Available Online at www.ijcsmc.com

International Journal of Computer Science and Mobile Computing

A Monthly Journal of Computer Science and Information Technology

ISSN 2320–088X
IMPACT FACTOR: 6.199

IJCSMC, Vol. 8, Issue. 7, July 2019, pg.27 – 32

Automated Bell Pepper Harvesting using Robotic Vision System

Silpa Ajith Kumar[1]; Nikhila.S[2]; J. Satheesh Kumar[3]

[1]Department of Electronics & Instrumentation Engineering, Dayananda Sagar College of Engineering, India
[2]Department of Electronics & Instrumentation Engineering, Dayananda Sagar College of Engineering, India
[3]Department of Electronics & Instrumentation Engineering, Dayananda Sagar College of Engineering, India

[1] silpaajithkumar@gmail.com; [2] nikhilamsrit@gmail.com; [3] jsatheeshngl@gmail.com

Abstract— In recent years automatic vision based technology has become important to many areas including agricultural fields and food industry. Robotic harvesting offers an attractive solution to reducing labour costs while enabling more regular and selective harvesting techniques. The automation technology used in harvesting the yellow bell pepper makes use of open source computer vision platform to detect the crop amidst the foliage using various image processing techniques and send appropriate signals to move the robot to harvest the crop. The web camera feeds real time images to the microcontroller where the digital image is filtered to remove noise and subjected to various feature extraction such as colour detection and size determination and the processed image is displayed over the internet .The detected bell pepper can be harvested by moving the robot with appropriate commands sent over a web application which serves as a communication platform between the user and the robot interfaced using the Bluetooth module.
Keywords— Agriculture automation, Bell pepper harvesting, Computer vision, Robotic vision system

I. Introduction

The horticulture industry remains heavily reliant on manual labour, and as such is highly affected by labour costs. In Australia, harvesting labour costs in 2013-14 accounted for 20% to 30% of total production costs [1]. These costs along with other pressures such as scarcity of skilled labour and volatility in production due to uncertain weather events is putting profit margins for farm enterprises under tremendous pressure. A potential solution to this problem can be provided by robotic harvesting by reducing the costs of labour and increasing fruit quality. For these reasons, there has been growing interest in the use of agricultural robots for harvesting fruit and vegetables over the past three decades [2, 3]. The development of such platforms includes numerous challenging tasks, such as manipulation and picking. However, the development of an accurate fruit detection system is a crucial step toward fully-automated harvesting robots, as this is the front-end perception system before subsequent manipulation and grasping systems; if fruit is not detected or seen, it cannot be picked.

The current scenario of increasing population, losses in handling, processing and the increased expectation of food products of high quality and safety standards calls for the need of accurate, fast and objective quality determination of food and agricultural products. Agriculture is one of the largest economic sectors and it plays the major role in economic development of our country. In our country the ever-increasing population, losses involved in processing and the increasing demand of fruits of high quality with good appearance, there is a need for the development of accurate, fast and focused quality determination of food and agricultural products like fruits and vegetables. Whereas grading is done based on the overall quality features of fruits by considering a number of attributes like shape, size, colour etc. Fresh market fruits like apples, oranges and banana are graded into categories based on several factors such as colour, shape, size and presence defects or bruises, blemishes on it. Fruit market is getting highly selective, requiring their suppliers to distribute the fruits of high standards of quality and presentation as well. So there is an increasing need to supply quality fruits within a short period of time has given rise to the development of automated grading of fruits to improve the quality. As the major source of national income is from agriculture, it becomes the backbone of every countries economy. If the overall production is good then it will directly increase the annual income of the cultivators and ultimately the national income of the country.

With the development of image processing technology and computer software and hardware, it is feasible to detect fruits quality by using vision detecting technology. Image processing is a form of information processing for which the input is a digital image, such as photographs or frames of video; the output is not necessarily an image, but can be for instance a set of features of the image. Most image-processing techniques involve treating the image as a two-dimensional signal and applying standard signal processing techniques to it. A pixel, short for picture element, is a dot that contains information about the picture. Whenever a picture is acquired, these tiny bits of information are gathered by the camera's sensor. The information is being stored in a 3 plane of information. Each plane represents three colours that are red, green and yellow plane. Each plane has the intensity from 0 up to 255 or 8-bit of information per plane. These three colour combination makes up all the colour we could see in an RGB images. Generally, the quality of fruit shape, colour and size can be evaluated using various image processing techniques thereby bringing a paradigm shift in replacing the traditional methods. The technology is developing rapidly, not only advancing the production capabilities of farmers but also advancing robotics and automation technology.

II. LITERATURE SURVEY

Although many researchers have tackled the problem of fruit detection, such as the works presented in [4–9], the problem of creating a fast and reliable fruit detection system persists, as found in the survey by [10]. This is due to high variation in the appearance of the fruits in field settings, including colour, shape, size, texture and reflectance properties. Furthermore, in the majority of these settings, the fruits are partially abstracted and subject to continually-changing illumination and shadow conditions.

Halstead et al. [11] developed a robotic vision system which works on the Faster RCNN Frame Work. However the limitation with vision only system is witnessed in the tracking system which relies on accurate detections and the results was 4.1% of the visual ground truth. When applied to small juvenile fruit, which are visually very small, this leads to errors in the estimate of fruit present.

C. Lehnert et al [12], implemented an autonomous harvesting system that can autonomously harvest sweet pepper in protected cropping environments. The approach combines effective vision algorithms with a novel end-effector to enable successful harvesting of sweet peppers. The main limitation to this approach occurred during the detachment stage wherein obstructions from leaves or strings caused 40% of the detachment stages and also the suction cup collided with the obstructions causing the tool to separate prematurely The most common detachment failure was found to be the cutting tool missing either side of the peduncle. In this work the cutting point was calculated by assuming the peduncle protrudes vertically from the centre of the sweet pepper. This assumption occasionally breaks since some sweet peppers have peduncles that do not grow vertically. To improve the detachment reliability, future work can be aimed not only at detecting sweet peppers, but also at detecting the peduncle.

S. T. Nuske et al [3] discusses about the development of a system based on computer vision that can provide high resolution automated crop yield estimation for vineyard management. The algorithm is designed to detect and count crop images collected from the camera and combine the measurements of clusters per vine and berries per cluster, with a single estimate of berries per vine. The image detection can detect berries of all colours, even those that are similarly coloured to the background of leaves.

A pixel-level segmentation approach for object detection has been adopted in all of the above-mentioned works, and most of these works have examined fruit detection predominantly for yield estimation [4, 8]. The limited studies that have conducted accurate fruit detection have done so for fruits in controlled glasshouse environments. As such, the issue of fruit detection in highly challenging conditions remains unsolved. This is due to the high variability in the appearance of the target objects in the agricultural settings, which meant that the classic methods of sliding window approaches, although showing good performance when tested on datasets of selected images [13], cannot handle the variability in scale and appearance of the target objects when deployed in real farm settings.

Recently, deep neural networks have made considerable progress in object classification and detection [14,15,16]. The state-of-the-art detection framework on PASCAL-VOC [17] consists of two stages. The first stage of the pipeline applies a region proposal method, such as selective search [18] and edge box [19] to extract regions of interest from an image and then feed them to a deep neural network for classification. Although it has high recall performance, this pipeline is computationally expensive, which prevents it from being used in real time for a robotic application. Region Proposal Networks (RPNs) [20–22] solve this problem by combining a classification deep convolutional network with the object proposal network, so the system can simultaneously predict object bounds and classify them at each position, the parameters of the two networks are shared, which results in a much faster performance , making it suitable for robotic applications.

III.METHODOLOGY

The integration of Internet of Things in the field of agriculture provides an opportunity to revolutionize the age-old practices of farming-from sowing to harvesting. The automation technology used in harvesting the yellow bell pepper makes use of open source computer vision platform to detect the crop amidst the foliage using various image processing techniques and send appropriate signals to move the robot to harvest the crop.

The web camera on the robot takes a real-time image of the cultivation and sends the frame to the Raspberry Pi B+ microcontroller wherein the image is subjected to a sequence of image processing techniques as per the code embedded within the microcontroller. The code is written using Python Software and Open Source Computer Vision platform. Various library packages in the open cv allows to process the image captured in frames and extract various features that helps the user to identify the crop using pre-specified color range values to differentiate the yellow bell-pepper from the leaves of the plant.

Before the captured image is processed to extract features, the frame is first filtered to remove any Gaussian noise in the digital image .Gaussian noise in digital images arise during acquisition e.g. sensor noise caused by poor illumination and/or high temperature, and/or transmission e.g. electronic circuit noise. In digital image processing Gaussian noise can be reduced using a spatial filter. Each pixel in the image is convoluted with the kernel of the filter to remove the noise embedded in the Image. When smoothing an image, an undesirable outcome may result in the blurring of fine-scaled image edges and details because they also correspond to blocked high frequencies hence the filtered image is subjected to morphological transformations to restore the quality of the image.

The image is converted from BGR colour Space to HSV colour Space and the upper and lower limits of the colour that has to be detected is incorporated within the code, any colour within the specified range is detected and the estimation of the size is carried out using edge detection and an circle with the appropriate radius is drawn over the object of interest. The processed image is sent over the Wi fi to centralized system and the user can decide to harvest the crop. Once the user decides to harvest the crop he/she can man oeuvre the bot using the blue tooth module attached to the Bot. A specially designed Web-Application allows the user to connect the Bot and to send commands to the Bot .The transmitted commands on receiving are further transmitted to the Arduino microcontroller .The microcontroller then sends out the necessary signals to the interfaced motor driver which controls the movement of the wheels. The Bot can then be moved to the location of the crop and further the gripper of the bot can be enabled to move and cut the fruit from the peduncle. This allows the farmer to completely automate the harvesting process.

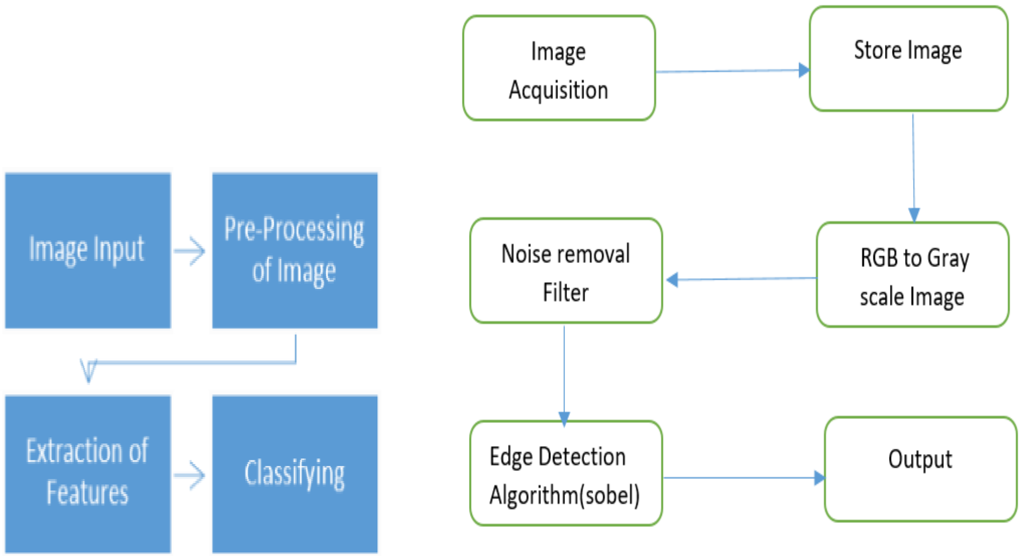

Figure 1: Block Diagram of image analysis and image processing

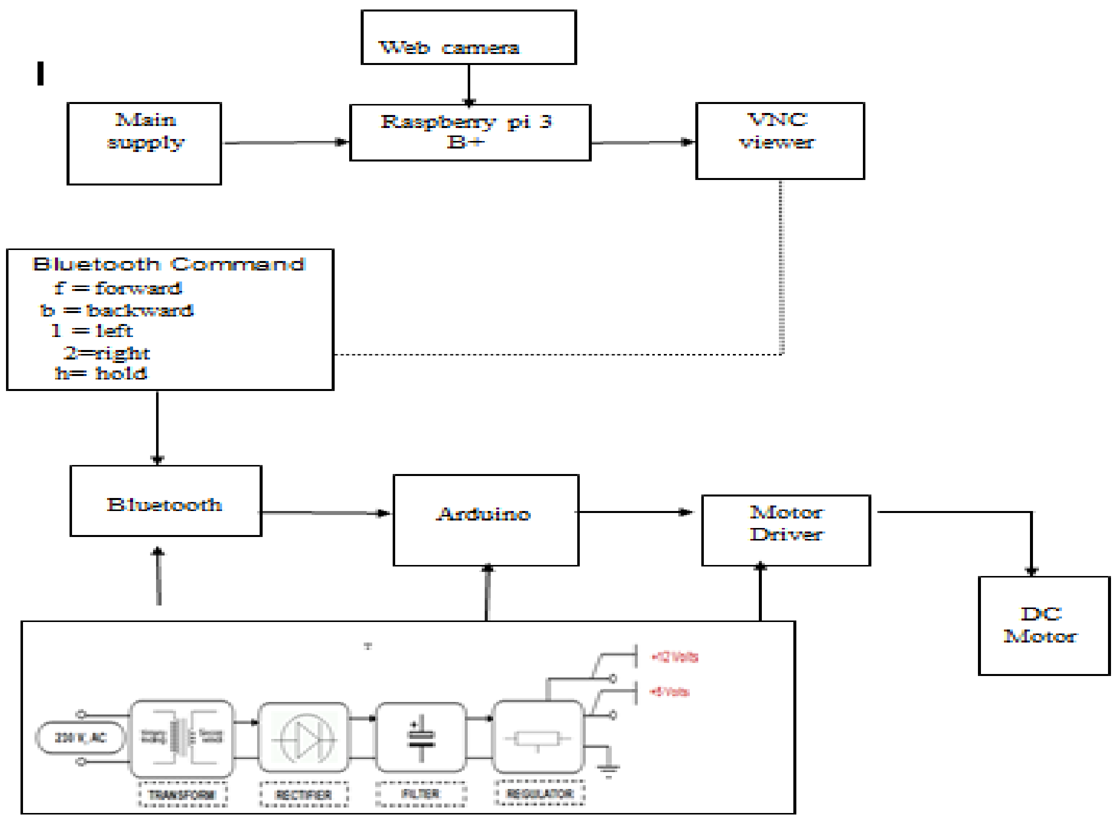

Figure 2: Block diagram of the proposed method

IV. EXPERIMENTAL RESULTS

The bell pepper harvesting using robotic vision system has been implemented successfully and is tested on hardware. Experimental results verify the effective developed operation of the system. When compared with other technologies, it is surely successful in providing a novel affordable solution to automate the agricultural process and also provide platform to the long neglected agriculture sector to avail the benefits of technological advancements and to a great extent increase the efficiency of farming and reduce the burden on farmers.

In a country like India, where agriculture is the backbone of the economy and a means of livelihood for most of the population this technology is going to improve the lives for generations to come and benefit the country in the long run. In the years to come, with lack of human resource posing as a major threat to farming, the automation system provides a complete solution and also develops new market place for business ventures to capitalize and make profits and to move forward with a technological revolution in the agriculture.

The Arduino UNO co-ordinates the movement of the Robot and contains the code to control the manoeuvre. The Arduino UNO is a microcontroller board based on the Microchip ATmega328P microcontroller and developed by Arduino. The HC-05 Bluetooth Module can be used in a Master or Slave configuration, making it a great solution for wireless communication. This serial port Bluetooth module is fully qualified Bluetooth V2.0+EDR (Enhanced Data Rate) 3Mbps Modulation with complete 2.4GHz radio transceiver and baseband. The model B+ is the final revision of the original Raspberry pi, The Raspberry Pi 3 model B+ is the latest product in the Raspberry Pi 3 range, boasting a 64-bit quad core processor running at 1.4GHz, dual-band 2.4GHz and 5GHz wireless LAN, Bluetooth 4.2/BLE, faster Ethernet, and PoE capability via a separate PoE HAT The dual-band wireless LAN comes with modular compliance certification, allowing the board to be designed into end products with significantly reduced wireless LAN compliance testing, improving both cost and time to market.

A robotic arm module is divided into two major working modules, one is the gripper module and other is gearbox module. These both modules are made up from laser cut metal and acrylic which assure their durability in various robotics applications. The gear box module consists of a worm gear assembly which increases torque so that the end effector can pick up more loads. The gripper module is specially designed for pick and place objects. These modules can be combined together to form a pick and place assembly with an ability to lift heavy loads. This assembly can be used in a robotic system to automate existing pick and place system.

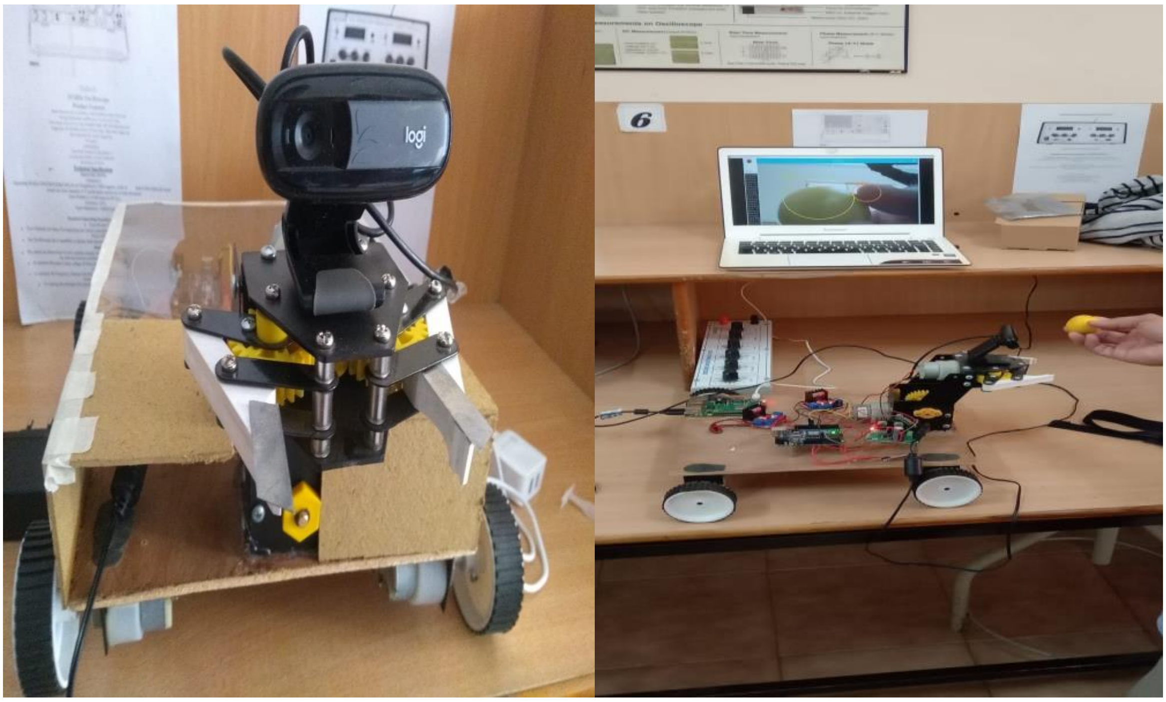

Figure 3: Real Time working of the Robotic Vision System

V. CONCLUSIONS

Computer vision method can provide high resolution automated crop yield estimation for bell pepper harvesting. Our approach is where the ripeness of the bell pepper is detected based on color of the fruit. Hence, the Web camera on the Robot takes a real-time image of the cultivation and sends the frame to the Raspberry Pi B+ microcontroller wherein the Image is subjected to a sequence of image processing techniques as per the code embedded within the microcontroller. If the bell pepper is detected as completely yellow which can be viewed through VNC viewer, then the user decides to harvest the crop he/she can manoeuvre the Bot using the Bluetooth Module attached to the Bot. The transmitted commands on receiving are further transmitted to the Arduino Microcontroller .The Microcontroller then sends out the necessary signals to the interfaced motor driver which controls the movement of the wheels. The Bot can then be moved to the location of the crop and further the gripper of the Bot can be enabled to move and cut the fruit from the peduncle. This allows the farmer to completely automate the harvesting process. Hence, the robotic harvesting offers an attractive potential solution to reducing labour costs while enabling more regular and selective harvesting, optimizing crop quality.

REFERENCES

[1] ABARE. Australian Vegetable Growing Farms: An Economic Survey, 2013–14 and 2014–15; Research report; Australian Bureau of Agricultural and Resource Economics (ABARE): Canberra, Australia, 2015.

[2] Kondo, N.; Monta, M.; Noguchi, N. Agricultural Robots: Mechanisms and Practice; Trans Pacific Press: Balwyn North Victoria, Australia, 2011.

[3] Bac, C.W.; van Henten, E.J.; Hemming, J.; Edan, Y. Harvesting Robots for High-Value Crops: State-of-the-Art Review and Challenges Ahead. J. Field Robot. , 31, 888–911, 2014.

[4] Nuske, S.T.; Achar, S.; Bates, T.; Narasimhan, S.G.; Singh, S. Yield Estimation in Vineyards by Visual Grape Detection. In Proceedings of the 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS ’11), San Francisco, CA, USA, 25–30 September 2011.

[5] Nuske, S.; Wilshusen, K.; Achar, S.; Yoder, L.; Narasimhan, S.; Singh, S. Automated visual yield estimation in vineyards. J. Field Robot. , 31, 837–860,2014.

[6] Yamamoto, K.; Guo,W.; Yoshioka, Y.; Ninomiya, S. On plant detection of intact tomato fruits using image analysis and machine learning methods. Sensors , 14, 12191–12206,2014.

[7] Wang, Q.; Nuske, S.T.; Bergerman, M.; Singh, S. Automated Crop Yield Estimation for Apple Orchards. In Proceedings of the 13th Internation Symposium on Experimental Robotics (ISER 2012), Québec City, QC, Canada, 17–22 June 2012.

[8] Bac, C.W.; Hemming, J.; van Henten, E.J. Robust pixel-based classification of obstacles for robotic harvesting of sweet-pepper. Comput. Electron. Agric. 2013, 96, 148–162.

[9] Hung, C.; Nieto, J.; Taylor, Z.; Underwood, J.; Sukkarieh, S. Orchard fruit segmentation using multi-spectral feature learning. In Proceedings of the 2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Tokyo, Japan, 3–7 November 2013; pp. 5314–5320.

[10] Kapach, K.; Barnea, E.; Mairon, R.; Edan, Y.; Ben-Shahar, O. Computer vision for fruit harvesting robots-state of the art and challenges ahead. Int. J. Comput. Vis. Robot. 2012, 3, 4–34.

[11] Halstead, Michael & Mccool, Chris & Denman, Simon & Perez, Tristan & Fookes, Clinton. “Fruit Quantity and Quality Estimation using a Robotic Vision System, ”IEEE Robotics and Automation Letters. PP. 10.1109/LRA.2018.2849514.,2018.

[12] C. Lehnert, A. English, C. McCool, A. Tow, and T. Perez, “Autonomous sweet pepper harvesting for protected cropping systems,” IEEE Robotics and Automation Letters, 2017.

[13] Song, Y.; Glasbey, C.; Horgan, G.; Polder, G.; Dieleman, J.; van der Heijden, G. Automatic fruit recognition and counting from multiple images. Biosyst. Eng. 2014, 118, 203–215.

[14] Russakovsky, O.; Deng, J.; Su, H.; Krause, J.; Satheesh, S.; Ma, S.; Huang, Z.; Karpathy, A.; Khosla, A.;Bernstein, M.; et al. Imagenet large scale visual recognition challenge. Int. J. Comput. Vis. 2015, 115, 211–252.

[15] Simonyan, K.; Zisserman, A. Two-stream convolutional networks for action recognition in videos. In Proceedings of the Advances in Neural Information Processing Systems, Montréal, QC, Canada, 8–13 December 2014; pp. 568–576.

[16] Krizhevsky, A.; Sutskever, I.; Hinton, G.E. Imagenet classification with deep convolutional neural networks. In Proceedings of the Advances in Neural Information Processing Systems, Tahoe City, CA, USA, 3–8 December 2012; pp. 1097–1105.

[17] Everingham, M.; Eslami, S.M.A.; van Gool, L.; Williams, C.K.I.; Winn, J.; Zisserman, A. The pascal visual object classes challenge: A retrospective. Int. J. Comput. Vis. 2015, 111, 98–136.

[18] Uijlings, J.R.; van de Sande, K.E.; Gevers, T.; Smeulders, A.W. Selective search for object recognition. Int. J. Comput. Vis. 2013, 104, 154–171.

[19] Zitnick, C.L.; Dollár, P. Edge boxes: Locating object proposals from edges. In Computer Vision–ECCV 2014; Springer: Zurich, Switzerland, 2014; pp. 391–405.

[20] Ren, S.; He, K.; Girshick, R.; Sun, J. Faster R-CNN: Towards real-time object detection with region proposal networks. In Proceedings of the Advances in Neural Information Processing Systems, Montréal, QC, Canada, 7–12 December 2015; pp. 91–99.

[21] He, K.; Zhang, X.; Ren, S.; Sun, J. Spatial pyramid pooling in deep convolutional networks for visual recognition. IEEE Trans. Pattern Anal. Mach. Intell. 2015, 37, 1904–1916.

[22] Girshick, R. Fast r-cnn. In Proceedings of the IEEE International Conference on Computer Vision, Santiago, Chile, 13–16 December 2015; pp. 1440–1448.

