

Short-term Solar Irradiance Forecasting from Sky Images




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NeurIPS 2021 Workshop
Tackling Climate Change with Machine Learning

Background

- Global warming have become critical issue.

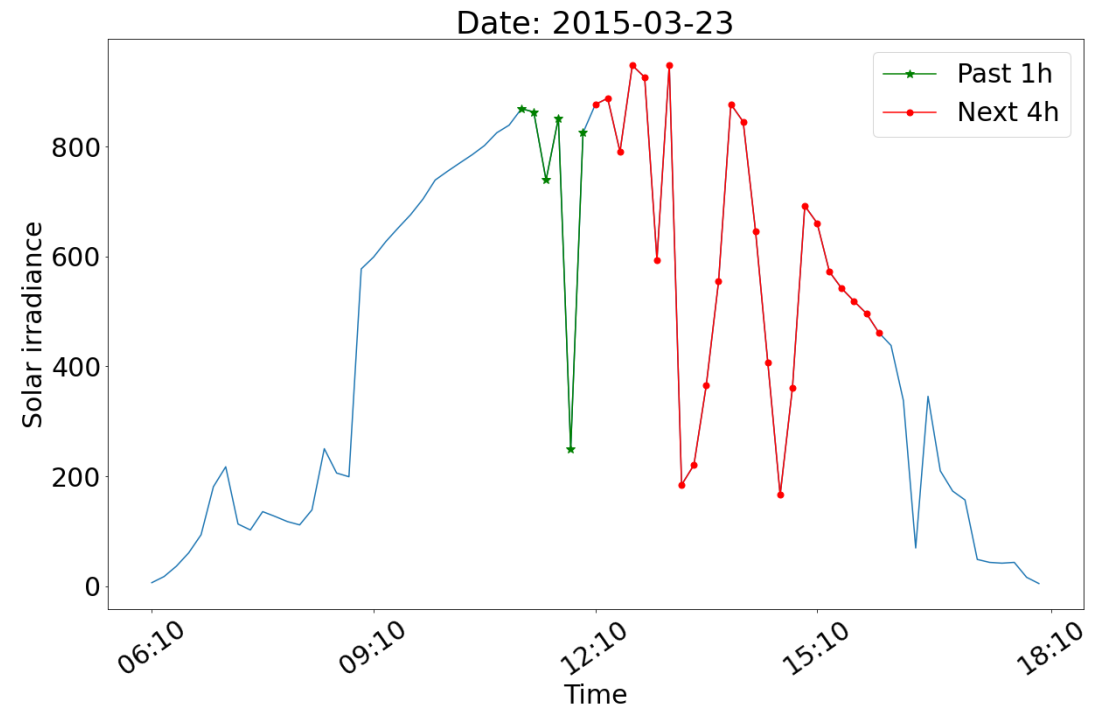




Producing solar power is not fully manageable due to the unstable environmental factors.
→ Solar power forecasting helps the operation to be more stable.

Background

- Forecasting: forecast future solar irradiance using historical sky images and auxiliary data.
 - Deterministic intra-hourly predictions.
 - Future solar irradiance diverse over a relatively long-term (> 1 hour).



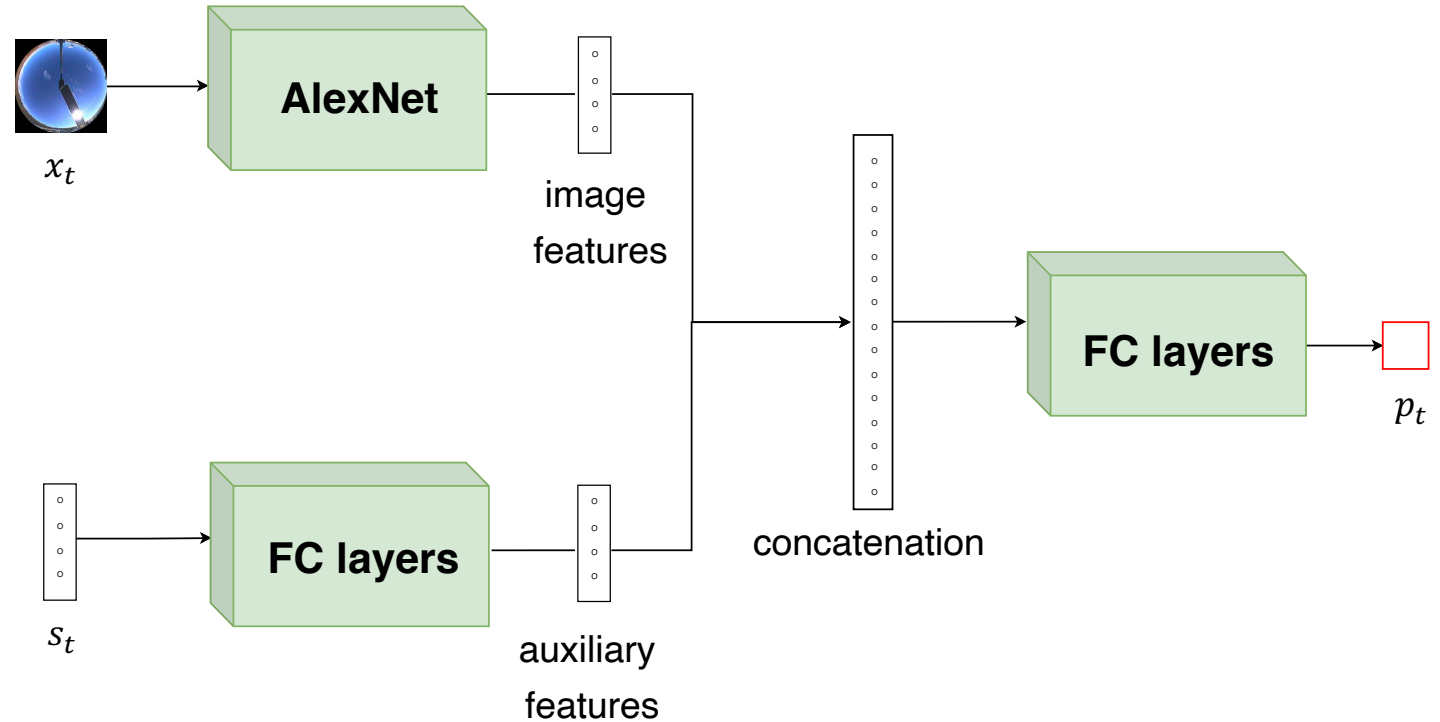
Example of forecasting: Use data in the past 1 hour to predict solar irradiance for the next 4 hours

Methodology

- We propose two models for solar irradiance forecasting:
 1. Deterministic forecasting model.
 2. Stochastic forecasting model.
- Each model contains three components:
 1. A nowcasting model
 2. An auxiliary LSTM
 3. A model for predicting future sky images.

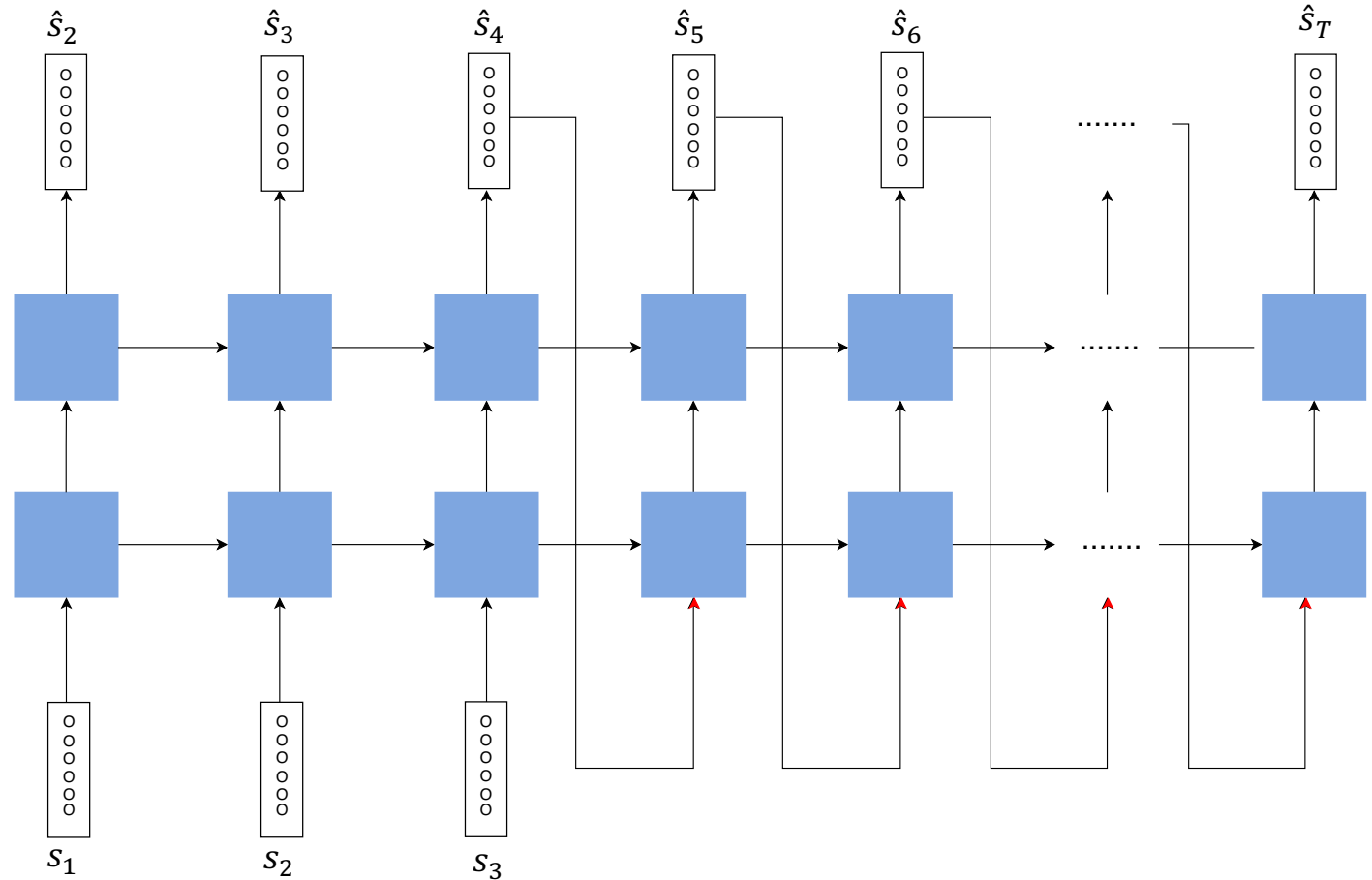
The nowcasting model

- Estimate solar irradiance at a specific timestep using:
 - Sky image
 - Auxiliary data.



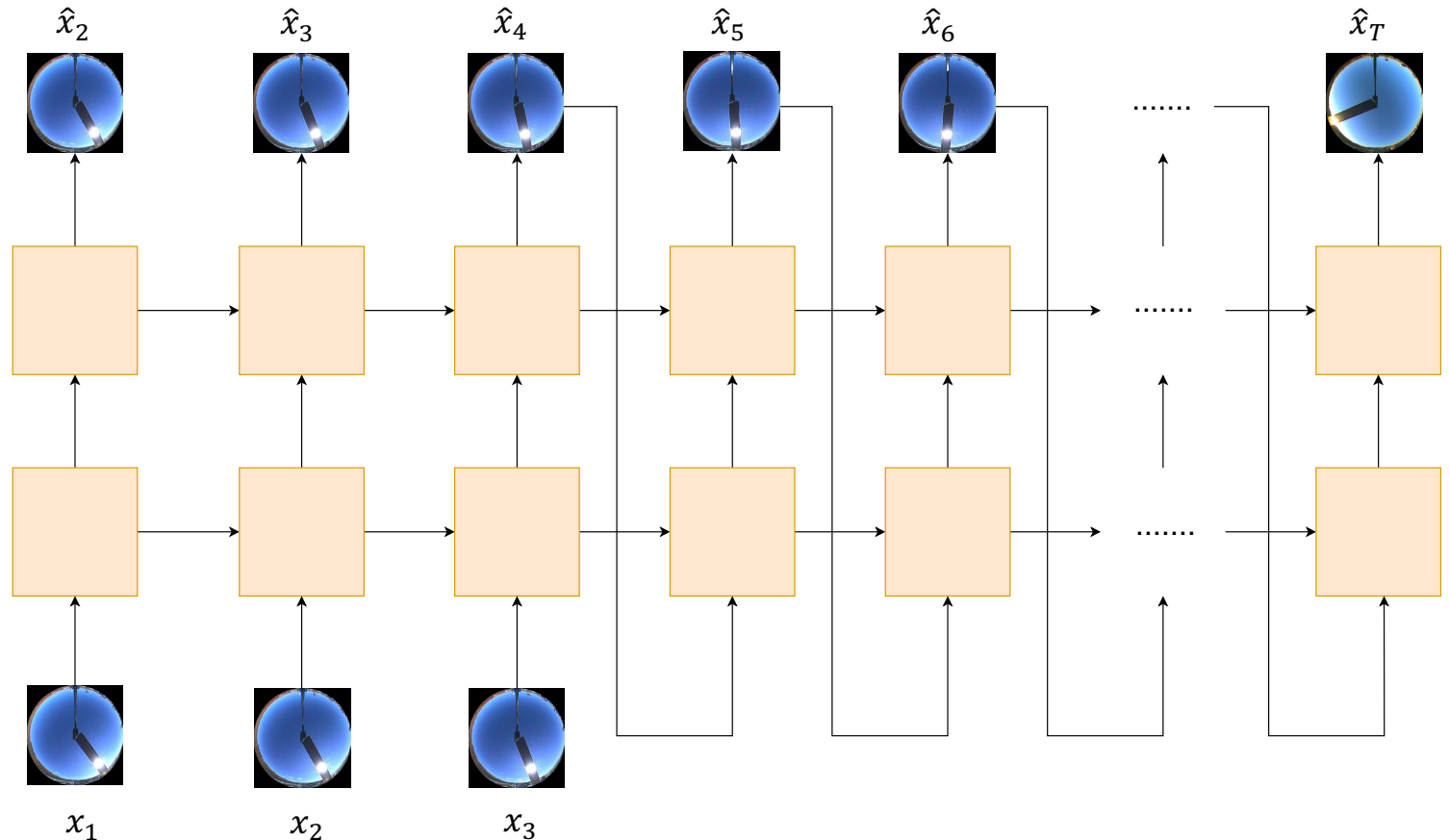
The auxiliary LSTM model

- Has a LSTM structure
- Aim to predict future auxiliary data **autoregressively** given the historical ones.



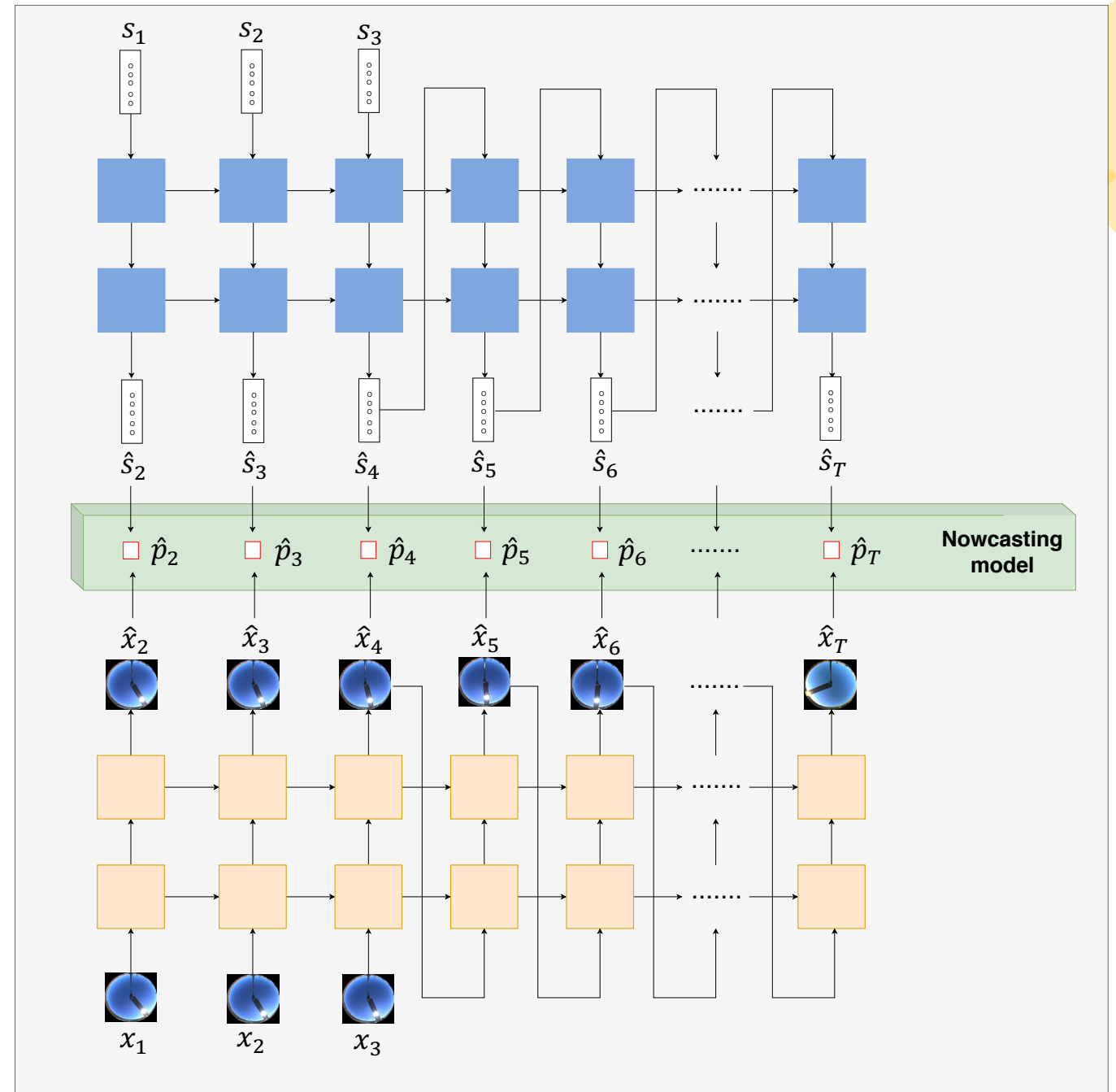
The PredRNN model [1]

- Spatial-temporal model
- Aim to predict future sky images
autoregressively given the historical ones.



The deterministic forecasting model

- Contains three components:
 - The nowcasting model
 - The auxiliary LSTM
 - The PredRNN model
- Prediction process:
 - Step 1: PredRNN predicts future images
 - Step 2: Auxiliary LSTM predicts future auxiliary data
 - Step 3: The nowcasting model predicts future solar irradiance.



Loss function

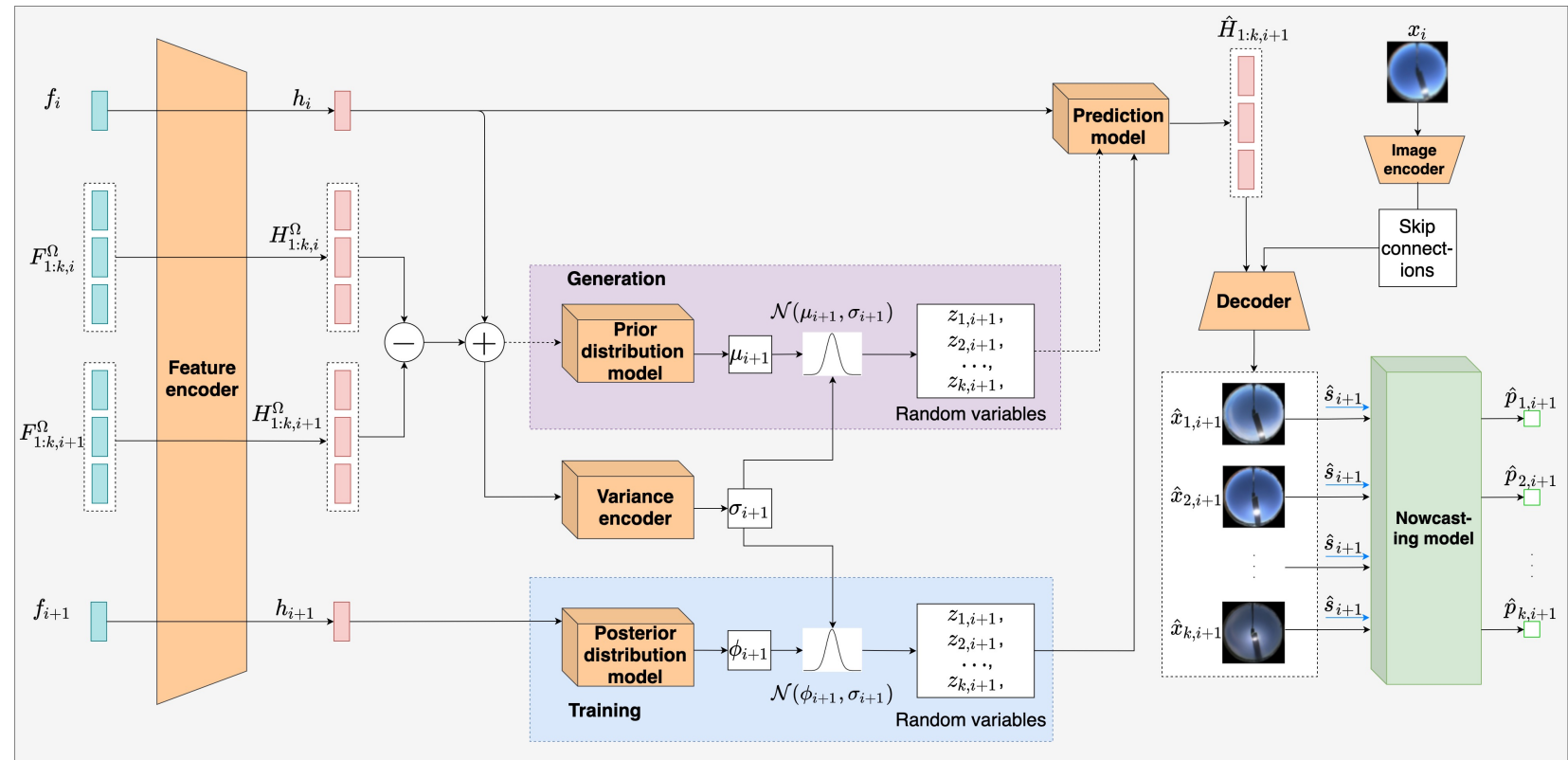
$$\mathcal{L}_{det} = \frac{1}{M + T - 1} \left(\sum_{i=1}^{M+T-1} \underbrace{\|p_{i+1} - \hat{p}_{i+1}\|_1}_{\text{Solar irradiance loss}} + \alpha \underbrace{\|x_{i+1} - \hat{x}_{i+1}\|_1}_{\text{Image loss}} \right)$$

Where:

- p_{i+1} and \hat{p}_{i+1} are ground-truth and predicted solar irradiance at timestep $i + 1$
- x_{i+1} and \hat{x}_{i+1} are ground-truth and predicted image at timestep $i + 1$

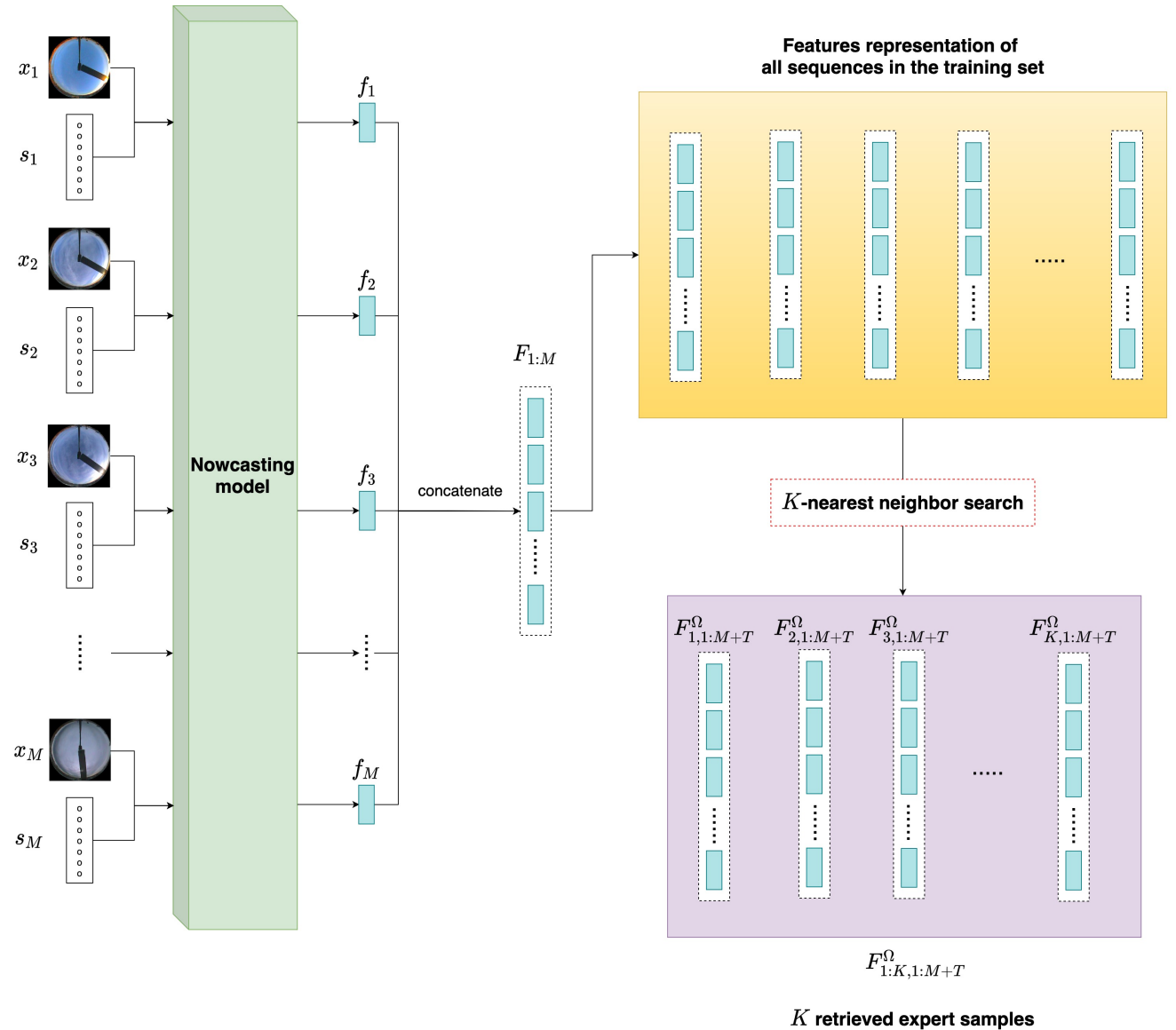
The stochastic forecasting model

- Contains three components:
 - The nowcasting model
 - The auxiliary LSTM
 - The VPEG model
- VPEG model [2] aims predicts a distribution of future sky images.
- Contain three phases:
 - Expert samples retrieval
 - Training phase
 - Generation phase



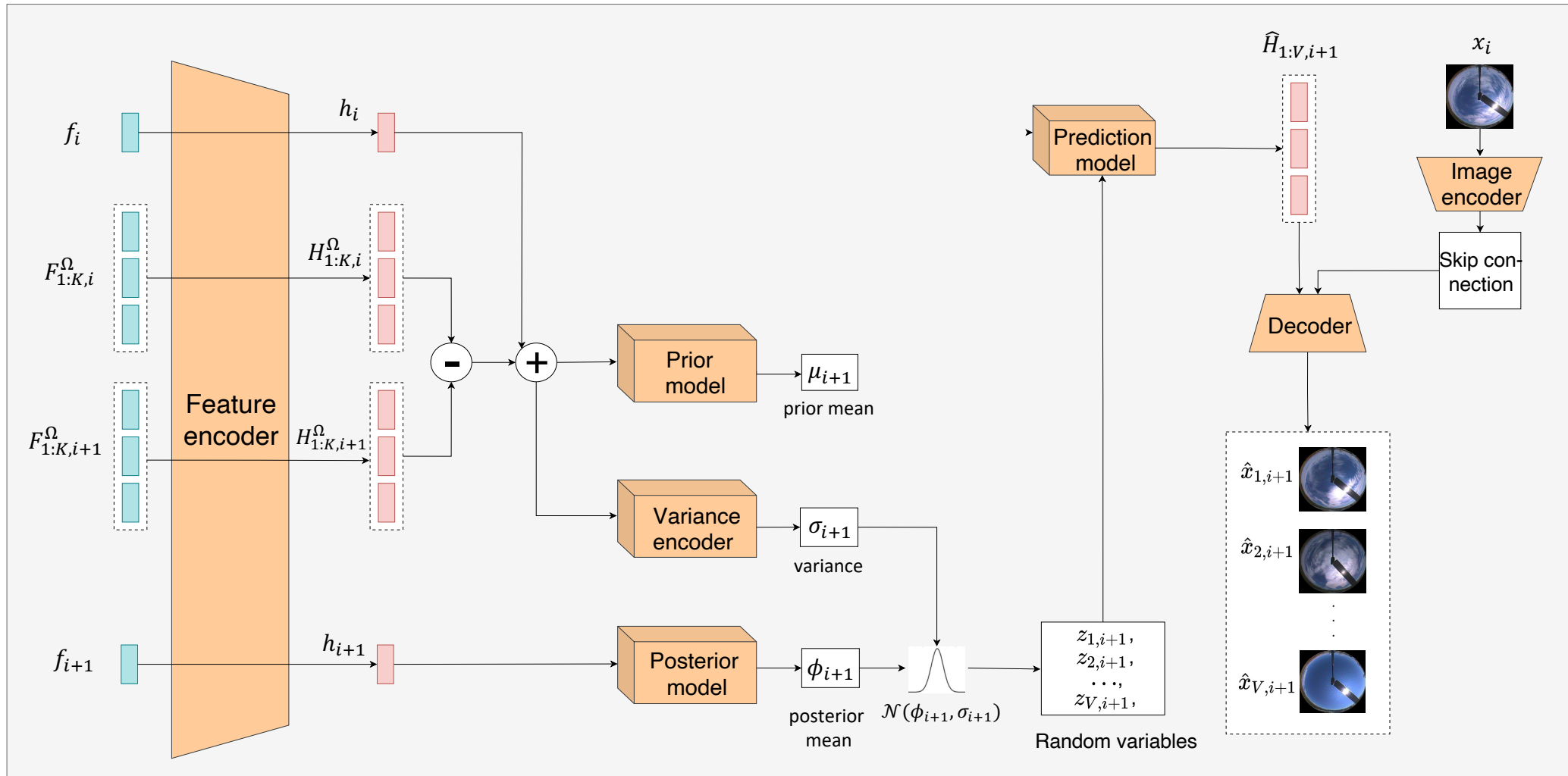
Retrieval phase

- Use the output of the last hidden layer of the nowcasting model.
- Each sequence is represented as a sequence of features f .
- Perform K -nearest neighbor search to retrieve K expert examples.



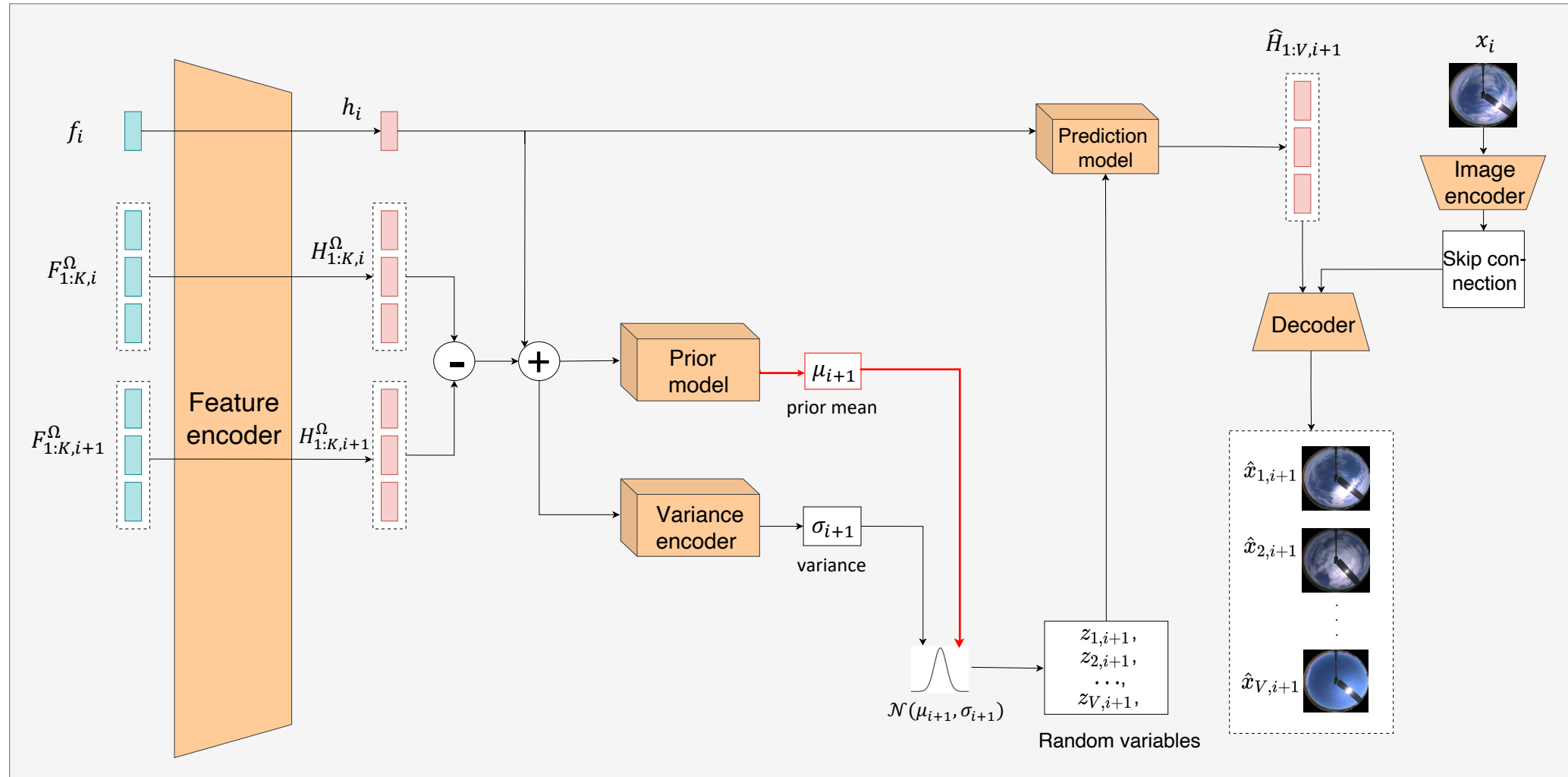
Training phase

The prior mean is also predicted



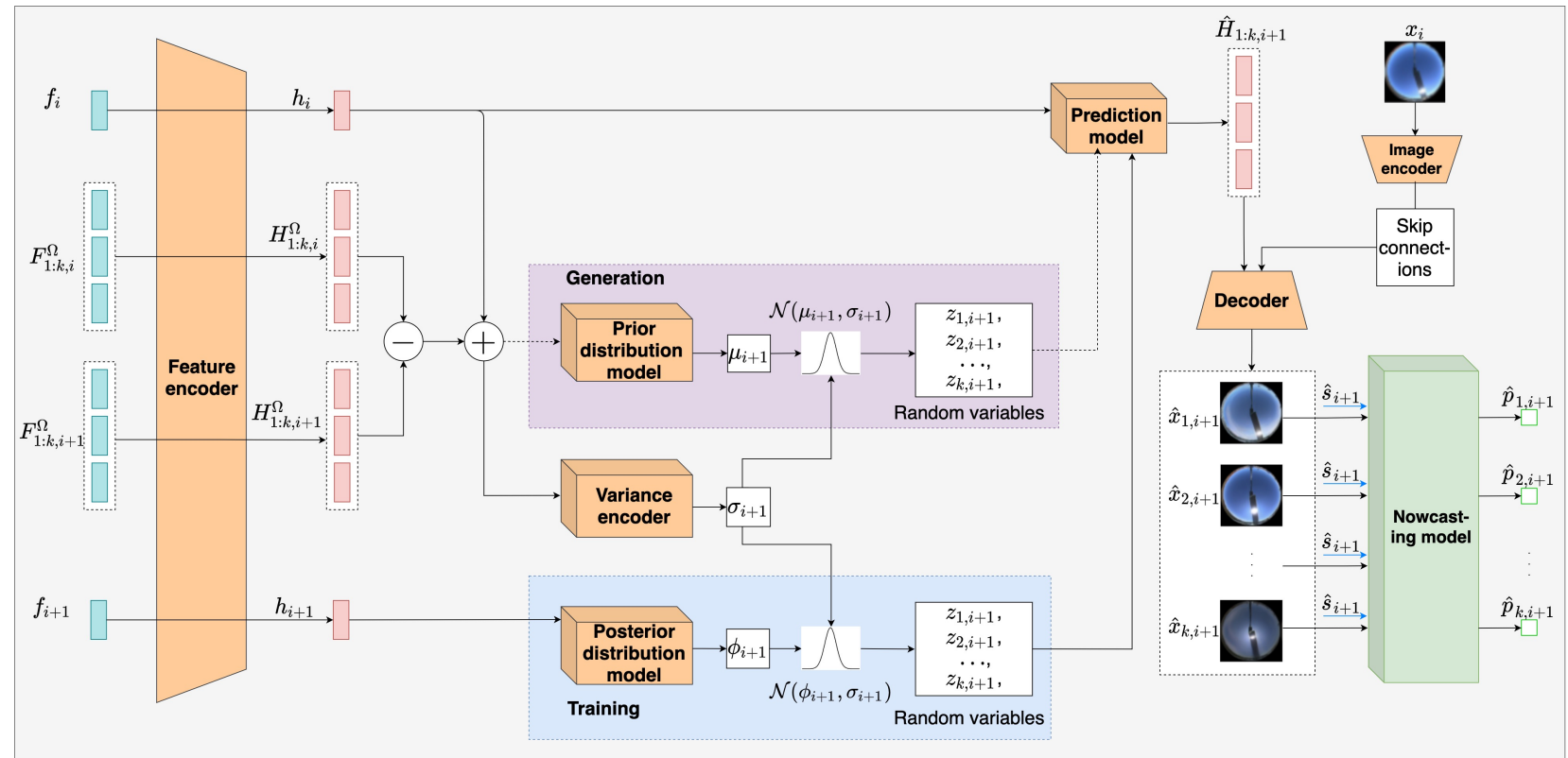
Generation phase

Use the prior distribution (instead of the posterior distribution)



The stochastic forecasting model

- Prediction process:
 - Step 1: VPEG generates multiple future images.
 - Step 2: Auxiliary LSTM predicts future auxiliary data.
 - Step 3: The nowcasting model predicts multiple future solar irradiance.



Loss function

$$\mathbf{Loss} = \lambda_1 \mathbf{image\ loss} + \lambda_2 \mathbf{expectation\ loss} + \lambda_3 \mathbf{variance\ loss} + \lambda_4 \mathbf{solar\ loss}$$

$$\mathbf{image\ loss} = ||\mathbf{best\ predicted\ image} - \mathbf{ground\ truth\ image}||_2^2$$

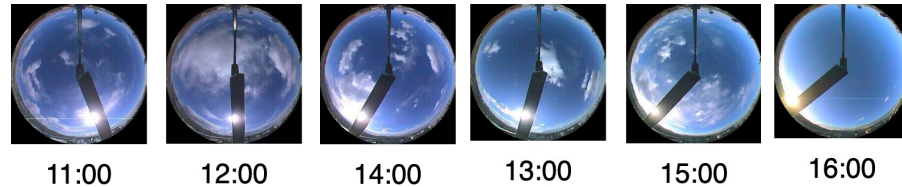
$$\mathbf{expectation\ loss} = ||\mathbf{prior\ mean} - \mathbf{posterior\ mean}||_2^2$$

$$\mathbf{variance\ loss} = ||\mathbf{variance\ of\ predictions} - \mathbf{variance\ of\ expert\ samples}||_2^2$$

$$\mathbf{solar\ loss} = ||\mathbf{best\ predicted\ solar\ irradiance} - \mathbf{ground\ truth\ solar\ irradiance}||_1$$

Experiment setups

- Golden, Colorado Dataset:
 - Contains sky images and auxiliary data recorded from 2004 to 2016.
 - Auxiliary data contains date, time, clear-sky irradiance, azimuth angle and zenith angle
 - Data in 2015 and 2016 is used as test sets.



- Evaluation metrics:
 - Normalized mean absolute percentage error (nMAP):

$$nMAP = \frac{1}{N} \sum_{n=1}^N \frac{|p_n - \hat{p}_n|}{\frac{1}{N} \sum_{n=1}^N p_n} \times 100$$

- Diversity: Average L1 difference of each pair of predictions.

Result

	nMAP							
	Test 2015				Test 2016			
	+1h	+2h	+3h	+4h	+1h	+2h	+3h	+4h
Siddiqui [3]	17.9	25.2	31.6	39.1	16.9	25.0	31.9	39.5
Our deterministic model	21.6	25.7	30.1	35.6	19.2	23.3	27.2	32.7
Our stochastic model (best prediction)	19.7	21.2	22.5	27.8	17.4	19.1	21.2	25.5

- ➔ Our deterministic model outperform the state-of-the-art model for predictions in the far future.
- ➔ The best prediction of the stochastic model better than the that of the deterministic models.

[3] Siddiqui, T.A., Bharadwaj, S. and Kalyanaraman, S., 2019, January. A deep learning approach to solar-irradiance forecasting in sky-videos. In *2019 IEEE Winter Conference on Applications of Computer Vision (WACV)* (pp. 2166-2174). IEEE.

Diversity in the predictions of the stochastic model

Diversity								
	Test 2015				Test 2016			
	+1h	+2h	+3h	+4h	+1h	+2h	+3h	+4h
Our stochastic model	77.4	91.5	97.5	100.2	70.1	82.2	88.0	90.0

- ➔ The diversity increases as we predict further into the future.
- ➔ Our stochastic model is able to capture uncertainties in the future.

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