

SHORT-TERM SOLAR FORECASTING USING SKY CAMERA BACKED BY A CONVOLUTIONAL NEURAL NETWORK

By

Joel Wong

DipLang, BCompSc/BEng(Hons)(Computer)(Newcastle)

Thesis

submitted in fulfilment of the requirements for the Degree of

Master of Philosophy in Computer Science



School of Information and Physical Sciences
The University of Newcastle
Callaghan, New South Wales 2308, Australia
December 2022

This research was supported by an Australian Government Research
Training Program (RTP) Scholarship

Statement of Originality

I hereby certify that the work embodied in the thesis is my own work, conducted under normal supervision. The thesis contains no material which has been accepted, or is being examined, for the award of any other degree or diploma in any university or other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made. I give consent to the final version of my thesis being made available worldwide when deposited in the University's Digital Repository, subject to the provisions of the Copyright Act 1968 and any approved embargo.

Joel Tze-Bean Wong, December 2022

Name of the Candidate, Month Year

Acknowledgements

I would like to acknowledge the support I received from the CSIRO for this project. Without the funding, data, compute resources and work environment this project would never have even started. It has been a privilege to pick up and extend on the existing solar forecasting work at a time when Australia is integrating so much solar energy into the grid.

I am very grateful to my supervision team of Dr Alexandre Mendes, Sam West and Professor Stephan Chalup, who have all been hugely instrumental in my growth as both a person and a researcher. You never failed to encourage me in all the times where I felt like I had hit a wall, and your excitement and thinking aloud about even small results was infectious.

For my friends and family, I am thankful for all of the support and willing ears, listening to my poor explanations of overly technical details with interest and offering encouragement when I was stuck. I am truly blessed to have had so much support in all of my studies.

Contents

| | | |
|----------|---|-----------|
| 1 | Introduction | 1 |
| 1.1 | Background and Significance | 1 |
| 1.1.1 | Motivation | 2 |
| 1.1.2 | Approaches to Solar Forecasting | 5 |
| 1.2 | Research Objectives | 11 |
| 1.3 | Organisation of the Thesis | 12 |
| 2 | Literature Review | 13 |
| 2.1 | Search Methodology | 14 |
| 2.2 | Methods | 16 |
| 2.3 | Datasets | 25 |
| 2.4 | Metrics | 27 |
| 2.5 | Wider Context | 29 |
| 2.6 | Summary | 30 |
| 3 | Experimental Setup | 37 |
| 3.1 | Data Collection and Preprocessing | 37 |
| 3.2 | Dataset Splits | 43 |
| 3.3 | Model Architecture | 45 |
| 3.4 | Experiment Strategy | 46 |
| 4 | Results | 49 |
| 4.1 | Baseline Performance | 51 |
| 4.2 | Architecture Sweep | 52 |
| 4.3 | Crop Size and Lookback horizon | 54 |
| 4.4 | Input Terms and Spacing | 55 |
| 4.5 | Learning Rate | 57 |
| 4.6 | Horizon | 58 |

| | | |
|----------|---|-----------|
| 4.7 | Visualisations and Case Studies | 59 |
| 4.8 | Final considerations and 2016 data | 66 |
| 4.9 | Summary | 67 |
| 5 | Discussion | 69 |
| 5.1 | Comparison with SUNSET | 69 |
| 5.2 | The efficacy of Crops | 73 |
| 5.3 | How to evaluate models | 75 |
| 5.4 | Probabilistic and Spatial forecasts | 77 |
| 6 | Conclusion and Final Remarks | 79 |
| A | Additional Results | i |

List of Figures

| | | |
|-----|---|----|
| 1.1 | Elements in an Electrical Grid. | 3 |
| 1.2 | Example of two layers of cloud. | 5 |
| 1.3 | Different models excel at different temporal and spacial horizons. | 6 |
| 1.4 | Comparison of traditional approaches with Deep Learning approaches. | 8 |
| 2.1 | The basic SUNSET architecture. | 17 |
| 2.2 | Zhang et al.’s proposed LSTM-based architecture. | 19 |
| 2.3 | PhyDNet architecture. | 21 |
| 2.4 | ECLIPSE architecture. | 22 |
| 2.5 | Gao and Liu’s ViT architecture. | 25 |
| 3.1 | Data collection setup. | 38 |
| 3.2 | Black dot in the sun is directly from the output of the camera. | 39 |
| 3.3 | Comparison of crop options. | 41 |
| 3.4 | Dataset splits for 2015 data. | 43 |
| 3.5 | Line plots of the irradiance of examples days from each category | 44 |
| 3.6 | Architecture of the proposed Solpred model. | 46 |
| 3.7 | Architecture Sweep. | 48 |
| 4.1 | Median RMSE vs Ensemble RMSE | 50 |
| 4.2 | Image sequence with crops | 55 |
| 4.3 | Image sequence for the 19th of December case study. | 60 |
| 4.4 | Image sequence for the 25th of April case study. | 61 |
| 4.5 | Time series plots for the December 19th case study | 62 |
| 4.6 | Time series plots for 25th of April at 2, 5 and 7 minute forecast horizons. | 63 |
| 4.7 | Example visualisation of final Convolutional layer activations. | 64 |
| 4.8 | Scatter plot. Solpred vs actual values for various data categories. | 65 |
| S1 | Final Convolutional layer activations, Solpred 19th December | ii |

| | | |
|----|--|---------------------|
| S2 | Final Convolutional layer activations, SUNSET* 19th December | iii |
| S3 | Final Convolutional layer activations, Solpred 25th April | iv |
| S4 | Final Convolutional layer activations, SUNSET* 25th April | v |

List of Tables

| | | |
|------|--|----|
| 2.1 | Search Parameters for database search. | 14 |
| 2.2 | Search Results from the databases, and the remaining results after manual filtering. | 15 |
| 2.3 | Summary of papers found | 32 |
| 2.3 | <i>(Continued)</i> Summary of papers found | 33 |
| 2.3 | <i>(Continued)</i> Summary of papers found | 34 |
| 2.3 | <i>(Continued)</i> Summary of papers found | 35 |
| 4.1 | Baseline results Black Mountain dataset, with category breakdowns. | 52 |
| 4.2 | Baseline results on Stanford, California dataset. | 52 |
| 4.3 | Architecture Sweep results on Black Mountain dataset. | 53 |
| 4.4 | Architecture Sweep results for Stanford, California dataset. | 53 |
| 4.5 | Crop size sweep on Black Mountain dataset. | 54 |
| 4.6 | Crop size sweep on Black Mountain dataset. | 55 |
| 4.7 | Input configuration sweep on Black Mountain dataset. | 56 |
| 4.8 | Input spacing sweep on Black Mountain dataset. | 57 |
| 4.9 | Black Mountain dataset, testing additional auxiliary data | 57 |
| 4.10 | Learning rate sweep on Black Mountain dataset. | 58 |
| 4.11 | Black Mountain dataset, comparison of forecast horizons | 58 |
| 4.12 | Black Mountain dataset, summary of 7 case studies, 20 minutes each. | 59 |
| 4.13 | Black Mountain dataset, 2015 test data by weather category. | 66 |
| 4.14 | Black Mountain dataset, 2016 test data. | 67 |

Abstract

A time series forecasting model based on a convolutional neural network, named “Solpred”, was developed to process images of the sky from a ground based camera, forecasting solar irradiance up to 15 minutes in the future. Accurate irradiance forecasts are a key factor in being able to proactively manage changes in energy output from solar power sources in an electricity grid, enabling a greater penetration of solar power. Solpred produced a deterministic forecast with a skill of 23.4% using RMSE vs naive persistence at a 2-minute forecast horizon of GHI, and a skill of 25.5% at a 15-minute forecast horizon of GHI. This was compared against a re-implementation of the SUNSET model proposed by Sun, Szűcs, and Brandt [1], which achieved 21.6% at a 2-minute horizon and 22.1% at a 15-minute horizon. The reasons for this difference in performance is investigated, with the absence of batch normalisation layers being found to produce the largest increase in performance.

Various input and output configurations were applied to test the limits of the Solpred architecture, with a key finding that sun-centred image cropping improved the skill of the model from 16.4% to 23.4% at a 2-minute forecast horizon. This suggests an easy improvement in performance for models, but also implies a limitation in how the architecture extracts spatial features using convolutional layers. The convolutional layers struggle to perform the spatial reasoning tasks required for solar forecasting, suggesting that they could be augmented with more flexible modules such as transformer encoders or recurrent modules when dealing with spatial reasoning tasks.

