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ANOMALY DETECTION WITH MACHINE LEARNING ALGORITHMS IN CROWDED SCENES IN UMN ANOMALY DATASET

ABSTRACT

In recent years, keeping security under control in crowded environments has been a common problem. Camera systems are used to ensure security in crowded environments. When the video images recorded by the cameras are examined, it is checked whether there is any dangerous and unusual movement in the environment and appropriate measures are developed. Human behavior must be modelled to detect normal and abnormal behaviors in crowded scenes. In this study, crowded scenes in three different environments in the UMN Anomaly Data Set were examined. Random Forest, Support Vector Machines and k Nearest Neighbour algorithms, which are one of the machine learning methods in these three different environments, are applied. As a result of algorithms applied, the abnormal behaviour (like escape) of people in a crowded scene has been detected. Performance criteria such as accuracy, sensitivity, precision and F1 score of these applied algorithms were calculated and compared.

Keywords: Artificial Intelligence, Machine Learning, Anomaly Detection, Crowded Analyse, Algorithm

1. INTRODUCTION

The understanding and processing of human behavior by machines can be achieved through machine learning. Machine learning is a diverse field that has attracted a lot of attention in recent years. Detecting movements on human behavior, motion tracking, scene modelling, and understanding of behavior (human activity recognition and determination of activity types) has become an area of great interest in computer vision and machine learning. Depending on the rapid development of technology, it is necessary to examine and analyse the behavior of people operating in crowded areas. Since the examination of video images recorded by camera systems requires an intense effort, it was necessary to make video surveillance systems under computer control and in an automatic manner. The aim here is to recognize, detect or learn movements that can be called unusual activity/event. Different problems were encountered in the mentioned automatic video surveillance systems. The fact that the definition of anomaly in the videos is variable and uncertain according to the characteristics of the space and the human community is accepted as one of the biggest problems encountered [1]. As a result of the ambiguity of the boundary between normal and abnormal behaviors displayed in the images obtained from the cameras and the problems encountered in obtaining sample training data for abnormal behaviors, modelling possible behaviors in the scene in the image and accepting behaviors that do not conform to this model as abnormal is the most common anomaly detection approach. The aim is to identify, recognize or learn interesting events that could be contextually defined as

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"doubtful event" [2], "irregular behavior like in Figure 1" [3], unusual behaviour "unusual activity/event" [4]. Abnormal events can be analysed locally and globally in the videos obtained [1]. The behaviors exhibited individually are defined as different behaviors according to the crowd, as local anomaly, and sudden changes displayed in the video for any reason (fire, etc.) as a global anomaly. Anomaly detection; Detection and monitoring is carried out with 3 different methods: behavior analysis and activity analysis of people. [5] In addition, holistic approaches deal with the components in a scene as a whole without examining them separately [3 and 6]. With this feature, it is more successful than individual approaches [7].

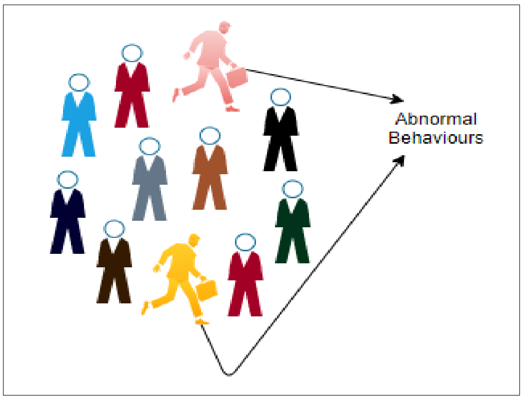

Figure 1. Abnormal activity in a crowded scene

In this study, a data set consisting of video images containing the movement of people in three different crowded scenes that are accessible was studied. In these data sets, abnormal movements of people in crowded scenes were detected in video images. First, the video images are divided into photo frames. Regardless of proportion, most of these divided squares were used as training and the remaining images as test data. K Nearest Neighbour, Support Vector Machines and Random Forest algorithms were used to detect anomalies on these data sets. When the performance criteria of algorithms are examined, it is seen that Support Vector Machines and k Nearest Neighbour algorithms show higher performance.

2. RESEARCH SIGNIFICANCE

With the development of technology, the detection and analysis of abnormal behavior has become a popular research area. Due to the security concern that increases especially because of the increase in the population, video images are used to detect anomalies in metro stations, shopping malls, stadiums, airports, military facilities, health facilities such as monitoring daily activities and fall detection in elderly people's.

3. MATERIALS AND METHOD

Machine learning methods are divided into three groups as supervised, unsupervised and reinforced learning. In this study, algorithms of the supervised learning method were used. Supervised learning takes a specific set of input data and known responses to the data, then trains a model to generate plausible predictions to respond to new data. In this study, the scenes in the data set named UMN Anomaly Dataset [8], which are open to access, were studied. The block diagram of the study is given in the Figure 2.

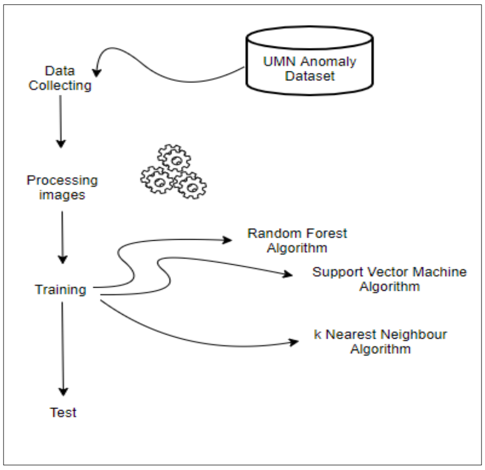

Figure 2. Blok diagram of proposed method

The abnormal movements in this data set were performed by machine learning algorithms. Since the video images in the scenes analysed are in ".avi" format, they were first converted into ".jpeg" format. Divided pixels were applied HOG (Histogram of Oriented Gradient). The HOG feature extraction method gives successful results especially in object and pattern recognition. Performs feature extraction with the gradient values and orientation angles of the pixels in the HOG method. The main purpose of this method is to represent the image in the form of local histograms [9]. HOG images of some scenes in the UMN data set are given in Figure 3.

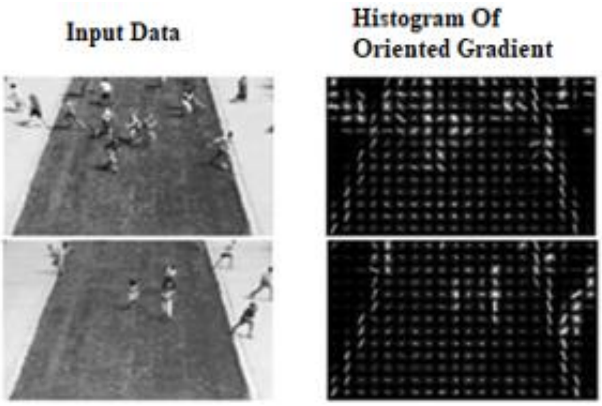

Figure 3. HOG images of UMN anomaly detection dataset scene -1

The UMN anomaly dataset is contains 22 video (11 videos for training and 11 videos for testing) and 7739 frames with a 320×240 resolution. Videos are recorded in 1 indoor and 2 outdoor scenes. Each video starts with normal behavior and ends with an abnormal behavior like escape. Example scenes are shown in Figure 4.

Figure 4. Normal/abnormal motion scenes belonging to UMN anomaly data set scene 1

7739 pieces of data were processed in the UMN anomaly data set. 7347 of these data were used for training purposes and the remaining 392 were used to test the trained algorithm. K is implemented using Nearest Neighbour, Support Vector Machine and Random Forest algorithms. By comparing the input data of the K-NN algorithm with neighbouring data, it is ensured that the cluster closest to k neighbour is included in that cluster. While applying the k-NN algorithm, the optimal k value was accepted as 2. The Support Vector Machine algorithm works similarly. It is based on assigning similar data to the same classes [9]. As a result of the algorithms applied with the random forest algorithm, the desired abnormal behavior was determined. Images of several data sets of these determinations are given in Figure 5.

4. FINDINGS AND DISCUSSIONS

The UMN anomaly data set is consisting of 7739 pieces of data were processed. 7347 of these data were used for training purposes, and the remaining 392 were used to test the trained algorithm. "k" is implemented using Nearest Neighbours, Support Vector Machine and Random Forest algorithms. By comparing the input data with neighbouring data, the k-NN algorithm has ensured that the cluster closest to k neighbours is included in that cluster. While applying the k-NN algorithm, the optimal k value was accepted as 2. Support Vector Machine algorithm works similarly. It is based on assigning similar data to the same classes. Random forest algorithm the desired abnormal behaviour was determined as a result of the applied algorithms. Images of several data sets of these determinations are given in Figure 4.

Figure 5. Outputs from data set after applying algorithms

The accuracy values of the algorithms are given in Table 1. According to the table, as seen in Table 1, the highest accuracy value with 95% belongs to the Nearest Neighbour algorithm. The lowest accuracy value was seen in the Random Forest algorithm with 50%.

Table 1. Accuracy values of algorithms

Algorithm	UMN Anomaly Dataset		
	Scene 1	Scene 2	Scene 3
K Nearest Neighbour	95	92.80	75
Support Vector Machines	91.25	89.38	85
Random Forest	56.25	68.49	50

Performance criteria of the algorithms are given separately in Table 2, Table 3 and Table 4. The lowest accuracy value of the Random Forest algorithm was seen in Scene 3 with 50%. It was seen that this was due to the low data in Scene 3 compared to other scenes and the low data quality.

Table 2. Random forest algorithm's performance metrics

Performance Metrics (%)	UMN Anomaly Dataset		
	Scene 1	Scene 2	Scene 3
Accuracy	56.25	68.49	50
Recall	53.33	61.34	50
Precision	100	100	100
F1 Score	69.56	76.03	66.66

Similarly, when the accuracy values of the Support Vector Machines algorithm are examined, it is seen that the highest value belongs to Scene 1 with 91.25% and the lowest value belongs to Scene 3 with 75%. As the data quality decreases and the number of data decreases, the correct prediction ability of the algorithm also decreases. Table 3 shows the values of the criteria such as accuracy, sensitivity and precision of the Support Vector Machine algorithm applied to the data sets.

Table 3. Support vector machine algorithm's performance metrics

Performance Metrics (%)	UMN Anomaly Dataset		
	Scene 1	Scene 2	Scene 3
Accuracy	91.25	89.38	75
Recall	100	82.48	66.66
Precision	85	100	100
F1 Score	91.89	90.39	79.99

Table 4 when examined for performance criteria of k Nearest Neighbour algorithm, it is seen that the highest accuracy value belongs to Scene 1 with 95% and the lowest accuracy value belongs to Scene 3 scene in k-Nearest Neighbour algorithm as in other algorithms.

Table 4. k nearest neighbour algorithm's performance metrics

Performance Metrics (%)	UMN Anomaly Dataset		
	Scene 1	Scene 2	Scene 3
Accuracy	95	92.80	85
Recall	90.90	88.81	76.92
Precision	100	97.94	100
F1 Score	95.23	93.15	86.95

5. CONCLUSION

Video surveillance has begun to be widely used due to the security concerns highlighted today. In this study, the abnormal behaviours observed on human behaviors in three different crowded environments in a data set open to access were determined. This determination was carried out with k-Nearest Neighbour, Support Vector Machine and Random Forest algorithms, which are among the supervised learning algorithms. In order to compare the performances of these applied algorithms, accuracy, recall, precision and f1 score values are calculated and presented in tables. When these presented values were examined, it was seen that the performance of the algorithms and the quality of the data processed and the number of data played an important role.

NOTICE

This study is based on "Anomaly Detection on Human Behaviour in Crowded Scenes with Machine Learning Algorithm" name the master thesis.

REFERENCES

[1] Sezer, E.S. and Can, A.B., (2018). Anomaly Detection in Crowded scenes using log-euclidean covariance matrix, VISIGRAPP 2018 - Proceedings of the 13th International Joint Conference on Computer Vision, Imaging and Computer Graphics Theory and Applications, Vol:4, No:Visigrapp, 279–286.

[2] Cong, Y., Yuan, J., and Liu, J., (2011). Sparse Reconstruction Cost for Abnormal Event Detection, Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, No. June 2014, 3449–3456.

[3] Wang, X., Ma, X., and Grimson, W.E.L., (2009). Unsupervised Activity Perception in Crowded and Complicated Scenes Using Hierarchical Bayesian Models, IEEE Transactions on Pattern Analysis and Machine Intelligence, 31(3):539–555.

[4] Wiliem, A., Madasu, V., Boles, W., and Yarlagadda, P., (2008). Detecting Uncommon Trajectories, Proceedings-Digital Image Computing: Techniques and Applications, DICTA 2008, No. January, 398–404.

[5] Popoola, O.P. and Wang, K., (2012). Video-based Abnormal Human Behavior Recognitiona Review, IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, 42(6):865–878.

[6] Zhou, B., Wang, X., Tang, X. (2012). Understanding collective crowd behaviors: Learning a Mixture model of Dynamic pedestrian-Agents, Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2871–2878.

[7] Hu, M., Ali, S., and Shah, M., (2008). Learning Motion Patterns in Crowded Scenes Using Motion Flow Field, Proceedings - International Conference on Pattern Recognition, 2–6.

[8] Chong, Y.S. and Tay, Y.H., (2017). Abnormal Event Detection in Videos Using Spatiotemporal Autoencoder, Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), Vol:10262 LNCS, 189–196.

[9] Monitoring Human Activity, URL: http://mha.cs.umn.edu/ (Accessing Time: February, 10, 2019)

[10] https://veribilimcisi.com/2017/07/19/destek-vektor-makineleri-support-vector-machine/.