using machine learning methods such as CNN. This Project provides the results to Identification of Human activities task using the set of images representing five different categories of daily life activities. The usage of images also webcam to find out the live activities of the users that could improve classification results of Identification of Human activities is beyond the scope of this research.

Keywords**—** *CNN, IHA, Prediction, Testing, Training*

1. INTRODUCTION

Human activity recognition (HAR) is a well-known studies subject matter that includes the precise identification of different activities, sampled in a number of methods. In unique, Images-based IHA makes use of trained dataset, such. They are not intrusive for the customers, as they do no longer involve video recording in private and home context, much less sensitive to environmental noise, cheap and efficient in phrases of strength intake [8]. Moreover, the extensive diffusion of one of the most important challenges in sensor-primarily based IHA is the data illustration. Traditional type strategies are based on functions which can be engineered and extracted from the kinetic indicators. However, these functions are mainly picked on a heuristic base, according with the mission to hand. Often, the function extraction process requires a deep expertise of the software area, or human experience, and still consequences in shallow features simplest [5]. Moreover, regular IHA methods do now not scale for complicated movement patterns, and in most instances do no longer perform well on dynamic statistics, this is, information picked from non-stop streams. On this regard, automated and deep techniques are gaining momentum inside the area of IHA. With the adoption of information-driven tactics for signal category, the procedure of selecting significant capabilities from the facts is deferred to the studying model. In specific, CNNs have the capability to stumble on each spatial and temporal dependency amongst alerts, and might correctly version scale invariant features. In this paper, we observe convolution neural networks for the IHA hassle. The dataset we collected is composed of sixteen sports from the Otago exercise application. We train numerous CNNs with signals coming from exceptional sensors, and we compare the outcomes so that you can discover the maximum informative sensor placement for decrease-limb activities. Our findings display that, in maximum scenarios, the performance of a unmarried sensor is comparable to the overall performance of more than one sensors, however the utilization of multiple sensor configurations yields slightly higher effects. This suggests that collinear ties exist many of the alerts sampled with sensors on special placements

2. RELATED WORK

CNN for Identification of Human activities (IHA) and their parameters

Types of layers:

1. Input Layer
2. Convolution Layer
3. Activation Function Layer
4. Pool Layer
5. Fully-Connected Layer

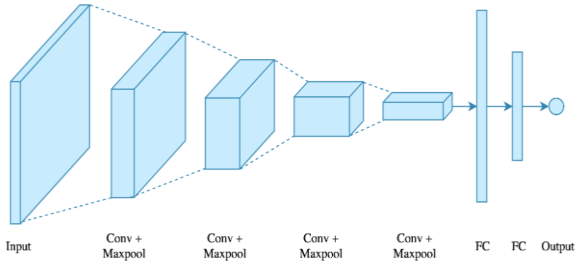

Fig. 1: CNN Flow

3. IMPLEMENTATION

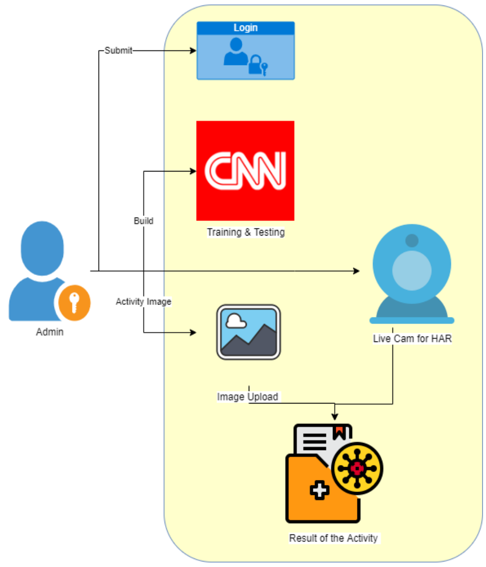

Fig. 2: System Architecture

- Admin Login
- Prediction
- Training
- Testing Image
- Result message

4. DATA SET

Link:http://human-pose.mpiinf.mpg.de/#download

Identification of Human activities dataset is a nation of the artwork benchmark for assessment of articulated human pose estimation. The dataset consists of around 25K pictures containing over 40K humans with annotated frame joints. The photographs were systematically collected using a longtime taxonomy of every day human activities. Overall the dataset covers 410 human sports and each picture is provided with an interest label. Each photograph changed into extracted from a YouTube video and provided with preceding and following un-annotated frames. In addition, for the take a look at set we obtained richer annotations including body part occlusions and three-D torso and head orientations. Following the best practices for the performance evaluation benchmarks within the literature we withhold the check annotations to save you over fitting and tuning on the take a look at set. We are working on an automated evaluation server and overall performance analysis equipment based totally on wealthy take a look at set annotations.

```
from PIL import Image, ImageTk
import requests
class_labels = ['boating', 'exercise', 'music', 'running','swimming']
test_image = image.load_img(img, target_size=(128, 128))
test_image = image.img_to_array(test_image)
test_image = np.expand_dims(test_image, axis=0)
```

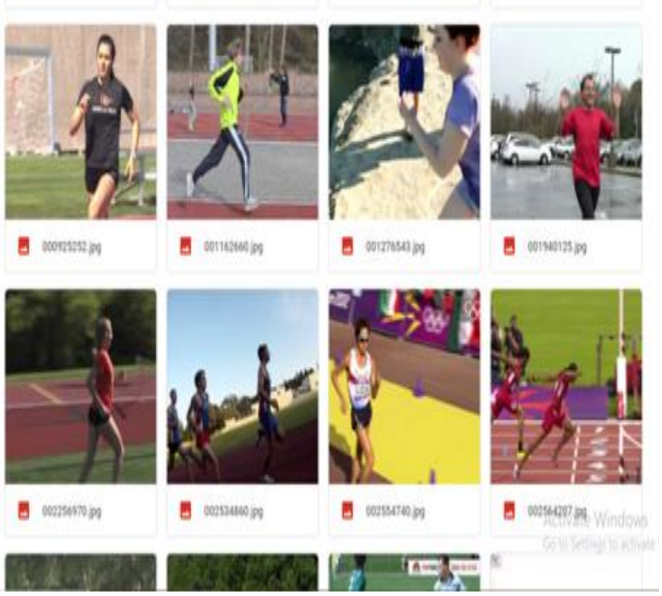

Fig. 3: Training Dataset of Running images

Fig. 4: Training Dataset of Sleeping Images

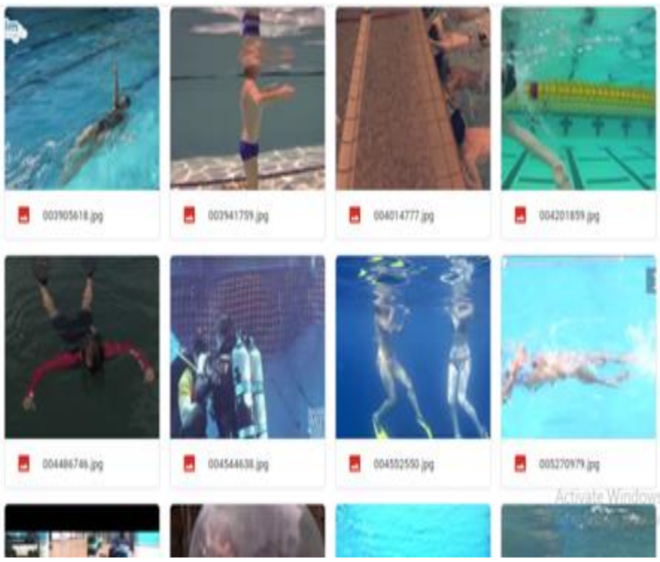

Fig. 5: Training Dataset of Swimming Images

5. EXPERIMENTAL RESULTS

Results are done on performed on groups of multiple people. One image may contain multiple groups, Split testing images into groups, Evaluation is performed on sufficiently separated people, using approximate location and scale of each person is allowed.

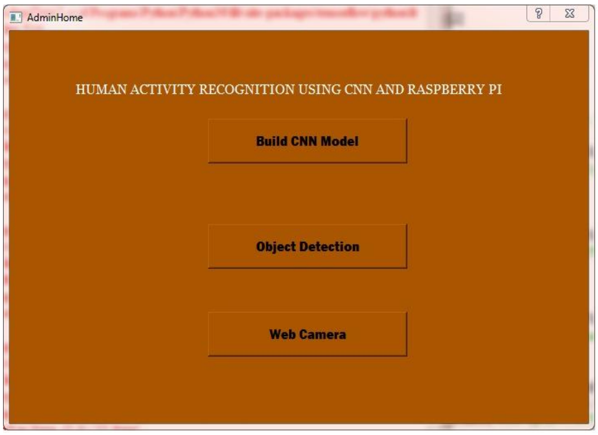

Fig. 6: Home Screen of the application

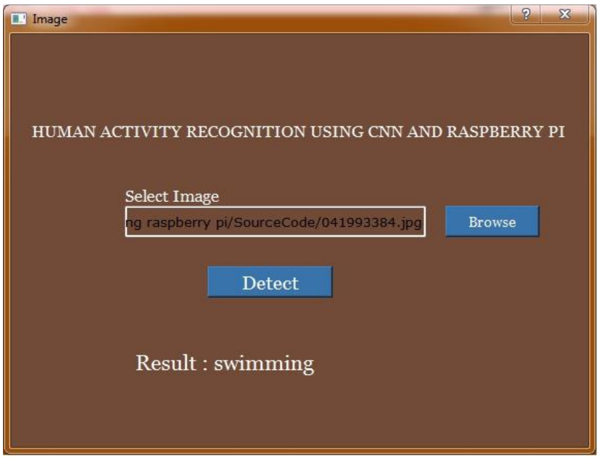

Fig. 7: Image upload Screen Swimming Activity

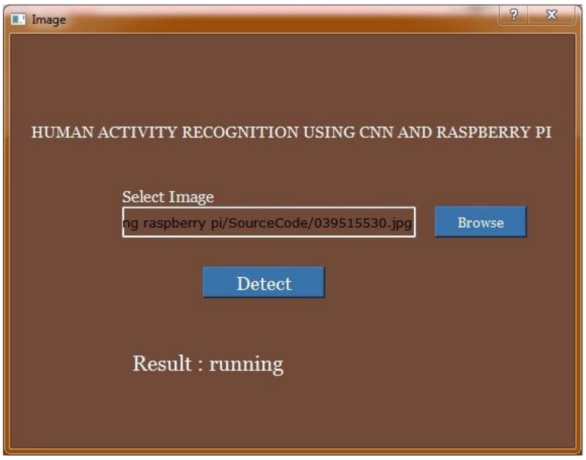

Fig. 8: Testing Running Activity

6. CONCLUSION

In this paper, we presented a CNN model for the IHA problem. We focused on a set of activities extracted from a common exercise program for fall prevention, training our model data sampled from different Actives, in order to explore the classification capabilities of each individual unit, as well as groups of units. Our experimental results indicate the results can be used to address the problem of activity recognition in the context of exercise programs.

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