2022 Smart Technologies, Communication and Robotics (STCR) | 978-1-6654-6047-7/22/$31.00 ©2022 IEEE | DOI: 10.1109/STCR55312.2022.10009275

Forecasting North Indian Ocean Tropical Cyclone Intensity

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***Abstract*—India is prone to tropical cyclones annually, originating from the North Indian Ocean basin. Tropical cyclones are destructive and sudden natural occurrences that annually wreak havoc by taking a huge toll on human lives and property. This engenders a need for accurately forecasting the scale of such mass-destructive events, to provide us with enough time to take precautionary measures that can reduce the death toll and minimize costs. Using the CyINSAT dataset, which gives a multimodal and temporal resolution for TCs occurred from 2014 to 2022, this paper employs and compares multiple techniques to solve the wind speed forecasting issue. All models involve recurrent networks along with image feature extractors, which are used together to predict the next wind speeds from a sequence of images. The architectural differences between these models mainly focus on the nuances involved in handling the current wind speed. The proposed architecture gives higher importance to the currently recorded wind speeds and performs significantly better than the baseline models. It successfully obtained an RMSE of 6.31, MAE of 0.093 and MAPE of 4.53.**

***Index Terms*—tropical cyclones, forecasting, time series, deep learning**

I. Introduction

One of the harmful meteorological events is a tropical cyclone, commonly referred to as a hurricane or typhoon. They are massive circumferential catastrophes with maximum sustained wind gusts reaching 119 kph and torrential rainfall which develop amid warm tropical waters. Given its significant influence, precise tropical cyclone strength forecast is however one issue that is of utmost significance. The Arabian Sea as well as the Bay of Bengal are typically the sources of tropical cyclones that predominantly affect the 7,516 km of the shoreline of the Indian peninsula, the Lakshadweep Islands, and the Andaman & Nicobar Islands. The India Meteorological Department keeps an eye on every storm that develops inside the North Indian Ocean from 100°E to 45°E.

Forecasting frameworks are separated into quantitative and statistical approaches that rely on many parameters and variables. Highly complex processes are extensively incorporated into numerical models. The precision and accuracy of the mechanism can be impacted by complex computations and an inadequate comprehension of such procedures. In comparison to numerical models, statistical models are far more versatile and demand less processing when the numerous constraints of numerical models are accounted for. Numerous statistical approaches have already been investigated, including the Generalized Additive Model (GAM) [1] and the Statistical Hurricane Intensity Prediction Scheme (SHIPS) [2].

Numerous strategies have gained interest in recent times to remedy this problem as an outcome of various machine learning developments. Convolutional Neural Networks have proven to be quite powerful when it comes to the processing and extraction of image representations from satellite imagery. One such implementation is a CNN based on LeNet-5 to extract features from satellite imagery and estimate the intensity [3]. To train from wind and geopotential altitude fields, two CNNs are coupled in another approach. In this instance, additional factors that directly influence the development of a hurricane must be accounted for. A majority of these methodologies downplay the significance of oceanographic and meteorological data.

II. Literature Survey

Deep Learning has been used extensively in the prediction and damage evaluation of major weather events. We focus on deep learning to solve the problem of tropical cyclone intensity prediction from .infrared images of cyclones in the Indian Ocean. Wang et al. [4] propose TC-3DCNN to solve the problem. This method utilises the oceanic and atmosphere weather parameters and visualises their values as images, which are then fed to the model to learn the intensity of the cyclone. In order to predict hurricane intensity, Devaraj et al. [5], propose I-DCNN a deep convolutional network that uses cropped IR images of the hurricanes of the Atlantic and Pacific oceans with the wind speed at 6-h interval data, provided by

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the HURDAT2 database. They augment images based on the wind speed of the cyclone to achieve better results, along with using K-fold cross-validation.

Wimmers et al [6] use a different approach to this problem, by using satellite passive microwave data collected in the HURDAT2 dataset. Their proposed model DeepMicroNet is a deep convolutional network, followed by 2 fully connected layers, and a softmax activation to provide class probabilities. They attempt to predict the wind speed, by dividing the range of the wind speed data into 33 discrete class intervals. The paper also presents a detailed hyperparameter analysis and independent case testing of the model. Pan et al [7] use recurrent neural networks to predict the intensity in a 24-hour range. They use the Western North Pacific TC database to train the model, which is provided by CMA/STI. Their proposed method DLM uses intensity and longitude-latitude data directly, instead of using cyclone satellite imagery.

Another technique to forecast tropical cyclones is proposed by Biswas et al [8], which uses LSTMs. The paper studies different types of architectures involving BiLSTMs, Stacked LSTMs and proposes a 2-layered BiLSTM model. They use a record of cyclones called the Best Track Dataset, which is a tabular data of 341 cyclones with an average of 27 recordings for each cyclone. Dawood [9] et al use the HURSAT-B1 database to train their proposed model Deep-PHURIE for hurricane intensity prediction. Deep-PHURIE is a novel convolution network architecture, whose outputs are smoothed out using weighted averaging of the past 5 outputs. The paper analyses the performance with their previously presented predictor PHURIE, and statistically proves the superiority of the proposed model over PHURIE. Guangchen Chen et al. [10] propose a semi-supervised learning model that aims to forecast cyclone intensity. Their approach uses a hybrid similarity measurement method to Jie Lian et al. [11] Yuqiao Wu et al. [12] Zili Liu et al. [13] After careful examination of several papers that deal with this problem, we have identified the following research gaps, that we aim to fill using our techniques. Most of the papers reviewed use the HURDAT dataset or some version of it which uses images of the hurricanes in the Atlantic and Pacific oceans; little to no work has been done on the cyclones in the Indian Ocean. The images used in some models also include IR imaging, but hardly any paper uses the water vapour spectrum of the IR band to factor in the humidity present in the atmosphere. A few papers aim to forecast the intensity of the cyclone in the next timesteps. The majority of the work focuses on the prediction of intensity from the current image.

III. METHODOLOGY

A. Dataset

CyINSAT dataset has been used which covers cyclones that have taken place in India from 2014 to 2022. It is a multimodal and temporal dataset containing images as well as the numerical parameters of the cyclone, such as maximum wind speed and pressure at every timestamp. Each timestamp consists of 4 channels of satellite images from the Indian National Satellite (INSAT): IR1, IR2, MIR, WV [14].

The images are arranged in temporal batches of size 12. This means 12 images will be used as input to predict the wind speed at the next time step.

B. Training Details

All models adhere to similar training details to ensure they are comparable. The models are trained using the Adam optimizer with a learning rate of 1e-3 and a weight decay of 1e-6 for ten epochs with a mini-batch size of four. The loss function used is a standard MSE Loss metric, and all recurrent layers have a sequence length of 12, equal to the dataset's window size.

C. Image Recurrence Model

The initial approach for forecasting involves a simple network that extracts features from images at each timestep and feeds the feature into a recurrent block as shown in Fig. 1.

The feature extraction is done using Resnet18 with frozen pre-trained weights to reduce the number of training parameters. This is important because each instance of data has 12 sequential images of cyclones, where each image has 4 channels. Due to the large size of each instance, backpropagation of gradients through time becomes extremely expensive.

The recurrent block is made up of LSTM with sequence length equal to the temporal batch size of 12 and 128 hidden dimensions. Each image in the sequence is first converted to an encoded representation of its features through the feature extraction block, and the sequence is fed through the LSTM. This ensures the output contains information not only about the last recorded image of the cyclone but also about the previous sequence leading up to it. The output from the recurrent block is passed on to a fully connected layer followed by a ReLU activation function to predict the wind speed at the next step.

For comparing performance, the LSTM in the recurrent block is replaced with GRU while maintaining the rest of the network architecture which has obtained similar results as the former model. The image recurrence model is a baseline due to its simplistic approach to forecasting.

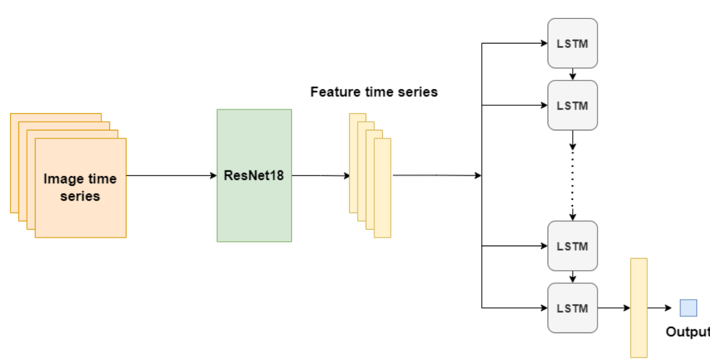

Fig. 1. Image Recurrence

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D. Image-WindSpeed Recurrence Model

In an attempt to increase the amount of data available to the network, a multi-modal approach is implemented that uses the input image sequence along with the recorded wind speeds for every image in the input sequence to forecast wind speed at the next timestep, which is depicted in Fig. 2.

The feature extraction block used is the same as the baseline model, which consists of a frozen resnet18 having pretrained weights. The recurrence block, however, is modified to introduce multi-modality to the proposed model. This is done by adding the wind speed data at each time step to the extracted features and feeding the result through the LSTM layer. The output now contains information about the image sequence of the cyclone as well as the recorded wind speeds during the sequence. This helps the model accurately predict the next wind speed and provides an improvement over the baseline model.

E. Image Recurrence with Dense WindSpeeds

To further reinforce the effect of recorded wind speeds on the final prediction they are directly added to the fully connected layer of the Image Recurrence model. This ensures that the classification block has enough information to accurately forecast wind speed at the next time step.

This approach also uses a frozen resnet18 as its feature extraction block and a recurrent block that uses LSTM with a sequence length of 12 and 128 hidden dimensions.

While the overall approach is multimodal in nature, the recurrent block processes images only as opposed to the Image-WindSpeed Recurrence approach. The output of the recurrent block is a representation of the sequence of image features. This representation is concatenated along with the sequence of current wind speed labels and passed to the classification block as shown in Fig. 3.

Contrary to the previous approach which feeds the wind speeds through the LSTM along with the features, this maximizes the overall impact of the wind speeds on the classification block and provides more context for forecasting.

IV. Results

The availability of temporal satellite images containing a myriad of channels facilitates forecasting different parameters

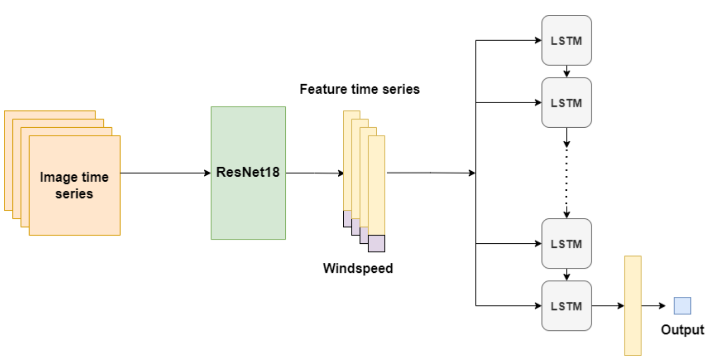

Fig. 2. Image-WindSpeed Recurrence Model

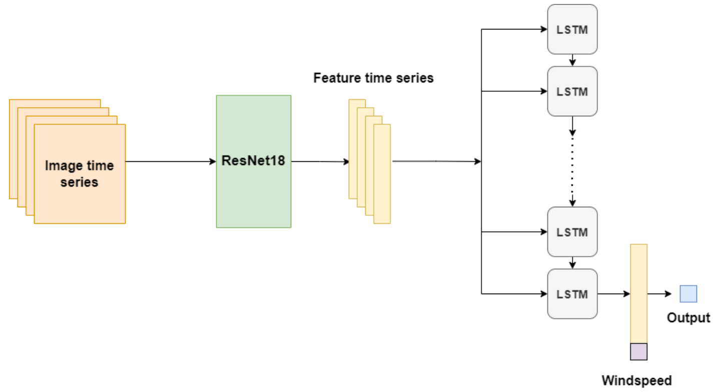

Fig. 3. Image Recurrence with Dense WindSpeeds

of a given tropical cyclone. In this experiment, we use half-hourly images of the Indian Ocean region, along with wind-speed for the given image. A hybrid deep learning architecture is used to forecast these values given a fixed set of past images and values. The architecture is as shown in Fig. 1, and serves as a baseline to compare the precision of other approaches. The metrics used to evaluate the models' efficiency include Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE) and Mean Absolute Scaled Error (MASE). This baseline model is evaluated on the forecasting and prediction metrics and the scores for these metrics are shown in Table I. These metrics show a decreasing trend with successive approaches, which indicates a higher precision rate in the values forecasted by the models. The metrics are essentially varied measures of an error on a given test set of data.

MAPE tends to reflect errors in terms of the ratio to the demand of that particular time series, which in turn promotes low forecast values. MAPE scores of the Image Recurrence with Dense WindSpeeds model are the least which proves the fact that the model is able to make better forecasts irrespective of the demand. On the other hand, RMSE values provide information on single erroneous predictions, by weighting the individual errors by a square root function, a lower RMSE value corroborates the fact that no single prediction is incorrect by a large margin. MAE values show the average absolute error values, instead of simply adding error values, MAE sums up the magnitude of errors to avoid omitting information. The lowest MAE values for the Image Recurrence with Dense WindSpeeds model reinforce that the model can make predictions that are accurate irrespective of the dataset biases.

The results shown in the table show that the Image Re-

TABLE I
COMPARISON OF VARIOUS MODELS

Model	RMSE	MAPE	MAE
Image Recurrence Model	26.23	0.566	36.63
Image-WindSpeed Recurrence Model	13.72	0.497	21.64
Image Recurrence with Dense WindSpeeds	6.31	0.093	4.53

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currence with Dense WindSpeeds model is capable of making predictions that are least erroneous on average, have no outlier predictions with absurdly high errors, and are scale-invariant as compared to some of the elementary methods.

V. Conclusions

The proposed model successfully forecasts cyclone wind speeds from satellite images, with minimum average error, lowest outlier errors and the least scaled error values. The model can precisely predict the wind speed of the next time step given a series of images. This model can handle multiple parameters simultaneously with good scalability; for example, wind speed can be replaced for atmospheric pressure, humidity, etc. The model is assessed using the regression metrics: MAPE, RMSE and MAE. The future scope of this model is to improve the ability of the model to learn the time series of the other atmospheric variables of hurricanes to model their growth accurately. It would be beneficial if it could forecast the tropical cyclone along with its several parameters over an extended period.

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