ICEB 2018 Proceedings

International Conference on Electronic Business (ICEB)

Winter 12-6-2018

Action Research on Development and Application of AIoT Traffic Solution

Wen-Hsin Wang

Yao-Tang Hsu

Wang, W.H. & Hsu, Y.T. (2018). Action research on development and application of AIoT traffic solution. In *Proceedings of The 18th International Conference on Electronic Business* (pp. 90-97). ICEB, Guilin, China, December 2-6.

Action Research on Development and Application of AIoT Traffic Solution

(Full Paper)

Wen-Hsin Wang*, National Chengchi University, Taiwan, alice.ntu@gmail.com
Yao-Tang, Hsu, National Chengchi University, Taiwan, yc.yc5888@gmail.com

ABSTRACT

AIoT solution based on the AI (*Artificial Intelligent*) and IoT (*Internet of Things*) is considered state-of-the-art technology and has emerged in various business environments. To enhance intelligent traffic quality, maximize energy saving and reduce carbon emission, this study applied an AIoT technology based on traffic counting modules and people behavior modules as traffic inference systems. Applications of the IoT technology based on WiFi, 3G/4G and NB-IoT (*Narrowband IoT*) was conducted gradually in key demonstration roads and cities worldwide, and the development and evaluation results were aligned to an action research framework. The five phases in the action research included designing, collecting data, analyzing data, communicating outcome, and acting phases. During the first two phases, problems of functional operations in traffic were verified and designed for network services by ICT (*Information and Communication Technology*) and IoT technologies to collection traffic big data. In the third phase, stakeholders may use basic statistic or further deep learning methods to solve traffic scheduling, order and road safety issues. During the fourth and fifth phases, the roles and benefits of stakeholders participating in the service models were evaluated, and issues and knowledge of the whole application process were respectively derived and summarized from technological, economic, social and legal perspectives. From an action research approach, AIoT-based intelligent traffic solutions were developed and verified and it enables MOTC (*Ministry of Transportation and Communications*) and stakeholders to acquire traffic big data for optimizing traffic condition in technology enforcement. With its implementation, it will ultimately be able to go one step closer to smart city vision. The derived service models could provide stakeholders, drivers and citizens more enhanced traffic services and improve policies' work more efficiency and effectiveness.

Keywords: AI, AIoT, IoT, intelligent traffic and smart city

*Corresponding author

INTRODUCTION

According to Google CEO Sundar Pichai said "We're moving from a 'Mobile-First' to an 'AI-First' World" that human beings are entering the world of artificial intelligence. Most people may be slowly accepting the term artificial intelligence. When AI from science fiction movies, the film director Steven Spielberg had a movie directly called AI artificial intelligence in 2001. However, the film gradually came true along with the development of IoT and AI technology. When Google's AI AlphaGo defeated world's top human Go player, AI quickly entered to our lives (Whitwam, 2017). For example, more and more of our mobile handheld devices uses AI for face and image recognition. Now many online customer services also use AI robots to support customer inquiry service. The AI voice assistant can not only tell you the time, weather, but also play music, order food and shopping for you. AI applications have been applied around us gradually. The applications and services covered are far more than what we imagined and continue to spread rapidly. It's no wonder that Sundar Pichai's Google no longer calls itself a search engine company but he would say that Google is an AI company. AI is undoubtedly a mainstream.

When it comes to transportation, most people come into commuting and traffic jams every day. The reason is that most people live in cities. The urbanization causes population concentration is unavoidable. According to statistics, there will be 70% population concentrated in the city in 2050. In emerging countries such as Asia and Africa, up to 90% of people live in cities. It is not difficult to imagine that commuting and traffic jams will be a major problem that these cities need to overcome. To be able to overcome traffic problems, we must first understand the state of traffic.

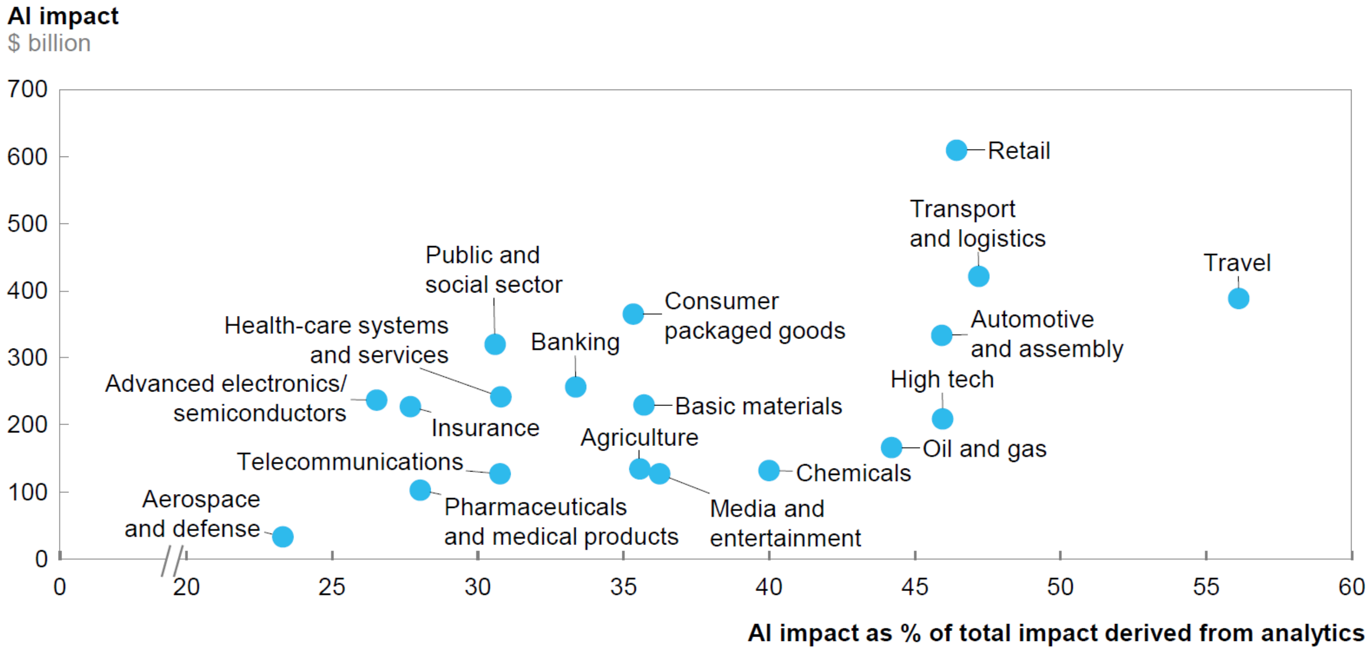
London, England, was a city that had long been suffered from traffic problems. Therefore, in 1904 and 1935, respectively, traffic statistics were calculated for the main roads in London. It can be found that the traffic volume is much improved, and the entire traffic flow has an overflow effect. It is obviously an urban expansion. According to this report in London in 1936, the record traffic is not only to understand the current traffic situation, but to plan the construction strategy of the entire city. Therefore, traffic statistics are essential for major cities around the world. In the Americas, California, Texas, Canada, Brazil, Europe, London, Barcelona, Japan, Australia and Taiwan, there are public traffic statistics available for references. In many countries, even video streaming on the web allows people to watch the traffic in real time and understand the current traffic conditions of major roads and intersections for commuting or travel.

LITERATURE REVIEW

AI Impact and Value

According to McKinsey's report in Figure 1, the total annual value potential of AI alone across 19 industries and nine business functions in the global economy came to between $3.5 trillion and $5.8 trillion. This constitutes about 40 percent of the overall $9.5 trillion to $15.4 trillion annual impact that could potentially be enabled by all analytical techniques. For the potential value of AI in travel sector, the aggregate dollar impact is $0.3~0.5 trillion and about 7.2~11.6% impact of industry revenues; for the potential value of AI by transportation and logistics, the aggregate dollar impact is $0.4~0.5 trillion and about 4.9~6.6% impact of industry revenues (McKinsey & Company, 2018).

The US government had counted traffic statistics in Pittsburgh, about 42 hours per person per year is spent on traffic jams, generating $160 billion in losses and 25 billion kilograms of carbon emissions. This is undoubtedly a huge cost. After implementing intelligent traffic control, there is a significant improvement that it can be effectively shortened 40% congestion time and 25% reduction in commuting time and a 21% reduction in carbon emissions. Understanding the traffic information, the government can change the traffic number or road plan according to the statistical results. For example, the traffic time ratio of the main road and the branch line, whether the traffic lane should be added, whether the traffic plan should be set, or the traffic plan can be set (Patel, 2016).



Source: McKinsey & Company (2018).

Figure 1: AI impact.

AI, Neural Networks and Deep Learning

It is too early to write a complete history of deep learning, and some of the details are controversial. However, we can trace back a well-recognized overview of incomplete origins and identify some pioneers. can already trace an admittedly incomplete outline of its origins and identify some of the pioneers. They include Warren McCulloch and Walter Pitts, who as early as 1943 proposed an artificial neuron, a computational model of the "nerve net" in the brain. Bernard Widrow and Ted Hoff at Stanford University, developed a neural network application by reducing noise in phone lines in the late 1950s (McCulloch & Pitts, 1943). Around the same time, Frank Rosenblatt, an American psychologist, introduced the idea of a device called the Perceptron, which mimicked the neural structure of the brain and showed an ability to learn (Goldstein, 1997). MIT's Marvin Minsky and Seymour Papert then put a damper on this research in their 1969 book "Perceptrons", by showing mathematically that the Perceptron could only perform very basic tasks (Rosenblatt, 1958). Their book also discussed the difficulty of training multi-layer neural networks (Minski & Papert, 1969). In 1986, Geoffrey Hinton at the University of Toronto, along with colleagues David Rumelhart and Ronald Williams, solved this training problem with the publication of a now famous back propagation training algorithm— although some practitioners point to a Finnish mathematician, Seppo Linnainmaa, as having invented back propagation already in the 1960s. Yann LeCun at NYU pioneered the use of neural networks on image recognition tasks and his 1998 paper defined the concept of convolutional neural networks, which mimic the human visual cortex (Rumelhart, Hinton & Williams, 1986). In parallel, John Hopfield popularized the "Hopfield" network which was the first recurrent neural network (LeCun, Haffner, Bottou, & Bengio, 1999). This was subsequently expanded upon by Jurgen Schmidhuber and Sepp Hochreiter in 1997 with the introduction of the long short-term memory (LSTM), greatly improving the efficiency and practicality of recurrent neural networks (Hopfield, 1982).

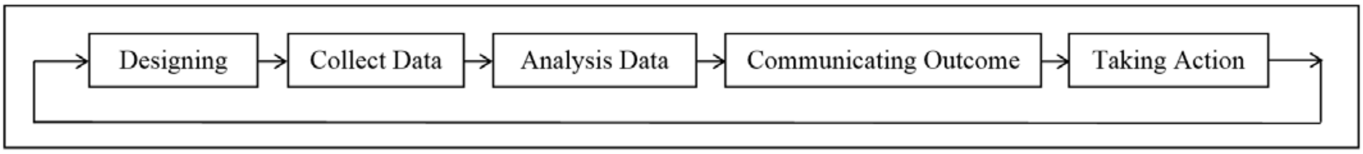
Hinton and two of his students in 2012 highlighted the power of deep learning when they obtained significant results in the well-known ImageNet competition, based on a dataset collated by Fei-Fei Li and others (Hochreiter & Schmidhuber, 1997). At the same time, Jeffrey Dean and Andrew Ng were doing breakthrough work on large scale image recognition at Google Brain (Krizhevsky, Sutskever & Hinton, 2012). Deep learning also enhanced the existing field of reinforcement learning, led by researchers such as Richard Sutton, leading to the game-playing successes of systems developed by DeepMind (Dean *et al.*, 2012). In 2014, Ian Goodfellow published his paper on generative adversarial networks, which along with reinforcement learning has become the focus of much of the recent research in the field (Sutton & Barto, 1998). Continuing advances in AI capabilities, experts are focus their research on different domains in various industries.

Neural networks are a subset of machine learning techniques. Basically, they are based on simulating connected "neural units" AI systems that loosely modeling how neurons interact in the brain. Since the 1940s, computational models inspired by neural connections have been studied and re-emphasized as computer processing capabilities have increased and large training data sets which have been used to successfully analyze input data such as images, video, and speech. AI practitioners refer to these techniques as "deep learning," since neural networks have many ("deep") layers of simulated interconnected neurons. Before deep learning, neural networks often had only three to five layers and dozens of neurons; deep learning networks can have seven to ten or more layers, with simulated neurons numbering into the millions.

AI practitioners refer to these techniques as "deep learning," since neural networks have many ("deep") layers of simulated interconnected neurons. Before deep learning, neural networks often had only three to five layers and dozens of neurons; deep learning networks can have seven to ten or more layers, with simulated neurons numbering into the millions. In this paper, we only analyzed the developments and applications instead of neural network techniques.

METHODOLOGY

Application of the IoT technology based on WiFi, 3G/4G and NB-IoT was conducted gradually in key demonstration roads and cities worldwide, and the development and evaluation results were aligned to an action research framework. Figures 2 shows the five phases in the action research included designing, collect data, analysis data, communicating outcome, and acting phases. During the first two phases, problems of functional operations in traffic were verified and designed for network services by ICT and IoT technologies to collection traffic big data. In the third phase, stakeholders may use basic statistic or further deep learning methods to solve traffic scheduling, order and road safety issues. During the fourth and fifth phases, the roles and benefits of stakeholders participating in the service models were evaluated, and issues and knowledge of the whole application process were derived and summarized from technological, economic, social and legal perspectives, respectively. From an action research perspective, AIoT-based intelligent traffic solutions were developed and verified and it enables MOTC and stakeholders to acquire traffic big data for optimizing traffic condition using technology enforcement.



Source: This study.

Figure 2: Action research study framework.

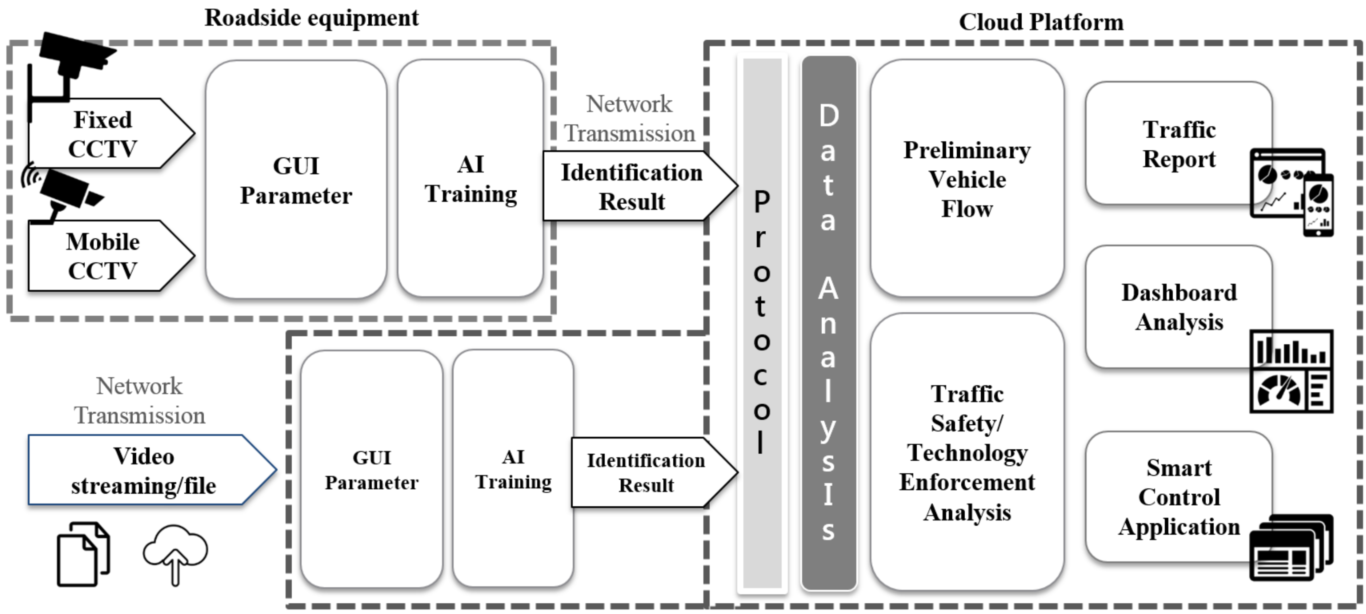
Baskerville and Wood-Harper (1996) suggested that action research was ideal as a systems development methodology for information systems research. We adopted a five-phase, cyclical process, which can be described as an ideal exemplar of the original formulation of action research (Susman and Evered, 1978) to development of an intelligent traffic flow solution architecture as shown in Figure 3. At the analysis and action taking phase, we collaborated in active intervention with stakeholders. We summary AI video solutions include two parts as show in table 1: 1) video capture part included capture, recording and streaming, 2) deep learning part included people counting, traffic monitoring and law enforcement.

Table 1: AI video soliton of video capture and deep learning SDK.

AI Video Solution	Video Capture	Capture	cropping, scaling, resizing, OSD blending	NVIDIA GPU / INTEL
		Recording	H.264/H.265 Metadata	
		Streaming	RTMP/RTSP/TS/HLS	
	Deep Learning	People Counting	enter/exit/dwell time, crowd counting	NVIDIA

		Traffic Monitoring	vehicle types, vehicle counting, waiting time	TensorFlow / TensorRT
		Law Enforcement	illegal parking, wrong direction, cross lane	

Source: This study.



Source: This study.

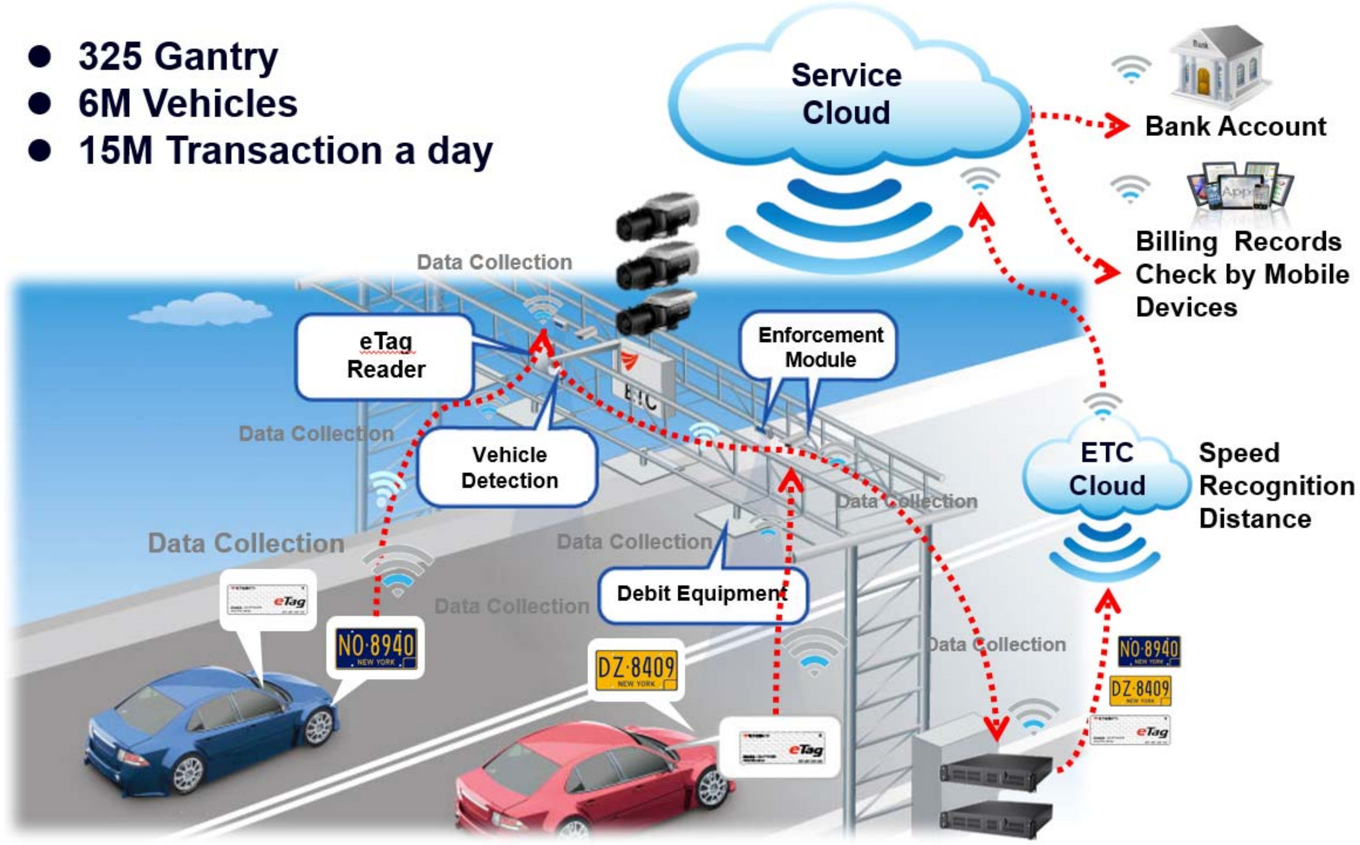
Figure 3: Intelligent traffic flow solution architecture.

IMPLEMENTATION AND PRACTICE

Figure 4 shows Taiwan started to use infrared sensing to radio frequency identification (RFID) mode with free installation of e-Tag and it began to operate in Keelung. In 2017, it has not only accumulated more than 6 million customers, the usage rate is as high as 94%, and the license plate identification and deduction accuracy were close to 99.99%. At the same time, it saves the time for users to decelerate and inductive deduction and reduces carbon emissions (CO_2) and fuel consumption every year with the amount of 42% and 32% respectively. Taiwan and other countries' ETCs are different in that the e-Tag supply chain can find synergies in Taiwan and upstream and integrate one-stop integration. It integrates all the charging and law enforcement equipment into a single gantry project, and it takes only a short period of time. It will be completed in 9 months, and now even the whole factory can be exported overseas.

Due to the importance of traffic flow monitoring, the US Federal Highway Administration published a white paper on traffic flow monitoring in 2016, which lists several devices such as coils, microwaves, infrared, ultrasonic, etc., but one of them is counting traffic. Not only can it detect the number of cars, but also include the functions of vehicle identification and steering counting, which is the image detector. In fact, this 2016 report does not yet include AI image recognition technology, but since the arrival of 2018, AI's recognition ability is able to accurately and accurately count vehicle types.

Artificial intelligence image recognition advantage: 1) car model identification – high correct rate models and vehicle identification to provide accurate traffic data, 2) traffic count – vehicle type, traffic flow direction and counting, providing road junction number adjustment system reference, 3) parking management – use identification and counting to control vehicles in the yard and provide parking space information, 4) technology enforcement – if not drive by lane, illegal turn, road shoulder, red line violation, etc.



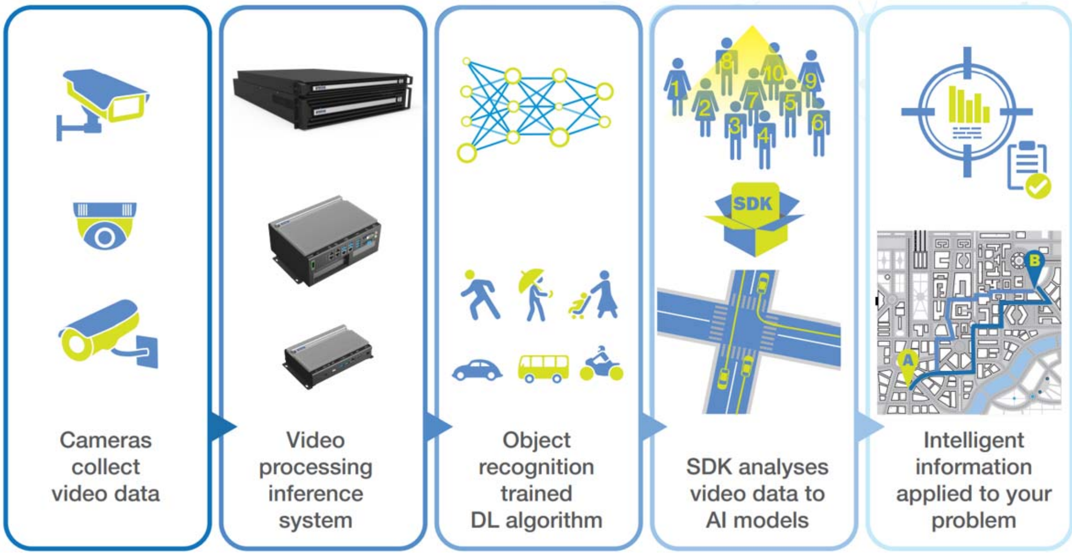
Source: This study.

Figure 4: Taiwan ETC practice.

RESULT

In the first stage of designing phase, difficulties and problems in current functional operations in traffic were identified by interviewing with stakeholders and police authorities. In the second stage of collect data phase, we can use ICT and IoT technology for collecting required and identifying data by leverage sensing device and various network transmission technology. In the third stage of analysis phase, we can use basic statistic or further deep learning methods to solve traffic scheduling, order and road safety issues. After analysis and communicating outcome with stakeholders, we design the scenario of traffic inference applications shown in Figure 5 and summarized two modules of AI video solutions shown in Figure 7 and 8: [1] vehicle counting modules: 1) section vehicle counting, 2) road dwell time & occupy rate, 3) intersection vehicle counting, 4) parking lot management. [2] people behavior modules: 1) people counting, 2) electronic fence and platform falling detection, 3) dwell time, 4) crowd and queue detection. Traffic inference system covered from notes to cloud server shown in Figure 6, and it can be remote control online by stakeholders to optimize traffic condition. In the fourth stage of communication outcome, we may review the performance with stakeholders. We will move to stage fifth of acting and implement it once it comforts to the requirements and regulations. If not, it will move in endless cycles until usefulness and effectiveness.

From an action research perspective, AIoT-based intelligent traffic solutions were developed and verified and it enables MOTC and stakeholders to acquire traffic big data for optimizing traffic condition using technology enforcement. With its implementation, it will ultimately be able to go one step closer to smart city vision. The derived service models could provide stakeholders, drivers and citizens more enhanced traffic services and improve polices work efficiency and effectiveness.



Source: This study.

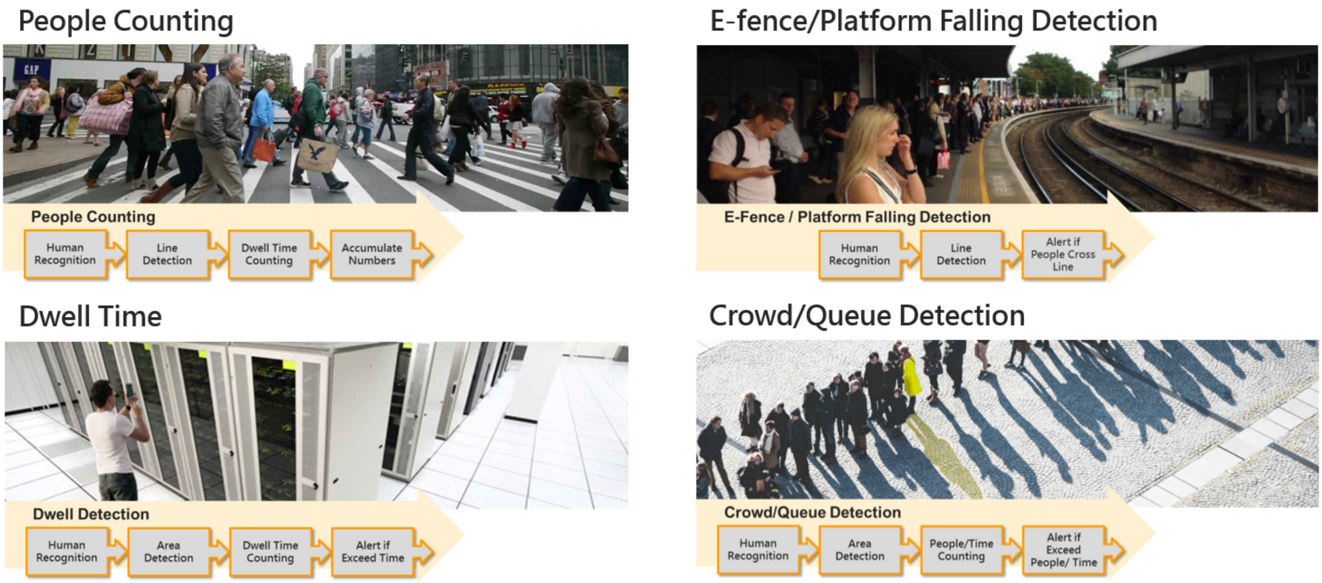
Figure 5: Scenario of traffic inference applications.

Source: This study.

Figure 6: Traffic inference systems covered from notes to cloud server.

Source: This study.

Figure 7: Traffic counting modules.



Source: This study.

Figure 8: People behavior modules.

DISCUSSION

Prohibiting traffic violations has always been a very important thing in traffic management, but we can't always send polices to stand at the intersection to see if anyone is going backwards, if anyone runs a red light, and if anyone has stopped in a red line. Therefore, the implementation of a technology for law enforcement is very important.

There was a serious car accident before, but the accident vehicle should not be driven at that time. Because it is unlikely that there will always be police forces picking up there, some companies or drivers happen to be illegal at that time. It caused a serious car accident but this should be avoided. For example, if an illegal truck or gravel car is found on the road at the entrance and exit, the system will send a message to the background of the IoT platform. The mechanism to deal with, such as connecting to the police unit to ask the police to ban, or the traffic information panel along the road to warn the driver has been banned in violation of the rules if these companies and driving know, even if the intersection does not stand the police, their violation will be fine. If unlawful driver is punished, no one will dare to do it, and the accident will be reduced.

CONCLUSION

From an action research perspective, IoT-based intelligent traffic services were developed and verified. AIoT services enable intelligent traffic to acquire traffic information from node to server and build an inference system from server to mode. It will ultimately be able to go one step closer to provide optimized traffic suggestions. The derived service models could provide citizens more enhanced convenient traffic services and improve its efficiency and effectiveness in smart city.

REFERENCES

[1] Baskerville, R. L., & Wood-Harper, A. T. (1996). A critical perspective on action research as a method for information systems research. *Journal of information Technology*, *11*(3), 235-246.

[2] Goldstein, A. (1997) “Bernard Widrow oral history,” IEEE Global History Network, 1997.

[3] Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. *Neural computation*, *9*(8), 1735-1780.

[4] Hopfield, J. J. (1982). Neural networks and physical systems with emergent collective computational abilities. *Proceedings of the national academy of sciences*, *79*(8), 2554-2558.

[5] Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks. In *Advances in neural information processing systems*, 1097-1105.

[6] LeCun, Y., Haffner, P., Bottou, L., & Bengio, Y. (1999). Object recognition with gradient-based learning. In *Shape, contour and grouping in computer vision* (pp. 319-345). Springer, Berlin, Heidelberg.

[7] McCulloch, W. S., & Pitts, W. (1943). A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics*, *5*(4), 115-133.

[8] McKinsey & Company. (2018). Retrieved from https://www.mckinsey.com/~/media/mckinsey/featured%20insights/artificial%20intelligence/notes%20from%20the%20ai%20frontier%20applications%20and%20value%20of%20deep%20learning/notes-from-the-ai-frontier-insights-from-hundreds-of-use-cases-discussion-paper.ashx/ (September 30, 2018).

[9] Minski, M. L., & Papert, S. A. (1969). Perceptrons: an introduction to computational geometry. *MA: MIT Press, Cambridge*.
[10] Patel, P. (2016). Pittsburgh's AI Traffic Signals Will Make Driving Less Boring. IEEE Spectrum. Retrieved from https://spectrum.ieee.org/cars-that-think/robotics/artificial-intelligence/pittsburgh-smart-traffic-signals-will-make-driving-less-boring/ (September 30, 2019).
[11] Rumelhart, D. E., Hinton, G. E., & Williams, R. J. (1986). Learning representations by back-propagating errors. *nature*, *323*(6088), 533.
[12] Rosenblatt, F. (1958). The perceptron: a probabilistic model for information storage and organization in the brain. *Psychological review*, *65*(6), 386.
[13] Susman, G. I., & Evered, R. D. (1978). An assessment of the scientific merits of action research. *Administrative science quarterly*, 582-603.
[14] Sutton, R. S., & Barto, A. G. (1998). *Reinforcement learning: An introduction*. MIT press.
[15] Whitwam, R. (2017). Google's AlphaGo Defeats World's Top Human Go Player. ExtremeTech. Retrieved from https://www.extremetech.com/extreme/249750-googles-alphago-defeats-worlds-top-human-go-player/ (September 30, 2018).