Predicting tree failure likelihood for utility risk mitigation via a novel convolutional neural network

1 Introduction

Utilities have been concerned with tree-related outages for many years, but much of the work to quantify them has been done in-house: Utilities contract with a consultant who analyzes tree-related outages (or interruptions). In general, tree-related outages are due to contact between tree parts and power lines. Sometimes, the contact is due to growth of branches into the lines; sometimes it is due to branch failure; sometimes it is due to tree failure (either uprooting or trunk failure). When outages occur, the economic costs can be substantial. For example, from 2005 to 2015, [1] computed the annual economic cost of outages in the US state of Connecticut; the mean was approximately $8.3 bn. Outages due to contact from branch growth or branch failure can be mitigated by line clearance tree trimming. Estimates vary, but the annual amount that utilities spend on tree trimming operations is typically in the billions of dollars [2]. Despite the comparatively high annual cost of tree trimming, studies have repeatedly shown that trimming branches away from the wires reduces the number of outages (sometimes classified as "preventable" outages). In Massachusetts, USA, for instance, tree failure was responsible 40% of preventable tree-caused outages, but removing or severely pruning high risk trees improved reliability by 20% to 30% [3]. A more recent (and sophisticated) analysis in Connecticut showed that enhanced tree trimming reduced outages during storms [4]. And using a statistical model to predict outages based on data from two Gulf Coast states in the USA, Nateghi et al. [5] demonstrated that prediction models were less uncertain when they included the effect of tree trimming; models including wind speed without considering the effect of trimming were not as accurate.

Trimming can be effective because both structurally-deficient and structurally-sound branches adjacent to or overhanging the lines in proximity are removed, reducing the likelihood of contact. However, it cannot eliminate tree-related outages. Failure of trees away from the right-of-way can still impact the lines and cause outages [2]. The proportion of tree failures away from the wires that cause outages varies and has not been rigorously quantified. Guggenmoos [6] estimated that 95% of tree-caused outages in the Pacific Northwest region of the US, were due to tree failure, and Wismer [7] reported approximately 25% of interruptions in Illinois, USA, were caused by trees that uprooted or broke in the stem. Predicting the likelihood of failure is an inexact science, but tree risk assessment best management practices have been developed [8, 9]. Risk includes assessing the likelihood of failure, the likelihood of impact, and the severity of consequences. The likelihood of failure depends on the anticipated loads on the tree and its load-bearing capacity. The likelihood of impact depends on proximity to the target (the lines, poles, and other hardware—"infrastructure"—in the case of utility tree risk assessment), the target's occupancy rate (which is constant for utility lines) and whether the target is sheltered, for example by neighboring trees. Severity of consequences depends on the damage done to the infrastructure and, more importantly in some cases, the economic costs and disruption associated with outages—this, in turn, is partially related to the size of the tree or tree part that fails, and how much momentum it has when it impacts the infrastructure.

Individual tree risk assessment can be costly because of the time it requires. In some situations, a less time-consuming assessment may be justified to reduce costs, i.e. a "Level 1" assessment (Smiley et al. 2017). Studies have shown that trees with greater risk ratings were more likely to be detected from Level 1 risk assessments conducted in a moving vehicle in Rhode Island, USA [10] and Florida, USA [11] . The utility of Level 1 assessments in these areas suggests that artificial intelligence (AI) tools may be an effective way to reduce the cost of tree risk assessment.

AI-based image analysis is relatively widely used, even in engineering applications, such as earthquake risk assessment [12, 13] and structural health monitoring [14]. A relevant application for tree species identification using a convolutional neural network (CNN) was even recently demonstrated [15]. Yet, AI has not been applied to the problem of tree-utility line risk assessment—one that is complicated by the very large number of tree species to be considered, seasonal variation in tree appearance and associated risk and local meteorological conditions. However, the flexibility and power of CNNs, appears promising. In this paper, we demons In the remainder of this paper, we first provide a background on CNN which is critical for sustainability in critical infrastructural systems. Our goal is to further demonstrate an innovative automated approach to tree risk assessment using an AI tool that can be readily deployed for use in various locations and also continually improved through subsequent training on new datasets.

2 Background

The groundbreaking study of Hubel and Wiesel [16] showed that visual perception in cats was a result of the activation or inhibition of groups of cells in the visual cortex known as "receptive fields." Further, they attempted to map the cortical architecture in cats and monkeys [17, 18, 19]. Subsequent attempts were then made to model neural networks that could be trained to automatically recognize visual patterns with modest performance [20, 21, 22, 23]. However, the breakthrough came with "neocognitron" [24], which was a self-learning neural network for pattern recognition that was robust to changes in position and shape distortion, a problem that plagued earlier efforts, including "cognitron" [23] proposed a few years earlier.

A few notable efforts demonstrated the neural networks for handwritten digit recognition [25, 26], but these required significant preprocessing and feature extraction. [27] soon afterward introduced a multilayer neural network that mapped a feature in each neuron (representing a "local receptive field") via convolution. This network could also be trained by backpropagation like other existing neural networks and featured pooling operations for better distortion and translation invariance. Further developments from this milestone yielded the LeNet-5 convolutional neural network which attained accuracy levels that rendered it commercially viable.

The big data revolution coupled with technological advancements that have made it possible to capture and store high resolution images have raised challenges that continue to be surmounted with successively high-performing architectures. Over the past decade, some of these efforts resulted in significant breakthroughs in performance. AlexNet [28], with 5 convolutional layers and 3 dense layers—one of the largest CNNs of its time, won the ILSVRC-2012[1] competition with a top-5 error rate of 15.3% and served as a landmark in the Deep Learning subdomain. Zeiler and Fergus [29] then introduced ZFNet, besting the performance of AlexNet, and pioneered visualization techniques

[1]ImageNet Large Scale Visual Recognition Challenge; held annually from 2010 through 2017.

that were foundational for model inference and interpretability. In the same year, GoogLeNet, a 22-layer network, was proposed [30], featuring the novel “Inception module,” which allowed for efficiency and accuracy in a very deep network. Subsequent improvements have been proposed to the original inception framework [31, 32]. VGGNet [33] also pushed the boundaries of depth with up 19 layers, achieving state-of-the-art performance at ILSVRC-2014. Finally, ResNet [34] addressed the accuracy degradation problem that arises with increasing depth in a network by succesively fitting smaller sets of layers to the residual and employing skip connections. With these innovations, an unprecedented level of depth was achieved. Implementations with with 34, 50, 101 and 152 layers were demonstrated. ResNet-152 won first place in ILSVRC-2015.

Along with these developments in their architectures, CNNs have demonstrated viability for applications to image classification, object and text detection, object and document tracking, labeling, speech, among several other related fields [35]. Paragraph on applications to be completed—with particular attention paid to tree-related efforts.

3 Data and Methods

3.1 Image data description

The training dataset consists of 505 images, each having an original size of 4032×3024 pixels. Based on the ISA’s Tree Risk Assessment Qualification (TRAQ) protocol, four categories of tree failure likelihood are defined. In this paper we only focus on three:

- **Probable**: failure expected under normal weather conditions within a given timeframe
- **Possible**: failure expected under extreme weather conditions; but unlikely during normal weather conditions
- **Improbable**: failure unlikely either during normal or extreme weather conditions

3.2 Pre-processing

3.3 Convolutional neural network

4 Results and Discussion

Model	**Training metrics**			**Validation metrics**		
	Error	Precision	Recall	Error	Precision	Recall
SafeTree						
GoogleNet (InceptionV3)						
ResNet50						
VGGNet						
AlexNet						

Table 1 Comparing our model SafeTree with state-of-the-art CNN architectures trained on our data

5 Conclusion

References

[1] Marcello Graziano, Peter Gunther, Adam Gallaher, Fred V. Carstensen, and Brian Becker. “The Wider Regional Benefits of Power Grids Improved Resilience through Tree-Trimming Operations Evidences from Connecticut, USA”. In: *Energy Policy* 138 (Mar. 1, 2020), p. 111293.

[2] Siegfried Guggenmoos. “EFFECTS OF TREE MORTALITY ON POWER LINE SECURITY”. In: *Journal of Arboriculture* 29.4 (2003), pp. 181–196.

[3] P. Simpson and R. Van Bossuyt. “TREE-CAUSED ELECTRIC OUTAGES”. In: *Journal of Arboriculture* 22 (1996), pp. 117–121.

[4] Jason R. Parent, Thomas H. Meyer, John C. Volin, Robert T. Fahey, and Chandi Witharana. “An Analysis of Enhanced Tree Trimming Effectiveness on Reducing Power Outages”. In: *Journal of Environmental Management* 241 (July 1, 2019), pp. 397–406.

[5] Roshanak Nateghi, Seth Guikema, and Steven M. Quiring. “Power Outage Estimation for Tropical Cyclones: Improved Accuracy with Simpler Models”. In: *Risk Analysis* 34.6 (2014), pp. 1069–1078.

[6] Siegfried Guggenmoos. “Tree-Related Electric Outages Due To Wind Loading”. In: *Arboriculture and Urban Forestry* 37.4 (2011), pp. 147–151.

[7] Shaun Wismer. *Targeted Tree Trimming Offers Reliability Benefits*. T&D World. May 16, 2018. URL: https://www.tdworld.com/vegetation-management/article/20971285/targeted-tree-trimming-offers-reliability-benefits (visited on 01/13/2021).

[8] E. Thomas Smiley, Nelda Matheny, and Sharon Lilly. *Best Management Practices - Tree Risk Assessment, Second Edition*. P1542. International Society of Arboriculture, 2017, p. 86.

[9] John W. Goodfellow. *Best Management Practices - Utility Tree Risk Assessment*. P1321. International Society of Arboriculture, 2020, p. 95.

[10] C. J. Rooney, H. D. Ryan, David V. Bloniarz, and B. Kane. “THE RELIABILITY OF A WINDSHIELD SURVEY TO LOCATE HAZARDS IN ROADSIDE TREES”. In: *Journal of Arboriculture* 31.2 (2005).

[11] A. K. Koeser, D. C. McLean, G. Hasing, and R. B. Allison. “Frequency, Severity, and Detectability of Internal Trunk Decay of Street Tree Quercus Spp. in Tampa, Florida, U.S.” In: *Arboriculture & Urban Forestry* 42.4 (2016), pp. 217–226.

[12] Pengcheng Jiao and Amir H. Alavi. “Artificial Intelligence in Seismology: Advent, Performance and Future Trends”. In: *Geoscience Frontiers* 11.3 (May 1, 2020), pp. 739–744.

[13] Hadi Salehi and Rigoberto Burgueño. “Emerging Artificial Intelligence Methods in Structural Engineering”. In: *Engineering Structures* 171 (Sept. 15, 2018), pp. 170–189.

[14] Billie F. Spencer, Vedhus Hoskere, and Yasutaka Narazaki. “Advances in Computer Vision-Based Civil Infrastructure Inspection and Monitoring”. In: *Engineering* 5.2 (Apr. 1, 2019), pp. 199–222.

[15] Geoffrey A. Fricker, Jonathan D. Ventura, Jeffrey A. Wolf, Malcolm P. North, Frank W. Davis, and Janet Franklin. “A Convolutional Neural Network Classifier Identifies Tree Species in Mixed-Conifer Forest from Hyperspectral Imagery”. In: *Remote Sensing* 11.19 (19 Jan. 2019), p. 2326.

[16] D. H. Hubel and T. N. Wiesel. "Receptive Fields of Single Neurones in the Cat's Striate Cortex". In: *The Journal of Physiology* 148.3 (Oct. 1959), pp. 574–591.

[17] D. H. Hubel and T. N. Wiesel. "Receptive Fields, Binocular Interaction and Functional Architecture in the Cat's Visual Cortex". In: *The Journal of Physiology* 160.1 (Jan. 1962), pp. 106–154.2.

[18] David H. Hubel and Torsten N. Wiesel. "Receptive Fields and Functional Architecture in Two Nonstriate Visual Areas (18 and 19) of the Cat". In: *Journal of Neurophysiology* 28.2 (Mar. 1, 1965), pp. 229–289.

[19] D. H. Hubel and T. N. Wiesel. "Receptive Fields and Functional Architecture of Monkey Striate Cortex". In: *The Journal of Physiology* 195.1 (1968), pp. 215–243.

[20] Frank. Rosenblatt. *Principles of Neurodynamics; Perceptrons and the Theory of Brain Mechanisms.* Washington: Spartan Books, 1962. 616 p.

[21] Matthew Kabrisky. *A Proposed Model for Visual Information Processing in the Human Brain.* University of Illinois Press, 1966. 124 pp.

[22] H. Giebel. "Feature Extraction and Recognition of Handwritten Characters by Homogeneous Layers". In: *Zeichenerkennung Durch Biologische Und Technische Systeme / Pattern Recognition in Biological and Technical Systems.* Ed. by Otto-Joachim Grüsser and Rainer Klinke. Berlin, Heidelberg: Springer, 1971, pp. 162–169.

[23] Kunihiko Fukushima. "Cognitron: A Self-Organizing Multilayered Neural Network". In: *Biological Cybernetics* 20.3 (Sept. 1, 1975), pp. 121–136.

[24] Kunihiko Fukushima. "Neocognitron: A Self-Organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position". In: *Biological Cybernetics* 36.4 (Apr. 1, 1980), pp. 193–202.

[25] Kunihiko Fukushima. "Neocognitron: A Hierarchical Neural Network Capable of Visual Pattern Recognition". In: *Neural Networks* 1.2 (Jan. 1, 1988), pp. 119–130.

[26] John Denker, W. Gardner, Hans Graf, Donnie Henderson, R. Howard, W. Hubbard, L. D. Jackel, Henry Baird, and Isabelle Guyon. "Neural Network Recognizer for Hand-Written Zip Code Digits". In: *Advances in Neural Information Processing Systems* 1 (1988), pp. 323–331.

[27] Yann LeCun, Bernhard E Boser, John S Denker, Donnie Henderson, R E Howard, Wayne E Hubbard, and Lawrence D Jackel. "Handwritten Digit Recognition with a Back-Propagation Network". In: *Advances in Neural Information Processing Systems 2.* Neural Information Processing Systems. 1989, p. 9.

[28] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E. Hinton. "ImageNet Classification with Deep Convolutional Neural Networks". In: *Advances in Neural Information Processing Systems* 25 (2012), pp. 1097–1105.

[29] Matthew D. Zeiler and Rob Fergus. "Visualizing and Understanding Convolutional Networks". In: *Computer Vision – ECCV 2014.* Ed. by David Fleet, Tomas Pajdla, Bernt Schiele, and Tinne Tuytelaars. Lecture Notes in Computer Science. Cham: Springer International Publishing, 2014, pp. 818–833.

[30] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. *Going Deeper with Convolutions.* Sept. 16, 2014. URL: http://arxiv.org/abs/1409.4842 (visited on 01/18/2021).

[31] Christian Szegedy, Vincent Vanhoucke, Sergey Ioffe, Jonathon Shlens, and Zbigniew Wojna. *Rethinking the Inception Architecture for Computer Vision*. Dec. 11, 2015. URL: http://arxiv.org/abs/1512.00567 (visited on 01/13/2021).

[32] Christian Szegedy, Sergey Ioffe, Vincent Vanhoucke, and Alex Alemi. *Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning*. Aug. 23, 2016. URL: http://arxiv.org/abs/1602.07261 (visited on 01/18/2021).

[33] Karen Simonyan and Andrew Zisserman. *Very Deep Convolutional Networks for Large-Scale Image Recognition*. Apr. 10, 2015. URL: http://arxiv.org/abs/1409.1556 (visited on 01/18/2021).

[34] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. *Deep Residual Learning for Image Recognition*. Dec. 10, 2015. URL: http://arxiv.org/abs/1512.03385 (visited on 01/13/2021).

[35] Jiuxiang Gu, Zhenhua Wang, Jason Kuen, Lianyang Ma, Amir Shahroudy, Bing Shuai, Ting Liu, Xingxing Wang, Gang Wang, Jianfei Cai, and Tsuhan Chen. "Recent Advances in Convolutional Neural Networks". In: *Pattern Recognition* 77 (May 1, 2018), pp. 354–377.