UNIVERSITI PUTRA MALAYSIA

MODELING OF ROAD GEOMETRY AND TRAFFIC ACCIDENTS BY HIERARCHICAL OBJECT-BASED AND DEEP LEARNING METHODS USING LASER SCANNING DATA

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By

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Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

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Chairman : Professor Biswajeet Pradhan, PhD
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Road traffic accidents are global concerns since they affect human life, economy, and road transportation systems. Rapid information acquisition and insight discovery are key tasks in transportation management. Specifically, extraction of geometric road features such as slopes and superelevation are essential information to understand the effects of road geometry on road traffic accidents. However, to understand these effects clearly and accurately, proper modeling techniques should be used. This study aims to develop methods to extract geometric road features (e.g., vertical gradients, superelevation, width, design speed) and establish associations between those features and road traffic accidents including frequency and accident severity. There was a need for efficient segmentation algorithm, optimization strategy, feature extraction and classification, and robust statistical and computational intelligence models to accomplish the set aims. Experimental results regarding road geometry extraction indicated that the proposed methods could achieve relatively high accuracy (~ 85% - User's Accuracy) of road detection from airborne laser scanning data. Our method improved the overall accuracy of classification by 7% outperforming the supervised k nearest neighbour method. In addition, the results also showed that the proposed hierarchical classification method could extract geometric road elements with an average error rate of 6.25% for slope parameter and 6.65% for superelevation parameter, and it is transferable to other regions of similar environments. On the other hand, the geometric regression model predicted the number of accidents in the North-South Expressway with a reasonable accuracy (R^2 = 0.64). This model also could identify the most influential factors contributing to the number of accidents. Experiments on deep learning models showed that the recurrent neural network performs better than the feedforward neural networks, statistical bayesian logistic regression, and convolutional neural networks. This study also suggests that transfer learning could improve the forecasting accuracy of the injury severity by nearly 10%.

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

PERMODELAN GEOMETRI JALAN DAN KEMALANGAN LALULINTAS DENGAN OBJEK HIRAEKI DAN KAEDAH *DEEP LEARNING* MENGGUNAKAN IMBASAN DATA LASER

Oleh

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Kemalangan jalan raya adalah kebimbangan global kerana ia mempengaruhi kehidupan manusia, ekonomi, dan sistem pengangkutan jalan raya. Pemerolehan maklumat yang cepat dan penemuan wawasan adalah tugas utama dalam pengurusan pengangkutan. Khususnya, pengekstrakan ciri-ciri jalan geometri seperti cerun dan penyempurnaan adalah maklumat penting untuk memahami kesan geometri jalan raya pada kemalangan jalan raya. Walau bagaimanapun, untuk memahami kesan-kesan ini dengan jelas dan tepat, teknik pemodelan yang betul harus digunakan. Kajian ini bertujuan untuk membangunkan kaedah untuk mengekstrak ciri-ciri jalan geometri (cth., Kecerunan menegak, superelevasi, lebar, kelajuan reka bentuk) dan mewujudkan persatuan antara ciri-ciri dan kemalangan jalan raya termasuk kekerapan dan keterukan kemalangan. Terdapat keperluan untuk algoritma segmentasi yang berkesan, strategi pengoptimuman, pengekstrakan dan klasifikasi ciri, dan model perisikan statistik dan komputasi yang mantap untuk mencapai matlamat yang ditetapkan. Hasil eksperimen mengenai pengekstrakan geometri jalan menunjukkan bahawa kaedah yang dicadangkan dapat mencapai ketepatan yang agak tinggi (~ 85% - Akurasi Pengguna) pengesanan jalan dari data pengimbasan laser udara. Kaedah kami meningkatkan ketepatan keseluruhan klasifikasi sebanyak 7% yang melebihi kaedah jiran terdekat yang diselia. Di samping itu, keputusan juga menunjukkan bahawa kaedah klasifikasi hierarki yang dicadangkan dapat mengekstrak unsur jalan geometri dengan kadar kesilapan purata 6.25% untuk parameter cerun dan 6.65% untuk parameter superelevasi, dan ia boleh dipindahkan ke kawasan lain yang serupa persekitaran. Sebaliknya, model regresi geometri meramalkan bilangan kemalangan di Lebuhraya Utara-Selatan dengan ketepatan yang munasabah (R^2 = 0.64). Model ini juga dapat mengenal pasti faktor-faktor yang paling berpengaruh yang menyumbang kepada bilangan kemalangan. Eksperimen dalam model pembelajaran mendalam menunjukkan bahawa rangkaian neural berulang lebih baik daripada rangkaian saraf

feedforward, regresi logistik bayesian statistik, dan rangkaian saraf convolutional. Kajian ini juga menunjukkan bahawa pemindahan pembelajaran dapat meningkatkan ketepatan ramalan keterukan cedera oleh hampir 10%.

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This thesis was submitted to the Senate of the 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;
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LIST OF ABBREVIATIONS

LiDAR	Light Detection And Ranging
ALS	Airborne Laser Scanning
MLS	Mobile Laser Scanning
TLS	Terrestrial Laser Scanning
3D	Three Dimension (s)
OBIA	Object-Based Image Analysis
DEM	Digital Elevation Model
DL	Deep Learning
2D	Two Dimension (s)
FOV	Field of View
RNN	Recurrent Neural Network (s)
TL	Transfer Learning
IMU	Inertial Measurement Unit
DSM	Digital Surface Model
NN	Neural Network (s)
UAV	Unmanned Aerial Vehicle (s)
ACO	Ant Colony Optimization
SVM	Support Vector Machine (s)
GNSS	Global Navigation Satellite System
GIS	Geographic Information System
GR	Geometric Regression
GPS	Global Positioning System
PCA	Principal Component Analysis
TOF	Time of Flight
UPM	Universiti Putra Malaysia
ML	Machine Learning

LR	Logistic Regression
CNN	Convolutional Neural Network (s)
HD	High Definition
NSE	North-South Expressway
PSO	Particle Swarm Optimization
LULC	Land Use and Land Cover
EA	Evolutionary Algorithm (s)
RF	Random Forest
GLONASS	Global Orbiting Navigation Satellite System
USGS	United States Geological Survey
DTM	Digital Terrain Model
MCC	Multiscale Curvature Classification
EDM	Electronic Distance Measurement
RMS	Root Mean Square
PCD	Phase Coded Disk
DT	Decision Tree
SPOT	Système Pour l'Observation de la Terre
MRS	Multi-Resolution Segmentation
NDVI	Normalized Difference Vegetation Index
GVF	Gradient Vector Flow
RANSAC	RANdom SAmple Consensus
CRF	Conditional Random Field
CAD	Computer-Aided Design
ETC	Electronic Toll Collection
NB	Negative Binomial
MA	Moving Average
AR	Autoregressive

KNN	K-Nearest Neighbors
MLPNN	Multilayer Perceptron Neural Networks
RBFNN	Radial Basis Function Neural Networks
SAP	Smeed Accident Prediction
SLPNN	Single-Layer Perceptron Neural Network
GRNN	General Regression Neural Network
MLR	Multilayer Regression
GDP	Gross Domestic Product
MSE	Mean Square Error
ReLU	Rectified Linear Unit
GA	Genetic Algorithms
LSTM	Long Short-Term Memory
GCPs	Ground Control Points
PLUS	Projek Lebuhraya Usaha Sama
VIF	Variance Inflated Factor
DGPS	Differential Global Positioning System
AADT	Average Annual Daily Traffic
BD	Bhattacharyya Distance
POF	Plateau Objective Function
SNR	Signal-To-Noise Ratio
MS	Mean Shift
UA	User’s Accuracy
ED	Euclidean Distance
SGD	Stochastic Gradient Descent
BPTT	Backpropagation Through Time
OA	Overall Accuracy
AIC	Akaike Information Criterion

APM	Accident Prediction Model
MCMC	Markov Chain Monte Carlo
BGR	Brooks-Gelman-Rubin
DIC	Deviance Information Criterion
PC	Personal Computer
GPUs	Graphics Processing Units
KIA	Kappa Index of Agreement
BLR	Bayesian Logistic Regression

CHAPTER 1

INTRODUCTION

1.1 Background of Study

Transportation systems specifically road transport are highly essential to economic activities. They play a vital role in marketing products and providing citizens with ease of access to points of contact for business activities, health, education, and agriculture. Road transportation systems must be safe and efficient to keep the above services active. However, almost every road section has a significant risk of traffic accidents—a primary global concern due to many fatalities and economic losses every year. For example in Malaysia, the recent statistics show that deaths per 100,000 people are nearly 24 for all road users (Global Status Report on Road Safety 2015). Mainly, expressways and highways in urban areas are potential sites of fatal traffic accidents. On an average, 18 people are killed daily nationwide in road accidents as per a survey conducted in 2015. In 2016, the number of fatalities jumped to 7,152 from 6,706 deaths in the earlier year (Malaysian Road Transport Department, 2017). In addition, Malaysia had the highest fatality risk (per 100,000 population) among the Asian countries. The majority of road accident fatalities involve motorcyclists, making up 50% of the total number of accidents (Manan and Várhelyi, 2012). Unless action is taken, the number of deaths is expected to increase in the coming years.

Given all above, recent developments in laser scanning technology have improved spatial data acquisition in road environments. These developments have helped to build geometric road models that can help assessing road safety and make accurate and valid predictions on road traffic accidents. Laser scanning systems or LiDAR (Light Detection And Ranging) are the latest technology to capture the 3D geometry of various objects such as 3D point clouds on large surfaces accurately and densely.

Furthermore, they offer rapid and cost-effective data acquisition about road corridors and surrounding environments. Most of the road inventory information can be extracted from the original design of the roads. However, road geometric elements such as pavement roughness, vertical gradients, and horizontal curves change over time due to construction, degradation in road conditions, and vegetation growth (Shamayleh and Khattak, 2003). Apart from that, collecting data by conventional measurement methods are not safe, and the surveyor may not find safe sight distances to get readings necessary to calculate vertical grades and side slopes of the road (Uddin, 2008). The conventional measurement methods are relatively expensive to produce detailed topographic models and time-consuming. On the other hand, photogrammetry and optical satellite imagery have the disadvantages of poor visibility/ cloudy daytime, the relatively low accuracy of required topographic models, and computationally are not efficient to generate topographic maps due to the requirements of collecting dense points distributed uniformly in the focus area (Uddin, 2008).

Therefore, LiDAR technology is a promising method for acquiring data about road corridors. In general, LiDAR sensors have higher spatial resolution than satellite-based sensors, wider Field of View (FOV), and lower cost than traditional aerial photogrammetric and surveying methods for right projects. By evaluating specific height information in LiDAR data, along with high-resolution orthophotos, objects such as road can be distinguished efficiently from other objects. Overall, LiDAR data is practical for extracting road geometry and roadside features that many applications including traffic accident modeling can benefit (Lee and Mannering, 2002). Thus, developing methods that can extract accurately and rapidly road information from LiDAR data to improve road safety is highly crucial.

One way to improve road safety is by developing accurate prediction models of traffic accidents using road geometry and sophisticated Machine Learning (ML) and statistical techniques. However, development of such models is not straightforward and needs careful analysis and optimization to be practical for transportation agencies.

The research of geometric road modeling from LiDAR data has progressed a lot since the development of advanced LiDAR systems. Various algorithms, data processing workflows, and practical guidelines have been proposed by different researchers and showed a significant performance compared to the traditional methods (Poullis and You, 2010; Fix et al., 2016). The latest methods combine LiDAR data with other ancillary information (e.g., road centerline, road attributes, knowledge about road shape and geometry) in hierarchical forms to create accurate three-dimensional (3D) models of road sections (Holgado- Barco et al., 2015). A hierarchical model (or a model with multiple levels of processing) is defined as a data processing model that combines sub-models (usually different algorithms) at several processing stages to solve specific problems. For instance, in a study by Holgado- Barco et al. (2015), a hierarchical model was developed by combining segmentation algorithms and Principal Component Analysis (PCA) to model road geometry from mobile LiDAR data. These methods have shown promising advantages over traditional methods. However, their main limitation is the dependency on the accuracy and the completeness of the ancillary information used to obtain the road features. Thus, progress should be made to overcome such limitations and advance the road extraction algorithms, and such developments will open up new areas for transportation applications.

The literature shows the momentous development of modeling approaches for predicting road traffic accidents including statistical and soft computing algorithms (Hosseinpour et al., 2014; Karlaftis and Vlahogianni, 2011; Pei et al., 2011). The traditional methods significantly focused on hand-crafted features identified by experts in the transportation field and used to model accident frequency and injury severity using statistical techniques such as Logistic Regression (LR) and Support

Vector Machine (SVM). However, as generating handcrafted features requires experts and time, researchers thought about alternatives such as Neural Networks (NN), Evolutionary Algorithms (EA) and developing powerful statistical models that can better handle accident data without expensive feature engineering (Yu et al ., 2014). A part of these developments, the availability of data and having powerful computing resources such as processing on GPUs (Graphical Processing Units) have led to rethinking about NN methods. Deep Learning (DL), a recent groundbreaking development in ML community, has shed light on using NN models more efficiently than before. DL allows computational models to learn hierarchal representations of data with multiple levels of abstraction at different processing layers. In addition, in limited data situations, Transfer Learning (TL) can be used in DL models to overcome over-fitting problems. Overall, combining DL and TL with careful fine-tuning in a single workflow is expected to provide sufficient prediction power for models designed to simulate traffic accidents based on historical records.

Since the above shows the importance of having robust tools to model road geometry for road safety assessment, the primary goal of this thesis is to investigate issues surrounding the development of methods that can accurately and efficiently model road geometry and make predictions on road traffic accidents at high-speed expressways. This first chapter serves as an overview of the entire thesis.

Besides the state of the general topic and background of the study, it provides the statement of the problem, the gap of knowledge. The importance of the proposed research, the research questions, aims and research objectives, the thesis contribution, the scope of the topic, and outlines the order of information in the rest of this thesis.

1.2 The Statement of Problem

Everyone in this world wants to have safe transportation systems to travel from a place to another easily and securely. However, today there are many issues and challenges making transportation systems less safe than they should be. Among these issues, rapid urbanization over various landscape forms, population growth and migration of people from rural to urban areas. Other challenges include lack of technical tools that can support road safety managers to simulate future scenarios and make better plans to solve problems related to road safety efficiently. If these problems continue, failure of transportation systems would significantly affect the stability and development of modern cities as transportation systems are the heart of the cities.

Specifically, there are a need to construct 3D models for highways and establish relationships among road geometry features (e.g., vertical and horizontal curves, side slopes) and road traffic accidents to improve safety assessments for road transportation. Research shows that using object-based methods (or OBIA—Object-Based Image Analysis) which take into consideration not only the spectral information, but also other geometric, textural, and contextual information for extracting features from data is more powerful than pixel-based methods (Gudex-Cross et al., 2017). However, OBIA methods need careful optimization of the segmentation process and the choice of relevant features as well as rule sets that are transferable to other areas without significant loss of accuracy (Robb et al., 2015). Although many optimization methods have been proposed for OBIA, the proposed methods lack optimization of the two main steps of OBIA, segmentation, and classification at the same time. Choosing segmentation parameters that can produce the best the possible segmentation quality and classification accuracy will help producing more accurate and complete road features.

On the other hand, technical tools are essential to make predictions for future scenarios of road safety. There are two main groups of predictive models namely, statistical (e.g., LR) and computational intelligence (e.g., NN). The former requires extensive engineering works and significant efforts to extract relevant features for accident frequency and injury severity predictions. The latter requires relatively large datasets for training and careful optimization of model's hyper-parameters. NN due to limited data suffers from over-fitting, lack of generalization and computing the importance of accident predictors and modeling the temporal/contextual structures inherent in the accident data. The traditional feed-forward NN does not allow compositionality with the adequate flexibility to improve the generalization and predictive ability of the model. However, the recent DL methods allow compositionality and using accident data as sequential data allowing modeling their inherent temporal and contextual structures. With additional information such as spatial-temporal relationships among accident events, it is expected to improve the accuracy and generalization of the models. Additionally, the volume of traffic accident data usually plays a significant role in deciding a proper prediction modeling approach. With limited data (i.e., <500 records), simple models (i.e., statistical models with fixed parameters) are often preferred. However, some sophisticated modeling approaches such as DL models have higher prediction capabilities and attract many attentions in recent years. Their implementation with limited data requires the development of sophisticated models with TL methods, which the traffic accident literature lacks.

1.3 Research Objectives

The master goal of this thesis is to contribute to the efficient road geometric modeling from LiDAR data and to the prediction of traffic accidents on highways. For being practical, this objective has to be split up into smaller and more specific goals, which may be organized into methodological aims as follows:

1. To delineate road geometry in two dimensions (2D) using an integrated ACO and OBIA methods with a novel two-stage optimization strategy for the segmentation step.
2. To extract road geometry (i.e., 3D) from mobile LiDAR data using a hierarchal classification technique that combines Mean Shift (MS) segmentation, SVM, and PCA.

3. To develop and validate a Geometric Regression (GR) model for predicting the frequency of traffic accidents using road geometry information.
4. And, to develop and validate a Deep Learning approach using TL for forecasting the injury severity of road traffic accidents using historical accident records.

1.4 Research Questions

This thesis comprehensively addresses the following research questions:

1. OBIA based requires optimizing segmentation parameters (e.g., scale, shape, compactness). In this step, an objective function is designed to judge a sub-optimal combination of parameters that can achieve an accurate segmentation process as possible.

However, it is not known if optimization of segmentation and classification processes at the same time will improve the performance of feature extraction or not?

2. To what extent the integration of meta-heuristic optimization methods such as ACO and OBIA can improve modeling of road geometry.
3. Can hierarchical classification (combination of several algorithms) process mobile LiDAR data efficiently for delineating 3D road geometric features such as vertical gradients and superelevation?
4. GR is one of the modeling methods that can be used to model the frequency of traffic accidents. How efficient is this model for processing traffic accident data for the Malaysian context?
5. DL due to data availability and improvements in computing power is getting popular for many applications. How much is the prediction power of DL for modeling road traffic accidents? In addition, can new NN architectures such as RNN and Convolutional Neural Networks (CNN) outperform the traditional feed-forward NN?
6. Is TL an efficient method for modeling injury severity of traffic accidents of a limited volume data in the context of DL architectures or not?

1.5 Thesis Contributions

Significant efforts have been made in the literature on pursuing solutions for geometric modeling of roads from LiDAR data and advancing prediction models of road traffic accidents using both statistical and soft computing techniques. However, the existing studies still have some major concerns as discussed in Section 1.1 and Section 1.2. As a result, there is a need to develop new techniques or making improvements on the existing techniques to provide better solutions for road safety assessment based on road geometry.

This thesis mainly contributes to the development of new methods for image segmentation, extracting road features in 2D and 3D from Airborne and Mobile LiDAR data, modeling accident frequency and injury severity using DL-based methods. First, it develops a new optimization strategy for OBIA classification based on a two-stage optimization approach. The method optimizes the two basic steps of OBIA, namely, segmentation and classification, to realize accurate road extraction from LiDAR data. This is achieved by selecting an optimal scale parameter first to maximize class separability and optimal shape and compactness parameters to optimize the final image segments.

The second contribution of this thesis is the development of a hybrid approach that combines ACO and OBIA-based feature extraction for LiDAR data classification and road geometry extraction. In this approach, ACO is used to find the best combination of features to use in OBIA for road extraction. In addition, since this approach only extracts 2D information of a road, it was necessary to develop a semi-automated approach for delineating 3D road geometry from mobile LiDAR data without information about vehicle trajectory, which the state-of-the-art methods lack.

Third, this thesis then goes beyond just extracting information about roads from LiDAR data but further uses that information with some additional data about road traffics and environment to make predictions on traffic accidents. In particular, it develops a model based on GR for predicting traffic accident frequency. Furthermore, it also designs and implements models based on DL such as RNN and CNN to simulate the injury severity of traffic accidents utilizing the temporal structure of accident data. Finally, when data on traffic accidents are scarce, this thesis provides a model that can work based on TL concept to overcome the need for DL models for large datasets and to avoid overfitting problems.

1.6 Scope of Study

This study has three main scopes as follows:

1. Only two types of LiDAR systems, airborne and mobile-based were studied for road geometry modeling, and other systems (e.g., terrestrial) were not investigated. The latter systems are efficient for detailed assessments of transportation assists (e.g., bridge, culvert, and tunnel) which is not the case of the current study.
2. The validations of these models in this thesis were based on an area in Malaysia. No transferability to other countries has been investigated due to the non-availability of data and permission to access to police reports on traffic accidents elsewhere. However, various experiments and evaluations were

conducted, analyzed and discussed on a comprehensive data that have more than a thousand of historical records of traffic accidents.
3. The data duration was from 2009 to 2015 due to the availability of the relevant data.

1.7 Thesis Organization

The thesis is split into five chapters.

The **first chapter** introduces the research topic and gives a brief background of the study, the statement of the problem, research questions and objectives, thesis contribution and significance of the study.

The **second chapter** provides an overview of the available models and discusses several important and relevant studies. It provides a cohesive review on several topics such as LiDAR, geometric road modeling, and traffic accident modeling.

The **third chapter** explains the various steps of data processing and analysis, which makes up the newly proposed models for geometric road modeling and analyzing road traffic accident data.

The **fourth chapter** discusses the results of the experiments and simulations conducted in the current research and presents evaluations of the proposed models on real datasets.

The **last chapter** summarizes the main findings of the research and offers recommendations for future work.

REFERENCES

Abadi, M., Agarwal, A., Barham, P., Brevdo, E., Chen, Z., Citro, C., ... & Ghemawat, S. (2016). Tensorflow: Large-scale machine learning on heterogeneous distributed systems. arXiv preprint arXiv:1603.04467.

Abdelwahab, H., & Abdel-Aty, M. (2001). Development of artificial neural network models to predict driver injury severity in traffic accidents at signalized intersections. Transportation Research Record: Journal of the Transportation Research Board, 1746, 6-13.

Abdelwahab, H., & Abdel-Aty, M. (2002). Artificial neural networks and logit models for traffic safety analysis of toll plazas. Transportation Research Record: Journal of the Transportation Research Board, 1784, 115-125.

Aghdam, M. H., Ghasem-Aghaee, N., & Basiri, M. E. (2009). Text feature selection using ant colony optimization. Expert systems with applications, 36(3), 6843-6853.

Akar, Ö., & Güngör, O. (2013). Classification of multispectral images using Random Forest algorithm. Journal of Geodesy and Geoinformation, 1(2).

Akel, N. A., Kremeike, K., Filin, S., Sester, M., & Doytsher, Y. (2005). Dense DTM generalization aided by roads extracted from LiDAR data. ISPRS WG III/3, III, 4, 54-59.

Akgüngör, A. P., & Dogan, E. (2008). Estimating road accidents of Turkey based on regression analysis and artificial neural network approach. Advances in Transportation studies, 2008(16), 11-22.

Al-Ghamdi, A. S. (2002). Using logistic regression to estimate the influence of accident factors on accident severity. Accident Analysis & Prevention, 34(6), 729-741.

Alharthy, A., & Bethel, J. (2003). Automated road extraction from LIDAR data. Paper presented at the Proceedings of the ASPRS Annual Conference.

Alkheder, S., Taamneh, M., & Taamneh, S. (2017). Severity Prediction of Traffic Accident Using an Artificial Neural Network. Journal of Forecasting, 36(1), 100-108.

Alwan, H. B., & Ku-Mahamud, K. R. (2012, December). Optimizing support vector machine parameters using continuous ant colony optimization. In Computing and Convergence Technology (ICCCT), 2012 7th International Conference on (pp. 164-169). IEEE.

Amiridis, K., & Psarianos, B. (2015). Three Dimensional Road Design By Applying Differential Geometry And Conventional Design Approach Criteria. Paper presented at the Transportation Research Board 94th Annual Meeting.

Arastounia, M. (2012). Automatic classification of lidar point clouds in a railway environment. University of Twente, Netherlands, 83.

Baatz, M. (2000). Multiresolution segmentation: an optimization approach for high quality multi-scale image segmentation. Angewandte Geographische Informations verarbeitung XII, 12-23.

Baczyński, D., & Parol, M. (2004). Influence of artificial neural network structure on quality of short-term electric energy consumption forecast. IEE Proceedings-Generation, Transmission and Distribution, 151(2), 241-245.

Baltsavias, E. P. (1999). Airborne laser scanning: basic relations and formulas. ISPRS Journal of Photogrammetry and Remote Sensing, 54(2), 199-214.

Baltsavias, E. P. (1999b). A comparison between photogrammetry and laser scanning. ISPRS Journal of Photogrammetry and Remote Sensing, 54(2), 83-94.

Bayer, J., Osendorfer, C., Korhammer, D., Chen, N., Urban, S., & van der Smagt, P. (2013). On fast dropout and its applicability to recurrent networks. arXiv preprint arXiv:1311.0701.

Bazi, Y., & Melgani, F. (2006). Toward an optimal SVM classification system for hyperspectral remote sensing images. Geoscience and Remote Sensing, IEEE Transactions on, 44(11), 3374-3385.

Belton, D., & Lichti, D. D. (2006). Classification and segmentation of terrestrial laser scanner point clouds using local variance information. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 36(5), 44-49.

Blake, A., & Isard, M. (1998). Active Contours: The Application of Techniques from Graphics, Vision, Control Theory and Statistics to Visual Tracking of Shapes in Motion. Secaucus. Springer0Verlag, London.

Blaschke, T. (2010). Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 65(1), 2-16.

Blaschke, T., & Strobl, J. (2001). What's wrong with pixels? Some recent developments interfacing remote sensing and GIS. GeoBIT/GIS, 6(1), 12-17.

Bousquet, O., & Bottou, L. (2008). The tradeoffs of large scale learning. In Advances in neural information processing systems (pp. 161-168).

Boyko, A., & Funkhouser, T. (2011). Extracting roads from dense point clouds in large scale urban environment. ISPRS Journal of Photogrammetry and Remote Sensing, 66(6), S2-S12.

Brennan, R., & Webster, T. (2006). Object-oriented land cover classification of lidar-derived surfaces. Canadian Journal of Remote Sensing, 32(2), 162-172.

Cai, H., & Rasdorf, W. (2008). Modeling Road Centerlines and Predicting Lengths in 3- D Using LIDAR Point Cloud and Planimetric Road Centerline Data. Computer- Aided Civil and Infrastructure Engineering, 23(3), 157-173.

Cánovas-García, F., & Alonso-Sarría, F. (2015). A local approach to optimize the scale parameter in multiresolution segmentation for multispectral imagery. Geocarto International, 30(8), 937-961.

Cao, C., & Sun, Y. (2014). Automatic Road Centerline Extraction from Imagery Using Road GPS Data. Remote Sensing, 6(9), 9014-9033. doi: 10.3390/rs6099014

Cao, L. Y., & Xia, L. Z. (2007, November). An ant colony optimization approach for SAR image segmentation. In Wavelet Analysis and Pattern Recognition, 2007. ICWAPR'07. International Conference on (Vol. 1, pp. 296-300). IEEE.

Castelli, M., Gonçalves, I., Trujillo, L., & Popovič, A. (2017). An evolutionary system for ozone concentration forecasting. Information Systems Frontiers, 19(5), 1123-1132.

Charaniya, A. P., Manduchi, R., & Lodha, S. K. (2004). Supervised parametric classification of aerial lidar data. Paper presented at the Computer Vision and Pattern Recognition Workshop, 2004. CVPRW'04. Conference on.

Chen, D., & He, X. (2015). Fast automatic three-dimensional road model reconstruction based on mobile laser scanning system. Optik-International Journal for Light and Electron Optics, 126(7), 725-730.

Chen, L.-C., & Lo, C.-Y. (2009). 3D road modeling via the integration of large-scale topomaps and airborne LIDAR data. Journal of the Chinese Institute of Engineers, 32(6), 811-823. doi: 10.1080/02533839.2009.9671565

Chen, Q., Zhao, Y., Pan, S., & Wang, Y. (2016). Survey of the influence of the width of urban branch roads on the meeting of two-way vehicle flows. PLoS one, 11(2), e0149188.

Choi, E., & Lee, C. (2003). Feature extraction based on the Bhattacharyya distance. Pattern Recognition, 36(8), 1703-1709.

Choi, Y.-W., Jang, Y.-W., Lee, H.-J., & Cho, G.-S. (2008). Three-dimensional LiDAR data classifying to extract road point in urban area. Geoscience and Remote Sensing Letters, IEEE, 5(4), 725-729.

Chollet, F. (2015). Keras.

Chung, J., Gulcehre, C., Cho, K., & Bengio, Y. (2014). Empirical evaluation of gated recurrent neural networks on sequence modeling. arXiv preprint arXiv:1412.3555.

Clode, S., Kootsookos, P. J., & Rottensteiner, F. (2004). The automatic extraction of roads from LIDAR data. Paper presented at the ISPRS 2004.

Clode, S., Rottensteiner, F., Kootsookos, P., & Zelniker, E. (2007). Detection and vectorization of roads from lidar data. Photogrammetric Engineering & Remote Sensing, 73(5), 517-535.

Cohen, L. D. (1991). On active contour models and balloons. CVGIP: Image understanding, 53(2), 211-218.

Collobert, R., & Weston, J. (2008, July). A unified architecture for natural language processing: Deep neural networks with multitask learning. In Proceedings of the 25th international conference on Machine learning (pp. 160-167). ACM.

Comaniciu, D., & Meer, P. (2002). Mean shift: A robust approach toward feature space analysis. IEEE Transactions on pattern analysis and machine intelligence, 24(5), 603-619.

Congalton, R. G. (1981). The use of discrete multivariate analysis for the assessment of Landsat classification accuracy. Mater thesis, Virginia Polytechnic Institute and State University, Blacksburg, VA.

Dean, J., Corrado, G., Monga, R., Chen, K., Devin, M., Mao, M., ... & Ng, A. Y. (2012). Large scale distributed deep networks. In Advances in neural information processing systems (pp. 1223-1231).

Deka, L., & Quddus, M. (2014). Network-level accident-mapping: distance based pattern matching using artificial neural network. Accident Analysis & Prevention, 65, 105-113.

Delen, D., Sharda, R., & Bessonov, M. (2006). Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks. Accident Analysis & Prevention, 38(3), 434-444.

Delen, Dursun, Ramesh Sharda, and Max Bessonov. "Identifying significant predictors of injury severity in traffic accidents using a series of artificial neural networks." Accident Analysis & Prevention 38.3 (2006): 434-444.

Dial, G., Gibson, L., & Poulsen, R. (2001). IKONOS satellite imagery and its use in automated road extraction. Automatic Extraction of Man-Made Objects from Aerial and Space Images, 3, 357-367.

Ding, S., Xu, X., & Nie, R. (2013). Extreme learning machine and its applications. Neural Computing and Applications, 25(3-4), 549-556. doi: 10.1007/s00521-013-1522-8

Donahue, J., Anne Hendricks, L., Guadarrama, S., Rohrbach, M., Venugopalan, S., Saenko, K., & Darrell, T. (2015). Long-term recurrent convolutional networks for visual recognition and description. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 2625-2634).

Dong, N., Huang, H., & Zheng, L. (2015). Support vector machine in crash prediction at the level of traffic analysis zones: Assessing the spatial proximity effects. Accid Anal Prev, 82, 192-198. doi: 10.1016/j.aap.2015.05.018

Dorigo, M., & Stützle, T. (2003). The ant colony optimization metaheuristic: Algorithms, applications, and advances. In Handbook of metaheuristics (pp. 250-285). Springer US.

Dorigo, M., Birattari, M., & Stützle, T. (2006). Ant colony optimization. Computational Intelligence Magazine, IEEE, 1(4), 28-39.

Duan, Y., Lv, Y., Liu, Y. L., & Wang, F. Y. (2016). An efficient realization of deep learning for traffic data imputation. Transportation Research Part C: Emerging Technologies, 72, 168-181.

Duchi, J., Hazan, E., & Singer, Y. (2011). Adaptive subgradient methods for online learning and stochastic optimization. Journal of Machine Learning Research, 12(Jul), 2121-2159.

Eberhart, R., & Kennedy, J. (1995, October). A new optimizer using particle swarm theory. In Micro Machine and Human Science, 1995. MHS'95., Proceedings of the Sixth International Symposium on (pp. 39-43). IEEE.

El-Basyouny, K. & T. Sayed (2010) Application of generalized link functions in developing accident prediction models. Safety science, 48, 410-416.

El-Basyouny, K., & Sayed, T. (2006). Comparison of two negative binomial regression techniques in developing accident prediction models. Transportation Research Record: Journal of the Transportation Research Board, (1950), 9-16.

Elberink, S. O., & Vosselman, G. (2006). Adding the third dimension to a topographic database using airborne laser scanner data. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci, 36, 92-97.

Elvik, R. (2013). International transferability of accident modification functions for horizontal curves. Accid Anal Prev, 59, 487-496. doi: 10.1016/j.aap.2013.07.010

Engelbrecht, A. P. (2007). Computational intelligence: an introduction. John Wiley & Sons.

ESRI. Locate Outliers. 2016. http://pro.arcgis.com/en/pro-app/tool-reference/3d-analyst/locate-outliers.htm. Accessed Jan 19, 2016.

Evans, J. S., & Hudak, A. T. (2007). A multiscale curvature algorithm for classifying discrete return LiDAR in forested environments. Geoscience and Remote Sensing, IEEE Transactions on, 45(4), 1029-1038.

Ferraz, A., Mallet, C., & Chehata, N. (2016). Large-scale road detection in forested mountainous areas using airborne topographic lidar data. ISPRS Journal of Photogrammetry and Remote Sensing, 112, 23-36.

Fix, A., Amediek, A., Ehret, G., Groß, S. M., Kiemle, C., Reitebuch, O., & Wirth, M. (2016). On the benefit of airborne demonstrators for space borne lidar missions.

Friedl, M. A., & Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. Remote Sensing of Environment, 61(3), 399-409.

Gardner, M. W., & Dorling, S. R. (1998). Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences. Atmospheric environment, 32(14), 2627-2636.

Ghasemloo, N., Reza Mobasheri, M., Madanchi Zare, A., & Memar Eftekhari, M. (2013). Road and Tunnel Extraction from SPOT Satellite Images Using Neural Networks. Journal of Geographic Information System, 05(01), 69-74. doi: 10.4236/jgis.2013.51007

Ghasemlou, K., Aydi, M. M., & Yildirim, M. S. (2015). Prediction of pedal cyclists and pedestrian fatalities from total monthly accidents and registered private car numbers. Archives of Transport, 34(2), 29-35.

Gikas, V. (2012). Three-dimensional laser scanning for geometry documentation and construction management of highway tunnels during excavation. Sensors, 12(8), 11249-11270.

Gikas, V., & Stratakos, J. (2012). A novel geodetic engineering method for accurate and automated road/railway centerline geometry extraction based on the bearing diagram and fractal behavior. Intelligent Transportation Systems, IEEE Transactions on, 13(1), 115-126.

Glymour, C., Madigan, D., Pregibon, D., & Smyth, P. (1997). Statistical themes and lessons for data mining. Data mining and knowledge discovery, 1(1), 11-28.

Goepfert, J., & Rottensteiner, F. (2009). Adaptation of roads to ALS data by means of network snakes: IntArchPhRS 38-3/W8.

Gong, J., Zhou, H., Gordon, C., & Jalayer, M. (2012). Mobile terrestrial laser scanning for highway inventory data collection. In Computing in Civil Engineering (2012) (pp. 545-552).

Gong, L., Zhang, Y., Li, Z., & Bao, Q. (2010). Automated road extraction from LiDAR data based on intensity and aerial photo. Paper presented at the Image and Signal Processing (CISP), 2010 3rd International Congress on.

Göpfert, J., Rottensteiner, F., & Heipke, C. (2011). Using snakes for the registration of topographic road database objects to ALS features. ISPRS Journal of Photogrammetry and Remote Sensing, 66(6), 858-871.

Goulette, F., Nashashibi, F., Abuhadrous, I., Ammoun, S., & Laurgeau, C. (2006). An integrated on-board laser range sensing system for on-the-way city and road modelling. International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 34(A).

Graves, A., Mohamed, A. R., & Hinton, G. (2013, May). Speech recognition with deep recurrent neural networks. In Acoustics, speech and signal processing (icassp), 2013 ieee international conference on (pp. 6645-6649). IEEE.

Grote, A., Heipke, C., & Rottensteiner, F. (2012). Road network extraction in suburban areas. The Photogrammetric Record, 27(137), 8-28.

Guan, H., Li, J., Chapman, M., Deng, F., Ji, Z., & Yang, X. (2013). Integration of orthoimagery and lidar data for object-based urban thematic mapping using random forests. International journal of remote sensing, 34(14), 5166-5186.

Guan, H., Li, J., Yu, Y., Ji, Z., & Wang, C. (2015). Using mobile LiDAR data for rapidly updating road markings. IEEE Transactions on Intelligent Transportation Systems, 16(5), 2457-2466.

Guan, H., Li, J., Yu, Y., Wang, C., Chapman, M., & Yang, B. (2014). Using mobile laser scanning data for automated extraction of road markings. ISPRS Journal of Photogrammetry and Remote Sensing, 87, 93-107.

Guan, J., Wang, Z., & Yao, X. (2010). A new approach for road centerlines extraction and width estimation. Paper presented at the Signal Processing (ICSP), 2010 IEEE 10th International Conference on.

Gudex-Cross, D., Pontius, J., & Adams, A. (2017). Enhanced forest cover mapping using spectral unmixing and object-based classification of multi-temporal Landsat imagery. Remote Sensing of Environment, 196, 193-204.

Hamedianfar, A., & Shafri, H. Z. (2014). Development of fuzzy rule-based parameters for urban object-oriented classification using very high resolution imagery. Geocarto International, 29(3), 268-292.

Hamedianfar, A., & Shafri, H. Z. M. (2016). Integrated approach using data mining-based decision tree and object-based image analysis for high-resolution urban mapping of WorldView-2 satellite sensor data. Journal of Applied Remote Sensing, 10(2), 025001-025001

Hamedianfar, A., Shafri, H. Z. M., Mansor, S., & Ahmad, N. (2014). Improving detailed rule-based feature extraction of urban areas from WorldView-2 image and lidar data. International Journal of Remote Sensing, 35(5), 1876-1899.

Han, L., Luo, S., Yu, J., Pan, L., & Chen, S. (2015). Rule extraction from support vector machines using ensemble learning approach: an application for diagnosis of diabetes. IEEE journal of biomedical and health informatics, 19(2), 728-734.

Hand, D. J. (2000). Data mining: new challenges for statisticians. Social Science Computer Review, 18(4), 442-449.

Hanspal, N.S. Allison, B.A., Deka, L., & Das, D.B. (2013). Artificial neural network (ANN) modelling of dynamic effects on two-phase flow in homogeneous porous media. Journal of Hydroinformatics, 15(2), 540–554.

Hartfield, K. A., Landau, K. I., & Van Leeuwen, W. J. (2011). Fusion of high resolution aerial multispectral and LiDAR data: Land cover in the context of urban mosquito habitat. Remote Sensing, 3(11), 2364-2383.

Hashmienejad, S. H. A., & Hasheminejad, S. M. H. (2017). Traffic accident severity prediction using a novel multi-objective genetic algorithm. International Journal of Crashworthiness, 1-16.

Hatger, C., & Brenner, C. (2003). Extraction of road geometry parameters from laser scanning and existing databases. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 34(3/W13), 225-230.

He, Y., Song, Z., & Liu, Z. (2017). Updating highway asset inventory using airborne LiDAR. Measurement, 104, 132-141.

Hernández, J., & Marcotegui, B. (2009, September). Filtering of artifacts and pavement segmentation from mobile lidar data. In ISPRS Workshop Laserscanning 2009.

Herumurti, D., Uchimura, K., Koutaki, G., & Uemura, T. (2013). Urban road extraction based on hough transform and region growing. Paper presented at the Frontiers of Computer Vision,(FCV), 2013 19th Korea-Japan Joint Workshop on.

Hinton, G. E., Rumelhart, D. E., & Williams, R. J. (1985). Learning internal representations by back-propagating errors. Parallel Distributed Processing: Explorations in the Microstructure of Cognition, 1.

Hinton, G. E., Srivastava, N., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. R. (2012). Improving neural networks by preventing co-adaptation of feature detectors. arXiv preprint arXiv:1207.0580.

Hirpa, D., Hare, W., Lucet, Y., Pushak, Y., & Tesfamariam, S. (2016). A bi-objective optimization framework for three-dimensional road alignment design. Transportation Research Part C: Emerging Technologies, 65, 61-78.

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

Hofmann, P. (2014). Defining Robustness Measures for OBIA Framework: A Case Study for Detecting Informal Settlements. In Q. Weng (Ed.), Global Urban Monitoring and Assessment through Earth Observation (pp. 303-324). CRC Press.

Holgado-Barco, A., Gonzalez-Aguilera, D., Arias-Sanchez, P., & Martinez-Sanchez, J. (2014). An automated approach to vertical road characterisation using mobile LiDAR systems: Longitudinal profiles and cross-sections. ISPRS Journal of Photogrammetry and Remote Sensing, 96, 28-37.

Holgado- Barco, A., Riveiro, B., González- Aguilera, D., & Arias, P. (2017). Automatic Inventory of Road Cross- Sections from Mobile Laser Scanning System. Computer- Aided Civil and Infrastructure Engineering, 32(1), 3-17.

Hong, H., Pradhan, B., Jebur, M. N., Bui, D. T., Xu, C., & Akgun, A. (2016). Spatial prediction of landslide hazard at the Luxi area (China) using support vector machines. Environmental Earth Sciences, 75(1), 40.

Hu, X., Li, Y., Shan, J., Zhang, J., & Zhang, Y. (2014). Road Centerline Extraction in Complex Urban Scenes From LiDAR Data Based on Multiple Features. Geoscience and Remote Sensing, IEEE Transactions on, 52(11), 7448-7456.

Hu, X., Tao, C. V., & Hu, Y. (2004). Automatic road extraction from dense urban area by integrated processing of high resolution imagery and lidar data. International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences. Istanbul, Turkey, 35, B3.

Huang, C.-L., & Dun, J.-F. (2008). A distributed PSO–SVM hybrid system with feature selection and parameter optimization. Applied Soft Computing, 8(4), 1381-1391.

Huang, H., Zeng, Q., Pei, X., Wong, S. C., & Xu, P. (2016). Predicting crash frequency using an optimised radial basis function neural network model. Transportmetrica: A Transport Science, 12(4), 330-345.

Huang, W., Song, G., Hong, H., & Xie, K. (2014). Deep architecture for traffic flow prediction: Deep belief networks with multitask learning. IEEE Transactions on Intelligent Transportation Systems, 15(5), 2191-2201.

Hui, Z., Hu, Y., Jin, S., & Yevenyo, Y. Z. (2016). Road centerline extraction from airborne LiDAR point cloud based on hierarchical fusion and optimization. ISPRS Journal of Photogrammetry and Remote Sensing, 118, 22-36.

Ibrahim, S., & Lichti, D. (2012). Curb-based street floor extraction from mobile terrestrial LiDAR point cloud. ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 39, B5.

Im, J., Jensen, J. R., & Hodgson, M. E. (2008). Object-based land cover classification using high-posting-density LiDAR data. GIScience & Remote Sensing, 45(2), 209-228.

Immitzer, M., Atzberger, C., & Koukal, T. (2012). Tree species classification with random forest using very high spatial resolution 8-band WorldView-2 satellite data. Remote Sensing, 4(9), 2661-2693.

Jaakkola, A., Hyyppä, J., Hyyppä, H., & Kukko, A. (2008). Retrieval algorithms for road surface modelling using laser-based mobile mapping. Sensors, 8(9), 5238-5249.

Jabari, S., & Zhang, Y. (2013). Very high resolution satellite image classification using Fuzzy rule-based systems. Algorithms, 6(4), 762-781.

Jadaan, K. S., Al-Fayyad, M., & Gammoh, H. F. (2014). Prediction of road traffic accidents in jordan using artificial neural network (ANN). Journal of Traffic and Logistics Engineering, 2(2), 92-94.

Jalayer, M., Gong, J., Zhou, H., & Grinter, M. (2015). Evaluation of remote sensing technologies for collecting roadside feature data to support highway safety manual implementation. Journal of Transportation Safety & Security, 7(4), 345-357.

Kang, M. W., Jha, M. K., & Schonfeld, P. (2012). Applicability of highway alignment optimization models. Transportation Research Part C: Emerging Technologies, 21(1), 257-286.

Kang, M.-W., Shariat, S., & Jha, M. K. (2013). New highway geometric design methods for minimizing vehicular fuel consumption and improving safety. Transportation Research Part C: Emerging Technologies, 31, 99-111. doi: 10.1016/j.trc.2013.03.002

Karlaftis, M. G., & Vlahogianni, E. I. (2011). Statistical methods versus neural networks in transportation research: Differences, similarities and some insights. Transportation Research Part C: Emerging Technologies, 19(3), 387-399.

Kass, M., Witkin, A., & Terzopoulos, D. (1988). Snakes: Active contour models. International Journal of Computer Vision, 1(4), 321-331.

Kennedy, J. (2010). Particle swarm optimization Encyclopedia of Machine Learning (pp. 760-766): Springer.

Kennedy, J., & Optimization, R. E. P. S. (1995). IEEE Int. Paper presented at the Conf. on Neural Networks.

Kingma, D., & Ba, J. (2014). Adam: A method for stochastic optimization. arXiv preprint arXiv:1412.6980.

Klang, D. (1998). Automatic detection of changes in road data bases using satellite imagery. International Archives of Photogrammetry and Remote Sensing, 32, 293-298.

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

Kumar, P., Lewis, P., & McCarthy, T. (2017). The Potential of Active Contour Models in Extracting Roads from Mobile Laser Scanning Data.

Kumar, P., McElhinney, C. P., Lewis, P., & McCarthy, T. (2013). An automated algorithm for extracting road edges from terrestrial mobile LiDAR data. ISPRS Journal of Photogrammetry and Remote Sensing, 85, 44-55.

Kumar, P., McElhinney, C. P., Lewis, P., & McCarthy, T. (2014). Automated road markings extraction from mobile laser scanning data. International Journal of Applied Earth Observation and Geoinformation, 32, 125-137. doi: 10.1016/j.jag.2014.03.023

Kunt, M. M., Aghayan, I., & Noii, N. (2011). Prediction for traffic accident severity: comparing the artificial neural network, genetic algorithm, combined genetic algorithm and pattern search methods. Transport, 26(4), 353-366.

Lak, A. M., Zoej, M. J. V., & Mokhtarzade, M. (2016). A new method for road detection in urban areas using high-resolution satellite images and Lidar data based on fuzzy nearest-neighbor classification and optimal features. Arabian Journal of Geosciences, 9(5), 1-11.

Lam, J., Kusevic, K., Mrstik, P., Harrap, R., & Greenspan, M. (2010, May). Urban scene extraction from mobile ground based lidar data. In Proceedings of 3DPVT (pp. 1-8).

Lary, D. J., Alavi, A. H., Gandomi, A. H., & Walker, A. L. (2015). Machine learning in geosciences and remote sensing. Geoscience Frontiers. doi: 10.1016/j.gsf.2015.07.003

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436-444.

Lee, J., & Mannering, F. (2002). Impact of roadside features on the frequency and severity of run-off-roadway accidents: an empirical analysis. Accident Analysis & Prevention, 34(2), 149-161.

Lek, S., Belaud, A., Dimopoulos, I., Lauga, J., & Moreau, J. (1995). Improved estimation, using neural networks, of the food consumption of fish populations. Marine and Freshwater Research, 46(8), 1229-1236.

Li, C., Wang, J., Wang, L., Hu, L., & Gong, P. (2014). Comparison of classification algorithms and training sample sizes in urban land classification with Landsat thematic mapper imagery. Remote Sensing, 6(2), 964-983.

Li, L. L., & Wang, J. K. (2012, October). SAR image ship detection based on Ant Colony Optimization. In Image and Signal Processing (CISP), 2012 5th International Congress on (pp. 1100-1103). IEEE.

Li, M., Stein, A., Bijker, W., & Zhan, Q. (2016). Region-based urban road extraction from VHR satellite images using Binary Partition Tree. International Journal of Applied Earth Observation and Geoinformation, 44, 217-225.

Li, P., & He, J. (2016). Geometric design safety estimation based on tire–road side friction. Transportation Research Part C: Emerging Technologies, 63, 114-125.

Li, X., Cheng, X., Chen, W., Chen, G., & Liu, S. (2015). Identification of Forested Landslides Using LiDar Data, Object-based Image Analysis, and Machine Learning Algorithms. Remote Sensing, 7(8), 9705-9726.

Li, X., Lord, D., Zhang, Y., & Xie, Y. (2008). Predicting motor vehicle crashes using support vector machine models. Accident Analysis & Prevention, 40(4), 1611-1618.

Li, Z., Liu, P., Wang, W., & Xu, C. (2012). Using support vector machine models for crash injury severity analysis. Accident Analysis & Prevention, 45, 478-486.

Lin, X., Zhang, J., Liu, Z., Shen, J., & Duan, M. (2011). Semi-automatic extraction of road networks by least squares interlaced template matching in urban areas. International Journal of Remote Sensing, 32(17), 4943-4959. doi: 10.1080/01431161.2010.493565

Linn, K. A., Gaonkar, B., Satterthwaite, T. D., Doshi, J., Davatzikos, C., & Shinohara, R. T. (2016). Control-group feature normalization for multivariate pattern analysis of structural MRI data using the support vector machine. NeuroImage, 132, 157-166.

Lipton, Z. C., Berkowitz, J., & Elkan, C. (2015). A critical review of recurrent neural networks for sequence learning. arXiv preprint arXiv:1506.00019.

Liu, Y., Bian, L., Meng, Y., Wang, H., Zhang, S., Yang, Y., ... & Wang, B. (2012). Discrepancy measures for selecting optimal combination of parameter values in object-based image analysis. ISPRS journal of photogrammetry and remote sensing, 68, 144-156.

Liu, Y., Monteiro, S. T., & Saber, E. (2016, July). Vehicle detection from aerial color imagery and airborne LiDAR data. In Geoscience and Remote Sensing Symposium (IGARSS), 2016 IEEE International (pp. 1384-1387). IEEE.

Long, M., Wang, J., & Jordan, M. I. (2016). Deep transfer learning with joint adaptation networks. arXiv preprint arXiv:1605.06636.

Longley, P. A., Goodchild, M. F., Maguire, D. J., & Rhind, D. W. (2001). Geographic information system and Science. England: John Wiley & Sons, Ltd.

Lv, Y., Duan, Y., Kang, W., Li, Z., & Wang, F. Y. (2015). Traffic flow prediction with big data: a deep learning approach. IEEE Transactions on Intelligent Transportation Systems, 16(2), 865-873.

Lv, Y., Tang, S., & Zhao, H. (2009, April). Real-time highway traffic accident prediction based on the k-nearest neighbor method. In Measuring Technology and Mechatronics Automation, 2009. ICMTMA'09. International Conference on (Vol. 3, pp. 547-550). IEEE.

Ma, X., Yu, H., Wang, Y., & Wang, Y. (2015). Large-scale transportation network congestion evolution prediction using deep learning theory. PloS one, 10(3), e0119044.

Manan, M. M. A., & Várhelyi, A. (2012). Motorcycle fatalities in Malaysia. IATSS research, 36(1), 30-39.

Manan, M. M. A., Jonsson, T., & Várhelyi, A. (2013). Development of a safety performance function for motorcycle accident fatalities on Malaysian primary roads. Safety science, 60, 13-20.

Matkan, A. A., Hajeb, M., & Sadeghian, S. (2014). Road extraction from lidar data using support vector machine classification. Photogrammetric Engineering & Remote Sensing, 80(5), 409-422.

McElhinney, C. P., Kumar, P., Cahalane, C., & McCarthy, T. (2010, June). Initial results from European Road Safety Inspection (EURSI) mobile mapping project. In ISPRS Commission V Technical Symposium (pp. 440-445).

Mena, J. B. (2003). State of the art on automatic road extraction for GIS update: a novel classification. Pattern Recognition Letters, 24(16), 3037-3058. doi: 10.1016/s0167-8655(03)00164-8

Mia, M. M. A., Biswas, S. K., Urmi, M. C., & Siddique, A. (2015). An algorithm for training multilayer perceptron (MLP) for Image reconstruction using neural network without overfitting. Int J Sci Techno Res, 4(2), 271-275.

Ming, D., Li, J., Wang, J., & Zhang, M. (2015). Scale parameter selection by spatial statistics for GeOBIA: Using mean-shift based multi-scale segmentation as an example. ISPRS Journal of Photogrammetry and Remote Sensing, 106, 28-41.

Minh, N. Q., & Hien, L. P. (2011). Land cover classification using LiDAR intensity data and neural network. Journal of the Korean Society of Surveying, Geodesy, Photogrammetry and Cartography, 29(4), 429-438.

Moghaddam, F. R., Afandizadeh, S., & Ziyadi, M. (2011). Prediction of accident severity using artificial neural networks. International Journal of Civil Engineering, 9(1), 41.

Mokhtarzade, M., & Zoej, M. V. (2007). Road detection from high-resolution satellite images using artificial neural networks. International journal of applied earth observation and geoinformation, 9(1), 32-40.

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. ISPRS Journal of Photogrammetry and Remote Sensing, 66(3), 247-259.

Munoz, D., Vandapel, N., & Hebert, M. (2008). Directional associative markov network for 3-d point cloud classification.

Nicholls, D. (1999). Presidential Address: Statistics into the 21st century (with discussion). Australian & New Zealand Journal of Statistics, 41(2), 127-139.

Ogwueleka, F. N., Misra, S., Ogwueleka, T. C., & Fernandez-Sanz, L. (2014). An artificial neural network model for road accident prediction: a case study of a developing country. Acta Polytechnica Hungarica, 11(5), 177-197.

Olden, J. D., & Jackson, D. A. (2002). Illuminating the “black box”: a randomization approach for understanding variable contributions in artificial neural networks. Ecological modelling, 154(1), 135-150.

Oord, A. V. D., Kalchbrenner, N., & Kavukcuoglu, K. (2016). Pixel recurrent neural networks. arXiv preprint arXiv:1601.06759.

Oude Elberink, S. J., & Vosselman, G. (2009). 3D information extraction from laser point clouds covering complex road junctions. The Photogrammetric Record, 24(125), 23-36.

Pagounis, V., Tsakiri, M., & Palaskas, S. (2007). Road safety analysis: terrestrial laser scanning to improve road safety.

Parpinelli, R. S., Lopes, H. S., & Freitas, A. A. (2002). Data mining with an ant colony optimization algorithm. Evolutionary Computation, IEEE Transactions on, 6(4), 321-332.

Pascanu, R., Mikolov, T., & Bengio, Y. (2013, February). On the difficulty of training recurrent neural networks. In International Conference on Machine Learning (pp. 1310-1318).

Pauly, M., Gross, M., & Kobbelt, L. P. (2002, October). Efficient simplification of point-sampled surfaces. In Proceedings of the conference on Visualization'02 (pp. 163-170). IEEE Computer Society.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Vanderplas, J. (2011). Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12(Oct), 2825-2830.

Pei, X., Wong, S. C., & Sze, N. N. (2011). A joint-probability approach to crash prediction models. Accident Analysis & Prevention, 43(3), 1160-1166.

Pei, Y., Wang, W., & Zhang, S. (2012, March). Basic ant colony optimization. In Computer Science and Electronics Engineering (ICCSEE), 2012 International Conference on (Vol. 1, pp. 665-667). IEEE.

Poullis, C., & You, S. (2010). Delineation and geometric modeling of road networks. ISPRS Journal of Photogrammetry and Remote Sensing, 65(2), 165-181.

Pradhan, B., Jebur, M. N., Shafri, H. Z. M., & Tehrany, M. S. Data Fusion Technique Using Wavelet Transform and Taguchi Methods for Automatic Landslide Detection From Airborne Laser Scanning Data and QuickBird Satellite Imagery.

Priyanka, A., & Sathiyakumari, K. (2014). A comparative study of classification algorithm using accident data. International Journal of Computer Science & Engineering Technology (IJCSET), 5(10), 1018-1023.

Pu, S., Rutzinger, M., Vosselman, G., & Elberink, S. O. (2011). Recognizing basic structures from mobile laser scanning data for road inventory studies. ISPRS Journal of Photogrammetry and Remote Sensing, 66(6), S28-S39.

Raschka, S. (2015). Python machine learning. Packt Publishing Ltd.

Rees, W. G. (2000). The accuracy of digital elevation models interpolated to higher resolutions. International journal of remote sensing, 21(1), 7-20.

Robb, C., Willis, I., Arnold, N., & Guðmundsson, S. (2015). A semi-automated method for mapping glacial geomorphology tested at Breiðamerkurjökull, Iceland. Remote Sensing of Environment, 163, 80-90.

Sadek, A., Spring, G., & Smith, B. (2003). Toward more effective transportation applications of computational intelligence paradigms. Transportation Research Record: Journal of the Transportation Research Board, (1836), 57-63.

Samadzadegan, F., & Bigdeli, B. (2009). Combining Multiple Classifiers for Automatic Road Extraction from Lidar Data.

Sarikaya, R., Hinton, G. E., & Deoras, A. (2014). Application of deep belief networks for natural language understanding. IEEE/ACM Transactions on Audio, Speech and Language Processing (TASLP), 22(4), 778-784.

Sarle, W. S. (1994). Neural networks and statistical models.

Schindler, K., & Van Gool, L. (2008, June). Action snippets: How many frames does human action recognition require?. In Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on (pp. 1-8). IEEE.

Sebari, I., & He, D.-C. (2013). Automatic fuzzy object-based analysis of VHSR images for urban objects extraction. ISPRS Journal of Photogrammetry and Remote Sensing, 79, 171-184.

Semeida, A. M. (2015). Derivation of level of service by artificial neural networks at horizontal curves: a case study in Egypt. European Transport Research Review, 7(1). doi: 10.1007/s12544-014-0152-2

Shamayleh, H., & Khattak, A. (2003, August). Utilization of LiDAR technology for highway inventory. In Proceedings of the 2003 Mid-Continent Transportation Research Symposium, Ames, Iowa.

Shin, H. C., Roth, H. R., Gao, M., Lu, L., Xu, Z., Nogues, I., ... & Summers, R. M. (2016). Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE transactions on medical imaging, 35(5), 1285-1298.

Sohn, S. Y., & Lee, S. H. (2003). Data fusion, ensemble and clustering to improve the classification accuracy for the severity of road traffic accidents in Korea. Safety Science, 41(1), 1-14.

Sohn, S. Y., & Shin, H. (2001). Pattern recognition for road traffic accident severity in Korea. Ergonomics, 44(1), 107-117.

Song, J.-H., Han, S.-H., Yu, K., & Kim, Y.-I. (2002). Assessing the possibility of land-cover classification using lidar intensity data. International Archives of Photogrammetry Remote Sensing and Spatial Information Sciences, 34(3/B), 259-262.

Song, M., & Civco, D. (2004). Road extraction using SVM and image segmentation. Photogrammetric Engineering & Remote Sensing, 70(12), 1365-1371.

Srivastava, N., Hinton, G. E., Krizhevsky, A., Sutskever, I., & Salakhutdinov, R. (2014). Dropout: a simple way to prevent neural networks from overfitting. Journal of Machine Learning Research, 15(1), 1929-1958.

Stoica, R., Descombes, X., & Zerubia, J. (2004). A Gibbs point process for road extraction from remotely sensed images. International Journal of Computer Vision, 57(2), 121-136.

Su, L. (2009). Optimizing support vector machine learning for semi-arid vegetation mapping by using clustering analysis. ISPRS Journal of Photogrammetry and Remote Sensing, 64(4), 407-413.

Sutskever, I., Martens, J., & Hinton, G. E. (2011). Generating text with recurrent neural networks. In Proceedings of the 28th International Conference on Machine Learning (ICML-11) (pp. 1017-1024).

Taamneh, M., Taamneh, S., & Alkheder, S. (2016). Clustering-based classification of road traffic accidents using hierarchical clustering and artificial neural networks. International Journal of Injury Control and Safety Promotion, 1-8.

Tao, C. V. (2000). Mobile mapping technology for road network data acquisition. Journal of Geospatial Engineering, 2(2), 1-14.

Tehrany, M. S., Pradhan, B., & Jebur, M. N. (2014). Flood susceptibility mapping using a novel ensemble weights-of-evidence and support vector machine models in GIS. Journal of Hydrology, 512, 332-343.

Tieleman, T., & Hinton, G. (2012). Lecture 6.5-rmsprop: Divide the gradient by a running average of its recent magnitude. COURSERA: Neural networks for machine learning, 4(2).

Ton, J., Jain, A. K., Enslin, W. R., & Hudson, W. D. (1989). Automatic road identification and labeling in Landsat 4 TM images. Photogrammetria, 43(5), 257-276.

Uddin, W. (2008). Airborne laser terrain mapping for expediting highway projects: Evaluation of accuracy and cost. Journal of Construction Engineering and Management, 134(6), 411-420.

Vosselman, G. (2009, September). Advanced point cloud processing. In Photogrammetric week (Vol. 9, pp. 137-146).

Vosselman, G., & Zhou, L. (2009). Detection of curbstones in airborne laser scanning data. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 38, 111-116.

Wang, C., M. A. Quddus & S. G. Ison (2011) Predicting accident frequency at their severity levels and its application in site ranking using a two-stage mixed multivariate model. Accident Analysis & Prevention, 43, 1979-1990.

Wang, G., Zhang, Y., Li, J., & Song, P. (2011). 3D road information extraction from LIDAR data fused with aerial-images. Paper presented at the Spatial Data Mining and Geographical Knowledge Services (ICSDM), 2011 IEEE International Conference on.

Wang, J., González-Jorge, H., Lindenbergh, R., Arias-Sánchez, P., & Menenti, M. (2013). Automatic estimation of excavation volume from laser mobile mapping data for mountain road widening. Remote Sensing, 5(9), 4629-4651.

Wang, J., Zheng, Y., Li, X., Yu, C., Kodaka, K., & Li, K. (2015). Driving risk assessment using near-crash database through data mining of tree-based model. Accident Analysis & Prevention, 84, 54-64.

Wang, X., & Abdel-Aty, M. (2006). Temporal and spatial analyses of rear-end crashes at signalized intersections. Accident Analysis & Prevention, 38(6), 1137-1150.

White, R. A., Dietterick, B. C., Mastin, T., & Strohman, R. (2010). Forest Roads Mapped Using LiDAR in Steep Forested Terrain. Remote Sensing, 2(4), 1120-1141. doi: 10.3390/rs2041120

Wild, C. J., & Pfannkuch, M. (1999). Statistical thinking in empirical enquiry. International Statistical Review, 67(3), 223-248.

Williams, K., Olsen, M. J., Roe, G. V., & Glennie, C. (2013). Synthesis of transportation applications of mobile LiDAR. Remote Sensing, 5(9), 4652-4692.

Wulder, M. A., White, J. C., Nelson, R. F., Næsset, E., Ørka, H. O., Coops, N. C., . . . Gobakken, T. (2012). Lidar sampling for large-area forest characterization: A review. Remote Sensing of Environment, 121, 196-209.

Xiao, L., Wang, R., Dai, B., Fang, Y., Liu, D., & Wu, T. (2017). Hybrid Conditional Random Field based Camera-LIDAR Fusion for Road Detection. Information Sciences.

Xie, Z., & Yan, J. (2013). Detecting traffic accident clusters with network kernel density estimation and local spatial statistics: an integrated approach. Journal of Transport Geography, 31, 64-71.

Xu, C., & Prince, J. L. (1997). Gradient vector flow: A new external force for snakes. Paper presented at the Computer Vision and Pattern Recognition, 1997. Proceedings., 1997 IEEE Computer Society Conference on.

Xu, C., W. Wang, P. Liu, R. Guo & Z. Li (2014) Using the Bayesian updating approach to improve the spatial and temporal transferability of real-time crash risk prediction models. Transportation research part C: emerging technologies, 38, 167-176.

Xu, S., Wang, R., & Zheng, H. (2017). Road Curb Extraction from Mobile LiDAR Point Clouds. IEEE Transactions on Geoscience and Remote Sensing, 55(2), 996-1009.

Xue, B., Zhang, M., & Browne, W. N. (2013). Particle swarm optimization for feature selection in classification: A multi-objective approach. IEEE transactions on cybernetics, 43(6), 1656-1671.

Yager, N., & Sowmya, A. (2003, January). Support vector machines for road extraction from remotely sensed images. In CAIP (pp. 285-292).

Yan, G., Mas, J. F., Maathuis, B., Xiangmin, Z., & Van Dijk, P. (2006). Comparison of pixel- based and object- oriented image classification approaches—a case study in a coal fire area, Wuda, Inner Mongolia, China. International Journal of Remote Sensing, 27(18), 4039-4055.

Yan, W. Y., Shaker, A., & El-Ashmawy, N. (2015). Urban land cover classification using airborne LiDAR data: A review. Remote Sensing of Environment, 158, 295-310. doi: 10.1016/j.rse.2014.11.001

Yan, W. Y., Shaker, A., Habib, A., & Kersting, A. P. (2012). Improving classification accuracy of airborne LiDAR intensity data by geometric calibration and radiometric correction. ISPRS Journal of Photogrammetry and Remote Sensing, 67, 35-44. doi: 10.1016/j.isprsjprs.2011.10.005

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.

Yang, G. Y. C. (1995). Geological mapping from multi-source data using neural networks. Geomatics Engineering, University of Calgary.

Yen, K. S., Ravani, B., & Lasky, T. A. (2011). LiDAR for Data efficiency (No. WA-RD 778.1).

Yilmaz, A., Aci, C., & Aydin, K. (2016). Traffic accident reconstruction and an approach for prediction of fault rates using artificial neural networks: A case study in Turkey. Traffic Injury Prevention, 17(6), 585-589.

Youn, J., Bethel, J. S., Mikhail, E. M., & Lee, C. (2008). Extracting urban road networks from high-resolution true orthoimage and lidar. Photogrammetric Engineering & Remote Sensing, 74(2), 227-237.

Yu, L., Hermann, K. M., Blunsom, P., & Pulman, S. (2014). Deep learning for answer sentence selection. arXiv preprint arXiv:1412.1632.

Yu, Y., Li, J., Guan, H., Jia, F., & Wang, C. (2015). Learning hierarchical features for automated extraction of road markings from 3-D mobile LiDAR point clouds. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 8(2), 709-726.

Yuan, X., Zhao, C. X., Cai, Y. F., Zhang, H., & Chen, D. B. (2008, December). Road-surface abstraction using ladar sensing. In Control, Automation, Robotics and Vision, 2008. ICARCV 2008. 10th International Conference on (pp. 1097-1102). IEEE.

Zai, D., Chen, Y., Li, J., Yu, Y., Wang, C., & Nie, H. (2015, July). Inventory of 3D street lighting poles using mobile laser scanning point clouds. In Geoscience and Remote Sensing Symposium (IGARSS), 2015 IEEE International (pp. 573-576). IEEE.

Zampa, F., & Conforti, D. (2009). Mapping with mobile lidar. GIM international, 23(4), 35-37.

Zeng, Q., & Huang, H. (2014). A stable and optimized neural network model for crash injury severity prediction. Accident Analysis & Prevention, 73, 351-358.

Zeng, Z., Wan, J., & Liu, H. (2016). An entropy-based filtering approach for airborne laser scanning data. Infrared Physics & Technology.

Zhang, J., Duan, M., Yan, Q., & Lin, X. (2014). Automatic vehicle extraction from airborne LiDAR data using an object-based point cloud analysis method. Remote Sensing, 6(9), 8405-8423.

Zhang, Q., & Couloigner, I. (2007). Accurate centerline detection and line width estimation of thick lines using the radon transform. Image Processing, IEEE Transactions on, 16(2), 310-316.

Zhang, W. (2010, June). Lidar-based road and road-edge detection. In Intelligent Vehicles Symposium (IV), 2010 IEEE (pp. 845-848). IEEE.

Zhang, Y., & Yan, L. (2007). Road surface modeling and representation from point cloud based on fuzzy clustering. Geo-spatial Information Science, 10(4), 276-281. doi: 10.1007/s11806-007-0106-0

Zhang, Y., Maxwell, T., Tong, H., & Dey, V. (2010). Development of a supervised software tool for automated determination of optimal segmentation parameters for ecognition (pp. 5-7). na.

Zhao, J., & You, S. (2012). Road network extraction from airborne LiDAR data using scene context. Paper presented at the Computer Vision and Pattern Recognition Workshops (CVPRW), 2012 IEEE Computer Society Conference on.

Zhao, J., You, S., & Huang, J. (2011). Rapid extraction and updating of road network from airborne LiDAR data. Paper presented at the Applied Imagery Pattern Recognition Workshop (AIPR), 2011 IEEE.

Zhou, L., & Vosselman, G. (2012). Mapping curbstones in airborne and mobile laser scanning data. International Journal of Applied Earth Observation and Geoinformation, 18, 293-304.

Zhou, W. (2013). An object-based approach for urban land cover classification: integrating LiDAR height and intensity data. Geoscience and Remote Sensing Letters, IEEE, 10(4), 928-931.

Zur, R. M., Jiang, Y., Pesce, L. L., & Drukker, K. (2009). Noise injection for training artificial neural networks: A comparison with weight decay and early stopping. Medical physics, 36(10), 4810-4818.