Solar Panel Soiling State Classification

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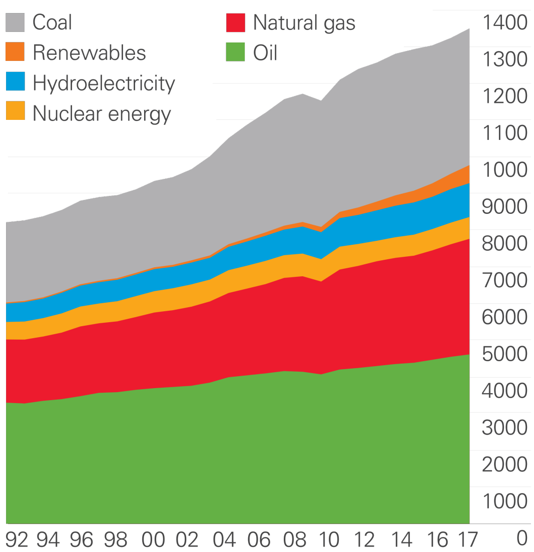
Abstract—Solar energy investment is seeing an increased focus as Australia tries to reduce its carbon footprint. One of the main challenges with generation from large solar arrays is keeping the solar panels free from soiling, to limit power loss. This paper aims to develop a solar panel soiling state classification model based on Convolutional Neural Network architectures. Training data is collected using Google image search. Implemented models are based on Googlenet architectures which demostrate mixed results, suggesting the need for more data to improve model performance.

Index Terms—Convolutional Neural Network, Deep Learning, Solar Array.

1 Introduction

Australia has the highest average solar radiation per square metre of any continent in the world. There is approximately 58 million petajoules of incident solar radiation on Austrlian soil annually - enough to meet Australia's energy demands by a multiple of 10000 [1]. Historically, Australia has used coal as its main source of generation and solar resources have remained largely unused - this is in line with global energy trends.



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British Petroleum (BP) indicate coal, oil, and natural gas account for 85% of goblal energy consumption [2]. Energy from these fuels is generated from their combustion and are a major source of global greenhouse gas emissions contributing to global warming [3]. In contrast, renewable sources of energy, which are comprised of wind, geothermal, solar, and biomass produce far fewer greehouse gas emissions, however, they only contribute a mere 3.5% to global energy consumption. This is easy to see in a longitudinal breakdown, shown in Figure 1. The graph also indicates that energy demand is increasing. If coal, oil, and natural gas remain core sources of generation, this will result in greenhouse gas emissions rising, accelerating global warming. This is problematic given the well understood impact that global temperature increase has on the environment.

The Intergovernmental Panel on Climate Change (IPCC) released a report in 2018 highlighting the link between greenhouse gas emissions and the increase in global temperatures citing human induced warming of 1°C above pre-industrial levels in 2017, increasing at a minimum of 0.1°C per decade. The report forewarns of adverse environmental consequences assuming maintained rates of CO_2 emissions. These include an increase in temperature of 1.5°C above pre-industrial levels; increased frequency and intensity of heat waves; loss of biomass and a decrease in the number of species populations in climate sensitive areas; sea level rise; and food insecurity [4].

Fortunately, the solar power industry is growing in Australia. As of September 2018, Australia had over 10131MW of installed PV solar power. Approximately, 3366MW were installed in the preceding 12 months [5]. In fact, the Australian renewable energy industry is on track to install more than 10GW of new solar power during 2018 and 2019 - a rate which, if sustained, would see Australian generation reach 50% renewables by 2025 [6].

Generation from large- and mid-sized solar arrays face the unique maintenance challenge of keeping the solar panels free from soiling. Soiling occurs due to an accumutaion of dust, pollen, leaves, bird droppings or snail trails [7]. An IBM research lab in 2018 demonstrated that Fully Convolutional Neural Networks can be used to help determine the soiling states of solar panels. Approximately 45000 images of solar panels in various states of soiling were collected. Trained models were successfully able to use object detection to locate the soiled regions of solar panels. Additionally, models could classify types of soiling, and provide an estimate of the power loss experienced by an individual panel [8].

This paper proposes the use of a CNNs to classify images of solar panels as soiled or clean. A simple classification model like this could be used in an automatic visual inspection system, deployed on drones equipped with RGB cameras, to determine soiling states for large solar arrays. Successful development of this technology would allow scheduling of cleaning routines for maintenance cost optimisation. Cost savings would be realised through reductions in labour required for manual visual inspections. Additionally, data could be used to determine optimal cleaning sequences for maximum power efficiency.

2 Background / Formulation

A Convolutional Neural Network (CNN) is a class of artificial neural network, which has an underlying architecture suited to learning shapes, edges, and colours in images. The main feature of a CNN is a convolving filter, which is often visualised as a small patch which slides over the image. This allows model weights to be shared for different sections of the image, which would not occur when using vanilla (fully connected) neural networks. An example of a convolutional filter can be seen in Figure 2.

CNNs are recognised as state-of-the-art methods for image classification, as seen in models such as GoogleNet [9], ResNet [10], and VGG [11]. Of course, recent CNNs, such as VGG, are very deep and contain a significant number of weights - this has two well understood effects:

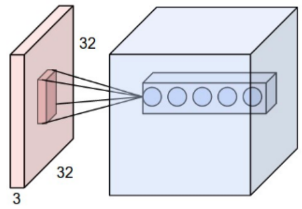

Fig. 2: An example of a convolutional layer - the small panel is convolved across the image producing the output (shown in blue).

1) High numbers of model weights requires more data to ensure that the model is adequately trained;
2) Deep models dramatically increase the computation required for classification, making inference slower [12]. This is demonstrated pictorially in Figures 3 and 4.

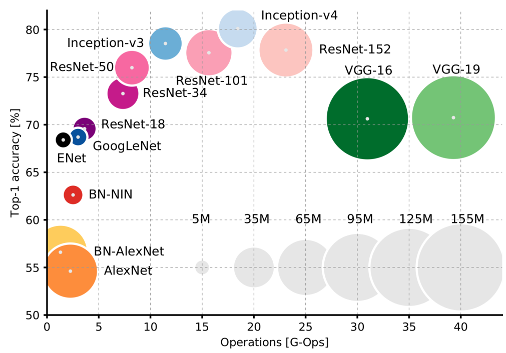

Fig. 3: A trade off exists between the number of operations, accuracy, and the number of parameters in a model.

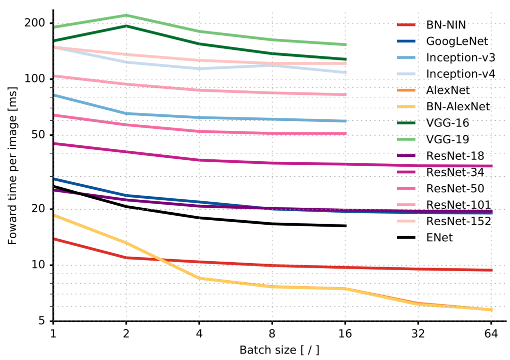

Fig. 4: Comparison of inference time versus batch size for different model architectures.

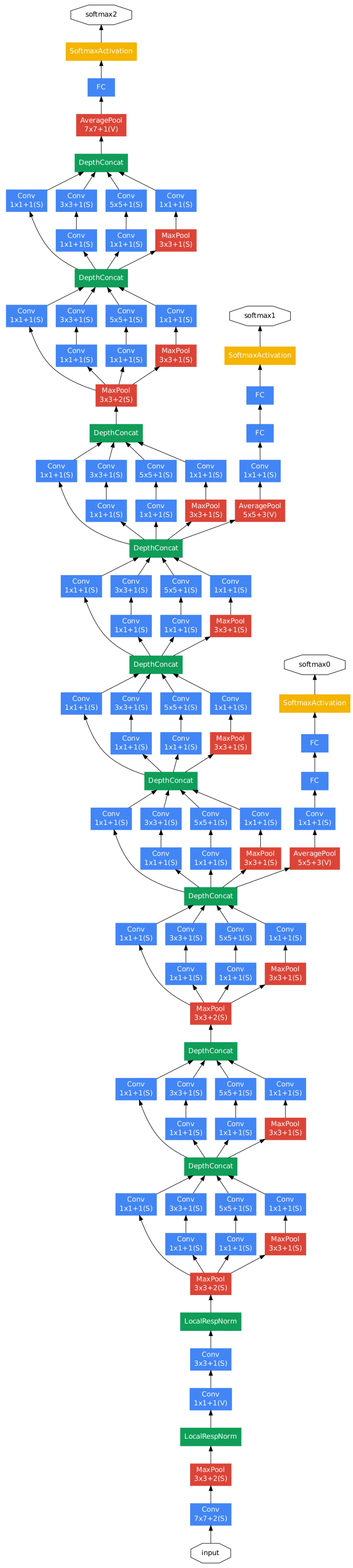

Fig. 5: Googlenet architecture, with all the bells and whistles.

Given the lack of available image data for soiled solar panels, a model with too many parameters poses a risk of underfitting. This would yield poor classification results. Additionally, inference needs to be fast. A trained model deployed on a drone, used for soiling classification of a large solar panel array, will need to be able to process image data quickly. To help ensure performance requirements are met, some minimum benchmarks were perscribed for a secondary data set, not related to the solar panel classification problem. These include:

1) A hurdle rate of 75% accuracy on model classification
2) An inference speed of less than 10ms for a single image

Googlenet was selected as the best model architecture for the task. When considering state-of-the-art CNN models, Alexnet ranks as one of the fastest, however, suffers in terms of clasification accuracy. Conversely, VGG has very high accuracy, but poor inference speed. Googlenet strikes a balance between these two extremes. Alternatively, a custom model could be developed which would be optimal in design and highly effective for this specific task, however, this is expensive. Goolenet is readily availability and requires no modification meaning it's simple, easy and cheap. Parallels can be drawn to development of embedded systems where design choices must be made between using highly optimised ASIC, which are expensive, or off-the-shelf sub-optimal IC allowing for rapid system development, but poorer performance.

3 Data Acquisition

Image data was collected for threee distinct categories: clean solar panels, soiled solar panels, and images with no solar panels. Image data was aquired from Google images. Collection was automoated using a Python module called `google_images_download`. Keywords used to search for each category can be seen in Table 1.

TABLE 1: Keywords used in Google Image searches.

Classification Category	**Keywords**
Clean Solar Panels	*Clean Solar Panels*
Soiled Solar Panel	*Dirty Solar Panel* *Dusty Solar Panel*
No Solar Panel	*Roof* *Rooftops*

Each keyword search from the module returned 100 images, however, not all images were suitable and some were discarded during a manual review. This left 39 images for the Clean Solar Panel category; 102 images for the Soiled Solar Panel category; and 161 images for the No Solar Panel category. The final image sets were resized to 256×256. This introduced some distortion, due to unequal scaling for images that did not have square dimensions.

Fig. 6: Example of an image of clean solar panels.

Fig. 7: An example of an image of soiled solar panels.

Fig. 8: An example of an image of no solar panels.

Distortion could be avoided by image cropping, however, this would have added further complexity to pre-processing. Samples of images collected for the Clean Solar Panel, Soiled Solar Panel, and No Solar Panel can be seen in Figures 6, 7, and 8, respectively. The number of images for each class were doubled using a trick in which images are flipped from left to right and added back to the class. This resulted in a total of 604 images, broken downs as follows:

- **Clean solar panels:** 78
- **Dirty solar panels:** 204
- **No solar panels:** 322

The data was split into training and validation sets. Approximately 25% of the images were held for the validation set.

4 Results

4.1 Trial Data

To help analyse model performance independently of the solar panel data, the Googlenet model was trained on a trial data set consisting of approximately 10000 images. Images were split into training and validation sets of size 9000 and 1000, respectiviely. The model was trained over 3 epochs using a batch size of 100. Reported accuracy was greater than 96%, as shown in Figure 9.

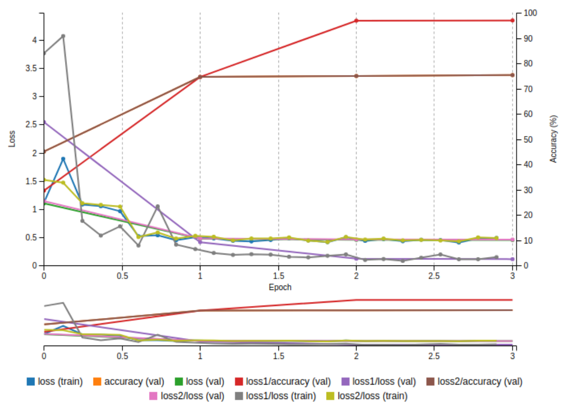

Fig. 9: Googlenet trained using the trial dataset showed decreasing loss on training and validation sets. Accuracy was greater than 95% on the third epoch.

Model performance was also evaluated against a set of unseen test data which resulted in an accuracy of 75.40%. Further, the inference speed of the model was reported as approximately 5ms for a single image.

4.2 Solar Panel Data

Model weights were re-initialised and re-trained using the solar panel image data set. Training was undertaken using 50 epochs with a batch size of 10. A higher number of epochs was selected given that the data set was very small. Reported accuracy was approximately 80%, as shown in Figure 10.

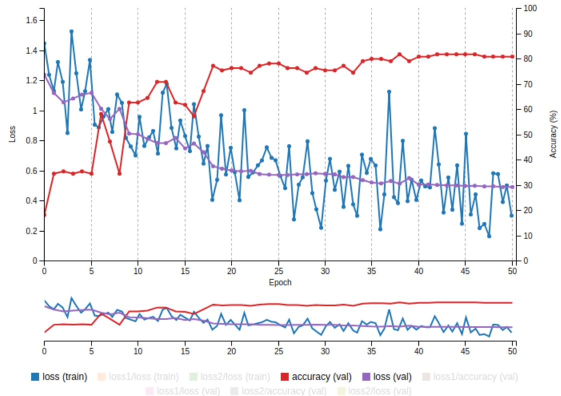

Fig. 10: Googlenet trained using the collected solar panel dataset showed decreasing loss on training and validation sets. Accuracy was approximately 80% on epoch 50.

Trained model performance was evaluated against an unseen data set comprised of 15 images from each class. The model accuracy was reported as 62%. A normalised confusion matrix can be seen in Figure 11.

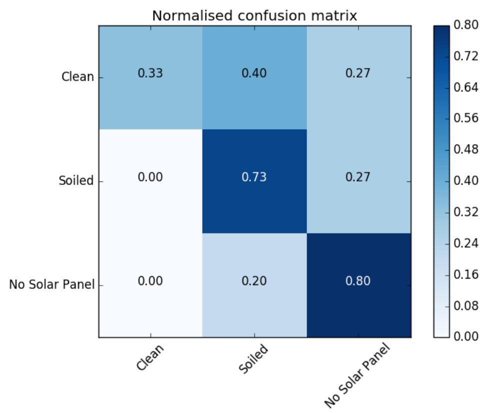

Fig. 11: Confusion matrix showing reasonable classification performance for soiled and no solar panel categories, however, classification of clean solar panels was poor.

5 DISCUSSION

The Googlenet model trained on the trial dataset performed adequately, meeting the 75% accuracy hurdle rate and an infernce speed almost twice as fast as the 10ms benchmark. The same cannot be said for the model performance on the solar dataset. Overall model accuracy for the solar application is only 63%. The confusion matrix highlights that the model had particular difficulty when attempting to classify a clean solar panel - it was in error 67% of the time when classifying these image types. The most likely explanation for this poor performance is the lack of data for this class. Images of clean solar panels only make up 12% of the total images. Classification of soiled solar panels, and the classification of no solar panels performs notably better, as seen in the confusion matrix. It must be highlighted, however, that these positive results may be falsely inflated given the two classes represent a majority of the training data and there is a very clear distinction between images with solar panels, and images without solar panels. It is likely that introducing more clean solar panel images, whilst improving the performance of clean solar panel classification, will degrade performance when classifying soiled solar panels. Classification of no solar panel is likely to remain unchanged under this scenario. A solar panel soiling classificaiton experiment undertaken by IBM, discussed earlier, performed significantly better than the results seen here. It must be noted, however, that the dataset for this experiment was much larger (approximately 45000 images) [8]. It should also be noted that IBM's study obtained images from a fixed RGB camera pointed at a single solar panel system with static panel orientation throughout the experiment. In contrast, this experiment obtained images from Google of different sized solar systems, viewed at varying angles, in various locations. This suggests that to avoid poor results a significant amount of data would be required to overcome scene variability.

Finally, model hyperparameters such as the batch size, the number of epochs, and optimisation algorithms could be altered during the training phase, however, without a larger dataset the improvements to model performance are likely to be limited.

6 CONCLUSION / FUTURE WORK

Googlenet provided a suitable framework for fast image classification, delivering a reasonable level of accuracy without compromising on inference speed. Model acccuracy of 75% was achieved on a trial data set, while maintaining an inference time of 5ms for a single image. The application of a Googlenet architecture to the classification of 3 distinct soiling states for solar panels showed moderate performace for the no solar panel and the soiled solar panel test sets. Unfortunately, limited size of training datasets meant the model did not generalise well on the final clean solar panel classification category.

The development of a large dataset would likely prove the most fruitful approach to bolstering model performance for this application. Previous studies have used in excess of 45000 images for model training datasets which resulted in reliable prediction of soiling state and approximation of power loss for a single panel. One approach to collecting additional data might be to partner with a large scale solar generation project and use aerial drones equipped with RGB cameras to capture more images of solar panels in known soiling states.

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