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Review Paper on IoT Thread Detection using Deep CNN Classifier

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Abstract*: Abnormal activity will lead to uncommon changes in the crowd behavior. In other words, the crowd motion changes conform to certain rules for valid behaviors, while for abnormal events the motion changes are uncontrolled. The motion-changed rules to detect and localize abnormal behavior in crowd videos. Specifically, we first generate the motion patterns based on the descriptor of collectiveness. Then each frame pair is represented as a transfer matrix whose elements are the difference of a set of motion patterns. Thereafter, the motion-changed rules are constructed in the transformation space using a bag-of-words approach. Finally, the proposed approach measures the similarity between motion-changed rules and the incoming video data to examine whether the actions are anomalous. The approach is tested on the UMN dataset and a challenging dataset of crowd videos taken from the railway station. The experimental results demonstrate the effectiveness of the proposed method for detection abnormal behavior*

Keywords: High performance liquid chromatography, Pharmaceutical impurity profiling, Pharmaceutical quality control, stationary phase, pharmaceutical drugs

I. INTRODUCTION

Detecting abnormal behavior is of great importance to transportation and public safety, and is very challenging as it is affected by many complex factors, such as emergent behaviors and complex situations. In the literature, there are two kinds of methods. One attempted to represent the crowd motion behavior. studied crowd collectiveness, a metric indicating the degree of individuals acting as a union in collective motion. The other studies used a statistical learning model to distinguish anomalies based on low-level features and proposed a method for group-level activity recognition using a divisive clustering method to group subjects. Presented an approach for detecting changes in the global crowd motion behavior based on motion vectors in world coordinates. The main drawback is that the low-level image properties were insufficient to capture the essence of abnormal behavior. Used the Social Force model to detect uncommon behavior using particle advection based on the optical flow field. Uunusual orientations lead to changes in crowd motion behavior that are not similar to normal values. In light of this, this project attempts to accomplish this task based on the motion-changed rules. For this, we first generate the motion patterns based on the descriptor of collectiveness. Then the frame pair is represented as a transfer matrix whose elements are the difference of a set of motion patterns. Then the frame pair is represented as a transfer matrix whose elements are the difference of a set of motion patterns. The abnormality detection is reduced to construct a similarity map of new observations concerning all of the trained motion-changed rules. A new normal observation would have high similarity, while an abnormal event would have low similarity. The proposed approach is tested on the UMN dataset and a challenging dataset of crowd videos. The result will demonstrate the effectiveness of the proposed method for detecting abnormal behavior.

1.1 Objectives

- To identify action in input Image or video dataset.
- To recognize abnormal behaviour in Image or video dataset.
- To study and analysis of deep learning models for abnormal behaviour detection.
- To detect abnormal behaviour using deep Learning technique

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II. LITERATURE REFERENCES

In the literature, deep convolutional neural networks (CNNs) have demonstrated remarkable success in image classification but typically require large training datasets and provide suboptimal results that require further improvements.

HishamAbdeltawaba et al. [1] author proposed a framework started by an accurate localization of the LV blood pool center-point using fully convolutional neural network (FCN) architecture called FCN1. Then, a region of interest (ROI) that contains the LV is extracted from all heart sections. The extracted ROIs are used for the segmentation of LV cavity and myocardium via a novel FCN architecture called FCN2. The FCN2 network has several bottleneck layers and uses less memory footprint than conventional architectures such as U-net. Furthermore, a new loss function called radial loss that minimizes the distance between the predicted and true contours of the LV is introduced into model. Following myocardial segmentation, functional and mass parameters of the LV are estimated. Automated Cardiac Diagnosis Challenge (ACDC-2017) dataset was used to validate framework, which gave better segmentation, accurate estimation of cardiac parameters, and produced less error compared to other methods applied on the same dataset. Furthermore, they showed that segmentation approach generalizes well across different datasets by testing its performance on a locally acquired dataset. To sum up, the author proposes a deep learning approach that can be translated into a clinical tool for heart diagnosis.

Fabian Isensee, et al. [2] author presents a method that addresses named limitations by integrating segmentation and disease classification into a fully automatic processing pipeline. They used an ensemble of UNet inspired architectures for segmentation of cardiac structures such as the left and right ventricular cavity (LVC, RVC) and the left ventricular myocardium (LVM) on each time instance of the cardiac cycle. For the classification task, information is extracted from the segmented time-series in form of comprehensive features handcrafted to reflect diagnostic clinical procedures. Based on these features they trained an ensemble of heavily regularized multilayer perceptions (MLP) and a random forest classifier to predict the pathologic target class. They evaluated their method on the ACDC dataset (4 pathology groups, 1 healthy group) and Achieve dice scores of 0.945 (LVC), 0.908 (RVC) and 0.905 (LVM) in a cross-validation over the training set (100 cases) and 0.950 (LVC), 0.923 (RVC) and 0.911 (LVM) on the test set (50 cases). Their report of a classification accuracy of 94% on a training set cross-validation and 92% on the test.

Christian F. Baumgartner et al [3] author present a fully automated framework for segmentation of the left (LV) and right (RV) ventricular cavities and the myocardium (Myo) on short-axis cardiac MR images. They investigate various 2D and 3D convolutional neural network architectures for this task. Experiments were performed on the ACDC2017 challenge training dataset comprising cardiac MR images of 100 patients, where manual reference segmentations were made available forend-diastolic (ED) and end-systolic (ES) frames. Author found that processing the images in a slice-by-slice fashion using 2D networks is beneficial due to a relatively large slice thickness. However, the exact network architecture only plays a minor role. Author report mean Dice coefficients of 0.950(LV), 0.893 (RV), and 0.899 (Myo), respectively with an average evaluation time of 1.1 s per volume on a modern GPU.

Elias Grinias et al [4]. Present a fast fully automatic method for cardiac segmentation in ED and ES short axis MRI. At first we extract a region where the whole heart is situated, using a new, time-based approach. Then, the segmentation in LV, myocardium and right ventricle (RV) is obtained for a slice in a basal ED slice where both cavities are well distinguished. The extracted regions are tracked for the whole slice sequence backwards and forwards in ED. In all cases the segmentation is based on MRF optimization in four classes, two for the blood areas, and one for the myocardium and the background. Subsequently the segmentation in the ES images is based on the result of ED segmentation. As the epicardium is not well delineated, a smoothing process based on spline curves is used for obtaining the final result. The Author consider that, with an unsupervised method, they have obtained good results for LV and satisfactory for the RV and the myocardium on the ACDC 2017 datasets.

Safial Islam Ayon et al [5] compared a number of computational intelligence techniques for the prediction of coronary artery heart disease. Seven computational intelligence techniques named as Logistic Regression (LR), Support Vector Machine (SVM), Deep Neural Network (DNN), Decision Tree (DT), Naïve Bayes (NB), Random Forest (RF), and K-Nearest Neighbor (K-NN) were applied and a comparative study was drawn. The performance of each technique was evaluated using Statlog and Cleveland heart disease dataset which are retrieved from the UCI machine learning repository database with several evaluation techniques. From the study, it can be carried out that the highest accuracy of

98.15% obtained by deep neural network with sensitivity and precision 98.67% and 98.01% respectively. The outcomes of the study were compared with the outcomes of the state of the art focusing on heart disease prediction that outperforms the previous study.

Kathleen et al. [6] Presents, the deep neural network classification and prediction models were created based on a deep learning algorithm. The DNN models were used to diagnose coronary heart disease and were applied to dataset of 303 clinical instances from the Cleveland Clinic Foundation. The models were trained and tested using randomly generated training and testing datasets, respectively. The performances of the developed DNN models were evaluated using diagnostic accuracy, probability of misclassification error, specificity, precision, AUC, sensitivity, F-score, and K-S test.

Some supervised deep learning models have been reported for fetal ultrasound images and videos. Temporal HeartNet could automatically predict the visibility, viewing plane, location, and orientation of the heart in fetal ultrasound videos [7]. SonoNet could detect the fetal structures via bounding boxes in fetal ultrasound videos, such as the brain, spine, abdomen, and also the four standardized transverse scanning planes of fetal heart, which were the four-chamber view (4CV), three-vessel view (3VV), right ventricular outflow tract (ROVT), and left ventricular outflow tract (LOVT) [8]. These models focused on plane-based detection of fetal heart and their input data depended on the skill levels of examiners. However, it is still difficult for non-experts to identify the cardiac substructures and describe the scanning planes precisely. The application of image segmentation methods to fetal ultrasound has been reported.

Arnaout et al. used plane-based detection of fetal heart for CHD screening, and performed segmentation of the thorax, heart, spine, and each of the four cardiac chambers using U-net to calculate standard fetal cardiothoracic measurements [9]. We previously employed the time-series information of fetal ultrasound videos in the module that calibrates segmentation results of the ventricular septum [10]. These pixel-by-pixel detection techniques are useful to detect the target with a small shape changing by the fetal heartbeat. In fetal ultrasound, deep learning-based detection of cardiac abnormalities is still challenging because CHD is relatively rare and noisy acoustic shadows affect ultrasound images, making it a daunting task to prepare complete training datasets. To overcome these issues, we have to consider an applied method for the detection of cardiac structural abnormalities using small and incomplete datasets.

III. SYSTEM ARCHITECTURE

Thereafter, the motion-changed rules are constructed in the transformation space using bag-of-words approach. Finally, the proposed approach measures the similarity between motion-changed rules and the incoming video data to examine whether the actions are anomalous. A new normal observation would have high similarity, while an abnormal event would have low similarity. The proposed approach is tested on the UMN dataset and a challenging dataset of crowd videos taken from the railway station. The experimental results demonstrate the effectiveness of the proposed method for detection abnormal behavior. The steps of the proposed abnormal behavior detection algorithm. The first step is to generate the motion patterns based on the descriptor of collectiveness. And then we construct the transformation space of motion patterns from frame pairs. Generally, the normal behaviors are the high frequency of occurrence in the transformation space.

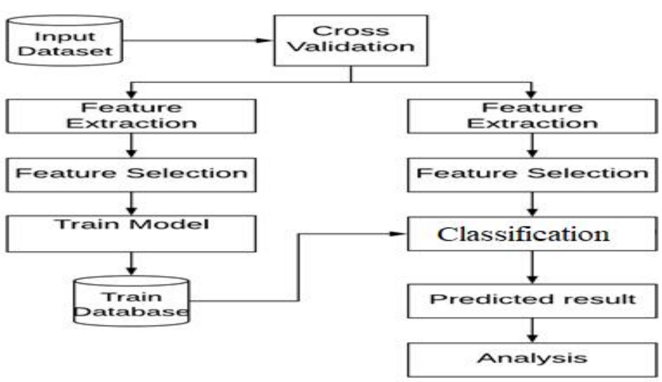

Figure 1. System Architecture

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3.1 Applications

- Better understanding of human activities.
- Reliable recognition of human-to-human or human-to-object interactions.
- Recognizes social human interactions easy access to data though given platforms.

3.2 Advantages

- Although the latter is more promising due to its flexibility for describing observed data and generalization capabilities, it still yields some errors.
- The main drawback is that the low-level image properties were insufficient to capture the essence of abnormal behavior. A more advanced approach which was to build hierarchy models with specific features based on the domain knowledge.
- In other words, the crowd motion change conforms to certain rules for valid behaviors, while for abnormal events the motion changes are uncontrolled. For this, this system discovers the motion-changed rules to detect and localize abnormal behavior in crowd videos.

IV. SUMMARY

If you follow the “checklist”, your paper will conform to the requirements of the publisher and facilitate a problem-free publication process.

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