Solar Irradiance Prediction

IFT 6759 - Project 1
Team 1

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Introduction

Forecasting Solar Energy.

The effective irradiance of the sun is called Global Horizontal Irradiance (GHI).
Using Satellite images to predict GHI at four time stamps.
$T = T_0$, $T = T_0 + 1h$, $T = T_0 + 3h$, $T = T_0 + 6h$.

DATASETS

Datasets: GOES-13 + SURFRAD

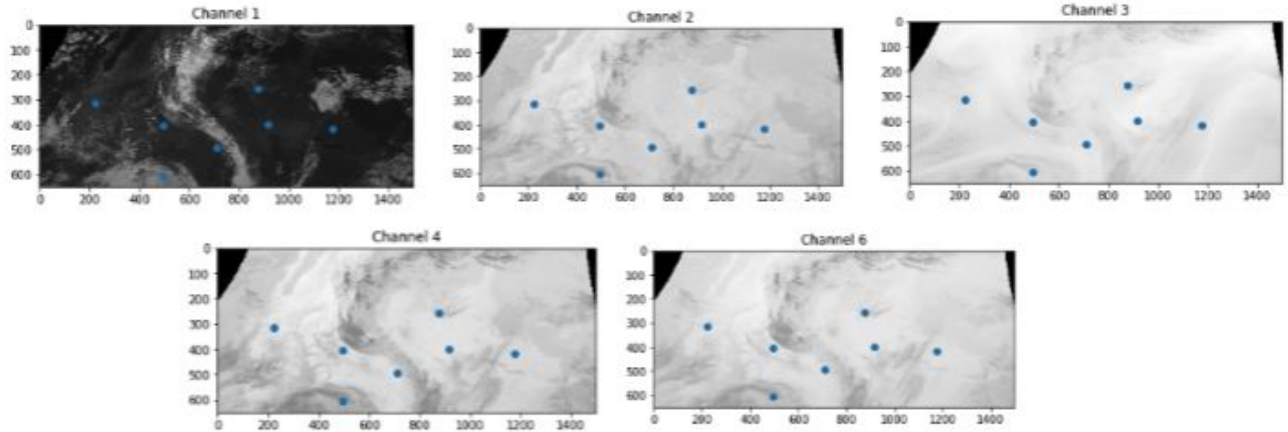


Figure 1: Sample of an image with its five channels represented separately, along with its corresponding station locations (seven blue dots). GOES-13 covers all of the continental United States.

Existing Solutions

Clear sky models estimate the terrestrial solar radiation under a cloudless sky as a function of the solar elevation angle, site altitude, aerosol concentration, water vapor, and various atmospheric conditions.

The clear sky model accounts only for some effects of the atmosphere on solar irradiance. It predicts the solar irradiance when the sky is clear. It takes into account surface pressure, zenith angle, turbidity, etc.

Does not capture **complex temporal phenomena** (clouds, winds, etc.).

Data Analysis

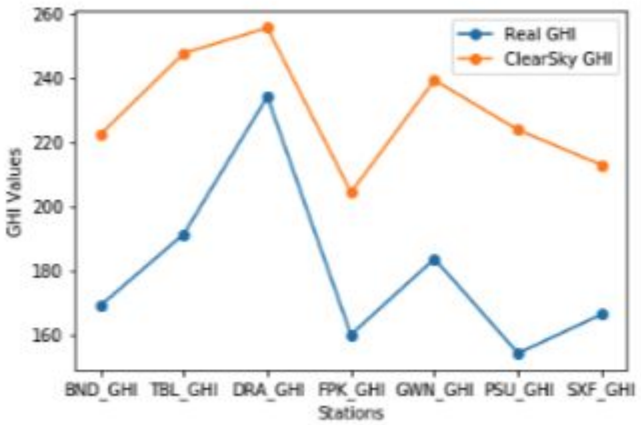


Figure 2: The difference between the real GHI values (lower values) and ClearSky GHI values (higher values). Both GHI values are averaged over all years and stations.

Data Analysis

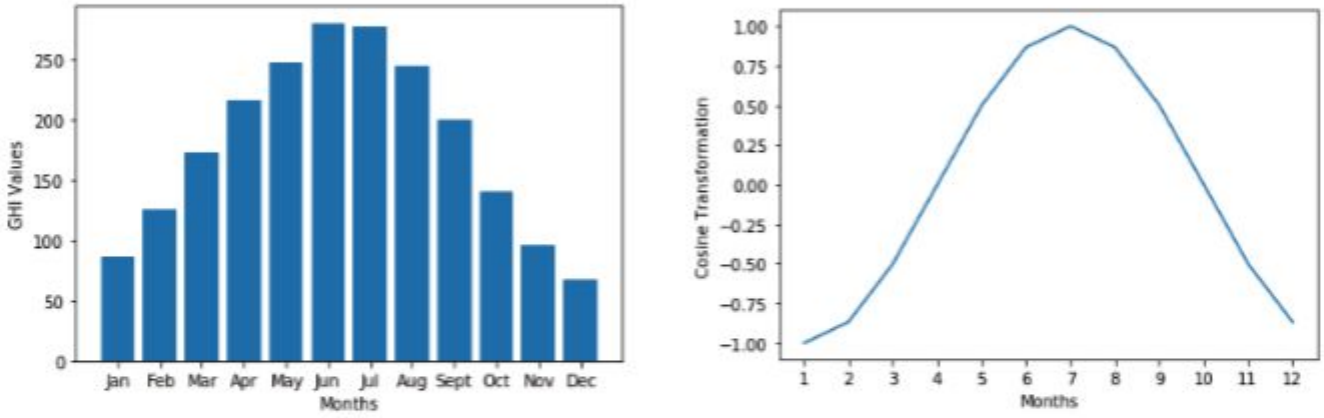


Figure 3: The left graph represents the real GHI values (y-axis) per month (x-axis) averaged over all years and stations. The right graph represents the real GHI values after applying a cosine transformation (y-axis) per month (x-axis)

Data Analysis

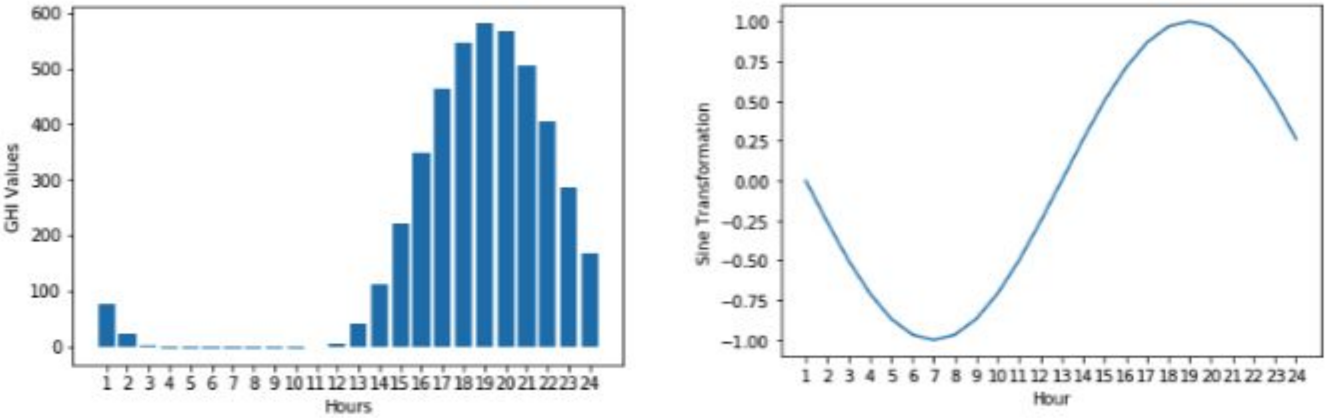


Figure 4: The left graph represents the real GHI values (y-axis) per hour in a day in UTC (x-axis) averaged over all years and stations. The right graph represents the real GHI values after applying a sine transformation (y-axis) per hour in a day in UTC (x-axis)

Models

CNN + Dense

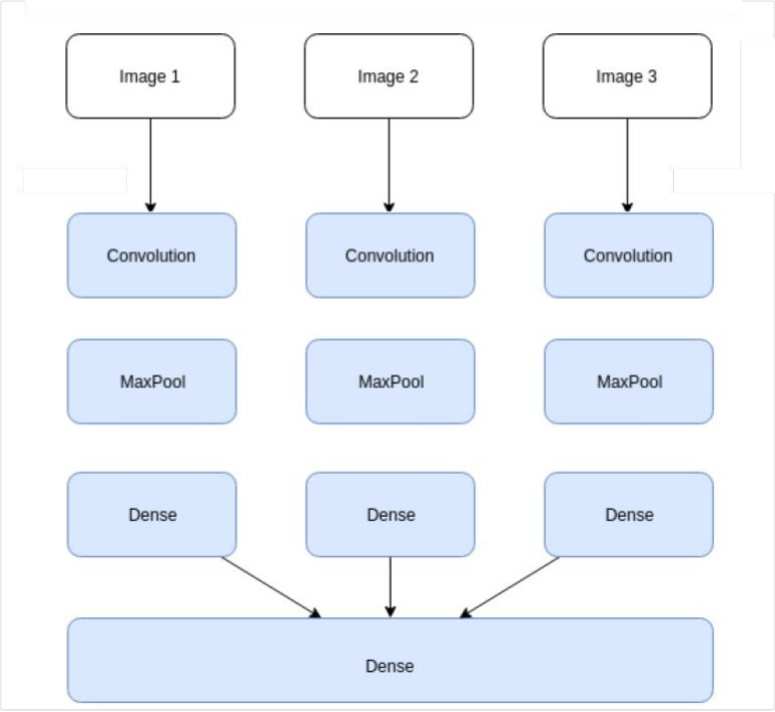


Image 1
Image 2
Image 3
Convolution
Convolution
Convolution
MaxPool
MaxPool
MaxPool
Dense
Dense
Dense
Dense

CNN + LSTM

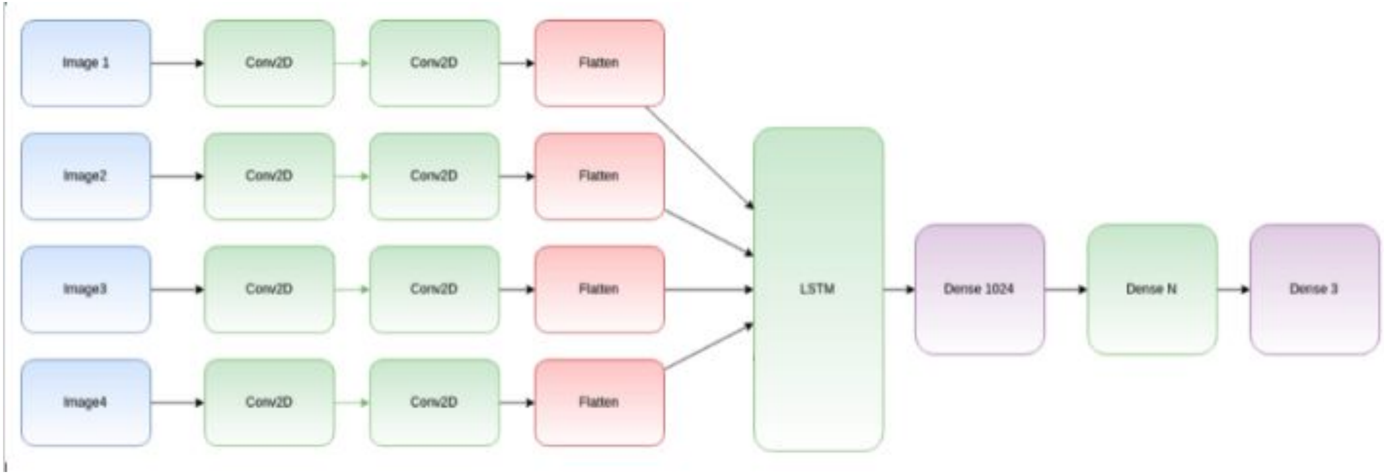
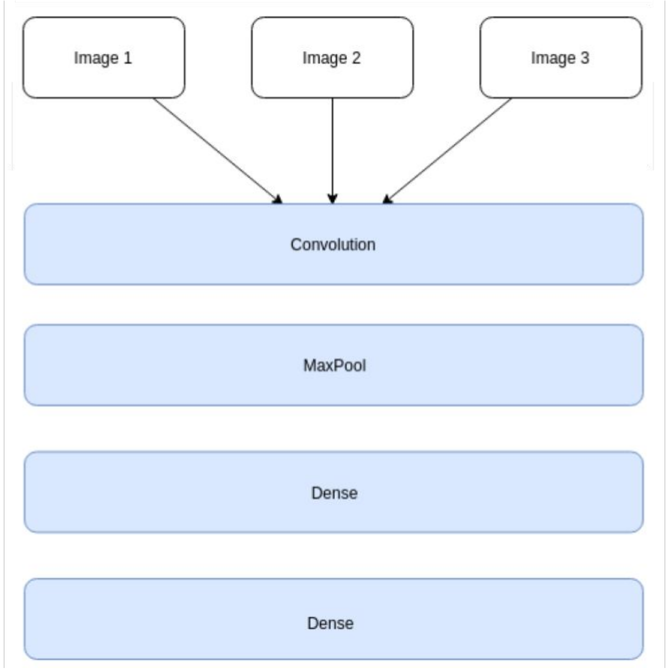


Image 1
Conv2D
Conv2D
Flatten
Image2
Conv2D
Conv2D
Flatten
Image3
Conv2D
Conv2D
Flatten
Image4
Conv2D
Conv2D
Flatten
LSTM
Dense 1024
Dense N
Dense 3

3D CNN



Results

RMSE

Algorithms	BS	LR	$RMSE_1$	$RMSE_2$
ClearSky Baseline	n/a	n/a	205	-
Conv2D with non-sequence	128	0.01	142.36	109.21
	128	0.001	139.74	107.56
	256	0.001	136.14	104.59
	512	0.01	133.83	106.52
	512	0.001	122	105.24
Conv3D with sequence	128	0.001	-	102.81
	128	0.01	-	103.16
	256	0.001	128.32	**99.01**
	512	0.01	147.02	101.10
	512	0.001	145.28	100.88
Conv2D with sequence + LSTM	128	0.001	139.12	105.22
	128	0.01	-	107.12
	256	0.001	142.06	103.09
Conv2D with sequence + Dense	256	0.001	149.51	109.06
	128	0.001	154.11	106.99

Table 1: Results from five different models with their respective best hyperparameters, where **BS** stands for **batch size** and **LR** stands for **learning rate**. Validation RMSE was trained over time periods as follows: training: years 2010-2014 and validation: year 2015. **$RMSE_1$** represents the RMSE on the validation set **without residual labels**. **$RMSE_2$** represents the RMSE on the validation set **with residual labels**.

Loss Curves

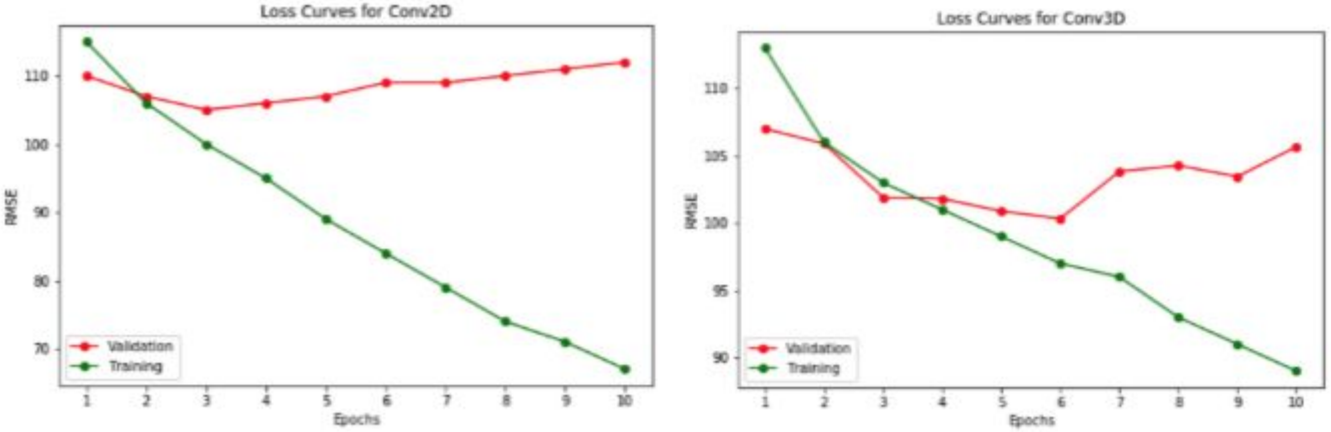


Figure 7: The left graph represents the training and validation curves on the Conv2D model with sequential images and the right graph represents the training and validation curves on the Conv3D model with sequential images, which was our best performing model.

Conclusions

- Best performing model is a 3D-Convolutional Neural Network using sequential images with a look-back temporal window of 4 timesteps, using dilated filters, batch normalization, and residual labels (from Clear Sky GHI)
- The high data regime was our biggest challenge
- Injecting temporal metadata (hour and month) to our model helped capture time-based effects along with the satellite imagery which captured spatial interactions.

Contributions

- Basic CNN used to look at present and past satellite images to predict GHI values at seven different locations, which out performs baseline methods (ie. ClearSky Model).
- Concatenate spatial and temporal metadata as inputs to our model.
- Manipulate our labels using ClearkSky GHI

  residual_label = real_GHI - ClearSky_GHI

Future Work

- ❖ Use higher resolution satellite images
- ❖ Experiment with different window look-back sizes for the images (we only experimented with a window of size 4)
- ❖ Use a better ClearSky model in order to get better residual labels

Questions?