UNIVERSITI PUTRA MALAYSIA

DEEP LEARNING APPROACH FOR AUTOMATED GEOSPATIAL DATA COLLECTION

JALAL IBRAHIM AL-AZIZI

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By

JALAL IBRAHIM AL-AZIZI

Thesis **Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the degree of Doctor of Philosophy**

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DEDICATION

Dedicated to my beloved parents Ibrahim and Mufidh Al-Azizi, who have instilled in me the value of education and their belief that I can do it. Also, dedicated to my father in low Mufid Hamzah, my friends Yazin and Mustfa for their encouragement during my studies. Brothers, sisters, daughters, and my boss Eng. Ayesha Lootah and their words of wisdom and encouragement.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Chairman : Associate Professor Helmi Zulhaidi Mohd Shafri, PhD
Faculty : Engineering

Geospatial data collection and mapping are considered to be one of the key tasks for many users of spatial information. Traditionally, data collection and mapping can be done using a variety of methods, such as mobile mapping, remote sensing and conventional survey methods. Each method has its advantages, accuracy, costs and limitations. It is therefore essential to assess the requirements of the project in order to ensure that the relevant data quality is acquired at the lowest possible cost. However, one of the greatest barriers is the availability of digital spatial data and attributes. Often this problem arises because these methods are considered costly and require considerable effort and time.

With advancements in technology, such as object recognition through Artificial Intelligence technology, this has led to novel approaches to the extraction of features for a number of applications. Information is expected to be more accurate and readily available in real-time at lower operational and field observation costs. Several research groups have therefore investigated the detection of road objects, e.g. road signs. The main drawback of these works, however, is that none of these studies used low-cost sensors to generate geospatial maps in their studies. In addition, some of these studies are considered expensive and require a considerable amount of time to process the information collected.

In this study, I presented a new approach to real-time geospatial data collection and map generation by integrating deep learning and geomatics technologies. The proposed solution runs on a laptop which is connected with a single vision sensor, e.g. camera, receiver to capture photographs or videos,

and the location unit e.g. using global navigation satellite system to record the user location (geographic coordinates). For some selected classes, a customized data set and a prototype framework "DeepAutoMapping" have been built.

"DeepAutoMapping" was developed on the basis of convolutional neural networks inspired by recent rapid advancements in deep learning literature to detect, locate and recognize four main street objects (trees, street light poles, traffic signs, and palms) based on a defined object detection dataset. The prototype calculates the positioning of the detected object using a geographic coordinate system and then generates a geospatial database including object ID, object name, single photograph or video sequence (based on the type of test), distances, bearings, user and object coordinates. It allows users to verify the results in real time without the need to revisit the site.

Various evaluation and test scenarios have been conducted to validate outputs. The findings show that the overall proposed approach is easy to use, provides a high detection accuracy of 88% with 6% false detection and a positioning accuracy of 6.16 m for video streaming and 9.99 m for single photography in the outdoor environment.

Compared to the current data collection methods available, the proposed solution can be considered as a pipeline for the fastest and cheapest methods of data survey and geospatial map generation. In addition, a new research area for geospatial data collection using deep learning will be opened up.

Keywords: Geospatial Data, Mapping and Localisation, Deep Learning Neural Networks, Positioning, GIS, Computer Vision for Automation, Survey Method

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENDEKATAN PEMBELAJARAN MENDALAM BAGI PENGUMPULAN DATA GEOSPATIAL TERAUTOMASI

Oleh

JALAL IBRAHIM AL-AZIZI

Februari 2020

Pengerusi : Profesor Madya Helmi Zulhaidi Mohd Shafri, PhD
Fakulti : Kejuruteraan

Pengumpulan data geospatial dan pemetaan dianggap sebagai salah satu tugas penting bagi pengguna-pengguna informasi spatial. Secara tradisionalnya, pengumpulan data dan pemetaan boleh dilakukan dengan menggunakan cara-cara yang berbeza seperti pemetaan mudah alih, penderiaan jauh dan kaedah-kaedah tinjauan konvensional. Setiap cara memiliki kelebihan-kelebihannya, ketetpatan, kos dan hadnya. Oleh itu, adalah sangat mustahak untuk menilai keperluan projek untuk memastikan kualiti data yang diperoleh dengan kos yang terendah. Namun, salah satu halangan terbesar adalah berkaitan dengan ketersediaan spatial digital dan atribut digital. Sering kali, masalah ini adalah disebabkan oleh kaedah-kaedah ini dianggap mahal, dan memerlukan usaha dan masa yang banyak.

Dengan adanya kemajuan teknologi seperti pengenalan objek melalui Kecerdasan Buatan (AI), teknologi ini telah membawa kepada pendekatan baru dalam pengekstrakan ciri dalam beberapa aplikasi. Adalah dijangkakan bahawa maklumat boleh mempunyai ketepatan yang lebih tepat dan boleh didapati dalam masa nyata dengan kos operasi dan kos pemerhatian lapangan yang lebih rendah. Oleh itu, beberapa kumpulan penyelidik telah menjalankan penyiasatan terhadap pengesanan objek di jalan raya seperti tanda lalu lintas. Walau bagaimanapun, kelemahan utama dalam penyelidikan ini adalah tiada penyelidik yang menggunakan sensor kos rendah untuk menghasilkan peta geospatial dalam penyelidikan mereka. Tambahan pula, beberapa kajian itu juga dianggap mahal kerana memerlukan masa yang banyak untuk memproses maklumat yang terkumpul.

Dalam kajian ini, pengkaji telah mengemukakan pendekatan baru bagi pengumpulan data geospatial waktu nyata dan pembuatan peta dengan mengintegrasikan pembelajaran mendalam dan teknologi geomatik. Cadangan penyelesaian ini dijalankan pada komputer riba yang dihubungkan dengan sensor penglihatan tunggal seperti kamera iaitu penerima untuk menangkap gambar atau merakam video serta unit lokasi seperti menggunakan GNSS untuk merakam lokasi pengguna (koordinat geografi). Suatu set data tersuai telah dibina untuk kelas tertentu dan kerangka prototaip.

Oleh itu, "DeepAutoMapping" telah dihasilkan berdasarkan Rangkaian Neural Convolutional, hasil daripada pembangunan pesat baru-baru ini yang dijelaskan dalam literatur pembelajaran mendalam untuk mengesan, menyetempatkan dan mengenali empat objek utama di jalan iaitu pokok, tiang lampu jalan, tanda lalu lintas dan pokok palma berdasarkan objek yang ditentukan pada set data pengesanan. Prototaip akan mengira kedudukan objek yang dikesan menggunakan sistem koordinat geografi dan kemudiannya menghasilkan pangkalan data geospatial termasuklah ID objek, nama objek, urutan gambar tunggal atau video (berdasarkan jenis ujian), jarak, bearing dan koordinat pengguna & objek. Dalam masa nyata, pengguna dapat mengesahkan keputusan tanpa perlu melawat tapak tersebut.

Penilaian dan senario ujian yang berbeza telah dilakukan untuk mengesahkan keputusan tersebut. Hasil kajian menunjukkan bahawa pendekatan yang dicadangkan secara keseluruhannya mudah digunakan dan juga memberikan ketepatan pengesanan yang tinggi iaitu 88% dengan pengesanan palsu 6% dan ketepatan kedudukan dalam jarak 6.16 m untuk pengaliran video dan 9.99 m untuk satu fotograf di persekitaran luar.

Sebagai perbandingan dengan kaedah pengumpulan data yang wujud ketika ini, cadangan penyelesaian ini boleh dianggap sebagai saluran kepada kaedah yang terpantas dan termurah bagi kaedah tinjauan data dan pembuatan peta geospatial. Selain itu, pendekatan ini akan membuka bidang penyelidikan baru untuk pengumpulan data geospatial dengan menggunakan pembelajaran mendalam.

Kata Kunci: Data Geospatial, Pemetaan dan Penempatan, Rangkaian Neural Pembelajaran Mendalam, Penentududukan,

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I also take this opportunity to extend my heartfelt thanks to my parents (my mother, my father, my sisters, my brothers Mohammed, Ahmad and Taha), my family and friends who have always been with me and have given me boundless love and encouragement to pursue whatever career I choose. Their unwavering and continuous support has given me the strength, motivation and willingness to continue my research.

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This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfilment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

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Declaration by Members of Supervisory Committee

This is to confirm that:

- the research conducted and the writing of this thesis was under our supervision;
- supervision responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2012-2013) were adhered to.

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LIST OF ABBREVIATIONS

Symbol	Definition
ACC	Adaptive Cruise Control
AI	Artificial Intelligence
ANN	Artificial Neural Network
AP	Average Precision
API	Application Programming Interface
AR	Augmented Reality
BSD	Berkeley Software Distribution
CNN	Convolutional Neural Network
CPU	Central Processing Unit
CV	Computer Vision
DL	Deep Learning
DNN	Deep Neural Network
DV	Digital Video
FPS	Frame Per Second
GIS	Geographic Information System
GNSS	Global Navigation Satellite System
GPRS	General Packet Radio Services
GPS	Global Positioning System
GPU	Graphics Processing Unit
GSM	Global System for Mobile communication
GUI	Graphical User Interface
IMU	Inertial Measurement Unit

INS	Inertial Navigation System
JNDI	Java Naming and Directory Interface
IoU	Intersection over Union
JSON	JavaScript Object Notation
KML	Keyhole Markup Language
Lat	Latitude
Long	Longitude
mAP	mean Average Precision
ML	Machine Learning
NN	Neural Network
NNs	Neural Networks
R-CNN	Regions With Convolutional Neural Network
RS	Remote Sensing
SDK	Software Development Kit
SORT	Simple Online and Real-time Tracking
SSD	Single Shot Detector
UPM	Universiti Putra Malaysia
YOLO	You Only Look Once
WGS84	World Geodetic System 1984
XML	Extensible Markup Language

CHAPTER 1

INTRODUCTION

Geospatial data plays a key role in several important applications, such as navigation, planning, and researches (Khutwad et al., 2017). Hence, field data observations and mapping are fundamental to collecting and analysing all geospatial data. Therefore, significant research efforts have been expended into developing techniques for collecting, storing, analysing, processing, and representing geospatial data, eventually resulting in the development of the Geographic Information System (GIS) (Goodchild, 2009).

From the perspective of this study, these methods can be categorised into: 1) conventional data collection, 2) modern data collection, and 3) smart data collection. Each of these methods has its own benefits, accuracy, costs and limitations (Schaefer & Woodyer, 2015). It is important to assess the project requirements in order to ensure that the relevant data quality is acquired at the lowest cost (Ganendra & Zakaria, 2007). However, one of the major drawbacks of these current methods is that building a geospatial information database for large size projects tends to be expensive and requires considerable effort and time Silva et al., (2000) and B. Yang et al., (2013) associated with the use of different platform types; navigation techniques, and mapping technologies. Even an “inexpensive” system may cost over 2,000USD. For example, conventional land survey techniques require specific instruments, such as the global navigation satellite system (GNSS), the receiver or the total station instruments, to gather information. Additionally, separate teams are required for the survey work, processing of the raw data, and analysis of the outputs. For certain requirements, such as street data collection, the conventional data collection and survey methods require street closures to guarantee the safety of the surveyors (Figure (1.1)).

Figure 1.1 : Geospatial data collection using conventional survey methods

The use of satellite images for the extraction of features is an example of modern data collection (Renaud & Thierry, 2003). However, this method requires an expert to perform the analysis and is dependent on up-to-date satellite images, aerial photographs, or light detection and ranging (LiDAR) data, which are expensive and not readily available. For example, Osco et. al. (2020) provided a Convolutional Neural Network (CNN) method for estimating the number and location of multispectral imagery UAV citrus trees. However, the imagery considers expensive and not always available.

Another modern data collection that introduced some automation in geospatial map generation is mobile mapping (Puente et al., 2011a). Mobile mapping (Figure (1.2)) is the process of collecting geospatial data from a mobile vehicle that is typically fitted with a range of photographic, radar, laser, Light Detection And Ranging (LiDAR), or remote sensing systems (Puente et al., 2011b). However, such solutions can be expensive and require special instruments and software, permits to drive the vehicles in the required zones, and an expert to run the process and to analyse the output.

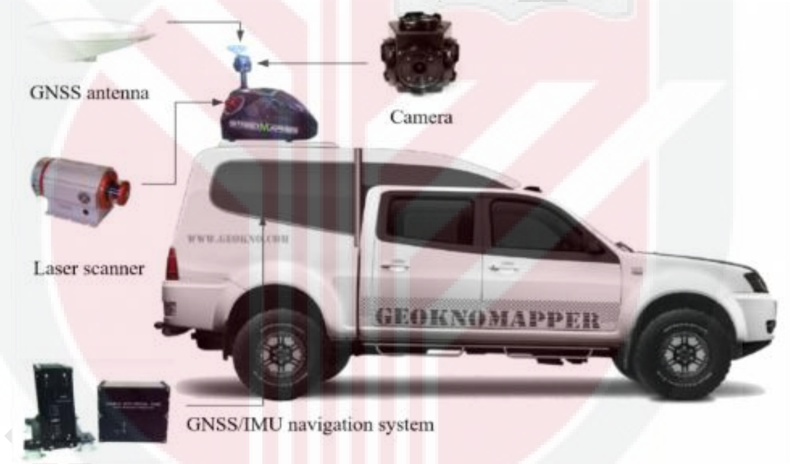

Figure 1.2 : Mobile Mapping Solution components

Furthermore, several recent studies have explored the collection and mapping of geospatial data using portable sensors. For example, Martinez et al., (2017) introduced a generic module to collect data from different mobile device sensors, whereas Korpilo et al., (2017) used a smart device to log the Global Positioning System (GPS) data to explore the spatial distribution and density of recreational movement for multiple-use in urban forests. Additionally, Lwin and Murayama, (2011) demonstrated a real-time field data collection method using mobile phones to collect field data in a practicable manner. However, the abovementioned solutions are time-consuming (Maeda et al., 2018), as the user has to stop at each feature, record the measurements, input the object descriptions, and then store the information; despite this, the output may be flawed owing to human intervention. Examples are shown in Figures (1.3) and (1.4).

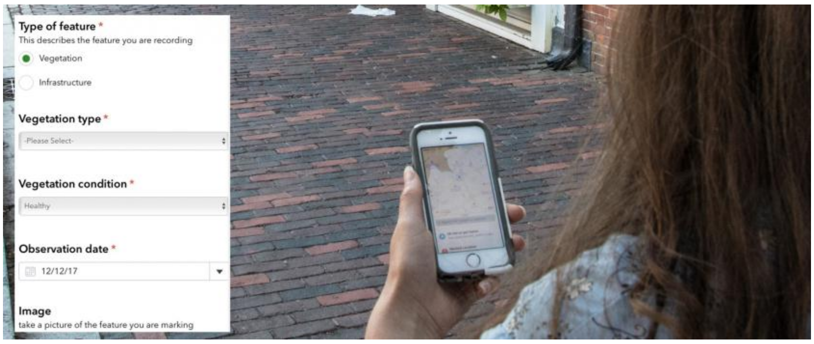

Figure 1.3 : Data collection using a portable device. It requires human interaction

Figure 1.4 : Another example of data collection using a portable device. Data collector has to stop near each street feature and enter the required information

This chapter is organized as follows. First, the chapter discusses the problem statements and conducted researches related to this work. Second, the research main and objectives and contributions, and the last section detriments the scope of work.

1.1 Problem statement

Over the past years, a number of data collection related studies have focused on proposing solution to enable reducing the data collection and processing time, cost and minimisation of errors. For example, several research groups have contributed to the topic of data collection and mapping using portable sensors. According to Klimaszewski-Patterson et al., (2010), Delail et al., (2012) and Clark, (2015), e.g. a smartphone embedded with GNSS and vision sensors. Nevertheless, these solutions require the user's action to get the outputs in order to generate the desired digital maps, which may lead to human errors and mistakes. Other research groups, e.g. Vakalopoulou et al., (2015) and Nahhas et al.,(2018) applied deep learning to detect of buildings using LIDAR–orthophoto fusion and very high-resolution multispectral data, although these are dependent on the LiDAR and satellite image availability, resolution, and date.

Recently and with advancements in portable devices, and technologies such as artificial intelligence (Russell J & Norvig, 2016), computer vision (Pulli et al., 2012; Gary et al., 2008) and deep learning (Deng & Yu, 2013; Goodfellow et al., 2015), it is now possible to detect and recognise objects from images and video sequences recorded with portable devices (Damodharan et al., 2017). In instances where professional digital cameras are not accessible, easily accessible simple cameras can provide a useful alternative image and video recording device for several geometrics' applications, such as data collection and mapping. For example, (Wegner et al., 2016) proposed an algorithm for the identification and classification of urban forest trees and their types and (Nassar et. al. 2019) used faster Regions-Convolutional Neural Networks (R-CNN) algorithm to detect the traffic signs. (Song et. al. 2019) set up a high-definition vehicle object dataset from the surveillance cameras perspective and proposed an object detection and tracking system for highway surveillance video scenes. However, building a deep learning application on portable devices capable of localising and identifying objects in a single photograph or stream video and suitable for data collection purposes is still a core challenge in computer vision and geospatial fields as it requires special processing and integration techniques.

Few empirical studies have proposed various methods and techniques regarding detection, recognition and localisation of objects. For example, Montoya, (2003) explored the use of an off-the-shelf low-cost and rapid method of data collection for the development of a building inventory based on the combination of Remote Sensing (RS), GPS, Digital Video (DV), and GIS. However, the solution requires a post office processing and the output depends on the existing building GIS layer data. Mills et al., (2010) introduced the spatial video technology by taking advantage that each frame of the video is linked to a coordinate. The video can be played in a GIS environment and will align with other spatial data. As a result, each frame is imported to GIS environment at the same location. However, the solution does not show any generation of geospatial data.

Kršák and Toth (2012) described the traffic sign detection and recognition system to calculate the approximate GPS position of the traffic signs. The vehicle's position obtained from a common GPS receiver is shifted by a constant value in latitude and longitude because signs are usually located on the left or right side of the road. This is a simple but not an accurate method, and there was no evaluation on the accuracy of the calculated position. Hazelhoff et al., (2012) defined a framework for road-sign detections using a panoramic image. Detections of the same traffic sign from multiple images are combined, and a position is calculated by straightforward geometric calculations. A capturing interval of 5m causes large differences in perspective and emerging hypothesis of sign location, which are clustered around the sign position. The accuracy of the calculated position was not part of the author's extensive experiments.

Welzel et al., (2014) provided two methods for absolute traffic sign localisation for driver assistance purposes. However, two main drawbacks have been noticed in their approach. The first drawback is that the proposed solution is limited to detect a single object, and the second drawback is that the solution is based on a single image which did not show any geospatial data outputs. Woudsma et al., (2015), in their findings, presented a single-panoramic image processing of a street marking using high quality positing system (GPS and Inertial Measurement Unit (IMU)) and pixel for the transformation of geographic coordinates. They managed to obtain up to 10m location accuracy. However, the proposed approach requires pre-processing, and is limited to single images and certain geographical region of interest. (Piarsa et. al. 2015) have developed a rural road mapping geographic framework that can conduct the coordination process in real time using GPS technology, so the user can assess the exact location of the road coordinate and at the same time directly observe the road condition. The key feature of this geographic framework is road mapping. Road mapping is achieved first by determining the position of the road which will be the starting point of the route, then by determining the other point of the route which will be achieved in two ways; 'use button' or 'use time'. This simple where the user location is considered as the object locations.

More new recent approach to geospatial data collection, which has just started using machine learning techniques for geospatial collection. For example, Rao et al., (2017) proposed an approach for visitors by providing information about the detected buildings. The authors used deep learning method to detect certain object, to estimate the site locations by considering the concept of a distance threshold, and then obtain the object description from the stored database and display for the user. The research did not show any geospatial or map data generation. This system only works offline, and can only detect images. Also, the accuracy of the research was not mentioned whether it's too low to provide any samples for test data according to the findings.

Shah et al.,(2017) proposed a framework capable of detecting, localising, and recognising trees using deep learning. However, the approach requires the quadcoptor equipped inertial device, and it is necessary to run the quadcoptor over the survey area twice. In this work, an innovative approach was proposed that uses deep learning integrated with geospatial technologies and computer vision to provide a real-time low-cost solution for geospatial data collection and geospatial data generation for certain street features. This system only works offline, and can only detect images. Also, the accuracy of the research was not mentioned as well, whether it is too low to provide any samples for test data according to them. Nuakoh et al., (2019a) modified VGG-16 to detect traffic signs. This system only works offline, and can only detect single images. They also did not mention the accuracy of the research as well as being too low to provide any samples for test data according to them. Nuakoh et al., (2019b) proposed a traffic sign detector based on You Only Look Once (YOLO)v3, and a classifier based on custom CNN. Detection efficiency is found to be superior to previous detectors, based on the detection speed, with traffic-sign being considered as a single class. The proposed detector can detect nearly all types of traffic signs and may be able to regress correct bounding boxes for most of the signs detected. A number of very small traffic signs could not be identified correctly and a few false positive detections were also possible.

Chen et. al., (2019) showed that a CNN based object detector's low-level features have the potential to improve the detection accuracy of small objects. However, they did not show any geospatial data outputs. Zhang et. al., (2019) suggested an automated method to detect and position road objects located at intersections from street-level images. The approach proposed is based on two deep learning pipelines: one for semantic segmentation, and the other for object recognition. However, they can only verify the effectiveness of our proposed positioning algorithm at crossroads and T-junctions. Doval et. al., (2019) used YOLOv3 algorithm to identify, recognize and 3D locate traffic signs in various scenarios, and a new dataset for traffic sign detection. They also introduced updated architecture to improve results of detection at lower resolutions and to reduce their performance at higher resolutions. However, the outputs show only the distance and no locations and coordinates were presented. Tabernik and Skocaj, (2020) discussed the issue of detecting and identifying a large number of traffic sign categories for the main purpose of automating the management of traffic sign inventories. They suggested several modifications to mask R-CNN which would improve the ability to learn on the traffic signs domain. In addition, authors have suggested a technique for data increase based on geometric distribution and appearance distortions. But they also have high error rates for groups of traffic signs, mainly due to overlapping with other groups, small viewing angles and high occlusions.

1.2 Novelty and research objectives

In summary, a review of existing literatures indicates that implementation of a low operational and field observations costs approach using deep learning and computer vision techniques integrated with geospatial science to automate the geospatial data collection process is full of unanswered questions. Some scholars mentioned estimating the object detection positioning, but the descried solutions either considered expensive or did not show the geospatial map outputs. For this reason, this research aims to produce low cost system that uses contemporary and freely available technologies including deep learning, computer vision and geospatial technologies to produce this a low operational and field observations costs for data collection and geospatial map generations. The objectives of this research are:

i. To build an object detection dataset by training a large number of images
ii. To examine the level of accuracy in positioning and availability obtained using low cost sensors by applying deep learning and computer vision technologies with respect to the ground truth government database.
iii. To develop a prototype and portable application “DeepAutoMapping” in order to evaluate the proposed algorithm.

The scope of work encompasses building the dataset for object detection on the target street objects, tracking the detection objects, estimating the distances and directions to each detected object, calculating the geographic coordinates for each object and then storing the outputs in geospatial dataset. The work includes building a prototype application to test and evaluate the outputs. The prototype can be used as a static mode using single photograph or a moving mode using streaming video inputs. Though it is configured to work on straight-line roads, but feature work can also be updated to work on curved roads.

The proposed solution may be considered as one of the fastest, most economic and real-time survey method and mapping solution that enhances the efficiency of spatial data collection not only for GIS applications, such as mapping of street features for street asset management, but also for different applications which required obtaining the information in real-time such as driver assistance systems, some urban planning studies, and road assist management where the decision maker should take the required decision on site.

1.3 Scope of work

The problem addressed in this thesis takes into consideration that the areas under observation are flat. Where the slope of the ground has a direct impact on the results, which is not part of this research study.

1.4 Summary

Geospatial data plays a key role in many important applications, such as navigations, assists in maintenance, planning, and studies, and helps managers in taking the correct decision. One of the biggest bottlenecks is related to the cost and availability of spatial and attributes data. Different research groups have investigated on the use of deep learning to detect and locate some certain objects. However, the drawbacks of these researches are that none of these researches have generated any geospatial outputs and maps, which requires an expensive instrument such as drone. Thus, this study proposes a robust, fast, and low-cost solution for auto map generation for main road features in real-time.

1.5 Thesis structure

This thesis consists of five chapters. A brief background and literature review have been provided in Chapter Two. Chapter Three describes the methodologies and implementation procedures. Chapter Four provides the conducted tests, evaluations, and results achieved. Chapter Four also gives an illustration of the outputs and discussion. The final chapter summarises the conclusion and contributions of this research which provides possible directions for future work.

REFERENCES

Abadi, M., Barham, P., Chen, J., Chen, Z., Davis, A., Dean, J., Devin, M., Ghemawat, S., Irving, G., Isard, M., Kudlur, M., Levenberg, J., Monga, R., Moore, S., Murray, D. G., Steiner, B., Tucker, P., Vasudevan, V., Warden, P., Zheng, X. (2016). TensorFlow : A System for Large-Scale Machine Learning. *12th USENIX Symposium on Operating Systems Design and Implementation*, 265–283.

Ahmed, R. E. (2016). GPark: Vehicle parking management system using smart glass. *Journal of Sensors*, *2016*. https://doi.org/10.1155/2016/6260372.

Al-azizi, J. I., & Shafri, H. Z. M. (2017a). Performance Evaluation of Pedestrian Locations Based on Contemporary Smartphones. *International Journal of Navigation and Observation*, 10.

Al-azizi, J. I., & Shafri, H. Z. M. (2017b). *Smartphones in Mecca Area : Positioning Availability and Accuracy Analysis*. 1–4

Alexey AB. (2019). *Windows and Linux version of Darknet Yolo v3 & v2 Neural Networks for object*

detection. https://github.com/AlexeyAB/darknet#when-should-i-stop-training

Bathija, A. (2019). Visual Object Detection and Tracking using YOLO and SORT. *International Journal of Engineering Research and Technology (IJERT)*, *8*(11), 705–708. https://www.ijert.org

Bewley, A., Ge, Z., Ott, L., Ramos, F., & Upcroft, B. (2016). Simple online and realtime tracking. *Proceedings - International Conference on Image Processing, ICIP*, *2016-Augus*, 3464–3468. https://doi.org/10.1109/ICIP.2016.7533003

Bradski, G. R., & Pisarevsky, V. (2002). *Intel's Computer Vision Library: applications in calibration, stereo segmentation, tracking, gesture, face and object recognition*. 796–797. https://doi.org/10.1109/cvpr.2000.854964

Bresson, G., Alsayed, Z., Yu, L., & Glaser, S. (2017). Simultaneous Localization and Mapping: A Survey of Current Trends in Autonomous Driving. *IEEE Transactions on Intelligent Vehicles*, *2*(3), 194–220. https://doi.org/10.1109/tiv.2017.2749181

Brostow, G. J., Fauqueur, J., & Cipolla, R. (2009). Semantic object classes in video: A high-definition ground truth database. *Pattern Recognition Letters*, *30*(2), 88–97. https://doi.org/10.1016/j.patrec.2008.04.005

Byun, S. H., Hajj, G. A., & Young, L. E. (2002). *Assessment of GPS Signal Multipath Interference*.

Cao, Y.-T., Wang, J.-M., Sun, Y.-K., & Duan, X.-J. (2013). Circle Marker Based Distance Measurement Using a Single Camera. *Lecture Notes on Software Engineering*, *1*(4), 376–380. https://doi.org/10.7763/LNSE.2013.V1.80.

Chen, E. H., Röthig, P., Zeisler, J., & Burschka, D. (2019, October). Investigating Low Level Features in CNN for Traffic Sign Detection and Recognition. In *2019 IEEE Intelligent Transportation Systems Conference (ITSC)* (pp. 325-332). IEEE.

Chen, G., Choi, W., Yu, X., Han, T., & Chandraker, M. (2017). Learning Efficient Object Detection Models with Knowledge Distillation. *Nips*, *Nips*, 1–10. https://doi.org/10.1074/jbc.M706848200

Chen, X., Fang, H., Lin, T.-Y., Vedantam, R., Gupta, S., Dollar, P., & Zitnick, C. L. (2015). Microsoft COCO Captions: Data Collection and Evaluation Server. *ArXiv Preprint ArXiv:1504.00325.*, 1–7. https://doi.org/10.1093/mnras/stv1365

Clark, J. (2015). *Location Gathering : An Evaluation of Smartphone-Based Geographic Mobile Field Data Collection Hardware and Applications*.

Cordts, M., Omran, M., Ramos, S., Rehfeld, T., Enzweiler, M., Benenson, R., Franke, U., Roth, S., & Schiele, B. (2016). The Cityscapes Dataset for Semantic Urban Scene Understanding. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2016-Decem*, 3213–3223. https://doi.org/10.1109/CVPR.2016.350

Craglia, M. (2015). Spatial Data Infrastructures. *International Encyclopedia of the Social & Behavioral Sciences: Second Edition*, 130–135. https://doi.org/10.1016/B978-0-08-097086-8.72058-7

CUDA. (2019). https://www.geforce.com/hardware/technology/cuda

Cvpr, A., & Id, P. (2017). *Speed / accuracy trade-offs for modern convolutional object detectors - 3562*. Cvpr. https://doi.org/10.1109/CVPR.2017.351

Dai, J., Li, Y., He, K., & Sun, J. (2016). R-FCN : Object Detection via Region-based Fully Convolutional Networks. *Advances in Neural Information Processing Systems*, 379–387.

Damodharan, P. P., Aravind, P., Gomathi, K., Keerthana, R., & Manishasamrin, K. (2017). Controlling Input Device Based On Iris Movement Detection Using Artificial Neural Network. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, *2*(2), 634–642.

Danielsson, T. L. (2016). *Developing a Location Based Augmented Reality Application for Android Devices*. Luleå University of Technology.

Delail, B. Al, Weruaga, L., & Zemerly, M. J. (2012). CAViAR: Context aware visual indoor augmented reality for a University Campus. *Proceedings of the 2012 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology Workshops, WI-IAT 2012*, 286–290. https://doi.org/10.1109/WI-IAT.2012.99

Deng, L., & Yu, D. (2013). Deep Learning: Methods and Applications. In *Foundations and Trends® in Signal Processing* (Vol. 7, Issues 3–4). https://doi.org/10.1136/bmj.319.7209.0a

Dettmers, T. (n.d.). *A Full Hardware Guide to Deep Learning*. https://timdettmers.com/2018/12/16/deep-learning-hardware-guide/

Ding, S., Lin, L., Wang, G., & Chao, H. (2015). Deep feature learning with relative distance comparison for person re-identification. *Pattern Recognition*, *48*(10), 2993–3003. https://doi.org/10.1016/j.patcog.2015.04.005.

Doval, G. N., Al-Kaff, A., Beltrán, J., Fernández, F. G., & López, G. F. (2019, October). Traffic Sign Detection and 3D Localization via Deep Convolutional Neural Networks and Stereo Vision. In *2019 IEEE Intelligent Transportation Systems Conference (ITSC)* (pp. 1411-1416). IEEE.

Fu, C., Liu, W., Ranga, A., Tyagi, A., & Berg, A. C. (2017). DSSD : Deconvolutional Single Shot Detector. *ArXiv Preprint ArXiv:1701.06659.*

Fu, L., Wu, L., Jian, M., Yang, Y., & X, W. (2019). MF-SORT: Simple Online and Realtime Tracking with Motion Features. *International Conference on Image and Graphics*, 157–168.

Fu, M. Y., & Huang, Y. S. (2010). A survey of traffic sign recognition. *2010 International Conference on Wavelet Analysis and Pattern Recognition, ICWAPR 2010*, *July*, 119–124. https://doi.org/10.1109/ICWAPR.2010.5576425

Gallego, A.-J., Pertusa, A., & Gil, P. (2018). Automatic Ship Classification from Optical Aerial Images with Convolutional Neural Networks. *Remote Sensing*, *10*(4), 511. https://doi.org/10.3390/rs10040511

Ganendra, T. R., & Zakaria, Z. (2007). Application Of Innovative Airborne Lidar Survey System For A Highway Project In Malaysia. *Malaysian Road Conference, 7th*, 1–11.

Gary, B., Kaehler, A., Bradski, G., & Kaehler, A. (2008). *Learning OpenCV: Computer vision with the OpenCV library*. O'Reilly Media, Inc.

Geiger, A., Lenz, P., & Urtasun, R. (2012). Are we ready for autonomous driving? the KITTI vision benchmark suite. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 3354–3361. https://doi.org/10.1109/CVPR.2012.6248074

Girshick, R. (2015). Fast R-CNN. *Proceedings of the IEEE International Conference on Computer Vision*, *2015 Inter*, 1440–1448. https://doi.org/10.1109/ICCV.2015.169

Gökçe, F., Üçoluk, G., Şahin, E., & Kalkan, S. (2015). Vision-Based Detection and Distance Estimation of Micro Unmanned Aerial Vehicles. *Sensors*, *15*(9), 23805–23846. https://doi.org/10.3390/s150923805

Goodchild, M. F. (2009). Geographic information systems and science: Today and tomorrow. *Annals of GIS*, *15*(1), 3–9. https://doi.org/10.1080/19475680903250715

Goodfellow, I., Bengio, Y., Courville, A., Goodfellow, I., Bengio, Y., & Courville, A. (2015). Deep Learning. In *Nature Methods* (Vol. 13, Issue 1). https://doi.org/10.1038/nmeth.3707

Grevelink, E. (2017). *A Closer Look at Object Detection, Recognition and Tracking*. https://software.intel.com/en-us/articles/a-closer-look-at-object-detection-recognition-and-tracking

gsmarena. (2019). *Samsung Galaxy S9*. https://www.gsmarena.com/samsung_galaxy_s9-8966.php

Håkansson, M. (2019). Characterization of GNSS observations from a Nexus 9 Android tablet. *GPS Solutions*, *23*(1), 1–14. https://doi.org/10.1007/s10291-018-0818-7

Haseeb, M. A., Guan, J., Ristić, D., & Gräser, A. (2018). DisNet : A novel method for distance estimation from monocular camera. *10th Planning, Perception and Navigation for Intelligent Vehicles*.

Hazelhoff, L., Creusen, I., & De With, P. H. N. (2012). Robust detection, classification and positioning of traffic signs from street-level panoramic images for inventory purposes. *Proceedings of IEEE Workshop on Applications of Computer Vision*, 313–320. https://doi.org/10.1109/WACV.2012.6163006

Holzmann, C., & Hochgatterer, M. (2012). Measuring distance with mobile phones using single-camera stereo vision. *Proceedings - 32nd IEEE International Conference on Distributed Computing Systems Workshops, ICDCSW 2012*, 88–93. https://doi.org/10.1109/ICDCSW.2012.22

Hou, X., Wang, Y., & Chau, L. P. (2019). Vehicle tracking using deep SORT with low confidence track filtering. *2019 16th IEEE International Conference on Advanced Video and Signal Based Surveillance, AVSS*

2019, 1–6. https://doi.org/10.1109/AVSS.2019.8909903

Howard, A. G., & Wang, W. (2012). MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. *ArXiv Preprint ArXiv:1704.04861*.

Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., Fischer, I., Wojna, Z., Song, Y., Guadarrama, S., & Murphy, K. (2017). Speed/accuracy trade-offs for modern convolutional object detectors. *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR*, *2017-Janua*, 3296–3305. https://doi.org/10.1109/CVPR.2017.351

Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., Fischer, I., Wojna, Z., Song, Y., Guadarrama, S., Murphy, K., Jonathan Huang, Vivek Rathod, Chen Sun, Menglong Zhu, Anoop Korattikara, Alireza Fathi, Ian Fischer, ZbigniewWojna, Yang Song, S. G. and K. M., Huang, J., Rathod, V., Sun, C., Zhu, M., Korattikara, A., Fathi, A., Fischer, I., … Murphy, K. (2017). Speed/accuracy trade-offs for modern convolutional object detectors. *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, *2017-Janua*, 3296–3305. https://doi.org/10.1109/CVPR.2017.351

Huang, R., Pedoeem, J., & Chen, C. (2018). YOLO-LITE : A Real-Time Object Detection Algorithm Optimized for Non-GPU Computers. *ArXiv Preprint ArXiv:1811.05588*. https://arxiv.org/abs/1811.05588

Huber, D. (2011). Background Positioning for Mobile Devices - Android vs. iPhone. *INFOCOM 2011: Proceedings of the 30th IEEE International Conference on Computer and Communications*, 1–7.

Javatpoint. (2019). *Subsets of Artificial Intelligence*. https://www.javatpoint.com/subsets-of-ai

Jia, P., Cheng, X., Xue, H., & Wang, Y. (2017). Applications of geographic information systems (GIS) data and methods in obesity-related research. *Obesity Reviews*, *18*(4), 400–411. https://doi.org/10.1111/obr.12495

Jia, Y., Shelhamer, E., Donahue, J., Karayev, S., Long, J., Girshick, R., Guadarrama, S., & Darrell, T. (2014). Caffe: Convolutional Architecture for Fast Feature Embedding. *ArXiv Preprint ArXiv:1408.5093*.

Joseph, R., & Ali, F. (2018). YOLOv3: An Incremental Improvement. *ArXiv Preprint ArXiv:1804.02767*.

Jüngel, M., Mellmann, H., & Spranger, M. (2007). Improving vision-based distance measurements using reference objects. *In Robot Soccer World Cup (pp. 89-100). Springer, Berlin, Heidelberg.*

Kang, M., & Lim, Y. (2017). High performance and fast object detection in road environments. *2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA)*, 1–6. https://doi.org/10.1109/IPTA.2017.8310148

Kanjee, R., Bachoo, A. K., & Carroll, J. (2013). Vision-based Adaptive Cruise Control using pattern matching. *2013 6th Robotics and Mechatronics Conference (RobMech)*, 93–98. https://doi.org/10.1109/RoboMech.2013.6685498

Kayid, A., Khaled, Y., & Elmahdy, M. (2018). *Performance of CPUs/GPUs for Deep Learning workloads*.

Khutwad, J., Konde, B., Deokate, A., & Kadam, P. A. A. (2017). Hazards Reporting Based on Real-Time Field Data Collection Using Personal Mobile Phone. *International Journal of Advance Engineering and Research Development*, *4*(04), 1–5. https://doi.org/10.21090/ijaerd.78931

Kim, D., & Paik, J. (2015). Three-dimensional simulation method of fish-eye lens distortion for a vehicle backup rear-view camera. *Journal of the Optical Society of America A-Optics Image Science and Vision*, *32*(7), 1337–1343. https://doi.org/10.1364/JOSAA.32.001337

Kim, I., & Yow, K. C. (2015). Object Location Estimation from a Single Flying Camera. *The Ninth International Conference on Mobile Ubiquitous Computing, Systems, Services and Technologies*, *c*, 82–88.

Klimaszewski-Patterson, A., Biociências, I. De, Federal, U., Grosso, D. M., Fernando, A., Klimaszewski-Patterson, A., Biociências, I. De, Federal, U., Grosso, D. M., & Fernando, A. (2010). Smartphones in the Field: Preliminary Study Comparing GPS Capabilities Between a Smartphone and Dedicated GPS Device. *Applied Geography Conferences*, 36–40.

Kogure, K., & Takasaki, Y. (2019). GIS for empirical research design: An illustration with georeferenced point data. *PLoS ONE*, *14*(3), 1–16. https://doi.org/10.1371/journal.pone.0212316

Korpilo, S., Virtanen, T., & Lehvävirta, S. (2017). Smartphone GPS tracking—Inexpensive and efficient data collection on recreational movement. *Landscape and Urban Planning*, *157*, 608–617. https://doi.org/10.1016/j.landurbplan.2016.08.005

Kršák, E., & Toth, Š. (2012). Traffic Sign Recognition and Localization for Databases of Traffic Signs. *Acta Electrotechnica et Informatica*, *11*(4), 31–35. https://doi.org/10.2478/v10198-011-0039-2

Lachapelle, G., Kuusniemi, H., Dao, D. T. H., Macgougan, G., & Cannon, M. E. (2004). HSGPS Signal Analysis and Performance. *Journal of the Institute of Navigation*, *September 2003*, 29–43.

Lecun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, *521*(7553), 436–444. https://doi.org/10.1038/nature14539

Lee, J.-G., Kang, M., Lee, J.-G., & Kang, M. (2015). Geospatial Big Data : Challenges and Opportunities Procedia Computer Science Geospatial Big Data : Challenges and Opportunities. *Big Data Research*, *2*(2), 74–81. https://doi.org/10.1016/j.bdr.2015.01.003

Li, Z., Peng, C., Yu, G., Zhang, X., Deng, Y., & Sun, J. (2017). Light-Head R-CNN: In Defense of Two-Stage Object Detector. *Defense of Two-Stage Object Detector*, *arXiv prep*, 1–9. http://arxiv.org/abs/1711.07264

Lin, T., Ai, F., & Doll, P. (2018). Focal Loss for Dense Object Detection. *Computer Vision and Pattern Recognition*.

Lin, T., Doll, P., Girshick, R., He, K., Hariharan, B., Belongie, S., & Ai, F. (2017). Feature Pyramid Networks for Object Detection. *Computer Vision and Pattern Recognition*.

Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C.-Y., & Berg, A. C. (2016). SSD: Single shot multibox detector. *European Conference on Computer Vision*, 21–37. https://doi.org/10.1007/978-3-319-46448-0_2.

Lwin, K. K., & Murayama, Y. (2011). Web-Based GIS System for Real-Time Field Data Collection Using a Personal Mobile Phone. *Journal of Geographic Information System*, *3*(October), 382–389. https://doi.org/10.4236/jgis.2011.34037

MacEachren, A. M., Gahegan, M., Pike, W., Brewer, I., Cai, G., Lengerich, E., & Hardistry, F. (2004). Geovisualization for knowledge construction and decision support. *IEEE Computer Graphics and Applications*, *24*(1), 13–17. https://doi.org/10.1109/MCG.2004.1255801

Maeda, H., Sekimoto, Y., Seto, T., Kashiyama, T., & Omata, H. (2018). *Road Damage Detection Using Deep Neural Networks with Images Captured Through a Smartphone*. 4–6. https://doi.org/10.3390/ijerph13010031

Mahammed, M. a, Melhum, A. I., & Kochery, F. a. (2013). Object Distance Measurement by Stereo Vision. *International Journal of Science and Applied Information Technology*, *2*(2), 5–8.

Martinez, A., Ramirez, F., Estrada, H., & Torres, L. A. (2017). *Generic module for collecting data in smart cities*. *XLII*(October), 4–6.

Microsoft. (2019). https://www.microsoft.com/accessories/en-us/products/webcams/lifecam-hd-3000/t3h-00011

Mills, J. W., Curtis, A., Kennedy, B., Kennedy, S. W., & Edwards, J. D. (2010). Geospatial video for field data collection. *Applied Geography*, *30*(4), 533–547. https://doi.org/10.1016/j.apgeog.2010.03.008

Missinglink.a. (2019). *The Complete Guide to Artificial Neural Networks: Concepts and Models*. https://missinglink.ai/guides/neural-network-concepts/complete-guide-artificial-neural-networks/?cv=1

Montoya, L. (2003). Geo-data acquisition through mobile GIS and digital video: An urban disaster management perspective. *Environmental Modelling and Software*, *18*(10), 869–876. https://doi.org/10.1016/S1364-8152(03)00105-1

SORT*: Calculate distance, bearing and more between Latitude/Longitude points*. (2019). https://www.movable-type.co.uk/scripts/latlong.html

Nahhas, F. H., Shafri, H. Z. M., Sameen, M. I., Pradhan, B., & Mansor, S. (2018). Deep Learning Approach for Building Detection Using LiDAR–Orthophoto Fusion. *Journal of Sensors*, *2018*, 1–12. https://doi.org/10.1155/2018/7212307

Namavar Jahromi, A., Hashemi, S., Dehghantanha, A., Choo, K. K. R., Karimipour, H., Newton, D. E., & Parizi, R. M. (2020). An improved two-hidden-layer extreme learning machine for malware hunting. *Computers and Security*, *89*, 101655. https://doi.org/10.1016/j.cose.2019.101655.

Nassar, A. S., & Lefevre, S. (2019, May). Automated Mapping Of Accessibility Signs With Deep Learning From Ground-level Imagery and Open Data. In *2019 Joint Urban Remote Sensing Event (JURSE)* (pp. 1-4). IEEE.

Nasse, F., Thurau, C., & Fink, G. A. (2009). Face detection using gpu-based convolutional neural networks. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *5702 LNCS*, 83–90. https://doi.org/10.1007/978-3-642-03767-2_10

Nuakoh, E. B., Roy, K., Yuan, X., & Esterline, A. (2019a). Deep learning approach for U.S. traffic sign recognition. *ACM International Conference Proceeding Series*, 47–50. https://doi.org/10.1145/3342999.3343016

Nuakoh, E. B., Roy, K., Yuan, X., & Esterline, A. (2019b). Real-Time Traffic Sign Recognition using YOLOv3 based Detector. *ACM International Conference Proceeding Series*, 47–50. https://doi.org/10.1145/3342999.3343016
OpenCV. (2019). https://opencv.org/

Osco, L. P., de Arruda, M. D. S., Junior, J. M., da Silva, N. B., Ramos, A. P. M., Moryia, É. A. S., ... & Li, J. (2020). A convolutional neural network approach for counting and geolocating citrus-trees in UAV multispectral imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, *160*, 97-106.

Piarsa, I. N., Hadi, E. S., & Wirdiani, N. K. A. (2015). Rural Road Mapping Geographic Information System Using Mobile Android. *International*

Journal of Computer Science Issues (IJCSI), *12*(3), 95.

Piewak, F. (2017). *Fully Convolutional Neural Networks for Dynamic Object Detection in Grid Maps (Masters Thesis)*. http://arxiv.org/abs/1709.03138.

Puente, I., González-Jorge, P., Arias, P., & Armesto, J. (2011a). Land-Based Mobile Laser Scanning System : A Review. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. https://doi.org/10.5194/isprsarchives-XXXVIII-5-W12-163-2011

Puente, I., González-Jorge, P., Arias, P., & Armesto, J. (2011b). Land-Based Mobile Laser Scanning Systems : a Review. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. https://doi.org/10.5194/isprsarchives-XXXVIII-5-W12-163-2011

Pulli, K., Baksheev, A., Kornyakov, K., & Eruhimov, V. (2012). Real-time computer vision with OpenCV. *Communications of the ACM*, *55*(6), 61. https://doi.org/10.1145/2184319.2184337

PyTorch. (2019). https://pytorch.org/

Radovic, M., Adarkwa, O., & Wang, Q. (2017). Object Recognition in Aerial Images Using Convolutional Neural Networks. *Journal of Imaging*, *3*(2), 21. https://doi.org/10.3390/jimaging3020021

Rao, J., Qiao, Y., Ren, F., Wang, J., & Du, Q. (2017). A Mobile Outdoor Augmented Reality Method Combining Deep Learning Object Detection and Spatial Relationships for Geovisualization. *Sensors*, *17*(9), 1951. https://doi.org/10.3390/s17091951

Redmon, J. (2013). *Darknet: Open Source Neural Networks in C*. http://pjreddie.com/darknet/

Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2015). You Only Look Once: Unified, Real-Time Object Detection. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 779–788. https://doi.org/10.1109/CVPR.2016.91

Redmon, J., & Farhadi, A. (2018). *YOLO: Real-Time Object Detection*. https://pjreddie.com/darknet/yolo/

Redmon, J., & Farhadi, A. (2017). YOLO9000: Better, Faster, Stronger. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 7263–7271. https://doi.org/10.1109/CVPR.2017.690

Reininger, M., Miller, S., Zhuang, Y., & Cappos, J. (2015). A first look at vehicle data collection via smartphone sensors. *SAS 2015 - 2015 IEEE Sensors*

Applications Symposium, Proceedings. https://doi.org/10.1109/SAS.2015.7133607

Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *39*(6), 1137–1149. https://doi.org/10.1109/TPAMI.2016.2577031

Renaud, P., & Thierry, R. (2003). Urban street mapping using quickbird and Ikonos Images. *IEEE International Geoscience and Remote Sensing Symposium (IGARSS 2003)*, *3*, 1721–1723.

Rieke, M., Bigagli, L., Herle, S., Jirka, S., & Kotsev, A. (2018). *GeoSpatial IoT - the Need for an Event-Driven Spatial Data Infrastructure*. *August*. https://doi.org/10.20944/preprints201808.0132.v1

Robustelli, U., Baiocchi, V., & Pugliano, G. (2019). Assessment of Dual Frequency GNSS Observations from a Xiaomi Mi 8 Android Smartphone and Positioning Performance Analysis. *Electronics*, *8*(1), 91. https://doi.org/10.3390/electronics8010091

Rowe, J. (2017). *The Continuing Importance of GPUs For More Than Just Pretty Pictures*. https://www10.mcadcafe.com/blogs/jeffrowe/2017/03/16/the-continuing-importance-of-gpus-for-more-than-just-pretty-pictures/

Russell J, S., & Norvig, P. (2016). *Artificial intelligence: a modern approach*. Pearson Education Limited.

Saipullah, K., Ismail, N. A., Anuar, A., & Sarimin, N. (2013). Comparison of feature extractors for real-time object detection on android smartphone. *Journal of Theoretical and Applied Information Technology*, *47*(1), 135–142.

Samra, A. A., Al-sharif, I., Skaik, A., El-rebai, F., El-talli, H., & Shbair, M. (2018). Self-Adaptive Traffic Recommendation System Beijing City as a Case Study. *International Journal of Computer Science and Mobile Computing*, *7*(3), 51–67.

Schaefer, M., & Woodyer, T. (2015). Assessing absolute and relative accuracy of recreation-grade and mobile phone GNSS devices: A method for informing device choice. *Area*, *47*(2), 185–196. https://doi.org/10.1111/area.12172

Schwieger, V., Key, G., Gps, H., & Techniques, L. C. (2008). High-Sensitivity GPS – an Availability, Reliability and Accuracy Test. *Generations Journal Of The American Society On Aging*, *June*, 1–17.

Shah, U., Khawad, R., & Krishna, K. M. (2017). Detecting , localizing , and recognizing trees with a monocular MAV : Towards preventing deforestation. *IEEE Nternational Conference on Robotics and Automation (ICRA)*, 1982–1987.

Sharma, S. U., & Shah, D. J. (2017). A Practical Animal Detection and Collision Avoidance System Using Computer Vision Technique. *IEEE Access*, *5*(January 2015), 347–358. https://doi.org/10.1109/ACCESS.2016.2642981

SILVA, J. F. C. F. C., Camargo, P. O. O., Oliveira, R. A., Gallis, R. B. A., GUARDIA, M. C., REISS, M. L. L., & Silva, R. A. C. A. C. (2000). A Street Map Built By a Mobile Mapping System. *International Archives of Photogrammetry and Remote Sensing 33*, *B2;PART 2*, 510–517.

SimpleCV. (2019). http://simplecv.org/

Socher, R. (2014). RECURSIVE DEEP LEARNING FOR NATURAL LANGUAGE PROCESSING AND COMPUTER VISION. In *Richard Socher PhD Thesis* (Issue August).

Solaiman, B., Burdsall, B., & Roux, C. (2002). *Hough transform and uncertainty handling. Application to circular object detection in ultrasound medical images*. *33*, 828–831. https://doi.org/10.1109/icip.1998.999072

Song, H., Liang, H., Li, H., Dai, Z., & Yun, X. (2019). Vision-based vehicle detection and counting system using deep learning in highway scenes. *European Transport Research Review*, *11*(1), 51.

Sotelo, M. a., Fernandez, D., Naranjo, J. E., Gonzalez, C., Garcia, R., Pedro, T. De, & Reviejo, J. (2004). Vision-based adaptive cruise control for intelligent road vehicles. *2004 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS) (IEEE Cat. No.04CH37566)*, *1*, 64–69. https://doi.org/10.1109/IROS.2004.1389330

Stallkamp, J., Schlipsing, M., Salmen, J., & Igel, C. (2011). The German Traffic Sign Recognition Benchmark: A multi-class classification competition. *Proceedings of the International Joint Conference on Neural Networks*, *June 2014*, 1453–1460. https://doi.org/10.1109/IJCNN.2011.6033395

Stein, G. P., Mano, O., & Shashua, A. (2003). Vision based ACC with a Single Camera Bounds on Range and Range Rate Accuracy. *Intelligent Vehicles Symposium, IEEE*, 120–125.

Stiglitz, R., Mikhailova, E., Post, C., Schlautman, M., Sharp, J., Pargas, R., Glover, B., & Mooney, J. (2017). Soil color sensor data collection using a GPS-enabled smartphone application. *Geoderma*, *296*, 108–114. https://doi.org/10.1016/j.geoderma.2017.02.018

Sutskever, I., Vinyals, O., & Le, Q. V. (2014). Sequence to sequence learning with neural networks. *Advances in Neural Information Processing Systems*, *4*(January), 3104–3112.

Tabernik, D., & Skocaj, D. (2020). Deep Learning for Large-Scale Traffic-Sign Detection and Recognition. *IEEE Transactions on Intelligent Transportation Systems*, *21*(4), 1427–1440. https://doi.org/10.1109/TITS.2019.2913588

Taheri, S., Veidenbaum, A., & Haghighat, M. R. (2017). *OpenCV . js : Computer Vision Processing for the Web*.

Tang, S. (2015). *Object Detection based on Convolutional Neural Network*. 8.

Thambawita, D. R. V. L. B., Ragel, R., & Elkaduwe, D. (2014). To use or not to use: Graphics processing units (GPUs) for pattern matching algorithms. *2014 7th International Conference on Information and Automation for Sustainability: "Sharpening the Future with Sustainable Technology", ICIAfS 2014*, *December*, 1–5. https://doi.org/10.1109/ICIAFS.2014.7069585

Tomè, D., Monti, F., Baroffio, L., Bondi, L., Tagliasacchi, M., & Tubaro, S. (2015). *Deep convolutional neural networks for pedestrian detection*. https://doi.org/10.1016/j.image.2016.05.007

Tzutalin. (2015). *LabelImg*. https://github.com/tzutalin/labelImg

Vakalopoulou, M., Karantzalos, K., Komodakis, N., & Paragios, N. (2015). Building Detection In Very High Resolution Multispectral Data With Deep Learning Features. *In Geoscience and Remote Sensing Symposium (IGARSS)*, *IEEE ,2015*, 1873–1876.

Vasari, P. (2019). *Overfitting vs Underfitting in Machine Learning*. http://datajango.com/over-fitting-vs-under-fitting-in-machine-learning/

Wegner, J. D., Branson, S., Hall, D., Schindler, K., & Perona, P. (2016). Cataloging public objects using aerial and street-level images - Urban trees. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, *2016-Decem*, 6014–6023. https://doi.org/10.1109/CVPR.2016.647

Welzel, A. A., Auerswald, A., & Wanielik, G. (2014). Accurate camera-based traffic sign localization. *2014 17th IEEE International Conference on Intelligent Transportation Systems, ITSC 2014*, 445–450. https://doi.org/10.1109/ITSC.2014.6957730

Wong, A., Shafiee, M. J., Li, F., & Chwyl, B. (2018). Tiny SSD: A tiny single-shot detection deep convolutional neural network for real-time embedded object detection. *Proceedings - 2018 15th Conference on Computer and Robot Vision, CRV 2018*, 95–101. https://doi.org/10.1109/CRV.2018.00023

Woudsma, T., Hazelhoff, L., With, P. H. N. D., & Creusen, I. (2015). Automated Generation of Road Marking Maps from Street-level Panoramic Images.

IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC, *2015-Octob*, 925–930. https://doi.org/10.1109/ITSC.2015.155

Xiang, Y., Kim, W., Chen, W., Ji, J., Choy, C., Su, H., Mottaghi, R., Guibas, L., & Savarese, S. (2016). Objectnet3D: A large scale database for 3D object recognition. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *9912 LNCS*, 160–176. https://doi.org/10.1007/978-3-319-46484-8_10

Yang, B., Fang, L., & Li, J. (2013). Semi-automated extraction and delineation of 3D roads of street scene from mobile laser scanning point clouds. *ISPRS Journal of Photogrammetry and Remote Sensing*, *79*, 80–93. https://doi.org/10.1016/j.isprsjprs.2013.01.016

Yang, D., & Wegner, S. (2018). *Samsung Galaxy S9 Teardown*. Techinsights. https://www.techinsights.com/blog/samsung-galaxy-s9-teardown

Yi, Z., Yongliang, S., & Jun, Z. (2019). An improved tiny-YOLOv3 pedestrian detection algorithm. *Optik*, *183*(January), 17–23. https://doi.org/10.1016/j.ijleo.2019.02.038

You, Q., Luo, J., Jin, H., & Yang, J. (2016). *Building a Large Scale Dataset for Image Emotion Recognition: The Fine Print and The Benchmark*. http://arxiv.org/abs/1605.02677

Yovcheva, Z. (2015). *User-Centred Design of Smartphone Augmented Reality in Urban Tourism Context* (Issue August). Bournemouth University.

Zhao, Z. Q., Zheng, P., Xu, S. T., & Wu, X. (2019). Object detection with deep learning: A review. *IEEE transactions on neural networks and learning systems*, *30*(11), 3212-3232.

Zhang, C., Fan, H., Li, W., Mao, B., & Ding, X. (2019). Automated detecting and placing road objects from street-level images. *arXiv preprint arXiv:1909.05621*.

Zhang, Qiaoping, & Couloigner, I. (2004). A framework for road change detection and map updating. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *35*, 12–23.

Zhang, Q. S., & Zhu, S. C. (2018). Visual interpretability for deep learning: a survey. *Frontiers of Information Technology & Electronic Engineering*, *19*(1), 27-39.

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LIST OF PUBLICATIONS

Jalal Ibrahim Al-Azizi, and Helmi Zulhaidi Mohd Shafri, “Smartphones in Mecca Area: Positioning Availability and Accuracy Analysis.” IEEE Workshop on Geosciences & Remote Sensing. 8-9 Nov, 2016. University Putra Malaysia.

Jalal Ibrahim Al-Azizi, and Helmi Zulhaidi Mohd Shafri. "Performance Evaluation of Pedestrian Locations Based on Contemporary Smartphones." International Journal of Navigation and Observation 2017 (2017).

Jalal Ibrahim Al-Azizi,Helmi Zulhaidi Mohd Shafri, Shaiful Jahari Bin Hashim, and Shattri B Mansor, “Low-Cost and Real-Time Geospatial Map Generation Method Using Deep Learning and Video Streams”. [Submitted to earth science informatics].

Jalal Ibrahim Al-Azizi,Helmi Zulhaidi Mohd Shafri, Shaiful Jahari Bin Hashim, and Shattri B Mansor, “DeepAutoMapping: a new single-camera approach for road-asset data collection and map generation using deep learning”. [Submitted to International journal of geographical information science]

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