Solar Panel Soiling State Classification

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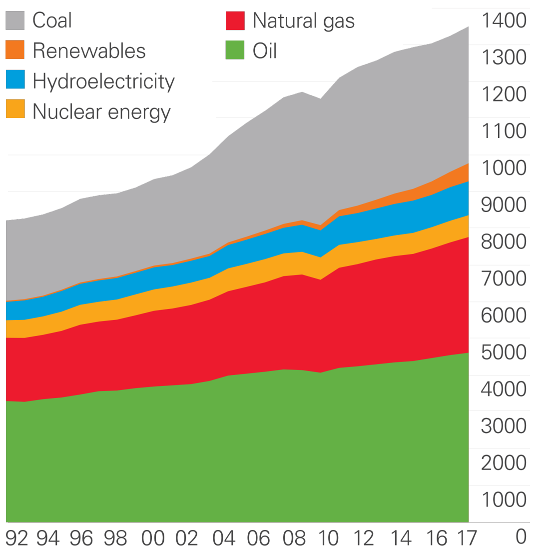
Abstract—An abstract is meant to be a summary of all of the relevant points in your presented work. It is designed to present a high-level overview of the report, providing just enough detail to convey the necessary information The abstract may often mention a one-sentence summary of the results. While the type of voice chosen for the paper (active or passive) may be up for debate, you should avoid the use of I and me in the report. It usually is kept to a length of 150 - 200 words. Example: You should not write, I present two different neural networks for classifying my data. Instead, you should try to say, Two different neural networks are used for classification

Index Terms—Robot, IEEEtran, LaTeX, deep learning.

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 the main source of generation. Solar resources have remained largely unused - this is in line with global trends in energy consumption.



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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 is a major source of global greenhouse gas emissions which contribute 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 shown in a longitudinal breakdown, seen in Figure 1. The graph also shows that energy demand is increasing. If coal, oil, and natural gas remain core sources of generation then this will most likely result in greenhouse gas emissions rising, accelerating the rate of global warming. This is problematic given the well understood impacts 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 impact assuming maintained rates of CO2 emissions. These include an increase 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. Soilng comes in the form of 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 network like this could be used to set up an automatic visual inspection system, using drones equipped with RGB cameras, to determine soiling states for large solar arrays. This is of interest as it would allow scheduling of cleaning routines for maintenance cost optimisation. Cost savings would be realised 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 can be thought of as a small patch which slides over the image allowing model weights to be shared for different sections of the image. An example of this 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. The large number of weights in these models have two main effects:

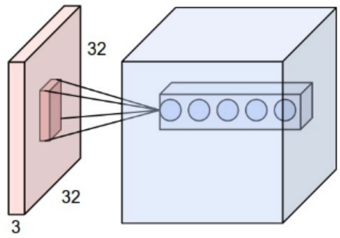

Fig. 2: text

1)

At this stage, you should begin diving into the technical details of your approach by explaining to the reader how parameters were defined, what type of network was chosen, and the reasons these items were performed. This should be factual and authoritative, meaning you should not use language such as I think this will work or Maybe a network with this architecture is better... Instead, focus on items similar to, A 3-layer network architecture was chosen with X, Y, and Z parameters Explain why you chose the network you did for the supplied data set and then why you chose the network used for your robotic inference project.

- example

1) example

3 Data Acquisition

This section should discuss the data set. Items to include are the number of images, size of the images, the types of images (RGB, Grayscale, etc.), how these images were collected (including the method). Providing this information is critical if anyone would like to replicate your results. After all, the intent of reports such as these are to convey information and build upon ideas so you want to ensure others can validate your process. Justifying why you gathered data in this way is a helpful point, but sometimes this may be omitted here if the problem has been stated clearly in the introduction. It is a great idea here to have at least one or two images showing what your data looks like for the reader to visualize.

4 Results

This is typically the hardest part of the report for many. You want to convey your results in an unbiased fashion. If you results are good, you can objectively note this. Similarly, you may do this if they are bad as well. You do not want to justify your results here with discussion; this is a topic for the next session. Present the results of your robotics project model and the model you used for the supplied data with the appropriate accuracy and inference time For demonstrating your results, it is incredibly useful to have some charts, tables, and/or graphs for the reader to review. This makes ingesting the information quicker and easier.

5 DISCUSSION

This is the only section of the report where you may include your opinion. However, make sure your opinion is based on facts. If your results are poor, make mention of what may be the underlying issues. If the results are good, why do you think this is the case? Again, avoid writing in the first person (i.e. Do not use words like I or me). If you really find yourself struggling to avoid the word I or me; sometimes, this can be avoid with the use of the word one. As an example: instead of : I think the accuracy on my dataset is low because the images are too small to show the necessary detail try: one may believe the accuracy on the dataset is low because the images are too small to show the necessary detail. They say the same thing, but the second avoids the first person. Reflect on which is more important, inference time or accuracy, in regards to your robotic inference project.

6 CONCLUSION / FUTURE WORK

This section is intended to summarize your report. Your summary should include a recap of the results, did this project achieve what you attempted, and is this a commercially viable product? For Future work,address areas of work that you may not have addressed in your report as possible next steps. For future work, this could be due to time constraints, lack of currently developed methods / technology, and areas of application outside of your current implementation. Again, avoid the use of the first-person.

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