Chapter 7

Conclusion and future work

This chapter recalls the context of the thesis, summarizes the main contributions of this work, and finally outlines the future research directions towards extending the capabilities of smartphones sensors in various other domains.

Conclusion

This thesis has studied various problems encountered while extending the capabilities of smartphone sensors for applications in smart transport. The principal objective of this work was to develop effective and efficient approaches for smart transport, utilizing the sensing and processing capabilities of smartphones. This work considered two tasks, *i.e.,* locomotion modes recognition and processing smart transport tasks using smartphones. While training the model for locomotion modes recognition, we encountered the problem of unseen classes (locomotion modes) and noisy labels in the training dataset collected from the smartphone's sensors. Furthermore, we considered the problems of the resources constraints (processing power, storage, and battery) and device heterogeneity during task processing on smartphones. These problems are more common and frequently occur in real-world scenarios; therefore, employing suitable mechanisms results in the effective utilization of the smartphone's sensing and processing capabilities in smart transport. This thesis has made four major research contributions to resolve the problems encountered while using smartphones' sensing and processing capabilities in smart transport.

In chapter 3, we covered the problem of unseen locomotion modes in the training dataset collected from the smartphone's sensors. We proposed a deep learning-based model named DeepZero to identify seen and unseen locomotion modes using smartphones. Unlike existing approaches, the DeepZero model utilized the concept of ZSL by learning the mapping between features and the attribute matrix of the class labels. The model constructed an attribute matrix by fusing three semantic matrices. The attribute matrix is constructed by using only the class labels of datasets. The attribute and features from deep learning models are used during the construction of the classifier. The chapter demonstrated several experiments to evaluate the performance of the DeepZero model on locomotion mode datasets. The results showed that the model provided an accuracy $> 94\%$ for seen classes and $> 80\%$ on one unseen class.

In chapter 4, we covered the second problem of the noisy labels in the dataset collected from the smartphone's sensors. To cope with the problem, we proposed a deep learning-based LRNL approach for recognizing the locomotion modes using sensory data with noisy labels. Unlike existing approaches, the LRNL approach built an ensemble model to enhance the recognition capability of the classifier without having any prior information about the concentration of noisy labels. The ensemble model incorporates three models, i.e., conventional, noise adaptive, and noise corrective, for handling different concentrations of noisy labels in the training dataset. The noise adaptive model proposed a noise adaptive loss function that reduces the discrepancy between true labels and predicted labels using dynamic variables. Next, the noise corrective model used a low-rank estimate of true labels for handling noisy labels. We also carried out several experiments to validate the effectiveness of the proposed approach using a collected and two existing datasets.

In chapter 5, we proposed a system to handle resource constraints of the smartphone while executing the smart transport tasks. This chapter presented a transportation system incorporating Fog computing for passenger assistance. Unlike the existing work, TSF considered offloading portions of the task to the neighboring FDs for its parallel execution within a time constraint. We first presented neighboring FDs selection criteria to identify the best suitable FDs for offloading the task. A competitive game is then formulated in which the primary FD decides the fractions of task it offloads to s-FDs. TSF is validated by setting up a prototype and performing various experiments to study the impact of task execution deadline, data size, and various game parameters.

Finally, in chapter 6, we proposed an FFL technique to train a model for a given task at the participant devices using its local dataset. Unlike the existing work, the FFL technique trained the model on participant devices with resource heterogeneity. We first presented an approach to obtain the generic model, which is not arbitrarily large or small and suitable for most participant devices. Next, we proposed an early halting approach for faster training of the resized model, which fits the insufficient and colossal resource devices. We also did a real-world study to evaluate the feasibility and performance of the proposed technique.

Future Directions

This thesis work has made contributions towards the investigation of the different challenges encountered while extending the capabilities of smartphone sensors for applications in smart transport. The primary objective is to mitigate the negative impact of unseen and noisy labels in the transport dataset collected using smartphones sensors. Further, we introduced different mechanisms to successfully process the sensory dataset on smartphones. It reduced the task execution delay despite limited resources. By using the results in our work, one can effectively design appropriate approaches to handle different challenges encountered while using the smartphone for data collection and processing in smart transport. We believe that the proposed work would motivate further research towards the effective utilization of the hidden potential of the smartphone and its sensors. This thesis also provides a pathway of using smartphones to adapt different contexts and challenges to develop user interaction techniques. The work described here can be extended further in the following directions:

- This work provided the mechanism of constructing a human-annotated semantic matrix in zero-shot learning to improve recognition performance. Therefore, constructing more unique and precise human-annotated matrices could be another possible extension of this work.
- This work only covered the problem of noisy labels in the training datasets; however, the persistence of noise in the sensory instance along with noisy labels is still a research challenge. Thus, handling noise in both instances and labels could be the future work in this area.
- We believe that the proposed work must motivate further research in assisting passengers and drivers of the vehicles using Fog computing.
- The FFL technique considered the heterogeneity in three resources (memory, processing power, and bandwidth). We will consider the heterogeneity in other parameters (such as data sources and sampling rate) in the future. We also plan to consider the imbalanced dataset while training a recognition model.