Enhanced Cyclone Intensity Estimation Using Deep Learning Models

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ABSTRACT

Every year in India, tropical cyclones pose one of the greatest threats to life and property. They include a variety of hazards, each of which can have a significant impact on life and property, such as storm surge, flooding, extreme winds, tornadoes, and lighting. These hazards interact with one another, substantially increasing the risk of loss of life and material damage. According to a study on extreme weather events, as many as 117 cyclones hit India in 50 years from 1970 to 2019, claiming over 40,000 lives. Due to advancements in technology, detection of cyclones has become much easier. Cyclones are categorized into various categories based on their intensity which is calculated by various methods and sources. Estimation of the intensity of cyclone helps them to categorize. In this paper we are trying to estimate the intensity of cyclones by using the state-of-the-art deep learning models as they are pre-trained on large data sets.

Keywords: *Tropical cyclones, Hazards, Intensity estimation, Deep learning models, Detection, Data sets, Cyclone intensity, Weather prediction, Disaster management.*

1. INTRODUCTION

Cyclone is a large mass of air that rotates around a strong center of low atmospheric pressure. It is characterized by spiralling winds. It is caused by atmospheric disturbances that are formed in a low-pressure area in sea. The term 'Cyclone' is derived from the Greek word 'Cyclos' that means 'Coils of Snake'.

1.1 TROPICAL CYCLONE INTENSITY ESTIMATION

Tropical cyclones, which annually threaten life and property in India, manifest as a variety of hazards, including storm surges, flooding, extreme winds, tornadoes, and lightning. These hazards, interacting with each other, significantly elevate the risk of loss of life and material damage. Over a span of 50 years from 1970 to 2019, India experienced approximately 117 cyclones, resulting in over 40,000 fatalities. Despite these alarming statistics, advancements in technology have led to a significant decrease in the mortality rate due to tropical cyclones in the past decade. The India Meteorological Department employs the Tropical Cyclone Intensity Scale, consisting of seven categories, to classify cyclones based on their intensity. To improve the accuracy of intensity estimation and facilitate timely precautionary measures, this paper aims to leverage deep learning models trained on a dataset comprising infrared and raw cyclone imagery sourced from 2012 to 2021.

1.2 MOTIVATION

The motivation behind this study stems from the substantial impact of tropical cyclones on various regions globally, with particular emphasis on India. Despite efforts to mitigate the effects of these natural disasters, a significant number of lives are lost each year due to storm-related incidents. Accurate intensity estimation of tropical cyclones is imperative for ensuring public safety and minimizing economic losses. While long-term planning measures are essential, short-term actions depend heavily on the accurate prediction of a cyclone's future characteristics. By employing advanced deep learning techniques on satellite imagery, this paper aims to enhance the efficiency and accuracy of intensity estimation, thereby enabling timely and effective mitigation strategies.

1.3 ISSUES AND CHALLENGES

Traditional methods of cyclone intensity estimation rely on statistical techniques, such as the Dvorak Technique, which can be time-consuming and prone to delays in forecasting. Despite the development of advanced techniques based on the Dvorak Technique, the complexity of these methods poses challenges in achieving real-time intensity estimation. Additionally, the assessment of cyclone intensity becomes particularly challenging when cyclones occur over the ocean, where direct measurements are costly and difficult to obtain. Since they are not cost-effective it is an issue.

1.4 OBJECTIVE

The primary objective of this study is to streamline the process of cyclone intensity estimation by leveraging infrared satellite imagery from the INSAT-3D satellite. By utilizing state-of-the-art deep learning models trained on a comprehensive dataset, this paper aims to develop a direct approach for estimating cyclone intensity. The ultimate goal is to enhance the speed and accuracy of intensity estimation, thereby facilitating timely alerts and minimizing the loss of life and property resulting from cyclones.

2. LITERATURE SURVEY

2.1 Introduction

Satellite cloud images (SCIs) have emerged as a valuable data source for Tropical Cyclone (TC) research. Despite significant progress in utilizing SCIs for studying TCs, accurately estimating TC intensity remains a persistent challenge. Traditional methods such as the Dvorak Technique have limitations, particularly in terms of subjectivity and the time required for mastery. However, recent advancements in deep learning, particularly Convolutional Neural Networks (CNNs) combined with INSAT 3D images, show promise in addressing these challenges. By automating the intensity estimation process and eliminating manual analysis, CNNs offer a more efficient and accurate approach to TC intensity estimation.

2.2 Review of Relevant Research Papers

[1] Paper delves into the efficacy of satellite cloud images (SCIs) as a primary data source for tropical cyclone research. Despite the significant advancements achieved in various SCI-based studies, the accurate and efficient estimation of cyclone intensity remains a persistent challenge. The paper underscores the need for innovative methodologies to improve intensity estimation accuracy and reliability.

[2] The authors explore the application of deep learning techniques, specifically convolutional neural networks (CNNs), for cyclone intensity estimation using INSAT-3D imagery. By automating the intensity estimation process and eliminating the subjectivity inherent in manual analysis, CNNs offer promising avenues for resolving existing challenges in cyclone intensity estimation.

[3] Paper critically examines the Dvorak Technique, highlighting its limitations and flaws. Chief among these limitations is the inherent subjectivity of storm

center selection and scene type determination procedures, which can introduce variability and inaccuracies in intensity estimates. Additionally, the paper underscores the steep learning curve associated with mastering the Dvorak Technique, further complicating its widespread adoption.

[4] Study explores the potential of Special Sensor Microwave Imager (SSM/I) data for automatic cyclone intensity estimation. By leveraging extracted characteristics from SSM/I imagery, the study aims to demonstrate the feasibility of automated intensity estimation methods. However, the study acknowledges the limitations of using "snapshot" characteristics alone and underscores the importance of incorporating historical TC data for improved estimation accuracy.

[5] When an air parcel experiences displacement from its initial position, a restoring force acts upon it, compelling it to revert to its original equilibrium position. However, due to inertia, the air parcel tends to overshoot this equilibrium, leading to oscillatory motion around the initial position. Simultaneously, this displacement gives rise to a wave that propagates through the medium, whether it be a solid, liquid, or gas, serving as the conduit for wave propagation. The interplay between a physical restoring force and the medium's properties constitutes the foundational elements of wave motion across various mediums, encompassing atmospheric, oceanic, and seismic waves, among others.

The characteristics and behavior of a wave are dictated by the nature of the restoring force generating it and the medium facilitating its propagation, each possessing unique properties. By employing scaling arguments based on the primitive equations and considering horizontal scales of fluid motion, certain prominent categories of waves observed in the atmosphere can be delineated. These include sound (acoustic) waves, mesoscale waves, and planetary (Rossby) waves, each exhibiting distinct features and behaviors.

[6] The discussion centered on the evolution of the Advanced Objective Dvorak Technique (AODT), emphasizing its development aimed at maximizing the effectiveness of utilizing geostationary satellite infrared imagery across all tropical cyclone intensities. Furthermore, enhancements to the AODT included the integration of additional Dvorak technique rules to enhance the stability of intensity estimates over time. Additionally, there was a suggestion that incorporating supplementary spectral information could potentially enhance the efficacy of the technique even further.

[7] The Advanced Dvorak Technique (ADT) employs longwave-infrared temperature measurements from geostationary satellites to gauge the intensity of tropical cyclones (TCs). Originating from Vern Dvorak's NOAA-developed operational technique over three decades ago, ADT follows a systematic approach where users identify primary cloud patterns and measure various TC cloud top parameters to derive initial intensity estimates. Rules governing TC development and intensity fluctuations over time aid users in scene selection and intensity change rate determination.

While the Dvorak Technique remains the go-to method for TC intensity estimation in regions lacking aircraft reconnaissance, it grapples with inherent subjectivity in storm center selection and scene type determination. Mastering its regional nuances can be time-consuming, and its empirical development lacks computer-assisted analysis to establish statistical relationships between environmental parameters and intensity.

[8] This study presents findings from a near-real-time objective method designed to assess the intensity of tropical cyclones using satellite infrared imagery within the North Atlantic Ocean basin. The method quantifies the degree of organization or axisymmetry within the infrared cloud pattern of a tropical cyclone, serving as an indirect indicator of its maximum wind speed. The resulting maximum wind speed derived by the method stands as an independent measure of

tropical cyclone intensity. Seventy-eight tropical cyclones observed during the 2004–09 seasons are utilized both for training and independent testing of the intensity estimation technique. Two separate tests are conducted to evaluate the technique's accuracy in estimating tropical cyclone intensity. The optimal outcomes from these assessments reveal a root-mean-square intensity error ranging between 13 and 15 knots (where 1 knot ≈ 0.5 meters per second) for the two test datasets.

[9] An objective technique for obtaining features associated with the shape and dynamics of cloud structures embedded in tropical cyclones from satellite infrared images is described. As the tropical cyclone develops from an unstructured cloud cluster and intensifies, the cloud structures become more axisymmetric about an identified reference point. Using variables derived from remotely sensed data, the technique calculates the gradient of the brightness temperatures to measure the level of symmetry of each structure, which characterizes the degree of cloud organization of the tropical cyclone. The results presented show that the technique provides an objective measure of both the structure and the intensity of the tropical cyclone from early stages, through intensification, maturity, and dissipation.

[10] The history of meteorology demonstrates that progress in weather analysis and prediction often occurs through incremental studies. However, certain groundbreaking works have the potential to significantly accelerate this process, particularly when they pertain to high-impact weather events affecting large populations. In this paper, we examine the contributions of Vernon F. Dvorak, whose pioneering use of satellite observations of cloud patterns revolutionized the monitoring of tropical cyclones worldwide. We explore the evolution of this original technique and how modern spaceborne instruments are being utilized to augment Dvorak's visionary approach.

3. PROPOSED METHODOLOGY

Instead of following the statistical approach for calculating the intensity of cyclone, we are using the state-of-the-art deep learning models on the infrared satellite images of INSAT 3D which was launched by ISRO for weather observation. These State-of-the-art deep learning models include ResNet50, InceptionV3, Densenet201, InceptionResnetV2. These models were chosen because of less number of parameters to train which results in less computation power and less training time.

3.1 Inception V3

The Inception V3 is a deep learning model for image categorization that is based on Convolutional Neural Networks. The Inception V3 is an improved version of the fundamental model Inception V1, which was introduced in 2014 as GoogLeNet. It was created by a Google team, as the name implies (Opengenius, 2022). The inception V3 model is simply an improved and optimized version of the inception V1 model. Several strategies were employed by the Inception V3 model to optimize the network for better model adaptability.

• It is more efficient.

• It has a larger network than the Inception V1 and V2 models, yet its speed is not affected.

• It is less computationally expensive.

• As regularizers, it employs auxiliary Classifiers.

The Inception v3 model, which was launched in 2015, features 42 layers and a reduced error rate than its predecessors. Let's have a look at the various optimizations that improve the Inception V3 model. The primary changes made to the Inception V3 model are as follows:

• Convolutional Factorization into Smaller Convolutions

• Asymmetric Convolutions from Spatial Factorization

• The Usefulness of Auxiliary Classifiers

• Reducing Grid Size Effectively

The inception V3 model has 42 layers in total, which is slightly more than the preceding inception V1 and V2 models. However, the efficiency of this model is quite outstanding. We'll get to it shortly, but first, let's take a closer look at the components that make up the Inception V3 model.

3.2 ResNet50

Deeper neural networks are more difficult to train. When deeper networks can begin to converge, a degradation problem emerges: as network depth increases, accuracy becomes saturated (which is somewhat unsurprising) and rapidly deteriorate. Surprisingly, such degradation is not caused by overfitting, because adding more layers to a sufficiently deep model increases training error, as stated in and extensively validated by our tests. The degradation (of training accuracy) indicates that not all systems are similarly easy to optimize (Kahe, 2015). ResNet50 is a ResNet model version having 48 Convolution layers, 1 MaxPool layer, and 1 Average Pool layer. It can perform 3.8 x 109 floating point operations. It is a popular ResNet model. AlexNet won top place in the LSVRC2012 classification challenge in 2012. Since then, ResNet has been the most intriguing thing to happen in the computer vision and deep learning worlds. ResNet, short for Residual Networks, is a traditional neural network that serves as the foundation for many computer vision applications. In 2015, this model won the ImageNet challenge. Because of the foundation that ResNets provided, it was possible to train ultra-deep neural networks, which means that a network may have hundreds or thousands of layers and still function well. ResNet first introduced the concept of skip connection. The ResNet-50 has over 23 million trainable parameters.

ResNets were initially applied to image identification tasks, but as stated in the study, the framework can also be utilized for non-computer vision tasks to improve accuracy. ResNet reduces the top-1 error by 3.5% resulting from the successfully reduced training error. The Resnet50 architecture includes the following component:

• Convolution with a kernel size of 7 * 7 and 64 distinct kernels, each having a stride size of 2, yields 1 layer.

• Following that, we see max pooling with a stride size of 2.

• In the next convolution, there is a 1 * 1,64 kernel, followed by a 3 * 3,64 kernel, and finally a 1 * 1,256 kernel. These three layers are repeated three times in total, giving us nine layers in this phase.

• Following that, we see a kernel of 1 * 1,128 followed by a kernel of 3 * 3,128, and finally a kernel of 1 * 1,512. This phase was done four times, giving us a total of 12 layers in this step.

• Following that is a kernel of 1 * 1,256, followed by two more kernels of 3 * 3,256 and 1 * 1,1024, which is repeated six times for a total of 18 layers.

• Then a 1 * 1,512 kernel with two more of 3 * 3,512 and 1 * 1,2048, which was repeated three times for a total of nine layers.

• Following that, we perform an average pool and conclude with a fully linked layer having 1000 nodes and a softmax function, yielding 1 layer (Opengenius, 2021)

3.3 InceptionResNet V2

The Inception-ResNet-v2 convolutional neural network was trained on over a million photos from the ImageNet collection. The 164-layer network can categorize photos into 1000 object categories, including the keyboard, mouse, pencil, and many animals. As a result, the network has learned detailed feature representations for a diverse set of images. The network takes a 299-by-299 picture as input and returns a list of estimated class probabilities as output. It is created by combining the Inception structure and the Residual connection. Multiple-sized convolutional filters are mixed with residual connections in the Inception-Resnet block. The introduction of residual connections not only solves the degradation issue caused by deep structures but also shortens the training time.

3.4 Densenet201

Each layer receives feature maps from all layers that came before it, allowing for a more compact and thin network with fewer channels. The extra number of channels for each layer is the growth rate k. The "vanishing gradient" problem, however, develops when the CNN has more layers, or as it is deeper. This means that when the information's travel from the input to the output layers lengthens, some information may "vanish" or "get lost," which decreases the network's capacity to learn effectively. By altering the typical CNN architecture and streamlining the connectivity between layers, DenseNets alleviate this issue. DenseNet-201 is a convolutional neural network that is 201

layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224. Each layer in DenseNet receives extra inputs from all levels that came before it and transmits its own feature maps to all layers that came after it. You utilize concatenation. Each layer receives "collective knowledge" from the levels that came before it. The extra number of channels for each layer is the growth rate k.

When the size of feature maps varies, it is not possible to use the concatenation method. However, downsampling of layers, which minimizes the size of feature-maps through dimensionality reduction to enable faster calculation speeds, is a crucial component of CNNs. This is made possible by the division of DenseNets into DenseBlocks, where the size of the feature maps inside a block is kept constant but the number of filters between them changes. Transition Layers are the layers in between the blocks that cut the number of channels in half compared to the number of channels currently in use.

4. RESULTS AND DISCUSSIONS

Every pre-trained model is trained for 50 epochs and their respective best model is saved using callbacks from keras library and later used for evaluating on validation and test data.

4.1 Resnet

First model is built with Resnet50 as a base model and the trainable layers are set to freeze so that model weights doesn't change with training. Final model consists of 270,849 trainable parameters and 23,587,968 non-trainable parameters. The model is trained for 50 epochs on NVIDIA GeForce RTX 3050Ti GPU which results in 13.512 as Mean Absolute Error (MAE) on validation data and 45.324 on test data.

Below graph shows the training and validation losses graphs of the Resnet50 model.

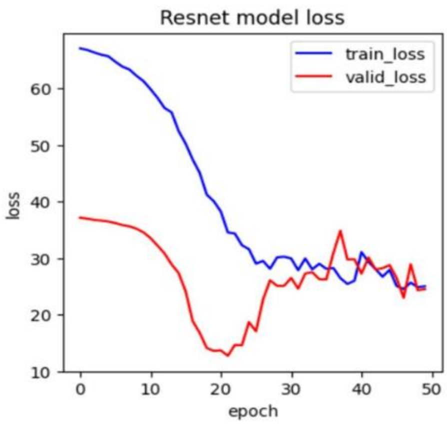

Figure 4.1: Training and validation loss of ResNet50

Below image shows the predictions of the resnet model on the test data.

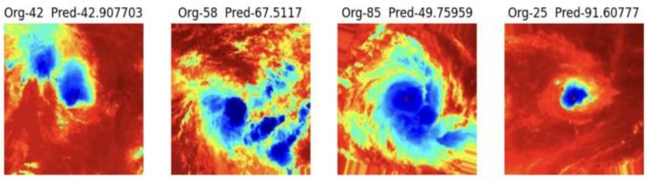

Figure 4.2: Predictions of ResNet50 on the test data

4.2 InceptionV3

Second model is built with InceptionV3 as a base model and the trainable layers are set to freeze so that model weights doesn't change with training. Final model consists of 270,849 trainable parameters and 21,803,040 non-trainable parameters. The model is trained for 50 epochs on NVIDIA GeForce RTX 3050Ti GPU which results in 18.030 as Mean Absolute Error (MAE) on validation data and 42.889 on test data.

Below graph shows the training and validation losses graphs of the Inceptionv3 model.

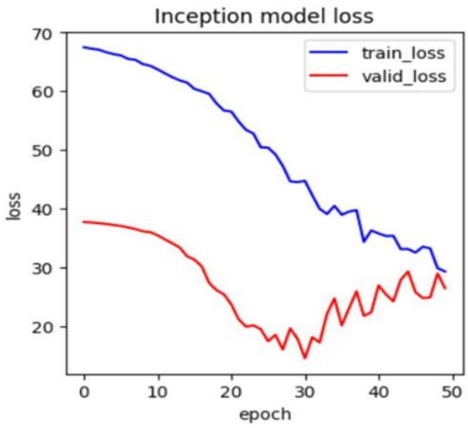

Figure 4.3: Training and validation loss of InceptionV3 model

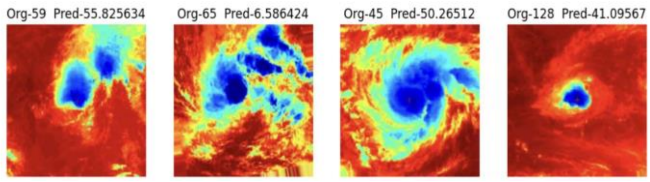

Figure 4.4 : Predictions of InceptionV3 on the test data

4.3 Densenet201

Third model is built with InceptionV3 as a base model and the trainable layers are set to freeze so that model weights doesn't change with training. Final model consists of 254,465 trainable parameters and 18,322,240 non-trainable parameters. The model is trained for 50 epochs on NVIDIA GeForce RTX 3050Ti GPU which results in 13.334 as Mean Absolute Error (MAE) on validation data and 42.523 on test data.

Below graph shows the training and validation losses graphs of the Densenet201 model.

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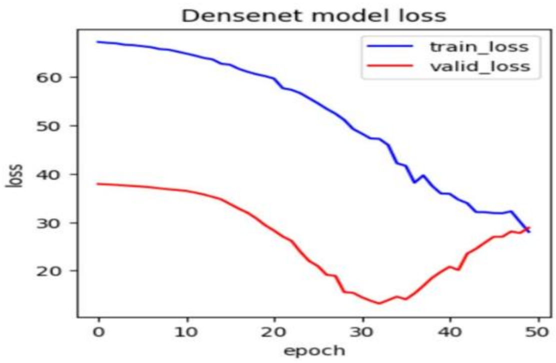

Figure 4.5: Training and validation loss of Densenet201 model

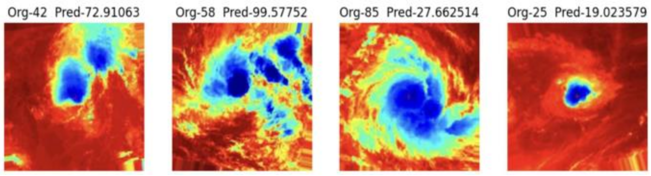

Figure 4.6 : Predictions of Densenet 201 on the test data

4.4 InseptionResnet V2

Fourth model is built with InceptionResnetV2 as a base model and the trainable layers are set to freeze so that model weights doesn't change with training. Final model consists of 205,313 trainable parameters and 54,336,992 non-trainable parameters. The model is trained for 50 epochs on NVIDIA GeForce RTX 3050Ti GPU which results in 14.256 as Mean Absolute Error (MAE) on validation data and 33.849 on test data.

Below graph shows the training and validation losses graphs of the Densenet201 model.

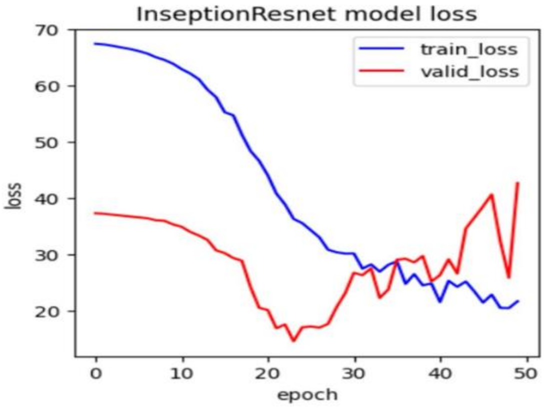

Figure 4.7: Training and validation loss of InseptionResnetV2 model

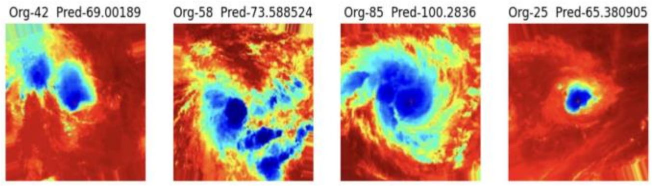

Figure 4.8 : Predictions of InceptionResnet V2 on the test data

The below graph shows the combined graph of all models loss on the validation data

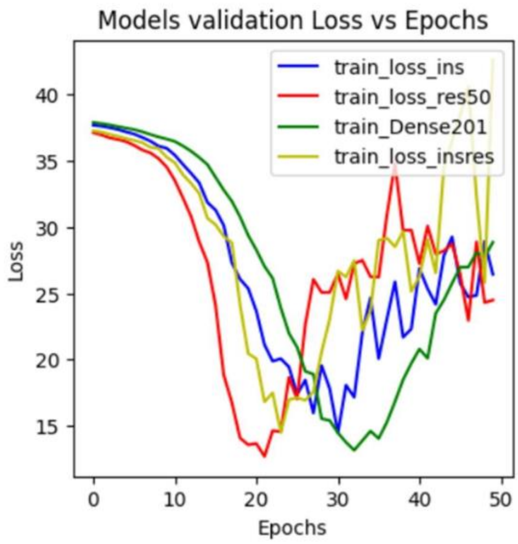

Figure 4.9 : Models validation losses on the validation data

Model Name	Training Loss	Validation Loss	Test Loss
Resnet50	40.839	13.512	45.324
InceptionV3	42.899	18.030	37.899
Densenet 201	41.250	13.334	42.533
InceptionResnetV2	38.038	14.256	33.849

Table 4.1 : Table showing the evaluation metrics of all the pre-trained models used

5. CONCLUSION

The direct approach utilizing infrared satellite images proves to be a swifter method compared to traditional statistical techniques. Leveraging pre-trained deep learning models further expedites the process, courtesy of their prior training on extensive datasets. To validate this assertion, we employed four pre-trained models on INSAT-3D infrared satellite images containing cyclone data spanning several years. After training these models for 50 epochs each using an NVIDIA GeForce RTX 3050Ti, DenseNet201 exhibited superior performance on validation data, while InceptionResNetV2 outperformed on the test data. This suggests the viability of employing this direct approach for cyclone intensity estimation. Selection of these four models was based on their top 1% accuracy, computational efficiency, and model size. Enhancements in performance can be achieved by training on larger datasets and selectively freezing certain layers to fine-tune the model weights during training.

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