Solar Irradiance Forecasting

Project Overview

Business Understanding

Irradiance is the amount of solar energy that reaches the earth's surface per unit area. This irradiance is the basis for the calculation of overall power production capacity; forecasting irradiance allows us to forecast production. Accurate irradiance forecasting is essential for renewable energy generators, especially solar power plants, to optimize their energy production and meet regulatory requirements.

In Australia, the grid rewards solar power plants that can predict their expected irradiance (really their power generation capability) for the next 5 minutes. This helps the grid balance the supply and demand of electricity and prevent blackouts or surges. Other countries and regions may soon adopt similar or stricter rules for solar power plants.

Objective

The aim of this project is to accurately forecast irradiance (GHI) with 30 minutes horizon and one minute granularity (IE, predicting t+1, t+2, t+3…, t+30) using provided historical data.

Dataset

Used public dataset from Folsom, California.

- Day ahead weather forecasts for closest weather stations (North American Mesoscale Forecast System (NAM))
- Satellite imagery from GOES-15
- Imagery from Whole Sky Cameras
- RGB Ratios from Whole Sky Camera Imagery
- Target dataset with irradiance measures at a minutely granularity

Exploratory data analysis (EDA)

1. **Day ahead weather forecasts for closest weather stations**: a public North American Mesoscale Forecast System (NAM) Hourly dataset from Folsom, California (Latitude 38.579454, Longitude -121.260320) includes forecast time period, **GHI Downward short-wave radiation flux (W/m2), Cloud cover, precipitation, Pressure, components of wind, temperature, Relative humidity** with 14980 records.

2. **Satellite imagery from GOES-15 dataset** used to extract **cloud cover ratio** using following equation 1 and **Average, Standard Derivation and Entropy** features

   Cloud Cover Ratio = Number of Cloud Pixels / Total Number of Cloud and Sky Pixels (Eq. 1)

   Average $\mu = \frac{1}{N}\sum_{i=1}^{N} v_i.$ (Eq. 2) **Standard Derivation** $\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(v_i - \mu)^2},$ (Eq. 3) **Entropy** $e = -\sum_{\substack{i=1 \\ p_i \neq 0}}^{N_B} p_i \log_2(p_i),$ (Eq. 4)

3. **Imagery from Whole Sky Cameras** used to extract **cloud cover ratio** using equation 1.

   Preprocessing Images:

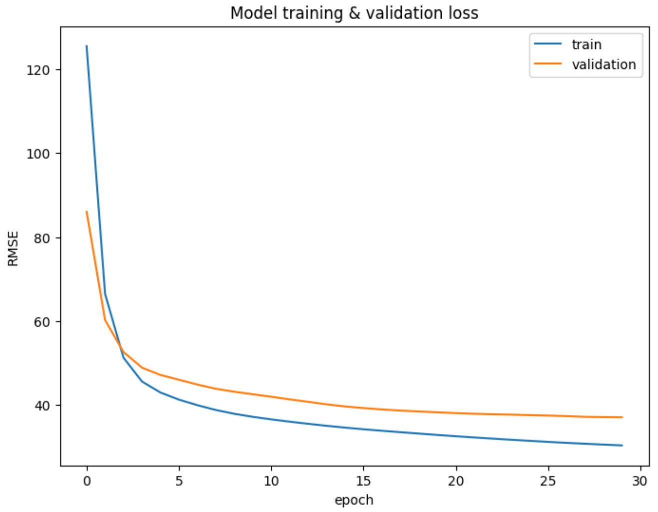
   1. Convert Fish-Eye Image to flat Image
   2. Detect Solar Position
   3. Convert the image into Color segmentation
   4. Classify the cloud and sky pixels using threshold pixel value
   5. Convert the cloud pixel to cloud cover ratio using Eq.1

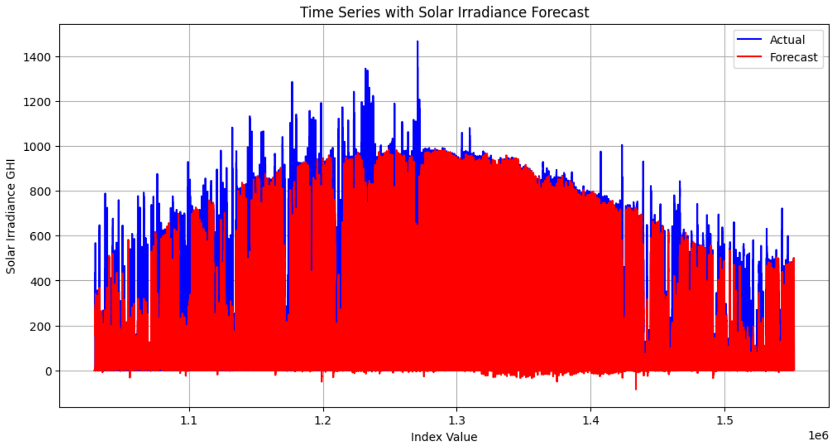
4. **RGB Ratios from Whole Sky Camera Imagery** includes the red-to-blue components with **Average, Standard Derivation and Entropy** features.

5. Target dataset with **irradiance measures** at a minutely granularity.

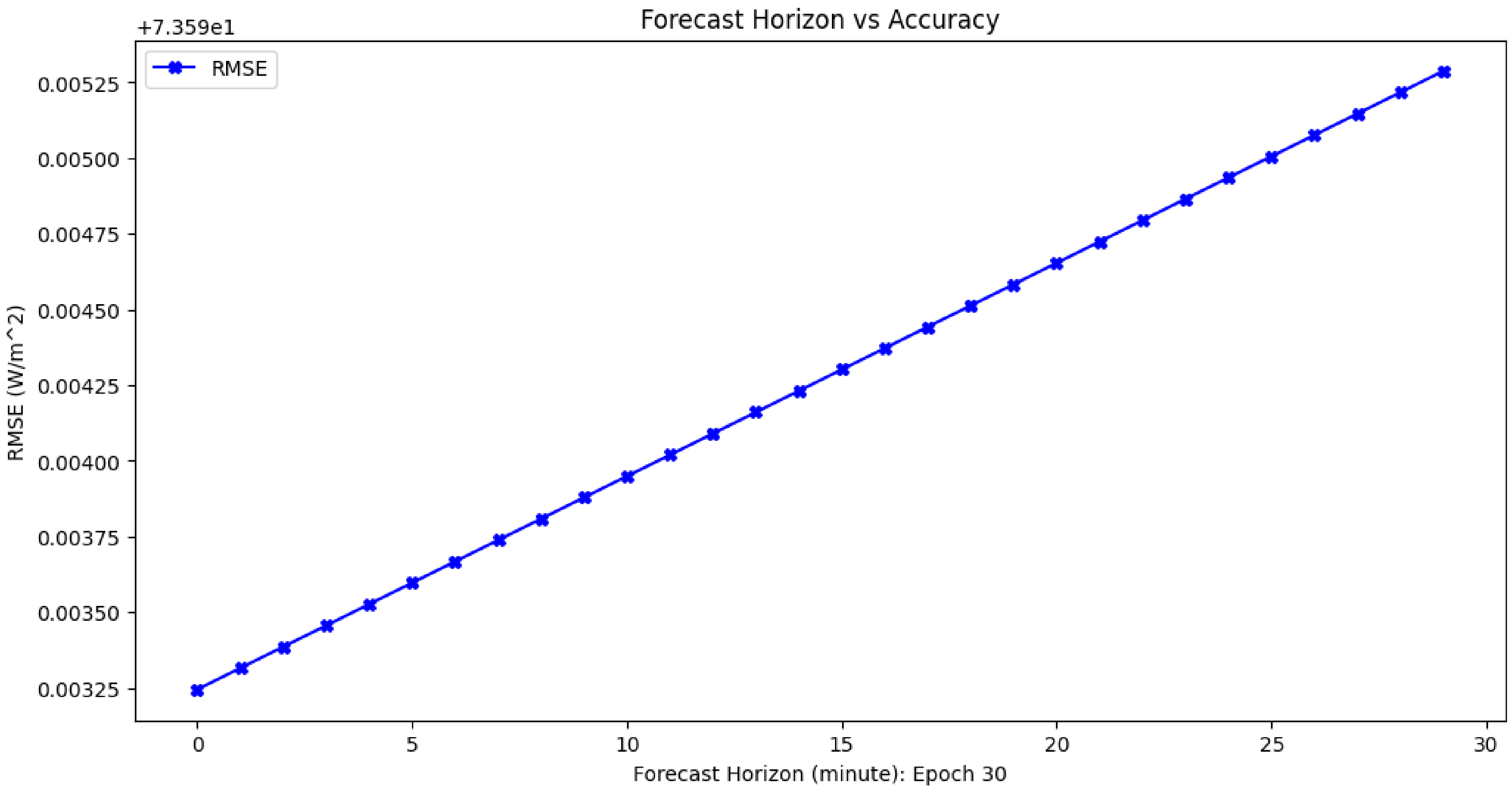
Model Implementation

- **Data Split** Use 2014 and 2015 for training data, and the data from 2016 to test
- **Data Normalized** by Min Max Standardization using `MinMaxScaler`
- **Data Lags** for forecast irradiance (GHI) with 30 minutes horizon and one minute granularity (IE, predicting t+1, t+2, t+3…, t+30).
- LSTM Model Building using Tensorflow
- Model Trained on 30 epochs and 70 batch size and calculate loss using Root Mean Square Error.





Autoregressive LSTM RNN Model



Question?