Intraday GHI Prediction Using Webcams

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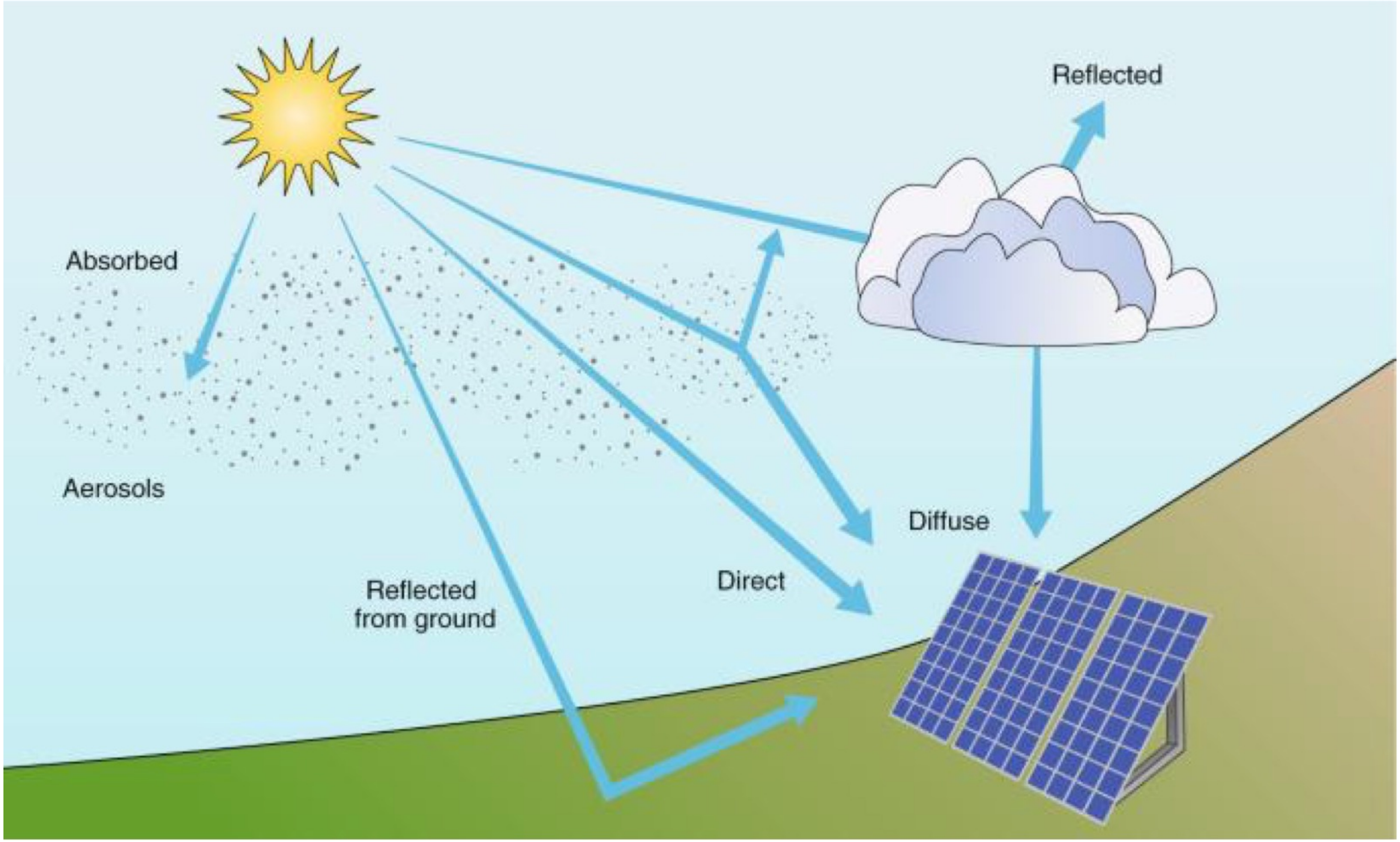
Global Horizontal Irradiance (GHI)

- GHI is the total solar radiation incident on a horizontal surface



Importance of GHI Prediction

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- This relies on the availability of high-performance solar irradiance forecasting tools at day-ahead and intraday time horizons.

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Table 1 - Summary of use cases for PV power forecasting (Alet et al., 2016)

Time horizon	Single site (10 m – 100 m) **PV plant owners** **PV plant operators**	MV distribution grid (1 km – 10 km) **DSOs** **Microgrid operators**	Transmission system (100 km – 1000 km) **TSOs** **Market operators**
15 min	Management of storage system	Management of active/reactive power	Activation of reserves
1 h	Management of storage system Intra-day trades	Storage and load management	Intra-day trades
24 h	Management of storage system Compliance with regulations Day-ahead trades	Storage and load planning	Booking of reserves Transmission scheduling Day-ahead trades
1 year	O&M contract	Planning of maintenance operations	Long-term trades
20+ years	Investment case	Infrastructure planning	Infrastructure planning

GHI Prediction

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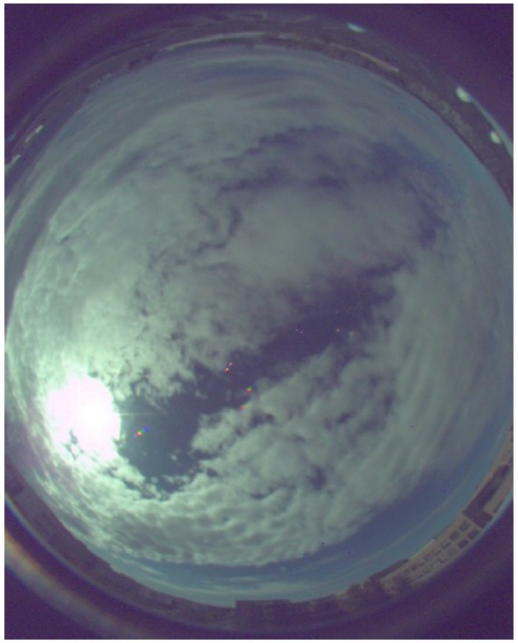
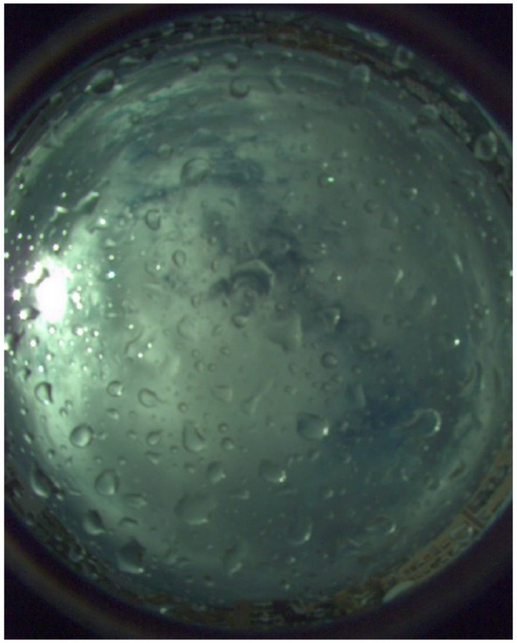
(a) Sunny



(b) Cloudy



(c) Rainy

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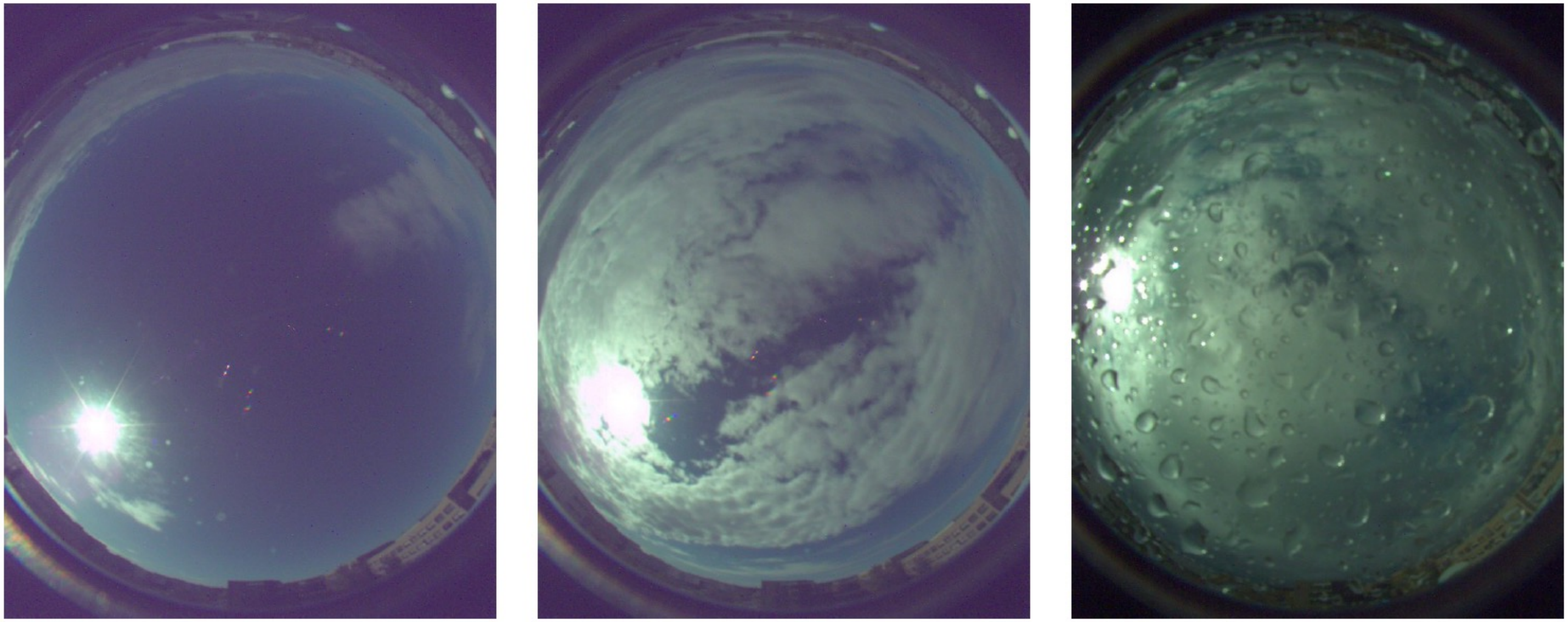

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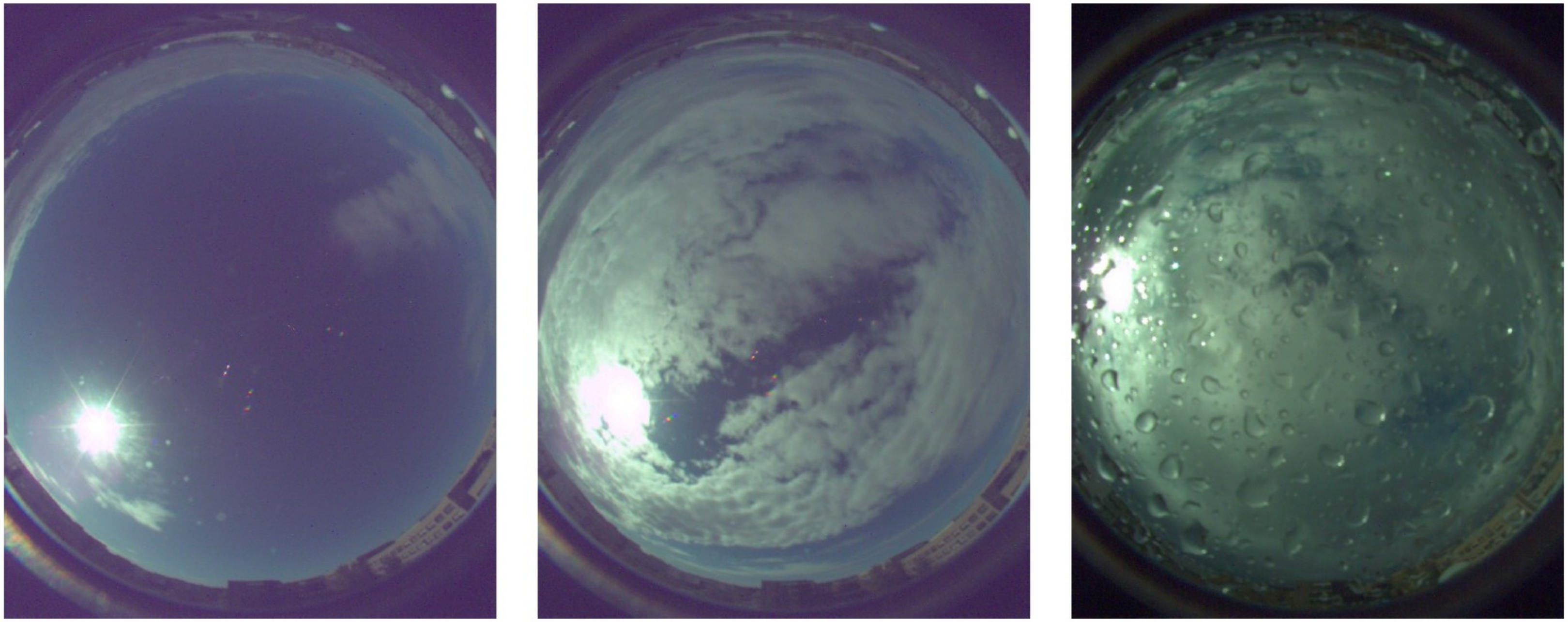


(a) Sunny (b) Cloudy (c) Rainy

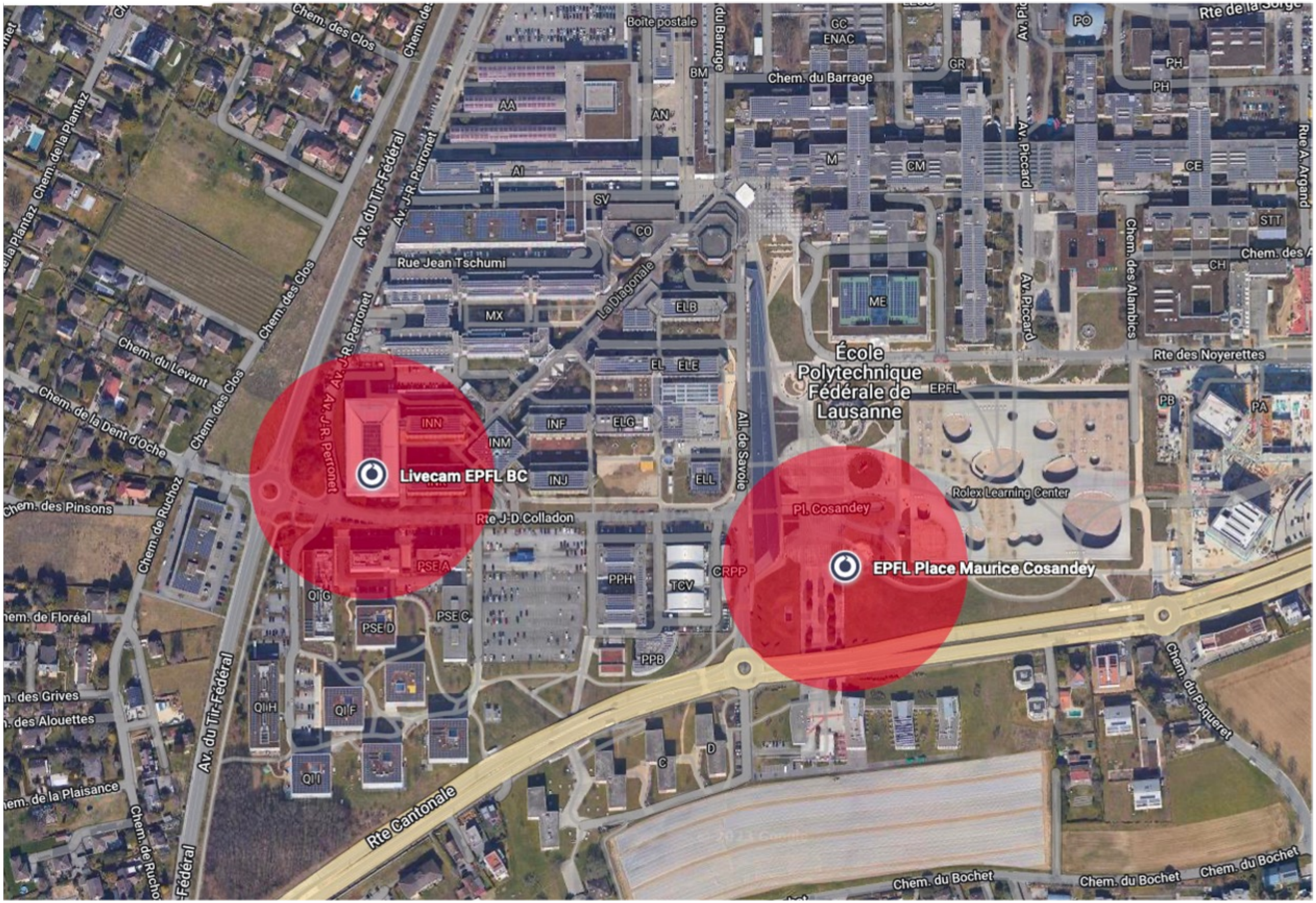
- However, time series models are not suitable for GHI predictions in the 1 – 6 hour range.
- Problem with all-sky cameras?

Our Approach

- Use images from public webcams

Data Description

1. **X1.npy** and **X2.npy**: two sets of 10000 RGB images (250x250x3) collected from two different cameras located on campus. The images are 360°.



Data Description

1. **X1.npy** and **X2.npy**: two sets of 10000 RGB images (250x250x3) collected from two different cameras located on campus. The images are 360°.

2. **common_time.npy**: time of the collected images. So the first element of the array common_time corresponds to the first images in X1 and in X2 were collected and so on.

```
array([datetime.datetime(2021, 12, 6, 8, 50),
       datetime.datetime(2021, 12, 6, 9, 10),
       datetime.datetime(2021, 12, 6, 9, 20), ...,
       datetime.datetime(2023, 1, 4, 12, 0),
       datetime.datetime(2023, 1, 4, 12, 10),
       datetime.datetime(2023, 1, 4, 12, 20)], dtype=object)
```

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3. **ground_truth.npy**: measured GHI value at time of image collection. Example: the first element of this array is the GHI value collected at the first element in the array 'common_time'.

	Time	Ground Truth
0	2021-12-06 08:50:00	21.0
1	2021-12-06 09:10:00	34.0
2	2021-12-06 09:20:00	52.0
3	2021-12-06 09:30:00	70.0
4	2021-12-06 09:50:00	82.0
...	...	...
9995	2023-01-04 11:40:00	191.0
9996	2023-01-04 11:50:00	171.0
9997	2023-01-04 12:00:00	166.0
9998	2023-01-04 12:10:00	165.0
9999	2023-01-04 12:20:00	172.0

10000 rows × 2 columns

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4. **labels.npy**: GHI value 2 hours in advance from the time of image collection. In general, it will be a forward version (+2 hours) of the ground_truth. It won't always be the case as we stop collecting images at night so you don't have the ground_truth values at night and hence you won't be able to get the GHI value 2 hours in advance. That is why it is provided to you.

Data Description - Labels

	Time	Ground Truth	labels
0	2021-12-06 08:50:00	21.0	132.0
1	2021-12-06 09:10:00	34.0	126.0
2	2021-12-06 09:20:00	52.0	136.0
3	2021-12-06 09:30:00	70.0	143.0
4	2021-12-06 09:50:00	82.0	134.0
5	2021-12-06 10:30:00	121.0	116.0
6	2021-12-06 10:40:00	129.0	128.0
7	2021-12-06 10:50:00	132.0	208.0
8	2021-12-06 11:00:00	136.0	305.0
9	2021-12-06 11:40:00	143.0	137.0
10	2021-12-06 11:50:00	134.0	293.0
11	2021-12-06 12:00:00	137.0	142.0
12	2021-12-06 12:10:00	126.0	381.0
13	2021-12-06 12:20:00	115.0	305.0
14	2021-12-06 12:30:00	116.0	230.0
15	2021-12-06 12:40:00	128.0	238.0
16	2021-12-06 13:10:00	337.0	86.0
17	2021-12-06 13:30:00	119.0	94.0
18	2021-12-06 13:40:00	137.0	63.0
19	2021-12-06 13:50:00	293.0	51.0

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5. **meteo_data.csv**
   a. **Time**: Matches time of images provided
   b. **Air_temp**: Air temperature (°C) 2 meters above ground
   c. **Wind_speed**: Wind speed (m/s), ten minutes mean
   d. **Wind_dir**: wind direction (°), ten minutes mean

- **Example: Observation interval for 10-minute values:**
  At "06.12.21 08:50", Wind_speed = 1 m/s means that the wind speed from 08:40 to 08:50 had a mean speed of 1 m/s. Similarly for wind direction.

Data Description - Meteo

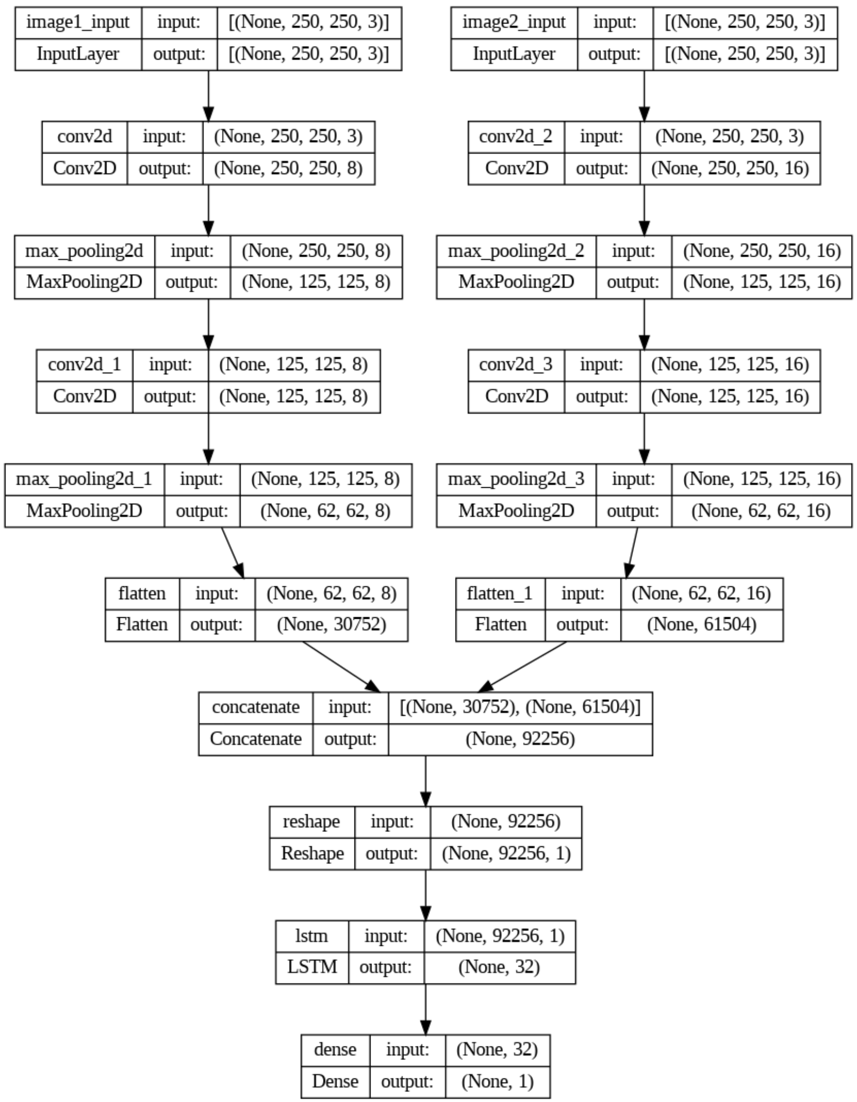
	time	Air_temp	Wind_speed	Wind_dir
0	06.12.21 08:50	1.6	1.0	324
1	06.12.21 09:10	1.8	1.2	331
2	06.12.21 09:20	1.7	1.7	329
3	06.12.21 09:30	1.8	1.3	325
4	06.12.21 09:50	1.9	1.0	326
...	...	...	...	...
9995	04.01.23 11:40	7.3	0.5	288
9996	04.01.23 11:50	7.3	0.7	165
9997	04.01.23 12:00	7.5	1.0	250
9998	04.01.23 12:10	7.6	1.2	261
9999	04.01.23 12:20	7.7	0.8	218

10000 rows × 4 columns

Network Architecture

- We asked Chat GPT: “We want a neural network in python that has CNN and LSTM layers to predict solar irradiance from an input of 2 RGB images”

```
# Define input shape
input_shape = (250, 250, 3)

# Define inputs
input1 = Input(shape=input_shape, name='image1_input')
input2 = Input(shape=input_shape, name='image2_input')

# CNN layers for image 1
x1 = Conv2D(8, (3, 3), activation='relu', padding='same')(input1)
x1 = MaxPooling2D((2, 2))(x1)
x1 = Conv2D(8, (3, 3), activation='relu', padding='same')(x1)
x1 = MaxPooling2D((2, 2))(x1)
x1 = Flatten()(x1)

# CNN layers for image 2
x2 = Conv2D(16, (3, 3), activation='relu', padding='same')(input2)
x2 = MaxPooling2D((2, 2))(x2)
x2 = Conv2D(16, (3, 3), activation='relu', padding='same')(x2)
x2 = MaxPooling2D((2, 2))(x2)
x2 = Flatten()(x2)

# Concatenate the outputs of the CNN layers
x = concatenate([x1, x2])
# (batch_size, time_steps, seq_len)
x = tf.keras.layers.Reshape((-1, 1))(x)
# LSTM layer
x = LSTM(32, activation='relu', return_sequences=False)(x)

# Output layer
output = Dense(1, activation='relu')(x)

# Define the model
model = tf.keras.Model(inputs=[input1, input2], outputs=output)

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')
```



Network Architecture – Time Distributed

- Modified with Time Distributed
- Modify your input to have one X with shape (10000, 2, 250, 250, 3)
  You can use X = np.stack((X1,X2), 1)

```
img_size = 250
channels = 3

input = tf.keras.layers.Input(shape=(img_size, img_size, channels))
input_sequence1 = tf.keras.layers.Input(shape=(2,img_size, img_size, channels))

# CNN Block 1
first_input = tf.keras.layers.TimeDistributed(Conv2D(8, kernel_size=3, activation='relu'))(input_sequence1)
first_input = tf.keras.layers.TimeDistributed(MaxPooling2D(pool_size = 2))(first_input)
first_input = tf.keras.layers.TimeDistributed(Conv2D(8, kernel_size=3, activation='relu'))(first_input)
first_input = tf.keras.layers.TimeDistributed(MaxPooling2D(pool_size = 2))(first_input)

# CNN Block 2
first_input = tf.keras.layers.TimeDistributed(Conv2D(16, kernel_size=3, activation='relu'))(first_input)
first_input = tf.keras.layers.TimeDistributed(MaxPooling2D(pool_size = 2))(first_input)
first_input = tf.keras.layers.TimeDistributed(Conv2D(16, kernel_size=3, activation='relu'))(first_input)
first_input = tf.keras.layers.TimeDistributed(MaxPooling2D(pool_size = 2))(first_input)

# Flattening and Reshaping for LSTM
flt = tf.keras.layers.TimeDistributed(Flatten())(first_input)
flt = tf.keras.layers.Reshape((1, -1))(flt)

# LSTM
lstm1 = tf.keras.layers.LSTM(32, activation='relu', return_sequences=True)(flt)

# Output
dense1 = tf.keras.layers.Dense(1, activation='relu')(lstm1)

# Setting input and ouput of model
model = tf.keras.models.Model(inputs=[input_sequence1], outputs=dense1)

model.compile(optimizer="Adam", loss='mse')

# Remember X_train should be something like (samples, number of images per sample, image width, image height, channels) so (10000,2,250,250,3)
history = model.fit(np.asarray(X_train), np.asarray(y_train), ...)
```

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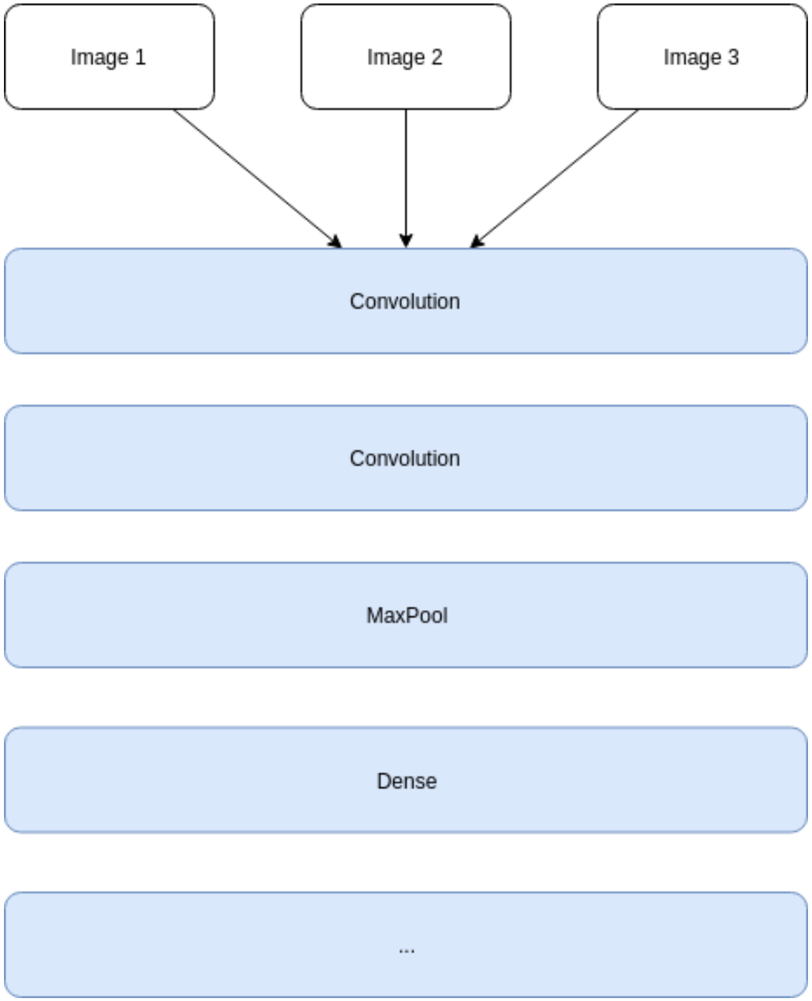

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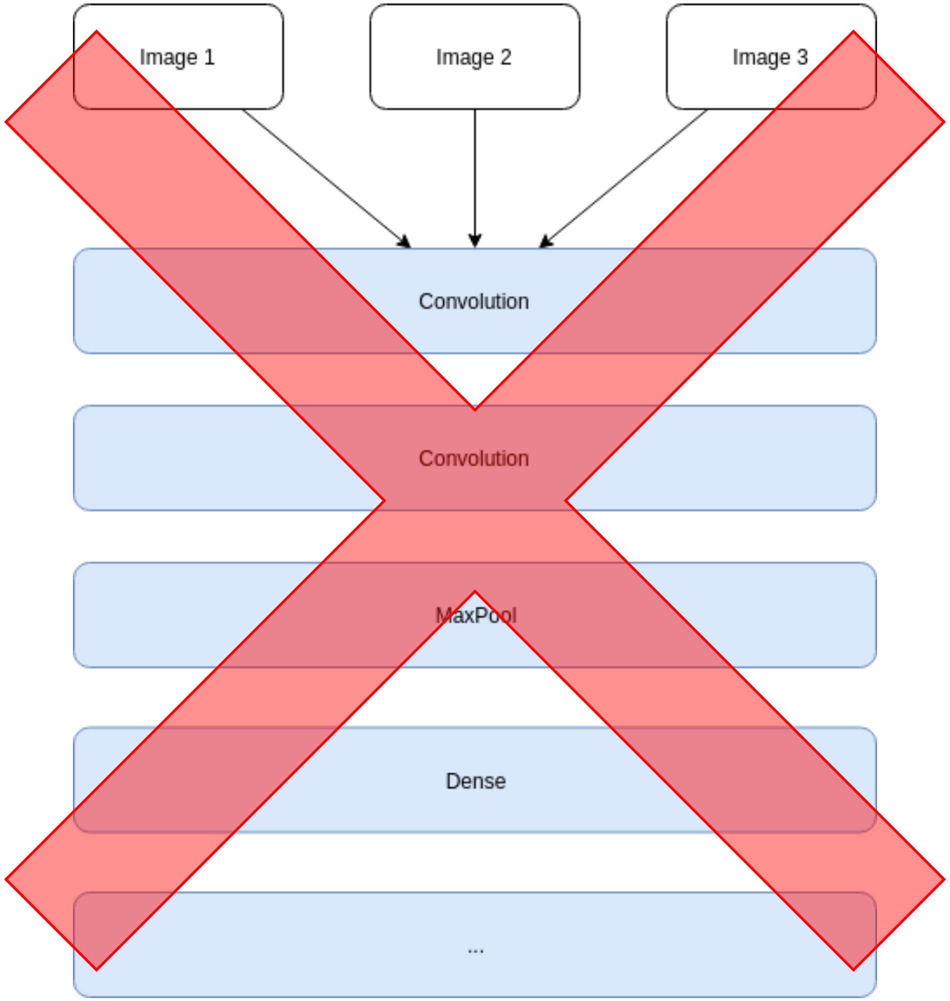

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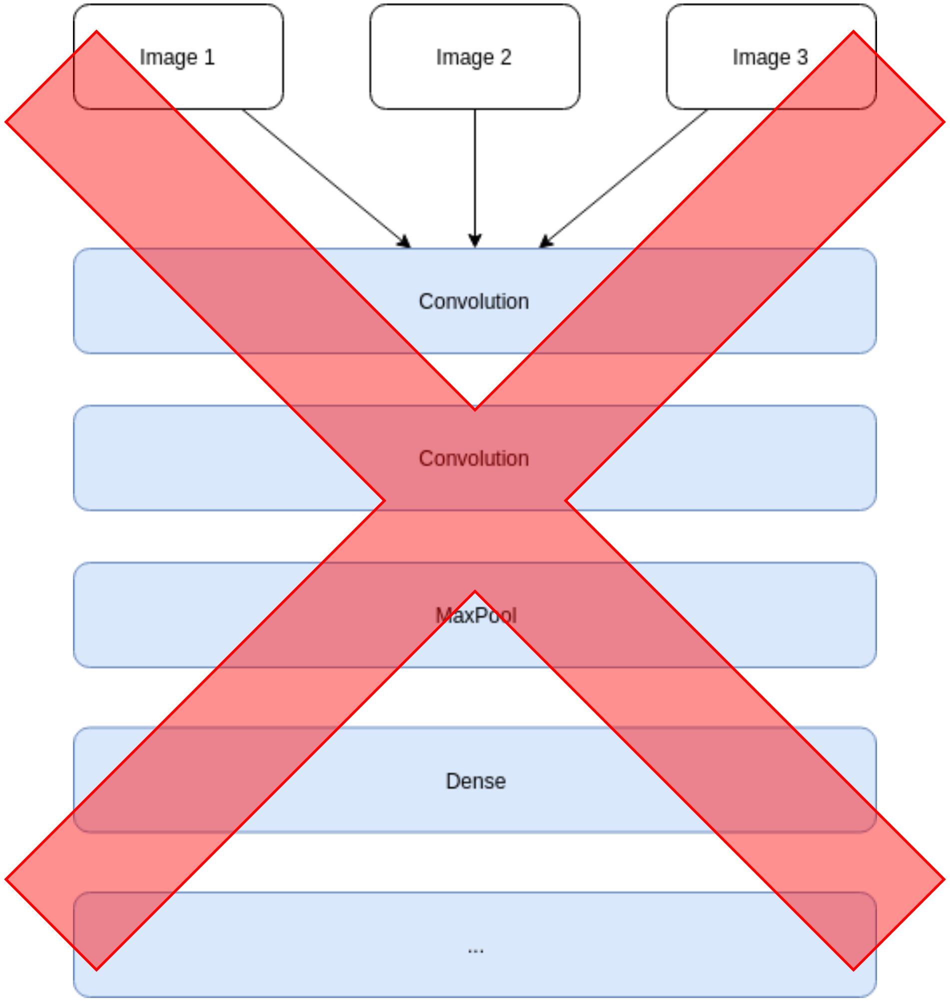

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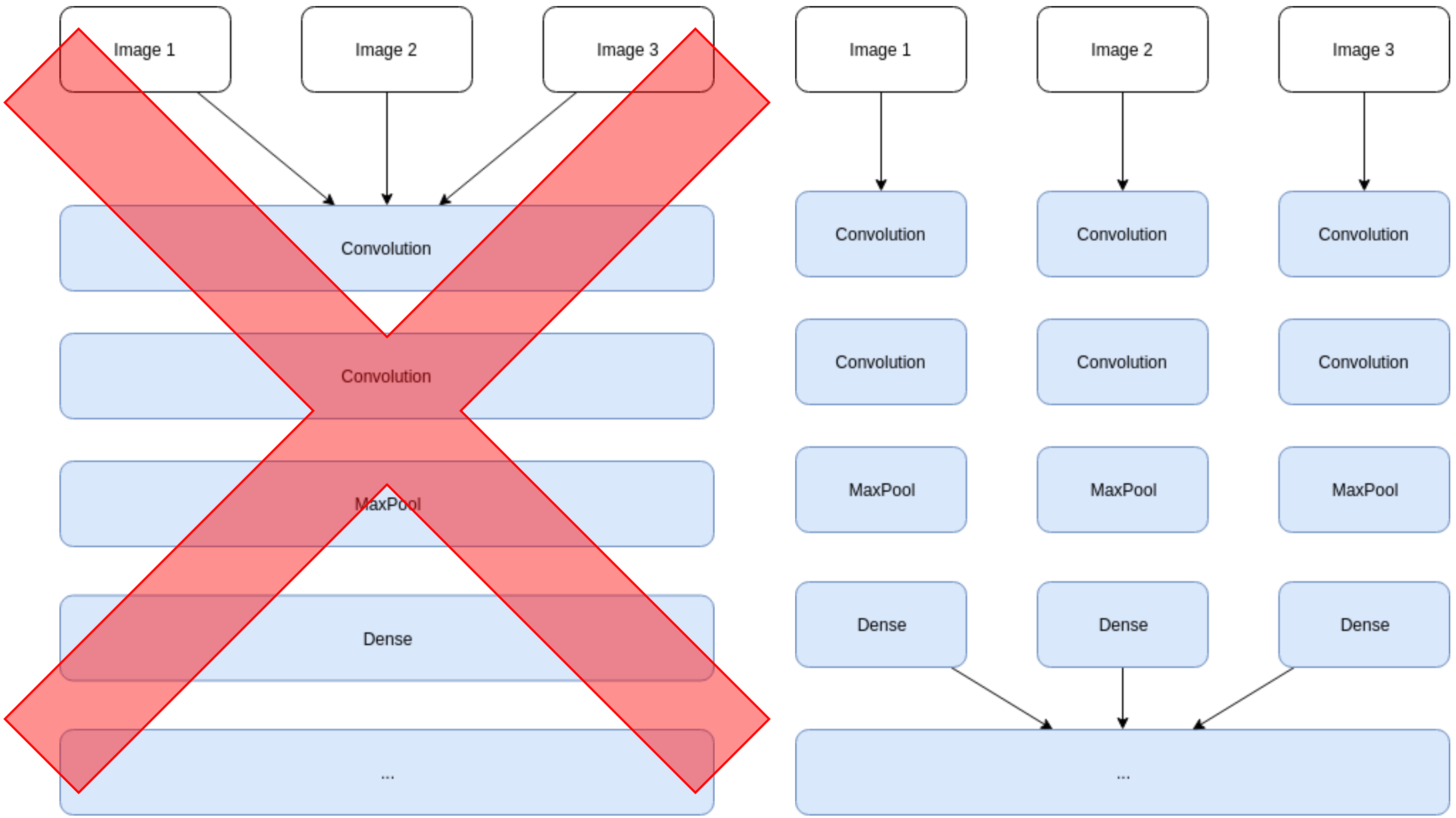

- Requires long training as we need to train several convolution flows (one per input image)

Network Architecture – Time Distributed

- The Time Distributed Layer applies the same instance of the layer to each image.
- So we don't have different sets of weights for this layer.
- The same set of weights are applied to all images.
- By using this layer, we will not be increasing the complexity of the model. Yet, the model has the ability to learn from different images separately with just one layer.