Satellite to Radar: Sequence to Sequence Learning for precipitation nowcasting

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Fig. 1. A supercell thunderstorm at twilight in SW Oklahoma.

ABSTRACT

The forecasting of rain is a complex problem with centuries of scientific work. The implications of weather for individuals and companies continue to be important. Machine Learning approaches have been shown to outperform state of the art physics based models of weather for short term predictions. We introduce a new type of model **Sat2Rad**. Our model takes as input multi-spectral satellite data and outputs radar reflectivity at a set of time-steps ranging from 15 to 180 minutes in the future. This model is novel for precipitation nowcasting because it uses several satellite spectral bands instead of using radar data as input.

Additional Key Words and Phrases: Machine Learning, Sequence to Sequence, Radar, Satellite, Storms, Forecasting

1 INTRODUCTION

Precipitation forecasting is essential to reduce the risk of life threatening situations. Different types of rainfall ranging from mist to heavy rain have a major impact for different societal sectors including agriculture, aviation, outdoor events, and the energy industry. By having timely and accurate predictions of rainfall which in turn indicate the potential for destructive storms we can prevent injuries, assist companies in predicting energy production and use resources efficiently.

A particularly strong threat is posed by rain storms and thunderstorms. Storms are one of the most destructive weather events in nature, capable of destroying human structures and even lead to loss of life [9]. Predicting storms is crucial and presents it's own set of challenges.

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At present meteorologists are able to successfully predict many instances of precipitation. Techniques that are used in practice range from manual analysis of current weather data (e.g radar or satellite images) to complex physics based simulations of our atmosphere with Numerical Weather Prediction (NWP) models. Various traditional precipitation nowcasting methods are based on *optical flow*. Optical flow functions in two steps, first cumulonimbus clouds are identified, and then their movement is tracked to predict the location of precipitation. Thus in this the case, the *cell-lifecycle* [18] is not taken into account [13].

Machine Learning (ML) approaches have also been developed to predict precipitation. An improvement of machine learning models over NWP models is that they are much faster to produce predictions, thus ML models are more suitable for real-time or near-real-time predictions, such as required in disaster response and energy management. According to the universal approximation theorem [6], deep neural networks have the property of being able to approximate any function provided they have the correct weights, thus it is suggested that machine learning models can incorporate sources of predictability beyond optical flow such as the cell-lifecycle among others [13].

Thus far most machine learning approaches for precipitation nowcasting have focused on predicting a next frame in a time series of radar reflectivity data [2, 19, 20]. However taking this approach may eliminate the possibility of learning the cell-lifecycle, due to the fact that the model only sees precipitation itself but not the cloud that is causing the precipitation.

We propose to use multi-spectral satellite data to learn spatio-temporal mappings between sequences of satellite data and precipitation data in the near future. If this is successful *cumulonimbus* clouds could be predicted from when they are mere *cumulus* clouds and prior. An additional advantage is that contrary to radar data, satellite data is readily available over oceans and remote communities which allows for the prediction of precipitation over these regions. We will work towards creating a model by answering the following main research question:

RQ1: *How can a deep learning model be trained to predict radar data with multi-spectral satellite data ?*

This research question will be answered by looking at the following sub research questions:

(1) *what is necessary to build a well performing model ?*
(2) *what methods can be used to create this model ?*
(3) *what is the effectiveness of the trained model ?*
(4) *what are the conditions under which the model can and cannot be used ?*

2 MAIN CONTRIBUTION

This proposal has the potential to contribute a deep learning model capable of predicting precipitation in the short term with only satellite images.

3 RELATED WORKS

In this section we will discuss the existing work in precipitation nowcasting via machine learning. This section is structured by the type of input data used in the approaches, first we list radar based learning and then we discuss satellite based approaches.

3.1 Radar Based Nowcasting

Recurrent neural networks (RNNs) have been created to learn temporal relationships in data, therefore they are a natural candidate to the task of learning spatio-temporal patterns of weather. The LSTM architecture was developed by Hochreiter and Schmidhuber [8], to solve the problem of vanishing and exploding gradients in RNNs and is widely used. Taking LSTM as a base and adapting the weights to kernels, ConvLSTM [19] was introduced for the task of precipitation nowcasting. Multiple layers of ConvLSTM are used in this paper to obtain a sequence to sequence architecture. A further improvement of ConvLSTM is trajGRU which was proposed by Shi et al. [20] to be able to learn the *location-variant* structure for recurrent connections.

Pure convolutional neural networks have also been used to predict precipitation. As demonstrated by Bai et al. and Gering et al. [3, 7] convolutional neural architectures can outperform recurrent neural networks for a variety of sequence modelling tasks. This is the reason why many works on precipitation nowcasting have opted for pure convolutional networks [1, 2].

Due to machine learning models attempting to minimize loss, *blurry predictions* can be produced by models. This can be alleviated by using generative models which sample from the possible futures and do not seek to provide a best average fit. Generative Adversarial Networks have been successfully applied to the task of precipitation nowcasting [14].

3.2 Satellite Based Nowcasting

In their study Chen et al. built a [5] MLP to forecast radar data from satellite data. The researchers used a combination of low earth orbit satellite passive microwave and infrared channels from two different satellites. Their model is developed to predict up to 1.5 hours in the future by recursive predictions of the model.

A study that does not predict precipitation but uses lightning as a marker for extreme precipitation was performed by Brodehl et al. [4] this study uses a convolutional network to predict lightning events, and contributes the important observation that both the visual and infrared channels are significant in differing ways to predict lightning.

The approach taken by the researchers of MetNet [21] is to combine a convolutional block for spatial downsampling, then a ConvLSTM block for temporal encoding and finally a Axial attention block [22]. MetNet is able to perform more accurate forecasts than NWP models for up to 8 hours. In this study the input data that is used is both satellite and radar data as well as the elevation, time of the year and latitude and longitude values.

4 BACKGROUND

In order to understand this research it is important to be acquainted with the machine learning techniques that will be used. Furthermore insight into this study can be enhanced by having more in depth information on the used data-sets and the meteorological theory.

For the machine learning aspect of this research it is important to understand multi layer perceptrons (MLPs) [17]. Furthermore it is important to understand convoutional neural networks and what benefits they afford in relation to MLPs [12]. It is also crucial to have an understanding of recurrent neural networks (RNNs) and their extension to include convolutions [19].

To have an understanding of the meteorological context of this project it is recommended to have an understanding of radar data [15], satellite data specifically the kind used in this project [16].

5 METHODOLOGY

We choose to structure our project based on the CRISP-DM framework.

5.1 Business and Data Understanding

From a business perspective the data.

5.2 Data Preprocessing

satellite data

radar data

Issue during data cleaning was missing radar data.

5.3 Training

Using pytorch, pytorch ligthing, zenml, mlflow

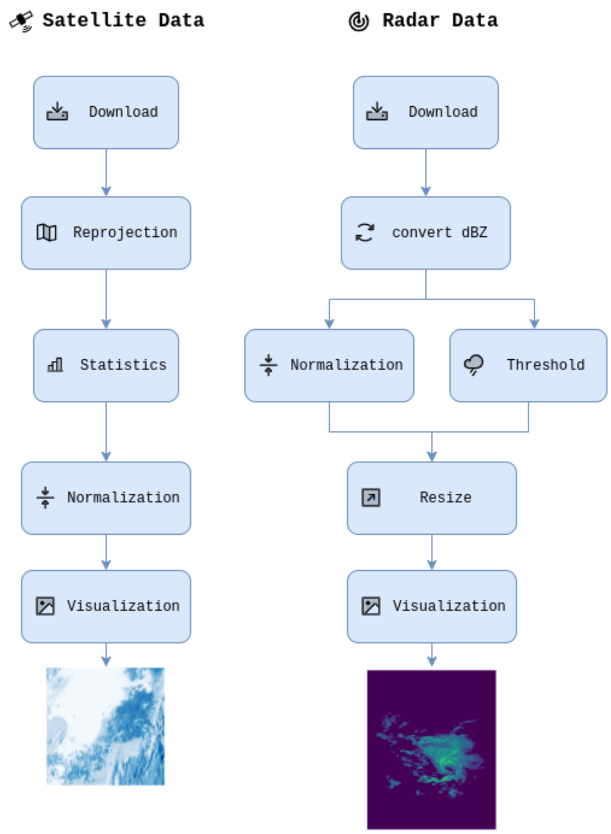

Fig. 2. Preprocessing Pipeline

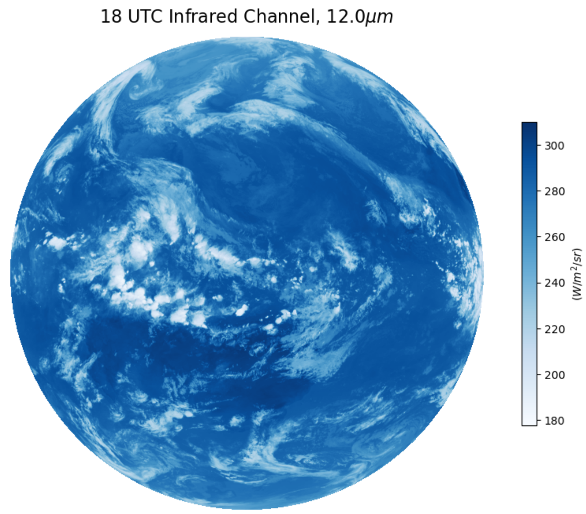

Fig. 3. Satellite Image: Infrared Channel 18UTC 12.0μm

5.4 Performance Evaluation

6 RESULTS

6.1 Data

6.1.1 Dataset Details. We have obtained a multi-year structured archive of radar composites with a temporal resolution of 5 minutes. These radar composites are made from 5 Doppler radars that provide a good coverage of the Benelux area (See figure 6). The readings of these radars can be combined to produce radar reflectivity data (see figure 4).

Additionally we have obtained satellite data from EUMETSAT at a `3x3km` spatial resolution and 15 minute temporal resolution. This data has been captured with the SEVIRI sensor [16], which produces multi-spectral satellite imagery (See figures 5 and 3).

6.1.2 Data Cleaning. UMAP [10] will be used to cluster the data from the satellite and radar to find outliers and potential data imbalances.

6.1.3 Preprocessing Details. Several options exist for preprocessing of the data. One could reproject the satellite images to match the area and geographic projection of the radar images, however this requires heavy computation and studies such as [21] have shown the importance of the context (i.e data from outside the region of interest) for the predictions. We will preprocess our satellite images by cropping them to a smaller dimension to reduce the required parameters of the model, with padding outside the area of interest. We will standardize the pixel data from all images to floating point data between `0` and `1`.

6.2 Implementation Details

In this research we will work with `python` as it is the *de facto* programming language for data science and machine learning. We will use the machine learning framework `pytorch` due to the high degree of availability of open-source model implementations that we can use as a base for our work, for instance this repository: [11].

To track our experiments we will use the open-source experiment tracker `mlflow` which allows us to record and track the performance of our experiments. With `mlflow` it is possible to record the configuration, data and code used for each experiment. This will free our time from manually tracking all experiments and their performance.

We will use the Machine Learning Operations (*MLops*) platform `zenml`. MLops is a concept that describes all work done to support the core process of training and deploying machine learning models, similar to *DevOps* for software development. The use of `zenml` allows us to quickly experiment by structuring our code in modules named *steps*. Steps can be arbitrarily combined in `zenml` to form *pipelines*. To give a concrete example we will create a pipeline named *training*, which will contain the steps: *load_data*, *train* and *evaluate*. `zenml` also allows us to muster compute resources, by connecting to *Amazon web services*.

6.3 Metrics

We plan to use the following metrics to evaluate our model:

$$MSE = \frac{\sum(\hat{y}_i - y_i)^2}{n} \tag{1}$$

$$MAE = \frac{\sum |\hat{y}_i - y_i|}{n} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum(\hat{y}_i - y_i)^2}{n}} \quad (3)$$

Additional metrics come from the study [20], where the authors created *B-MSE* and *B-MAE* due to the fact that the frequencies of different rainfall levels are imbalanced. Models trained with conventional *MSE* or *MAE* are biased towards predicting low amounts of precipitation. This can be solved with a loss function that weights the higher precipitation more strongly. The weighting function w can be found in the study as well.

$$BMSE = \frac{\sum w(\hat{y}_i) \cdot (\hat{y}_i - y_i)^2}{n} \quad (4)$$

$$BMAE = \frac{\sum w(\hat{y}_i) \cdot (\hat{y}_i - y_i)^2}{n} \quad (5)$$

6.4 Experiments

The input and output data will be the full data as discussed in the data section, and will not change based on the experiments, since we know from literature that all the data from satellite channels can be useful.

(1) Use ConvLSTM architecture.
(2) Use MetNet architecture
(3) Evaluate the best performing model by running it over a month of data, and analyse the performance by performing aggregations of the predicted data and the ground truth.

7 CONCLUSIONS

At this point in the research we have created an introduction for the research. We have also performed a literature review of available work in the field of precipitation nowcasting. We have written the methods that we will use to perform the research and listed expected results. And we have visualized some of the data from our dataset.

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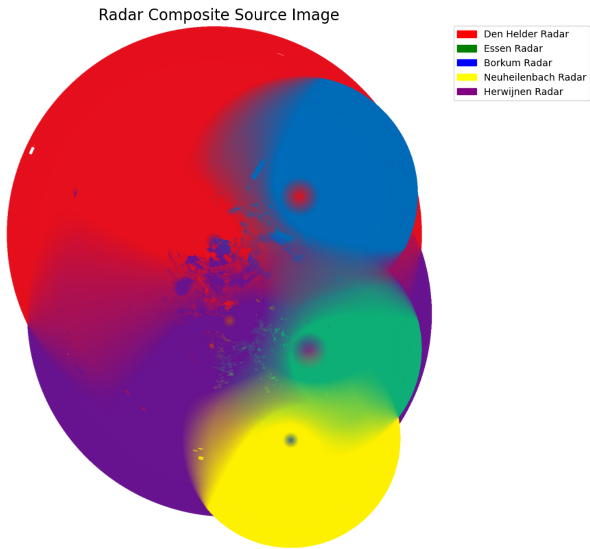

Fig. 6. Satellite Image: Infrared Channel 18UTC 12.0μm

Table 1. Reflectivity in dBZ versus Rainrate

LZ(dBZ)	R(mm/h)	R(in/h)	Intensity
5	(mm/h)	<0.01	Hardly noticeable
10	0.15	<0.01	Light mist
15	0.3	0.01	Mist
20	0.6	0.02	Very light
25	1.3	0.05	Light
30	2.7	0.10	Light to moderate
35	5.6	0.22	Moderate rain
40	11.53	0.45	Moderate rain
45	23.7	0.92	Moderate to heavy
50	48.6	1.90	Heavy
55	100	4	Very heavy/small hail
60	205	8	Extreme/moderate hail
65	421	16.6	Extreme/large hail

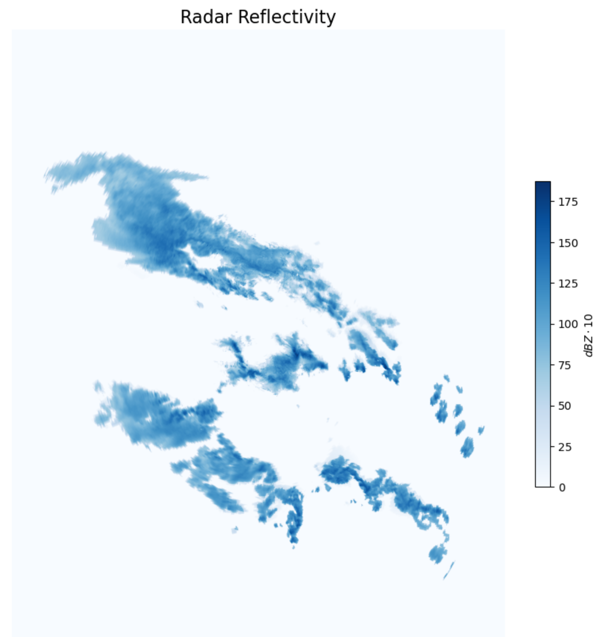

Fig. 4. Radar Reflectivity

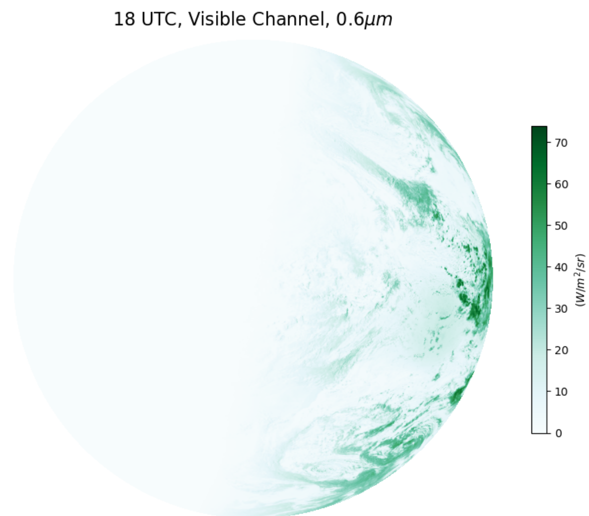

Fig. 5. Satellite Image: Visible Channel 18UTC 0.6μm

A APPENDIX