UNIVERSITI PUTRA MALAYSIA

DEVELOPMENT OF RIVER WATER LEVEL ESTIMATION FROM SURVEILLANCE CAMERAS FOR FLOOD MONITORING SYSTEM USING DEEP LEARNING TECHNIQUES

NUR ‘ATIRAH BINTI MUHADI

DEVELOPMENT OF RIVER WATER LEVEL ESTIMATION FROM SURVEILLANCE CAMERAS FOR FLOOD MONITORING SYSTEM USING DEEP LEARNING TECHNIQUES

By

NUR 'ATIRAH BINTI MUHADI

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

September 2022

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

DEVELOPMENT OF RIVER WATER LEVEL ESTIMATION FROM SURVEILLANCE CAMERAS FOR FLOOD MONITORING SYSTEM USING DEEP LEARNING TECHNIQUES

By

NUR ‘ATIRAH BINTI MUHADI

September 2022

Chair : Associate Professor Ahmad Fikri Abdullah, PhD
Faculty : Engineering

Around 70% of global disasters are related to hydro-meteorological events such as drought, floods, and cyclones. Therefore, researchers and experts carried out many studies on flood hazards in order to reduce the impact of flood magnitude and flood frequency. In Malaysia, a telemetric forecasting system is currently been used in flood monitoring systems. However, data information obtained from this system is one spatial dimension and one point-based station, thus it cannot represent the dynamics of the surface water extent. Therefore, this study introduces a visual surveillance concept to monitor the flood event in a specific area, based on surveillance cameras and computer vision approaches to obtain instant flood inundation information during flood events. A deep learning approach was proposed for water segmentation so that it can be applied to various water scenarios and backgrounds. However, conventional image segmentation techniques were also carried out to ensure the usage of deep learning is worth it. The conventional segmentation methods used in this work are thresholding, region growing, and hybrid technique known as GeoRegion. The findings demonstrated that these methods are handcrafted and the algorithms need to be changed when applying to different images, which is not practical to be used during flood disasters. Hence, deep learning technique was chosen for water segmentation procedure in this work. Two different networks were applied in this study, namely DeepLabv3+ and SegNet, for detecting water regions before estimating water levels from surveillance images. Water level estimation was predicted based on the elevations from LiDAR data. Based on the experimental results, it was found that the DeepLabv3+ network performed better than the SegNet network by achieving above 93% for overall accuracy and IoU metrics, and approximately 82% for boundary F1 score (BF score). The Spearman’s rank correlation obtained between water level measured by the sensor and water level estimated from the proposed framework was 0.92 which indicates a strong relationship. By integrating the estimated water level with a 3D model developed from LiDAR data, flood simulation was performed. Besides,

volume of water was also computed from the 3D model. The findings demonstrate that the water volume increased as water level increased. Lastly, a graphical user interface was developed for water segmentation and water level estimation analysis that could be applied during the flood events. Hence, the proposed work can help in improving the current monitoring and emergency warning abilities against flood events, serving as a complement to the currently used quantitative precipitation forecasts and in-situ water-level measurements.

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

PEMBANGUNAN ANGGARAN ARAS AIR SUNGAI DARIPADA KAMERA PENGAWASAN BAGI SISTEM PEMANTAUAN BANJIR MENGGUNAKAN TEKNIK PEMBELAJARAN MENDALAM

Oleh

NUR 'ATIRAH BINTI MUHADI

September 2022

Pengerusi : Profesor Madya Ahmad Fikri Abdullah, PhD
Fakulti : Kejuruteraan

Sekitar 70% daripada bencana global berkaitan dengan peristiwa hidro-meteorologi seperti kemarau, banjir dan taufan. Oleh itu, penyelidik dan pakar banyak menjalankan kajian tentang bahaya banjir bagi mengurangkan kesan magnitud banjir dan kekerapan banjir. Di Malaysia, sistem ramalan telemetrik kini digunakan dalam sistem pemantauan banjir. Walau bagaimanapun, maklumat data yang diperoleh daripada sistem ini adalah berbentuk satu dimensi spatial dan stesen berasaskan titik, justeru ia tidak dapat mewakili keluasan air permukaan yang dinamik. Oleh itu, kajian ini memperkenalkan konsep pengawasan visual untuk memantau kejadian banjir di kawasan tertentu, berdasarkan kamera pengawasan dan pendekatan penglihatan komputer untuk mendapatkan maklumat banjir segera semasa kejadian banjir. Pendekatan pembelajaran mendalam telah dicadangkan untuk mengenalpasti kawasan berair supaya ia boleh digunakan pada pelbagai senario dan latar belakang. Walau bagaimanapun, teknik pembahagian imej konvensional juga telah dijalankan untuk memastikan penggunaan pembelajaran mendalam berbaloi. Kaedah pembahagian konvensional yang digunakan dalam kerja ini ialah *thresholding*, *region growing* dan teknik hibrid yang dikenali sebagai GeoRegion. Penemuan menunjukkan bahawa kaedah ini adalah buatan tangan dan algoritmanya perlu diubah apabila digunakan pada imej yang berbeza, dan ianya tidak praktikal untuk digunakan semasa bencana banjir. Oleh itu, teknik pembelajaran mendalam telah dipilih untuk prosidur pembahagian air dalam kerja ini. Dua rangkaian berbeza telah digunakan dalam kajian ini, iaitu DeepLabv3+ dan SegNet, untuk mengesan kawasan air sebelum menganggar paras air daripada imej pengawasan. Anggaran aras air telah diramalkan berdasarkan ketinggian daripada data LiDAR. Berdasarkan keputusan percubaan, didapati bahawa rangkaian DeepLabv3+ berprestasi lebih baik daripada rangkaian SegNet dengan mencapai melebihi 93% untuk ketepatan keseluruhan dan *intersection-over-union* (IoU), dan kira-kira 82% untuk skor sempadan F1 (*BF score*). Korelasi pangkat Spearman yang diperolehi antara

paras air yang diukur oleh penderia dan paras air yang dianggarkan daripada rangka kerja yang dicadangkan ialah 0.92 yang menunjukkan hubungan yang kukuh. Dengan menggunakan anggaran paras air dan model 3D yang dibangunkan daripada data LiDAR, simulasi banjir telah dilakukan. Selain itu, isipadu air juga dikira daripada model 3D. Penemuan menunjukkan bahawa isipadu air meningkat apabila paras air meningkat. Akhir sekali, antara muka grafik pengguna telah dibangunkan untuk pembahagian air dan analisis anggaran paras air yang boleh digunakan semasa kejadian banjir. Oleh itu, kerja yang dicadangkan boleh membantu dalam meningkatkan pemantauan semasa dan kebolehan amaran kecemasan terhadap kejadian banjir, selain daripada berfungsi sebagai pelengkap kepada ramalan hujan kuantitatif yang digunakan pada masa ini dan pengukuran aras air di lapangan.

ACKNOWLEDGEMENTS

In the Name of Allah S.W.T, the Most Benevolent and the Most Merciful

First of all, I would like to take this opportunity to express my profound gratitude and deep regards to my supervisor, Assoc. Prof. Dr. Ahmad Fikri Abdullah for his exemplary guidance, monitoring, and constant encouragement throughout this research work. The blessing, help, and guidance given by him from time to time shall carry me a long way in the journey of life upon which I am about to embark.

I would like to take this opportunity to express a deep sense of gratitude to Assoc. Prof. Dr. Siti Khairunniza Bejo and Dr. Muhamad Razif Mahadi@Othman for their co-supervision, valuable information, and guidance, which helped me in completing this task through various stages. I am indebted to the staff members of the Department of Biological and Agricultural Engineering, for the valuable information provided by them in their respective fields. I am also grateful to be awarded the Putra Grant, GPB (Project code: UPM/800-3/3/1/GPB/2019/9678700) provided by Universiti Putra Malaysia for funding my research.

Thank you to my lovely parents and family, the pillars of my strength who always give me an abundance of love and support. I am grateful to my parents, for supporting my passion for studying without doubts or conditions. To my friends, Afiah, Maimunah, Hidayu, Kak Aisyah, Min and Veena who always keep me alive, thank you very much.

May Allah bless all of you.

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:

Ahmad Fikri bin Abdullah, PhD
Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Chairman)

Siti Khairunniza binti Bejo, PhD
Associate Professor
Faculty of Engineering
Universiti Putra Malaysia
(Member)

Muhammad Razif bin Mahadi@Othman, PhD
Senior Lecturer
Faculty of Engineering
Universiti Putra Malaysia
(Member)

ZALILAH MOHD SHARIFF, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 8 December 2022

Declaration by Members of Supervisory Committee

This is to confirm that:
- the research and the writing of this thesis were done under our supervision;
- supervisory responsibilities as stated in the Universiti Putra Malaysia (Graduate Studies) Rules 2003 (Revision 2015-2016) are adhered to.

Signature: ____________________
Name of Chairman of Supervisory Committee: Associate Professor Dr. Ahmad Fikri Abdullah

Signature: ____________________
Name of Member of Supervisory Committee: Associate Professor Dr. Siti Khairunniza Bejo

Signature: ____________________
Name of Member of Supervisory Committee: Dr. Muhammad Razif Mahadi@Othman

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

NADMA	National Disaster Management Administration
MCO	Movement control order
GDP	Gross domestic product
NSC	National Security Council
NDMRC	Natural Disaster Management and Relief Community
NSC	National Security Council
WHO	World Health Organization
DID	Department of Irrigation and Drainage
NaFFWS	National Flood Forecasting and Warning System
GIS	Geographic Information System
UAV	Unmanned aerial vehicles
LiDAR	Terrestrial light detection and ranging
SMS	short message service
MMD	Malaysian Meteorological Department
RTUs	Remote telemetry units
FCM	Fuzzy c-means
AI	Artificial intelligence
NLP	Natural language processing
HSV	hue, saturation, and value
SAR	synthetic aperture radar
EM	expectation-maximization
MRI	magnetic resonance imaging
CNN	convolutional neural network
ANN	artificial neural network

SVM	support vector machine
LBWLE	landmark based water-level estimation
DEM	digital elevation model
GUI	graphical user interface
TLS	terrestrial laser scanning
LTE	Long-term Evolution
VGG	Visual Geometry Group
ReLU	rectified-linear non-linearity
ASPP	atrous spatial pyramid pooling
IoU	intersection over union
BF score	boundary F1 score
TP	true positives
FP	false positives
TN	true negatives
FN	false negatives
RMSE	root mean square error
UI	user interface
FCN	fully convolutional network
CCTV	closed-circuit television
m	metre
km^2	kilometres square

CHAPTER 1

INTRODUCTION

1.1 Overview

Flood frequency was increased by 33% in 2020 as compared to the average occurrence for the past 10 years (2010 – 2019) (UNDRR, 2020a). The flood issue has gained global attention with significant efforts made to develop effective flood prevention and monitoring solutions. Researchers and experts around the world have carried out many studies that included the use of modern techniques such as artificial intelligence to reduce the impact of flooding events. This chapter discusses the study background as well as its scope and limitations.

1.2 Flood definition

A flood is defined as a rise in water body and overflowing water into land that is usually dry. Different societies often have different perspectives on the definition of flood. From the ecological perspective, a flood is defined as an unusual discharge that exceeds the riverbanks; hence, inundating the floodplain. On the other hand, a hydrologist defines flood as high discharges that cause a sudden peak in water level and lead to the inundation of land adjacent water bodies. Contrarily, from the social perspective flood is defined as discharge of a water body that causes damage (Havinga et al., 2006). Ward (1978) defined flood as a natural process of overflowing water body into land that is not normally submerged. In 2020, the frequency of floods rose to 61.66% of the total 313 major natural disasters that occurred worldwide (UNDRR, 2020a). Figure 1.1 illustrates the frequency of natural disasters according to disaster types in 2020.

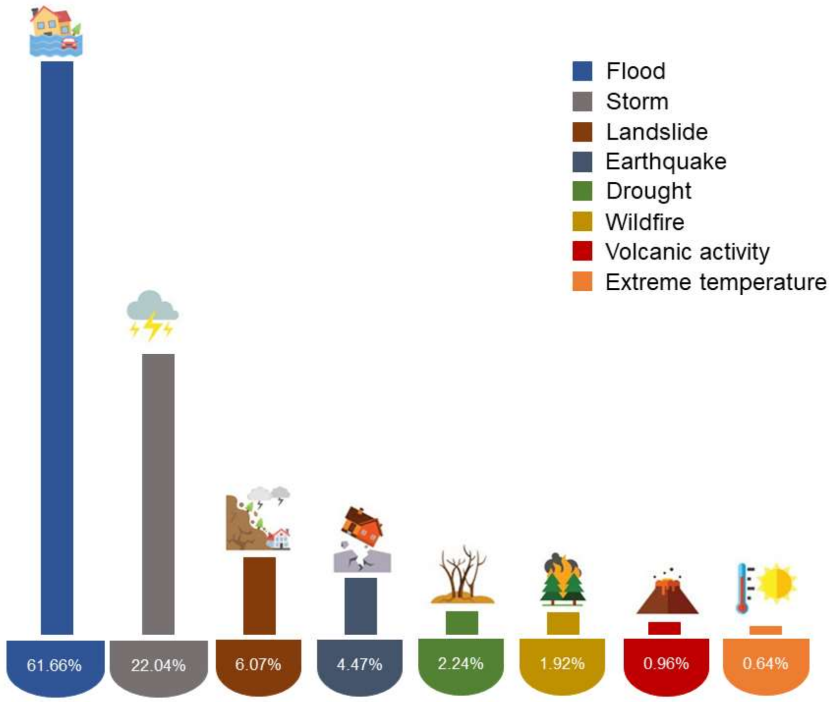

Figure 1.1: Number of occurrences according to disaster types worldwide in 2020 (UNDRR, 2020a)

1.3 Floods in Malaysia

Malaysia is located in Southeast Asia, which is geographically located outside the "Pacific Rim of Fire" (Chan, 2015). Therefore, Malaysia is free from severe natural disasters, such as earthquakes, volcanic eruptions, and typhoons. Even though Malaysia does not suffer from such extreme disasters, Malaysia still experiences disasters, such as floods, landslides, and drought. Flood is the most common natural disaster in Malaysia due to its geographical location and characteristics. Figure 1.2 illustrates the frequency distribution of disasters in Malaysia for 2018. Furthermore, Malaysia has the highest percentage (67%) of the population exposed to floods amongst ASEAN member states from July 2012 to January 2019, as reported in the ASEAN Risk Monitor and Disaster Management Review (AHA Centre, 2019b).

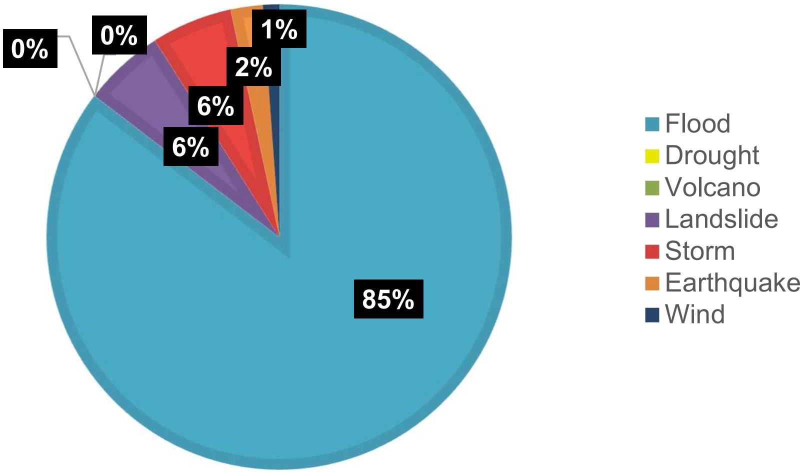

Figure 1.2: Distribution of disasters by hazards shows that flood is the most frequent disaster in Malaysia in 2018 (AHA Centre, 2019a)

Overall, 189 river systems are flowing directly into the sea throughout Malaysia, including Sabah and Sarawak. It was reported that 10.1% or 33, 298 km2 of Malaysian land is exposed to flood risk (DID, 2012). Floods in Malaysia can be classified as flash and monsoon floods. Flash flood is a sudden event and it rises and falls rapidly, while monsoon flood lasts for days. Nonetheless, this work focuses only on monsoon floods in Malaysia.

1.3.1 Causes of floods

There are two main causes of flood, which are natural and human-induced. Omran et al. (2018) reported that the massive flood that happened in Kelantan in 2014 was contributed equally by natural and human factors. The basic cause of flood in Malaysia is influenced by monsoon winds, heavy rainfall, and runoff. Malaysia has two monsoon seasons each year, which are the northeast monsoon that occurs from November to March, and the southwest monsoon which occurs from May to September. Since heavy rainfall and strong winds occur during the monsoon season, flood risk is higher during that period. Pahang, Kelantan, and Terengganu often experience floods due to heavy rains during the northeast monsoon.

Other than the monsoon, climate change is another worrying factor that contributes to extreme changes in weather and temperature. These changes indirectly melt glaciers and increase sea levels, which eventually cause an increase in the number of flood disasters. Furthermore, sediments carried by rivers from higher slope areas are deposited and this reduces the river capacity, which contributes to serious flood incidents. Therefore, the water easily overflows the riverbanks during floods. In addition, the topography of an area is one of the major factors that determine its flood susceptibility. A low-level area is highly affected by floods during rainfall, especially if it is located near rivers.

On the other hand, many man-made activities influence the flooding problem. It was revealed that human factors, such as land clearing, unmanaged drainage systems, and uncontrolled development, contributed more weightage to flood events in Sarawak (Abid et al., 2021). Deforestation and land clearing are some development processes that could increase the flood risk. Land clearing for agricultural purposes by irresponsible parties in Kuala Krai, Kelantan had decreased the number of trees and increased the probability of flood occurrence (Omran et al., 2018). Unplanned urban development, uncontrolled construction works, and a major change in land use could also contribute to the flooding problem. In developing countries, urbanisation usually starts from downstream to upstream, which increases the impacts and damages of floods.

Moreover, urban cities like Kuala Lumpur are susceptible to floods due to less storage capacity in the urban basin and more surface runoff. Klang Valley, for instance, experienced an increased runoff with respect to urban development in that area (DID, 2009). Artificial surfaces like cement, concrete and tar could not absorb water as dense vegetation area does; hence, the rainfall immediately ends up in drains and rivers. Therefore, too much water flows into the river which exceeds its discharge capacity, and thus results in flooding events. Unmanaged drainage was one of the factors that contributed to the massive flood in Kuala Krai, Kelantan (Omran et al., 2018). Lack of action from the authorities in cleaning the drainage and widening the drainage systems have worsened the flood situation in 2014.

In addition, exploitation of hill land for rapid housing, uncontrolled agriculture, and other developments damages the hill environment and affect downstream areas (Weng Chan, 1997), which lead to flooding problem. Besides, human-induced flood may occur due to poor designs such as constructions at bridges and culverts. Lastly, low levels of civic consciousness amongst Malaysians who continue to throw rubbish into rivers and drains can contribute to flood incidents.

1.3.2 Recent flood events

In the past five years, Malaysia experienced several natural disasters, including floods. The recent flood struck on 18 December 2021, causing more than 50,000 people to be evacuated and at least 50 deaths. The 11 affected states were Selangor, Pahang, Kelantan, Terengganu, Kuala Lumpur, Perak, Melaka, Negeri Sembilan, Sabah and Sarawak. Two days of torrential rain caused the worst floods in years, which led rivers to overflow and caused floods in towns and villages; hence, major roads were cut off. Many motorists were stranded and trapped in their vehicles for hours. Figure 1.3 illustrates the timeline of flood from 2017 to 2021.

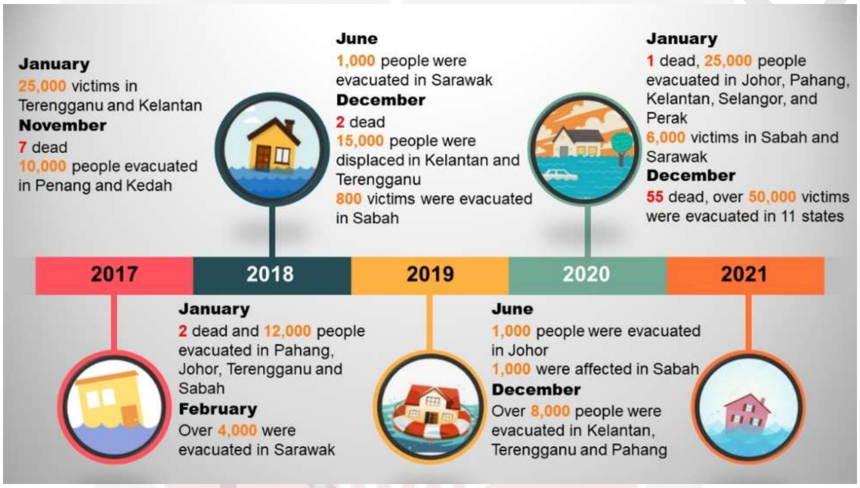

Figure 1.3: History of floods from 2017 to 2021 in Malaysia

Records showed that major floods normally occur at the end of the year and Kelantan, Terengganu, Pahang, and Johor were amongst the states that were frequently hit by floods, especially during the monsoonal seasons.

1.4 Flood monitoring system in Malaysia

After the severe flooding events in December 2014, the Malaysian Government established National Disaster Management Agency (NADMA), which allows better coordination between agencies related to natural disasters. NADMA enables the implementation of a new flood forecasting and warning project called the National Flood Forecasting and Warning System (NaFFWS) through the Department of Irrigation and Drainage (DID). NaFFWS is an integrated system for flood forecasting and river monitoring with dissemination of flood warning that uses telemetry data, radar data and forecasts.

NaFFWS can forecast monsoon floods seven days in advance and provide dissemination of flood warnings two days earlier. NaFFWS was successfully developed in three catchments in Malaysia and now it has been broadened to 11 more river basins before the scheme is extended nationwide (Wallington, 2017). The system uses historical rainfall and flow data and then develops models of runoffs, river channels, and flood plains before combining the data with weather forecasts and ground measurements to predict water levels. Lastly, the system is configured to run continuously and operationally, which also automatically generates forecasts and warnings.

Since 2000, DID has adopted a telemetry system to monitor real-time rainfall and water levels from hydrological stations, and the data are transmitted to DID offices for local use. The rainfall and water level data are also published in Infobanjir.water.gov.my, which is an Internet-based national flood monitoring system established for the public. However, there are times when the system encountered data transmission problems or the rainfall or water level sensors had technical issues (Bopi et al., 2016).

Besides, DID has already installed several surveillance cameras at different water level monitoring stations in Selangor. The cameras are used to observe the situation on-site and monitor the water level of river. Images from the camera are shared with the public on the official website of InfoBanjir Selangor at http://infobanjirjps.selangor.gov.my/camera.html and the images on the website will be updated every 15 minutes.

1.5 Problem statement

In Malaysia, the DID has adopted a telemetry system to monitor real-time water levels using in-situ water level sensors from hydrological stations. These data are used in real-time flood monitoring and can also be used to provide flood forecasting. Nevertheless, the main restriction of this means is the failure of the sensor when the water level exceeds the sensor position during flood events. When it happens, the water level sensors will fail to give accurate readings. Besides, due to high installation and maintenance costs, the installation of the sensors is often neglected in the small-scale river areas, which results in data scarcity to describe the local situation (Lo et al., 2015). Because of the limitations of current practice, a visual sensing technique is proposed as an alternative to obtain real-time flood information. Surveillance camera has become a popular option to be used as the input source for flooding events monitoring, especially in small-scale areas (Filonenko et al., 2015; Lo et al., 2015). Besides, DID has installed surveillance cameras or closed-circuit television (CCTV) cameras at several water level monitoring stations, mostly in Selangor, so that the authority can instruct residents to evacuate when water is at the dangerous level. After the massive floods in December 2021, a total of 120 CCTV cameras were installed nationally and will be operational in 2022 (Bernama, 2021). Moreover, Kuala

Lumpur City Hall (DBKL) is planning to install 4,000 surveillance cameras in the city to visually detect floods as well as to help the authorities in flood rescue operations (Jaafar, 2022). Nonetheless, there is no proper discussion on how the authorities would use the technology other than by observing the on-site situation remotely. It will be a waste not to make full use of the existing infrastructure.

Extraction of water regions is an important task in utilising surveillance images in flood studies. The water regions can be identified by using various computer vision techniques. Many studies were conducted on the application of computer vision including deep learning approach in flood disasters by using satellite imagery (Martinis et al., 2015; Silveira & Heleno, 2009; Thayammal et al., 2021; Zhou et al., 2020) and unmanned aerial vehicles (UAVs) (Ansari et al., 2021; Gebrehiwot et al., 2019; Popescu et al., 2015, 2017; Rahnemoonfar et al., 2021). However, the usage of computer vision to exploit surveillance images in flood applications is still lacking. Focusing on flood applications in specific, only a few researchers adopted deep learning technique to extract water information from surveillance images. Due to its expensive cost in terms of computational resources and intensive training, deep learning should only be used if the given problem could not be solved by simpler methods to justify the cost of using it. Therefore, this research proposes to apply computer vision techniques, from the conventional computer vision-based to deep learning-based, to find the most reliable method that can be used for water segmentation during flood events. In order to fully utilise the surveillance technology, the potential of estimating water levels from segmented images is investigated. Having to depend on stick gauges or objects present in the fields could limit the practicality of water level estimation from surveillance images. Since LiDAR data offer higher accuracy of digital elevation model (DEM), this present work suggests to use virtual markers extracted from LiDAR data for water level estimation coupled with the segmented surveillance image. Apart from that, the lack of flood data, especially during/after flooding events and limited information on flooded areas in small/local events make it difficult to validate the flood forecasting models (Molinari et al., 2019). A 3D model could help in providing water volume information and describing The ability to capture water level values and record them in a structured database might be useful when there is a problem with the telemetry system. Therefore, a smart flood monitoring system by developing a graphical user interface specifically designed for water segmentation and water level estimation is proposed.

1.6 Research questions

The proposed study aims to address the following research questions:

i. Can deep learning be used efficiently in extracting water region information by using surveillance images?

ii. Can water levels be estimated from surveillance images and LiDAR data?

iii. Can water volume be determined from 3D model generated from LiDAR data? How to extract and record data in a structured manner (database) automatically from the surveillance cameras?

1.7 Objectives

The main aim of this study is to develop a smart flood monitoring system by identifying water regions and estimating water levels from surveillance technology. The specific objectives of this research are as follows:

i. To investigate the efficiency of conventional image processing and deep learning approaches to segment flooded regions from surveillance images.

ii. To estimate water levels by exploiting the segmented images coupled with elevation values extracted from light detection and ranging (LiDAR) data.

iii. To compute water volume from 3D model generated from LiDAR data and to design a graphical user interface (GUI) for segmenting water regions and extracting water levels and status from surveillance images.

The result of this study will be valuable in improving the flood monitoring system as well as reducing the impact of flooding by developing better practices and advanced tools for flood management systems in Malaysia.

1.8 Scope and limitations

The main scope of work for this study is to identify the water regions using several segmentation techniques and estimate water levels by integrating the results with the elevation values extracted from LiDAR data before developing a graphical user interface (GUI) from surveillance technology so that near real-time information could be obtained during the flooding events. This work only covers flood disasters that had happened until December 2021. Besides, it focuses on flood monitoring during the flooding events without discussing the whole flood management cycle. The present study only focuses on river floods and the extent of flood to adjacent areas along the river. As this study uses a single surveillance camera, the study only covers narrow rivers with width of 30 m. It is also assumed that the surveillance camera is fixed and there are no changes in terms of camera angles from time to time.

Another limitation of the proposed study is the limitation of waterbody detection due to the bridge or pier that is present in the image. Therefore, the water region could not be detected accurately if it is located under the bridge or pier. Besides, only daytime images were used since this study used an RGB camera that requires light to produce a good quality image. In this study, the proposed water segmentation approach can be applied to various river images regardless of the image locations. However, the suggested water level estimation was highly dependent on locality. To do the water level estimation, it needs to have prior elevation information; hence, the concept does not apply to all images. Besides, this study did not consider sedimentation issues that may influence the water level of rivers.

1.9 Thesis outline

The thesis is organised into six chapters. Chapter 1 provides an overview of the research with a brief explanation about its relevance. The chapter includes the research questions and objectives, scope and limitations. Chapter 2 consists of a literature review that covers several related topics. Chapter 3 explains the setup for data acquisition by using surveillance cameras, image segmentation methods and deep learning semantic segmentation. It also describes the process of designing a smart data collection by using a graphical user interface (GUI) for extracting water information from surveillance images. Chapter 4 addresses the results and findings for each research objective. Chapter 5 discusses the experimental results and related explanations of the proposed work. Lastly, Chapter 6 summarises conclusions of the proposed work as well as provides recommendations for future studies.

REFERENCES

Abdel-Maksoud, E., Elmogy, M., & Al-Awadi, R. (2015). Brain tumor segmentation based on a hybrid clustering technique. *Egyptian Informatics Journal*, *16*(1), 71–81.

Adams, R., & Bischof, L. (1994). Seeded region growing. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *16*(6), 641–647.

AHA Centre. (2019a). *ASEAN Disaster Information Network*. Retrieved 10 March 2019 from http://adinet.ahacentre.org.

AHA Centre. (2019b). *ASEAN Risk Monitor and Disaster Management Review (ARMOR).* In Jakarta: ASEAN Coordinating Centre for Humanitarian Assistance on disasterr management (AHA Centre). Retrieved from https://ahacentre.org/publication/armor.

Akiyama, T. S., Marcato Junior, J., Gonçalves, W. N., Bressan, P. O., Eltner, A., Binder, F., & Singer, T. (2020). Deep Learning Applied to Water Segmentation. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLIII-B2-2*(B2), 1189–1193.

Alqazzaz, S., Sun, X., Yang, X., & Nokes, L. (2019). Automated brain tumor segmentation on multi-modal MR image using SegNet. *Computational Visual Media*, *5*(2), 209–219.

Amit, S. N. K. B., & Aoki, Y. (2017). Disaster detection from aerial imagery with convolutional neural network. *Proceedings - International Electronics Symposium on Knowledge Creation and Intelligent Computing, IES-KCIC 2017*, 239–245.

Ansari, E., Akhtar, M. N., Abdullah, M. N., Othman, W. A. F. W., Bakar, E. A., Hawary, A. F., & Alhady, S. S. N. (2021). Image Processing of UAV Imagery for River Feature Recognition of Kerian River, Malaysia. *Sustainability*, *13*(17), 9568.

Archana, K. S., & Sahayadhas, A. (2018). Automatic rice leaf disease segmentation using image processing techniques. *International Journal of Engineering and Technology(UAE)*, *7*(27), 182–185.

Azimi, M. A., Syed Zakaria, S. A., & Majid, T. A. (2019). Disaster risks from economic perspective: Malaysian scenario. *IOP Conference Series: Earth and Environmental Science*, *244*(1).

Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). SegNet: A Deep Convolutional Encoder-Decoder Architecture for Image Segmentation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *39*(12), 2481–2495.

Baheti, B., Innani, S., Gajre, S., & Talbar, S. (2020). Semantic scene segmentation in unstructured environment with modified DeepLabV3+. *Pattern Recognition Letters*, *138*, 223–229.

Bangira, T., Alfieri, S. M., Menenti, M., & van Niekerk, A. (2019). Comparing thresholding with machine learning classifiers for mapping complex water. *Remote Sensing*, *11*(11).

Baroffio, L., Bondi, L., Cesana, M., Redondi, A. E., & Tagliasacchi, M. (2015). A visual sensor network for parking lot occupancy detection in Smart Cities. *IEEE World Forum on Internet of Things, WF-IoT 2015 - Proceedings*, 745–750.

Baydargil, H. B., Serdaroglu, S., Park, J. S., Park, K. H., & Shin, H. S. (2018). Flood Detection and Control Using Deep Convolutional Encoder-decoder Architecture. *2018 International Conference on Information and Communication Technology Robotics, ICT-ROBOT 2018*, 1–3.

Benjdira, B., Ouni, K., Al Rahhal, M. M., Albakr, A., Al-Habib, A., & Mahrous, E. (2020). Spinal cord segmentation in ultrasound medical imagery. *Applied Sciences (Switzerland)*, *10*(4), 1–24.

Bernama. (2021). *Flood warning system to be fully operational nationwide in 2022*. Bernama.Com. Retrieved 12 January 2022 from https://www.bernama.com/en/news.php?id=2039287

Bhola, P. K., Nair, B. B., Leandro, J., Rao, S. N., & Disse, M. (2019). Flood inundation forecasts using validation data generated with the assistance of computer vision. *Journal of Hydroinformatics*, *21*(2), 240–256.

Bin, Z., Dalin, J., Fang, W., & Tingting, W. (2009). A design of parking space detector based on video image. *ICEMI 2009 - Proceedings of 9th International Conference on Electronic Measurement and Instruments*, 2253–2256.

Bini, S. A. (2018). Artificial Intelligence, Machine Learning, Deep Learning, and Cognitive Computing: What Do These Terms Mean and How Will They Impact Health Care? *Journal of Arthroplasty*, *33*(8), 2358–2361.

Bischke, B., Bhardwaj, P., Gautam, A., Helber, P., Borth, D., & Dengel, A. (2017). Detection of Flooding Events in Social Multimedia and Satellite Imagery using Deep Neural Networks. *MediaEval*, 13–15.

Boonpook, W., Tan, Y., Ye, Y., Torteeka, P., Torsri, K., & Dong, S. (2018). A deep learning approach on building detection from unmanned aerial vehicle-based images in riverbank monitoring. *Sensors (Switzerland)*, *18*(11).

Bopi, N. B., Ismail, A. F., Zabidi, S. A., & Hasan, M. K. (2016). Development of a River Basin Monitoring System for Malaysia. *International Journal of U- and* *e- Service, Science and Technology*, *9*(7), 349–360.

Borges, P. V. K., Mayer, J., & Izquierdo, E. (2008). A probabilistic model for flood detection in video sequences. *2008 15th IEEE International Conference on Image Processing*, 13–16.

Bradley, D., & Roth, G. (2007). Adaptive Thresholding using the Integral Image. *Journal of Graphics Tools*, *12*(2), 13–21.

Brownlee, J. (2019). Deep Learning for Computer Vision: Image Classification , Object Detection , and Face Recognition in Python. *Machine Learning Mastery*.

Bulan, O., Loce, R. P., Wu, W., Wang, Y., Bernal, E. A., & Fan, Z. (2013). Video-based real-time on-street parking occupancy detection system. *Journal of Electronic Imaging*, *22*(4), 041109.

Buscombe, D., & Ritchie, A. C. (2018). Landscape classification with deep neural networks. *Geosciences (Switzerland)*, *8*(7), 1–23.

CFE-DM. (2019). Malaysia Disaster Management Reference Handbook. In *Center for Excellence in Disaster & Humanitarian Assistance (CFE-DM)* (June).

Chakraborty, A., & Chakraborty, D. (2019). Computerized Seed and Range Selection Method for Flood Extent Extraction in SAR Image Using Iterative Region Growing. *Journal of the Indian Society of Remote Sensing*, *47*(4), 563–571.

Chakravarthy, S., Sharma, R., & Kasturi, R. (2002). Noncontact level sensing technique using computer vision. *IEEE Transactions on Instrumentation and Measurement*, *51*(2), 353–361.

Chan, N. W. (2015). *Resilience and Recovery in Asian Disasters*. 239–265.

Chaudhary, P., D'Aronco, S., Moy De Vitry, M., Leitão, J. P., & Wegner, J. D. (2019). Flood-water Level Estimation From Social Media Images. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *4*(2/W5), 5–12.

Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2014). Semantic image segmentation with deep convolutional nets and fully connected crfs. *ArXiv Preprint ArXiv:1412.7062*, *40*(4), 834–848. 184

Chen, L.-C., Papandreou, G., Kokkinos, I., Murphy, K., & Yuille, A. L. (2017). Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected crfs. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *40*(4), 834–848.

Chen, L.-C., Papandreou, G., Schroff, F., & Adam, H. (2017). Rethinking atrous convolution for semantic image segmentation. *ArXiv Preprint ArXiv:1706.05587*.

Chen, L.-C., Zhu, Y., Papandreou, G., Schroff, F., & Adam, H. (2018). Encoder-Decoder with Atrous Separable Convolution for Semantic Image Segmentation. *Proceedings of the European Conference on Computer Vision (ECCV)*, 801–818.

Chen, Y., Fan, R., Yang, X., Wang, J., & Latif, A. (2018). Extraction of urban water bodies from high-resolution remote-sensing imagery using deep learning. *Water (Switzerland)*, *10*(5).

Choné, G., Biron, P. M., Buffin-Bélanger, T., Mazgareanu, I., Neal, J. C., & Sampson, C. C. (2021). An assessment of large-scale flood modelling based on LiDAR data. *Hydrological Processes*, *35*(8), 1–13.

Creutin, J. D., Muste, M., Bradley, A. A., Kim, S. C., & Kruger, A. (2003). River gauging using PIV techniques: A proof of concept experiment on the Iowa River. *Journal of Hydrology*, *277*(3–4), 182–194.

Csurka, G., Larlus, D., & Perronnin, F. (2013). What is a good evaluation measure for semantic segmentation? *Procedings of the British Machine Vision Conference 2013*, 32.1-32.11.

Dang, L. M., Hassan, S. I., Im, S., Mehmood, I., & Moon, H. (2018). Utilizing text recognition for the defects extraction in sewers CCTV inspection videos. *Computers in Industry*, *99*, 96–109.

Dao, P. D., & Liou, Y. A. (2015). Object-based flood mapping and affected rice field estimation with landsat 8 OLI and MODIS data. *Remote Sensing*, *7*(5), 5077–5097.

Delibaltov, D., Wu, W., Loce, R. P., & Bernal, E. A. (2013). Parking lot occupancy determination from lamp-post camera images. *IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC*, *Itsc*, 2387–2392.

DOSM. (2022). *Special Report on Impact of Floods in Malaysia 2021*. Department of Statistics Malaysia, Malaysia.

DID. (2009). DID Manual (Volume 1 – Flood Management). In *DID Malaysia* (Vol. 1). Department of Irrigation and Drainage (DID) Malaysia.

DID. (2018). *Hydrological standard for water level station instrumentation*. Department of Irrigation and Drainage (DID) Malaysia.

Erwin, Saparudin, Nevriyanto, A., & Purnamasari, D. (2018). Performance analysis of comparison between region growing, adaptive threshold and watershed methods for image segmentation. *Proceedings of the International MultiConference of Engineers and Computer Scientists*, *1*, 157–163.

Etter, S., Strobl, B., van Meerveld, I., & Seibert, J. (2020). Quality and timing of crowd-based water level class observations. *Hydrological Processes*, *34*(22), 4365–4378.

Feng, W., Sui, H., Huang, W., Xu, C., & An, K. (2019). Water Body Extraction from Very High-Resolution Remote Sensing Imagery Using Deep U-Net and a Superpixel-Based Conditional Random Field Model. *IEEE Geoscience and Remote Sensing Letters*, *16*(4), 618–622.

Fernandez-Moral, E., Martins, R., Wolf, D., & Rives, P. (2018). A New Metric for Evaluating Semantic Segmentation: Leveraging Global and Contour Accuracy. *IEEE Intelligent Vehicles Symposium, Proceedings*, *2018-June*, 1051–1056.

Filonenko, A., Wahyono, Hernandez, D. C. C., Seo, D., & Jo, K. H. (2015). Real-time flood detection for video surveillance. *IECON 2015 - 41st Annual Conference of the IEEE Industrial Electronics Society*, 4082–4085.

FloodList. (2017a). *Malaysia – 25,000 Evacuate Floods in Terengganu and Kelantan*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-floods-terengganu-kelantan-january-2017

FloodList. (2017b). *Malaysia – Severe Storm and Floods Leave 7 Dead, 10,000 Displaced*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-penang-kedah-floods-november-2017

FloodList. (2017c). *Malaysia – Thousands Displaced by Floods in Kelantan and Terengganu*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-floods-kelantan-terengganu-november-2017

FloodList. (2018a). *Malaysia – Floods Worsen Leaving 2 Dead and 12,000 Evacuated*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-floods-worsen-january-2018

FloodList. (2018b). *Malaysia – Thousands Evacuated After Floods in Sarawak State*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-sarawak-february-2018

FloodList. (2019a). *Malaysia – 2 Dead, 15,000 Displaced as Floods Worsen in Kelantan and Terengganu*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-floods-kelantan-terengganu-december-2019

FloodList. (2019b). *Malaysia – Evacuations After Floods in Sarawak*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-floods-sarawak-june-2019

FloodList. (2019c). *Malaysia – Thousands Evacuate After Second Wave of Floods in Johor*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-floods-johor-december-2019-2

FloodList. (2019d). *Malaysia and Thailand – Thousands Displaced After Second Wave of Floods*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-thailand-floods-december-2019

FloodList. (2020a). *Malaysia – 1,000 Evacuate Flooded Homes in Johor*. Retrieved 1 July 2021 from http://floodlist.com/asia/malaysia-floods-johor-june-2020

FloodList. (2020b). Retrieved 1 July 2021 from *Malaysia – Hundreds Displaced by Floods in Sabah*. http://floodlist.com/asia/malaysia-floods-sabah-october-2020

FloodList. (2020c). Retrieved 1 July 2021 from *Malaysia – Thousands Evacuate Floods in Kelantan, Terengganu and Pahang*. http://floodlist.com/asia/malaysia-floods-kelantan-terengganu-pahang-december-2020

Fu, G., Liu, C., Zhou, R., Sun, T., & Zhang, Q. (2017). Classification for high resolution remote sensing imagery using a fully convolutional network. *Remote Sensing*, *9*(5), 1–21.

Garcia-Garcia, A., Orts-Escolano, S., Oprea, S., Villena-Martinez, V., & Garcia-Rodriguez, J. (2017). *A Review on Deep Learning Techniques Applied to Semantic Segmentation*. 1–23. arXiv preprint arXiv:1704.06857.

Gašparovič, M., & Klobučar, D. (2021). Mapping floods in lowland forest using sentinel-1 and sentinel-2 data and an object-based approach. *Forests*, *12*(5).

Gebrehiwot, A., Hashemi-Beni, L., Thompson, G., Kordjamshidi, P., & Langan, T. E. (2019). Deep convolutional neural network for flood extent mapping using unmanned aerial vehicles data. *Sensors (Switzerland)*, *19*(7).

Geetha, M., Manoj, M., Sarika, A. S., Mohan, M., & Rao, S. N. (2017). Detection and estimation of the extent of flood from crowd sourced images. *2017 International Conference on Communication and Signal Processing (ICCSP)*, 603–608.

Giannakeris, P., Avgerinakis, K., Karakostas, A., Vrochidis, S., & Kompatsiaris, I. (2018). People and Vehicles in Danger - A Fire and Flood Detection System in Social Media. *2018 IEEE 13th Image, Video, and Multidimensional Signal Processing Workshop, IVMSP 2018 - Proceedings*, 1–5.

Gibson, E., Li, W., Sudre, C., Fidon, L., Shakir, D. I., Wang, G., Eaton-Rosen, Z., Gray, R., Doel, T., Hu, Y., Whyntie, T., Nachev, P., Modat, M., Barratt, D.

C., Ourselin, S., Cardoso, M. J., & Vercauteren, T. (2018). NiftyNet: a deep-learning platform for medical imaging. *Computer Methods and Programs in Biomedicine*, *158*, 113–122.

Gilmore, T. E., Birgand, F., & Chapman, K. W. (2013). Source and magnitude of error in an inexpensive image-based water level measurement system. In *Journal of Hydrology*, 496, 178–186.

Guillén, N. F., Patalano, A., García, C. M., & Bertoni, J. C. (2017). Use of LSPIV in assessing urban flash flood vulnerability. *Natural Hazards*, *87*(1), 383–394.

Halfawy, M. R., & Hengmeechai, J. (2014). Efficient Algorithm for Crack Detection in Sewer Images from Closed-Circuit Television Inspections. *Journal of Infrastructure Systems*, *20*(2), 04013014.

Hammond, M. J., Chen, A. S., Djordjević, S., Butler, D., & Mark, O. (2015). Urban flood impact assessment: A state-of-the-art review. *Urban Water Journal*, *12*(1), 14–29.

Haris, K., Efstratiadis, S. N., Maglaveras, N., & Katsaggelos, A. K. (1998). Hybrid image segmentation using watersheds and fast region merging. *IEEE Transactions on Image Processing*, *7*(12), 1684–1699.

Hasanzadeh Nafari, R., Ngo, T., & Lehman, W. (2016). Calibration and validation of FLFArs-A new flood loss function for Australian residential structures. *Natural Hazards and Earth System Sciences*, *16*(1), 15–27.

Hassaballah, M., & Awad, A. I. (2020). *Deep Learning in Computer Vision: Principles and Applications*. Taylor & Francis Group.

Havinga, H., Roovers, G., Stamm, J., & Fischenich, C. (2006). Sustainable waterways within the context of navigation and flood management. *Floods, from Defence to Management: Symposium Proceedings of the 3rd International Symposium on Flood Defence, Nijmegen, The Netherlands, 25-27 May 2005,* 360.

Hawari, A., Alamin, M., Alkadour, F., Elmasry, M., & Zayed, T. (2018). Automated defect detection tool for closed circuit television (cctv) inspected sewer pipelines. *Automation in Construction*, *89*, 99–109.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.

Hsu, S.-Y. Y., Chen, T.-B. B., Du, W.-C. C., Wu, J.-H. H., & Chen, S.-C. C. (2019). Integrate Weather radar and monitoring devices for urban flooding surveillance. *Sensors (Switzerland)*, *19*(4), 1–15.

Ichihashi, H., Notsu, A., Honda, K., Katada, T., & Fujiyoshi, M. (2009). Vacant parking space detector for outdoor parking lot by using surveillance camera and FCM classifier. *IEEE International Conference on Fuzzy Systems*, 127–134.

IFRC. (2021). *Emergency Plan of Action (EPoA) Malaysia : Floods* (Issue January).

Isikdogan, F., Bovik, A. C., & Passalacqua, P. (2017). Surface water mapping by deep learning. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *10*(11), 4909–4918.

Jaafar, H. (2022). DBKL Bakal Gunakan 4,000 Kamera CCTV Bagi Mengesan Banjir Di Kawasan Berpotensi. *Vocket Tech*. Retrieved 25 March 2022 from https://vocket.tech/dbkl-bakal-gunakan-4000-kamera-cctv-bagi-mengesan-banjir-di-kawasan-berpotensi/

Jacquier, P., Abdedou, A., & Soulaïmani, A. (2019). Reduced-Order Flood Modeling Using Uncertainty-Aware Deep Neural Networks. *Journal of Computational Physics*, *384*, 289–307.

Jaehyoung, Y. U., & Hernsoo, H. (2010). Remote detection and monitoring of a water level using narrow band channel. *Journal of Information Science and Engineering*, *26*(1), 71–82.

Jafari, N. H., Li, X., Chen, Q., Le, C. Y., Betzer, L. P., & Liang, Y. (2021). Real-time water level monitoring using live cameras and computer vision techniques. *Computers and Geosciences*, *147*, 104642.

Jie Feng, Wei, Y., Tao, L., Chao Zhang, & Sun, J. (2011). Salient object detection by composition. *2011 International Conference on Computer Vision*, 1028–1035.

Jonkman, S. N., Vrijling, J. K., & Vrouwenvelder, A. C. W. M. (2008). Methods for the estimation of loss of life due to floods: A literature review and a proposal for a new method. *Natural Hazards*, *46*(3), 353–389.

Jyh-Horng, W., Chien-Hao, T., Lun-Chi, C., Shi-Wei, L., & Fang-Pang, L. (2015). Automated Image Identification Method for Flood Disaster Monitoring In Riverine Environments: a Case Study in Taiwan. *AASRI International Conference on Industrial Electronics and Applications (IEA 2015)*, 27–28.

Kaljahi, M. A., Palaiahnakote, S., Anisi, M. H., Idris, M. Y. I., Blumenstein, M., & Khan, M. K. (2019). A scene image classification technique for a ubiquitous visual surveillance system. *Multimedia Tools and Applications*, *78*(5), 5791–5818.

Kang, W. X., Yang, Q. Q., & Liang, R. P. (2009). The comparative research on image segmentation algorithms. *Proceedings of the 1st International Workshop on Education Technology and Computer Science*, *2*, 703–707.

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

Kaur, A., & Singh, N. (2014). Region Growing and Object Extraction Techniques. *International Journal of Science and Research (IJSR)*, *3*(10), 712–715.

Kaur, D., & Kaur, Y. (2014). Various Image Segmentation Techniques: A Review. *International Journal of Computer Science and Mobile Computing*, *3*(5), 809–814.

Khan, S., Muhammad, K., Hussain, T., Ser, J. Del, Cuzzolin, F., Bhattacharyya, S., Akhtar, Z., & de Albuquerque, V. H. C. (2021). DeepSmoke: Deep learning model for smoke detection and segmentation in outdoor environments. *Expert Systems with Applications*, *182*, 115125.

Kim, K., & Davis, L. S. (2011). Object detection and tracking for intelligent video surveillance. *Studies in Computational Intelligence*, *346*, 265–288.

Kim, Y., Park, H., Lee, C., Kim, D., & Seo, M. (2013). Development of a Cloud-based Image Water Level Gauge. In *IT Converg. Pract. (INPRA)*, *2*(1), 22-29.

Lai, C. L., Yang, J. C., & Chen, Y. H. (2007). A real time video processing based surveillance system for early fire and flood detection. *2007 IEEE Instrumentation & Measurement Technology Conference IMTC 2007*, 1–6.

Lankton, S., Nain, D., Yezzi, A., & Tannenbaum, A. (2007). Hybrid geodesic region-based curve evolutions for image segmentation. *Medical Imaging 2007: Physics of Medical Imaging*, *6510*, 65104U.

Layek, A. K., Poddar, S., & Mandal, S. (2019). Detection of flood images posted on online social media for disaster response. *2019 2nd International Conference on Advanced Computational and Communication Paradigms, ICACCP 2019*, 0–5.

LeCun, Y., & others. (1989). Generalization and network design strategies. *Connectionism in Perspective*, *19*, 143–155.

Li, Y., Martinis, S., & Wieland, M. (2019). Urban flood mapping with an active self-learning convolutional neural network based on TerraSAR-X intensity and interferometric coherence. *ISPRS Journal of Photogrammetry and Remote Sensing*, *152*, 178–191.

Li, Z., Wang, R., Zhang, W., Hu, F., & Meng, L. (2019). Multiscale features supported deeplabv3+ optimization scheme for accurate water semantic segmentation. *IEEE Access*, *7*, 155787–155804.

Liu, L., Liu, Y., Wang, X., Yu, D., Liu, K., Huang, H., & Hu, G. (2015). Developing an effective 2-D urban flood inundation model for city emergency management based on cellular automata. *Natural Hazards and Earth*

System Sciences, *15*(3), 381–391.

Lo, S.-W. W., Wu, J.-H. H., Lin, F.-P. P., & Hsu, C.-H. H. (2015). Cyber surveillance for flood disasters. *Sensors (Switzerland)*, *15*(2), 2369–2387.

Lo, S. W., Wu, J. H., Chen, L. C., Tseng, C. H., & Lin, F. P. (2014). Flood tracking in severe weather. *Proceedings - 2014 International Symposium on Computer, Consumer and Control, IS3C 2014*, *27*, 27–30.

Lo, S. W., Wu, J. H., Chen, L. C., Tseng, C. H., Lin, F. P., & Hsu, C. H. (2016). Uncertainty comparison of visual sensing in adverse weather conditions. *Sensors (Switzerland)*, *16*(7), 1–18.

Lo, S. W., Wu, J. H., Lin, F. P., & Hsu, C. H. (2015). Visual sensing for urban flood monitoring. *Sensors (Switzerland)*, *15*(8), 20006–20029.

Lopez-Fuentes, L., Rossi, C., & Skinnemoen, H. (2017). River segmentation for flood monitoring. *Proceedings - 2017 IEEE International Conference on Big Data, Big Data 2017*, 3746–3749.

Lopez-Fuentes, L., van de Weijer, J., González-Hidalgo, M., Skinnemoen, H., & Bagdanov, A. D. (2018). Review on computer vision techniques in emergency situations. *Multimedia Tools and Applications*, *77*(13), 17069–17107.

Marin-Perez, R., García-Pintado, J., & Gómez, A. S. (2012). A real-time measurement system for long-life flood monitoring and warning applications. *Sensors*, *12*(4), 4213–4236.

Martin, D. R., Fowlkes, C. C., & Malik, J. (2004). Learning to detect natural image boundaries using local brightness, color, and texture cues. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *26*(5), 530–549.

Martinis, S., Kuenzer, C., Wendleder, A., Huth, J., Twele, A., Roth, A., & Dech, S. (2015). Comparing four operational SAR-based water and flood detection approaches. *International Journal of Remote Sensing*, *36*(13), 3519–3543.

Martinis, S., Twele, A., & Voigt, S. (2009). Towards operational near real-time flood detection using a split-based automatic thresholding procedure on high resolution TerraSAR-X data. *Natural Hazards and Earth System Science*, *9*(2), 303–314.

Mason, D. C., Davenport, I. J., Neal, J. C., Schumann, G. J. P., & Bates, P. D. (2012). Near real-time flood detection in urban and rural areas using high-resolution synthetic aperture radar images. *IEEE Transactions on Geoscience and Remote Sensing*, *50*(8), 3041–3052.

Matgen, P., Hostache, R., Schumann, G., Pfister, L., Hoffmann, L., & Savenije,

H. H. G. (2011). Towards an automated SAR-based flood monitoring system: Lessons learned from two case studies. *Physics and Chemistry of the Earth*, *36*(7–8), 241–252.

Merz, B., Kreibich, H., Thieken, A., Schmidtke, R., & Hydrology, S. E. (2004). Estimation uncertainty of direct monetary flood damage to buildings. *Natural Hazards and Earth System Sciences*, *4*, 153–163.

Mohamed, S., Ebenehi, I. Y., Adaji, A., Seow, T. W., Chan, N. W., Goh, K. C., & Abd Rahim, M. H. I. (2017). Impacts of flood on children and adults' health and ways to sustainable development. *IOP Conference Series: Materials Science and Engineering*, *271*(1).

Molinari, D., De Bruijn, K. M., Castillo-Rodríguez, J. T., Aronica, G. T., & Bouwer, L. M. (2019). Validation of flood risk models: Current practice and possible improvements. *International Journal of Disaster Risk Reduction*, *33*(May 2018), 441–448.

Mooney, J. G., & Johnson, E. N. (2014). Image Segmentation for Fruit Detection and Yield Estimation in Apple Orchards. *Journal of Field Robotics*, *33*(1), 1–17.

Moy de Vitry, M., Kramer, S., Wegner, J. D., & Leitão, J. P. (2019). Scalable Flood Level Trend Monitoring with Surveillance Cameras using a Deep Convolutional Neural Network. *Hydrology and Earth System Sciences Discussions*, 1–21.

Narayanan, R., Lekshmy, V. M., Rao, S., & Sasidhar, K. (2014). A novel approach to urban flood monitoring using computer vision. *5th International Conference on Computing Communication and Networking Technologies, ICCCNT 2014*, 1–7.

Nascimento, D. V., Galvão Filho, A. R., Fleury, G. R. D. O., Carvalho, R. V., Ribeiro, F. de S. L., & Coelho, C. J. (2021). *Automatic measurement of river water-level using image-based computer vision*. 1–8.

Nilsson, N. J. (1998). *Artificial intelligence: a new synthesis*. Morgan Kaufmann.

Ning, H., Li, Z., Hodgson, M. E., & Wang, C. (2020). Prototyping a social media flooding photo screening system based on deep learning. *ISPRS International Journal of Geo-Information*, *9*(2).

Nogueira, K., Fadel, S. G., Dourado, I. C., De Werneck, R. O., Munoz, J. A. V., Penatti, O. A. B., Calumby, R. T., Li, L. T., Dos Santos, J. A., & Torres, R. D. S. (2018). Exploiting ConvNet diversity for flooding identification. *IEEE Geoscience and Remote Sensing Letters*, *15*(9), 1446–1450.

Nyma, A., Kang, M., Kwon, Y. K., Kim, C. H., & Kim, J. M. (2012). A hybrid technique for medical image segmentation. *Journal of Biomedicine and Biotechnology*, *2012*.

O'Mahony, N., Campbell, S., Carvalho, A., Harapanahalli, S., Hernandez, G. V., Krpalkova, L., Riordan, D., & Walsh, J. (2019). Deep Learning vs. Traditional Computer Vision. In *Advances in Computer Vision* (Vol. 1, pp. 128–144). Springer Nature.

Oddo, P. C., & Bolten, J. D. (2019). The Value of Near Real-Time Earth Observations for Improved Flood Disaster Response. *Frontiers in Environmental Science*, *7*, 1–11.

Pan, J., Yin, Y., Xiong, J., Luo, W., Gui, G., & Sari, H. (2018). Deep learning-based unmanned surveillance systems for observing water levels. *IEEE Access*, *6*, 73561–73571.

Pashaei, M., Kamangir, H., Starek, M. J., & Tissot, P. (2020). Review and evaluation of deep learning architectures for efficient land cover mapping with UAS hyper-spatial imagery: A case study over a wetland. *Remote Sensing*, *12*(6).

Popescu, D., Ichim, L., & Caramihale, T. (2015). Flood areas detection based on UAV surveillance system. *2015 19th International Conference on System Theory, Control and Computing, ICSTCC 2015 - Joint Conference SINTES 19, SACCS 15, SIMSIS 19*, 753–758.

Popescu, D., Ichim, L., & Stoican, F. (2017). Unmanned aerial vehicle systems for remote estimation of flooded areas based on complex image processing. *Sensors (Switzerland)*, *17*(3).

Rahnemoonfar, M., Chowdhury, T., Sarkar, A., Varshney, D., Yari, M., & Murphy, R. R. (2021). FloodNet: A High Resolution Aerial Imagery Dataset for Post Flood Scene Understanding. *IEEE Access*, *9*, 89644–89654.

Raymond, S. T. L. (2020). *Artificial Intelligence in Daily Life*. Springer Singapore.

Sakaino, H. (2016). Camera-Vision-Based Water Level Estimation. *IEEE Sensors Journal*, *16*(21), 7564–7565.

Sarshar, N., & Halfawy, M. (2014). *Video Processing Techniques for Assisted CCTV Inspection and Condition Rating of Sewers Cloud-based Scalable Software for Optimal Long-Range Network-Level Bridge Improvement Programming View project Software for Automated Defect Detection in Sewer Closed* . 1–20.

Sghaier, M. O., Hammami, I., Foucher, S., & Lepage, R. (2018). Flood extent mapping from time-series SAR images based on texture analysis and data fusion. *Remote Sensing*, *10*(2), 1–30.

Shaari, M. S. M., Abd Karim, M. Z., & Hasan-Basri, B. (2017). Does flood disaster lessen GDP growth? Evidence from Malaysia's manufacturing and agricultural sectors. *Malaysian Journal of Economic Studies*, *54*(1), 61–81.

Sharma, N., Mishra, M., & Shrivastava, M. (2012). Colour Image Segmentation Techniques and Issues: an Approach. *International Journal of Scientific & Technology Research*, *1*(4), 9–12.

Silveira, M., & Heleno, S. (2009). Separation between water and land in sar images using region-based level sets. *IEEE Geoscience and Remote Sensing Letters*, *6*(3), 471–475.

Soomro, S., Munir, A., & Choi, K. N. (2018). Hybrid two-stage active contour method with region and edge information for intensity inhomogeneous image segmentation. *PLoS ONE*, *13*(1), 1–20.

Spearman, C. (1904). The Proof and Measurement of Association between Two Things. *The American Journal of Psychology*, *15*(1), 72–101.

Spirkovska, L. (1993). A Summary of Image Segmentation Techniques. In *NASA Technical Memorandum, 104022*. Ames Research Center.

Steccanella, L., Bloisi, D. D., Castellini, A., & Farinelli, A. (2020). Waterline and obstacle detection in images from low-cost autonomous boats for environmental monitoring. *Robotics and Autonomous Systems*, *124*, 103346.

Su, T. C., Yang, M. Der, Wu, T. C., & Lin, J. Y. (2011). Morphological segmentation based on edge detection for sewer pipe defects on CCTV images. *Expert Systems with Applications*, *38*(10), 13094–13114.

Sun, M., Zhang, G., Dang, H., Qi, X., Zhou, X., & Chang, Q. (2019). Accurate Gastric Cancer Segmentation in Digital Pathology Images Using Deformable Convolution and Multi-Scale Embedding Networks. *IEEE Access*, *7*, 75530–75541.

Talal, M., Panthakkan, A., Mukhtar, H., Mansoor, W., Almansoori, S., & Ahmad, H. Al. (2019). Detection of Water-Bodies Using Semantic Segmentation. *2018 International Conference on Signal Processing and Information Security, ICSPIS 2018*, 2018–2021.

Tapu, R., Mocanu, B., & Zaharia, T. (2017). DEEP-SEE: Joint Object Detection, Tracking and Recognition with Application to Visually Impaired Navigational Assistance. *Sensors*, *17*(11), 2473.

Thayammal, S., Jayaraghavi, R., Priyadarsini, S., & Selvathi, D. (2021). Analysis of Water Body Segmentation from Landsat Imagery using Deep Neural Network. *Wireless Personal Communications*, *0123456789*.

Thenkabail, P. S. (2015). *Remote sensing of water resources, disasters, and urban studies*. CRC Press.

Tong, X. Y., Xia, G. S., Lu, Q., Shen, H., Li, S., You, S., & Zhang, L. (2020). Land-cover classification with high-resolution remote sensing images using transferable deep models. *Remote Sensing of Environment*, *237*(June 2019), 111322.

Torres, D. L., Feitosa, R. Q., Happ, P. N., La Rosa, L. E. C., Junior, J. M., Martins, J., Bressan, P. O., Gonçalves, W. N., & Liesenberg, V. (2020). Applying fully convolutional architectures for semantic segmentation of a single tree species in urban environment on high resolution UAV optical imagery. *Sensors (Switzerland)*, *20*(2), 1–20.

Torres, D. L., Feitosa, R. Q., La Rosa, L. E. C., Happ, P. N., Marcato Junior, J., Gonçalves, W. N., Martins, J., & Liesenberg, V. (2020). Semantic segmentation of endangered tree species in Brazilian savanna using DEEPLABV3+ variants. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives*, *42*(3/W12), 355–360.

Tran, T., Kwon, O. H., Kwon, K. R., Lee, S. H., & Kang, K. W. (2019). Blood Cell Images Segmentation using Deep Learning Semantic Segmentation. *2018 IEEE International Conference on Electronics and Communication Engineering, ICECE 2018*, 13–16.

Tschentscher, M., & Neuhausen, M. (2012). Video-based parking space detection. *Proceedings of the Forum Bauinformatik*, *2007*, 159–166.

Tsubaki, R., Fujita, I., & Tsutsumi, S. (2011). Measurement of the flood discharge of a small-sized river using an existing digital video recording system. *Journal of Hydro-Environment Research*, *5*(4), 313–321.

UNDRR. (2020a). 2020 Global Natural Disaster Assessment Report. In *UN Annual Report*. China.

UNDRR. (2020b). *Disaster Risk Reduction in Malaysia Disaster: Status Report 2020*. China

Vandaele, R., Dance, S. L., & Ojha, V. (2021a). Automated Water Segmentation and River Level Detection on Camera Images Using Transfer Learning. *Lecture Notes in Computer Science*, *12544 LNCS*, 232–245.

Vandaele, R., Dance, S. L., & Ojha, V. (2021b). Deep learning for the estimation of water-levels using river cameras. *Hydrology and Earth System Sciences Discussions*, 1–28.

Varfolomeev, I., Yakimchuk, I., & Safonov, I. (2019). An Application of Deep Neural Networks for Segmentation of Microtomographic Images of Rock Samples. *Computers*, *8*(4), 72.

Vinet, L., & Zhedanov, A. (2011). A ‘missing’ family of classical orthogonal polynomials. *Journal of Physics A: Mathematical and Theoretical*, *44*(8), 085201.

Waldner, F., & Diakogiannis, F. I. (2020). Deep learning on edge: Extracting field boundaries from satellite images with a convolutional neural network. *Remote Sensing of Environment*, *245*, 111741.

Wan, L., Liu, M., Wang, F., Zhang, T., & You, H. J. (2019). Automatic extraction of flood inundation areas from SAR images: a case study of Jilin, China during the 2017 flood disaster. *International Journal of Remote Sensing*, *40*(13), 5050–5077.

Wang, L., Zhang, J., Liu, P., Choo, K.-K. R., & Huang, F. (2017). Spectral–spatial multi-feature-based deep learning for hyperspectral remote sensing image classification. *Soft Computing*, *21*(1), 213–221.

Wang, R. (2013). 3D building modeling using images and LiDAR: a review. In *International Journal of Image and Data Fusion*, *4*(4), 273–292.

Wang, R. Q., Mao, H., Wang, Y., Rae, C., & Shaw, W. (2018). Hyper-resolution monitoring of urban flooding with social media and crowdsourcing data. *Computers and Geosciences*, *111*, 139–147.

Wang, X. G., Jiang, A. H., Dai, J., Wang, Z. W., Zhang, S. N., & Guo, X. R. (2021). Flood Monitoring in Weifang City, Shandong Province based on Sentinel-1A SAR. *IOP Conference Series: Earth and Environmental Science*, *658*(1).

Ward, R. C. (1978). Floods: a geographical perspective. In *Macmillan Press, London*. Macmillan Press.

Warwick, K. (2012). *Artificial Intelligence: The Basics*. Taylor & Francis Group.

Witherow, M. A., Sazara, C., Winter-Arboleda, I. M., Elbakary, M. I., Cetin, M., & Iftekharuddin, K. M. (2018). Floodwater detection on roadways from crowdsourced images. *Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization*, *1163*, 1–12.

Yang, J. C., & Lai, C. L. (2008). Vision based fire/flood alarm surveillance system via robust detection strategy. *Conference Record - IEEE Instrumentation and Measurement Technology Conference*, 1085–1090.

Yu, L., Wang, Z., Tian, S., Ye, F., Ding, J., & Kong, J. (2017). Convolutional Neural Networks for Water Body Extraction from Landsat Imagery. *International Journal of Computational Intelligence and Applications*, *16*(1), 1–12.

Yuan, Q., Shen, H., Li, T., Li, Z., Li, S., Jiang, Y., Xu, H., Tan, W., Yang, Q., Wang, J., Gao, J., & Zhang, L. (2020). Deep learning in environmental remote sensing: Achievements and challenges. *Remote Sensing of Environment*, *241*, 111716.

Zawadzka, J., Truckell, I., Khouakhi, A., & Rivas Casado, M. (2021). Detection of flood damage in urban residential areas using object-oriented uav image analysis coupled with tree-based classifiers. *Remote Sensing*, *13*(19).

Zhang, Q., Jindapetch, N., Duangsoithong, R., & Buranapanichkit, D. (2018). Investigation of Image Processing based Real-time Flood Monitoring. *2018 IEEE 5th International Conference on Smart Instrumentation, Measurement and Application (ICSIMA)*, *November*, 1–4.

Zhao, Z. Q., Zheng, P., Xu, S. T., & Wu, X. (2017). Object Detection With Deep Learning: A Review. *IEEE Transactions on Neural Networks and Learning Systems*, *14*(8), 3212–3232.

Zhou, S., Kan, P., Silbernagel, J., & Jin, J. (2020). Application of Image Segmentation in Surface Water Extraction of Freshwater Lakes using Radar Data. *ISPRS International Journal of Geo-Information*, *9*(7).