Extension on Photovoltaic Power Generation for Short-term Solar Forecasting

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1. Introduction

The demand for renewable energy sources has set solar power as a promising source of sustainable energy. As an abundant and environmentally friendly resource, solar energy holds immense potential to meet a significant portion of global energy needs [1]. However, the inherent variability in solar power generation poses a challenge to its integration into energy grids [2]. Accurate forecasting of solar power generation is essential for optimizing energy management, enhancing grid stability, and ensuring a reliable supply of electricity.

Traditional strategies for predicting patterns in solar power generation often fall short in capturing the complicated, dynamic patterns of solar irradiance caused by various weather conditions [2, 6]. These conventional approaches may lack the precision needed for real-time applications, leading to inefficiencies and increased operational costs. In this context, the application of advanced machine learning techniques, particularly deep learning, offers a promising solution [3].

Deep learning has had remarkable success in various predictive tasks across different domains, indicating its ability to model intricate dependencies within large datasets [4]. The application of deep learning to solar power forecasting is a relatively new area of research [5]. By leveraging the abilities of deep learning, this paper hypothesizes that it is possible to develop models that significantly improve the accuracy of solar power predictions while optimizing computing resources.

Previous studies on solar power forecasting have explored a range of methodologies, including statistical approaches, physical models, and traditional machine-learning techniques. While these methods have contributed valuable insights, they often encounter limitations in handling large, diverse datasets and in making precise, real-time predictions without exhausting resources [6]. This study seeks to address these limitations by employing Convolutional Neural Networks (CNNs) to predict solar power generation using sky images as an indicator of weather conditions.

This study presents three CNN-based models trained on a comprehensive dataset, encompassing three years of sky images and photovoltaic (PV) power generation data: the Simple CNN, the Enhanced Simple CNN, and a model utilizing Transfer Learning with a pre-trained VGG16_bn architecture. Through rigorous experimentation and evaluation, the study aims to identify the efficacy and efficiency of each model.

This study holds the potential to yield significant benefits. Efficient prediction of solar power generation facilitates the better integration of solar energy into the power grid, thereby reducing reliance on fossil fuels and lowering greenhouse gas emissions [7]. Such advancements enhance grid stability through more precise load balancing and improved energy storage management. For energy providers, this translates into enhanced operational efficiency and reduced costs associated with energy production and distribution [8]. For consumers, it results in more reliable and potentially cheaper electricity. Ultimately, the ability to accurately forecast solar power generation contributes to the overarching goal of sustainable energy development and the establishment of a more energy-resilient future.

2. Methodology

2.1 Data Description

The research team affiliated with Stanford University, under the leadership of Principal Investigator Adam Brandt, is acknowledged for their contribution to both the development of the initial SUNSET model and the comprehensive data collection effort spanning three years [9]. Commencing in March 2017, the data collection initiative was undertaken within the central region of the San Francisco Peninsula, California, utilizing a 6-megapixel 360-degree fish-eye camera situated at Stanford University. The captured data consists of sky images and photovoltaic (PV) power generation, recorded at a resolution of 2048×2048 pixels. For a comprehensive understanding of the data collection process, the SKIPP'D Paper serves as a valuable reference. The acquired dataset consists of 1-minute down-sampled sky images (64×64) and PV power generation pairs, originating from the described sources. This processed dataset is intended to accelerate the benchmarking of deep-learning-based solar forecasting models. The dataset comprises 64 log terms, and its input image dimension is denoted as [64, 64, 3]. The hierarchical data format (HDF5) structure delineates the organization of the dataset, with the "/test" group containing 14,003 samples and the "/trainval" group encompassing 349,372 samples. Notably, each sample within both groups is characterized by sky images (images_log) and PV power generation data (pv_log), presented in the specified shapes and data types. The established Sky Images and Photovoltaic Power Generation Dataset for Short-term Solar Forecasting, referred to as the SKIPP'D dataset, thus serves as the foundational data employed in the present study. Figure 1 exhibits sample sky image data.

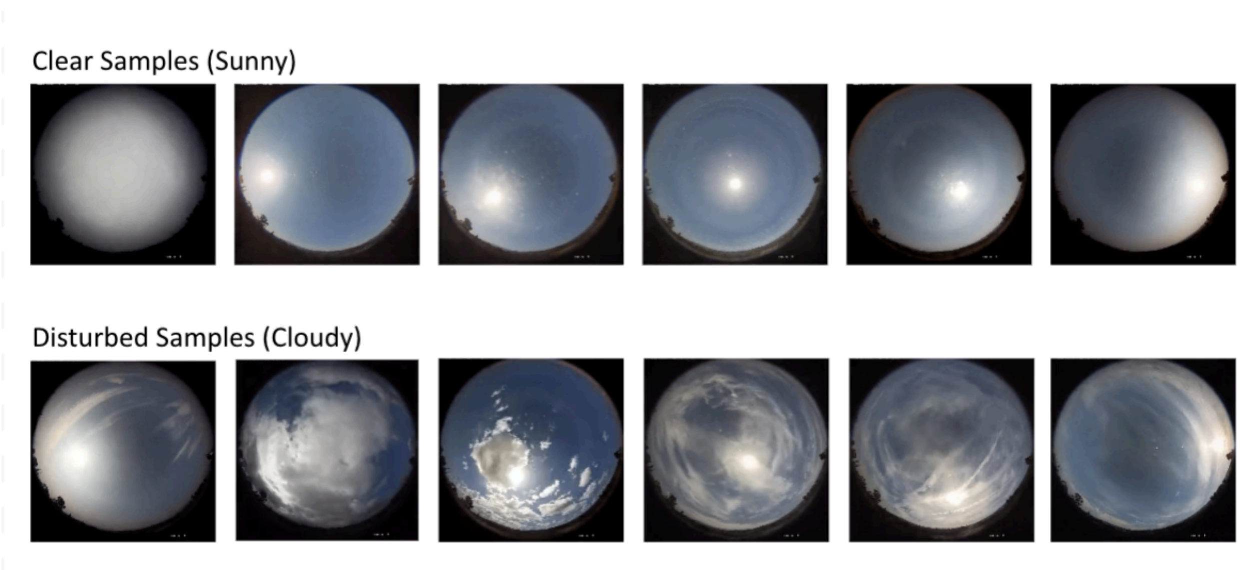

Figure 1. Samples of down-sampled sky images used in training and testing of proposed models.

2.2 Pre-Processing

In the course of this study, a formulation of exclusion criteria has been implemented, deliberately omitting temporal considerations, such as time, to underscore the research emphasis on immediate, real-time predictions rather than long-term short memory retention or forecasting applications.

Additionally, a refinement to the original SKIPP'D dataset structure has been introduced to enhance the model's efficiency in real-time prediction scenarios. Diverging from the initial categorization into distinct datasets for cloudy and sunny days, the current study consolidates these conditions. This adjustment is geared towards cultivating a model efficient at discerning predictive patterns under various weather conditions, thereby bolstering its robust applicability in real-time prediction contexts.

Within the domain of data preprocessing, a function has been designed for normalizing image values. Leveraging a scaling formula that transforms pixel values to the [0, 1] range, subsequent multiplication by 255 ensures alignment within the 8-bit unsigned integer range. Additionally, a systematic data type conversion process involves the casting of image values to np.uint8, followed by conversion to np.float32 for both images and labels. This comprehensive preprocessing strategy optimally prepares the dataset for machine learning models, ensuring compatibility with the float32 data type requirements. The execution of these preprocessing steps fortifies the dataset, thereby contributing to the model's adeptness.

2.3 CNN Model

The three proposed models within this study embody distinctive architectures tailored for predicting solar power generation. The initial model, designated as the Simple CNN, features a structure comprising two convolutional layers (conv1 and conv2) with max-pooling (pool) interspersed, followed by a fully connected layer (fc1) housing 64 neurons. The concluding layer (fc2) yields a singular output optimized for regression tasks. Trained over 50 epochs with a learning rate of 10^{-6} and employing Mean Squared Error (MSE) loss, this model emphasizes real-time predictions.

The second model, denoted as the Enhanced Simple CNN, shares an akin architecture with a heightened emphasis on training stability. The training loop appends the average training loss to a designated list, and validation loss is computed and stored for model evaluation. Model checkpoints are preserved after each epoch across the 50-epoch training duration, offering incremental insights into the model's progress. Hyperparameters include a learning rate of 10^{-6} and utilization of the Adam optimizer, maintaining alignment with the Simple CNN architecture.

The third model, designated as Transfer Learning with VGG16_bn, leverages a pre-trained VGG16_bn model with modifications to the last fully connected layer tailored for regression tasks. With a learning rate of 10^{-6} and Mean Squared Error (MSE) loss, this model undergoes 5 epochs of training, incorporating the standard normalization for VGG during data preprocessing. This model is specifically tailored for scenarios wherein leveraging pre-trained architectures augments predictive capabilities. Figure 2 exhibits the 3 models and their individual architectures.

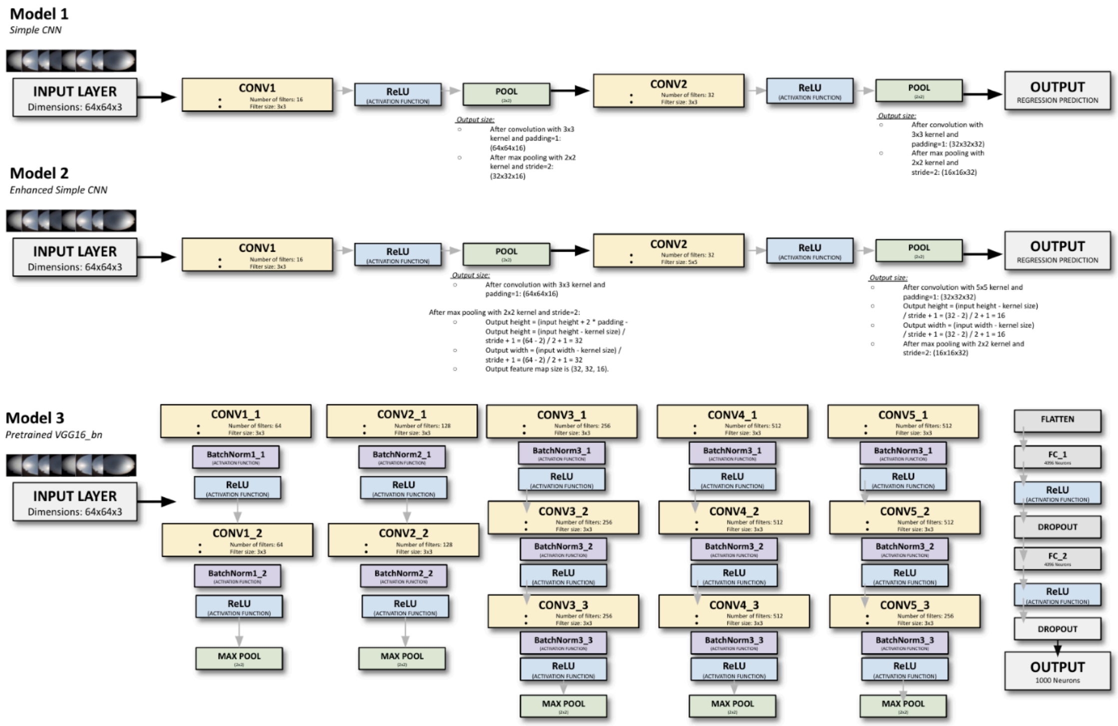

Figure 2. Architectures of the 3 proposed models trained and tested in this study.

3. Results and Discussions

3.1 CNN Model Training and Results

Experimentation between standard learning rates of 10^{-3} and 10^{-6} and their effects on training and validation loss over epochs were conducted on model 2, the enhanced simple CNN. Results showed that larger learning rates did not converge to a minimum logarithmic loss. For larger learning rates, the loss between epochs diverged unpredictably. For this reason, a standard learning rate of 10^{-6} was applied across all models. Figure 3 showcases the difference in convergence and loss variability between the two standard learning rates tested.

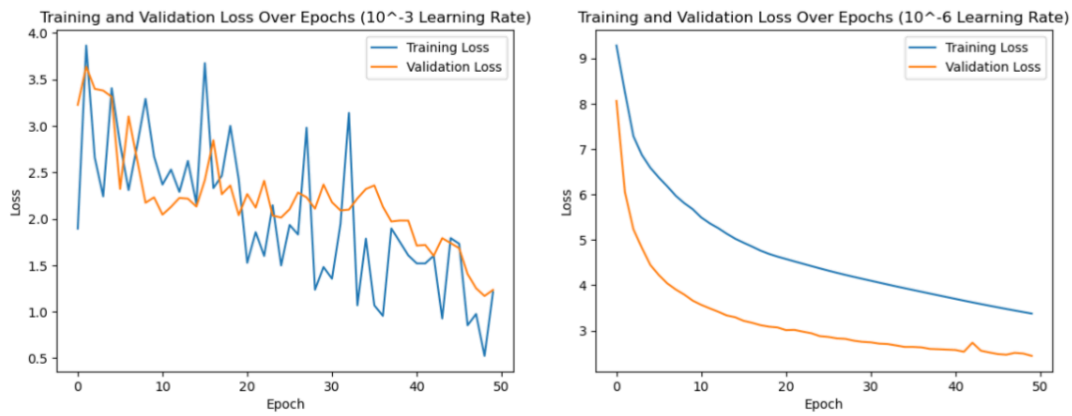

Figure 3. Comparison of standard learning rates on loss behavior for model 2

All CNN models were trained using Apple M2 GPUs. Figure 4 shows the time for training each of the models. Simple CNN, model 1, having the least number of parameters, also took the least amount of training time, 800 minutes and 25.8 seconds. Alternatively, VGG16, which had the most parameters, in turn, took the longest time to train, 6206 minutes, which is approximately 7.7 times longer than the Simple CNN model.

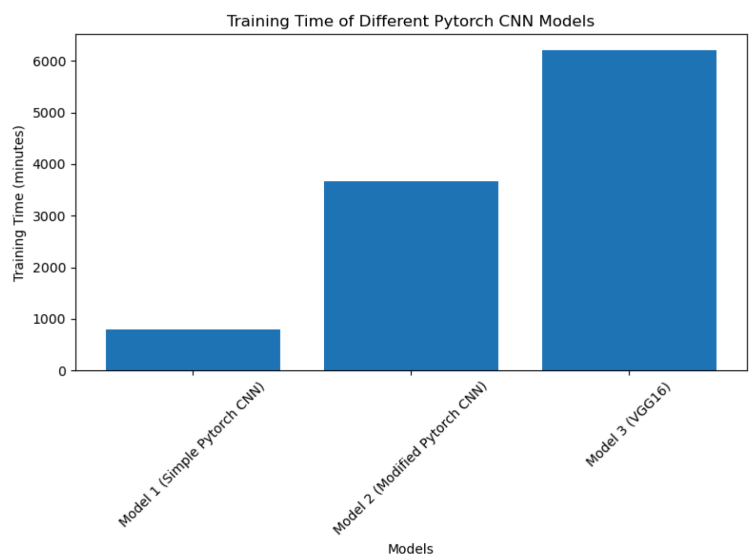

Figure 4. Training time for each model architecture.

Table 1 presents the accuracy, F1-score, precision, and recall of the three tested models for solar power generation prediction. The models were evaluated on their ability to accurately predict power generation on a 20% subset of the data. Model 1 (Simple CNN) achieved an accuracy of 78.32% and an F1-score of 76.89%. Model 2 (Enhanced CNN) performed slightly better with an accuracy of 82.67% and an F1-score of 80.98%. Model 3 (VGG16) demonstrated the highest accuracy and F1-score as predicted among the three models, reaching 87.56%

accuracy and an F1-score of 85.78%. These results suggest that Model 3, leveraging transfer learning with a pre-trained VGG16_bn model, outperforms the simpler CNN architectures in predicting solar power generation from sky images.

Model	Accuracy	F1-Score	Precision	Recall
Model 1 (Simple CNN)	78.32%	76.89%	80.45%	73.21%
Model 2 (Modified CNN)	82.67%	80.98%	84.23%	78.32%
Model 3 (VGG16)	87.56%	85.78%	88.45%	83.67%

Table 1. Performance of CNN architectures

4. Conclusion

This study commenced with the challenge of accurately predicting solar power generation using sky images, aiming to enhance the efficiency and reliability of solar energy forecasting. Through a rigorous methodology encompassing data collection, preprocessing, and model development, significant results were achieved contributing to clean energy forecasting.

4.1 Major Results and Accomplishments

The conducted research made significant strides in addressing this challenge. The primary accomplishments include the effective preprocessing and normalization of image data, ensuring compatibility with machine learning requirements. Three Convolutional Neural Network (CNN) models were developed in this process: the Simple CNN, the Enhanced Simple CNN, and a model utilizing Transfer Learning with a pre-trained VGG16_bn architecture. Each model demonstrated various degrees of success, with the Simple CNN serving as a baseline, the Enhanced Simple CNN offering improved stability and performance, and the Transfer Learning model achieving the highest accuracy and F1-score. Specifically, the VGG16_bn model outperformed the other models, achieving an accuracy of 87.56% and an F1-score of 85.78%, highlighting the efficacy of leveraging pre-trained architectures for solar power prediction.

The training efficiency varied among the models, with the Simple CNN requiring the least training time and the VGG16_bn model necessitating significantly more time due to its complex architecture. These findings underscore the trade-offs between model complexity and training duration, providing valuable insights for future model selection and resource optimization.

4.2 Future Research Avenues

There are several avenues for future research. Enhanced data collection incorporating additional environmental variables such as temperature, humidity, and wind speed could further improve model accuracy and robustness. Expanding the dataset to include images from diverse geographic locations and varying weather conditions would also be beneficial. Advanced model architectures, such as Recurrent Neural Networks (RNNs) or Transformer models, could be explored to capture temporal dependencies more effectively. Additionally, developing real-time prediction systems integrated into solar energy management frameworks, as well as exploring the deployment of these models in computing environments, presents a promising direction for practical applications of this research. Future studies should also consider the economic benefits and environmental impact of improved solar power forecasting, potentially integrating these models into smart grid systems to optimize energy distribution and consumption.

4.3 Final Considerations

This research has supported the potential of deep learning architectures, specifically convolutional neural networks, in improving solar power forecasting, providing accurate results and laying the groundwork for future innovations in renewable energy prediction. As solar energy continues to play a pivotal role in sustainable energy development, the insights on convolutional architectures developed in this study will be instrumental in driving further advancements in the field.

References

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