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Prediction of Tropical Cyclone Trajectory and Intensity Using a Particle Motion Based Machine Learning Framework in the Southern Indian Ocean

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Abstract

Tropical cyclones in the Southern Indian Ocean pose severe threats to coastal infrastructure and socio-economic stability, yet predicting their recurving trajectories and intensity remains a significant meteorological challenge. This study evaluates the performance of a particle-motion-based machine learning framework, utilizing the Trackpy library, to forecast cyclone behavior. Leveraging historical data from 2018 to 2025 (JTWC and IBTrACS), the model treats cyclones as physical particles with temporal inertia, employing a multi-lag feature to capture movement momentum. Evaluation using a dataset of 115 cyclones (78:22 train/test ratio) reveals that the Trackpy framework achieves high spatial precision, with Mean Squared Error (MSE) values of 0.1728 for latitude (±33.3 km) and 1.0250 for longitude (±53.2 km). While the intensity prediction yielded a higher MSE of 47.7544 (approximately 6.9-knot deviation), the model successfully captured major strengthening and weakening phases across prominent cyclones, including TC Wallace and TC Neville. These findings demonstrate that integrating temporal inertia is highly effective for maintaining trajectory consistency, establishing Trackpy as a robust architectural foundation for operational forecasting. Further optimization via hybrid models and additional meteorological variables is recommended to enhance intensity accuracy.

Keywords: Tropical Cyclone; Trackpy; Particle Motion; Machine Learning; Trajectory Prediction

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INTRODUCTION

Tropical cyclones are among the most destructive atmospheric phenomena that develop over oceanic regions, particularly in the southern Indian Ocean (Singh et al., 2025; Tiwari et al., 2022). This system is formed through complex interactions among high sea surface temperatures, atmospheric instability, and wind dynamics that support convection and the formation of cyclonic patterns (J. Wang et al., 2024; Zhao et al., 2022). Its existence not only affects regional meteorological conditions but also poses a significant threat to human safety, socio-economic stability, and the resilience of coastal infrastructure in neighboring countries, including Indonesia (Lamers et al., 2023; Song et al., 2021; Umakanth et al., 2024; S. Wang & Toumi, 2021). The impacts can include extreme rainfall, high waves, tidal flooding, and damage to infrastructure (Li et al., 2022; Wijetunge & Neluwala, 2023). Scientifically, the evolution of tropical cyclones is influenced by nonlinear interactions between ocean thermodynamic parameters such as ocean heat content and latent heat flux with mesoscale to synoptic-scale atmospheric dynamics (Bentamy et al., 2017; Fernández et al., 2023; Naskar et al., 2024; J. Zhou et al., 2021). The complexity of these interactions often results in unpredictable movement trajectories and rapid, sudden changes in intensity (Hong & Medina, 2025). This variability poses a major challenge for early warning systems, as prediction uncertainty can have direct implications for the effectiveness of disaster mitigation and response measures (Rahman et al., 2024).

Efforts to forecast tropical cyclone trajectories still face significant challenges, particularly in anticipating re-curving patterns, a phenomenon whereby cyclones undergo sudden changes in direction due to interactions with subtropical high-pressure systems, long-wave troughs, and vertical wind shear variations (Dube et al., 2024). This pattern is dynamic and highly sensitive to changes in synoptic-scale atmospheric conditions, often causing substantial deviations between model predictions and actual trajectories (Chen et al., 2015). The model's inability to consistently represent these directional transitions has direct implications for increased forecast uncertainty and potential delays in mitigation responses (Kam et al., 2024).

The importance of this research lies in the need for a more robust early warning system. Previous studies have utilised a machine learning-based approach to improve the accuracy of tropical cyclone track and intensity predictions (Z. Wang et al., 2022). This approach includes the use of recurrent neural networks (RNN), long short-term memory (LSTM), conventional regression models and ensemble techniques. These models generally utilise time series characteristics to capture temporal dependencies in meteorological data (Dhanka et al., 2025; Lockwood et al., n.d.; Ouma et al., 2022; Z. Wang et al., 2022; Yeasin et al., 2024). Although they demonstrate improved performance compared to traditional statistical approaches, most of these models treat meteorological data as purely numerical variables without taking into account the physical characteristics of cyclones as entities possessing mass momentum. This often leads to a failure to maintain track continuity when faced with data gaps or sharp changes in direction.

The objective of this study is to evaluate the effectiveness of domain adaptation within the Trackpy particle motion framework in predicting the tracks and intensities of tropical cyclones. By integrating the concept of temporal inertia, this study examines the model's ability to maintain prediction consistency through *multi-lag* features. The evaluation was conducted using *Mean Squared Error* (MSE) to identify Trackpy's potential as the foundation for a more stable computational architecture in cyclone forecasting in the Southern Indian Ocean, thereby supporting more precise disaster risk reduction efforts.

METHOD

Research Design

This study employs a computational experimental design using a particle-based motion framework to forecast tropical cyclone behavior - *Trackpy*. The core concept treats tropical cyclones as physical particles possessing temporal inertia, where the model utilizes historical movement memory to maintain trajectory consistency. Model performance is evaluated quantitatively through the precision of coordinate predictions (latitude and longitude) and maximum wind speed intensity.

Research Procedure

This research procedure began with the collection of historical data on tropical cyclones for the period 2018–2025, sourced from the JTWC and IBTrACS. In the initial stage, a *preprocessing* process was carried out to ensure the continuity of trajectories by handling missing data using the *third-order spline interpolation* method, followed by temporal sorting of the data. Subsequently, the dataset was split (*data splitting*) based on the unique identifier of each cyclone, rather than random row splitting, to prevent *data leakage* between cyclone lifecycles. The model was implemented by adapting the *continuous point tracking* algorithm using the Trackpy library to model cyclone movement. Finally, the model's efficacy was evaluated by comparing the prediction results against actual observations through visual trajectory analysis and the calculation of performance metrics in the form of *Mean Squared Error* (MSE).

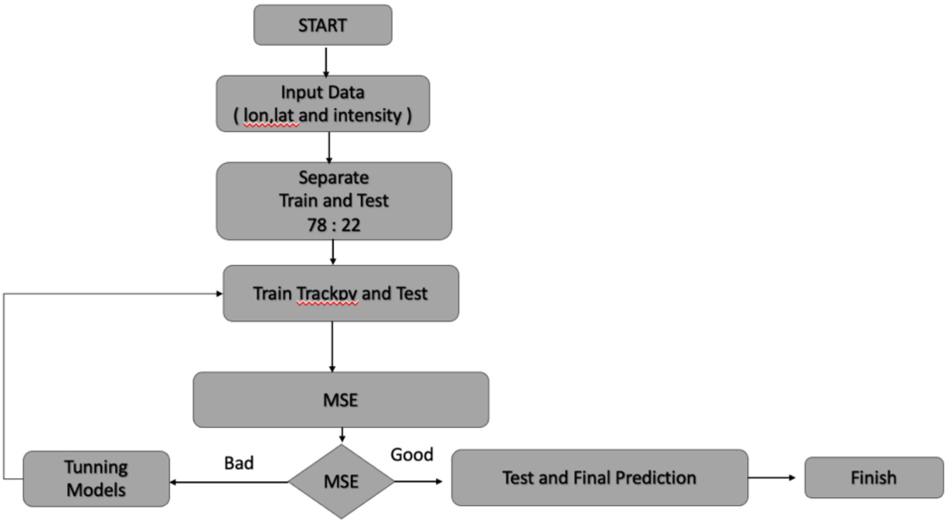

Figure 1. Processing Flow Diagram

Population and Sample

This study covers the southern Indian Ocean, bounded by the coordinates 5°–35°S and 40°–120°E, using a 6-hour temporal resolution. The research dataset consists of a total of 115 tropical cyclones comprising 3,115 data rows, which were subsequently divided chronologically to ensure the validity of testing on events occurring after the training period. A total of 78 cyclones, comprising 2,446 data rows, were allocated as training data to establish the cyclones' movement profiles and inertial characteristics, whilst the remaining 37 cyclones, comprising 669 data rows, were used as test data. This division based on the individual identity of each cyclone aims to evaluate the model's accuracy against previously unseen data whilst maintaining the relevance of predictions for future weather patterns. Data partitioning follows a 78:22 ratio for training, validation, and testing, while maintaining temporal coherence and spatial representation of TC characteristics in the study area (Sivakumar et al., 2024).

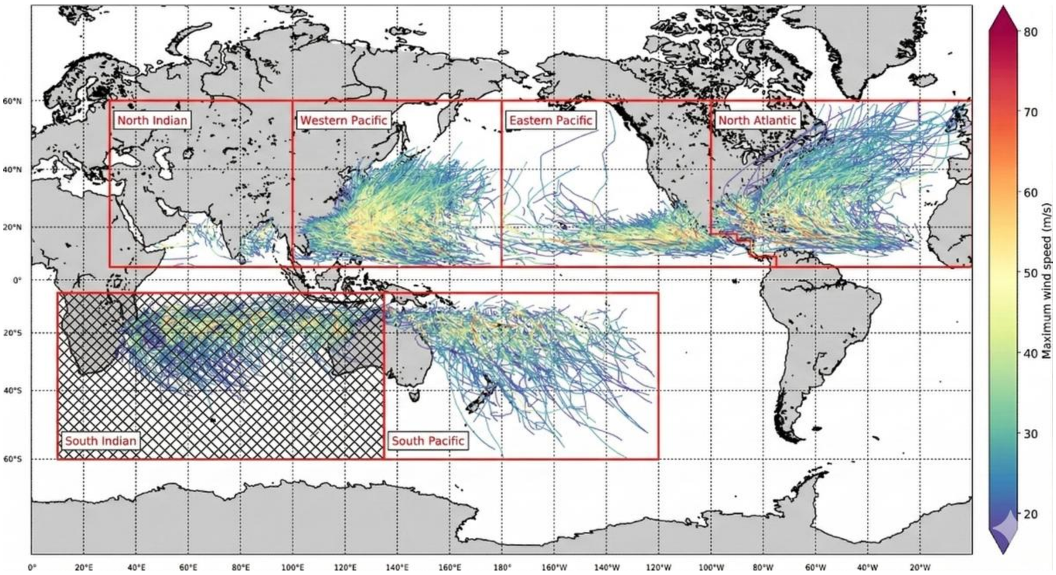

Figure 2. Research area in the shaded area

The focus of this research is concentrated in the southern Indian Ocean, specifically represented by the shaded zone in Figure 1. This location was chosen based on the significance of the region as an active formation zone and passageway for tropical cyclones in the southern hemisphere.

Table 1. Summary of data used

Category	Details
Number of Cylones	115 Cyclones
Number of Data Rows	3115 rows
Data Train	2446 rows (78 cyclones)
Data Test	669 rows (37 cyclones)

This cyclone dataset consists of 115 tropical cyclones with a total of 3,115 rows of observation data recorded at 6-hour intervals. The data has been divided into two subsets for model development purposes: training data consisting of 2,446 rows covering 78 cyclones, and test data consisting of 669 rows covering 37 cyclones. This division is designed with a ratio of approximately 78% for training and 22% for testing, ensuring that the model can comprehensively learn cyclone intensity and movement patterns while being tested on previously unseen data. Each row of data contains important information such as the cyclone name, observation time, latitude and longitude coordinates, intensity value (in knots), and status label (train/test), making this dataset highly relevant for applications predicting the path and strength of tropical cyclones in the southern Indian Ocean.

Research Instrument

The primary tool in this study is the Trackpy library, optimised through the construction of *multi-lag* features spanning up to five time steps backwards ($t - 5$ to t). These features are designed to capture the momentum of movement by calculating the position vector from 30 hours prior (5 *frames* x 6 hours), enabling the model to maintain directional consistency even when the cyclone experiences brief synoptic disturbances. In its implementation, tracking parameters are specifically defined, including the *search radius* as the maximum limit of particle displacement between *frames*, adjusted to the cyclone's maximum physical speed within the study area. Furthermore, the *memory* parameter is configured to determine the maximum number of *frames* during which an object may disappear yet remain identified as the same entity, in order to maintain the stability of the cyclone's identity during phases of temporary intensity weakening.

Particle-Based Framework: Trackpy

The method used is a particle-based approach implemented through the *Trackpy* library, often referred to as the PyTrack approach in the context of trajectory tracking. The basic concept of this method is to treat each cyclone as a physical particle with temporal inertia (Cai et al., 2025; Prigent et al., 2022). The core algorithm used is continuous point tracking (linking) that minimizes the distance deviation between time frames (Allan et al., 2016; Berghouse et al., 2024; Duarte, 2023). In this study, *Trackpy* was optimized with the *Multi-Lag* feature (up to 5 previous time steps) to capture the momentum of movement (Z. Wang et al., 2026). The basic equation for determining the distance between points (proximity) in the linking process is as follows:

$$\mathrm{d} = \sqrt{(x_{t+1} - x_t)^2 + (y_{t+1} - y_t)^2} \tag{1}$$

Where *x* and *y* represent the longitude and latitude coordinates at the time *t*.

Evaluation Metric: Mean Squared Error (MSE)

To quantitatively compare the performance of frameworks with observation data, this study uses *Mean Squared Error* (MSE) as the main evaluation metric. MSE measures the average square difference between actual values and predicted values. The smaller the MSE value, the higher the accuracy of the model in predicting trajectory and intensity (Hodson, 2022; Kumar et al., 2022). The MSE equation is defined as:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (2)$$

Where n is the number of data samples, y_i is the actual value (coordinate or intensity), and $\hat{y}_i$ is the predicted value from the model. Specifically for longitude coordinates, the difference $(y_i - \hat{y}_i)$ is calculated with a wrap-around correction 180° to maintain spatial continuity at the date line (Hodson, 2022).

RESULTS AND DISCUSSION

Results

Based on the results of data processing using the Trackpy library, a relatively measurable prediction error rate was obtained for three main parameters, namely latitude, longitude, and maximum wind speed intensity. Quantitatively, the average error value for latitude coordinates was recorded at 0.30°, while for longitude coordinates it was 0.48°, indicating a spatial deviation between the estimated model trajectory and observational data. To improve physical interpretation in accordance with meteorological standards, these values are converted using the *great-circle distance*, where the average spatial error is equivalent to approximately 33.3 km for latitude and 53.2 km for longitude (at the average latitude of the study area). Meanwhile, the error in intensity estimation was recorded at 4.8 knots, representing the difference between the predicted maximum wind speed and the actual value. These values indicate that the particle tracking approach implemented through Trackpy has a fairly good level of spatial precision, although there is still room for improvement in accuracy, particularly in representing longitudinal dynamics and intensity fluctuations, which tend to be more variable.

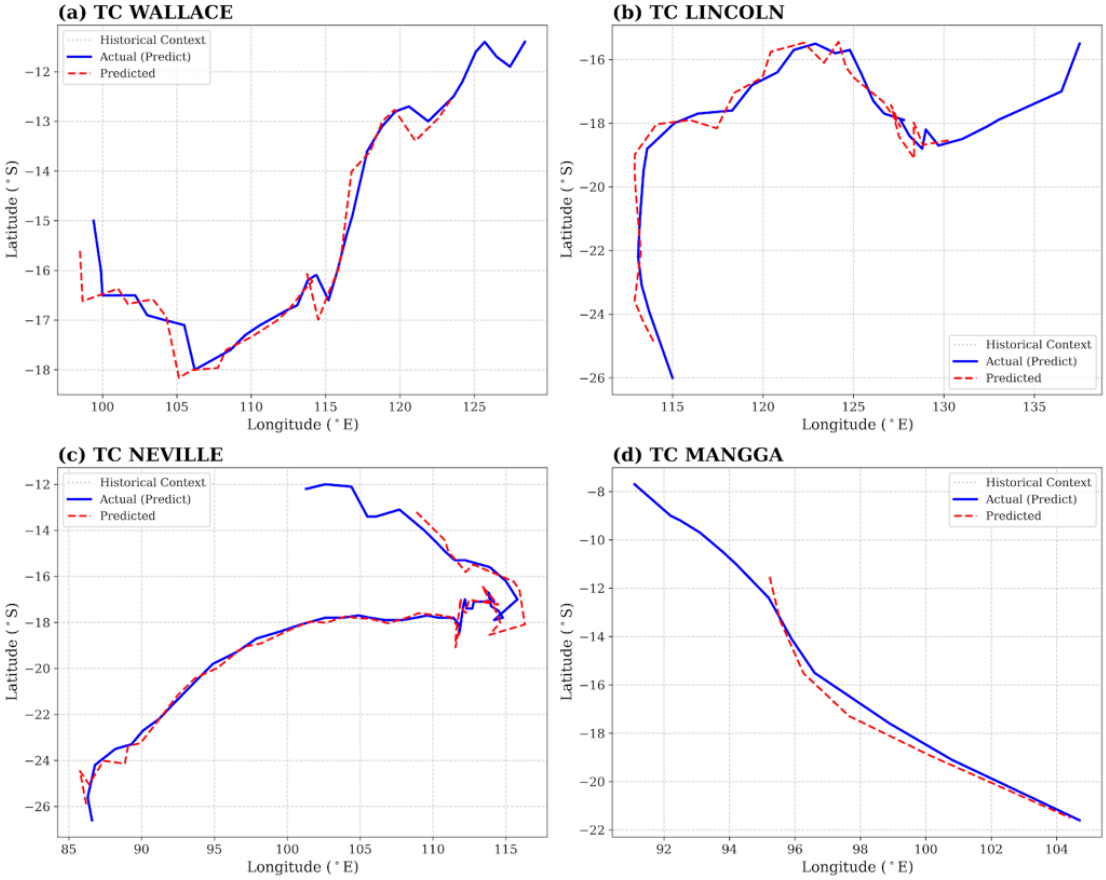

Figure 3. Cyclone tracks using Trackpy for: (a) TC Wallace, (b) TC Lincoln, (c) TC Neville, and (d) TC Mangga.

Figure 3 shows a comparison of the trajectories between trackpy (red line) and observations (blue line) for four tropical cyclones, namely TC Wallace, TC Lincoln, TC Neville, and TC Mangga. In general, the predicted tracks follow the actual movement patterns with a fairly good degree of spatial proximity, although there are deviations in some segments, especially when there are sharp changes in direction or curvature of the track (re-curving). In TC Wallace and TC Lincoln, there are small differences in the directional transition phase, while in TC Neville, the deviation is more apparent at the end of the track, which shows circular movement. Meanwhile, for TC Mangga, the prediction pattern relatively consistently follows the actual trajectory, which tends to move towards the southeast. Overall, this visualisation illustrates the model's ability to represent cyclone movement dynamics, while also highlighting areas where spatial discrepancies still occur.

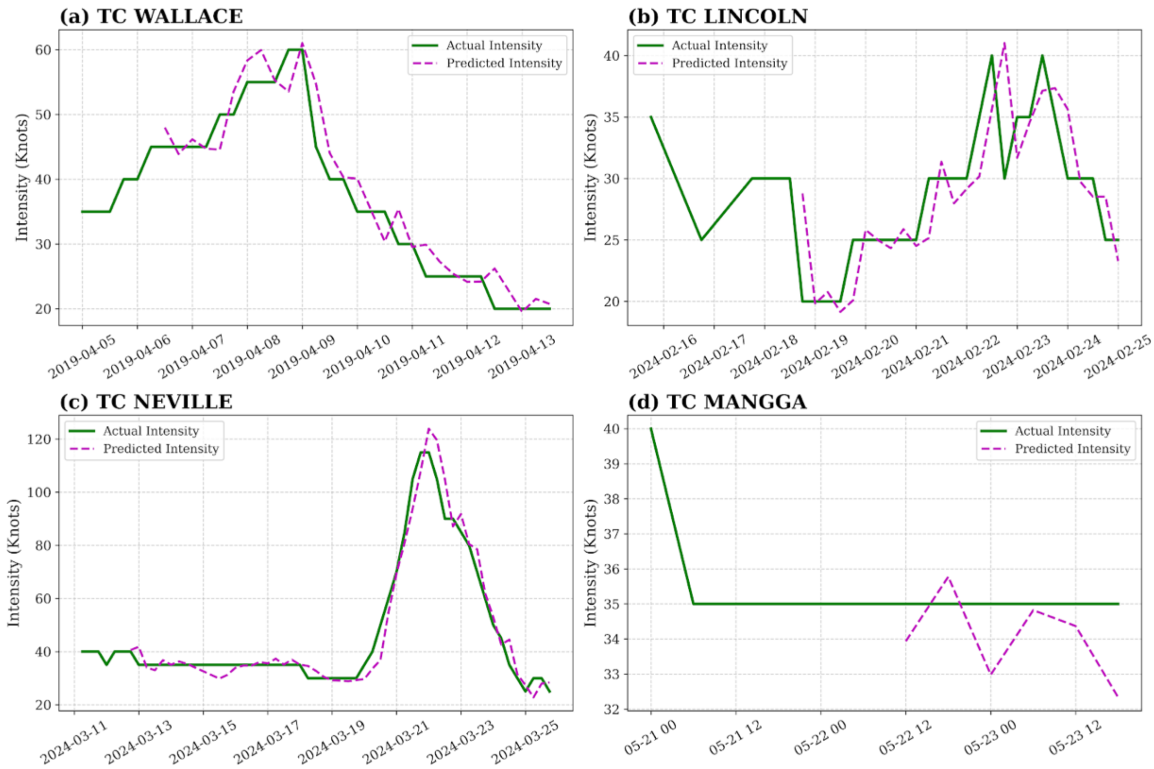

Figure 4. Cyclone intensity using Trackpy for: (a) TC Wallace, (b) TC Lincoln, (c) TC Neville, and (d) TC Mangga.

Figure 4 shows a comparison of intensity between trackpy (red line) and observations (blue line) for four tropical cyclones, namely TC Wallace, TC Lincoln, TC Neville, and TC Mangga. In general, the prediction pattern is able to follow the trend of actual intensity fluctuations, including the strengthening and weakening phases. In TC Wallace and TC Lincoln, the model was relatively good at capturing gradual variations despite deviations at the peak intensity. In TC Neville, there was a very significant increase in intensity exceeding 100 knots, and the model was able to represent this surge with a controlled margin of error. Meanwhile, in TC Mangga, the intensity variation tended to be more stable, and the prediction results showed a fairly consistent trend, although slightly underestimating the actual values at some observation times. Overall, this visualisation illustrates the model's ability to represent the dynamics of tropical cyclone intensity changes over time.

Discussion

The results of the evaluation using the MSE metric demonstrate Trackpy’s highly stable performance in predicting the spatial coordinates of tropical cyclones. The MSE value for latitude of 0.1728 indicates a very high level of precision with minimal deviation between predicted and actual positions. The slightly higher MSE value for longitude (1.0250) reflects the movement characteristics of cyclones in the Southern Indian Ocean, which tend to exhibit more dynamic zonal (west-east) variability compared to their meridional movement. However, with spatial errors remaining below the 60 km range, this model is able to maintain trajectory consistency within an acceptable margin of error for meteorological scales (Cyclone Warning in India Standard Operation Procedure, 2013) .

For the intensity parameter, Trackpy recorded an MSE value of 47.7544. If this value is interpreted through the Root Mean Squared Error (RMSE), the average wind speed deviation is around 6.9 knots. Given that tropical cyclones often have extreme wind speeds exceeding 64 knots, an error rate below 7 knots indicates that this model is reliable enough to capture fluctuations in storm strength. This success is driven by Trackpy's ability to utilise temporal inertia, where data from several previous time steps (multi-lag) is used to mitigate noise in historical data. Overall, the low MSE values for all three parameters confirm that Trackpy is an effective framework choice for operational tropical cyclone predictive modelling.

Table 2. Trackpy Evaluation Matrix for cyclone track and intensity

Parameter	Evaluation Metric	Value	Description
Latitude	MSE	**0.1728**	33.3 km error
Longitude	MSE	**1.0250**	53.2 km error
Intensity	MSE	**47.7544**	6.9 knots error

In meteorology, a tropical cyclone is a large-scale atmospheric system with significant mass momentum, so that its direction of movement tends to be continuous and does not change drastically in a short period of time (6 hours). Trackpy, designed to track continuous particle trajectories, is able to utilise the *multi-lag* feature to strengthen the model's ‘memory’ of previous movement trends. This is in line with the findings (H. Zhou et al., 2025) that consistent spatial proximity-based tracking minimises *linking* failures in data with disturbances. The better intensity precision of the Trackpy method (MSE 47.7544) also proves that temporal inertia is more effective in capturing wind strength evolution than pure mobility variables (Cui et al., 2024; Dai et al., 2025; Pourbeik et al., 2024). The particle-based approach (Trackpy) is superior for operational forecasting needs that require stability and absolute coordinate precision due to its ability to model system inertia. This finding supports recent literature by (Wenwei et al., 2021) which states that temporal memory integration (inertia-aware) is key to reducing uncertainty in tropical cyclone track prediction models in maritime regions (Diggikar et al., 2025).

CONCLUSION

This study successfully evaluated the particle-based Trackpy framework for predicting tropical cyclone trajectory and intensity, demonstrating that the integration of temporal inertia significantly maintains movement consistency. The model achieved high spatial precision with Mean Squared Error (MSE) values of 0.1728 for latitude and 1.0250 for longitude. For practical meteorological interpretation, these values correspond to an average spatial deviation of approximately 33.3 km (0.30°) for latitude and 53.2 km (0.48°) for longitude.While Trackpy proved highly reliable for tracking spatial movement, predicting intensity remains a more significant challenge, yielding an MSE of 47.7544 approximately 6.9 knots . These results indicate that while the model effectively captures major strengthening and weakening phases, its reliance on movement memory alone is insufficient for peak intensity accuracy.

RECOMMENDATION

Based on the results of this study, further development is recommended to integrate additional meteorological parameters such as sea surface temperature and vertical wind shear into the model in order to reduce the MSE value for intensity, which is still quite high. The use of a hybrid method that combines the Trackpy algorithm with a machine learning approach, such as Long Short-Term Memory (LSTM), is also predicted to improve the model's ability to capture non-linear patterns in cyclone strength fluctuations.

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AUTHOR CONTRIBUTIONS STATEMENT

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Budi Iman Samiaji	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Yulkifli		✓				✓		✓	✓	✓	✓	✓		
Yohandri	✓		✓	✓			✓			✓	✓		✓	
Nofi Yendri Sudiar					✓		✓			✓		✓		
Supari					✓		✓			✓		✓		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

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