Evaluating Deep Learning Models for Cyclone Intensity Estimation

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1. Introduction

Tropical cyclones (TC) rank among the most destructive natural disasters, involving strong winds, heavy rainfall, and storm surges, with socio-economic impacts. Accurate intensity estimation is integral to disaster management; early warning systems also reduce mortality and loss of property. The task of Tropical Cyclone Image to Intensity Regression (TCIR) (Boyo et al., 2018) involves predicting the maximum sustained wind speed using satellite imagery of tropical cyclones. It employs spectral bands such as Infrared, Water Vapor, and Passive Microwave, capturing significant features of the atmosphere and the ocean. Our study presents a comparison between deep learning models like DenseNet, ResNet, ConvNeXt (Liu et al., 2022), InceptionNetV3 (Szegedy et al., 2016), and EfficientNetV2 (Tan and Le, 2021), for TCIR. The performances are analysed in terms of predictive accuracy, computational resource usage, and effects of CBAM (Woo et al., 2018) on improving the deep learning-based forecast of tropical cyclones. Our code, results and extensive list of graphs can be accessed at https://github.com/lomash-relia/TCIR-comparative-study.

2. Data and Methodology

The TCIR dataset is rich in cyclone details, which include cyclone ID, region, Minimum Sea Level Pressure (MSLP), Maximum Sustained Wind (Vmax), location of the cyclone center, and the mean radius of 35-knot winds. Each timestamp is accompanied by images from four spectral channels, including IR, WV, Visible, and PMW. We utilized Southern Hemisphere cyclones available in the dataset. To improve feature learning, low Vmax data are undersampled and only IR, WV, and PMW channels used; followed by clipping and normalizing the image pixels with channel wise 99th percentile. The dataset was split into training, validation, and test sets (70:15:15 ratio). Training data undergo augmentation (random rotations, center cropping, resizing). For validation and test datasets, only center crop and resizing were applied. The prepared data was then hyperparameter-tuned for stable training and faster convergence. The training was terminated by employing the early stopping (patience=15) method, after the validation loss curve becomes flat, within 100 epochs maximum. It used AdamW optimizer with a learning rate (LR) of 1e-4 and weight decay at 1e-5, and reduced LR by a factor of 0.1 using "Reduce on Plateau" with patience of 5. Among the loss functions, the smooth L1 loss outperformed all others as it balances the benefits of L1 and L2. A CNN architecture can typically be seen as a feature extractor followed by a ANN. We replace the default classification ANNs with regression head. We divided the models into two groups. Group A consists of InceptionNetV3, ConvNeXt Tiny and Small, EfficientNetV2-S and V2-M, while group B includes ResNet (variants 18, 34, and 50) & DenseNet (variants 121 and 169) with and without CBAM.

3. Results and Discussion

Group A had model testing for feature extraction, while Group B was the experiment into the impact of CBAM on simple image regressors. The MAE, RMSE, R^2 score, FLOPs, and parameters are metrics in which EfficientNetV2 led the others by a high margin. Although InceptionNet and ConvNeXt had similar performance to ResNet and DenseNet, CBAM delivered slightly better results than the base architectures by 1 to 4% in this fine-grained image regression while not outperforming EfficientNetV2. EfficientNetV2-M performed slightly better than V2-S but has nearly double the number of parameters, making V2-S the better option for lightweight effective performance.

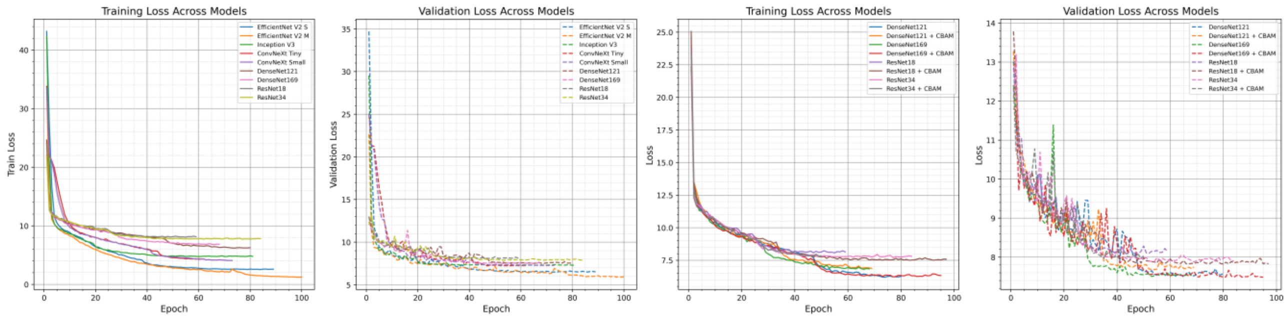

Figure 1 Training and validation loss trends for group A and group B models

Model	MAE	RMSE	R2 Score	Total Params	Total FLOPs	Epochs Trained	Epoch (min. Val Loss)
EfficientNet V2 M	6.118	8.944	0.902	5.286e+07	5.406e+09	100	97
EfficientNet V2 S	6.696	9.242	0.895	2.018e+07	2.876e+09	89	69
ConvNeXt Small	7.372	10.083	0.875	4.946e+07	8.705e+09	73	65
ConvNeXt Tiny	7.491	10.185	0.873	2.782e+07	4.470e+09	62	62
Inception V3	7.672	10.538	0.864	2.511e+07	5.729e+09	81	80
DenseNet169 + CBAM	7.69	10.645	0.861	1.410e+07	3.401e+09	95	95
DenseNet169	7.783	10.783	0.857	1.291e+07	3.397e+09	68	65
DenseNet121	7.854	10.933	0.853	7.217e+06	2.865e+09	80	65
DenseNet121 + CBAM	7.941	11.032	0.85	7.823e+06	2.868e+09	69	69
DenseNet201 + CBAM	8.119	11.416	0.84	2.039e+07	4.345e+09	76	76
ResNet50 + CBAM	8.257	11.407	0.84	2.543e+07	4.115e+09	76	76
ResNet18 + CBAM	8.265	11.537	0.836	1.140e+07	1.820e+09	97	80
ResNet34	8.295	11.607	0.834	2.142e+07	3.671e+09	84	69
ResNet34 + CBAM	8.439	11.519	0.837	2.150e+07	3.672e+09	50	49
ResNet18	8.497	11.783	0.829	1.131e+07	1.819e+09	59	39
ResNet50	8.579	11.969	0.824	2.403e+07	4.110e+09	49	48

Figure 2 Performance metrics comparison of different CNN models for cyclone intensity estimation

4. Conclusion and Future Work

EfficientNetV2 models perform best in our list for TCIR and achieved a final MAE of 6 to 7 knots. Self-supervised learning, Siamese networks, etc. should be analysed for this task. Incorporating domain knowledge and developing custom loss functions can further improve model quality.

5. References

Boyo, C., Buo-Fu, C., Hsuan-Tien, L., 2018. Rotation-blended CNNs on a new open dataset for tropical cyclone image-to-intensity regression., in: Proceedings of the 24th ACM SIGKDD. Presented at the International Conference on Knowledge Discovery and Data Mining (KDD).

Liu, Z., Mao, H., Wu, C.-Y., Feichtenhofer, C., Darrell, T., Xie, S., 2022. A ConvNet for the 2020s. https://doi.org/10.48550/arXiv.2201.03545

Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J., Wojna, Z., 2016. Rethinking the Inception Architecture for Computer Vision, in: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Presented at the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), IEEE, Las Vegas, NV, USA, pp. 2818–2826. https://doi.org/10.1109/CVPR.2016.308

Tan, M., Le, Q.V., 2021. EfficientNetV2: Smaller Models and Faster Training. t

Woo, S., Park, J., Lee, J.-Y., Kweon, I.S., 2018. CBAM: Convolutional Block Attention Module. https://doi.org/10.48550/arXiv.1807.06521