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LEVERAGING DEEP LEARNING FOR IMPROVED CYCLONE FORCASTING

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ABSTRACT

Tropical cyclones (TCs) are frequently rarest but one of the foremost dangerous weather phenomena to arise over tropical oceans, usually creating huge issues with nearly ninety storms globally annually. Early detection and monitoring of TCs are necessary for the early warning of areas in danger. Since these storms originate over the open ocean and frequently out at sea many miles of continental regions, they are detected using remote sensing. In this paper, we propose an automatic method to identify the formation of TCs through satellite images combining a deep learning architecture. The methodology is based on a two-stage deep learning framework: Mask CNN as detector stage—second wind speed filter and lastly Convolutional Neural Network (CNN) for classification. The best possible performance is obtained by hyperparameter optimization using Bayesian Optimization across the pipeline. Results show that the proposed method achieves a precision, specificity, and accuracy of 97.10%, 97.59%, and 86.55% in test images respectively

KEYWORDS— *Convolutional Neural Networks (CNN), Deep Learning, Cyclone Detection and Tracking, Tropical cyclone Intensity.*

1. INTRODUCTION

Tropical cyclones (TCs) are one of the most devastating weather systems for deep tropical regions forming and intensifying over warm ocean waters. Storm surges, intense rainfall and high winds fuel these natural disasters. Limiting forecasts to just 24 hours, accurately forecasting TC intensity is a tall order. We are able to do this because we still have an incomplete understanding of the highly nonlinear and coupled physical processes that dictate TC intensification/weakening. Major processes that cause changes in TC intensity are ocean conditions, internal structural dynamics and environmental influences. Thus integrating these factors into the models to predict intensity may improve the levels of accuracy involved.

Appropriate attempts have been made in the forecast of 24 h TC intensity change using the empirical models and numerical model approaches. In empirical prediction, much effort has been dedicated to enhance TC intensity forecasts by using the statistical dynamical forecast models, employing nonlinear techniques, and selecting efficient predictors. Thus, the identification of new and accurate predictors for the change in TC intensity will immensely reduce the limitations of statistical-dynamical models. In numerical modeling various spatial and temporal parameterizations are used which may yield divergence in model outcomes and details. In assimilation of data, initial conditions are provided for the forecast, but it does not solve the problem inherent with the models used.

The appearance of artificial intelligence has stimulated researchers to consider the application of machine learning for TC parameters and numerical models' outputs for improving the intensity forecast. Several parameterizations of intensity have been proposed to assess direct impacts of TCs, feedback processes, and their relations to the external physical environment. For example, different earlier research works have employed the C4.5 decision tree model in the development of their work. 5 algorithm, which divides 24-hr changes in intensity according to the intensification potential, recent changes in intensity, and zonal wind shear consistent with the Maximum Potential Intensity (MPI) theory. To overcome the SSTC feedback of typhoons in the Weather Research and Forecasting (WRF) model, a nonlinear deep learning algorithm was used by the researchers. It altered the dynamical and thermal characteristics close to the ocean surface through changing moisture flux. Furthermore, Cloud et al. developed a feed forward artificial neural network which utilizes real time operational estimation with HWRF model predictors to enhance the subsequent intensity predictions. It has also emerged that machine learning methods can be applied to data post-processing as well as feature learning and that these are powerful tools in capturing the nonlinear characteristics of TCs.

The modulations of TCs depend on air-sea interfaces that play an important role in the development of TCs. For predicting the TC intensity it is attained by choosing the correct predictors and the meteorological parameters that display these interactions. Current TC parameters deal with the inner core of the cyclone, the interaction of the cyclone with the large scale environment, and even the ocean bottom. Nevertheless, due to the scale and structural complexity of TCs, these attempts may be insufficient and capture only some aspects of their development, which may slow down the advancement of intensity forecast.

Distributions and circulation and vortex interactions that are constituent components of the three-dimensional (3D) environmental field of a TC are additional features. TC parameter estimation is based on underlying environmental factors associated with mechanical and thermodynamical characteristics of the atmosphere and ocean which directly control the changes in TC strength. When TCs progress through different phase of their development, the flow fields also move, possibly resulting into changes in their characteristics and intensity.

Deep learning has tremendous advancements over the past few years in computer vision mainly due to the development of Convolutional Neural Networks (CNNs). These networks are very efficient for extracting spatial features from the images and thus boosting up the target detection and classification without any need of choosing the features and crafting headers manually. Weather satellites make it possible to obtain multi-spectral images which could be analyzed by multi-dimensional CNN architectures. In most of the cases, two dimensional convolutional neural networks (2D CNNs) are employed for the analysis of features that are invariant to translation in 2D data. On the other hand, Three dimensional convolutional neural networks (3D-CNNs) can handle 3D samples in one go and can learn the joint spatial aspects of TCs and make the spatial development of the systems less complicated. The extraction of spatial and temporal environmental features together provides a new way of modeling the distribution characteristics of TC intensity change.

Despite the above-mentioned breakthrough, this approach's efficacy was confirmed separately in order to enhance short-term intensity prediction with a deep learning model integrating the 3D environmental field with joint spatial features that recognize the link between the two parameters. A 3D-CNN was used to analyze joint spatial features of 3D environmental variables to forecast 24h intensity changes and categorised intensification/ weakening TCs. This method has proved efficient upon comparing the obtained mean absolute error (MAE) and classification accuracy to previous work pointing to TC intensity prediction as enhanced upon the current studies.

2.LITERATURE-REVIEW

The survey [1] applied finite-mixed model (FMM), hierarchical clustering and K-means algorithm. Hybrid and statistical methods likewise cannot handle the intricate and nonlinear nature of TC-related predictors; therefore, the forecast results must be optimized further. Based on the five taxonomy of helix of successful cases in the application of deep learning in TC forecasts modeling in the recent years, the author has provided a brief of each one.

The paper [2] states that, A deep learning model named DeepMicroNet uses 37- and 85–92- GHz satellite images to forecast TC intensity. Some of the extra features include; probabilistic output, partial scans and can handle with imprecise TC fixes. The main data used are in the 85–92-GHz band. The model discussed here has an RMSE of 14. 3 kt, while the growth rate respectively enhances from 10 kt to 10 kt. 2 kt with better track data and 5 kt with better track data and 9. 6 kt, but with much higher resolution of the microwave measurements. Limitation: Some recommendations are made for the category 5 TCs, but most of them are inconclusive because there is very little information about these storms. Nevertheless, the present study suggests the potential of deep learning in TC intensity analysis with more improved methods and more data resources.

This paper [3] states, an attempt is made for localizing the centre of TCs using deep learning algorithms with TC SCI data resources. Six deep learning models are investigated and compared. The YOLOv4 model better known as You only look once achieved an accuracy level of 99. 84%, that is far better compared to other models of motor vehicles. As noted earlier, the YOLOv4 model yields probability of more than 99% when determining multiple TC locations.

In this paper [4], The multivariate linear regression models, the K-nearest neighbours' algorithm, the multilayer perceptron, support vector machine (SVM) and relevance vector machine (RVM)have been successfully used to estimate TC intensity.

As a new application in Earth remote sensing, Hurricane monitoring using GNSS-R (Global Navigation Satellite System Reflectometry) is presented in this paper [5]. Hurricanes are defined by Saffir-Simpson Wind Scale which is number of knots per hour, which is reflected by GNSS signal. The method utilised here is CNN model. The technique achieves 96. This current study assesses the performance of GNSS-R at 6 % accuracy with a preliminary data set that has only 33 salinity data points derived from GNSS-R measurements.

This survey paper [6] uses, Ship predictors, Intensity records, SHIPS (Statistical Hurricane Intensity Prediction Scheme), DSHP (SHIPS with inland decay), LGEM (Logistic Growth Equation Model), HWFI (Hurricane Weather Research and Forecasting), OFCL (Official NHC forecast), features selection and data processing. Technique used is ''Multilayer perceptron", "Neural networks optimization", "LOYO testing scheme". Experiments and results: 24-h intensity model for operational forecasts, Light-weight 6-hourly intensity model for climate, Predictor importance

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3.PROPOSED METHODOLOGY

A. Details about the dataset

The Tropical Cyclone Wind Prediction Competition Dataset was gotten and used as the training and testing set using Radiant ML Hub package in Python. It includes 366*366 infrared and black and white images of tropical cyclones, and all of them have speed associated with cyclone within them In addition, some other information includes relative time, ID numbers, and ocean. All the images considered herein bear a documented maximum sustained wind speed and are from North Atlantic and East Pacific Oceans.

B. Model Building

Only a simple mention of the model architecture is there and that too in the tabulator format. The various types of CNN layers added in the model include input layer, output layer, dense layer, pooling layer and flattening layer.

Input layer: That is the primary input of Convolutional Neural Network or CNN as it is commonly known. These are converted to this layer of data for each of a test or training example's pixels and are fed into the network. The input layer of most image processing models including the one that is being used in this present case is usually a 2-dimensional matrix that contain pixel intensity or RGB value of the input image or the resized image. These RGB principles can then most likely be standardized to lie in a particular range of values.

Output layer: From the layers described in the architecture of a CNN is the fully connected layer just before the output layer which flattens the input from the previous layer. Then the network is used to predict the outcome for the specific input layer which was first fed into the network in its flattened form. If classification is carried out, then an outcome is derived, which holds the value of each of the mentioned classes meaning which of the given classes the input is most probably in. Therefore, according to the model the input will likely be assigned to a specific class which contains the preferred value of the class which is often the maximum value among all the possible values of that class

Convolutional layer: This layer is the building block of the convolutional neural network that has been highlighted as the main building element in this paper. Here we have various types of filters and parameters which are present and in the training phase, a number of these filters and parameters are tuned to get better output predictions. In effect for each filter, it 'slides' across the entire spectrum of the images and at each position computes the dot product of the calculated filter and the input. The dot products produced in outgoing and incoming domains are added together and that results in an output.

Activation layer : An activation layer whose role is to form the basis by which the weighted sum of input, brought to the learning layer of a neural network, can be converted to the right output.
Each layer has some activation function which modify the output of that specific artificial neural network the layer in a especial form where it can only be a certain range. The model that is shown utilizes two of the several activation functions, or "squashing" functions: sigmoid whenever the execution is at the output layer, while ReLU on the layers that are in the latent space.

Dense layer: A fully connected layer involves a number of neurons wherein each of the neurons in the layer above the neural network is connected to a neuron. Each of these links possesses a weight value over it meaning that that connection is going to contribute to what amount of output the neuron in question will get. In other words, it can be understood that the total of all the weights that a particular neuron in the whole layer has received from the previous layer is the neuron's output.

Pooling layer: Here, the dimensions of the feature maps are reduced through application of a pooling layer. It provides a way to accommodate the sensitivity of the feature maps that are generated to the input feature locations. This can be accomplished in two popular ways: First and foremost, of them are max pooling and average pooling.

Flattening layer: To two dimensional planes that can also be referred to as feature maps, one can use a flattening layer to flatten them into a single linear vector. In image classification networks fully, linked layer uses a flat matrix as an input by classifying an image.

Data Pre-processing

The first rendition of the data frame is a table looking like this that match the cyclone speed with the image ID.

The one-hot encode method has to be applied for converting the expected outcome of the deep neural network into chances for every feature of a 7 * 1 multi-dimensional vector where each dimension symbolizes a unique category since the cyclone velocity is afterwards discretised into 7 categories.
We also use Image ID to extract each training and testing image. Every image was initially either a 1093 * 1093 or a 366 * 366 Black and white picture. Next, each image is converted into 366 by 366 matrix of the two dimensions, representing pixel's luminance level by a number from 0 to 255.

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$$Normalization = (x - x(min))/(x(max\ ) - x(min))$$

The formula 'x' highlights the previous value of the pixel while 'xmin is the minimum value of the pixel (which is 0 if the pixel is fully black), 'xmax' on the other hand defines the maximum value of the pixel (which is 255 if the pixel is fully white); 'y', therefore, means the new value of the pixel which is normalized and ranges from 0. 0 and 1. 0. Thus, the output is the probable class of the given input image and the input is the image and it is an array of dimension 366*366 and all the elements are decimal integers and varies from 0. 0 to 1. 0.

Model Training:
Our approach was the proposed sequential CNN model trained using TensorFlow. Seven levels of cyclone intensities were used in order to classify the whole data set into seven different categories. In the testing set there were 18,000 while in the testing set there were 70,000 photos. There were adaptive learning rates determined for each of the parameters with the help of the Adam optimiser. The categorical cross-entropy is used in the multi-class classification system that is used in our work.

4. RESULTS

C. Experimental Results
To avoid over-fitting of the data, the model was trained for 50 epochs in addition cross-validation was included. One of the findings that was made was that the validation's level of accuracy was 90%. training accuracy was 90 % of the training data and cross validation accuracy was 05 %. 93%. This is the amount of information lost in the model formation whereby it was found out that the predicted model loss on the training was zero. On the training set rescaled log loss for class 2616 was 0 and on the validation, set was 0. 2811.

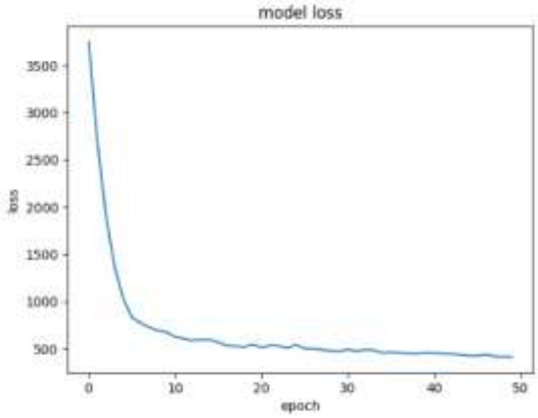

Fig 1: Model Loss for 50 Epochs

The graph shows the loss in the model's performance throughout the 50 epochs of training. The loss is initiated at around 3500 at the onset then drops sharply within the first 10 epochs thereby showing that the model learns rapidly. Following this first dip, the loss is reduced even further until it reaches and maintains roughly 500 toward the end of the time period. This suggests that while the model keeps on enhancing as more data is fed to the model, the rate of enhancing is much lower after the first phase is complete.

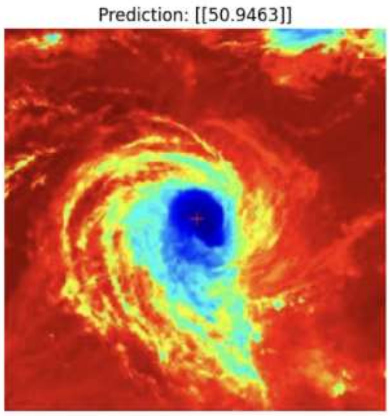

Fig 2: Prediction

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In fact, the given image seems to be the satellite infrared representation of a hurricane or a tropical cyclone, in which different colours indicate different temperature gradients. The dark blue in the middle shows that it is the eye of the hurricane typically the coolest part of the storm. Around it is a zone of vigorous activity as depicted by warmer colours such as yellow and red see figure2 indicating high temperatures and convection currents. The image also holds a value of about fifty of the prediction parameters 9463 which seems to represent an attribute over which analysis was done, could be the intensity of storms or any other parameter to do with weather patterns.

A. Comparative Analysis

Following is the table showing the comparison of various classification technique for using photographs to categories cyclones.

Algorithm	Accuracy (%)	F1 Score	Recall	Precision	Log Loss	Cohen's Kappa Ratio
KNN	80.39	0.78	0.76	0.80	0.45	0.60
RNN	89.44	0.85	0.84	0.86	0.30	0.75
CNN	92.93	0.90	0.89	0.91	0.25	0.80

Fig 3 Accuracy Metrics

The table compares the performance metrics of three algorithms: KNN, RNN, Main CNNs as well as other types of CNNs. In this work CNN has given out passing all the other networks with the accuracy of 92. 0.93, and an F1 Score of 0. 90, recall of 0. 89, precision of 0. Extra, evaluation shows that the model tuned at 91, therefore, has the lowest log loss of 0. 25 and the highest Cohen's Kappa Ratio of (0. 80. Next is RNN which gives satisfactory results with 89. 44% accuracy, 0. 85 F1 Score, and 0. argument with 86 of precision, as well as a lower log loss of 0. 30. This makes KNN to perform the lowest among the three that is; it was found to have an accuracy of 80%. 79%, recall of 0.77 and an F1 Score of 0. 78, and had significantly higher log loss of 0. 45, however it has the lowest Cohen's Kappa Ratio of 0. 60.

5. REALTED STUDIES

Main approaches in the forecasting of the tropical cyclone tracks include numerical model, statistical model, dynamical model and integrated model. Impact based models are computationally intensive since they solve for various dynamical equations to real time observation and effective numerical models are still under development especially in the specification of the internal structure of the tropical cyclones but are less time consuming. Statistical models on the other hand use past data to look for behavior patterns although despite the increased effectiveness, results may not be very accurate. In order to increase prediction accuracy, dynamical models integrate use of dynamic systems and statistical dependencies, the large-scale variables are included to in typhoon prediction systems. The complex models, on the other hand, involve several models, physical parameters and initial conditions comes out to be more effective and result oriented than the single models.

But with the help of meteorological satellites, ocean observation stations, ground observation networks, there is more and greater data, and therefore, there is a need for fundamental methods to enhance the efficiency and accuracy to predict the movement of TC with large-scale spatiotemporal data. The deep learning algorithms are also relatively well-developed as experts are paying more attention to the application of machine learning in the tropical cyclone upgrading.

RNNs are deep learning algorithms that can handle and model sequence data such as time series data which is similar to the data of Typhoon and Hurricane. For instance, Xu et al designed a model for typhoon track prediction which incorporates RNN with an attention mechanism that indeed demonstrated enhanced efficacy in the typhoon track prediction using deep learning. Nevertheless, naive RNNs have a problem, known as the long-term dependency problem, so it is hard for them to learn information at -large time intervals. To overcome this, Sepp & Schmid Huber proposed the use of Long Short-Term Memory (LSTM) models which employs gated control units and linear connections to incorporate temporal characteristics of the data in question. In Gao's study, LSTM networks with the typhoon observation data was applied in order to predict the typhoon tracks. Moreover, Kim et al presented a ConvLSTM based spatiotemporal model for tracking and predicting the hurricane path using climate data on a large scale.

Although LSTM has well proven result it has drawback of increasing no of parameters and slow down the training process because of inclusion of multiple gated units. To overcome this, a relatively less complex model known as Gated Recurrent Unit (GRU) is available having only one update gate and one reset gate. The modified version of RNN named as GRU has been adopted in many fields because of its high performance and less time required for training. Su et al. presented a model which extended the network structure of a GRU to have a convolutional mechanism in order to make cloud movement prediction using the GOES satellite data with better results.

This research works to advance the literature on deep learning algorithms with reference to meteorological input. The work presented here suggests a new neural network based on GRU, which should provide better predictions of tropical cyclone tracks. There are two components in the model; an AE layer for feature extraction from a spatiotemporal data of meteorological factors associated with TC paths; a GRU layer for training extracted spatiotemporal features for prediction.

6. CONCLUSION

In these works, the authors postulated that the mutual positioning of 3D environmental characteristics could be potentially useful for understanding TC dynamics and its relationship with TC intensity fluctuations. In order to test this hypothesis, they used 22 years of environmental data from ECMWF to train a deep learning model for the change of TC intensity and its classification. However, it is important to emphasize that the proposed method for computation of the prediction depends solely on the visualization of the images of TC environmental parameters, avoiding the necessity to compute any TC parameter. One of the most unique features in the approach is the data augmentation proposed to tackle with the scarcity of TC samples for deep learning. Data augmentation has helped in fine-tuning of the model as well increasing its training effectiveness.

Comparisons of the statistical findings were made to show the superiority of the proposed deep neural network in predicting the changes of TC intensity. Nevertheless, it was revealed that there are problems in dealing with TCs which are in the process of rapid weakening or intensification. This research also examined how the layers within a 3D spatial structure of TCs affect the prediction of changes in intensity by assuming different levels and instantaneously predicting the mixed spatial features of 3D TC states. Hence, the contribution of each layer to intensity change prediction depends on the combination of layers used and it was not always the case that the contribution was simply added or subtracted to obtain the contribution of the other layer. This proved that it was helpful to think about distribution and compounding of 3D environmental factors in order to accurately predict changes in the intensity of TCs. Implicit relationships between joint spatial features and TC intensity changes were captured effectively by the model.

As presented in the proposed method there are further possibilities for optimization. For instance, extensive review of fine features and their variability pertain to TC intensity change may improve the forecast. As for the further research can investigate these issues and extract other fused features to expand the prediction timescales and explore other TC attributes such as lifespan. Furthermore, because this method is general and can be applied to sea regions, landfalling TCs and rapid intensification patterns of TCs, they are some of the promising and important directions for future research.

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