A Comparative Study of Traffic Detection Using Google Map (GPS) and IoV

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

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Abstract

Everyone knows that time is money and nowadays people spend quite a large amount of time on the roads in their daily life. The reason behind this is nothing but 'Traffic'. Traffic detection and navigation has gone through many phases over the years. Once we had to depend on traffic prediction and now, we can check real time traffic updates by the means of services like Google Map. Google Map uses GPS to detect traffic. However, the problem with it is, Map uses historical traffic data and the individual GPS device count to detect the congestion of traffic. This may affect the accuracy in terms of vehicles. Depending only on the device count and past records, a proper real time data cannot be generated. The very important aspect of vehicle count, and vehicle size are totally ignored in this approach. Moreover, a real time representation of traffic will also require 24/7 surveillance. Another promising approach to detect traffic is using IoV (Internet of Vehicles) to count the number of connected vehicles rather than counting people in an area. As the world is moving towards IoT, traffic detection can evolve to a great extent with the introduction of IoV as well. In this work, we will be analysing the existing system google uses for traffic detection and compare it with a possible model to be used with the inclusion of IoV. To provide a verdict on which system will be better, we will be using traffic detection reports of google Map as preliminary data and possible outcome of the IoV model analysed.

Keywords: Traffic detection, Google Map, IoV, GPS, Navigation.

Dedication (Optional)

We would like to dedicate this thesis to our ever supporting and loving parents.

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Chapter 1

Introduction

1.1 Overview of Traffic Detection

During the last century, traffic sensing technologies evolved quickly. In the last several years, real-time detection of traffic has improved greatly, but there is still a great deal of opportunity to improve with increased demand for automobiles and economic efficiency. Accurate traffic detection can help people by many folds. It can help us to manage our time more efficiently. People mostly rely on Google Map live traffic updates. Currently, it is the most available and dependable option. In 2007, Google added Google Live Traffic to Google Map. Although there have been some issues with google Map lately, it is still the most preferred system. Traffic detection and navigation services of Google Map is obviously the number one choice all over the world, but it does not necessarily mean that it produces the most accurate results and cannot be improved further.

With the introduction of IoV the results can be more accurate. If we think about traffic, the first thing that comes to our mind is vehicles. More number of vehicles can result in large amounts of congestion. In 2019 alone, 92 million automobiles were manufactured globally [27]. This reflects the rapid increase of vehicles around the world every year. With this growth of vehicles, adaptation in traffic detection and management is a must.

In a dynamic world like todays where technologies are evolving every day, the traffic detection system should improve. Otherwise, it may cause issues for our day-to-day life on a large scale. There can be millions of vehicles on the roads at a time, but an efficient traffic detection can make it easy to navigate in the worst conditions. If an interconnected network of all the vehicles exists in future, imagine how much it can contribute to the traffic detection and management system. With continuous sharing of data each vehicle can form a web of traffic data and represent them as accurately as possible. Obviously, there will be a lot of obstacles and drawbacks, but the results will benefit the users a lot. With the rapid advancement of technologies like autonomous driving, traffic detection and management must take a leap forward towards the future.

1.2 Problem Statement

Everyone has experienced sitting in heavy traffic for hours more than once in their life. So, it can be assumed that navigating through heavy traffic is a common problem for the world. People using smart devices have the luxury to check live traffic updates on Map. It shows the present traffic status of the surrounding area. Now, as a general user the common scenario is to trust the available navigation system and plan our desired route accordingly, but sometimes the real status of the traffic can differ from the one shown in our system. This may lead to a huge disappointment and cost the user big time. For example, a user lives 10km away from his/her workplace. He/she must reach the office within 20 minutes. So, he/she checked the map and it showed two different routes. These two routes; let us say route 'A' and route 'B' were represented with the traffic status and an estimation of 15 minutes and 18 minutes, respectively. The user chose the faster route, which in this case is route 'A' and after travelling 5 minutes he/she found that a car crash ahead caused a huge congestion. Eventually, he/she had to take the other route and reach late at office. Later he/she found that the car crash and the congestion occurred a few minutes before he/she checked the map. Now, is there anyone to blame in this case? No one, because there are limitations of the traffic detection system that we are using. The problem in this example scenario was the live update of events and congestion not reflecting in the map. The factors involved in the analysis of traffic level matters way more than we think.

To be specific, real time traffic updates are a major issue. Google does its best to generate the accurate results but the data it uses may not help always. Maps highlight the streets with green, yellow, and red colors. These color coded streets indicates light traffic, moderate traffic, and heavy congestion respectively. Now, the system even calculates these data to recommend the fastest route for the user. While determining the fastest route to your destination, this feature is very useful, but have you ever thought about how Google knows the traffic conditions of your desired route?

Google Map detects and provides traffic suggestions relying on two sorts of data: the time it takes to move a certain stretch of the roadway on a certain day and the continuous information given by sensors/cell phones that record the rapid movement of cars. Google also gathers several secondary sources of traffic related information. Later on, they resorted to crowding to make the data analysis more accurate [1].

What's that crowdsourcing now? The commencement of crowdsourcing when someone uses Google Map for mobile with GPS enabled. We constantly notice mobile applications requesting permission to utilize our whereabouts. To assess traffic congestion, Google analyzes this precise user information. If you opt to activate My Location on Google Map, your phone transmits anonymous portions of data back to Google to describe how quickly you move [1]. Google combines your speed with other mobile phones on the road, traveling throughout the city at every stage across thousands of phones to get a very excellent image of real circumstances. These statistics are continually combined and returned in the Google Map traffic layers [1]. This is what crowdsourcing is all about. The more individuals that take part, the better the subsequent traffic reports get for everyone.

All these procedures that Google follows are reliable, but at the end of the day these are all predictions based on gathered data and calculations. There are certain levels of limitation in this process. With the introduction of IoV (Internet of Vehicle) the accuracy level can change to a significant extent. In terms of real time update every single detail matters. So, the concern is the accuracy of Google Map detection. Reports state that Google bought the community power navigation app 'Waze' on June 11, 2013 for around $1.1B [3]. The reason behind the acquisition of this start-up was the use of user generated data about various traffic events like jams, shortcuts, accidents, gas stations etc. The system acquires all the user-friendly traffic data, generated by the users themselves [10]. This helped Google improve the traffic update system.

Now, there is an underlying question here. Hypothetically, only ten persons boarded on ten different vehicles and they are travelling through the busiest street of the city on the busiest hour of the week. Map will show results based on the historical data, data gathered from the sensors and devices, and crowdsourcing along with the average speed required to travel between two points will be considered too. What if someone was travelling in a motorcycle and someone in a bicycle? What if someone was travelling in a car and someone in a truck? The sizes and the speed of the vehicles differ, right? Now, imagine 50 people travelling in a single public bus and they are feeding in data for Google to help Google calculate crowdsourcing results. 50 devices may result in congestion, but a single bus may not. So, we can get an idea about the problem from this example. Major aspects like vehicle size, vehicle type, maximum speed should be considered while calculating traffic results. To achieve this a 24/7 direct monitoring of the roads can be an option but this is not viable.

The solution is to find a way to include these valuable data to make a result based on everything considered. Deploying a 24/7 monitoring infrastructure on every single street is not possible due to cost inefficiency and the risk of failure at any point. An IoV based model can help to feed in almost every necessary data for traffic detection. Initially it may sound like imagination, but it is possible with the current set of advanced technologies available. If an interconnected network of vehicles moving simultaneously at the same location can share vehicular data and observable surrounding information between them and send these data to the servers for analysis, then it can contribute heavily to the process of live traffic detection. Introduction of VANETs (Vehicle ad-hoc networks) can prompt all the more ideal and intuitive methods of gathering such traffic information. A VANET utilizes vehicles and additionally cell phones as versatile nodes in a portable impromptu network to make a mobile network [7].

Currently, to detect the status of any vehicle, the use of On-Board Equipment (OBE) is widespread. Various sensors integrated with the vehicle helps to observe and determine the vehicles present status.A GPS recipient is able to get the location information; vehicle's speed can be measured using speedometer; using odometer the distance traversed inside a range can be obtained and different other internal sensor can acquire data about the vehicle's status. Integrating more necessary equipment, these smart vehicles can observe the surrounding vehicles which are not participating in the VANET and the current state of the road. These valuable traffic information can be conveyed to a server using cellular network [7].

There are numerous approaches now offered for traffic detection and management with wireless sensor networks. The Internet of Vehicles (IoV) potential stand out amongst these. The core notion of IoT for traffic control was extensively recognized and applied for smart city infrastructure building [15]. This deployment can bring promising changes in the traffic detection system. This IoV network can create detailed real-time traffic information, allowing certain basic traffic issues to be effectively handled from a fresh perspective.

Although, there are sufficient works in the field of traffic detection by using IoV, works related to the direct comparison between Google Map and IoV falls behind. The purpose of this research is to identify the improvements that the new IoV based model can bring along with its obstacles and drawbacks compared to the present system of traffic detection by Google.

1.3 Aims and Objective

As a comparative study we must find out all the ins and outs of both the approaches for traffic detection. First, we have to learn how Google Map detects real time traffic status. In this matter, we must go through the beginning to the present technologies and procedures used to detect traffic flow by Google. Then, we need to find out the drawbacks in the accuracy of Google Map traffic detection. Afterwards, we have to find out how the integration of IoV can enhance the accuracy of the real time traffic state detection. A possible model for traffic detection using IoV should be represented in order to visualize the whole scenario of the system. Finally, we should consider the drawbacks of implementing IoV at a large scale for this purpose. We must consider all the factors that can improve traffic detection and also all the factors that can cause issues while implementing the new system. As Google Map is currently doing a great job in this field, the sole purpose of this paper will be how to improve the existing system using IoV without any compensation. Major objectives of this research are:

- To understand thoroughly how Google detects traffic.
- To analyse Google's traffic detection procedure and its accuracy/efficiency.
- To deeply analyse the concept of IoV and its contribution in traffic detection.
- To analyse an IoV based model for traffic detection as an improvement.
- To present a verdict based on the benefits and drawbacks of the new model.

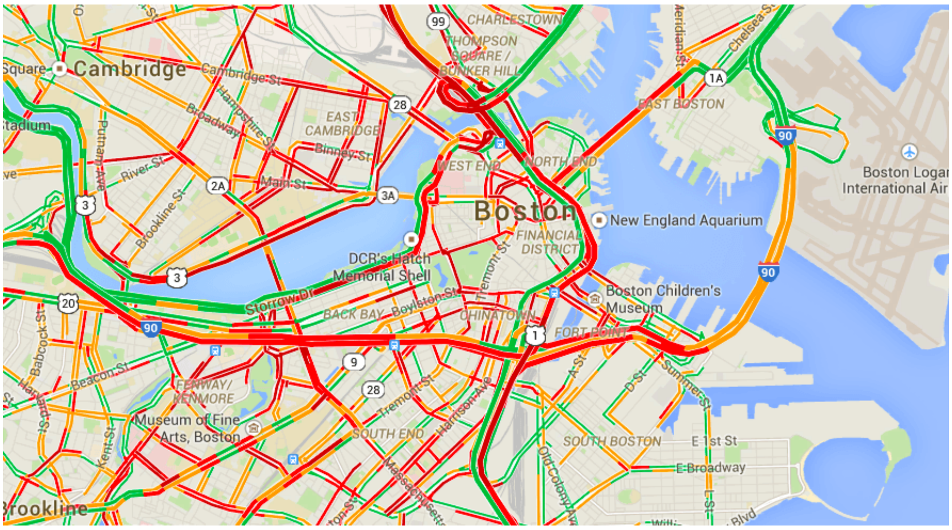

Figure 1.1: Google Map live traffic update

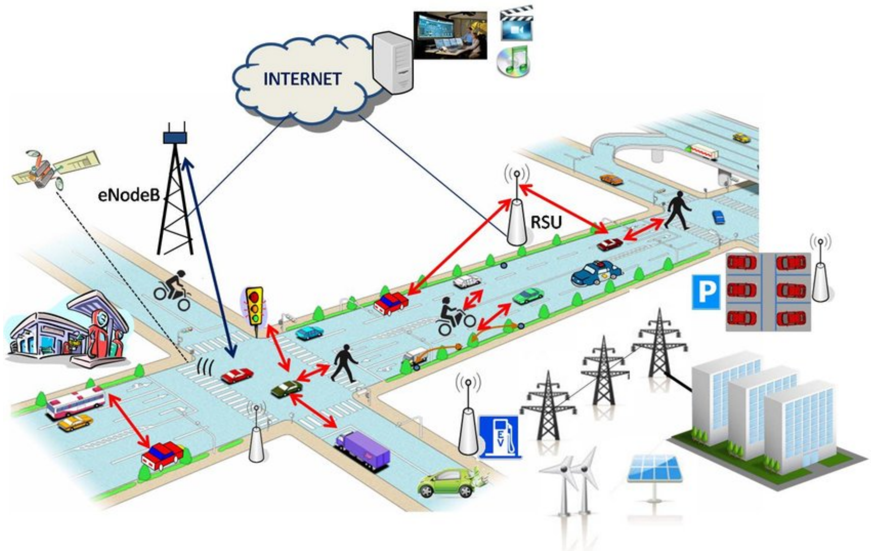

Figure 1.2: IoV model for traffic detection

Chapter 2

Literature Review

The whole review is mainly divided into three phases. One is about Google Map traffic detection system, another one is about implementing IoV to improve the accuracy and finally, reviewing some existing works in this field. Firstly, let us focus on Google Map.

2.1 Google Map

Google Map represents the traffic observations and optimal-route recommendation on the basis of two distinct forms of data: previously recorded information on the normal time it takes to drive between a specific section of the street at definite occasions on certain days, and constant information put together by sensors and cell phones showing how rapidly vehicles are voyaging directly around then [1]. When people keeps their devices on navigation mode, the speed of moving devices are monitored between two segments, which are pre-defined.

Previously, Google Map primarily relied upon information gathered using traffic sensors, a huge part of these were presented by government transportation organizations or privately owned businesses that spent significant time in accumulating traffic information. The sensors can recognize the size and speed of passing vehicles by utilizing radar, dynamic infrared or laser radar innovation. Afterwards, these valuable information is remotely transmitted to a server. [16]. When Google first showed interest to provide real time traffic updates to its user they faced lot of difficulties, even after being one of the most omnipresent companies of the time. Soon, they found that they are not the only entity who are interested in traffic detection. With the help of existing specialized sensor-based traffic detection companies Google was able to expand its traffic detection services.Google managers have concluded an agreement with INRIX, a software business which collects traffic data via sensors independently of its customers in 22 countries [16]. INRIX CEO Bryan Mistele told that they are providing [Google] much broader coverage and much better accuracy then what they have had available [2]. To provide real-time traffic updates, this data is proved to be more efficient. Once these information are gathered, they are included to the pool of chronicled information utilized for traffic volume forecast in future. However, only primary streets and highways were under the coverage of this sensor data. The sensor infrastructure were mostly installed on the busiest or traffic-prone routes only. [4]. This limitation can reduce the accuracy in terms of real time traffic updates. Furthermore, the data INRIX provides is not global too.

From 2009, Google opted for crowdsourcing for improving the accuracy of traffic detection. At the point when android clients use their Google Map app with location services enabled, the phone keeps sending data to Google anonymously. This persistent progression of information helps the organization realize how quick the vehicles are moving between places. Google Map constantly processes the information flowing in from every one of the vehicles out and about and sends it back in the form of color coded streets on the traffic layers [1]. As an ever increasing number of drivers utilize the application, the traffic expectations become more dependable because Google Map can perceive normal speed of vehicles going along a similar course. If Google Map needs more information to assess the traffic stream for a certain segment of the street, the traffic flow for that segment is displayed in gray. [28]. Google Map constantly refreshes depending on the tracked client information, traffic sensors, and satellite information to ensure the application is showing the most precise traffic conditions conceivable. However, still a human element was missing from the overall monitoring system of traffic detection.

After securing a deal with Waze in 2013, Google added that human component to its traffic estimations. Waze is a popular community powered navigation application. Using the app, drivers can report traffic events such as accidents, disabled vehicles, slowdowns, speed traps etc [5]. These continuous reports show up as individual marks on Google Map, with little symbols addressing things like construction signs, slammed vehicles or speed cameras [29].

In terms of real time traffic update, all these methods are reliable but still these are some predictions based on calculations. There are drawbacks in most of the cases. Historical data may not predict the live traffic correctly at all. Data collected from sensors and devices are not enough as they are installed in limited areas only. Sudden incidents are updated in the Map based on information sent by people. This may not be efficient enough. A real time update requires real time monitoring. Delay is not an option here.

The average crowd and average motion pace might be different from place to location, thus, crowdsourcing cannot be a viable alternative. This crowdsourcing approach has been used purposely on multiple occasions to address its constraints. Only around three years ago during a May Day event in Berlin, artist Simon Weckert spotted something unusual: Google Map showed that, although null automobiles were on the route, there was a gigantic barrier. Weckert knew soon enough that Google had been deluded into perceiving the jam on a vacant street by the number of people or more explicitly their cell phones. Then he personally chose to do it [22].

He only wants his iPhones, he remarked. He doesn't need to deal with others. Weckert has thus gathered about 99 iPhones from partners and rental organizations as navigation devices, which he placed into a tiny red car. The notion was straightforward. All day long, Weckert would walk up and down a certain path, usually irregular and travel his wagon stocked with a cellphone. The effect was not immediate; it took around an hour for Google Map to catch up. At last weckert tells us, however, that his car would be fitted with a long red line, showing traffic had been slow down, even if traffic was not available. He had effectively tricked the system into thinking a series of large buses were crawling back and forth [22].

Google always welcomed such use of the system by its user. They expressed their gratitude by stating that it helps them improve the system gradually. Google claims that they have now improved the system to distinguish between different types of vehicles. Such as cars, motorcycles etc. But they are yet to find a solution for a setup that Weckert did. Recently, they also claimed to identify stationary devices. People who are just being stationary at a place for long are not counted for traffic congestion calculation. Still there are gaps that need to be filled up.

Another important aspect of traffic detection is to predict the traffic ahead of time. When individuals explore with Google Map, location data can be utilized to comprehend traffic conditions on streets at that point. There might be a slight delay of the update due to analytical time cost. This information helps find current traffic estimates but whether a traffic jam will affect your drive right now, it does not account for what traffic will look like 10, 20, or even 50 minutes into your journey [24]. This is completely a separate part of discussion, because to achieve this successfully, only historical data or crowdsourcing data will not help. Artificial intelligence can contribute to solving this issue. Although, this case is beyond the scope of this research, it is worth mentioning because introduction of IoV can create much more opportunities like this. Existing traffic detection systems can be improved, and other valuable features can be integrated as well.

There was a time when Google Map used to only show us how long it would take to reach our destination based on predictions from historical data. By 2007, Google started to move towards real time traffic. Now real time traffic feature is delivered via Google Map in 50 countries of the world including our country, Bangladesh [30]. These real time traffic updates are very useful till date but limitation of accuracy can cause issues anytime.

These are issues of Google Map related to the traffic prediction. Issues related to navigation are not rare as well. There have been numerous reports from the users about wrong navigation information over the course of time. Even if this sounds harmless, this can be fatal at times. In most of the cases people may use their conscience to avoid unnecessary problems due to wrong route recommendation, but there are cases where people regretted their decision to blindly trust Map. One such horrible incident occurred when a teen from Russia was frozen to death in -50C, after being shown wrong route by Google Map [23]. Reports citing police investigators said that the Google Maps directions sent Sergey Ustinov and his companion Vladislav Istomin, on a neglected shortcut route on the planet's coldest inhabited area. They had not taken precautions for the extreme conditions and were quickly frostbitten when their radiator was damaged by a wooden spike on the old road. Ustinov was discovered frozen solid in his Toyota Chaser, while his companion was supernaturally alive yet experiencing intense hypothermia. These two teens had been driving from the planet's coldest city Yakutsk to the port of Magadan, on an expressway known as the Street of Bones. The course on 'Yandex Maps', a Russian application showed a distance of 1,180 miles on the Kolyma government expressway through Ust-Nera. However, Google Maps showed a preferable choice of 1,076 miles across the snow shrouded area [23]. Unfortunately they choose the latter option. Obviously, this cannot be stated as an example, this is one of those cases where the disaster could have been avoided by adapting necessary precautions, but this kind of incident is a warning that how much damage wrong navigation information can cause. There is no one to blame, but it remains a major problem while guiding a user who is not oriented with the location. Sometimes, Map directs the user to any unsafe route unwillingly because Map cannot monitor that route live.

Obviously, it is not possible to think about monitoring every single road of the world simultaneously. That requires a large amount of infrastructure and management cost. Imagine installing expensive sensors, cameras all over the world and deploying huge scale servers and computer vision technologies for traffic detection. This cannot be a viable solution at all. What can be done instead is to slowly move towards the use of the Internet of Vehicles for traffic detection and management. IoV is the future of traffic management and by future it does not mean very far ahead in the future. With the invention of IoT devices, smart cities are already in plans. In these smart cities traffic detection will be built upon the IoV network infrastructure. A large network of connected vehicles sending continuous updates to servers about everything on the road. That will surely make a more accurate result.

2.2 Internet of Vehicles (IoV)

With the rapid advancement of technologies and the growing urge for more intelligent and connected devices Internet of Things is breaking out faster than everyone imagined. IoT offers a smart environment of physical devices where these devices can communicate and interact with each other. According to recent predictions [26], 64 billion "things" will be connected to the Internet by 2025, of which vehicles will constitute a significant portion. With increasing numbers of vehicles being connected to the Internet of Things (IoT), the conventional Vehicle ad-hoc Networks (VANETs) are changing into the Internet of Vehicle (IoV).

Vehicular ad-hoc networks (VANETs) are implemented by applying the standards of mobile ad-hoc networks (MANETs), the unconstrained creation of a wireless network of mobile devices to the domain of vehicles [26]. VANETs were first referenced and presented in 2001 under "car-to-car ad-hoc mobile communication and networking" applications, where networks can be shaped and information can be relayed camong cars [26]. It was stated that to provide road safety, navigation, and other roadside services, vehicle-to-vehicle and vehicle-to-roadside communications architectures will co-exist in VANETs. VANETs are a vital piece of the intelligent transportation systems (ITS) framework. Sometimes, VANETs are referred as Intelligent Transportation Networks [26]. They are understood as having evolved into a broader "Internet of vehicles" [26].

VANET turns every participating vehicle or to be specific every participating intelligent entity including pedestrians, parking lots and so on into a wireless router or mobile node, enabling them to connect to each other in turn and create a network. VANET only covers a very small mobile network that is subject to mobility constraints and the number of connected nodes [6]. But when it comes to large and complex instances of traffic jams, bad behaviors from drivers, and complex street networks, VANET is not compatible anymore. These situations further hinder its utilization. Hence, for VANET, the objects involved in the process are transitory, arbitrary and unstable, and the scope of utilization is local and discrete, i.e., VANET is unable to provide a global and sustainable services/applications for customers [6]. Due to this shortcoming of VANET, Internet of Vehicles appeared into the scene. It is said that this Internet of Vehicles is the evolved version of conventional VANETs. Inter-connectivity for establishing a social network with smart objects as participants results in the formation of the Social Internet of Vehicle (SIoV), the vehicular instance of the Social IoT (SIoT).

In contrast to VANET, IoV has two main technology directions: vehicles' networking and vehicles intellectualize. If we breakdown Vehicles' networking, it is comprised of VANET (additionally called vehicles' interconnection), Vehicle Telematics (known as connected vehicles) and Mobile Internet (vehicle as a wheeled mobile terminal). Vehicles' intelligence is the coordination of driver and vehicle as a unit. This is more intelligent due to network technologies like deep learning, cognitive computing, swarm computing, uncertainty artificial intelligence, etc. So, IoV focuses on the intelligent integration of humans, vehicles, things and environments and is a larger network that provides services for large cities or even a whole country [6].

The Internet of Vehicles (IoV) can be viewed as a superset of VANET. It extends VANET's scale, structure, and applications. Unique in relation to the traditional Intelligent Transportation System (ITS), it puts more emphasis on data association among vehicles, humans, and roadside units (RSU). It is more likely to make people acquire real-time street traffic information effectively, to protect the travel convenience, and to improve the travel comfort [9]. As an important branch of Internet of Things, IoV is mostly utilized in urban traffic conditions to provide network access for drivers, passengers, and traffic management executives. Along with the vehicular data, environmental data is also an important factor in determining the traffic condition and optimizing navigation experience.

IoV environment is the mix of wireless network environment and other street conditions. Analysts need to think about moving vehicles and a general complex management system. There are number of genuine real-life scenarios that forces the necessity of vehicle networking technologies. For instance, driving on the interstate or in metropolitan situations, drivers wish to know the traffic circumstance of streets ahead of their trip and change their driving course as indicated by whether an accident or traffic jam occurs on their way. What better way to manage time spend on the roads efficiently? By making proper utilization of the advanced technology of IoV, people can reduce fuel consumption, and environmental pollution too [9].

Variety of data mining and monitoring applications can be developed to improve the efficiency of the roadway movement and other management requirements. Highlights like Busy Routes, Blocked Streets, Accidents, Construction, Moderate Traffic, Queries, etc. can be handled by these applications. We mentioned, SIoV already utilizing effectively settled features in the VANETs model like OBU (On Board Unit) and RSU (Side of the road Unit). OBUs address the vehicles on street and RSUs address the roadside foundations that are interconnected via internet [8].

Utilizing communication between vehicles, the roadside unit can learn a street's status progressively, and alongside the status of the vehicle, convey this traffic information to the cloud, where the average speed and other information are estimated through successive calculations. Unfortunately, the traffic departments do not employ this precious traffic data, so that they have no structure for feasible transmission, storage, and analysis.At now there is no routine information for drivers broken down by current trip time estimations and models for dynamic route planning.Transportation efficiency may be improved through use of data from linked cars.For promptly estimating and predicting the trip times, new algorithms may be created that combine the findings with the accident prediction for the driver to help prevent congestion. This strategy might also potentially lead to the construction, through the usage of smartphones and sensors, of efficient large-scale sensing applications. For example, one may collect traffic information and discern between degrees of congestion using driver smartphones rather of adding street-side cameras and loop detectors. The expenditure on specialized sensors can be reduced by such setups [13].

Because of the fast improvement of automotive telematics, present day vehicles are required to be associated through heterogeneous radio access technologies and can trade gigantic amount of data with the surrounding environment. With significant expansion of the network scale and conduction of both ongoing and long-haul data handling, the conventional Vehicular ad-hoc Networks (VANETs) are evolving to the Internet of Vehicles (IoV), which guarantees effective and intelligent prospects for the future transportation framework. Then again, vehicles are devouring as well as producing a tremendous sum and various sets of data, which is referred to as Big Data [18].

According to the studies [8], there are many factors that makes the existing social network of vehicles different from other conventional networks. The nodes involved in such vehicular network is very dynamic and they join or leave very fast. The connection links are mostly based on the similarity of configuration, travel route, similar owner preferences etc. The social interaction in this kind of network includes message exchange, status update subscription, status reputation score, sensory data consumption and so on. Data exchange is mostly anonymous here because the owner information and the vehicular identity is hidden. Owners are capable of customizing privacy settings. In a network comprised of vehicles, the topology updates rapidly due to the limited range of ad-hoc wireless network technology and the speed of vehicles. So, these key factors reflect that there is a comprehensive difference in terms of dynamic nature, social interactions, topology, privacy, and the usage of social network of vehicles.

Every network requires operating protocols. Selection of the routing protocol is one of the main issues in the area of vehicle networks for developing IoV. Only a few modest local networks were in the early Internet era. The notion of a worldwide linked network, the Internet, has been established with the invention of protocols for Internet, widely known as Internet Protocol Suite (TCP/IP) and its implementation in ARPANET [26]. Similarly, an extensive horizontal networking protocol suite is a necessary to achieve IoV and web of things. VANET-related studies are covered by several scholars. The researches aim to build applications, routing protocols and VANET simulation tools. However, only tiny and homogenous VANETs with their applications that are mainly concerned with effective traffic management and safety are represented in majority of those studies. In the last several years, it has become of interest to researchers to include large-scale and heterogeneous VANET networks. It helps to provide additional services [9].

At present, there are two major challenges that need to be addressed Two primary difficulties are now to be tackled in order to improve the estimation and monitoring of traffic congestion. The first is to codify key variables to evaluate and determine traffic jams in a large-scale road network and the second is to ensure forecast of traffic jams are precise, instantaneous and reliable. Existing solutions do not handle this difficulty fully and resolve it. These systems may be classified into two primary methods.One is the equipment-based approach to infrastructures, while the other is the traditional VANET method. GPS data and data from a small number of sensors are used for the infrastructure-based method in general, although the VANET technique includes large propagation delays and low dependability [19].

Overall, we can say that the integration of IoV can change the perspective of real time traffic detection. With the evolution of existing small-scale VANET, it can act as the backbone or prototype for the new IoV infrastructure. It can also improve the driver safety and security system too by gathering and analyzing more and more data from the interconnected environment.

2.3 Related Works

In this part, the paper aims to briefly review existing works on the field of developing and implementing IoV for traffic detection and management system. We have analyzed different works related to the implantation of IoV for traffic detection and found that it promises a lot to improve the existing navigation scenario but comes with a huge number of challenges ahead.

One major issue will be the huge volume of data all the communicating vehicles will generate. The actual idea of IoV implies that every vehicle on the road must be installed with a processor and equipped with multiple necessary sensors. While this may be a gigantic task, a greater downside is the heap created by such countless vehicles [15]. Failure to handle such big scale of data might be a common scenario. With the continuous effort to move towards smart cities, researchers are involved to verify different solutions to handle these data without any single point of failure. Distributing the database infrastructures into number of zones may serve the purpose of data management and processing efficiently.

Another challenging aspect of IoV is the security and user compliance. With such amount of private data where the communication is a continuous process between millions of nodes, security breach is one of the biggest concerns. Potential vulnerabilities might lie in any point in the framework. be it the processor on the vehicle, the router, or the central server itself. A single loop hole anywhere in signals or the nodes might result in the exploitation and thereby crash the entire system [15]. With this heterogenous access of data, various authentication protocol for IoV and network architectures with technologies like BlockChain are improving to overcome security related challenges and build a trustworthy vehicular network.

El-Sersy et al. [11] explained about two approaches of traffic information accumulation. One approach is the infrastructure-based and another one is infrastructure less approach. The infrastructure-based approach relies on client-server or peer-to-peer (P2P) models for data storage and communication that are based on centralized architecture. Most traffic information systems based on a centralized architecture are concentrated in a traffic management center, which collects and processes data from the street network through detection equipment. The results can be delivered to drivers on demand through broadcast services or mobile phones. The centralized approach relies on a fixed infrastructure and requires public investment from government agencies or other related operators to build, maintain, and manage such infrastructure. Many sensors need to be implemented to monitor traffic conditions.

The infrastructure less approach basically applies various data aggregation techniques to make the whole system scalable and to manage bandwidth usage. In general, with the increase in distance, traffic detection for a given area become less accurate. Using the store and forward technique, traffic information can be distributed across multiple VANET partitions [11]. Within a certain geographical location, these traffic information are object of interest to many vehicles. Thus, the broadcast method in V2V communication serves the objectives of infrastructure less approach. However, this approach has two major drawbacks in terms of remote information distribution. Firstly, it has a relatively higher delay in data exchange and secondly, the information is very limited in details (due to the distance-based data aggregation technique). Another problem is that several overlapping clusters may exist for the same area, making it very hard to distinguish or compare them. Therefore, the quality of V2V communication-based approaches depends extensively on the integrity of the aggregation techniques [11].

Yang et al. [6] proposed an abstract IoV network model, which considers various connections of vehicles, roads, environments, and pedestrians. Studies show that IoV has no definite network architecture yet. It is often assumed that IoV can easily adapt to the layered architecture of IoT but due to a very important factor IoV is very dynamic. That factor is the inclusion of human feature in IoV. Connected smart devices on the Internet of Things are meant to exchange data between the devices but Internet of Vehicles must deal with the actions/behavior of the driver simultaneously. Thus, it is very hard to follow any generalized method to develop an IoV based model but not impossible. Researchers are working on this field to come up with a fully scalable network model with necessary protocols. Various frameworks have been already proposed to implement IoV for traffic management initially.

Contreras-Castillo et al. [14] described the benefits of IoV, and the latest industry standards developed to facilitate its implementation. He also announced the recently proposed communication protocol that allows seamless integration and operation of IoVs. VANET's vehicle-to-vehicle communication protocol plays an important role in IoV to enable different levels of interaction between vehicles, humans, and roadside machines. If there is a problem with your current route, it can provide you with an alternative route efficiently and quickly. However, IoV extends beyond VANET (as described above), and focuses on the exchange of information between vehicles, humans, and the surrounding road infrastructure. Later in the paper, Contreras-Castillo briefly explained the basic VANET communication protocol applicable for IoV. According to the research [14], there are mainly three different protocol sets for different layers. These are:

1. Physical layer protocols
2. MAC layer protocols
3. Routing protocols in IoV

JiuJun's et al. [9] work provides reviews on the Internet of Vehicles (IoV) routing protocol leading up to the evaluation approach with routing algorithms. He provided five different taxonomies of the routing protocols. These are:

1. Transmission strategy
2. Information required
3. Delay sensitivity
4. Dimension of scenarios
5. Target network types

Kaiwartya et al. [12] announced a comprehensive IoV framework emphasizing on layered architecture, protocol stacks, network models, challenges and future scopes. The research specifically followed the background to the evolution of VANETs. With the motivation on IoV, an overview of IoV is also presented as a heterogeneous vehicular network. All five types of vehicular communications that are available currently, are included in the paper. Those are, Vehicle-to-Vehicle, Vehicle-to-Roadside, Vehicle-to-Infrastructure, Vehicle-to-Personal devices, and Vehicle-to-Sensors. Considering functionalities and representations of each layer, a five layered architecture of IoV is proposed and considering management, operational and security planes, a protocol stack for the layered architecture is structured as well. Finally, identifying three key network elements, a network model of IoV is presented. These elements are: Cloud, Connection, and Client.

Above discussion reflects that most of the concepts provided for IoV based traffic detection system focuses on inter vehicular communication, communication with roadside units and data generated by sensors. Historical data will be used always as a reference because any collected data will be included in the pool of historical data. We must keep in mind that while dealing with real time traffic events everything is time critical. The faster the communication and data computation, the better the results are. With such dynamic and complex data, computational efficiency and reliability is a major concern. Faster communication is a must in any IoV network. In this paper, we analyzed the scopes of improvement with possible IoV based model compared to the existing techniques proven by Google.

Chapter 3

Quantifying Accuracy of Google Map

3.1 Methodology

To understand the quality of an existing system, we must find a way to put a numerical value to its accuracy. Due to its dynamic behavior, it is very hard to measure the accuracy of traffic detection system. We know that the conventional traffic detection system using GPS lack fare bit of accuracy in terms of real-time update. As mentioned before, the system can be tricked intentionally or unintentionally. Upon discussions we decided to evaluate the accuracy of Google Map by comparing the estimation showed in the application and the exact outcome experienced. The initial idea was to gather real time traffic data of actual trips using Google Map and compare it with the actual event to find out the shortcomings. We planned to collect trip data by completing at least 100 trips of minimum 5km by ourselves or by anyone in touch with us. Unfortunately, during this Covid-19 pandemic the data collection process was totally interrupted, and we had to find an alternative. We opt to use traffic reports generated by reliable traffic detection organizations and process those datasets according to our requirement. We tried to collect authentic data and wish to expand it further. The step-by-step details of the method we used is as follows:

Step 1: Collecting traffic index report and real time traffic reports from reliable sources. We selected traffic detection organizations those provide data to Google.

Step 2: Prepare these collected reports as input dataset for our analysis.

Step 3: Processing these datasets according to the computational requirements of our research. In this case we tried to avoid potential mismatch in datasets and discarded unnecessary raw data. Afterwards we assigned the data fields to corresponding variables.

Step 4: Preparing the scatter plot diagram that reflects the datasets and helps to visualize them.

Step 5: Performing correlation analysis on the variables, to check the relationship between the data. We selected this method because, in a perfect scenario where Google Map will reflect the real-time traffic as accurately as possible, it will reflect on the correlation coefficient of the real experience VS Google Map estimation.

Step 6: Making decision based on the correlation coefficient of step 5. Finally, we put a verdict on the accuracy here.

The workflow diagram of all these steps are as follows:

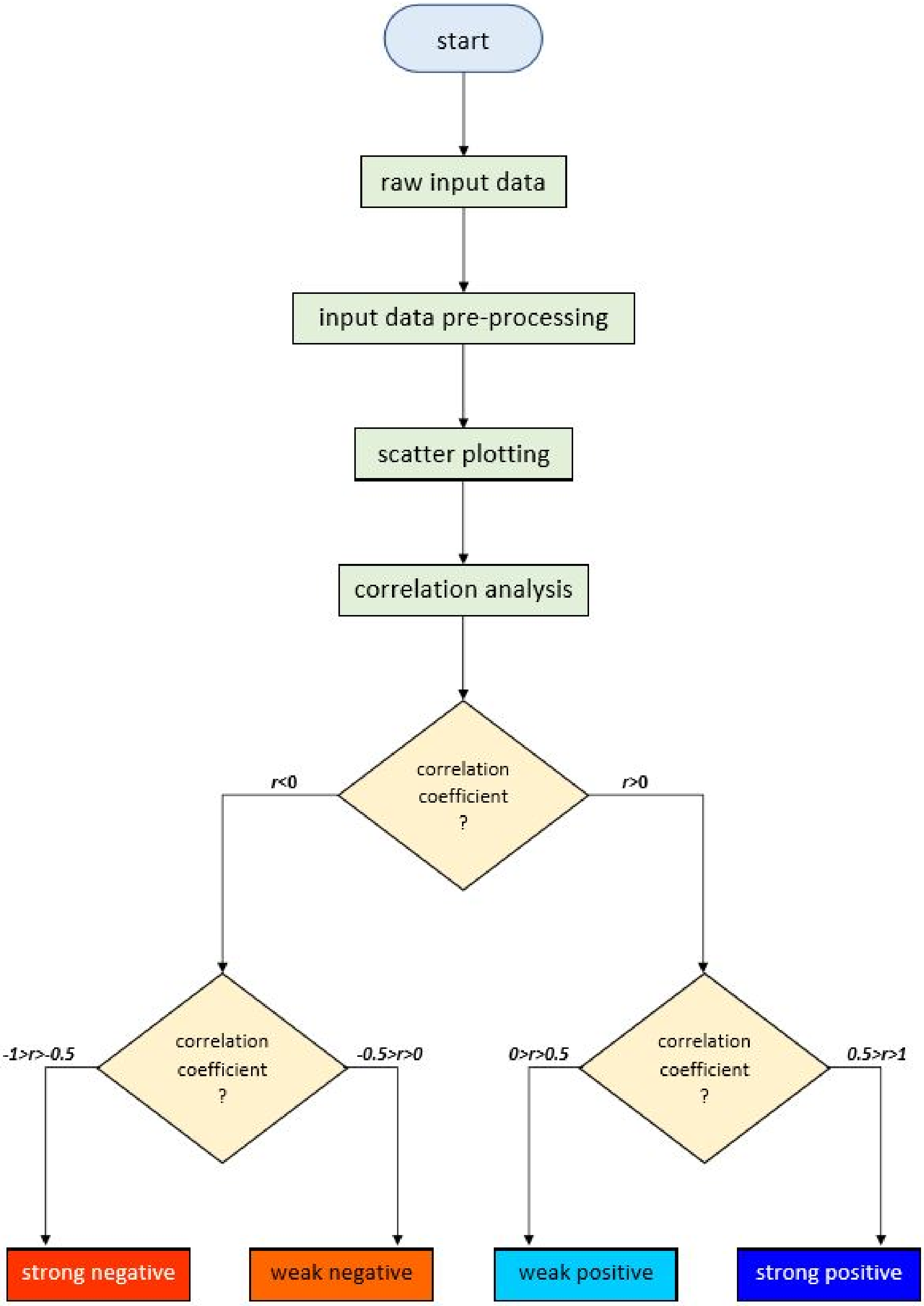

Figure 3.1: Flowchart for quantifying Google Map accuracy

3.2 Datasets Used

To understand the level of traffic detection accuracy by GPS, we choose to use average congestion level data of different places over the period of one year. To check the validity of this congestion data, hours lost in the congestion of those places and the last mile speed was also selected. The raw input data was collected from two different sources. The congestion level data was gathered from TomTom traffic index ranking 2019 and the other two attributes were gathered from INRIX 2019 Global Traffic Scorecard. INRIX is a specialized company that provides Google large coverage of traffic data using large scale sensor networks.

Although the data were traffic related and free access, it was not meant for determining the interrelation between congestion and real time situations. It required a significant level of pre-processing to be ready for our use. Figures 3.2 and 3.3 reflects the raw data before pre-processing from TomTom and INRIX, respectively.

RANK BY FILTER	WORLD RANK ▼	CITY	CONGESTION LEVEL 2019 ▼	CHANGE FROM 2018 ▼	
1	1	Bengaluru India	71%		›
2	2	Manila Philippines	71%		›
3	3	Bogota Colombia	68%	↑ 5%p	›
4	4	Mumbai India	65%	0%p	›
5	5	Pune India	59%		›
6	6	Moscow region (oblast) Russia	59%	↑ 3%p	›
7	7	Lima Peru	57%	↓ 1%p	›
8	8	New Delhi India	56%	↓ 2%p	›
9	9	Istanbul Turkey	55%	↑ 2%p	›
10	10	Jakarta Indonesia	53%	0%p	›

Figure 3.2: Snapshot of Traffic Index Ranking (2019) by TomTom

URBAN AREA	IMPACT RANK (2018 RANK)	HOURS LOST IN CONGESTION (2019 RANK)	YEAR-OVER-YEAR CHANGE	LAST MILE SPEED (MPH)
Bogota	1 (2)	191 (1)	3%	9
Rio de Janeiro	2 (1)	190 (2)	-5%	11
Mexico City	3 (5)	158 (6)	2%	12
Istanbul	4 (9)	153 (8)	6%	11
Sao Paulo	5 (10)	152 (9)	5%	13
Rome	6 (7)	166 (3)	1%	11

Figure 3.3: Snapshot of Global Traffic Scorecard (2019) by INRIX

3.3 Data Pre-Processing

The data we collected was genuine traffic data and it was a viable option for our research as well, but in its raw state the data was not ready for our use. Among the two datasets from the mentioned sources, the INRIX dataset alone contained entries of around 1000 (977) different locations and the congestion dataset from TomTom contained entries of 416 cities. So, there was an obvious mismatch. As a result, many entries of the INRIX report were not present in the report by TomTom. So, we had to list out only entries of those locations which are common in both the reports. Moreover, some additional data was also there which were not necessary for our purpose. According to the requirements of our calculation, we only needed the congestion index for different locations and hours lost at that given location due to congestion along with average last mile speed. Any data other than these were unnecessary for our purpose. First, we discarded the columns with data we do not need. Then, we prepared a list of entries of same places and from that list we selected 100 random places with nearly similar congestion level. At this point, the dataset of the 100 places with congestion level, hours lost, and speed level was ready for calculation. **Table 3.1** shows a portion of the dataset after pre-processing, **Table 3.2** is the representation of the dataset with congestion index land hours lost due to congestion and finally, **Table 3.3** is the representation of the dataset with congestion and speed. To minimize, only 10 entries for each table are shown here. For actual calculations, a total of 100 entries were used.

Location	**Congestion%**	**Hours lost**	**Last Mile Speed (MPH)**
Bogota	68	191	9
Moscow	59	128	15
Istanbul	55	153	11
Jakarta	53	150	18
Bangkok	53	90	13
Mexico City	52	158	12
Saint Petersburg	49	151	14
Dublin	48	154	10
Lodz	47	70	15
Rio de Janeiro	46	190	11

Table 3.1: Processed input data

Location	**Congestion%**	**Hours lost**
Bogota	68	191
Moscow	59	128
Istanbul	55	153
Jakarta	53	150
Bangkok	53	90
Mexico City	52	158
Saint Petersburg	49	151
Dublin	48	154
Lodz	47	70
Rio de Janeiro	46	190

Table 3.2: Congestion index and hours lost

Location	**Congestion%**	**Last Mile Speed (MPH)**
Bogota	68	9
Moscow	59	15
Istanbul	55	11
Jakarta	53	18
Bangkok	53	13
Mexico City	52	12
Saint Petersburg	49	14
Dublin	48	10
Lodz	47	15
Rio de Janeiro	46	11

Table 3.3: Congestion index and last mile speed

Here, we can see that the **tables 3.1, 3.2** and **3.3** all contains 10 entries of same locations, with their corresponding congestion index, hours lost due to this congestion and the average last mile speed. Our goal is to first check the relation between the congestion index and hours lost and then the relation between congestion index and the average last mile speed. Here, how the congestion data reflects the corresponding value of the other two data is our primary concern. The better the data relates to each other, the higher the accuracy level is.

3.4 Correlation Analysis

In statistics, to test relationships between quantitative variables or categorical variables Correlation is utilized. In other words, it is a proportion of how things are connected. The study of how variables are correlated is called correlation analysis [25]. Pearson correlation coefficient is a way to put a value to the relationship. The value of Correlation coefficients lies in between -1 and 1. A "0" signifies there is no connection between the factors by any stretch, while - 1 or 1 implies that there is an ideal negative or positive relationship. The formula to determine the correlation coefficient is as follows:

$$\mathbf{r} = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \tag{3.1}$$

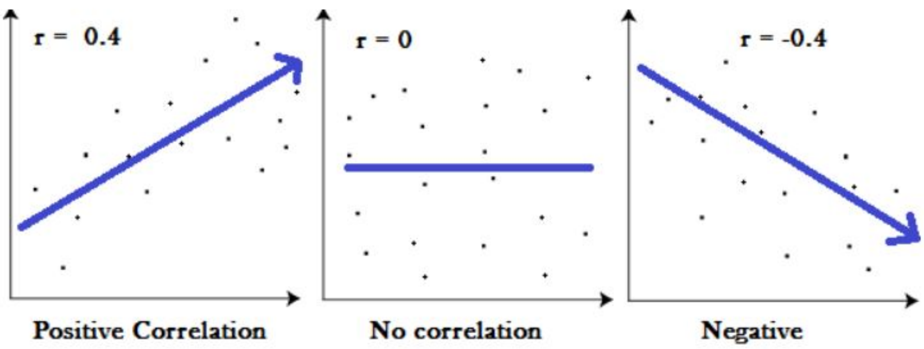

Figure 3.4: Pearson Correlation Coefficient

Although correlation analysis is not that reliable in terms of dynamic real-world data, yet we choose to use it for quantifying the accuracy. We assume that if a congestion data is to be precisely accurate, then it must strongly relate to the corresponding hours lost due to that congestion and speed during that congestion. If there is a weak relation between the congestion index and the corresponding hours lost, then we can say that there is a lack of accuracy in the process of GPS based estimation. Hypothetically, if we observer no correlation between the variables (which is not possible in this case), then we can say that there is no connection between congestion and hours lost due to congestion. For our first calculation, we

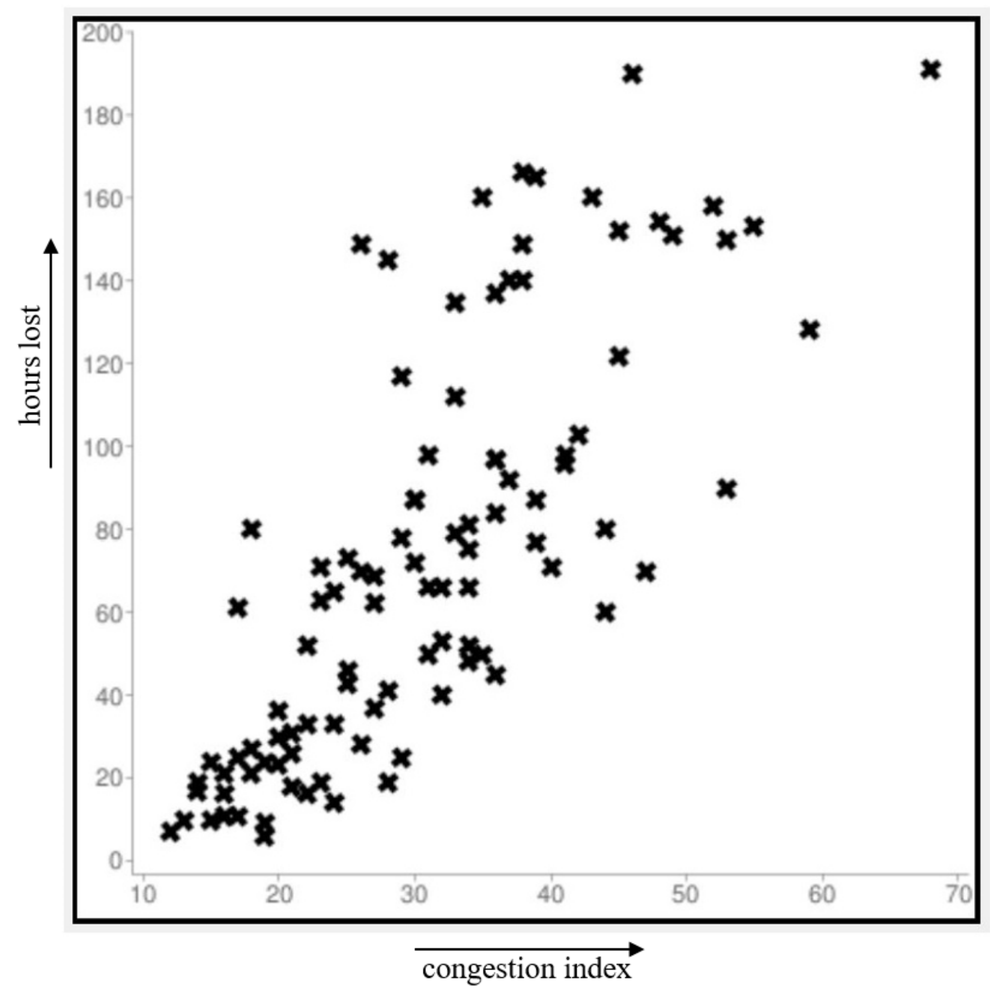

Figure 3.5: Scatter plot of congestion vs hours lost

used the data of **Table 3.2**, which is congestion data and hours lost. We did a scatter plot to check the relation between them.

Correlation coefficient:
Putting the values in equation 3.1 we get,

$$\mathbf{r} = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} = \mathbf{0.7760904837161}$$

Here, we plotted the congestion level data along x-axis and corresponding hours lost data along y-axis. The value of the correlation coefficient reflects that the variables tend to relate positively with more than average accuracy, but it is in between 0.5 and 1. So, we can observe that there are cases when hours lost might be low even after showing high congestion and vice versa. This might happen when false congestion is detected due to inaccurate crowdsourcing. The scatter plot also represents the inconsistency. We can also depict that, in case of lower congestion index the accuracy of corresponding hours lost data is comparatively higher but as the congestion index increases the accuracy is hampered. The data plot is more scattered in the higher range of congestion index.

For the next calculation, we used the data of **Table 3.3**, which is congestion data and last mile speed. According to the documentation of INRIX the **Last Mile Speed** is the speed at which a driver can hope to travel one mile into the focal business district during peak hour [21]. We did a scatter plot to check the relation between them same as the previous calculation.

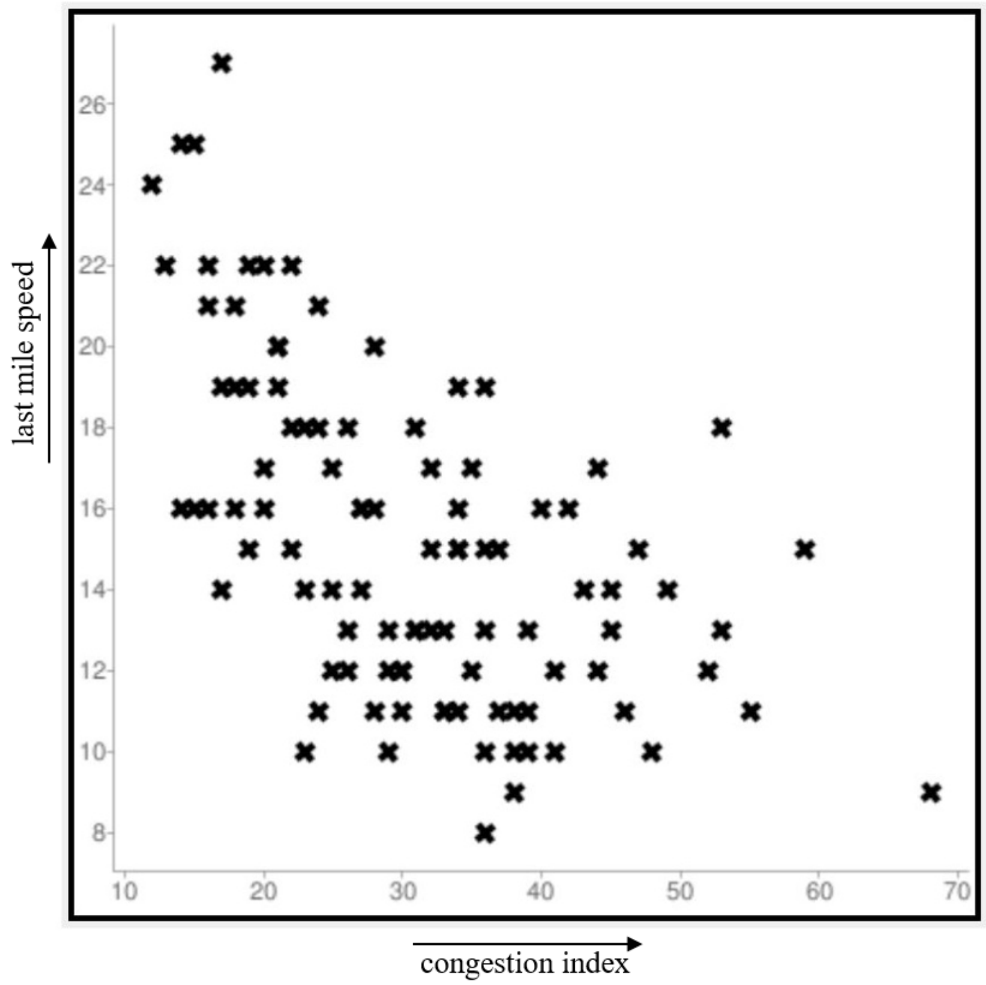

Figure 3.6: Scatter plot of congestion vs last mile speed

Correlation coefficient:
Putting the values in equation 3.1 we get,

$$\mathbf{r} = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} = \mathbf{-0.57233251952742}$$

Here, we plotted the congestion level data along x-axis and corresponding last mile speed (mph) data along y-axis. The value of the correlation coefficient reflects that the variables tend to relate negatively with average accuracy. Here the negative value of the coefficient means that the higher congestion level will result in lower speed value. The coefficient value is just below -0.5. So, the correlation is not strong enough to promise accurate result. We can also observe the scatter plot is way too dispersed. It represents that last mile speed is very much inconsistent with respect to congestion.

3.5 Result

Obviously, we cannot determine the real quantity of accuracy by judging with respect to these factors. There are a lot more factors affecting real time data. The environment is very much dynamic which implies to a lot of challenge, but the above analysis is gives a clear idea that there are possibilities of error in traditional GPS based traffic detection and navigation system. After comparing relevant datasets, we concluded that the GPS based process is not inaccurate at all but mathematically there is a fair amount of scope for improvement.

Chapter 4

Possible New IoV Model

Introduction of IoV promises to bring radical changes to traffic detection system. Due to continuous research with the thirst of moving toward smart cities, intelligent transportation system is not just a concept anymore. With already existing IoT network architecture, we can think about how to shape a possible IoV based model for traffic detection. Continuous surveillance through communication between vehicles is yet a bit overwhelming for the current world but the day is not far away. We can think of a vehicular network where every traffic related data are mined and processed to provide an improved navigation experience. Any infrastructure based on Internet of Vehicles, the focus of which will be to improve the existing GPS based traffic detection and management system, is yet to be globally implemented. A model for this kind of setup can be represented in accordance with the previous works but it is hard to generate a valid amount of experimental data and eventually prepare a report to for the accuracy comparison with conventional GPS frameworks. Inter vehicular communication in IoV model can be a better way to collect traffic information. If the intra vehicular network is also integrated in such a way that every little details of the vehicle's present status can be precisely monitored by sensors, then it is possible to enhance the level of accuracy. The model for implementing Internet of Vehicle is illustrated in three separate segments. Firstly, the communication systems included in the network. Secondly, the layered architecture used for the network model. Finally, the network model itself including the necessary network elements. Later, the scope of improvement in traffic detection and the implementation challenges is also discussed.

4.1 Communication in IoV Network

Any large-scale network includes one or more than one communication systems. In heterogenous networks multiple types of communication is a major feature. These communication systems make the network capable of exchanging data between different type of nodes. IoV has five different type of communication systems, which are required to gather all the necessary traffic information. These are:

1. Intra vehicle or vehicle to sensors (V2S) system
2. Vehicle to vehicle (V2V) system
3. Vehicle to infrastructure (V2I) system
4. Vehicle to cloud (V2C) system
5. Vehicle to pedestrian (V2P) system

Terms like Vehicle to Device (V2D), Vehicle to Network (V2N) are also associated. These are all subset of the V2X technology, which stands for vehicle to everything. In this V2X technology vehicles actively communicate with all the participants in a moving traffic [20].

Intra vehicle communication: This communication process can be named as vehicle to sensors (V2S) system also. The connected vehicles in an heterogenous vehicular network must be equipped with multiple sensors which are necessary for perceiving the state of the vehicle and the surrounding vehicles too. These sensors can communicate with each other and by integrating all the embedded sensors in a vehicle, the OBUs (On Board Units) generate necessary data that represents the status of the vehicle.

Vehicle to vehicle communication: In vehicle to vehicle (V2V) communication system all the participating vehicles communicate wirelessly to share the data of the vehicle and its surrounding. It contributes to the gathering of large-scale traffic information. Besides, it also enables the vehicles to efficiently detect and broadcast any significant traffic events happening in the surroundings.

Vehicle to infrastructure communication: Vehicle to infrastructure (V2I) communication is the wireless exchange of data between vehicles and roadside infrastructure commonly known as RSU (Road-Side Units). These infrastructures are vital for the IoV model because these are the components that can monitor the traffic and gather traffic flow data for the servers. Also, these infrastructures are the means to send necessary information to the vehicles.

Vehicle to cloud communication: In an IoV model all the nodes (vehicles and all other traffic elements) must be connected to the cloud. Cloud servers will be accountable for all the complex computation. Every node will continuously send valuable data to the cloud servers and after storing and analyzing these data servers will be responsible for sending back the results to the traffic layer. This is what vehicle to cloud communication is for.

Vehicle to pedestrian communication: As mentioned earlier, every element that participates in the formulation in traffic data formulation, is important for traffic congestion detection. In V2X technology pedestrians are as important as any other traffic elements. All the pedestrians are not necessarily fast-moving elements here, which is a case of fallback in terms of GPS based crowdsourcing. In IoV vehicle to pedestrian communication plays a significant role for traffic congestion detection and the pedestrians are also provided with valuable traffic information.

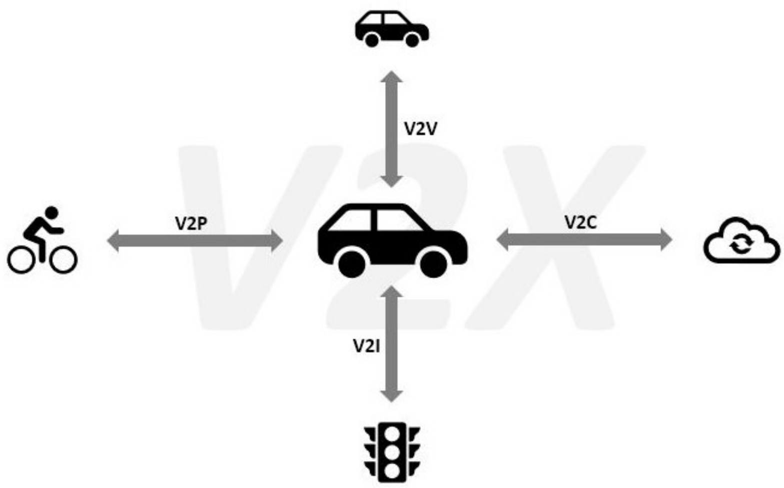

Figure 4.1: V2X communication technology

4.2 Layered Architecture

In the field of Internet of Vehicles most network models are developed based on a five layered architecture. These layers are:

1. Perception layer
2. Network layer
3. Artificial Intelligence layer
4. Application layer
5. Business layer

Among these five layers the business layer is not mandatory for our research, so we decided to exclude it. The core layers here are the perception, the network, and the application layer. Another important layer Artificial Intelligence is associated which is compulsory for the handling and analyzing of big data. This layer is responsible for cloud computing a complex decision making. All the details of the main four layers are described below:

Perception layer: This layer is the starting point of the whole traffic detection process and the first layer of the architecture. This layer is comprised of set of sensors, RSUs, smartphones and other personal devices which are the elements of the traffic detection framework. All these elements function together to form this perception layer and the primary objective of the layer is to perceive the entire environment and collect all information regarding the vehicle itself, surrounding traffic conditions and pedestrians. The data collected by this layer includes all the necessary traffic and vehicle related information. Some of these data are vehicle speed, vehicle condition, vehicle traffic density, surrounding crowd density, important traffic events (construction, accidents, roadblocks, public gatherings etc.), weather condition and so on. The layer also deals with the electromagnetic transformation and secure transmission of perceived data to the next layer, which is the network layer.

Network layer: This is the second layer of the architecture, which primarily receives all the perceived data from the perception layer. This layer is a heterogenous network which is the evolved version of the VANET. It is viewed as a virtual universal heterogeneous network involving technologies like WAVE, 4G/LTE, 5G, Wi-Fi and satellite networks. The perceived information from the lower layer is transferred securely to the next layer for processing. Main function of this layer is to differentiate and process various type of information received from the heterogeneous environment and represent those into a unified structure which can be identified and processed in each candidate networks. Lack of standard protocol set, interoperability and lack of coordination between the heterogenous network elements is the major obstacle for this layer.

Artificial Intelligence layer: The third layer in the architecture is regarded as the artificial intelligence layer. A virtual cloud infrastructure is the base of this layer. It is considered as the brain of IoV and the main computational unit. The function of this AI layer is to store, process and analyze the information received from network layer. The decision making also takes place is this layer based on the critical analysis of data. The major operational component of this layer includes different types of complex computing process and analysis techniques, such as: Vehicular Cloud Computing, Big Data Analysis and Expert System etc. Thus, this layer is also referred as the information management store.

Application layer: This is the last layer considered in the architecture suitable for our purpose but for industrial purpose there will be another addition layer above this one. This layer includes the smart applications that serves various purposes for the clients. Based on use cases, these are mainly traffic safety and efficiency, multimedia-based infotainment, and web-based utility applications. The goal of this layer is to provide smart services to end users. These services are basically the decisions based on critical and intelligent analysis of all the processed information by the AI layer. Application layer was also present in VANETs architecture. The focus of the layer in VANETs architecture was to provide safety and traffic efficiency information. Applications were not intended for commercial purpose. With the inclusion of the AI layer in IoV architecture multi-purpose smart applications are possible in this layer now.

These are the four functional layers in the IoV architecture which we prefer for our research. In a broader view, there is one additional layer on top of the application layer and that is the Business Layer. Another important function of the application layer is to provide application usage data of the end users to the business layer. The business layer then, helps to formulate strategies for the development of business models based on the statistical analysis of these data. The representation of these data is done using different types of analysis tools including graphs, flowchart, comparison tables, use case diagram, etc. However, this layer is not our primary concern for the research of traffic detection. Thus, we decided to consider this optional for the IoV architecture. The overall layered architecture and all the functions of these layers are summarized in the following table.

Layer	**Components**	**Functions**
Application layer	Smart applications.	Providing intelligent services to the end users.
AI layer	Cloud computing, big data analysis etc.	Storing, processing, analysis of data. Complex yet efficient decision making.
Network layer	Heterogenous networks.	Secured and fast transmission of unified structured data.
Perception layer	Sensors, RSUs, OBUs, devices etc.	Gathering data by efficiently perceiving the traffic environment.

Table 4.1: Layered architecture of IoV

4.3 IoV Network Elements and Model

In any network the most important factors are the network elements. The entire network is designed based on the elements involved in that network. IoV network is not different in this case. The core elements of the network are Cloud, Connection and Client. In such heterogenous network there will be too many types of component but to realize a structured model for the network these components can be categorized into the three building blocks mentioned above. In the network model all the client-side applications, the communication systems within the network and the computational segment of the network are illustrated. Few examples for the internal components of all three elements are also highlighted. Following figure represents the network model for IoV:

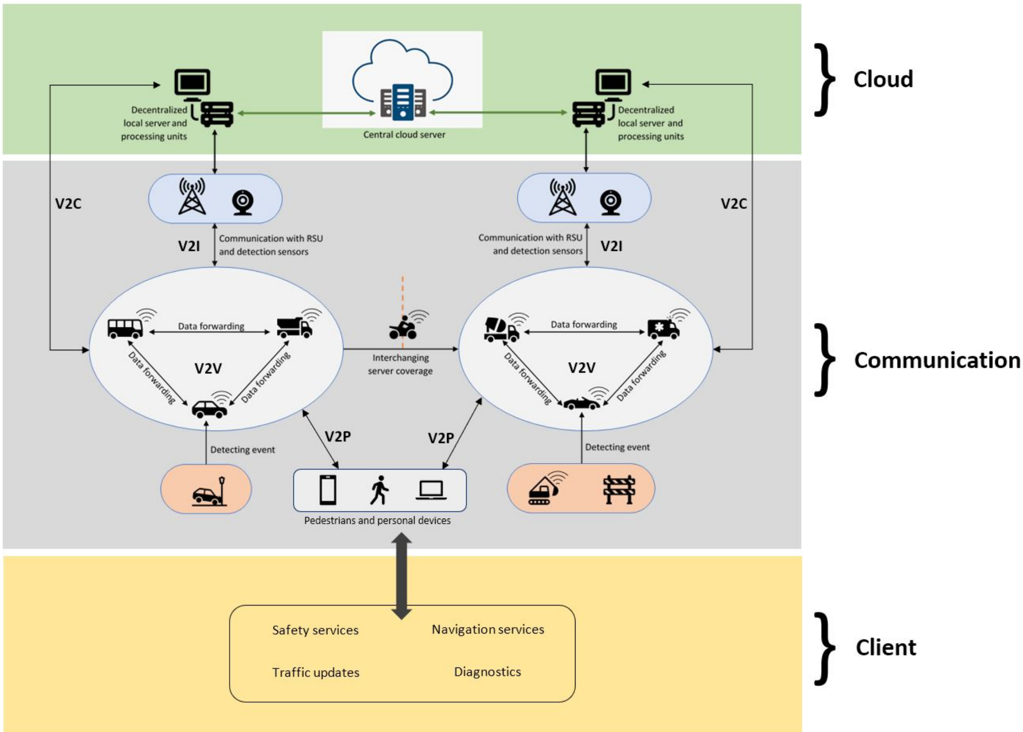

Figure 4.2: Model for Internet of Vehicle infrastructure

The protocol set for this network model is not discussed here because that is beyond the scope of this research. Moreover, a definite protocol set is yet to be discovered for the heterogenous vehicular networks.

4.4 Workflow Diagram and Algorithm

Based on the layered architecture and the network model, workflow diagram for the traffic detection was developed. The diagram visualizes the whole process of traffic detection initiating from the vehicles. The diagram is as follows:

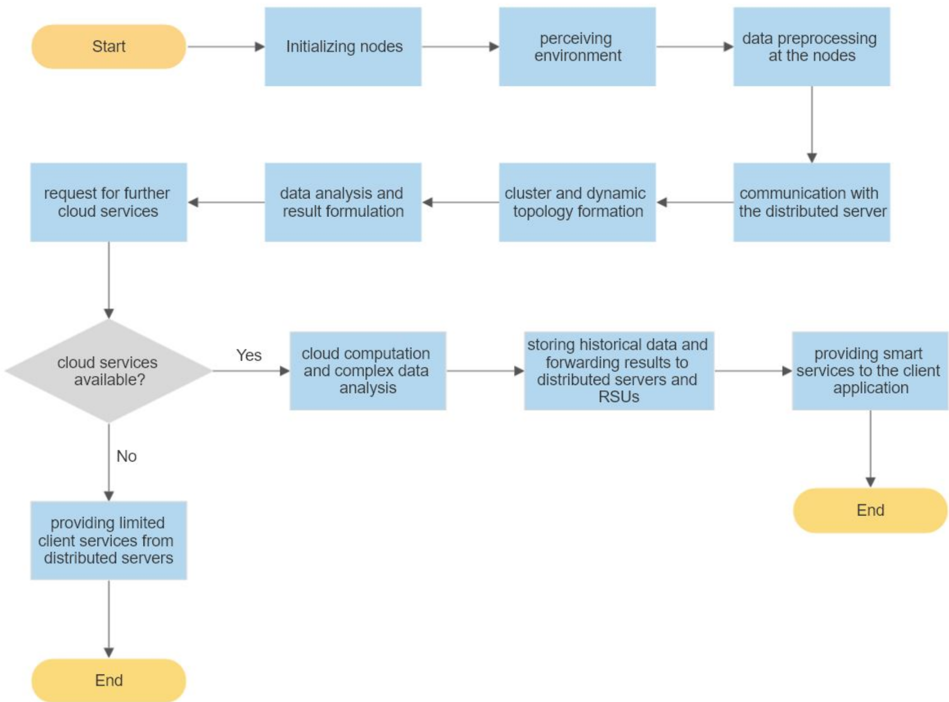

Figure 4.3: Workflow diagram for IoV

The Algorithm for this workflow fundamentally focuses on the distributed nature of the network and the unification of data at the nodes for minimizing computational loads on the servers. The algorithm also follows the dynamic clustering and topology formulation for rapidly connecting and disconnecting nodes (fast moving vehicles). The pseudo code for the algorithm is as follows:

Algorithm 1: Traffic detection by IoV

```
initialize vehicular nodes;
formulate vehicular status data by OBUs ;
perceive environment and traffic events through V2X communication ;
pre-process data into an unified structure for the servers ;
forward data to distributed servers ;
formulate cluster of nodes based on server coverage ;
handle dynamic changes in topology for incoming and outgoing vehicles ;
analyse gathered data and formulate initial results ;
request for cloud services ;
if cloud services available then
    perform cloud computation and complex data analysis ;
    utilize Artificial Intelligence for data analysis ;
    store results to the pool of historical data ;
    forward results to the distributed servers ;
    while node is connected to the server do
        provide smart client services ;
    end
    store to cache ;
else
    while node is connected to the server do
        provide limited client services ;
    end
    store to cache ;
end
```

4.5 Improvement Scopes in Traffic Detection

One of the main reasons behind such growing interest of researchers in the field of Internet of Vehicles is how much it promises in terms of traffic detection and efficient traffic management. According to most research, it will not only improve the scenario of traffic detection but also manage different traffic events very efficiently. As of now, an established IoV environment is yet to be realized. It is not possible for us to state that IoV is currently better than conventional GPS based framework because without actual use cases and test scenarios we cannot analyze the efficiency of IoV from paper works only. To prepare any kind of analytical report on the comparison between traffic detection by GPS based system and by IoV we need to generate proper traffic data using IoV infrastructure. Unfortunately, implementing any sort of IoV infrastructure even for test purposes is not viable for us now and it is very much expensive as well. We opt for analyzing the key factors that can play a direct role in traffic detection and management system in a IoV infrastructure. How these key factors will have an impact on traffic detection and management is discussed here:

Traffic data perception: The most important factor in an IoV network is the process of perceiving the traffic environment. If we compare the process of traffic data accumulation by GPS frameworks and IoV frameworks, then we can see how IoV can gather data that replicates the exact traffic scenario on the street. With the help of RSUs and OBUs accurate real time picture of the streets can be visualized. To explain this process elaborately, we can think of any traffic condition where vehicles are connected and continuously sharing data. Now, the OBUs in the vehicles will represent the status of the vehicle and combined network of sensors will prepare traffic data based on the surroundings. Afterwards, these data will be forwarded through the network. Data sent by any vehicle will also contain all the necessary vehicular information structured in a brand independent CVIM (Common Vehicle Information Model) [17]. Every vehicle in a IoV network will be identified by RFID (Radio Frequency Identification). Through this process every vehicle on the roads can be distinguished based on their sizes, types etc. All moving vehicles will generate an average speed data and time required to travel between two segments of a road. The dependency on the historic data and prediction-based traffic congestion estimation will decrease significantly. Moreover, with improved, accurate and efficient incoming of new data the accuracy of the pool of historical data will also improve. At present, using the GPS based system Google claims to assume the vehicle type, size etc. more accurately than before. Google does it by analyzing the change of your speed by utilizing the sensors in your device. However, it is still a prediction depending on the data analysis. With IoV this process will be completely revised because data gathered from any IoV network will contain accurate vehicular information. The same case is applicable for detecting the surrounding traffic density as well. All these will lead to the accurate detection of traffic conditions on the road in an IoV infrastructure.

Traffic events detection: Detecting nearby traffic events and providing updates to the drivers through applications and services accordingly is another defining factor of any efficient traffic detection and management system. Current GPS based systems handle this task by analyzing collected data and crowdsourced data. In addition, traffic event reported by users contribute a lot to this. Google uses community powered app Waze to provide traffic event updates on Google Map. Waze provides user submitted data of various traffic events such as, accidents, construction, roadblocks, congestion etc. This service acts as if streets are being monitored but there is lack of accuracy because any event that is not reported by users will not be updated. Again, false reports can exploit this system. IoV framework will handle this case from a completely different perspective. With continuous exchange of information between vehicles, infrastructures and devices any significant traffic events will be broadcasted real time. A smart vehicle or a smart device or any road-side unit can detect traffic events and share this information for all the nodes connected in the network. This will be the closest traffic detection can get to real time monitoring of streets. Various alerts like accidents, busy route, ambulance, fire truck etc. will help these emergency services navigate much faster.

Efficient computation: It is obvious that to develop any improved system, the computation must be efficient to. In IoV network every node is ultimately connected to a cloud server. With cloud computing and big data analysis the complex computation of any interconnected traffic environment will be much more efficient than ever before. In either case, the resources of connected vehicles are available for usage as cloud service as well as the vehicles can utilize smart cloud services. The system would eliminate computational and storage limitations at vehicles. In the cloud framework, vehicles will either form independent cloud within a group of vehicles or directly connect to the conventional cloud. In both cases the cloud can utilize the vehicle resources for smart cloud services. This can help in eliminating the computational load and the limitation of resources for cloud and connected vehicles. Cloud computation will be an essential part of the IoV network for providing various smart services to the clients in a connected drive environment. Parking helper, ride sharing, car-pooling, real time traffic events update, vehicle diagnostic these are only a few examples of the services that cloud computing in IoV will dictate. Moreover, with huge chunks of data incoming continuously, big data analysis can handle complex computation and produce more accurate results. Traffic congestion detection, route recommendation, smart navigation, travel time estimation, accident prediction, risk alert these can be improved by big data analysis. All of these will lead to a very efficient traffic detection and management framework.

In addition to the above-mentioned factors there are much more scopes for improving traffic detection by integrating Computer Vision system with IoV. This can lead to exactly 24/7 real time monitoring of the streets. With the help of artificial intelligence layer of IoV, people will have a better navigation experience with increased road safety instructions. With intensive use of artificial intelligence, another big step in the field of IoV will be autonomous driving. Autonomous driving is considered as the future of smart vehicles and connected drive. IoV can facilitate the interaction of the vehicles with the environment, pedestrians as well as other vehicles sensory information through the means of vehicle-to-x (V2X) [20].

While these are the factors that will facilitate improvements in the field of traffic detection and management, there are many more benefits that will come along with IoV. Following are few services that IoV can enable:

Anti-theft: The sensors installed in the smart cars of IoV are designed to function in a manner that the sensory network inside the car can identify unusual entry, breaking of window panes and forceful start of the vehicle. Upon detection of any such activity, the onboard processor will immediately lock down the entire vehicle. The system will also prevent the vehicle from starting and alert the police patrol. Moreover, vehicle theft will reduce in general because it will be much easier and efficient to track any stolen vehicle.

Avoiding accidents: Any prospective accident on the road can be identified using vehicle-to-vehicle communication. If any car loses control as a result of qualities like over-speed, the interchange of data in IoV can save lives through pneumatic pressure and distortion. By recognizing risky conduct and warnings, even probable accidents can be prevented. The visibility of people or roaming animals on the way is substantially diminished during the night or in adverse weather conditions. The result might be disastrous accidents. In order to prevent this, a sensorial network within the car will detect the presence or presence of human beings on the road and take quick measures to lower the vehicle speed or to use emergency brakes depending on the closeness of the vehicle. Body temperatures on the road or on the floor can be measured using onboard proximity sensors. Only the introduction of IoV makes them possible.

Emergency response: In the event of a collision or a crash in a neighboring car, the emergency response services within the car will be triggered instantly. They will submit the accident site's specific GPS coordinates and instantly transmit them for emergencies such as ambulance, fireworks, etc. This helps to decrease road and road life losses.

Vehicle alerts: The primary aim of the vehicle's sensory network is to monitor the vehicle's overall condition. Fundamental attributes of vehicles such as speed, pneumatic pressure, fuel level, condition of the pneumatic, motor oil level and so on are monitored and the user is notified when characteristics above or below predefined threshold levels are specified.

These are only a few of the services that IoV has to offer.

4.6 Implementation Challenges

Along with all these promising advantages, IoV also has few drawbacks. With the collection of such detailed user location and navigation data from the vehicles, compliance is always an issue. At present, everyone is aware of the risks of private data breach. While exchanging vehicular data between numerous nodes this extensively, chances of security breach is much higher. Security vulnerabilities of many major car brands were exposed in 2015 [31].

The heterogeneous IoV network topology requires the integration of many technologies, services and standards. Increased data security with a high number of cars is nonetheless required to protect the integrity of such heterogeneous networks. IoV also contains various security flaws, like with many other technologies. Vehicles operate in insecure, uncontrolled situations with major security threats in vehicles for infrastructure and vehicles for cloud communication models [14]. Cyber assaults can lead to IoVs being particularly susceptible. Vulnerable nodes can be exploited by malicious actions, which can result in vehicle data streams being manipulated with harmful results. For instance, once the cyber criminal has access to the modular system of data communication and sensor network of the automobile, he or she may control and manipulate the various automobile components, such as the brakes, the doors or even the automotive engine. A presentation at a BlackHat cybersecurity conference recently demonstrated that some software lets an attacker to control the Jeep Cherokee while they're going. [14]. This shows the possible risks awaiting IoV on the road ahead. Overall the risk is substantial and the safety of drivers, passengers, linked cars and infrastructure may have major repercussions. Security should thus be a top-level property in IoV. There have been several initiatives to fix security problems in the IoV. The National Institute of Standards and Technology has developed a framework for improving cyber security in critical infrastructure which may be implemented into IoV. Secure communication systems for VANET applications have also been developed by several researchers V2V and V2I [14]. IoV has to cope with some security requirements before it attracts a large end-user market. To maintain the privacy and security of end users, a solution that meets your security requirements needs to be developed. IOV security Standards and Guidelines are being actively formulated by the automotive security research and regulatory agencies. For providing a uniform communication and information sharing environment that allows transparent and seamless integration with current closed standards, new open standards are needed. This will also improve services and user experiences in the IoV ecosystem. With proper protocols and security measures the vulnerabilities can be eliminated in the future.

Implementation of such model at any scale requires so many resources and infrastructural facilitation. The heterogenous network of IoV can generate tremendous amount of data. Resource allocation and computational load management will be a massive challenge for the servers in such system. A server may easily get overwhelmed and result into single point of failure. The solution which we could think in this case is to decentralize the servers and utilize the resources of the nodes as well. If the servers are decentralized into local servers and they are dedicated to handle and process the data of their designated segment, then it will solve the issue to a great extent. The local servers will be connected to the central server for further data processing and historical data formulation. The local servers will reduce the computation load and reduce the processing delay. In terms of real time update which will be a major improvement. In a decentralized mode, fast moving vehicles will change the server coverage rapidly due to short but efficient local server coverage. These dynamic changes of connecting and disconnecting nodes should be broadcasted efficiently to cause immediate results.

Among all the challenges, the most deciding factor of the IoV network will fast connectivity. For successfully achieving real time traffic detection and management the communication system must function very fast. Even minor delays in data exchange can reduce the accuracy of traffic detection significantly. For improved accuracy IoV must be implemented with fast wireless connectivity. 5G networks will be able to server this purpose. In terms of connected nodes and data exchanged, IoV will generate extremely large figures and it will grow exponentially over time because any vehicles will have the ability to connect to anything at any time in this model. Faster exchange of data is the prime aspect to develop such model. Without network infrastructure of higher bandwidth, IoV will not be able to real-time traffic updates and other services. 5G communications will realize all the smart services IoV has to offer.

Keeping all the drawbacks and limitations in mind, we can assume that IoV can improve the results of traffic detection but only if all the limitations are eliminated. Without considering the above-mentioned factors developing any IoV model will not add much to traffic detection rather it may lead to failure only.

Chapter 5

Conclusion

5.1 Limitations

In this paper, we tried to visualize the traffic detection scenario by both Google Map (GPS) and IoV. According to our initial plans for our data analysis, we wanted to use real world traffic data by using both methods. This required extensive travelling and an established IoV infrastructure as well. Unfortunately, this was not possible because of the COVID-19 pandemic and lack of IoV infrastructure. We had to drop the idea of gathering actual trip data as we could not manage to travel at all. Therefore, we had to depend mostly on collecting data from different sources. Although these are traffic data, this are not meant for our research. Moreover, implementation of IoV infrastructure requires heavy hardware resources and expense. Even if we managed the resources there is no proper protocol set for this kind of heterogenous networks yet. We wanted to use a simulation of IoV network on SUMO (Simulation of Urban Mobility) and TransModeler as an alternative, but lack of training and familiarity to these systems was an obstacle here too. While analyzing the outcome of both the systems, real world data would help us present a more accurate comparison between the two systems. Depending on the alternatives is the main limitation of this paper.

5.2 Future Works

Our plan for this research is to collect travel data by using google map based on real trips and compare the accuracy of the result with the IoV counterpart. We aim to analyze the deep lying factors of a deployed IoV model. To make a proper comparison between both the approaches for traffic detection we need to quantify the performance using these two frameworks. As of now, we can do this by using Google Map that is the conventional GPS system but to do the same for IoV we need a functioning IoV environment. For now, we did elaborate analysis of the factors of IoV that will have an impact on traffic detection and management but in future we plan to use the IoV system to generate data and prepare performance reports based on that. The real-world condition is always very dynamic. So, results based on theoretical analysis may differ from the results based on real data analysis.

5.3 Conclusion

New technologies, such as mobile cloud computing and enhancements to infrastructure, have introduced new traffic and congestion prediction options.This research focuses on two aspects: the precision of methods presently utilized and more trustworthy traffic predictions under IoV. We reviewed traditional GPS based traffic prediction processes through both experimental reports and algorithm breakdown. Subsequently, we explained an IoV model including the underlying architecture, communication systems and the network elements. Then, we highlighted the key factors that can improve real time traffic detection and management to improve travelling experience for everyone. We also mentioned additional benefits of the IoV based approach. Finally, we discussed the possible outcome, challenges other issues such as security and safety of reliable traffic prediction. After the direct comparison between Google Maps (GPS) approach and IoV based approach, we concluded that upon considering the factors of IoV that will help to improve traffic detection and overcoming the challenges it may bring along, IoV can offer so much in the field of traffic detection. Until the successful deployment of an IoV infrastructure, conventional GPS based approach is reliable. We believe that traffic prediction through cloud assisted IoV will attract enormous attention and research efforts soon.

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