Pertanika Proceedings 1 (5): 41 - 45 (2025)

PERTANIKA JOURNALS

PERTANIKA PROCEEDINGS

Journal homepage: http://www.pertanika.upm.edu.my/

Cyclone Detection Using Machine Learning Techniques

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ABSTRACT

Cyclonic systems create severe dangers to people and buildings and environmental systems thus demanding precise real-time detection capabilities. Current cyclone detection methods use satellite imagery which analysed manually through human teams, however this process is time-consuming and prone to human error. The presented paper conducts an extensive exploration into machine learning techniques for cyclone detection purposes. By leveraging historical weather data, satellite imagery, and advanced computational models, this study propose a novel approach to enhance cyclone prediction accuracy. The paper reviews existing methodologies, details the proposed ML-based framework, and compares results against traditional approaches. Experimental evaluations demonstrate significant improvements in detection accuracy and prediction timelines, underscoring the potential of machine learning in meteorology.

Keywords: Computational models, cyclone detection, machine learning, meteorology, natural disaster management, real-time prediction, satellite imagery, weather forecasting

ARTICLE INFO

Article history:
Received: 29 August 2025
Published: 31 October 2025

DOI: https://doi.org/10.47836/pp.1.5.008

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INTRODUCTION

Early warning systems and disaster preparedness rely heavily on accurate cyclone detection as a fundamental process. Cyclones are powerful storms that produce destructive effects on human settlements and environmental systems. Detection of cyclones relies on using meteorological data

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with weather radar along with satellite imagery to monitor their development and track their position and intensity. Modern meteorological technology enables atmospheric condition observation followed by cyclone path prediction operations, providing valuable time for evacuations and safety measures. Geostationary Operational Environmental Satellites (GOES), coupled with satellite-based systems and polar-orbiting satellites, continuously provide storm development data, wind speed measurements, and cloud pattern information to aid early cyclone detection by experts. Weather radars support cyclone detection by generating instant precipitation and wind data measurements of the storm systems. Advanced numerical weather prediction models assist in cyclone detection by analysing environmental factors such as sea surface temperatures, atmospheric pressure, and wind patterns to create storm impact predictions. The application of multiple detection techniques enables meteorologists to improve prompt cyclone forecasts, reducing the risk of harm to both life and property.

RELATED WORK

Tan et al. (2022) developed a Gradient Boosting Decision Tree (GBDT) model using machine learning methods such as regression trees, employing a supervised learning mechanism to map the features of the target. This method involved determining the values of velocity and forecast error, which measured directional stability. By using the forecast error, the direction was detected. Xu et al. (2021) established a deep learning-based multilayer model to predict the intensity of cyclones, capable of handling different types of data like categorical and numerical data. In this method, by using the intensity between the images, cyclones were distinguished, and it had a significant skill in predicting the 24-hour intensity. Tong et al. (2023) considered a Deep Convolutional Neural Network (DCNN) to identify tropical cyclones. The findings indicated that if the model was trained with pre-processed images, it was unable to focus on the correct targets. Pinto et al. (2005) utilized General Circulation Models (GCM) for sensitivity analysis and cyclone detection. To detect the cyclone, this algorithm forecasts a subsequent place, and the cyclone was tracked based on the results of the identification scheme. Liu et al. (2022) developed a scatterometer-derived wind speed method for the characterization of cyclones, mainly used to assess the intensity of tropical cyclones. This approach first determined the cyclone's center based on the distinct features of the wind stress, and then it used HSCAT to compute the radial extent in addition to wind speed and intensity. Nerrise (2021) considered an agent-based modeling-machine learning (ABM-ML) model for predicting natural disasters like cyclones, providing real-time predictions. Mainly in this model, natural disasters were detected using values like wind intensity accuracy, average distance fallacy, and average intensity miscalculation, with very low cost. Roy (2016) used Artificial Neural Networks (ANN) to track cyclones using satellite images. In ANN, water temperature and

air atmosphere could be inferred by cloud motion detection. . The direction of the cyclone was detected by analysing cloud motion Yadav and Das (2023) developed the SATCON method to detect tropical cyclones. With the use of cloud photographs, this novel method of storm eye identification based on fuzzy logic and image processing. Singh et al. (2022) utilized deep learning algorithms for satellite imagery-based cyclone detection. By using accuracy, the cyclone was predicted after completing the testing of the dataset. By using the interpolation method, the accuracy was calculated, and then the cyclone was predicted. Lee et al. (2019) used a Multi-Dimensional Convolutional Neural Network (MCNN) to analyze tropical cyclones. In this method, both 2D and 3D CNNs were used to identify the relationship between the multi-spectral images.

EXISTING METHODS

Before the advent of modern technology, scientists identified cyclones by analysing climatic changes and patterns. With technological advancements, methods such as temperature sensors and satellite-based data have been employed for cyclone detection. A significant development in this field was the application of Artificial Intelligence (AI), particularly through transfer learning using pre-trained Convolutional Neural Networks (CNNs), to predict cyclones. This AI-driven approach provided early warnings, thereby helping to mitigate financial and other losses associated with cyclones. Transfer learning involves utilizing pre-trained CNN models such as InceptionV3, Xception, ResNet50, VGG16, and VGG19 to extract features from satellite images. These extracted features used as inputs to classifiers such as Logistic Regression or Random Forests for cyclone classification. Studies showed that InceptionV3 combined with Logistic Regression offered high accuracy and faster training times compared to other combinations. However, challenges such as overfitting and limited ability to learn task-specific features persist, even with transfer learning. Despite these challenges, the integration of AI in cyclone prediction represented a significant advancement in meteorological science, enabling more accurate and timely forecasts.

PROPOSED SYSTEM

A pre-trained Convolutional Neural Network named Nasnet was developed to differentiat cyclone image from the non-cyclone image. The Convolutional Neural Networks were widely known for their capacity to deal with images. In a convolutional neural network, when an image was passed the filters are applied on the images to extract the features. The neural network economical learned to recognise the photos based on their features during the training phase. The weights and biases were updated during this learning process basesd on performance. The special trait of Nasnet model is implies reinforced learning to perform image clarification. In Nasnet model, candidate architectures were initially generated to

perform classification for some fixed performance. If the candidate architecture reached the threshold, then it was considered accepted otherwise a new one was generated. The proposed system was designed to identify the cyclone image which could contribute to avoid physical losses after cyclone , such as floods and cloud bursts.

RESULTS

A Convolutional Neural Network (CNN) named NasNet was developed to classify images into cyclone and non-cyclone categories. The dataset comprises 928 cyclone images and 100 non-cyclone images in .jpg format. These imageswere processed through the NasNet model, which employed a reinforcement learning approach to generate candidate architectures and train them for optimal performance. Figure 1 shows the effectiveness of the NasNet model compared with the Xception model, where the blue line represents NasNet's performance and the black line represents Xception's performance.

In Figure 1, the performance of each model can be visualized in detail. The performance of Nasnet model was exceptionally well when compared with other models. A set of new images was passed to the constructed model to evaluate its classification. The classification percentage of the model reaches 90% when new images were passed through it.

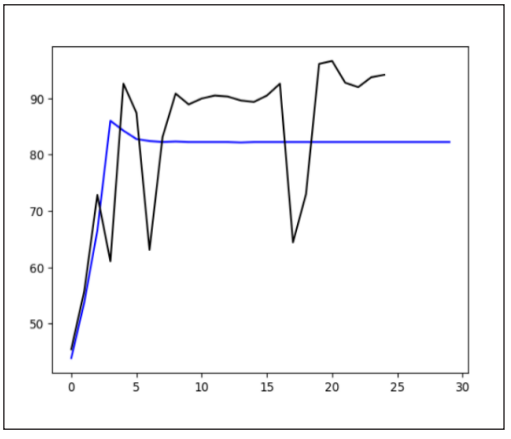


Figure 1. Comparison of performances between models
Note. Blue line represents NasNet's performance and the black line represents Xception's performance

ACKNOWLEDGEMENT

The authors sincerely acknowledge the support and constructive feedback received during the development of this research. We are also grateful for the valuable discussions and encouragement that contributed to the successful completion of this work.

REFERENCES

Lee, M., Cha, D. H., Moon, J., Park, J., Jin, C. S., & Chan, J. C. (2019). Long-term trends in tropical cyclone tracks around Korea and Japan in late summer and early fall. *Atmospheric Science Letters*, *20*(11), Article e939. https://doi.org/10.1002/asl.939

Liu, S., Lin, W., Portabella, M., & Wang, Z. (2022). Characterization of tropical cyclone intensity using the HY-2B scatterometer wind data. *Remote Sensing*, *14*(4), Article 1035. https://doi.org/10.3390/rs14041035

Nerrise, F. (2021). Predictive agent-based modeling of natural disasters using machine learning. *Proceedings of the AAAI Conference on Artificial Intelligence, 35*(18), 15976-15977. https://doi.org/10.1609/aaai.v35i18.17984

Pinto, J. G., Spangehl, T., Ulbrich, U., & Speth, P. (2005). Sensitivities of a cyclone detection and tracking algorithm: Individual tracks and climatology. *Meteorologische Zeitschrift*, *14*(6), 823-838. https://doi.org/10.1127/0941-2948/2005/0068

Roy, C. (2016). *An informed system development approach to tropical cyclone track and intensity forecasting*. Linkopings Universitet. https://doi.org/10.3384/diss.diva-123198.

Singh, S. K., Singh, R., Singh, C., & Singh, R. (2022). Assessment of the impact of ocean mean temperature on numerical simulations of tropical cyclones. *Meteorology and Atmospheric Physics*, *134*(6), Article 100. https://doi.org/10.1007/s00703-022-00937-y.

Tan, J., Yang, Q., Hu, J., Huang, Q., & Chen, S. (2022). Tropical cyclone intensity estimation using Himawari-8 satellite cloud products and deep learning. *Remote Sensing*, *14*(4), Article 812. https://doi.org/10.3390/rs14040812

Tong, B., Fu, J., Deng, Y., Huang, Y., Chan, P., & He, Y. (2023). Estimation of tropical cyclone intensity via deep learning techniques from satellite cloud images. *Remote Sensing*, *15*(17), Article 4188. https://doi.org/10.3390/rs15174188

Xu, W., Balaguru, K., August, A., Lalo, N., Hodas, N., DeMaria, M., & Judi, D. (2021). Deep learning experiments for tropical cyclone intensity forecasts. *Weather and Forecasting*, *36*(4), 1453-1470. https://doi.org/10.1175/WAF-D-20-0104.1

Yadav, M., & Das, L. (2023). Detecting tropical cyclone from the basic overview of life cycle of extremely severe cyclonic storm, Tauktae. *Revista de Climatología, 23*, 149-156. https://doi.org/10.59427/rcli/2023/v23.149-156