An effective tropical cyclone intensity estimation model using Convolutional Neural Networks

M. SWARNA, N. SUDHAKAR* and N. VADAPARTHI**

Acharya Nagarjuna University, Vijayawada, Guntur, Andhra Pradesh – 522510, India

*Bapatla Engineering College, Bapatla, Guntur, Andhra Pradesh – 522 102, India

**MVGR College of Engineering, Vizianagaram Andhra Pradesh – 535 005, India

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e mail : swarnamnkt@gmail.com

सार – उष्णकटिबंधीय चक्रवात भारत में प्रत्येक वर्ष होने वाली एक सामान्य प्राकृतिक आपदा है। आंकड़ों के अनुसार, बंगाल की खाड़ी में भारत के पूर्वी तट पर लगभग तीन चक्रवात आए, जिससे मानव जीवन, फसलों और संपत्ति को नुकसान पहुंचा। भारी क्षति को रोकने और कम करने के लिए चक्रवात का पहले से पूर्वानुमान करना आवश्यक है। उपयोग की जाने वाली तकनीक संख्यात्मक मॉडल पर आधारित होती है जिनसे बेहतर सटीक पूर्वानुमान प्राप्त करने के लिए विशेषज्ञता और उच्च कौशल की आवश्यकता होती है। संवेदी तंत्रिका संजाल के उपयोग से डोमेन ज्ञान, मानव त्रुटियों जैसे विभिन्न मुद्दों को दूर किया जा सकता है। अतः इस शोध पत्र में, हमने उष्णकटिबंधीय चक्रवात की तीव्रता का आकलन करने के लिए एक सरल और सुदृढ़ विधि से संवेदी तंत्रिका संजाल का उपयोग करके चक्रवात की तीव्रता का अनुमान लगाने का प्रयास किया है। अत्याधुनिक तकनीकों की तुलना में इससे कम कम्प्यूटेशन समय में बेहतर परिणाम प्राप्त हुए।

ABSTRACT. The tropical cyclones in India is a common natural disaster happening every year. As per the statistics, about three cyclones hit India's east coast in the Bay of Bengal, which damaged human lives, crops and property. It is essential to predict the cyclones in advance to prevent and reduce huge damage. The techniques used are based on numerical models that require vast expertise and higher skill sets to achieve better prediction accuracy. The usage of Convolutional Neural Networks shall overcome various issues like domain knowledge, the scope for human errors. Hence, in this paper, we attempted to predict cyclone intensity using Convolutional Neural Networks by proposing a simple and robust architecture for Tropical Cyclone intensity estimation. The results yielded better performance than the state-of-the-art techniques with reduced computation time.

Key words – Tropical cyclone, Convolutional Neural Networks, Intensity Estimation.

1. Introduction

Tropical Cyclone (TC) is defined by the rapid rotation of strong storms characterized by the low-pressure center, sober winds with a closed low-level atmosphere circulation and a spiral arrangement that produces a heavy rainfall. Depending upon the location and its strength, the tropical cyclones are typhoon, hurricane, cyclonic storm, tropical storm, cyclone and tropical depression.

"Tropical" refers to the geographical origin of the systems that are formed exclusively at tropical seas. "Cyclone" refers to the winds revolving in a circle by whirling around the clear central eye along their winds blowing in the counterclockwise direction in Northern Hemisphere and rotating in the clockwise direction in the Southern hemisphere. Because of the Coriolis effects, the currents in the northern and southern hemispheres circulate in opposite directions.

Usually, the tropical cyclones are formed at larger bodies of relatively warm water. The effect of TCs is observed to be more on the coastal regions. The stronger winds, higher storms and surges lead to huge damage to the agricultural lands, properties and plantations in the coastal areas. Tropical cyclones and hurricanes have a vital role in balancing the climatic conditions on the earth by transporting the heat due to ocean circulation patterns, as per the research done by Purdue University on the climate conditions of North America and Europe. However, the extent of damage caused by a tropical cyclone is very severe. Thus, to avoid huge damage, it is essential to predict the intensity of TC at the early stages.
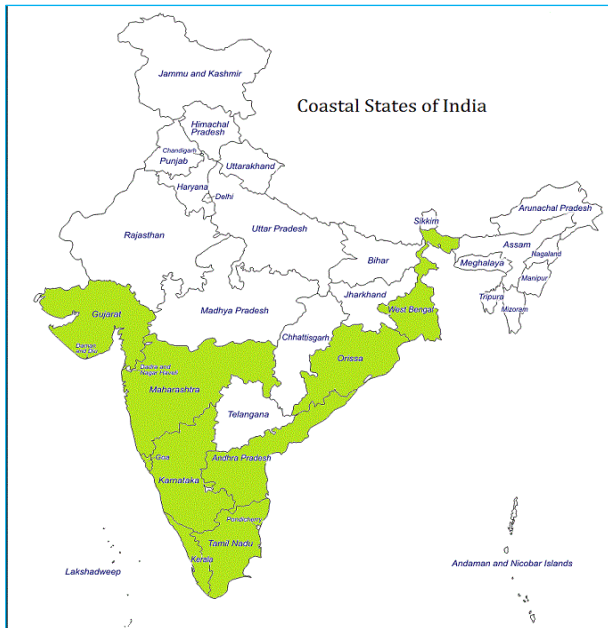
Fig. 1. Costal status of India

Fig. 2. Coastal areas effected due to TCs

There are 6 RSMCs worldwide in which the Indian Meteorological Department is one of the warning centers in the North Indian Ocean basin. However, the IMD uses specialized models that tend to give a lead time of 3-5 days, which is not sufficient to prevent the damage caused due to cyclones (Mohanty, 2015). Hence, it is essential to derive models that predict the cyclones well in advance and avoid the loss due to cyclones or hurricanes.

Among all the countries with long coastal areas having TCs, India is the 7th largest coastal area with an extent of 7,516.6 km spread along with ten states as shown in Fig. 1 and the shaded part resembles the coastal area of India. The maximum coastline is under the Bay of Bengal (BOB) and some part of the coastal area is under the Arabian Sea from the existing measurement. These areas suffer huge damage along with human lives every year due to the TCs. Fig. 2 represents the areas affected due to TCs at various intensity ranges. The darker areas are categorized as Very High Damage Risk Zone and the Low Damage Risk Zone's lighter ones.

As per the research study done by Alexander Manion *et al*. (2015), the average number of depressions leading to cyclones every year is3 in the Bay of Bengal (Amina Asif *et al*., 2018) months of October, November and December post-monsoon. The damage caused by the severe cyclones' severe loss has been listed in Table 1. Hence, to reduce the property loss and loss of human life and animal life, it is essential to estimate the intensity of tropical cyclones and assess the impact of the TC well in advance.
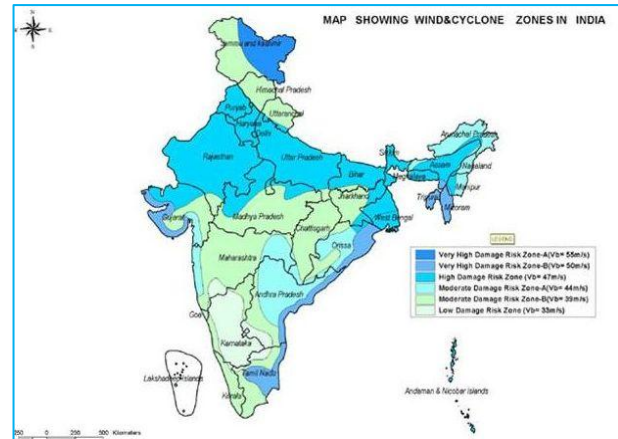
1.1. *Motivation*

The estimation of TCs till now is being done using a few statistical & dynamical approaches that need human intervention. The statistical techniques are most challenging in terms of accuracy when compared to the dynamical system. The models developed by Dvorak in 1974 and the improvements made until 1996 have helped obtain increased accuracy. The usage of EIR images extracted by satellites is being used for estimating the TC intensity. However, human intervention is still an aspect of focus that leaves lots of challenges like domain expertise, human errors.

The recent advancements in the information technology era and the highly sophisticated image recognition techniques have motivated us to focus on TC estimation using the Convolutional Neural Networks work on Satellite images. There are various models like LeNet, ResNet, AlexNet, Yolo, which are highly used for image recognition, object detection, classification. Hence, the usage of such models is of highly efficient than the existing methods.

1.2. *Our contribution*

The enormous application of Image recognition and object detection techniques with higher accuracy led us to experiment on satellite images for TC intensity estimation. One more advantage of using CNNs is that the features in the satellite images required for TC intensity estimation, such as The Shape of an eye, the eye's size, the direction of rotation, color, pattern, intensity, are generated phase convolution automatically. However, the existing models are highly dense in design and time taking. Hence, we have designed an efficient CNN model that reduces the estimation time and increases prediction accuracy.

TABLE 1

Cyclones with sever damages caused

Name of the Cyclone	Intensity as per IMD scale	Duration	3 - minute MSW (in km/h)	Sea pressure (in hPa)	Landfall location	Area affected	Loss of Lives (People)	Estimated loss (Rs.)	Basin
1990 Andhra Pradesh Cyclone BOB 01	Severe cyclonic storm	4th May, 1990 to 10th May, 1990	230	920	Andhra Pradesh	Andhra Pradesh	817	2,137.27 crore	BOB
1996 November Andhra Pradesh cyclone 07B	Very Severe cyclonic storm	4th November, 1996 to 7th November, 1996	145	988	50 km south of Kakinada, Andhra Pradesh	Andhra Pradesh	1,077	6,129.25 crore	NIO
Laila	Severe cyclonic storm	17th May, 2010 to 21st May, 2010	100	986	Near Bapatla, Andhra Pradesh	SriLanka, Ongole, Andhra Pradesh	36	1,603 crore	NIO
Nilam	cyclonic storm	28th October, 2012 to 1st November, 2012	85	990	Mahabalipuram	SriLanka, South India (Chennai and Andhra Pradesh)	30	1,710 crore	NIO
HUDHUD	Extremely Severe Cyclonic Storm	7th October, 2014 to 14th October, 2014	185	950	Near Visakhapatnam, Andhra Pradesh	Andaman & Nicobar, Andhra Pradesh, Odisha, Madhya Pradesh, Uttar Pradesh and Nepal	124	21,908 crore	NIO
Fani	Extremely Severe Cyclonic Storm	26th April, 2019 to 5th May, 2019	215	932	Near Puri, Odisha	West Bengal, Bangladesh, Bhutan, Odisha, Andhra Pradesh, East India and SriLanka	72	10,000 crore	NIO

In this paper, the CNN architecture has been designed specifically for intensity estimation. The remaining aspects of the proposed method are discussed as Section-II reviews the work done earlier on TCs estimation and Section-III details the proposed model, while the experimental results are discussed in Section-IV and finally, Section-V concludes the paper and throws light on the future scope of the work.

2.   Related work

Dvorak has developed an effective manual procedure for estimating the cyclone intensity and identifying the track using satellite images. He identified some patterns named them with *T* numbers (Dvorak, 1975 and 1984). This method is still in usage in many countries for identifying tropical cyclones and even for hurricanes. After that, the Objective Dvorak Technique (ODT) was developed by improving the Dvorak technique (Christopher *et al*., 1998). His methods were based on the satellite EIR images. However, this model's major constraint is that it cannot be applied for Tropical storms or weak tropical cyclones. The broad cloud anvil often covers the circulation center, making it difficult to find the cloud's center in the satellite image.

Rochard *et al*., 2002 developed an automated technique by considering Special Sensor Microwave Imager (SSM/I) data to avoid the drawbacks of the Dvorak technique. The satellite IR (Christopher *et al*., 2017; Greg, 2013; Oguz Demirci *et al*., 2007; Olga, 2010; Sophie, 2018; Xioqin and Hui, 2013) upper-level cloud images may cover the low-level and middle-level clouds. Without considering the low-level and middle-level clouds cyclone intensity estimation may lead to wrong analysis (Richard and Paul, 2002). The approach defined by Richard and Paul (2002) is a K-NN algorithm. The data set used was SSM/I satellite imagery data.

A mathematical model was proposed by Olga *et al*. (2010) to identify the movement of cyclones such that destruction caused by hurricanes can be minimized. In 2013, TC intensity was estimated based on a regression model using digital IR satellite image data in China (Matt, 2016; Miguel *et al*., 2011; Xioqin and Hui, 2013). However, this approach suffers less accuracy as the system used a fixed radius of wind speed fixed TC size. The ground reality is TC size differs from one stage to another (Reul *et al*., 2017; Mohanty, 1994) and it is also evident that upon an increase in the size of the TC, the radius of the wind speed, amount of rainfall also increases.

TABLE 2

Countries adopted various numerical models

Country Name	Name of the NWP model
US	National Centers for Environmental Prediction (NCEP), Navy Operational Global Atmospheric Prediction System (NOGAPS)
India	Limited Area model (LAM), QLM,WRF, HWRF, MME for TC, Polar WRF
Japan	Typhoon model of Japan meteorological department
Taiwan	GFDL and Typhoon - track forecast system.
UK	UK meteorological office global model

Over the decades, so much work has been done in predicting the cyclone intensity. The above-mentioned all works involve human intervention, more or less, even if it is an automated version. In early 2018, a model was proposed to predict the hurricane intensity using kernelized support vector regression, the ordinary least square method and the XG Boost algorithm. These machine learning techniques (Ali *et al*., 2012; Rita and Chandan Roy, 2009; Sophie, 2018; Thomas *et al*., 2017; Yuanfei *et al*., 2011) were compared only in the case of the best track with other existing models. Nevertheless, the models were not compared with the real-time data, which gave scope to further technical advancements (Amina Asif *et al*., 2018).

Kar and Banerjee (2018) proposed a manual technique concerning the Indian Ocean basin based on the feature vector generation using the Character Unique Feature vector (CUFV) algorithm. The feature vector is a tuple of mean, variance, Density and Decentrity calculated for each image and the accuracy for the model is observed to be 84%.

The models used, such as the Dvorak or the DAVT models, have their disadvantages in obtaining the accuracy of prediction for various reasons, like the NWP models' data is the EIR imagery, which applies only to certain basins like the North Atlantic basin. The advanced models of NWP were also observed to be non-standard as different models are being used in other basins. The main reason for using standard variable approaches is that the present statistic model based on the NWP model uses the current weather conditions at a specific basin or area along with Cloud top temperature.

The Indian Metrological Department has initiated a national program, "Forecast Demonstration Project of landfalling Tropical Cyclones for the purposed of providing the near real-time forecast (Mohapatra *et al*., 2011).

Few advanced weather forecasting models like WRF (Osuri *et al*., 2012, 2013), HWRF (Mohanty *et al*., 2013), the accuracy for 36 h the forecast is impressive for both the models. However, for the longer forecasts (> 36 h), the accuracy of the HWRF model is 37% for up to 84 h. For the WRF model, the accuracy is 27% with up to 72 h forecast lead only (Nadimpally *et al*., 2020).

An advanced model was proposed by Rithesh Pradhan *et al*. (2018) to estimate TC intensity using Convolutional neural networks (CNN) based on satellite IR images. However, this model has operated with 76.9% and 92% accuracy on two hurricane data sets. Although significant research has been done on estimating cyclone intensity and trajectory movement, challenges exist in accurately identifying TC intensity. Many basic parameters like Sea Surface Temperature (SST), humidity and wind speed are not considered by many authors while developing their complete automated models.

Usually, TC intensity can be estimated using either or ensembling of approaches like statistical, dynamical.

Statistical approach : By analyzing the previous cyclones' data, the current weather situation is predicted in terms of the initial condition, intensity and track.

Dynamical approach : By getting the current observations as numerical data related to weather and processes the data using computer models to forecast the future state, which is also called as Numerical Weather Prediction (NWP) model.

The Table 2 describes the adopted NWP models used by various countries (Rama Rao *et al*., 2006; Mohapatra *et al*., 2011 and Nadimipalli *et al*., 2020).

3.   Proposed model

This paper proposes the work based on CNN to estimate the intensity of the Tropical cyclone. Fig. 3
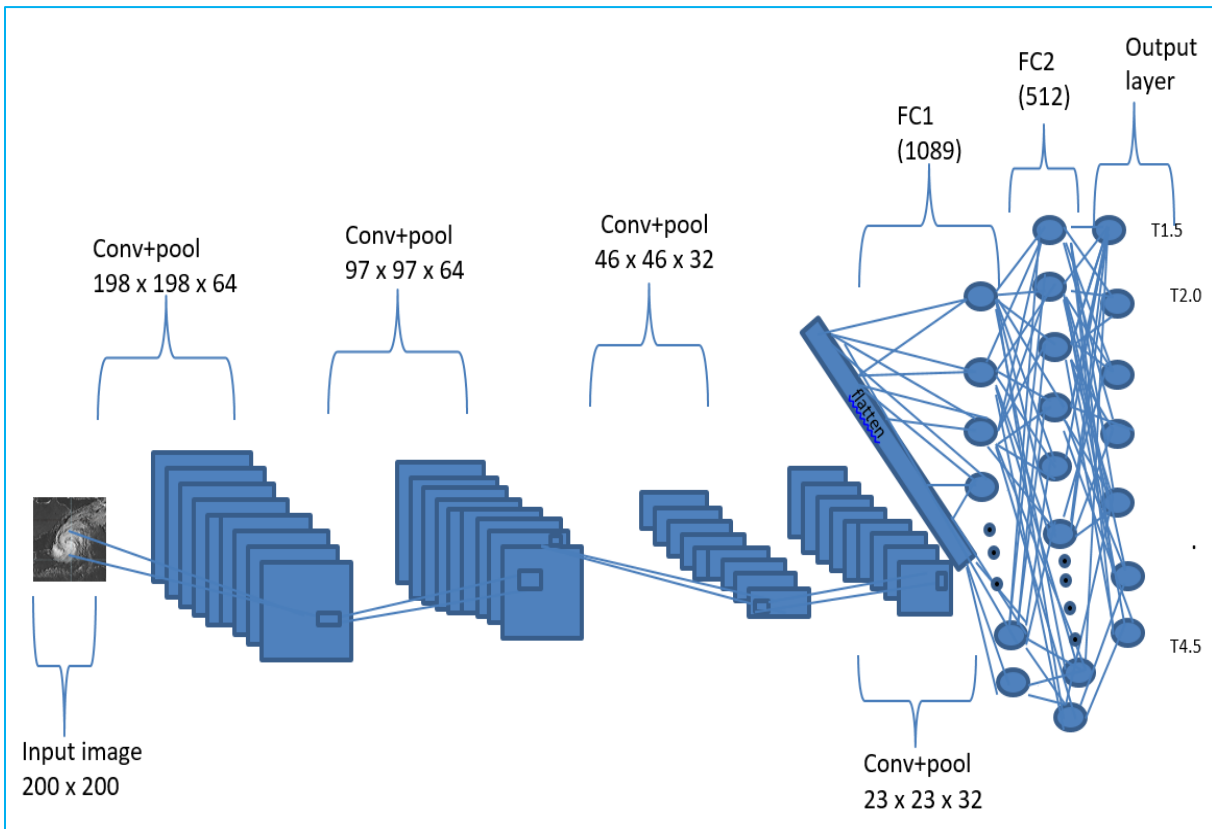
Fig. 3. Network architecture for cyclone intensity estimation depicting all steps of the model

depicts the architecture of our proposed model, which gave 99% accuracy.

3.1. *Data accumulation and design*

We collected cyclones' data that hit the North Indian Ocean basin from 2004 to 2019 from the IMD. The IMD provides all the satellite images extracted for every 30 mins. There are six different ideas, such as VIS, SWIR, MIR, WV, TIR1 and TIR2. However, we have considered VIS images for TC intensity prediction. The images were preprocessed, which is briefed in the next subsection.

The data set is extracted from IMD, New Delhi on GAJA, PHETHAI, LUBAN and HUDHUD cyclones. We have considered the above cyclones for experimentation as the intensity of these is very high and the availability of images was upto a T number of 5.0. The HUDHHUD intensity is extremely high, categorized as Very Severe Cyclone with a T number upto 4.5 as per the Dvorak technique. All phases of satellite images are available for training the model.

3.2. *Architecture*

3.2.1. *Segmentation and labeling*

Input image size is 200×200 and is a segmented image. Segmentation is done manually as per the RSMC report of IMD. IMD releases the RMSC report for each cyclone. In the RSMC report, *T* numbers are available every hour based on wind speed and sea pressure. The T1.0 has been considered a low-pressure area with a wind speed of <17 knots and higher intensity cyclones are called Super cyclonic storms. For the testing and training, we have taken visible category images as these are near to grayscale.

In contrast, IR category images consist of blue and red intensities, which might lead to misclassification. According to Dvorak, the intensity of cyclones has been classified as T1.5, T2.0, T2.5, T3.0, T3.5, T4.0, T4.5, T5.0 (Dvorak, 1995; Christopher *et al*., 1998, 2006). For every hour, say from 0000 UTC 2330 UTC corresponding image is segmented and classified as per the *T* numbers. In this way, all the images were classified.

TABLE 3

Configuration of our convolutional network

Layer (type)	Output Shape	No. of Parameters
conv2d_20 (Conv2D)	(None, 198, 198, 64)	1792
max_pooling2d_20 (MaxPooling	(None, 99, 99, 64)	0
conv2d_21 (Conv2D)	(None, 97, 97, 64)	36928
max_pooling2d_21 (MaxPooling	(None, 48, 48, 64)	0
conv2d_22 (Conv2D)	(None, 46, 46, 32)	18464
max_pooling2d_22 (MaxPooling	(None, 23, 23, 32)	0
conv2d_23 (Conv2D)	(None, 21, 21, 32)	9248
max_pooling2d_23 (MaxPooling	(None, 10, 10, 32)	0
flatten_5 (Flatten)	(None, 3200)	0
dense_ 15 (Dense)	(None, 1089)	3485889
dense_16 (Dense)	(None, 512)	558080
dense_17 (Dense)	(None, 7)	3591

Total params|: 4,113,992
Trainable params: 4,113,992
Non-trainable params: 0

3.2.2. *Convolution, pooling, optimization and activation*

Convolution neural network works on convolution and pooling operations. The convolution operation is a mathematical function that is useful in identifying the feature map. A feature map is a set of key portions of an image. Pooling operation is used for dimensionality reduction of the image. In our working model, there are four convolution + max pool layers, three dense layers. Convolution layers 1 and 2 consists of 64 filters of 3 × 3 and convolution layers 3 and 4 consist of 32 filters. The filter is applied to the input image and identifies the image features such as Shape, eye. When the filter is applied to the first 3 × 3 part of an input image, the features are equivalent or higher to the threshold value. The filter slides through the image horizontally and vertically and keeps on updating the features of the image. After applying the convolution operation, the output image is produced with 198 x 198 from equation (1).

$$M = \frac{N - K + 2P - 1}{S} + 1 \qquad (1)$$

M is the Shape of output, *N* is input image shape, *K* filters, *P* is padding and *S* is Stride.

Each convolution layer finalizes the feature vector based on activation functions like Relu, Sigmoid, Tanh and Leaky Relu. Apart from all these, optimizer plays a vital role in training. While training the network, the optimizer adjusts each neuron's weights to reduce each epoch's loss. This model is tested on different optimizers like SGD (Stochastic gradient descent), Adam, Adagard and Adadelta. This process continues till the dense layer. The thick coating is a fully connected layer that consists of a final feature vector. When a new image is given, that is classified according to the feature map.

3.2.2.1. *SGD (Stochastic gradient descent)*

Gradient descent is a widely used optimization technique that is suitable for most applications. There are three gradient descent types, such as Vanilla Batch Gradient Descent, Stochastic gradient descent and Mini Batch Gradient Descent. Stochastic Gradient Descent is faster in updating the weights and can also be used online. It also provides parameter update for each training example by using the following formula,

$$\theta_{t+1} = \theta_t - \alpha \delta J(\theta_t) \qquad (2)$$

where, θ_t weights of the previous iteration, α is the learning rate and *J* is the loss function.
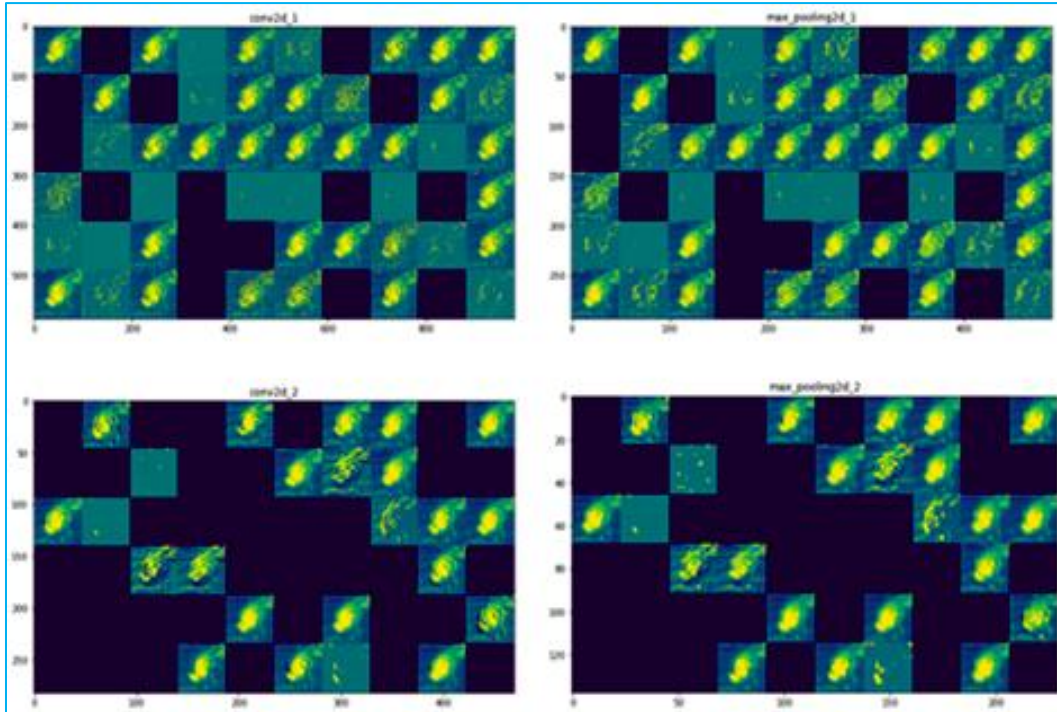
Fig. 4. Visualization of layers from convolution-1 to convolution-4

3.2.2.2. *Adagard*

This technique updates the frequent feature occurrences with smaller updates and infrequent features are updated with higher learning rates.

3.2.2.3. *Adadelta*

It is an extension for Adagard optimizer, which updates the parameters by considering both the previous and current gradient parameters. Adadelta does not store infrequent features.

3.2.2.4. *Adam*

This optimization technique is for computing the adaptive learning rate for each parameter. It is also observed that this technique works well in tuning the learning rate.

In our proposed model for the dataset used for experimentation, Adam optimizer has yielded promising results compared to other optimization techniques.

Our network architecture is depicted in Fig. 3. In each convolutional layer, the activation function used is ReLU. ReLU activation function $f(z)$ is defined in equation (3), where z is the value computed from the filter's dot matrix and the input image, which gives a pixel value of the output image.

$$f(z) = \begin{cases} 0 & z < 0 \\ z & z > 0 \end{cases} \tag{3}$$

Pooling, an operation that reduces the spatial dimension of the input image. In the proposed model, we have used max-pooling with padding = 1. Finally, the FC layer has a Softmax activation function with eight classes and the activation function is depicted by the equation (4). The soft max function is like a sigmoid function, which calculates the probability that an image falls into a class over all possible classes.

$$\sigma(z) = \frac{e^{(z_j)}}{\sum j = 1 \text{ to} n\, e^{(z_j)}} \tag{4}$$

4. Results and analysis

Any proposed work's experimentation shall have two important elements, *viz.*, dataset and the hardware. The proposed work has been implemented using Python on core i 5 and 8 GB RAM system. The data set is extracted from IMD, New Delhi on GAJA, PHETHAI, LUBAN and HUDHUD cyclones. The satellite images shall consist

TABLE 4

Different models with learning rate and accuracy levels

Optimizer algorithm	Learning rate	Accuracy
SGD	0.01	24
	0.5	20
	0.1	24
Adagard	0.01	20
	0.5	20
Adam	0.001	97%
Adadelta	0.001	15%

TABLE 5

Confusion matrix

Cyclone intensity level.	T1.5	T2.0	T2.5	T3.0	T3.5	T4.0	T4.5
T1.5	26	12	0	0	1	0	0
T2.0	0	129	1	0	0	0	0
T2.5	0	35	109	0	2	0	0
T3.0	0	59	17	135	3	0	0
T3.5	0	11	4	15	95	0	0
T4.0	0	1	2	5	14	37	1
T4.5	0	67	3	9	24	0	30

TABLE 6

Performance of proposed model

Cyclone intensity level	Precision	Recall	F1 score	Support
T1.5	0.68	0.72	0.76	125
T2.0	0.41	0.99	0.76	130
T2.5	1.00	0.62	0.76	60
T3.0	0.82	0.63	0.71	215
T3.5	0.80	0.75	0.77	146
T4.0	0.96	0.67	0.79	39
T4.5	0.97	0.23	0.37	133

of the parameters such as TC intensity, Sea pressure and Wind speed.

As the cyclones pattern seems nonlinear and the atmosphere is complex and dynamic, the model has been
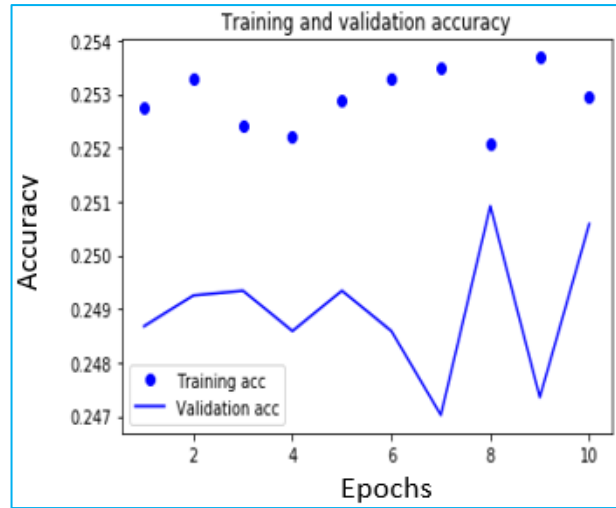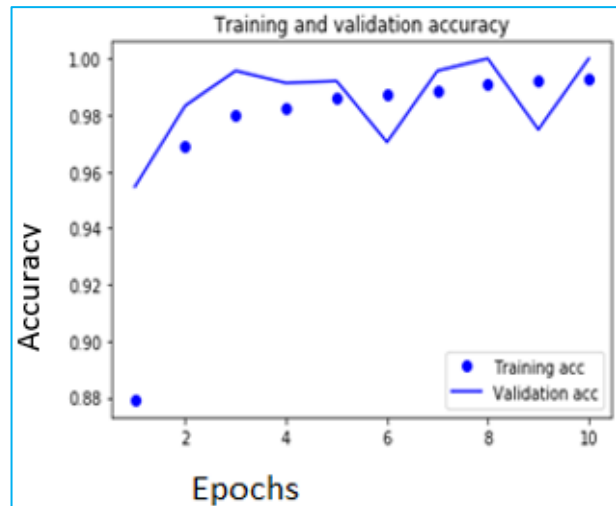

Fig. 5. Accuracy of SGD

Fig. 6. Accuracy of Adam

trained using different optimizers like SGD, Adagard, Adadelta and Adam. Table 4 depicts the experimental results of accuracy when various optimizers are used.

The Fig. 4 shows the output of each CNN layer as visualization, which consists of feature maps learned by the neurons corresponding to Adam optimizer.

Figs. 5 & 6 show the graphs of the performance of SGD and Adam. From the chart, it is clear that Adam optimizer's understanding is better than the performance of SGD.

Table 5 shows the confusion matrix specifies that the cyclone intensity T2.0 is misclassified most of the other *T* numbers as the intensity varies. Still, not much of the

variation is found in the isobars. The model is evaluated by precision, recall and F1-score shown in Table 6. The values clearly show that the model is outperformed well. After analyzing the new Test image, the developed model classifies the *T* numbers and specifies the range of wind speed to which it belongs.

The proposed technique is effective in terms of accuracy. The number of layers used in our model is less than the existing model developed by Ritesh Pradhan *et al*., 2018, which used eight layers resulting in reduced execution time.

5.   Conclusion and future work

The impact of cyclones has been highly devastating. To prevent huge damage, the prediction of the cyclone's occurrence well in advance is highly essential. The statistics indicate that the cyclone prediction had drastically reduced the loss of lives. The accuracy of the prognosis depends on the number of parameters used and the effectiveness of the model. On observing the proposed model's experimental results, it is evident that the model has yielded 97% accuracy compared to the existing model.

However, the proposed model uses the parameter wind speed to estimate the TC intensity. Suppose a new network is trained with sea pressure and fusioning with the current neural network. In that case, the prediction accuracy can be improved and nearby classes' misclassification can also be reduced.

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References

Ali, M. M., Jagadeesh, P. S. V., Lin, I. I. and Hsu, Je Yuan, 2012, "A Neural Network Approach to Estimate Tropical Heat Potential in the Indian Ocean", *IEEE Geoscience and remote sensing letters*, **9**, 6, 1114-1117.

Asif, Amina, Dawood, Muhammad, Jan, Bismillah, Khurshid, J. and DeMaria, Mark, 2018, "PHURIE : Hurricane Intensity Estimation from Satellite Imagery Using Machine Learning", *Neural Computing and Applications* - Springer. doi : 10.1007/s00521-018-3874-6.

Christopher, Velden, Bruce Harper, Frank Wells, John L. Beven II, Ray Zehr, Timothy Olander, Max Mayfield, Charles "CHIP" Guard, Mark Lander, Roger Edson, Lixion Avila, Andrew Burton, Mike Turk, Akihiro Kikuchi, Adam Christian, Philippe Caroff and Paul McCrone, 2006, "The Dvorak tropical cyclone intensity estimation technique a satellite-based method that has endured for over 30 years", *American metrological society*, **87**, 9, 1195-1210, https://doi.org/10.1175/BAMS-87-9-1195.

Christopher, Velden, Olander, Timothy, Herndon, Derrick and Kossin, James P., 2017, "Reprocessing The Most Intense Historical Tropical Cyclones in the Satellite Era Using the Advanced Dvorak Technique", *Monthly Weather Review*, **145**, 3, 971-983. doi: https://doi.org/10.1175/MWR-D-16-0312.1.

Christopher, Velden., Olander, Timothy L. and Zehr, Raymond M., 1998, "Development of an Objective Scheme to Estimate Tropical Cyclone Intensity from Digital Geostationary Satellite Infrared Imagery", *Weather and Forecasting*, **13**, 172-186. doi:10.1175/1520-0434(1998)013 <0172:DOAOST>.

Demirci, Oguz, Tyo J. Scott and Ritchie, Elizabeth A., 2007, "Spatial and spatiotemporal projection pursuit techniques to predict the extra-tropical transition of Tropical Cyclones", *IEEE transactions of Geoscience and Remote sensing*, **45**, 2, 418-425.

Dvorak, V., 1975, "Tropical cyclone intensity analysis and forecasting from satellite imagery", *Mon. Wea. Rev.*, **103**, 420-430.

Dvorak, V., 1984, "Tropical cyclone intensity analysis using satellite data", NOAA Tech. Rep. NESDIS 11, Vol. **47**.

Dvorak, V., 1995, "Tropical Clouds and cloud systems observed in satellite imagery: Tropical Cyclones", Workbook Vol. **2**.

Greg, Holland, L. and Cindy, Bruyere, 2013, "Recent Intense Hurricane Response to Global Climate Change", Springerlink.com (online), 617-627.

Kalsi, S. R., 2002 "Satellite-Based Weather Forecasting", Satellite Remote Sensing and GIS Applications in Meteorology, Proceedings of the Training Workshop 7-11 July, 2003, Dehra Dun, India, Agricultural Meteorology Programme (AgMP), 331-346.

Kar, C. and Banerjee, S., 2018, "An image processing approach for intensity detection of Tropical Cyclone using feature vector analysis", *International Journal of Image and Data Fusion*, 1-11. doi : 10.1080/19479832.2018.1491896.

Krishna Mohan, K. S., 2013, "Environmental Influences on the Frequency and Intensity of North Indian Ocean Tropical Cyclones", Ph. D. Thesis, February 2013.

Manion, Alexander, Evans, Clark, Olander, Timothy L., Velden, Christopher S. and Grasso, Lewis D., 2015, "An Evaluation of Advanced Dvorak technique - Derived tropical cyclone intensity estimates during extratropical transition using synthetic Satellite imagery", *American Meteorological Society, Weather and Forecasting*, **30**, 984-1009.

Matt, Hawcroft, Helen, Dacre, Richard, Forbes, Kevin, Hodges, Len, Shaffrey and Thorwald, Stein, 2016, "Using Satellite and Reanalysis Data to Evaluate the Representation of Latent Heating in Extratropical Cyclones In A Climate Model", Springerlink.com (Online), 2255-2278. doi : 10.1007/s00382-016-3204-6.

Miguel, F. Piñeros, Elizabeth, A. Ritchie and J. Scott, Tyo, 2011, "Estimating Tropical cyclone Intensity from infrared image data", *Weather and Forecasting – American meteorological society*, **26**, 5, 690-698.

Mohanty, U. C., 1994, "Tropical Cyclones in the Bay of Bengal and Deterministic Methods for Prediction of Their Trajectories", *Sadhana*, **19**, 4, 567-582.

Mohanty, U. C., Osuri, Krishna K. and Pattanayak, Sujata, 2015, "A Study on khigh-resolution mesoscale modeling systems for simulation of tropical cyclones over the Bay of Bengal", *MAUSAM*, **64**, 1, 117-134.

Mohanty, U. C., Osuri, Krishna K., Tallapragada, Vijay, Marks, Frank D., Pattanayak, Sujata, Mohapatra, M., Rathore, L. S., Gopalakrishnan, S. G. and Niyogi, Dev, 2015, "A great escape from Bay of Bengal 'Super Sapphire-Phailin', tropical cyclone - A Case of Improved weather forecast and societal response for disaster mitigation", *Earth Interactios*, **19**, 17, 1-11.

Mohapatra, M., Bandyopadhyay, B. K. and Tyagi, Ajit, 2011, "Best track parameters of tropical cyclones over the North Indian Ocean: A review", Natural Hazards, DOI 10.1007/s11069-011-9935-0.

Nadimpalli, Raghavendra Raju, Osuri, Krishna K., Mohanty, U. C., Das, Ananda Kumar, Kumar, Ankur, Sil, Sourav and Niyogi, Dev, "Forecasting tropical cyclones in the Bay of Bengal Using quasi-operational WRF and HWRF modeling systems: An assessment study", *Meteorology and Atmospheric Physics*, **132**, 1, 1-17. doi: 10.1007/s00703-019-00669-6.

Rama Rao, Y. V., Hatwar, H. R. and Agnihotri, Geeta, 2006, "Tropical cyclones prediction by numerical models in India Meteorological Department", *MAUSAM*, **57**, 1, 47-60.

Reul, N., Chapron, B., Zabolotskikh, E., Donlon, C., Mouche, A., Tenerelli, J., Collard, F., Piolle, J. F., Fore, A., Yueh, S., Cotton, J., Francis, P., Quilfen, Y. and Kudryavtsev, V., 2017, "A New Generation Of Tropical Cyclone Size Measurements From Space", *American Meteorological Society*, **98**, 11, 2367-2385. doi : https://doi.org/10.1175/BAMS-D-15-00291.1.

Richard, L. Bankert and Paul, M. Tag, 2002, "An Automated Method to Estimate Tropical Cyclone Intensity Using SSM/I Imagery", *Journal of Applied Meteorology and Climatology*, **41**, 5, 461-472. doi: 10.1175/1520-0450(2002)041 <0461:AAMTET>

Rita Kovordanyi and Chandan Roy, 2009, "Cyclone Track Forecasting Based on Satellite Image Using Artificial Neural Networks", *ISPRS Journal of the Photogram and Rem. Sen*., **64**, 6, 513-521.

Ritesh, Pradhan, Ramzan S., Aygun, Manil Maskey, Rahul Ramachandran and Danel J. Cecil, 2018, "Tropical Cyclone Intensity Estimation using a Deep Convolutional Neural Network*", IEEE Trans. on Image Processing*, **27**, 2, 692-702.

Rozanova, Olga S., Yu, Jui Ling, Hu and Chin Kun, 2010, "Typhoon Eye Trajectory Based on a Mathematical Model: Comparing with Observational Data", Nonlinear Analysis: Real-world applications 11, *Science Direct*, 1847-1867. https://doi.org/10.1016/j.nonrwa.2009.04.011.

Sophie Giffard Roisin, 2018, "Fused Deep Learning for hurricane track forecast from reanalysis data", Climate Informatics workshop proceedings 2018, Boulder, United states<hal-01851001>.

Thomas Loridan, Ryan P. Crompton and Eugene Dubossarsky, 2017, "A Machine Learning Approach to Modeling Tropical Cyclone Wind Field Uncertainty", American Meteorological Society, *Mon. Wea. Rev.*, **145**, 8, 3203-3221.

Xioqin, Lu and Hui, Yu, 2013, "An Objective Tropical Cyclone intensity Estimation Model based on Digital IR satellite Images", *Tropical Research and Review*, 233-241.

Yuan Fei, Wand, Wei, Zheng and Wen, Fu, 2011, "Back Propagation (BP) - Neural network for Tropical Cyclone Track Forecast", 19th International Conference Geoinformatics, IEEE.