Preface

The expeditious evolution of computing devices has transformed room-size machines into pocket-friendly mobile devices. This transformation leads to the development of low-cost, low-powered, and compact devices, like smartphones, smartwatches, smart bands, smart glasses, *etc.* These compact and battery-powered devices are powerful and can execute most of the tasks a user performs on a computer. Specifically, smartphones are widely adopted and the preferable choice for a significant number of users. Besides the computational capacity of simultaneously processing multiple tasks, smartphones possess richer sensing capabilities. Smartphones have various onboard sensors, including accelerometer, gyroscope, GPS, touch sensor, fingerprint sensor, heart rate sensor, *etc.* These onboard sensors facilitate unprecedented opportunities to perform various sensing and monitoring activities, which enriches the quality of life. A smartphone user is no longer assumed to be static and can conveniently move outside, *i.e.,* walk, run or may use different transportation modes like bus, train, car, bike, bicycle, *etc.* This movement of users generates a huge amount of sensory data on smartphones, which can be exploited for various sensing and monitoring applications in smart transport. Transportation mode detection is one of the potential applications in smart transport, which helps in estimating travel time, journey planning, route selection, *etc.*

In this thesis, we investigate the different challenges encountered while extending the capabilities of smartphone sensors for applications in smart transport. We consider two tasks in this work: a) transportation modes detection using smartphone sensors

and b) processing smart transport tasks on the smartphone. While considering the task of transportation modes detection, we identify two challenges, *i.e.*, unseen classes and noisy labels in the dataset. A class is said to be unseen if there exist no training instances of the class in the dataset; however, such instances may appear during testing. These challenges deteriorate the performance and increase the training time. We develop approaches to tackle unseen classes and noisy labels in the dataset. Further, the task processing on the smartphone also incurs challenges of resources inadequacy and execution delay. We also present the approaches to reduce the model's size running on the smartphone and task partitioning into multiple sub-tasks.

First, we propose a deep learning model, which incorporates the concept of zero-shot learning to detect both seen and unseen transportation modes using sensory values of smartphone sensors. The model builds a classifier by learning a mapping between the extracted features and semantic information of the class labels. Next, we present a deep learning-based approach to detect a transportation mode using deep learning models in the presence of noisy labels. Further, we propose a transport system that incorporates Fog computing to partition and execute the task fractions on multiple interconnected Fog devices (or smartphones). The system uses the competitive game approach and Knapsack algorithm to partition the task among Fog devices, ensuring minimal delay and cost of execution. Finally, we design an approach to train the model on participant devices using the local dataset with heterogeneous resources. We consider the scenarios where devices have sufficient, colossal, and insufficient resources to train the model. The approach uses knowledge distillation, known as student-teacher learning, to train resized generic models for insufficient and colossal resource devices. To speed up the training of the model at each participant device, the approach halts the teacher training after a certain halting epoch. We derive an expression to find the halting epoch for the given accuracy.