Estimating Tropical cyclone intensity using a deep belief network

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Abstract. The estimation of cyclone intensity is done by deep belief neural network in this paper. The cyclone estimation is useful for marine warnings and landfall evacuation planning so that prior decision can be taken. The satellite image is preprocessed and the noise is removed with median filtering. This model gives better accuracy and the algorithm converges earlier to reduce root mean square error. The hurricane or tropical cyclone causes a low pressure center, strong wind, thunderstorm and rain. The destruction of the cyclone depends on the intensity and location. The existing systems have a drawback of giving same pattern for the cyclones having same intensity. But the proposed model estimates the intensity for all regions.

1. INTRODUCTION
There are several methods in machine learning. Deep learning is one based on learning the dataset. Deep learning model categories are deep neural network, deep belief network and recurrent neural network. They find application in social fields. Neural network consists of nodes or neurons. The connections to the neurons are represented as weights. All inputs are modified by weights and summed up. The damages due to the cyclone are related to the speed of the wind.

Deep Belief Network (DBN) composes of latent variables in multiple layers. Connections are made between the layers only. The network is trained by the distribution of errors in the backward direction to compute the error in the output. For learning, the gradient descent optimization algorithm is used to adjust the weight of neurons after the calculation of gradient loss function.

Simpler neural network outperforms short term memory [1]. The authors tested climate on pacific [2]. Hurricane intensity is forecasted in [3]. The authors forecasted cyclone using deep learning [4]. The authors represented tropical cyclone in [5]. The authors proposed a network for tracking coordinates [6]. The authors used adversarial network in [7]. Sensor network is explained in [8]. Routing algorithm is explained in [9]. Networking is explained in [10]. Network architecture is explained in [11]. The authors explained network security in [12]. The complex network is explained in [13]. The authors used neural network for classification in [14].

2. Methodology
DBN is a graphical model. The network learns to extract a deep representation from the training data. The model gives a joint distribution between observed vector \( x \) and 1 number of hidden layers. kth hidden layer is \( h^k \).

\[
P(x, h^1, ..., h^l) = \prod_{k=2}^{l-2} P(h^k \mid h^{k+1}) P(h^{l-1}, h^l)
\]

\[x = h^0\]
Conditional distribution for hidden units at kth level is
\[ P(h^{k-1} | h^k) \]

Joint distribution is \[ P(h^{l-1} | h^l) \]

Greedy layer-wise training algorithm is an unsupervised method and it is applied to DBNs with Restricted Boltzmann Machines (RBMs). RBMs are the building blocks for each layer. The steps are as follows:
1. The top or first layer is RBM and trained with the raw input \( x = h^{(0)} \)
2. Representation of the input is taken from the first layer. The same input is data for the second layer. The mean activations (values) and samples are two solutions.
3. The second layer is now RBM and trained. The transformed data (samples or mean values) are training data.
4. Iterate (2 and 3) for all layers present. Samples or mean activations are propagated up.
5. All parameters are tuned.

2.1. Greedy-layer wise pre-training
Hidden layers are \( h^{(1)} \) and \( h^{(2)} \) with the weights of the respective layers \( W^{(1)} \) and \( W^{(2)} \) and \( \log p(x) \) is

\[
\log p(x) = KL(Q(h^{(1)} | x) \| P(h^{(1)} | x)) + H_{Q(x|h^{(1)} \| x)} + \sum_h Q(h^{(1)} | x)(\log p(h^{(1)}) + \log p(x | h^{(1)}))
\]

2.2. Restricted Boltzmann Machines

The energy function is linear for Boltzmann Machines (BMs). Hidden variables are never observed for representing complicated distributions. Hidden variables can be more to increase the BM capacity. RBM makes BM to the layers without visible and hidden connections.

The energy function \( E(v,h) \) of RBM is \( E(v,h) = -b^T v - c^T h - h^T W v \)
In RBMs, visible and hidden units are conditionally independent. Using this property
\[
p(h | v) = \prod_i p(h_i | v)
\]
\[
p(v | h) = \prod_j p(v_j | h)
\]

2.3. Architecture of the proposed system
Figure 1 shows the tropical cyclone intensity estimation system.
2.4. Median Filtering
Median filter is a linear Gaussian filter to smooth the impulse noise in the image. Median filter is a nonlinear filter used during the preprocessing to remove noise. It is also used to preserve the edges of an image. Each value in the filter is replaced by the median value of neighboring values. The filter neighbors create a window. It will be run through the entire image. For entries median calculation is simple.

2.5. Boundary Issues
When boundary is experienced, during median filtering, there will not be previous value for the first entry. So the first value will repeat itself for the window formation.

2.6. Contrast or brightness adjustment
There will not be contrast difference when the black and white in the image found are same. So the contrast should be adjusted.

2.7. Adjust contrast tool
This tool does the contrast stretching. The pixel values below the threshold will be assigned as black otherwise mapped as white. Thus a linear mapping is obtained with lighter or darker intensities. The entire dynamic range available to the data type is fitted with CLim property by the image tool. The dynamic range ranges from 0 to 255 in an image for 8 bit representation. Adjust Contrast tool is used. The contrast in the image is changed by mapping between image pixel values in display range and the dynamic range. The following Figure 2 shows this mapping.

![Figure 2. Display range to dynamic range mapping](image-url)
2.8. Back propagation
Example for a multilayer network is a back propagation neural network. It can learn various features in all layers to do classifications. It trains the network layers and computes error derivatives and updates weights. But it requires large training dataset.

2.9. Gray Image
A grayscale or black and white (gray) or binary or monochrome image tells the intensity information. Black color represents the weakest intensity.

2.10. Converting Color into Grayscale
Conversion of an arbitrary color image to grayscale image is not unique. Different weighting of the color channels for example red, green and blue represent the effect of shooting black-and-white film with different-colored photographic filters present in the cameras.

2.11. Colorimetric (Perceptual Luminance-Preserving) conversion to grayscale
This conversion method makes the color image and converted gray image to have same luminance. Keeping the luminance in the grayscale image will preserve other perceptual lightness features. The color images are featured in RGB color model. The primary colors are red, green and blue. Remaining colors are happening by the different mixed proportion of these three colors. Figure 3 is RGB color model with separate channel for three primary colors. In the figure equivalent gray images are also shown.

![Figure 3. RGB Color Image](image)

From gray image the color image can be retrieved by a reverse process like rotation and other manipulations.

3. Experimental analysis
First IR images and the details regarding the hurricane are needed. The IR images are taken with fifteen minutes gap from satellite. The hurricane data includes the name, time, date and year. The images are mentioned with wind speed. During preprocessing the various colored images are changed into gray images. The noise is removed by median filtering. The cyclone details are retained in the images. All satellite images are brought to a standard 256×256 pixel size. Within that image a 232×232 pixel size region is cropped and given as input to the system. During training and testing phase, original images and few gray images are treated as training dataset. RMSE values are measured in knots. The estimated speed is equal to the weighted average of two highest speeds with respect to their probabilities. The difference between the estimated speed and the
actual speed is the value of RMSE.

3.1. Uploading the input image
The initial step in the intensity estimation of TC is to collect and upload the satellite images acquired.

3.2. Before uploading image
Figure 4 shows the image before uploading to the system.

![Figure 4. The image before uploading](image)

3.3. After uploading image
Figure 5 shows the image after uploading in the system.

![Figure 5. The image after uploading](image)

3.4. Convert original image into gray image
In the first step, luminance and chrominance values are calculated. In the next step, RGB values of the cyclone color image have been reduced. In the last step of the process, the reduced RGB values have been added with chrominance values. Finally the image is converted into grayscale image. Figure 6 shows the grayscale image.

![Figure 6. Gray image](image)
3.5. Median filtered image

After the conversion of grayscale image, the consecutive step is the process of median filtering. Median filtering is done for image noise reduction in the grayscale image to reduce the noise and retains the information of the cyclone image. Figure 7 gives the median filtered image.

![Figure 7. Median filtered image](image)

3.6. Low pressure area

The initial step in the low pressure area identification is to find histogram of the cyclone image. The second step is to convert into a binary image which is obtained by thresholding a grayscale cyclone image. The next step is to obtain a labeled image. The low pressure area is identified by the outlines plotted. In this, the exterior boundaries of the cyclone image were traced. Figure 8 shows the low pressure area.

![Figure 8. Identification of low pressure area](image)

3.7. Output
Once the area had been identified, the training process of deep belief network works and the root mean square error is calculated. Finally, based on RMSE values, category of the intensity of tropical cyclone and the level of its effect are found. Figure 9 shows the output.

![Figure 9. The output display](image)

4. Conclusion
The deep belief neural network in this paper estimates the tropical cyclone intensity. The features are extracted from satellite images of hurricane. This task is made simple by using multiple convolutional layers. The layers are fully connected and use regularization techniques. The intensity of hurricane is estimated very shortly. The process needs less human effort. Accuracy is improved and RMSE is reduced by removing the colored grids and noise from the training and testing dataset. Black patched images present in the dataset are also removed to improve the estimation accuracy. The proposed system is deep and requires a large training dataset.

5. Future enhancement
Instead of using one typical image, the model could be based on different images for improvement. This work has been focused on estimating intensity of tropical cyclone. Similarly deep belief network technique can be tried to estimate intensity calculations for other natural calamities such as floods, earthquakes and tsunamis.

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