Leveraging KNIME and machine learning to enhance asset management of South Australia's power grid

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Decision Makin

ElectraNet

Speakers

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- Using KNIME since 2022



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Outline

- Introduction
 - □ ElectraNet and Forest Grove Technology
 - □ Business Case Presentation
- Insulator Detection and Identification
 - □ Machine Learning
 - □ Project presentation
 - \Box Outcomes
- Conclusion and Q&A





Introduction

- ElectraNet and Forest Grove Technology
- Business Cases Presentation





About ElectraNet

- Owner and operator of South Australia's electricity transmission network
- Extensive regional network covering 200 000 square km (~77 000 square mi)
- Supporting the \$140+ billion economy in South Australia



NT

WA

Interconnector

Not part of the NEM

Forest Grove

Data-Driven Decision Making

The Role of ElectraNet

Our Key Objectives:

- □ Affordability and reliability to our customers
- □ Transmission Network security and resilience
- □ Safety of our personnel
- □ Protect the environment



Our Assets





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Data and Technology







Technology Selection

ElectraNet's Selection Criteria:

- □ GUI based workflow Low Code/No Code
- □ Simple for analysts/engineers to utilise
- □ Faster and easy solution to deploy
- $\hfill\square$ Flexible solution







Forest Grove Technology – Our History

 Founded and operating out of Perth, WA, Forest Grove is one of Australia and NZ's leading specialist consulting firms, delivering end to end finance transformation and data analytics solutions. We have been helping business achieve success with their data for nearly two decades.



Data-Driven Decision Making

Forest Grove Technology – Snapshot

20 years experience in finance & analytics

- ightarrowEnd-to-end data solutions
- →Implementation & dedicated support

Leaders in **analytics** deployment

- \rightarrow Helping clients solve real business problems
- ightarrow Growing data literacy across teams

100+ customers across APAC

ightarrow Headquartered in WA

ightarrow Consultants in VIC, WA & QLD

ANZ S Asahi FOXTEL ElectraNet

Strategically chosen leading technologies

→ Innovation, self-service & support
→ Avoidance of black-box solutions

CONNECTED CONNEC

Diverse, professional team of **data**

experts Specialist, Varied skill sets & experience

 \rightarrow 14+ countries

Proven success & credentials – ~10 years w KNIME

- \rightarrow Long-term happy customers
- ightarrow International awards





Image Analytics – SAP data vs Nameplates

Business Case

- Test feasibility to extract nameplate information (e.g., model and make)
- Evaluate KNIME capabilities
- Identify inaccuracies in SAP data

Outcomes

- Built workflow to extract equipment details from nameplate
- KNIME proved to be versatile and useful for other types of use cases







Transmission Lines

- Overhead transmission lines are supported by several unique tower types.
- Over 15 000 towers supporting the network
- 72 000 insulators recorded in SAP
- 41000 photos of structures

Some important components for a Transmissions line are:

- 1. Conductor
- 2. Towers or Poles
- 3. Insulators





Transmission Lines











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Business Case

- SAP Data timely update
- SME's conduct manual audits to verify accuracy of data
- SAP Data validation and assessment using a second data source

Analytical Solution

- KNIME Workflow to detect insulators
- Recognise insulator attributes
- Deployment KNIME Workflow for SMEs to utilise





Insulator Detection and Identification

- Machine Learning
- Use Case Presentation
- Outcomes





Machine Learning - Definition

"Machine learning (ML) teaches computers to do what comes naturally to humans: learn from experience"

- Arthur Samuel (1959) [2]
- Algorithms "learn" information from data and improve their performance
- Training an algorithms result in a ML model
- Daily usage: deepl, chat GPT, Siri, ...

[1] Peck W.G., Machine Learning Techniques Using MATLAB, North Charleston, SC: CreateSpace Independent Publishing Platform, 2017.

[2] SamuelA.L., "SomestudiesinmachinelearningusingthegameofCheckers", IBMJournal of Research and Development, 1959, 3(3): pp. 210–229, https://doi.org/10.1147/rd.33. 0210.

 $Image \ source: \ https://ai.stackexchange.com/questions/15859/is-machine-learning-required-for-deep-learning-for-deep-learning-for-deep-learning-for-deep-learning-for-deep-learning-for-deep-learning-for-deep$



ARTIFICIAL INTELLIGENCE A program that can sense, reason, act, and adapt

MACHINE LEARNING

Algorithms whose performance improve as they are exposed to more data over time

DEEP FARNING

Subset of machine learning in which multilayered neural networks learn from vast amounts of data



Image Classification, Object Detection, and Instance Segmentation

- Image classification is a task in computer vision that aims to understand and categorize an image as a whole under a specific label.
- **Object detection** involves classification and location of multiple objects within an image.
- Instance segmentation is a computer vision task that involves identifying and separating individual objects within an image, including detecting the boundaries of each object.



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a-Driven Decision Making



Insulator Detection







Insulator Detection

The dataset is split into three subset:

- 1. Train Used to train (or retrain) a ML model. The model learns from the available data. The data needs to be representative from the reality.
- **2. Validation** Used to validate the ML model after each epoch or training iteration. It assesses the quality of the ML model and allows to identify overfitting.
- 3. Test Used as test dataset once the ML mode is ready to be deployed.

We labeled **257 images** for insulator detection. Using data augmentation allowed us to obtain **1492 labeled** images.

We changed the color, the orientation, the brightness, the blur, and the contrast.





- Training framework
 - □ CPU vs GPU

ElectraNet

□ CPU : 11 hour for one epoch

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ML Model

- YOLO (v8) You Only Look Once
 - Popular object detection and image segmentation model
 - □ Fast and accurate close to realtime
 - Continuous support of the community
 Existing Python frameworks
- Retrain of a pre-trained model
 - □ 300 epochs (training iteration)
 - □ Batch size of 2
 - □ Initial Learning rate of 0.01
- Images of various dimensions
- Cross Entropy Loss





Design: Deployment





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- Asset Information Team within ElectraNet
- Deployed in production as a Data Apps on KNIME Server
- Insights for the business



Insula Show	tor Recognition Result																Search:		
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Insulator Detection Output



Data-Driven Decision Making

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Insulator Detection Output and Error Analysis

Overall accuracy : ~98% (±0.25%)

Scorer View

Confusion Matrix

	glass (Predicted)	nci (Predicted)	porcelain (Predicted)	
glass (Actual)	78	0	1	98.73%
nci (Actual)	0	29	0	100.00%
porcelain (Actual)	0	2	158	98.75%
	100.00%	93.55%	99.37%	

Scorer Vie		Confu						
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Scorer View								
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horizontal	0	0	14	0	0	0	100.00%	
suspension	0	0	0	134	0	0	100.00%	
tension (Ac	0	0	0	0	49	0	100.00%	
vee (Actual)	0	0	0	0	1	55	98.21%	
	100.00%	100.00%	100.00%	100.00%	98.00%	100.00%		



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Project Outcomes

- Improving the SAP database accuracy
- Reducing the human error in analysis
- Generic methods
 - \Box Useable for other applications
 - $\hfill\square$ Retraining of the model
- Opened discussions with SMEs on how we can Utilise KNIME and ML to provide meaningful solutions
 - □ Success of the project and flexibility of KNIME
- Reducing manual work (Estimated to around 80%)
 - $\hfill\square$ Team focusing on our task of the business
- Can be run on demand
- Running over 24/7

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Estimate for 1 image per Tower – If no Human Interaction required

- ~15,000 images of towers
- Manual check takes ~2 minutes for a human (~21 days)
- Working days (~63 days)
- Loading and Auto check takes ~10 seconds for the ML model (~2 days)
- Saving ~61 days (~95%)

Estimate for 1 image per Tower – Interaction required on 20%

- ~3000 images requiring human interpretation
 - Manual check takes ~2 minutes for a human (~12 working days)
- Saving ~51 days (~81%)



What's Next ? Shackle Steel Loss Measurement

The shackle holding the insulators and electrical cables deteriorate due to the weather and the continuous strain.

Currently, engineers are manually measuring the steel loss proportion using images acquired by helicopter patrols.

This project aims to help ElectraNet engineers to evaluate the steel loss and to measure the size of the remaining hardware.





Thank You

For more information please contact:



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