Automating Visual Blockage Classification of Culverts with Deep Learning

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ABSTRACT
Blockage of culverts by transported debris materials is reported as main contributor in originating urban flash floods. Conventional modelling approaches had no success in addressing the problem largely because of unavailability of peak floods hydraulic data and highly non-linear behaviour of debris at culvert. This article explores a new dimension to investigate the issue by proposing the use of Intelligent Video Analytic (IVA) algorithms for extracting blockage related information. Potential of using existing Convolutional Neural Network (CNN) algorithms (i.e., DarkNet53, DenseNet121, InceptionResNetV2, InceptionV3, MobileNet, ResNet50, VGG16, EfficientNetB3, NASNet) is investigated over a custom collected blockage dataset (i.e., Images of Culvert Openings and Blockage (ICOB)) to predict the blockage in a given image. Models were evaluated based on their performance on test dataset (i.e., accuracy, loss, precision, recall, F1-score, Jaccard-Index), Floating Point Operations Per Second (FLOPs) and response times to process a single test instance. From the results, NASNet was reported most efficient in classifying the blockage with the accuracy of 85%; however, EfficientNetB3 was recommended for the hardware implementation because of its improved response time with accuracy comparable to NASNet (i.e., 83%). False Negative (FN) instances, False Positive (FP) instances and CNN layers activation suggested that background noise and oversimplified labelling criteria were two contributing factors in degraded performance of existing CNN algorithms.

CCS CONCEPTS
• Computing methodologies → Scene understanding.

KEYWORDS
Convolutional Neural Networks, Visual Blockage of Culverts, Intelligent Video Analytic, Image Classification.

1 INTRODUCTION
Cross-drainage structures (e.g., culverts, bridges) are prone to blockage by debris and reported as one of the main causes of flash floods in urban areas [8, 11, 13, 17, 23, 29, 31]. The 1998 and 2011 floods in Wollongong, Australia [6, 10, 11, 22, 28] and the 2007 flood in Newcastle, Australia [11, 30] are classical examples where blockage of cross drainage hydraulic structures caused the flash flooding.
2 ICOB DATASET

The dataset used for this investigation is referred as “Images of Culvert Openings and Blockage (ICOB)” and consisted of real culverts images collected before and after the flooding events. Main sources of images included WCC historical records, online records and custom captured local culvert images. WCC records were scrutinized using a Microsoft ACCESS based application for filtering the culvert images with visible openings. Final dataset included 929 images of culverts including both blocked and clear. Dataset contained images with high level of variation from each other (intra-class variation) in terms of culvert types, blockage accumulation, presence of debris materials, illumination conditions, culvert view point variations, scale variations, resolution, and backgrounds. This high level of diversity within a relatively small dataset makes it a challenging dataset for visual analytic, even for a binary classification problem.

ICOB dataset was manually labelled for binary classification of a given image with culvert as “clear” or “blocked”. A culvert being visually blocked or clear is not as simple and may require defining a detailed criteria in collaboration with flood management officers; however, for this article, simple occlusion based criteria was used. Following subjective annotation criteria was used for labelling ICOB.

- If all of the culvert openings are visible, classify it as “clear”.
- If any of the culvert opening is visually occluded by debris material or foreground object (e.g., debris control structure, vegetation, tree), classify it as "blocked".

In total, there were 487 images in “clear” class and 442 images in “blocked” class. Figure 1 shows the sample instances from each class of ICOB.

3 EXPERIMENTAL SETUP AND EVALUATION MEASURES

Experiments were planned to investigate the performance of existing CNN models for binary classification of ICOB. Pre-trained CNN models with ImageNet weights were used for this investigation and implemented using Keras with Tensorflow at backend. Images of dimension $224 \times 224 \times 3$ were used as input to model and average pooling technique was used. Data augmentations techniques including samplewise standard deviation normalization, horizontal flip, vertical flip, rotation, width sift and height shift were used in the simulations for improved performance. All the models were tuned with dropout of 0.2, ReLU activation and batch normalization with SoftMax at fully connected layer. Stochastic Gradient Descent (SGD) optimizer with constant learning rate of 0.01 and categorical entropy loss was used. Each model was trained for 30 epochs with dataset divided into train, validate and test (60%, 20%, 20%). All the simulations were performed using Nvidia GeForce RTX 2060 Graphical Processing Unit (GPU) with 6GB memory and 14 Gbps memory speed. Models were trained at full precision using Floating Point (FP-32) optimization.

Performance of the models was measured in terms of their test accuracy, test loss, precision score, recall score, F1 score, Jaccard-Index, and processing times. In addition, confusion matrices were plotted to assess the Type I and Type II errors. Type I (False Positive (FP)) and Type II (False Negative (FN)) errors are commonly used terms in machine learning and main goal of model is to minimize one of these two errors, depending on context that which error is more critical in the given task. By definition, a Type I error is concluding the existence of a relationship while in fact it does not exist (e.g., classifying an image as “blocked” while there is no blockage). Similarly, a Type II error is the rejection of the existence of relationship while in fact it exists (e.g., classifying an image as “clear” while there is blockage). For the given culvert blockage context, Type II error is more critical to be minimized in comparison to Type I error because having notified as blocked while there is no blockage is tolerable in comparison to having notified as clear while there is blockage. Type II error will result in damages because it may be very late for response team to clear the blockage before diversion of flow.

4 RESULTS AND DISCUSSIONS

Implemented CNN models were evaluated as per defined measures in Section 3 and results were compared. Table 1 presents the empirical results of all implemented models when evaluated for test dataset in terms of accuracy, loss, precision, recall, F1 score and
Table 1: Classification Performance of Implemented CNN Models for Blockage Detection.

| Model            | Test Accuracy | Test Loss | Precision Score | Recall Score | F1 Score | Jaccard-Index | FLOPs   |
|------------------|---------------|-----------|-----------------|--------------|----------|---------------|---------|
| DarkNet53        | 0.71          | 1.22      | 0.72            | 0.71         | 0.71     | 0.55          | 14.2 G  |
| DenseNet121      | 0.79          | 0.48      | 0.79            | 0.79         | 0.79     | 0.65          | 5.7 G   |
| InceptionResNetV2| 0.83          | 0.46      | 0.84            | 0.83         | 0.83     | 0.71          | 13.3 G  |
| InceptionV3      | 0.81          | 0.50      | 0.81            | 0.81         | 0.81     | 0.68          | 5.69 G  |
| MobileNet        | 0.79          | 0.50      | 0.80            | 0.80         | 0.79     | 0.66          | 1.15 G  |
| ResNet50         | 0.80          | 0.52      | 0.81            | 0.81         | 0.80     | 0.67          | 7.75 G  |
| VGG16            | 0.75          | 0.50      | 0.80            | 0.80         | 0.79     | 0.66          | 5.69 G  |
| EfficientNetB3   | 0.83          | 0.54      | 0.86            | 0.85         | 0.85     | 0.74          | 47.8 G  |
| NASNetLarge      | **0.85**      | **0.54**  | **0.86**        | **0.85**     | **0.85** | **0.74**      | **47.8 G** |

Jaccard-Index. From the results, NASNet was reported as the best among all others with F1 score of 0.85. EfficientNetB3 and InceptionResNetV2 were reported as the second best with relatively same performance (F1 score of 0.83). DarkNet preformed worst with the F1 score of 0.71.

Figure 2 shows the confusion matrices for the implemented CNN model to observe the Type I and Type II errors. From the figures, it can be observed that NASNet performed best in terms of lowest Type II error of only 8%, however, Type I error was reported 21%. On the other hand, EfficientNetB3 was reported with almost similar...
Table 2: Model Processing Times for Three Different Size Images.

| Model                | Model Processing Time (sec) | Total Execution Time (sec) |
|----------------------|-----------------------------|-----------------------------|
|                      | Image 1 | Image 2 | Image 3 |
| DarkNet53            | 0.05    | 0.12    | 0.2     | 0.35    |
| DenseNet121          | 0.09    | 0.17    | 0.24    | 0.39    |
| InceptionResNetV2    | 0.14    | 0.21    | 0.29    | 0.44    |
| InceptionV3          | 0.09    | 0.17    | 0.24    | 0.39    |
| MobileNet            | 0.06    | 0.13    | 0.21    | 0.36    |
| ResNet152            | 0.13    | 0.20    | 0.28    | 0.43    |
| ResNet50             | 0.08    | 0.15    | 0.23    | 0.38    |
| VGG16                | 0.08    | 0.15    | 0.23    | 0.38    |
| EfficientNetB3       | 0.09    | 0.16    | 0.24    | 0.39    |
| NASNetLarge          | 0.15    | 0.22    | 0.30    | 0.45    |

Type I and Type II errors (14% and 16%). From the FP instances, it was observed that for the cases where there are more than two openings and only one opening was blocked, algorithm classified it as clear. This insight lead to a suggestion in change of labelling criteria. A better approach could be to label image as blocked if half or more than half of openings are blocked otherwise label it as clear. Furthermore, if there is no debris material present in the image and occlusion is due to some foreground object not similar to debris in visual appearance, image should be labelled as clear. From the FN instances, it was observed that for the cases where image contained contents with visual appearance similar to blockage material, image was classified as blocked. This indicated the existence of background clutter/noise problem for this investigation.

Implemented CNN models were also compared for their processing times to investigate the relative response times. Purpose of these analysis was to investigate the hardware implementability of proposed models for real-world applications. Model inference time and image processing time were calculated as two measures to compare the models. Three different size images were used; image 1 of 2048 × 1536, image 2 of 3264 × 2448 and image 3 of 4032 × 3024. From the Table 2, it can be observed that MobileNet and DarkNet53 were fastest among others; however, were least accurate in this case. NASNet model was the slowest but most accurate in performance. As a trade-off, EfficientNetB3 model was relatively fast with accuracy towards higher end and recommended as a suitable choice to implement for on-board processing. It is important to mention that reported processing times are for relative comparison between models and not the actual measure of cutting edge hardware performance. However, given the availability of efficient computing hardware such Nvidia Jetson TX2 [9] and Nvidia Jetson Nano [7], it is highly probable to implement any of the implemented models for real-world applications (e.g., pedestrian detection [5], wildlife tracking [1]).

5 CONCLUSION AND FUTURE DIRECTIONS

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The analysis, it has been observed that NASNet model performed best among all in terms of classification performance, however, was the slowest in relative comparison of processing times. Based on the classification performance and processing times, EfficientNetB3 was recommended model to be deployed for real-world application. From the FP and FN instances, background noise and oversimplified labelling criteria were found potential factors for degraded performance. A visual attention based algorithm and/or detection-classification pipeline are the concepts that can be implemented to address the background noise problem. Furthermore, enhancement of dataset by injecting scaled physical model and computer generated synthetic images are potential future directions.

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REFERENCES

[1] Bilal Arshad, Johan Barthelemy, Elliott Pilton, and Pascal Perez. 2020. Where is my Deer?-Wildlife Tracking And Counting via Edge Computing And Deep Learning. In 2020 IEEE Sensors. IEEE, Rotterdam, Netherlands, 1–4.
[2] Bilal Arshad, Robert Ogie, Johan Barthelemy, Biswajeet Pradhan, Nicolas Verstaevel, and Pascal Perez. 2019. Computer Vision and IoT-Based Sensors in Flood Monitoring and Mapping: A Systematic Review. Sensors 19, 22 (2019), 5012.
[3] JE Ball, MK Babister, R Nathan, PE Weimann, W Weeks, M Retallick, and I Testoni. 2016. Australian Rainfall and Runoff-A guide to flood estimation. Commonwealth of Australia.
[4] Amitava Banerjee, UB Chitnis, SL Jadhav, JS Bhawalkar, and S Chaudhury. 2009. Hypothesis testing, type I and type II errors. Industrial psychiatry journal 18, 2 (2009), 127.
[5] Johan Barthelemy, Nicolas Verstaevel, Hugh Forehead, and Pascal Perez. 2019. Edge-computing video analytics for real-time traffic monitoring in a smart city. Sensors 19, 9 (2019), 2048.
[6] AJ Barthelness and EH Rigby. 2011. Culvert Blockage Mechanisms and their Impact on Flood Behaviour. In Proceedings of the 34th World Congress of the International Association for Hydro-Environment Research and Engineering. Engineers Australia, Barton, ACT, 380–387.
[7] Artiom Basulto-Lantsova, Jose A Padilla-Medina, Francisco J Perez-Pinal, and Alejandro I Barranco-Gutierrez. 2020. Performance comparative of OpenCV Template Matching method on Jetson TX2 and Jetson Nano developer kits. In 2020 10th Annual Computing and Communication Workshop and Conference (CCWC). IEEE, Las Vegas, NV, USA, 0812–0816.
[8] Janice Blanc. 2013. An analysis of the impact of trash screen design on debris related blockage at culvert inlets. Ph.D. Dissertation. School of the Built Environment, Heriot-Watt University.
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9. Han Cui and Naim Dahnoun. 2019. Real-Time Stereo Vision Implementation on Nvidia Jetson TX2. In 2019 8th Mediterranean Conference on Embedded Computing (MECO). IEEE, Badva, Montenegro, 1–5.

10. AJ Davis. 2001. An analysis of the effects of debris caught at various points of major catchments during Wollongong’s August 1998 storm event. Bachelor of Engineering Thesis, University of Wollongong.

11. Robert French and Malcolm Jones. 2015. Culvert blockages in two Australian flood events and implications for design. Australasian Journal of Water Resources 19, 2 (2015), 134–142.

12. Robert French and Malcolm Jones. 2018. Design for culvert blockage: the ARR 2016 guidelines. Australasian Journal of Water Resources 22, 1 (2018), 84–87.

13. R French, EH Rigby, and AJ Barthelmess. 2012. The non-impact of debris blockages on the August 1998 Wollongong flooding. Australasian Journal of Water Resources 15, 2 (2012), 161–169.

14. Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition. IEEE, Las Vegas, NV, USA, 770–778.

15. Andrew G Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, and Hartwig Adam. 2017. Mobilenets: Efficient convolutional neural networks for mobile vision applications. arXiv preprint arXiv:1704.04861 (2017).

16. Gao Huang, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q Weinberger. 2016. Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition. IEEE, Honolulu, Hawaii, 4700–4708.

17. Umair Iqbal, Pascal Perez, Wanqing Li, and Johan Barthelmy. 2021. How Computer Vision can Facilitate Flood Management: A Systematic Review. International Journal of Disaster Risk Reduction 53 (2021), 102030.

18. Rhys Hardwick Jones, William Weeks, and Mark Babister. 2016. Review of Conduit Blockage Policy Summary Report. WMA Water, 160 Clarence Street Sydney, NSW, 2000.

19. Paul Ollett, Bill Syme, and Phil Ryan. 2017. Australian Rainfall and Runoff guidance on blockage of hydraulic structures: numerical implementation and three case studies. Journal of Hydrology (New Zealand) 56, 2 (2017), 109–122.

20. Joseph Redmon and Ali Farhadi. 2018. Yolov3: An incremental improvement. arXiv preprint arXiv:1804.02767 (2018).

21. EH Rigby and P Silveri. 2001. The impact of blockages on flood behaviour in the Wollongong storm of August 1998. In 4th Conference on Hydraulics in Civil Engineering: The State of Hydraulics. Engineers Australia, Barton, ACT, 107–115.

22. EH Rigby and P Silveri. 2002. Causes and effects of culvert blockage during large storms. In Ninth International Conference on Urban Drainage (9ICUD). Engineers Australia, Lloyd Center Doubletree Hotel, Portland, Oregon, United States, 1–16.

23. Steven Roso, Michael Boyd, E Rigby, and Rudy VanDrie. 2004. Prediction of increased flooding in urban catchments due to debris blockage and flow diversions. In Proceedings of the 5th International Conference on Sustainable Techniques and Strategies in Urban Water Management (NOVATECH). Water Science and Technology, Lyon, France, 8–13.

24. Karen Simonyan and Andrew Zisserman. 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556 (2014).

25. Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alex Alemi. 2016. Inception-v4, inception-resnet and the impact of residual connections on learning. arXiv preprint arXiv:1602.07261 (2016).

26. Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jon Shlens, and Zbigniew Wojna. 2016. Rethinking the inception architecture for computer vision. In Proceedings of the IEEE conference on computer vision and pattern recognition. IEEE, Las Vegas, NV, USA, 2818–2826.

27. Mingxing Tan and Quoc V Le. 2019. Efficientnet: Rethinking model scaling for convolutional neural networks. arXiv preprint arXiv:1905.11946 (2019).

28. R Van Drie, MJ Boyd, and EH Rigby. 2001. Modelling of hydraulic flood flows using WBM2001. In 6th Conference on Hydraulics in Civil Engineering. Institution of Engineers Australia, Hobart, Australia, 523–531.

29. N Wallerstein, Colin R Thorne, and S Abt. 1996. Debris control at hydraulic structures, contract modification: management of woody debris in natural channels and at hydraulic structures. Technical Report. Nottingham University (United Kingdom) Department of Geography.

30. BMT WBM. 2008. Newcastle Flash Flood 8 June 2007 (the Pasha Bulker Storm) Flood Data Compendium. Prepared for Newcastle City Council, BMT WBM, Broadmeadow (2008).

31. W Weeks, G Wetheridge, E Rigby, A Barthelmes, and G O’Loughlin. 2013. Project 18: Blockage of Hydraulic Structures. Technical Report P11/S2/021. Engineers Australia, Water Engineering, 11 National Circuit Barton ACT 2600.

32. Barret Zoph, Vijay Vasudevan, Jonathon Shlens, and Quoc V Le. 2018. Learning transferable architectures for scalable image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition. IEEE, Salt Lake City, USA, 8697–8710.