Deep-PHURIE: Deep Learning based Hurricane Intensity Estimation from Infrared Satellite Imagery

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Abstract:

Hurricanes are among the most destructive natural phenomena on Earth. Timely prediction and tracking of hurricane intensities is important as it can help authorities in emergency planning. Several manual, semi and fully automated techniques based on different principles have been developed for hurricane intensity estimation. In this paper, a deep convolutional neural network architecture is proposed for fully automated hurricane intensity estimation from satellite infrared (IR) images. The proposed architecture is robust to errors in annotation of the storm center with a smaller root mean squared error (RMSE) (8.82 knots) in comparison to the previous state of the art methods. A webserver implementation of Deep-PHURIE and its pre-trained neural network model are available at the URL: http://faculty.pieas.edu.pk/fayyaz/software.html#Deep-PHURIE.

1. Introduction

Tropical cyclones (TC) are one of the most catastrophic phenomena on Earth. Most hurricanes occur in the tropical and subtropical region due to warm sea water. During the summer season, sunlight warms up the ocean water to form massive clouds in the upper atmosphere leading to the creation of hurricanes. Upon making landfall, tropical cyclones can cause extensive damage in the form of heavy rain, flooding and high-speed winds up to 200 miles per hour. In the year 2017, the damage caused by major hurricanes in the United States (Irma, Harvey, and Maria) was approximately $265 billion [1]. Accurate and timely prediction of hurricane intensity can help minimize damage by taking precautionary measures in areas under threat.

Several techniques have been developed for intensity estimation of tropical cyclones (TCs). One of the first such techniques was proposed by Dvorak during early age of the use of satellites for infrared imagery of hurricanes [2]. Dvorak's technique was based on the presence of specific patterns that a cyclone can take during its life cycle. The method requires locating the center of the TC and then assigns it to a specific pattern class (e.g., eye, banded, shear, etc.). Each pattern class is then associated with a corresponding T-number corresponding to a specific intensity value.

The original Dvorak technique was completely manual and vulnerable to subjective errors. A semi-automated version of the Dvorak technique was proposed in the Objective Dvorak technique [3]. The method predicted tropical cyclone intensity with same accuracy as by the Dvorak technique but was applicable only for strong storm systems and required manual center annotation.

The Advanced Dvorak Technique (ADT) proposed a new set of rules in comparison to the original Dvorak technique [4]. ADT considers the structure of curved bands around the center of the storm and constrained maximal intensity change over a specific time period. An important aspect of the method was the introduction of a regression equation for measuring cyclone intensity. ADT could measure intensity by using water vapor (6-7 μ m) and microwave channels (85-92 GHz) as well. ADT offered improved accuracy of intensity estimation but was not fully automated.

Pineros et al. [5] proposed a deviation angle variance (DAV) method based on the observation that cyclone intensity is inversely proportional to the variation in deviation angles of the gradient values for a given hurricane image around an annotated center. Sigmoid curve fitting between variance of the deviation angle histogram and intensities was used for prediction. The method used GOES-12 satellite IR images of hurricanes in years 2004-2009 in the North Atlantic Ocean. The Root Mean Squared Error (RMSE) between predicted and actual intensities was reported to be 24.8 knots (kt) when the model was trained on hurricanes data from the year 2004-2008 and tested on hurricane images of the year 2009. RMSE of 14.7kt was reported when the model was evaluated over randomly selected hurricanes over the years 2004-2008.

Ritchie et al. proposed an updated version of DAV with some additional constraints [6]. Hurricane data of the year 2010 was added and images with intensity less than 34kt were removed from the dataset. The RMSE reported was 12.9kt. Fetanat et al. used a k-nearest neighbor algorithm for cyclone intensity estimation [7]. The method used cyclone age (imagery from 6, 12 and 24 hours before current time) information. For a query image, the algorithm finds the 10 most similar images. The predicted intensity of a query image is taken as the mean value of the intensity of 10 nearest neighbor images.

PHURIE (PIEAS Hurricane Intensity Estimator) was proposed recently by Asif et al [8]. The method uses infrared (IR) images of GOES-12 satellite from the year 2004-2009. A total of 26 features were extracted by dividing the image into five circular bands of 8 pixels each, around the center. Standard deviation (SD), mean, entropy, maximum and minimum pixel values in each band and DAV proposed by Pineros et al. were used as features [5]. Support vector regression and Ordinary Least Squares regression (OLS) were used for model training. Performance evaluation was done using leave one year out cross validation. The RMSE reported with OLS and SVR was 11.2kt and 12.8kt, respectively. However, PHURIE requires annotation of the center for feature extraction.

Pradhan et al. developed a deep convolutional neural network for cyclone intensity estimation [9]. The dataset used in their study consists of a total of ~45,000 IR images of hurricanes from the year 2000-2016 from multiple satellites (Himawari, GOES, MTSAT, etc.). The training dataset size is increased using image augmentation through zooming and rotation. Also, images with more than 20% of dark pixels were removed. The network consists of 5-convolutional and 3-fully connected layers. The RMSE reported was 10.00kt for both Atlantic and Pacific hurricanes. Since the study uses training and evaluation images in which the center of the image always coincides with the center of the hurricane, the proposed scheme is not expected to produce good predictions when the center of the hurricane is not known *a priori*. The study does not report any robustness analysis of their system to errors in annotation of hurricane center in IR images. The use of 64 (10×10) convolution filters with a total of 37.5 million learnable parameters and three input channels per image make the method memory and computationally intensive. Furthermore, it is unclear whether the train-test split based performance evaluation protocol of this approach ensures that if images of a hurricane have been used in testing, no images of the same hurricane are part of training. This is important as it may lead to overestimation of prediction accuracy of the system.

In this paper, we propose a deep Convolutional Neural Network (CNN) for TC intensity estimation. The proposed model called Deep-PHURIE (Deep learning based PIEAS HURricane Intensity Estimator) gives low prediction errors in comparison to previous techniques. Based on our extensive benchmarking experiments, we expect the method to be robust to shifts or errors in annotated hurricane centers in images as well. Section 2 gives details of the methods used for development and performance evaluation of the proposed scheme. In section 3, we discuss different experiments performed for model evaluation. Conclusion and future work are discussed in section 4.

2. Method

In this section, details about dataset, machine learning models and experimental setup employed in our study are presented.

2.1 Dataset

In this study, publicly available dataset HURSAT-B1 (version 6) is used [10]. The dataset consists of hurricanes images from the year 1978-2015 taken by different satellites (GMS-5, MET-5, MET-7, GOE-8, GOE-10, GOE-13, GOE-15, MSG-3, FY2-E, HIM-8, etc.) in Atlantic, Pacific, and Indian basins. The dataset contains images from multiple channels such as water vapor, visible channel, near IR and split window. Size of the images in the dataset is (301×301) pixels with a spatial resolution of 8km/pixel. The images are taken every 3 hours and are centered at the centers of the storm system. Information about storms such as center position, intensity (measured as 1-minute sustained wind speed in knots), central pressure, etc., was taken from IBTrACS (International Best Track Archive for

Climate Stewardship) [11]. The hurricane imagery data is available in NetCDF format online at [12].

We restricted our study only to infrared (IR) channel images from the year 2001 to 2015. In line with previous methods, images with zero pixel intensity and those captured after the hurricane made landfall have been excluded from the dataset used in this study. The final dataset comprised of 172,716 IR images**.** Table 1 shows the number of images of different categories of storms in the dataset. In Table 2, we present the year-wise distribution of the images.

Table 1 Intensity distribution of images used in the study

Category	**Number of Images**
Pre-Developmental (< 20 kt)	14,318
Tropical Depression (20-34 kt)	75,541
Tropical Storm (35-64 kt)	55,377
Hurricane: (>64kt)	27,480
Total	**172,716**

Table 2 Hurricanes and images distribution by year.

Year	**Number of Images**	**Number of Hurricanes**
2001	9,140	86
2002	9,421	78

2003	12,675	86
2004	10,313	81
2005	13,708	95
2006	13,220	87
2007	11,297	84
2008	11,852	86
2009	12,782	94
2010	11,100	80
2011	11,215	84
2012	13,156	91
2013	11,620	96
2014	10,541	81
2015	10,676	93
Total	**172,716**	**1301**

2.2 Pre-processing

The images in dataset are of size 301×301 pixels, which are resized to 224×224 in order to reduce the amount of computation in convolution layers. Images with negative pixel values are excluded from the dataset to reduce noise effects.

2.3 Convolutional Neural Network Architecture

The goal of this study is to develop a deep learning-based model for hurricane intensity estimation using IR images. The proposed neural network model accepts 224×224 sized IR images as input and predicts the intensity of the hurricane in knots. The proposed network is 9-layers deep with 6-convolution layers, 2-fully connected layers, and an output layer as shown in Figure 1. At the first convolution layer, filters of size (5×5) with a depth of 32 are used, which results in 32 feature-maps. Rest of the filters throughout the network are of size (3×3). Each convolution layer is followed by a pooling layer for making the system robust and invariant to small geometric changes in images. Pooling also reduces the total number of computations. The proposed architecture uses Max-pooling of size (3×3) with a stride size of 2. Pooling reduces the length and width of an image which helps in reducing the total number of computations. Filters are learned at convolution layers using back-propagation [13].

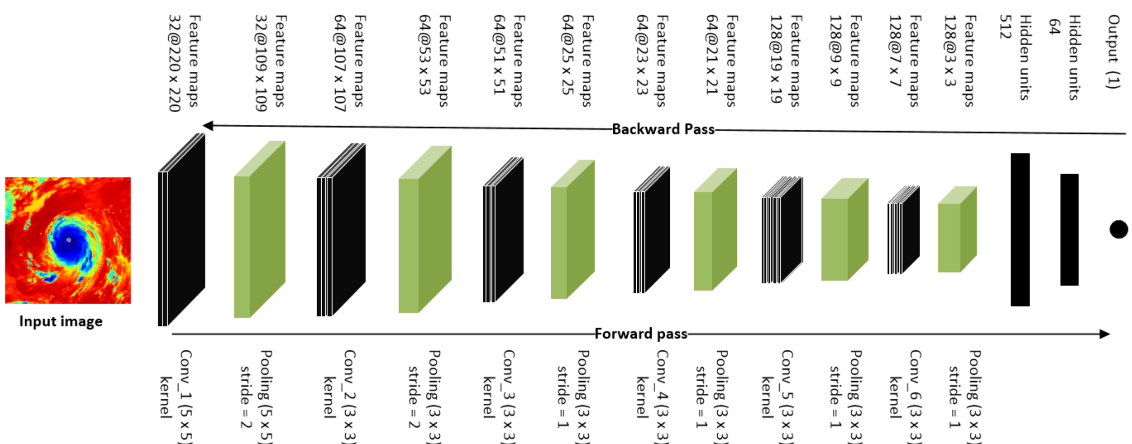


Figure 1 Network architecture

For training the network, back propagation with Mean Squared Error (MSE) as loss function is used. If y_i is target value (annotated hurricane intensity) for a given image $\boldsymbol{x}_i$ and the network prediction is $f(\boldsymbol{x}_i)$, the error is computed as below.

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}(\,f(\boldsymbol{x}_i) - \,y_i)^{\,2} \qquad (1)$$

We used Adam (adaptive moment estimation) optimizer for network weights optimization [14]. Deep networks, being high-capacity machines, are prone to overfitting [15]. Therefore, dropout, i.e., random dropping of some neurons during training, is used for performing regularization [16]. Batch normalization is also used which also acts as regularization and makes training faster [17]. Our proposed model has been trained on randomly translated, flipped and center cropped images from the year 2001-2014. The motivation behind using transformed images is that training over transformed images would help the model be invariant to shifts and scaling. It also helps the system to be robust to errors in annotation of the hurricane center.

Hyper-parameters of the model, such as learning rate, number of epochs, number of neurons in each layer, and number of filters in each convolution layer, etc., have been tuned by conducting multiple trials over a validation set comprising of hurricanes from the year 2015. Learning rate was tuned by selecting different values in the range 10^{-5} to 10^{-1} with an optimal value of 5×10^{-5}. The network was trained for 1000 epochs with early stopping at 50 epochs.

2.4 Post-Processing

The proposed model uses a single infrared image of a TC for intensity estimation. To reduce the effects of noise and model temporal evolution of the TC over time, we use exponentially weighted time averaging of predictions of images from 5 previous time steps. For TC intensity estimation at time t, the weighted average of the predicted intensity at the current time step and predicted TC intensities at 5 previous time steps $f(\boldsymbol{x}_{t-i}), i = 0,1,..,5$ is used with weights given by $w_i = 0.41e^{-i/2}$ as follows: $p(\boldsymbol{x}_t) = \sum_{i=0}^{5} w_i f(\boldsymbol{x}_{t-i}) =$

$0.41f(\boldsymbol{x}_t) + 0.25f(\boldsymbol{x}_{t-1}) + 0.15f(\boldsymbol{x}_{t-2}) + 0.1f(\boldsymbol{x}_{t-3}) + 0.06f(\boldsymbol{x}_{t-4}) + 0.03f(\boldsymbol{x}_{t-5})$. Note that the coefficients sum to 1.0 and decrease exponentially for images that are farther back in time. This, effectively, ensures that the current prediction is based on the current image as well as images acquired 3 to 12 hours prior to the current time instance. Similar or equivalent weighted averaging schemes have also been used in previous studies [7] [8] as well as in the original Dvorak techniques [3][4].

2.5 Experimental Setup

Different experiments were conducted to analyze the performance of our proposed model. We compared the performance with the previously proposed best method to setup a baseline for our study.

2.5.1 Baseline method

To establish a baseline, we analyzed the performance of our previous in-house intensity predictor PHURIE [8] by training it over images in the dataset used in this work.

2.5.2 Leave one year out (LOYO) cross-validation

The performance of the proposed model has been evaluated using leave one year out cross-validation. In this experimental setting, for every year, all the images of all hurricanes in that year are left out as a test set and the model is trained over the rest. The experiment is performed to compare the model's performance with PHURIE [8]. In line with the practical use case of a hurricane intensity predictor, this evaluation protocol ensures that if images of a hurricane have been used for performance assessment during testing, no images of that hurricane are used in training.

2.5.3 Random train-test split validation

In order to compare the performance of the proposed model with the CNN-based technique proposed by Pradhan et al [9], we divided the given data set randomly into a training set of 92, 502 images and a test set of 39, 645 images. It is important to note that, unlike leave one year out analysis above, this evaluation protocol does not ensure that there is no overlap between hurricanes used for training and performance evaluation of a predictor. As a consequence, it is expected that this evaluation protocol over-estimates the prediction accuracy of a model.

2.5.4 Center annotation error analysis

The training images used in the work are centered at the center of the hurricane. In order to assess the sensitivity of the proposed model to changes in center annotation, we analyze the change in RMSE of the predictions of the model for randomly shifted images. For this experiment, test images are shifted along both axes (x, y) by a random number of pixels within the range $[-r, +r]$. The predictions of the model are then recorded for different values of r in the range $[0,100]$ corresponding to a center annotation error of 0 to 800 km in an actual hurricane. The process was repeated 5 times for each test sample to get reliable estimates. The experiment is also repeated for two major hurricanes (Katrina 2005 and Rita 2005) with well-formed eye and uniform circular patterns. The data of hurricanes from the year 2005 were excluded from training for this purpose. In order to capture the robustness of the proposed model to center annotation errors, pixel shift is plotted against prediction errors.

2.5.5 Comparison with Aircraft Reconnaissance Data

Aircraft reconnaissance data for some of the hurricanes in our dataset are available. Aircraft reconnaissance provides reliable hurricane intensity estimates. In aircraft reconnaissance, specially designed aircraft of the National Oceanic and Atmospheric Administration (NOAA) are flown through a hurricane to record the intensity and other important characteristics. We performed error analysis for images of hurricanes that are within 3 hours of an aircraft pass through the hurricane. Hurricane data from 2005 was left out and the model was trained on the remaining hurricanes. The model performance was then evaluated on GOES-12 Satellite data of hurricanes from 2005 for which reconnaissance data was available.

2.5.6 Basin by Basin Error Analysis

Most of the previously proposed methods restrict their study to a specific ocean basin (i.e., Atlantic, Pacific or Indian). The performance of the proposed model was evaluated on Atlantic, Pacific, and Indian Basin Satellite Imagery exclusively. For this purpose, the data of hurricanes from 2005 was left for testing and model was trained on the rest.

2.5.7 Visualization of CNN feature maps

Deep neural networks have the ability to learn complex transformations. Understanding the behavior of convolution filters at different layers of the network is important and several approaches are availble in the literature for understanding predictions of a CNN. In CNNs, filters weights are updated at different layers of the network through back-propagation. Visualizing the filters helps in understanding the features learned by the neural network. Such visualizations can help us verify if important and problem-related features have been learned or not. We have used the open source CNN filter visualization toolbox keras-vis to identify activations of various filters and layers in the proposed model [18].

2.6 Implementation details and Deep-PHURIE Webserver

The proposed system was implemented using Python with Keras and sklearn machine learning libraries. To provide a convenient user interface, a free webserver for the proposed method has also been developed. The webserver together with the pre-trained model and a simple python script to run Deep-PHURIE is available at the URL: http://faculty.pieas.edu.pk/fayyaz/software.html#Deep-PHURIE. The webserver accepts IR image in .netcdf format and generates intensity predictions for the input image.

3. Results and Discussion

In this section, we discuss the results of the experiments discussed in the previous section.

3.1.1 Results of Leave One Year Out Cross-Validation

Figures 2 shows the root mean squared errors (RMSE) values averaged across all hurricanes in a year when then model has been trained on all other hurricanes in Leave One Year Out (LOYO) cross-validation as discussed in section 2.5.2. The mean RMSE of leave one year out cross-validation for the proposed model is 8.82 kt which is better than all previous approaches. Figure 3 shows the results of LOYO cross-validation for images when the intensity of the storm is >34kt, i.e., when the storm system has been classified as a tropical storm or hurricane. The mean RMSE for such cases is 9.4kts.

3.1.2 Comparison with PHURIE

The mean RMSE of leave one year out (LOYO) cross-validation for PHURIE and Deep-PHURIE are 12.38 knots and 8.82 knots, respectively. Note that both PHURIE and Deep-PHURIE have been trained and evaluated using the same evaluation protocol and the same data. It clearly shows that Deep-PHURIE performs significantly better than PHURIE. Performance comparison of both methods is shown in Figure 2.

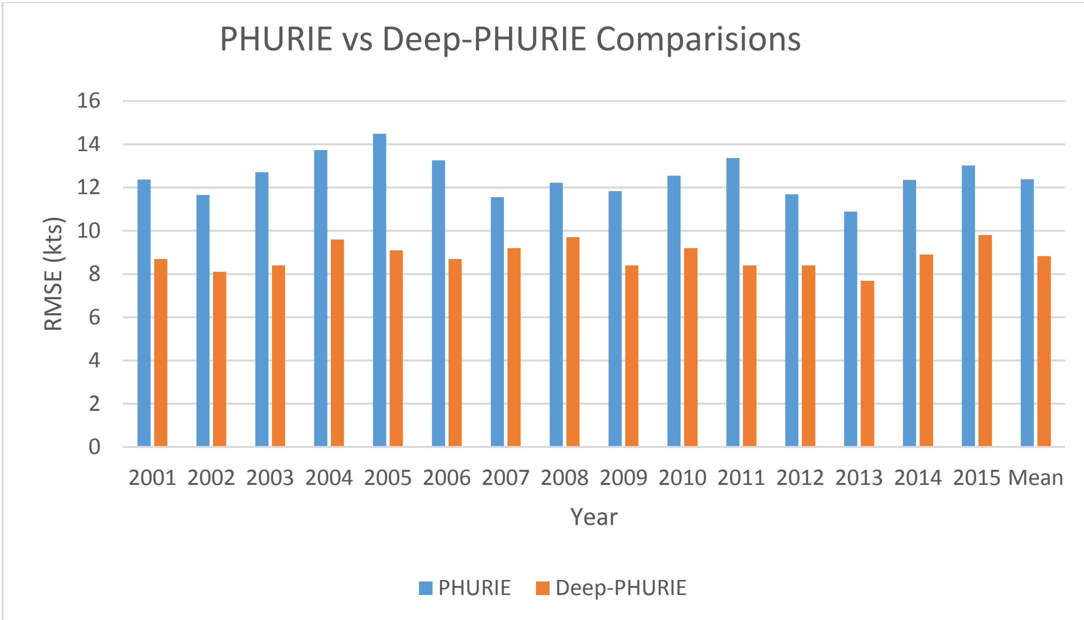


Figure 2 Performance comparison of PHURIE and Deep-PHURIE

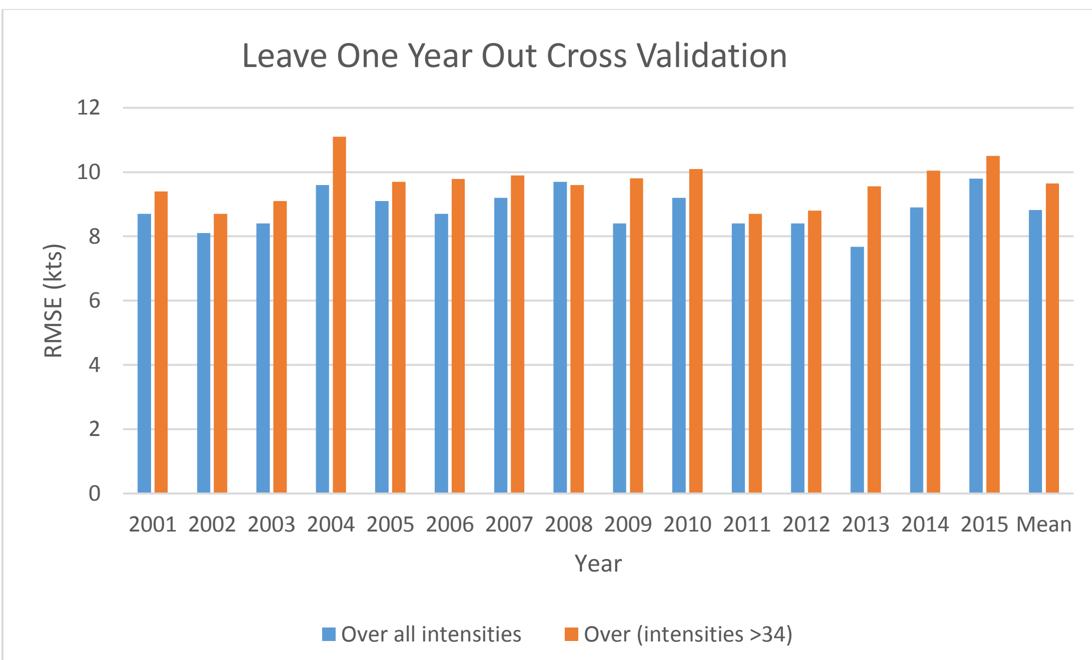


Figure 3 Leave One Year out cross validation results comparisons for all intensities and intensities >34 knot Hurricane images.

3.1.3 Random train test split

In order to compare the results of our proposed method with the CNN based approach proposed by Pradhan et al [9], we performed a random train-test split evaluation as well. With this evaluation protocol, the RMSE of the proposed method is 7.07 knots which is a considerable improvement to 10.0 knots reported by [9]. However, it must be emphasized that random train-test split is expected to over-estimate the true prediction performance of both systems due to the overlap of training and test sets with respect to hurricanes being used in the analysis.

3.1.4 Center annotation error analysis

We performed center annotation error analysis for PHURIE and our proposed method. Figure 4 shows the impact of pixel shift on PHURIE and the proposed method. The prediction error of PHURIE increases significantly with respect to random pixel shift (r) in comparison to the proposed scheme. For a pixel shift of 70-pixels, the increase in RMSE of the proposed method is only 1 knot compared to PHURIE whose RMSE increases to 27 knots. Thus, the proposed method is tolerant to high center annotation errors. A similar trend is noted for center annotation error analysis over major hurricanes in the year 2005 (see Figure 5). The robustness of the proposed scheme to errors in annotation of the center of the storm system is expected to be very helpful in a fully automated deployment of the proposed scheme.

The CNN-based prediction scheme by Pradhan et al. [9] does not report any center annotation error analysis and we were unable to perform such an analysis for their predictor as their prediction model is not publicly available. As discussed earlier, their approach uses training images in which the center of the hurricane image always coincides with the physical center of the hurricane. Therefore, it is not expected to be robust to errors in annotation of the hurricane center. For our proposed scheme, we have verified that robustness to center annotation errors is achieved only if the machine learning model has been trained on translated images in which the center of the hurricane has been shifted by an arbitrary amount. In order to show that training over shifted images is required for robustness against center annotation errors, we have performed a center annotation error analysis by training our CNN architecture with and without the use of translated images (Fig. 4). As can be seen in the plot below, the CNN is not robust to center annotation errors if it has not been trained on transformed images.

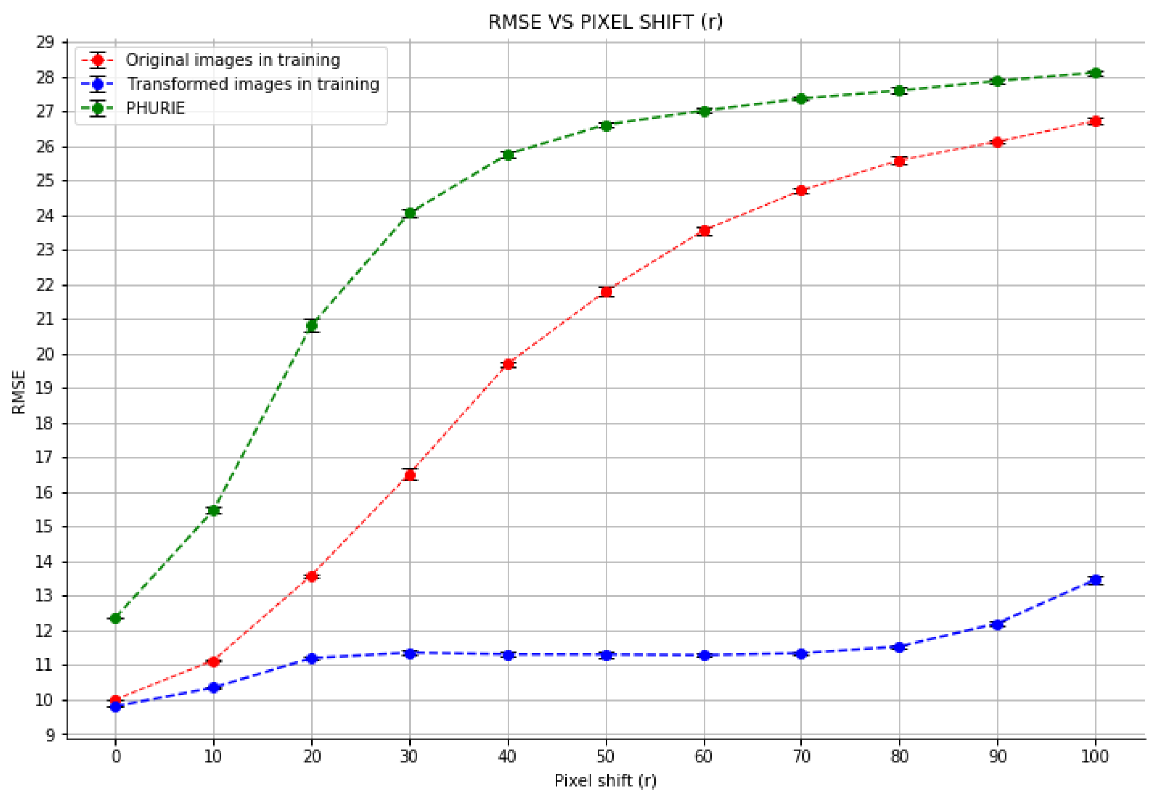


Figure 4 Prediction error with respect to error in center annotation. The error bars indicate the standard deviation in RMSE across a certain pixel shift.

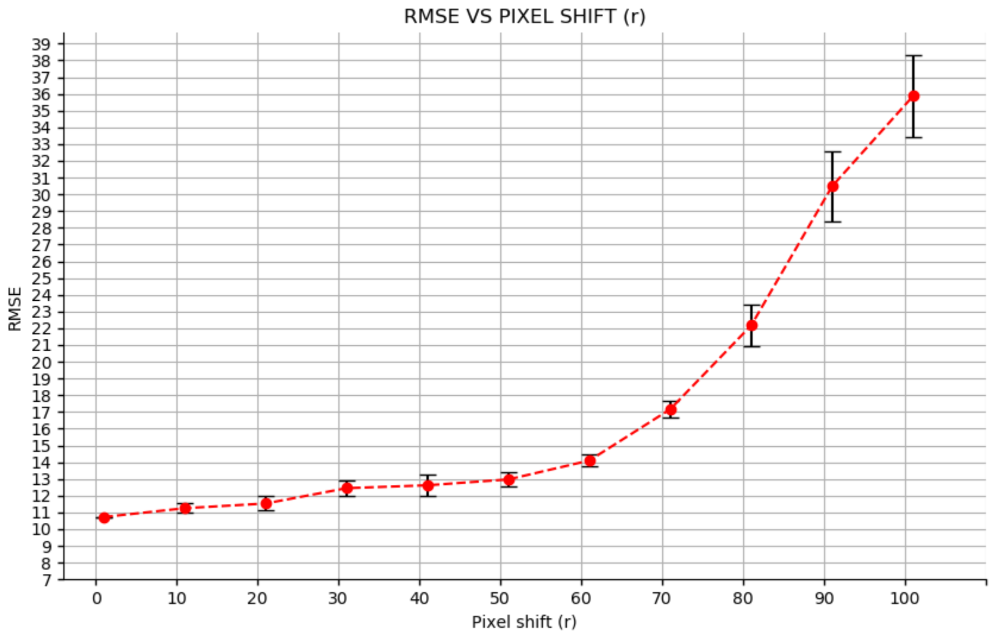


Figure 5 Prediction error of 2005 Major Hurricanes with respect to error in center annotation. The error bars indicate the standard deviation in RMSE across a certain pixel shift.

3.1.5 Comparison with Aircraft Reconnaissance Data

The comparison between the predictions of the proposed method with aircraft reconnaissance data from 2005 results in an RMSE of 11.7 knots in comparison to 10.7 knots when all images are utilized. This increase is a consequence of aircraft reconnaissance being restricted to large hurricane intensities. This shows that the generalization performance of the proposed method is satisfactory and the proposed scheme can perform well in practice.

3.1.6 Basin by Basin Error Analysis

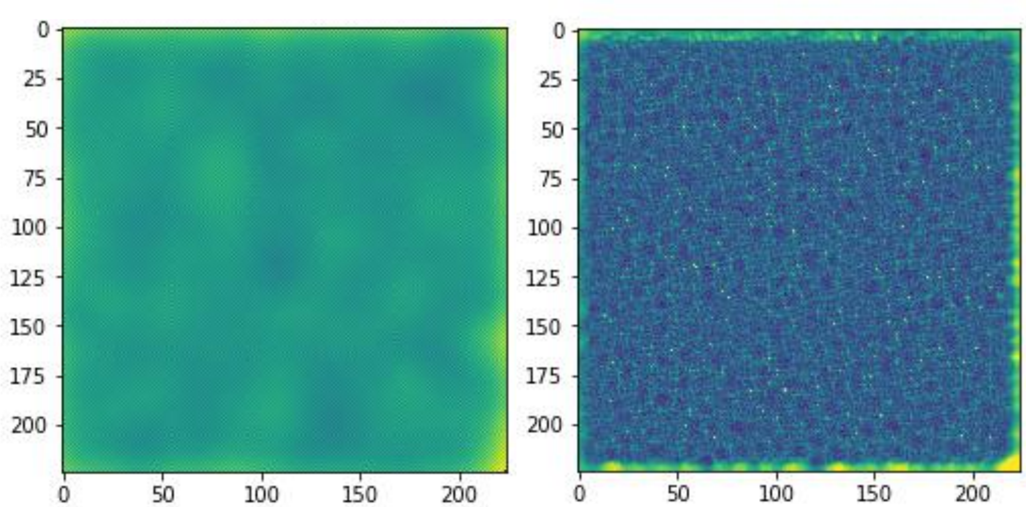
The performance of the proposed method was evaluated exclusively for Atlantic, Pacific, and Indian Basin Imagery. The experimental results are shown in Table 3. It is interesting to note that the proposed method gives better RMSE than Pradhan et al. [9]: their method gives RMSE scores of 10.0kts for Atlantic and Pacific basins whereas our method results in RMSE of 9.37kts and 8.7kts for these basins, respectively.

Table 3 Basin by Basin Error Analysis

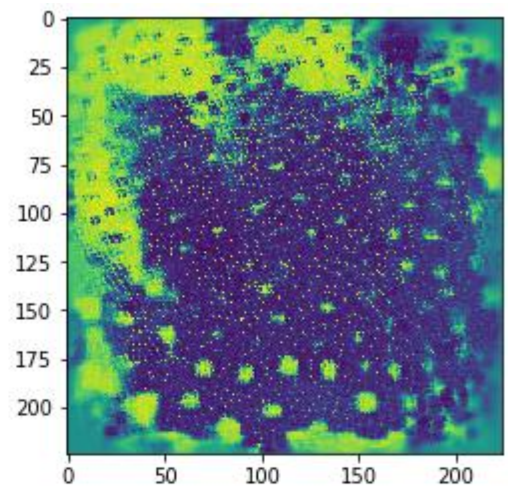
Basin	RMSE
Atlantic Basin	9.37
Pacific Basin	8.7
Indian Basin	8.9

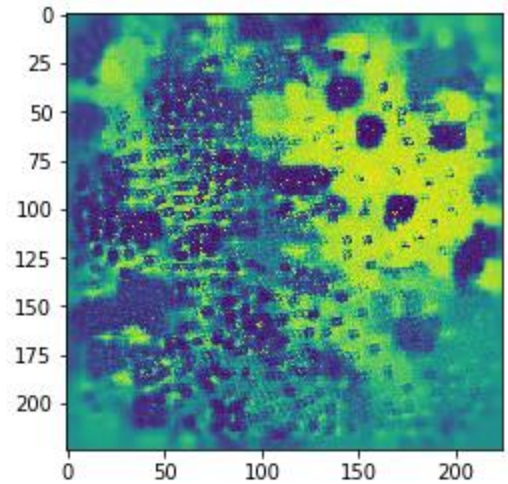
3.2 Feature-maps Visualization

Figure 6 (a) shows the visualization of feature-maps at convolution layer-1 of the network. Since these filters are at initial layers of the network (layer-1), no clear pattern can be seen. However, at layer-6, well-defined patterns can be observed as shown in Figure 6 (c). The activation maps of the fully connected and output layers (Figure 6(e) and (f)) show circular patterns similar in structure to the center of a hurricane. This shows that the network captures important information from training data for predicting the intensity.

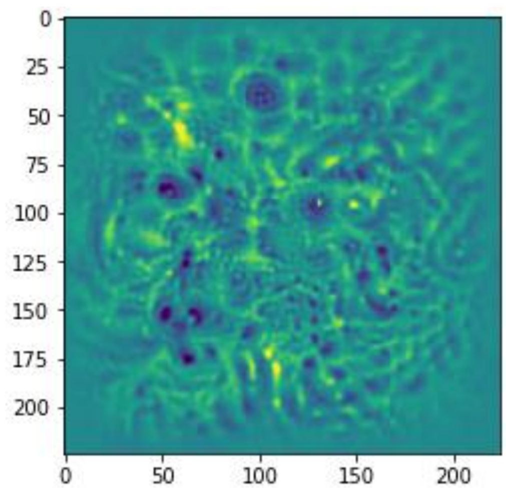


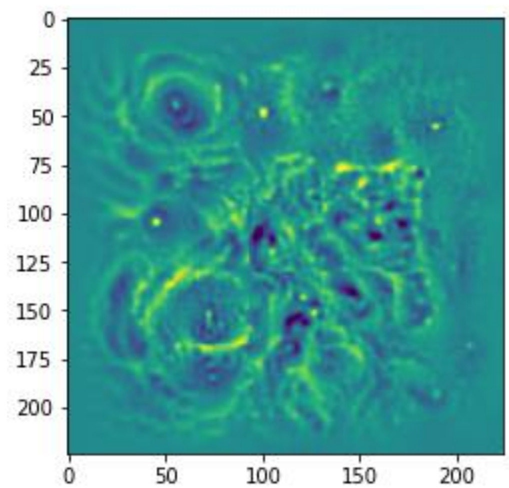
(a) (b)





(c) (d)





(e) (f)

Figure 6 Filters and activation-maps visualization at different layers of the network.

(a) Feature maps of convolution layer-1, (b) Feature maps of convolution layer-3

(c) Feature maps of convolution layer-6, (d) activation maps of fully connected layer-1,

(e) Activation maps of fully connected layer-2, (f) output layer activation maps

4. Conclusion and Future Work

With the use of deep learning, we have been able to design an accurate predictor of hurricane intensity that gives improved RMSEs in comparison to all previously proposed methods (see table-5). Apart from being more accurate, our method does not rely on any manual center annotation or handcrafted features. We have performed stringent benchmarking for the proposed scheme through different experiments. It is expected that the proposed system can be reliably used in practice. It can be further improved by complementing it with time-series forecasting data.

Table 4 PHURIE and Deep-PHURIE results comparisons.

Method	**RMSE (kt) after smoothing**
PHURIE [8]	11.2
Pradhan et al. [9]	10.0
Deep-PHURIE	**8.8**

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Conflict of interest: None Declared

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