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CycloCast – Predicting Cloud Formations in Cyclonic Conditions Using Indian Satellite Imagery

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Abstract

CycloCast is a deep learning-based forecasting model which predicts the future development of cyclonic weather cloud patterns from the satellite imagery taken from ISRO INSAT Series of satellites. Using a ConvLSTM network, it predicts future developments of cloud patterns at every 30 minutes based on a single input image sequence. The potential of predicting cloud coverage patterns makes CycloCast a valuable tool for meteorologists and disaster management authorities. In this paper we detail the data collection methods, data processing approaches such as adaptive thresholding and cyclone-based cropping, and the training approaches to achieve stable forecasting performance. CycloCast achieves a very high level of performance in forecasting cloud coverage patterns with a Cloud Coverage % of 85.6 and a Structural Similarity Index (SSIM) of 0.7765.

Introduction

The ability to accurately and timely forecast cloud development through the entire life of a cyclone is essential during cyclone monitoring because it conveys to meteorologists the important information on whether the cyclone is growing or dissipating. New techniques in deep learning, particularly in sequence modelling and Convolutional LSTM (ConvLSTM) architecture, have opened a new avenue for forecasting times of misrepresentation in spatio-temporal weather patterns. CycloCast uses the latest machine learning knowledge and satellite images to predict the evolution of cloud developments. The paper demonstrates the established ways via understanding the conscious data pre-processing with a defined ConvLSTM to amplify forecast outcomes. Previous ways of forecasting cyclonic cloud formation have either been convenient and theroetized much in computation weight or unreliable by projection. CycloCast proposes a system based on a hybrid CNN + ConvLSTM2D model along with cyclone-cycle data pre-processing to enable more computationally efficient forecast cycles and improved short-term forecast politics.

Related Work

New advancements in meteorology enabled by deep learning have led to new advances in cloud prediction and precipitation nowcasting. The earlier study by Shi et al. (2015) introduced ConvLSTM, which used a Convolutional LSTM (or ConvLSTM) to capture the space-time

dependencies using the meteorological observations present in the input data, and also opened the door for future research to pursue the more advanced attention and multi-scale processing techniques that can be utilized now. Other recent studies have also included Otsu thresholding and contour filtering in their preprocessing of satellite images (e.g., Berthomier et al. 2020; Grundner et al. 2021).
Currently, their models are either full-frame input, or they have not been customized for cyclone specific cases. CycloCast offers a new approach of coding patterns, through cyclone specific adaptive pre-processing using a CNN + ConvLSTM2D architecture that runs faster and incorporates more efficiently.

Methodology

The CycloCast framework uses a multi-step deep learning pipeline to provide superior short-term cloud forecasting in cyclonic systems. The pipeline uses adaptive preprocessing, a hybrid CNN - ConvLSTM2D model, and cyclone-based learning strategies to learn and forecast in cyclonic systems.

A. Data Preprocessing & Acquisition

Satellite imagery is acquired using the ISRO INSAT-3D satellite and is in the form of thermal images every 30 minutes. Initially, the were .h5 files which were extracted and normalized between [0, 255].
In order to control for cyclone specific features, a dynamic cropping method centered on the cyclone is used:

- Gaussian blur is applied first, in order to minimize atmospheric noise.
- Otsu thresholding was employed to isolate cloud regions.
- Morphological closing was used to connect the disparate patches of the segmented masks resulting from the Otsu thresholding.
- The largest contour is then identified and its centroid is used to crop out a fixed-size region centered over the active cyclone center.

This preprocessing pass is done to ensure that the model will only see the relevant cloud structures associated with cyclone activity. Thus, the model is given only relevant features to learn from, and any learning signal associated with background noise is minimized.

B. Model Architecture

CycloCast uses a hybrid architecture comprised of:

- An encoder based on CNN which extracts spatial features from the preprocessed image sequence.
- Two stacked ConvLSTM2D layers which learns the temporal dependencies across frames.
- A TimeDistributed upsampling layer which restores the spatial resolution of the predicted output.
- A final Conv layers to output the forecasted cloud image.

It takes an input of 5 frames, and predicts 1 future frame following short-term cloud evolution persistently in high resolution.

C. Training Strategy

Our data is structured in a PyTorch dataset class using a custom Dataset that loads an input-output sequence. The details of model training as follows:

- Loss Function: Mean Squared Error (MSE), but provided an optional weighting for the most recent frames, allowing the model to prioritize accuracy for the near-future.
- Optimizer: Adam optimizer. Optional ReduceLROnPlateau learning rate scheduler to Reduce learning rate in case validation loss is plateauing.
- Training Configuration: Images of 512×512 size, batch size of 8, maximum training epochs of 200, with early stopping to reduce amount of overfitting seen in the model.

Model checkpoints were saved after each epoch allowing for the ability to recovery only the intermediate progress, and compare intermediate performance.

D. Evaluation Metrics

Model performance was evaluated from:
Mean Absolute Error (MAE): average per-pixel error in prediction.
Structural Similarity Index (SSIM) - visual Similarity of predicted image and ground-truth image.
Cloud Cover Accuracy - predicted vs actual cloud coverage compared.
Within-Threshold accuracy - as percentage of pixels within the predicted pixel threshold.
Correlation Metrics - Pearson correlation and R^2 score reported for statistical correlation of actual cloud coverage percentage and predicted cloud coverage percentage.
If you want to have any additional diagrams or tables included with this section, or want an IEEE style version just let me know..

D. Evaluation Metrics

Performance is gauged through indicators such as Mean Absolute Error (MAE), Structural Similarity Index (SSIM), and estimation errors of cloud cover, and also statistical correlation and R^2 scores between estimated and actual cloud cover.

Data Collection

The dataset comprises satellite imagery obtained from the ISRO INSAT-3D satellite, which provides thermal images at 4 km spatial resolution at every half hour interval. Indian Ocean tropical cyclones such as AMPHAN, BIPARJOY, and TAUKTAE are currently included in the dataset. The

INSAT-3D thermal imageries for the complete lifecycle of the cyclone i.e from cyclone formation to dissipation are included in the study, ensuring a variety of cloudy conditions. Data for each cyclone is represented in separate folder which contains time-series images (at half –hour interval) that capture the progression of cloud formations during the cyclonic event.

Data Preprocessing

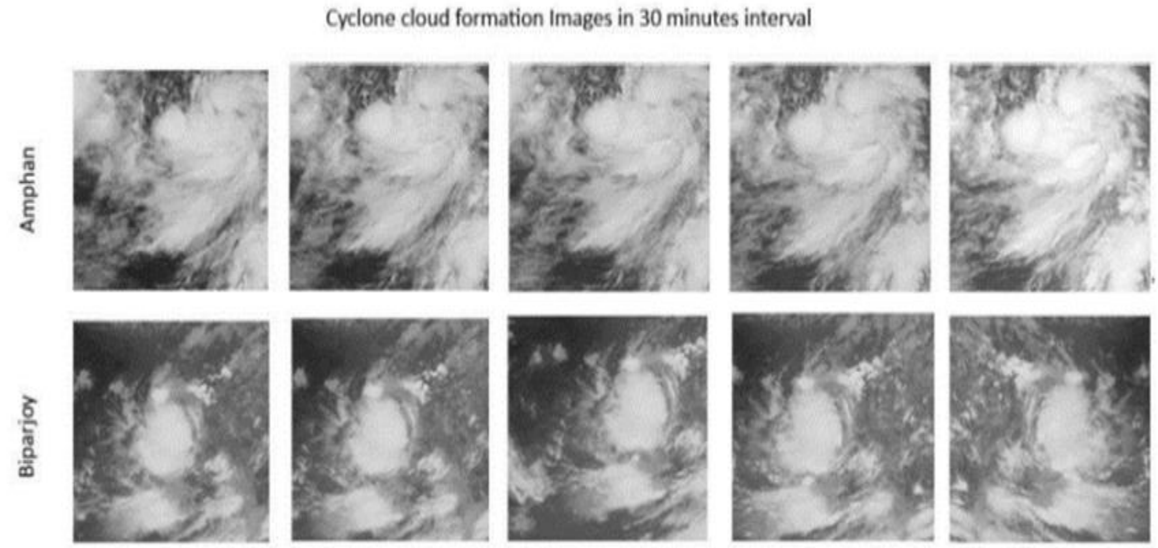
Preprocessing is necessary to give the model consistent and informative inputs. The process is as follows:

A. Loading Data

Satellite images in .h5 format are fetched by utilizing the h5py library.

B. Normalization

Images are normalized to a standard 0–255 range, representing raw sensor values in a usable format.



C. Cyclone-Centered Cropping

- The images are resized to a uniform target size.
- A Gaussian filter is utilized for noise reduction.
- Otsu's thresholding is utilized for discriminating the region of the cyclone.
- Morphological closing and contour detection methods separate the largest cloud formation region.
- A centroid is computed from image moments to accurately center the crop.

D. Output Format

These cropped images in turn are saved as PNG files to maintain a fixed size (e.g., 512×512) for input to models.

Model Training

The training is performed in PyTorch and makes use of a special dataset class to structure image sequence input and prediction target. Priorities are:

A. Dataset Building

Input streams of T images (e.g., T = 5) are stacked and displayed with the following target image.

B. Model Architecture

The ConvLSTM network consists of two layers in which the future cloud formation state is predicted using a convolutional layer.

C. Loss Function & Optimization

Mean Squared Error (MSE) loss is minimized using the Adam optimizer.

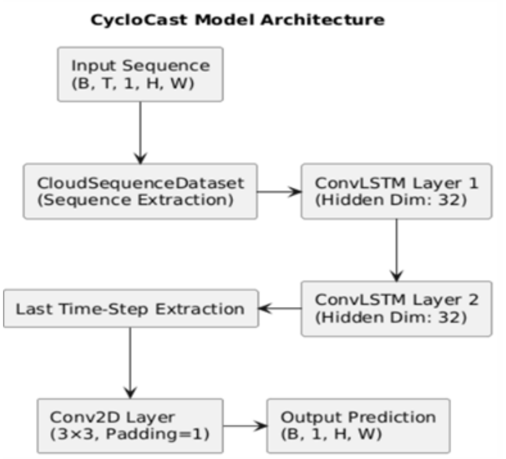
D. Hardware Utilization
Training is performed on a GPU to accelerate the process of computation.

Checkpoint Callback Configuration
To offer robustness and enable resumption of training:
A. Checkpoint Saving
The model state dictionary and optimizer state dictionary are saved after each epoch to a given folder.

B. Resuming Training
The training script checks for the presence of checkpoints, loading the most recent model if any, to resume training without loss of progress.

C. Epoch Tagging
Each checkpoint is tagged with the epoch number, enabling detailed monitoring of performance and model comparison over epochs.

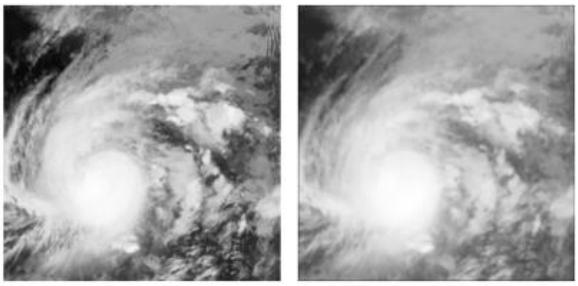
Model Training Procedure

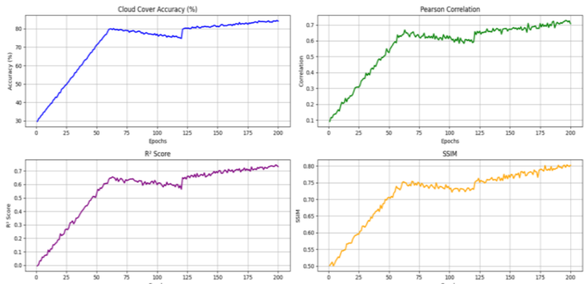


The training loop is structured as follows:
A. Batch Processing
We begin by shuffling our sequences nicely—shuffling a deck of cards, say—and then serving them up in bite-sized batches so the model sees a new mix each time.
B. Forward Pass
Then we take each batch and feed it into the ConvLSTM, let it mow through the time steps, and grab its best guess at the end.
C. Backpropagation
We compare that prediction to the actual picture, how far we were off, and we use that error signal and plug it back into the network to inform it where it was wrong.
D. Parameter Update
Our reliable optimizer steps in, adjusting the weights to nudge the model towards fewer mistakes the next time. E. Epoch Reporting Once we have gone through all the batches (one epoch), we log the loss and save a checkpoint—so we can keep track of progress or hit rewind if something goes wrong.
E. Epoch Reporting
After each epoch, loss values are printed, and model checkpoints are saved, facilitating continuous monitoring of model performance.

Results
Evaluation of CycloCast is based on multiple metrics:

Ground Truth Predicted Output





Training Metrics Across Epochs

A. Cloud Cover MAE
The average error in percentage cloud cover estimated is computed. Surprisingly, the optimal model produced an estimate of cloud cover to be 87%, which closely approximates the measured cloud cover of the target images.
B. Image MAE
The mean absolute error on a per-pixel basis between predicted and ground truth images.
C. SSIM
The Structural Similarity Index (SSIM) measures the perceived image quality of the synthesized images compared to the targets in terms of structural capture fidelity.
D. Within-Threshold Percentage
The proportion of pixels for which the absolute prediction error is below some given amount (e.g., 0.1) is measured, indicating overall prediction accuracy.

E. Statistical Metrics

Pearson correlation and R^2 value are computed between actual and forecasted cloud cover values to ascertain the strength of the relationship and variance explained by the model.

During the testing, a number of saved checkpoints were compared and the best model determined by using the lowest MAE of cloud cover. It appears from the findings that CycloCast is effective in reflecting the dynamics of cyclonic cloud formation, as is evident from the 87% cloud cover which is a critical determinant of the predictive potential.

Conclusion

CycloCast successfully integrates cyclone research-inspired preprocessing techniques with a hybrid CNN + ConvLSTM2D architecture to deliver improved predictions of cloud formation during cyclone events. It demonstrated satisfactory performance based on all metrics of interest (i.e. MAE, SSIM, R^2), achieved a good predictive accuracy with good robustness.

The preprocessing techniques (i.e. Gaussian blur, contour-based cropping) allowed CycloCast to minimize background noise, and coax the model to learn the relevant part of the cloud data contributing to a more thorough convergence and generalizability.

Planned future work will involve:

- Expanding our cyclone dataset, and adding multi-spectral images.
- Adding either attention mechanisms or transformer mechanisms.
- Testing CycloCast on real-time forecasting conditions, when the possibility arises. These directions will enhance both the scalability and future impact of CycloCast as a sustainable alternative to operational cyclone monitoring.

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