ABNORMAL ACTIVITIES DETECTION USING CONVOLUTIONAL NEURAL NETWORK

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ABSTRACT

Abnormal Activities Detection (AAD) is a widely studied computer vision problem. Applications of AAD include images like health care and human-computer interaction. As the imaging technique advances upgrades, novel approaches for AAD constantly emerge. Abnormal Activities Detection is a significant component of many innovative and human-behavior based systems. The ability to recognize various human activities enables the developing of intelligent control system. Usually the task of Abnormal Activities Detection is mapped to the classification task of images representing person's actions. This Paper addresses the problem of human activities' classification using deep learning methods such as Convolutional Neural Networks.

Keywords: Abnormal activity detection (AAD), Convolutional neural network, face recognition, deep learning

INTRODUCTION:

The idea of activity recognition in pervasive computing is of utmost importance because of its varied applications in real-life, particularly to handle human-centric problems such as security. The purpose of an activity recognition system is to recognize the basic daily life activities of human beings. Due to the diversity and complexity in human activities, the accuracy of human action recognition becomes challenging. Construction of activity models that identify and classify various human activities follow several approaches. This research discipline attracts video processing and machine learning communities as it finds applications in several fields of studies like medicine and healthcare, human-computer interaction, crime investigation and security systems. Applications of human activity recognition are not limited to health care and security. Human activity recognition system uses sensors for interpretation of gestures or motion of the human being, thus identifying the action that the human body makes. Understanding human activities hold within itself a recognition of the activity and pattern discovery of that activity. The initial part makes use of a predefined activity model to correctly detect human activity. Thus, there is a need to construct a high-level conceptual model for implementing the pervasive system for human activity recognition. Moreover, activity pattern discovery does not require predefined models as it uses only a few low-level sensor data that is captured in order to find the unknown patterns. Though there is a major difference in the two techniques they have a common target of improving the performance of human activity recognition systems. These techniques are also supportive of each other. They combine to enhance the performance by using the discovery of the activity pattern to define recognized activity. Abnormal activity recognition is considered as the most challenging task from images. Due to the traditional method depend on the computation of artificial features, and noise data has some influence on the extracted features. In this paper, a new hybrid deep learning structure was proposed to fuse the extracted features, which integrates convolutional neural network (CNN) and long short-term memory network (LSTM). Firstly, the video was pre processed and extracted visual features by CNN. Next, LSTM was used to learn the temporal features of visual features and added attention mechanism to select important features. Finally, the video feature vector obtained layer by layer to judge abnormal activity. An experiment is used to test the ability of the model on the standard dataset to recognize abnormal activity, the result shows that our experimental demonstrate high performance of recognition and outperform the state-of-art algorithms.

LITERATURE SURVEY:

- Extensive literature has been produced about sensor-based activity recognition. Bulling et al. [6] give a broad introduction to the problem, highlighting the capabilities and limitations of the classification models based on static and shallow features. Alsheikh et al. [2] introduce a first approach to HAR based on deep learning models. They generate a spectrogram image from an inertial signal, in order to feed real images to a convolutional neural network. This approach overcomes the need for reshaping the signals in a suitable format for a CNN, however, the spectrogram generation step simply replaces the process of feature extraction, adding initial overhead to the network training.[3]

- Zeng et al. use raw acceleration signals as input for a convolutional network [8], applying 1-D convolution to each signal component. This approach may result in loss of spatial dependencies among different components of the same sensor. They focus on public datasets, obtained mainly from embedded sensors (like smartphones), or worn sensors placed on the arm. A similar technique is suggested by
- Yang et al. In their work, they use the same public datasets, however, they apply 2-D convolution over a single-channel representation of the kinetic signals. This particular application of CNNs for the activity recognition problem is further elaborated by
- Ha et al., with a multi-channel convolutional network that leverages both acceleration and angular velocity signals to classify daily activities from a public dataset of upper-limb movements. The classification task they perform is personalized, so the signals gathered from each participant are used to train individual learning models. One of the missing elements in all the previously described contributions about deep learning models is a comparison of the classification performance of individual sensors or group of sensors. Our aim in this paper is to implement a deep CNN that can properly address the task of activity recognition, and then compare the results obtained with the adoption of different sensor combinations. We also focus on a set of exercise activities that are part of the Otago exercise program. To the best of our knowledge, this group of activities has never been explored before in the context of activity recognition.

EXISTING SYSTEMS:

- The System of existing literature focuses on finding patterns in passenger activity records.
- Such knowledge can be useful in a variety of applications, and plays a vital role in effectively finding and satisfying passenger needs.
- Examples include assessing the performance of the transit network identifying and optimizing problematic or flawed bus routes, improving the accuracy of passenger flow forecasted between

two regions and making service adjustments that accommodate variations in ridership on different days.

- In particular, estimated the crowdedness of various stations in the transportation network using AFC data measured the variability of transit behaviors on different days of the week.
- Existing studies that detect anomalies in urban sensing data can be divided into two categories: those based on locations, and those on trajectories.
- Along the line of location-based anomaly detection, presented a framework that learned the context of different functional regions in a city, which provided the basis of our feature extraction approach.

PROPOSED SYSTEM:

The different modules we used in our proposed system are:

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

Admin Login

Authentication and Authorization Authentication means confirming your own identity, whereas authorization means being allowed access to the system. In even more simpler terms authentication is the process of verifying oneself, while authorization is the process of verifying what you have access to any application

Training

Training a simple Convolutional Neural Network (CNN) to classify Activity images. Because this tutorial uses the Keras Sequential API [7], creating and training our model will take just a few lines of code.

The image dataset contains 1000 color images in 2 classes, with 1000 images in each class. The dataset is divided into 1000 training images and 1000 testing images. The classes are mutually exclusive and there is no overlap between them.

Prediction

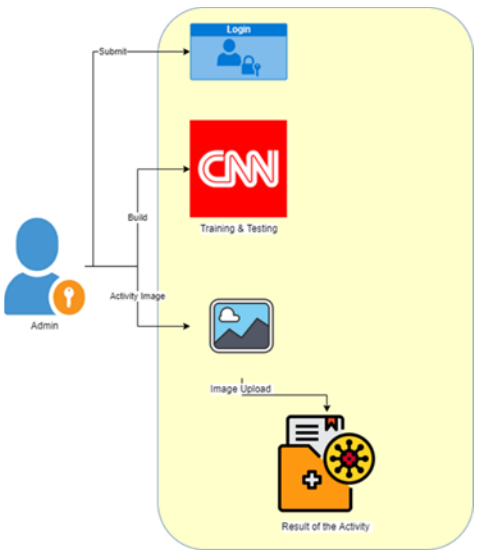
The CNN model will learn a function that maps a sequence of past observations as input to an output observation. We can divide the sequence into multiple input/output patterns called samples, where three-time steps are used as input and one-time step is used as output for the one-step prediction that is being learned

Testing Image

In this module user will give different activity images as image upload from this it will process from our “weights.h5” and created classifier we will get the output of user activity normal activity & abnormal activity

Result message

In this module it will show the results from the test images output of user activity normal activity & abnormal activity.



Convolution Neural Networks or covnets are neural networks that share their parameters

Types of layers:

- Input Layer
- Convolution Layer
- Activation Function Layer
- Pool Layer [1]
- Fully-Connected Layer

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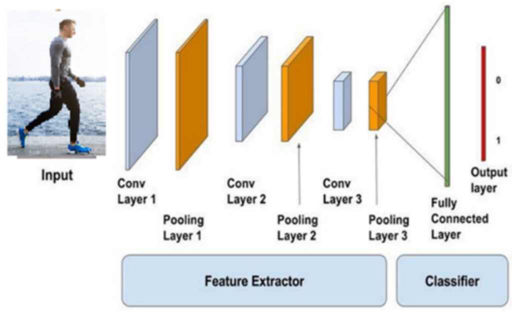


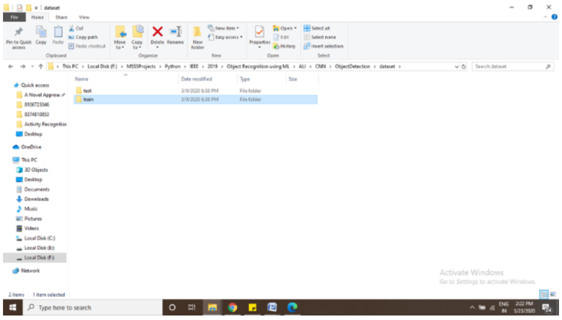
A convolutional layer within a neural network should have the following attributes:

- Convolutional kernels defined by a width and height (hyper-parameters).
- The number of input channels and output channels (hyper-parameter).
- The depth of the Convolution filter (the input channels) must be equal to the number channels (depth) of the input feature map convolution.

RESULTS:

Implementation of the Proposed System

System implementation is the practice of creating or modifying a system to create a new or replace an existing business process. It consists of converting hardware and files to the new system and also of training the user on how to handle the system.



In Dataset, we have train and test sets.

The Home Page

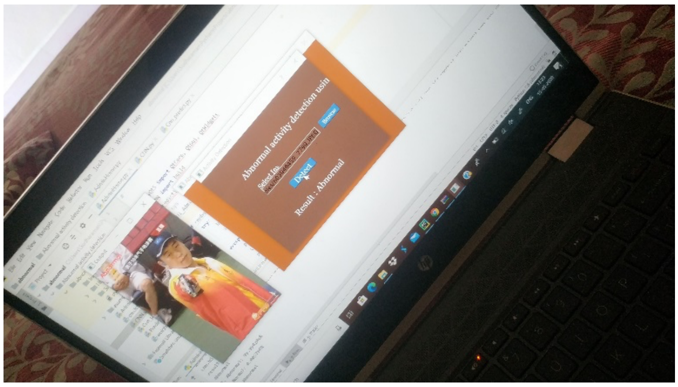
It can also be called the Index page.The system has two main features like:

- Build cnn model
- Object detection

Building a CNN Model takes 3 hours time for getting detected. If we want to add new feature like fire[4][5], we have to store the features of fire and use build CNN model option so that after sometime we can even detect the newly added feature. We have two different classifiers like abnormal and normal. We have two different datasets like train and test.

The image upload Page

Each user once logged in, is a legitimate user of the system and therefore given the privilege to perform functions such as upload a video or image, browse file and view result. Here the user can upload the image and check the result whether it is normal or abnormal and we can even see the percentages of abnormality and normalities down.



CONCLUSION:

After researching the several methods that exists for human activity recognition it is noticed that the best suitable methods will be the ones that follow the unsupervised learning model, taking into consideration the kind of datasets available, In this paper, we presented a CNN model for the Abnormal Activities Detection (AAD) problem. We focused on a set of Abnormal activities extracted from a common exercise program for fall prevention, training our model data sampled from different classifiers , in order to explore the classification capabilities of each individual unit, as well as groups of units. Our experimental results indicate that convolutional models can be used to address the problem of activity recognition in the context of exercise programs.

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