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It is further certified that the student has fulfilled all requirements of Comprehensive Examination, Candidacy, and SOTA for the award of Ph.D. Degree.

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I, ***Rahul Mishra***, certify that the work embodied in this Ph.D. thesis is my own bonafide work carried out by me under the supervision of ***Dr. Hari Prabhat Gupta*** from ***July 2017*** to ***February 2022*** at ***Department of Computer Science and Engineering***, Indian Institute of Technology (BHU) Varanasi. The matter embodied in this thesis has not been submitted for the award of any other degree/diploma. I declare that I have faithfully acknowledged and given credits to the research workers wherever their works have been cited in my work in this thesis. I further declare that I have not willfully copied any other's work, paragraphs, text, data, results, *etc.* reported in journals, books, magazines, reports, dissertations, theses, *etc.*, or available at websites and have not included them in this thesis and have not cited as my own work.

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Dedicated to my parents,

Mrs. Malti Mishra

and

Mr. Radhe Shyam Mishra

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List of Symbols

Symbol	Description
$\mathcal{D}$	Dataset with labeled instances
$\mathcal{A}$	Attribute matrix
$\mathbf{x}_i$	i^{th} instance of $\mathcal{D}$
$\mathcal{Z}$	Semantic matrix
$\mathcal{L}_{term}$	Loss term
$\mathcal{R}_{term}$	Regularization term
$\mathbf{Y}$	One-hot encoded true label matrix
$\mathbf{Y}'$	One-hot encoded noisy label matrix
$\mathbf{Y}_{te}$	One-hot encoded prediction matrix
$\mathbf{\Pi}$	Built classifier
δ	Distance threshold
$\mathbf{T}$	Low rank representation of $\mathbf{Y}$
$\mathcal{L}_a$	Loss term to conquer true label prediction
$\mathcal{L}_b$	Loss term to conquer false label prediction
$\mathcal{L}_{NAL}$	Noise adaptive loss
ϕ_i	Probability of true label for i^{th} instance in $\mathcal{D}$
E	Epochs for model training
e	e^{th} epoch, $1 \leq e \leq E$
$\mathbf{b}$	Bias vector
B	Bandwidth
$\mathbf{r}$	Reputation
η	Learning rate
$U(\cdot)$	Utility function
F_i	i^{th} Fog device $\in \mathcal{N}$
p_i	Price receive by Fog device F_i
$\mathcal{N}$	Set of Fog devices
$\mathcal{P}$	Set of participants

Symbol	Description
ϱ_i	i^{th} participant, $\varrho_i \in \mathcal{P}$
$\mathcal{S}_{ij}$	Signal to interface noise ratio between Fog devices F_i and F_j
τ_i	Portion of task executed at Fog device F_i
$\mathcal{L}_{DL}$	Distillation loss
$\mathcal{L}_{AL}$	Attention loss
$\mathcal{L}_{CE}$	Cross-entropy loss
R	Number of global iterations
$W^{[t]}$	Weight parameter matrix at iteration t, $1 \leq t \leq R$
h	Halting epoch, $1 \leq h \leq E$
M_o	Generic model
M_i	Model at participant ϱ_i, $\varrho_i \in \mathcal{P}$

Abbreviations

Abbreviation	**Description**
CE	Cross Entropy
CNN	Convolutional Neural Network
CR	Compression Ratio
DL	Distillation Loss
DNN	Deep Neural Networks
ED	Edge Device
FD	Fog Device
FFL	Fast Federated Learning
FL	Federated Learning
GPS	Global Positioning System
GRU	Gated Recurrent Unit
IMU	Inertial Measurement Unit
KD	Knowledge Distillation
LMR	Locomotion Mode Recognition
LRNL	Locomotion Mode Recognition with Noisy Labels
LSTM	Long Short Term Memory
NAL	Noise Adaptive Loss
NE	Nash Equilibrium
RoC	Rate of Convergence
RSU	Road Side Unit
SHL	Sussex-Huawei Locomotion
TMD	Transportation Mode Detection
TSF	Transportation System using Fog computing
WPM	Weight Parameter Matrices
ZSL	Zero-Shot Learning

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.