# CNN based Crowd Monitoring and Management System analysis and performance

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## ABSTRACT

Crowd monitoring and management system (CMMS) is very important for the protection of public place. Developing a strong CMMS is a task full of many challenges as distribution of irregular object, currency estimation, density variation, occlusion etc. The crowd accumulates in various places as Park, Airport, stadium, Hospital, religious and cultural points. Mostly crowd are monitored by **Closed Circuit Television (**CCTV) cameras. The **Closed-Circuit Television** (CCTV) cameras are having setting up problem, high power consumption, Limited coverage area, moving and continue monitoring resource. As a result, several researchers have focused on crowd monitoring and management problem including machine learning and vision of computer. The paper provides different machine learning techniques and methods for congestion monitoring and congestion management.

**Keywords:** crowd management, crowd monitoring, crowd density, crowd counting, crowd behaviour, convolutional neural network.

### 1.INTRODACTION

A person of a similar and different set present in the crowd would lead to same goal. These are presented as structured congestion and unstructured congestion. There are not many differences among the people participating in the movement for striving and put conflicts due to shatters nature of movements [2]. The public place, traffic monitoring, disaster management, safety monitoring, congestion monitor has been important applications. There are various parameters for crowd monitoring such as density, estimation, scene understanding, count, tracking, behaviour, and localization. The estimation of density provides congestion level in an important application. [3][5][7][8][15][14]. Other parameters reparent the baseline building block for various application. There are following methods used to count congestion level are cluster based, regression base and object detection [11][12][13]. Cluster based crowd counting involves identifying by the visual tracking feature and estimating the number of clusters is moving object [17]. The count based on regression approximates the crowd count by performing the crowd size regression. The count based on location the object is trained to count the object of the detector to know the position of everyone present in the crowd. However, the regression-based method works more well in a higher density condition that makes the density information for time adjusted images of congestion. The high-density congestion is essential for accurately counting and localising in the congestion. The precise location of the heads in the picture is called localization. There are steps to locate the head of human being. There are various challenging tasks to overcome the problem. The objective of crowd monitoring and crowd management is to find out the unusual behaviour of the people presented in the crowd [1]. The presented paper compares old tasks related to crowd monitoring and management and their model to the technologies associated with DCNN.

The rest of the paper organized as follows: Section 2 related work, Section 3 proposed Crowd monitoring and management system model, Section 4 validation of the proposed system model, and Section 5 conclusion.

## 2. RELATED WORK

There are various Crowd images and videos of different datasets are available based on these datasets some of the followings are explained.

The CUHK dataset collects different dataset of different locations as shopping Mall, Park, Airport and Street. The dataset includes 215 images and 475 videos [16].

The shanghai Tech dataset is used for masses of crowd count. It counts 330165 head on the base of 1198 image. This dataset is divided into two-parts part A and Part B. The Part A includes 482 pictures taken by the online would and Part B contains 716 pictures of crowd gathered in the streets of cites in Shanghai [18].

The Would expo dataset is used 10347 count cross scene crowds this dataset has a total 199923 pedestrian and 3980 frames and a size of 576×720 [10].

UCF-QNRF dataset includes 1535 images. In addition, it has large ranging of images from 400×300 to 9000×6000 sizes of frame videos for different densities crowds. The number of human frames 50 to 12000 across image with a size of 320×240.

The UCF-CC-50 dataset is a very complicated dataset. It includes different types of density and sense form different venues as stadium, political point, concerts, and marathons. The exact image considered is 50 and 1279 person. The data set has different resolution of image varies from 94 to 4593 [19].

USCD is the first data set used to count people. This data set is obtained through a camera mounted on a walking route. The video is 200 frames. The mall's database is collected through a camera mounted in the mall [20].

The feature matrix is constructed with the help of motion information and is designed to help nonlinear dimensionality reduction with Isometric mapping. ISOMAP has been used to detect crowd behaviour by monitoring crowd two data set have been used to detect crowd behaviour [27][35].

The technology of Gabor filters and support vector machine (SVM) accesses crowd through airborne camera system. The quality depends on training and image. The model deal with real-time congestion and developed a support system of Decision (SSD) and management of information (MI) models in order to monitoring.[26].

It is Enhanced context aware framework (ECAF) for crowd behaviour using False Negative Rate (FNR)on improving Basic context aware framework [28].

The author presented the anticipated Spatial Temporal Texture model to recognize the behaviour of the crowd in a different situation in real time. The anticipated model has given both Inference by Composition and Spatial Temporal Composition in normal result in Spatial Temporal Texture using a small amount of system memory resource in short period of time. The author has presented the Unsupervised abnormal crowd behaviour detection via the foreground partition algorithm and approximate middle filter.[29]

The author has detected and identified violent behaviour in the crowd using hybrid random matrix and DNN. The author also has described a solid and effective method for detecting the abnormality of each point of a human body based on optical flow path. The accuracy is 87.5% using public data set. [30].

An automated multiple human detection method has demonstrated the use of hybrid adaptive Gaussian mixture models to identify humans. The efficiency of the methods presented in the receiver operator output attribute in MAE and MRE and its use has given excellent results. Calculations of crowd management and monitoring using cluster methods are represented in mobile phones. Accurate with the methods presented in this model 92% is given [34][38].

The author presented Distinct multi person tracking system of the crowd using ordinary and extraordinary crowd counting at inside and outside. The system of monitoring uses Kalman filter and median filter. The accuracy is 95.50% by detecting the event [31].

Computational time has been significantly reduced by monitoring behavior to detect congestion behavior with the help of ISOMAP. Crowd behavior has been analysed by spatio-temporal model in collaboration with CUHK and UMN data sets. Accurate 98% and 88% results from the use of CHUK and UMPN data sets in spatio-temporal model, respectively [36].

The author has presented a model called Scale Aware model and Density Independent model for the localization and counting of extremely dense crowd in collaboration with the MAE model. DISAM performs head detection and takes care of head in images by scale methods. The author presented a system to identify the localization and discrepancies of the crowd present in real time and has given 99.6% accuracy of the system.[32][37]

The author has presented a model called SDCNN model for counting of the crowd and the strategy has reduced classification time and given exact result [33].

## 3. PROPOSED CROWD MONITORING AND MANAGEMENT SYSTEM

Congestion management and monitoring system (CMMS) consist of two major blocks. The monitoring system having some of the major sub block as behaviour. localization and Counting of crowds shown in figure 1.

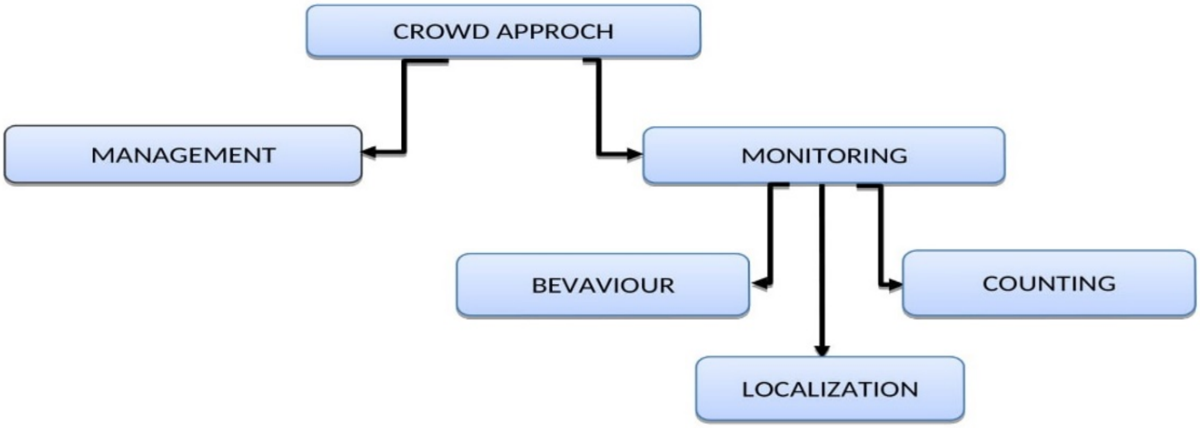


figure-1 Congestion monitoring and management approaches

### 3.1 MONITORING

Crowd monitoring system is divided into three following parts 1) crowd behaviour, 2) localization of crowd and 3) crowd counting.

#### 3.1.1 Crowd Behaviour

The behaviour of crowds is analysing and knowing ever thing at everywhere for maintaining a peaceful event in an organization. There are lot of difficulty in identifying abnormalities and normal behaviour through video. There are different technologies and methods to detect crowd behaviour. The optical flow method as well as the support vector machine is used to detect abnormal behaviour. The Multi-frame optical flow information (OFI) and Cascade deep auto encoder (CDAE) system are used to learn and knowing about crowd behaviour [6].

#### 3.1.2 Crowd Localization

The people are grouped into different area and task to know about the little information. There have been very few efforts to classified crowd in crowded place technology. The regression guided detection network (RD net) has developed for a RGB database to identify the head in a picture and to estimates the head count in the localized boundary area.[21][22][23]

#### 3.1.3 COUNTING

The Counting of persons in the crowd is determined by using Density Independent and scale aware model (DISAM) for localization and head counting. There are various technologies for counting 1) Google net and 2) BGG net for density of congestion. The Google net is an approximate estimate of the size of the crowd and the BGG net is the exact number of the person present in the crowd.[17][25]

### 3.2 MANAGEMANT

There is progress made in crowd management over the last few years. There are various models. The FSM model is to simulate congestion movement occurring in Hajj / Tawaf. They used to Round Robin methods of frame to remove the congestion in the Hajj [24]. It also displays an automated approach to detect and evaluate the video of the presented Framework for distributing congestion and traffic managers [4].

## 4. VALIDATION OF THE PROPOSED MODEL

CNN has been used to detect head and then the scale where head is presented to calculate the head present in the image like matrix forms. Sense scale in learned for crowd counting and produces a multipolar normalized density image [9]. Crowd density and crowd monitoring are measured by CNN in using for short-term memories. The CNN in crowd counting has been presented for a lot of reasons and issues such as scale variation low visibility etc. CNN based methods have performed well in images with density limits. CNN first architecture is Alexnet. It uses GPU for its to enhance performance. AlexNet architecture uses 5 types of layers- softmax layer, full connected layer, normalization layer, max-pooling layer, and convolutional layer. AlexNet Size 277×277×3 and 60 million parameters are used [39].

There are many problems associated with crowd management and monitoring as an example complex background variation of scale and localisation etc. Various techniques have been used to solve this problem. The location of person and object in complex background is still full of challenges. The formulation of the threshold value affect performance and is a topic of discussion and provides a direction for new discoveries. The training of the method of data set is compared in table No. 1.

| SNo. | Models | Wouldexpo'10 | UCF-QNRF | Shang hai Part A, B | | UCF-CC-50 |
|---|---|---|---|---|---|---|
| | | MAE | MAE | MAE (A) | MAE(B) | MAE |
| 1 | SDCN | --- | --- | 58.3 | 6.7 | 204.2 |
| 2 | CAN | 7.4 | 107 | 62.3 | 7.8 | 212.2 |
| 3 | LSCCNN | --- | --- | 66.4 | 8.1 | 222.6 |
| 4 | SANet | 8.2 | --- | 67.0 | 8.4 | 258.4 |
| 5 | DConNet | 9.1 | --- | 73.5 | 18.7 | 288.4 |
| 6 | SCNN | 9.4 | 228 | 90.4 | 22.6 | 318.1 |
| 7 | CMTL | --- | 252 | 101.3 | 26 | 322.8 |
| 8 | MCNN | 11.6 | 277 | 110.2 | 26.4 | 377.6 |

## 5. CONCLUSION

The crowd has been analysed for multiple applications based on image and video. There are various challenges in the localisation of congestion management and monitoring. The congestion management and monitoring has been taken together to recognise the cause of image dense in the crowd, with crowd counting. Congestion monitoring, management, counting, localisation, and behavior have been analysed based on several models. The model concept has applied to high-density images set for detection of the prominence of the view of image efforts using different data set. The development of CNN and the DCNN are useful to get many details of the crowd. Very large-scale crowds often generate conditions of abuse and panic. Many researchers' findings suggest that there are still many areas that need research such as localization in real-time processing, density estimation for WSN, and Information fusion of multiple sensors.

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