CHAPTER 7
CONCLUSION AND FUTURE DIRECTIONS

This chapter presents the conclusion of the work done in this thesis, along with suggestions for future research.

7.1 Conclusions

Crowd analysis is a very challenging task but is a crucial step towards developing an intelligent video surveillance system to control crowd disasters. The CA controls crowd calamities due to stampedes, riots, violence, or vandal activities; thereby, public and private properties are protected. The prominent tasks of CA are crowd counting and density estimation, crowd congestion-level analysis, crowd behavior analysis, and multitasking crowd analysis. The focus of this thesis is to develop some effective methods and models for different tasks of CA. The developed methods should be robust toward crowd shape changes, complex backgrounds, and varying crowd densities in complex crowd environments. In this thesis, novel methods using computer vision and deep learning approaches for different tasks of CA are proposed, followed by their testing and evaluation compared to other recent state-of-the-art methods.

Chapter 2 presented a brief literature review of state-of-the-art approaches for the four major tasks of CA: CCDE, CCA, CBA, and the multitasking CA. Several state-of-the-art methods and models using conventional machine learning and deep learning were analyzed for each task, and their comparative analysis was also performed. Furthermore, this chapter also discussed the details of the datasets and performance metrics used in the thesis.

Chapter 3 discussed two novel deep models for video-based CCDE. The first model is an attentive multi-stream CNN, whereas the second is a cascading of two deep architectures with weak supervision that had been proposed to address the issues with the state-of-the-art video-based CCDE. Three publicly available benchmark datasets were used to validate the models, and their performance was compared with recent state-of-the-art approaches, which showed the superiority of the proposed models.

Chapter 4 presented a novel two-stream multi-column architecture for CCA, which can process the frames in real-time. The proposed model addressed the limitations identified in the state-of-the-arts. The development of the largescale CCA dataset was also presented. The results were compared with the state-of-the-art approaches and demonstrated that the proposed model performed better than the state-of-the-art approaches.

Chapter 5 presented two deep models for the CBA. The first model is based on the OCC-based approach, whereas the second is based on the MCC-based approach. The first model exploits multiscale features from the designed spatial-temporal 3D Atrous-Net. The first model reduces the dimensionality of the multiscale features and predicts both normal and panic crowd behaviors using PCA and OC-SVM, respectively. The model is tested and evaluated using three benchmark datasets. The obtained results have been compared with the state-of-the-art approaches and show that the proposed model performed better than the recent state-of-the-art. The second model, a two-stream multiscale deep architecture, had been designed to fulfill the identified research gaps for Crowd Behavior Prediction. The proposed model was tested and evaluated using two largescale benchmark crowd behavior datasets. The obtained results beat the state-of-the-art approaches.

Chapter 6 presented a multitasking crowd analysis model focusing on crowd counting and behavior prediction. To fulfil the availability of largescale multitasking CA dataset. In this chapter, a multitasking CA dataset using available crowd behavior datasets was also developed. Around 1,20,000 frames were manually annotated. Apart from this, a multitasking CA model using the deep learning technique was proposed. The depth-wise separable CNN and flow attention blocks are the important modules of the proposed model. The identified research gaps were addressed by exploiting multiscale de-background features from the volume of a sequence of frames. The proposed model was tested and evaluated on the proposed multitasking dataset. The results obtained show that the proposed model performs better than the state-of-the-art approaches.

7.2 Suggestions for Future Research Work

The proposed work has scope for future research work. The followings are some of the prominent future works.

- Cross-domain models for video-based crowd analysis. The cross-domain models mainly focus on developing a model trained in one dataset that can easily apply to another without training the model. Some works can be found for image-based CCDE, but the performance needs improvement. So, there is ample scope to do research in this direction.
- Development of largescale crowd analysis dataset. There is a lack of largescale crowd analysis datasets containing millions of crowd videos. So, in this direction also, future research can be focused.
- Development of unmanned aerial vehicles (UAV)-based CA model to provide security and safety to people by patrolling in different areas. There is a huge demand for an automatic patrolling system using UAVs to minimize the overhead incurred during the manual process and provide people security and safety in real-

time. Hardly some works can be found in this research area. So, here also, there is ample scope to do research.

- Development of better CA models. The development of CA models is always in greater need. With the advancement of computer vision and deep learning approaches, more sophisticated and undiscovered models cab be developed for the CA, which could also be the future research scope.