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Advanced hybrid CNN-Bi-LSTM model augmented with GA and FFO for enhanced cyclone intensity forecasting

Franciskus Antonius Alijoyo [a,*], Taviti Naidu Gongada [b], Chamandeep Kaur [c], N. Mageswari [d], J.C. Sekhar [e], Janjhyam Venkata Naga Ramesh [f], Yousef A.Baker El-Ebiary [g], Zoirov Ulmas [h]

[a] Center for Risk Management and Sustainability Indonesia, School of Business and Information Technology STMIK LIKMI Bandung, Indonesia
[b] Dept of operations, GITAM school of Business, GITAM (Deemed to be) University, Visakhapatnam, India
[c] Computer Science & Information Technology Department, Jazan University, Jizan, Kingdom of Saudi Arabia
[d] Department of ECE, Ashoka Women's Engineering College, Kurnool, Andhra Pradesh, India
[e] NRI Institute of Technology, Guntur, Andhra Pradesh, India
[f] Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur Dist., Andhra Pradesh, India
[g] Faculty of Informatics and Computing, UniSZA University, Malaysia
[h] Artificial Intelligence Department, Tashkent State University of Economics, Tashkent, Uzbekistan

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ABSTRACT

Predicting cyclone intensity is an important aspect of weather forecasting since it influences disaster preparation and response. This framework addresses the pressing need for precise cyclone intensity prediction by presenting a unique predictive model based on a hybrid CNN and Bi-LSTM architecture optimized using a Genetic Algorithm (GA) enhanced Fruit Fly Optimizer (FFO). Existing methods have primarily relied on traditional machine learning models and meteorological data, demonstrating limitations in capturing the complex spatial-temporal patterns inherent in cyclone evolution. These drawbacks include insufficient feature extraction abilities, underutilization of convolutional neural networks (CNN), and poor model tuning. This unique method incorporates a hybrid CNN and Bi-LSTM architecture that is tuned by a Genetic Algorithm (GA) enhanced Fruit Fly Optimizer (FFO), resulting in higher cyclone intensity prediction accuracy. The experimental results are implemented in Python software, and they reveal that this method outperforms current models by an average of 21% when compared to existing methods such as VGG-16 achieved an accuracy of 78% and Ty 5-CNN (95.23%). The suggested CNN-Bi-LSTM model predicts cyclone strength with an excellent accuracy of 99.4%. This unique approach offers a possible avenue for increasing cyclone intensity prediction, hence improving disaster preparedness and risk mitigation efforts in sensitive locations.

1. Introduction

Cyclone strength, a crucial aspect of tropical cyclone forecasting, describes the extent of a cyclone's capacity for destruction, taking into account elements including wind speed, air pressure, and storm surge [1]. The ability of institutions and communities to make educated decisions to lessen the destructive effects of these natural disasters depends on precise cyclone strength forecast, which is of utmost importance for preparedness for catastrophes, risk evaluation, and quick evacuation operations [2,3]. For weather forecasters and academics, cyclones present a daunting challenge since their intensity is constantly shifting and vulnerable to fast change as it interacts with many environmental conditions [4]. A complex strategy involving advanced technologies like satellite data, computer modelling, and machine learning algorithms is needed to tackle this problem. Since small improvements in accuracy of forecasting can result in considerable reductions in the amount of physical damage, human casualties, and financial expenses connected with cyclone incidents, scientists in the area are always working to improve the reliability of cyclone intensity predictions. In order to improve resilience and disaster response capabilities in cyclone-prone regions around the world, constant attempts are being made to improve models for forecasting, utilise the potential of artificial intelligence, and utilise optimisation methods [5,6].

The increasing frequency and intensity of cyclonic activities around the world have made it important to improve cyclone intensity forecast. This is because it is crucial for disaster management, safety for people,

* Corresponding author.
E-mail address: franciskus.antonius.alijoyo63@gmail.com (F.A. Alijoyo).

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and climate research [7]. This climatic phenomenon highlights the critical need of precise forecasting by posing a serious risk to coastal individuals, economies, and ecosystems. The amount of damage and misery that a cyclone may cause are largely determined by the strength of the storm, which is generally defined by wind speed and accompanying risks like hurricane surges and heavy rainfall [8]. The ability to evacuate on time, allocate resources, prepare for a disaster, and minimise casualties and destruction of property all depend on accurate and timely forecasts [9]. The intricacy of cyclone factors, which is impacted by a wide range of meteorological factors and oceanic circumstances, is an important obstacle to weather forecasters and climate researchers. The creation of more complex, methods based on data was required since conventional forecasting algorithms frequently fail to capture these nuanced relationships. cyclones are becoming more erratic and could potentially prove more devastating due to the compounding consequences of changes in the climate, such as increasing sea levels and elevated sea surface temperatures [10].

There are serious ramifications when cyclone intensity predictions are inaccurate, affecting everything from infrastructure and individuals to industries and the natural world [11]. Cyclones, one of nature's most destructive calamities, have the potential to cause unimaginable destruction if they are overestimated or wrongly predicted. Reliable severity projections can prevent needless casualties and displacement of people by causing insufficient planning, delayed evacuations, and inefficient resource allocation. Affected populations are made even more vulnerable by the associated strong winds, storm surges, and torrential rains, which can seriously harm vital infrastructure like houses, utilities, transit systems, and institutions [12]. The effects on the ecosystem are similarly severe because cyclones can cause pollution of water, destruction of forests, and coastline erosion, upsetting fragile ecosystems and maintaining balance of the environment [13]. The impact on the economy is significant, resulting in damages to agriculture, billions of dollars in property damage, and interruptions to sectors of the economy that depend on reliable supply lines. The seriousness of the issue is exacerbated by the rising frequency and intensity of cyclonic occurrences, which are partly attributable to climate change, making precise forecasting a pressing global necessity [14]. It is impossible to exaggerate the importance of accurate cyclone intensity forecasting in a world where the human population continues to concentrate in coastal areas, urbanisation is on the rise, and interconnection increases the reach of catastrophic effects. It acts as the initial layer of defence against an increasingly dangerous and unreliable natural phenomenon, having a direct impact on disaster response plans, resource allocation, and community resilience. It also plays a crucial role in ensuring the safety of individuals, assets, and the long-term sustainability of areas at risk around the globe [15,16].

In order to improve forecast precision as well as dependability during times of such powerful natural disasters, a variety of meteorological methodologies, computational models, and data-driven strategies are now being used. In order to create forecasts using their knowledge of cyclone dynamics, traditional meteorological approaches rely on the skills of meteorologists who analyse historical data, satellite imagery, and atmospheric conditions [17]. Another key component is the use of Numerical Weather Prediction (NWP) models, which simulate processes in the atmosphere and provide predictions using intricate mathematical calculations [18]. Also, to take into account uncertainties, Ensemble Prediction Systems (EPS) execute a number of simulations with modest modifications in the initial conditions [19]. These techniques have significantly increased our capacity to forecast cyclone tracks, but there are still difficulties in accurately predicting intensity changes, which can occur suddenly and without warning. A new era of machine learning and artificial intelligence applications has been introduced in by recent developments in technology, where computers are taught on enormous datasets to identify patterns and connections in cyclone behaviour. These data-driven models, including Deep Learning Neural Networks and Random Forests, try to accurately represent the complicated relationships underlying cyclone development. current information is essential for tracking cyclone formation has been made available by the combination of Doppler radar detection and satellite remote sensing technology [20]. To improve cyclone intensity prediction and reduce the disastrous effects that these natural occurrences have on coastal populations, a variety of methodologies have been combined. To improve cyclone intensity prediction, these numerous methodologies have been used in an effort to lessen the disastrous effects that these natural occurrences have on coastlines, economic growth, and environments around the world.

The current approaches have some important shortcomings and limits, although being helpful in furthering our understanding of these powerful meteorological occurrences. Traditional meteorological methodologies, based on expert evaluation and past information, frequently find it difficult to accurately represent the quick and unpredictable variations in cyclone intensity, producing less accurate forecasts that might threaten efforts to prepare and public safety. Although advanced, parameterization and resolution issues confront Numerical Weather Prediction (NWP) models, which may limit their capacity to replicate the complex dynamics underlying cyclone development. Even while Ensemble Prediction Systems (EPS) provide probabilistic insights, they can be computationally expensive and might not fully account for all causes of uncertainty [21]. The integration of new scientific ideas into predicting practises can be hampered by some conventional approaches' reliance on empirical relations and heuristic criteria. Promising data-driven approaches have emerged in recent years from the emerging fields of machine learning and artificial intelligence, but they also struggle with problems including data scarcity, model interpretability, and overfitting. While satellite remote sensing and Doppler radar technologies give priceless real-time data, they may not completely cover cyclone zones and are subject to observational mistakes [22]. Therefore, an extensive awareness of the flaws in current prediction techniques is crucial because it emphasises the critical need to get past these obstacles and the significance of ongoing research and innovation in the search for more accurate cyclone intensity forecasts, which are essential for saving lives and reducing the catastrophic impact of these natural disasters on vulnerable coastal regions.

Conventional machine learning models and meteorological data frequently fail to capture the intricate spatial-temporal patterns found in cyclone evolution, resulting in unsatisfactory forecasts. This study aims to address these constraints by introducing a new predictive model. The study problem is to create a method that effectively extracts features from cyclone data using a hybrid CNN and Bi-LSTM architecture. The problem is to optimize model parameters to improve generalizability and predictive power, which necessitates the use of advanced methods such as the Genetic Algorithm (GA) enhanced Fruit Fly Optimizer. By addressing these concerns, the study hopes to give a more accurate and dependable approach to predicting cyclone strength, thereby increasing disaster preparedness and risk mitigation efforts in vulnerable coastal communities. This study's key contributions are given below:

- The study presents a hybrid CNN and Bi-LSTM architecture that combines the characteristics of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which excel in capturing spatial and temporal patterns, respectively. This fusion enables a more extensive examination of cyclone data, which improves prediction accuracy.
- The use of a GA-enhanced Fruit Fly Optimizer (FFO) to tune the model's parameters is an innovative method. This optimization technique allows the model to adapt and improve its performance iteratively, resulting in more accurate cyclone intensity prediction.
- The model effectively brings features from cyclone data by exploiting the hybrid architecture's capabilities. This is critical for capturing the complex spatial-temporal patterns that characterize cyclone evolution, adding to the model's excellent prediction ability.

A structured format is used to organize the paper. The Section 2 examines pertinent literature and looks at studies that are comparable to the one under examination. Outlining the particular difficulties that the research attempts to solve, Section 3 defines the problem statement. Section 4 goes into detail about the different parts and techniques that make up the methodology of the suggested model. A thorough discussion is started and the results are briefly summarized in Section 5. Section 6 concludes with an overview of the major findings and some thoughts on the implications for the future.

2. Related works

Using infrared geostationary satellite images from the northwest Pacific Ocean basin through a cascading deep Convolutional Neural Network (CNN) framework, the suggested Tropical Cyclone Intensity Identification and Evaluation Model (TCICE Net) is a novel method for estimating tropical cyclone intensity was proposed by C.-J. Zhang et al. [23]. The TC Intensity Classification (TCIC) component, one of TCICE Net's two main modules, divides tropical cyclone intensities into three unique groups using infrared satellite images. It then introduces three TC Intensity Estimation (TCIE) models built on CNN regression networks, each of which uses a different set of infrared imagery and TC best track data to produce intensity classifications for a given intensity. These TCIE models are painstakingly designed to take categorization mistakes included in the TCIC module into account, improving the general accuracy of intensities assessment. TCICE Net contributes to more accurate and trustworthy forecasts for tracking and minimising the effect of such possibly catastrophic weather events in the northwest Pacific Ocean basin by streamlining the categorization of tropical cyclone levels and improving the method of estimation by incorporating data from infrared satellite observations and historical track data. This model's ability to generalise and be resilient is constrained by its reliance on a dataset that is only from the northwest Pacific Ocean basin and uses best track data as reference strengths.

Tropical cyclones have sparked continuous efforts to improve their intensity forecast because of their propensity to cause significant human losses and economic destruction. Due to the spatial and temporal complexity of typhoon dynamics, recent research has focused on machine learning techniques. The Typhoon Intensity Spatio-Temporal Prediction Network (TITP-Net), an innovative deep learning model created to improve typhoon intensity forecasting, is introduced in this article by Jiang, Fan, and Wang [24]. Key physical components and multiple external factors influencing typhoon behaviour are carefully included in TITP-Net. Using a geographic attention module that uses two- and multidimensional convolutional procedures to identify spatio-temporal dependence, it maximises data utilisation. Extensive trials carried out within a thorough framework highlight TITP-Net's potential to advance typhoon intensity forecasting. TITP-Net is a promising method for improving our comprehension and predicting skills of such damaging weather-related events, with consequences for reducing their effects on society and the economy. It does this by seamlessly combining ecological and actual data and utilising spatio-temporal interactions. It is still difficult to estimate the short-term events with the model. Putting in place more complex networks can tax computing power and lengthen processing instances, which might restrict real-time application. Thus, to ensure practical utility in operational typhoon forecasting structures, a balance between complexity of models and computing capability must be found.

Ruttgers et al. discussed the crucial need for precise and timely typhoon forecasts, particularly for short lead times, also known as nowcasting, to save lives and reduce damage caused by these deadly storms [25]. They suggest a unique method that predicts the route and severity of typhoons in fractions of a second using a generative adversarial network (GAN) that runs effectively on a single graphics processing unit (GPU). The authors carried out parameter research with an emphasis on 6-hour track forecasts to better understand how meteorological variables affect typhoon predictions. According to their research, satellite photos combined with characteristics like learning velocity, temperature, pressure, and humidity have a good impact on forecast accuracy. In this framework, satellite images are replaced with reanalysis data on total cloud cover and vorticity fields to circumvent access issues and enable forecasts at 12-hour intervals. Track forecasts for both 6-hour and 12-hour intervals were produced using the study's ideal combination of factors, with corresponding averaged absolute errors of 44.5 and 68.7 kilometres, respectively. This study marks a significant development in typhoon forecasting, providing a potential approach for earlier and more precise forecasts, which are essential for emergency preparedness in typhoon-prone locations. More specifically, during the crucial period prior to a cyclone making landfall within the latitude range of 25–35 degrees North, the algorithm struggles to predict high wind speeds surpassing 60 knots with any degree of accuracy.

Wenwei et al. developed a deep learning-based multilayer perceptron (MLP) model that was created in an attempt to deal with the long-standing problem of improving tropical cyclone (TC) intensity predictions [26]. This model predicted changes in TC maximum wind speed within the Atlantic basin using the Statistical Hurricane Intensity Prediction Scheme (SHIPS) global predictors. The research involved two major experiments. In the first experiment, concentrating on a 24-hour forecast period, a leave-one-year-out (LOYO) testing strategy was used to reduce sampling restrictions. In comparison to four operational TC intensity models, the MLP model, which is significant, demonstrated the ability to correctly anticipate intensification events that occurred more quickly. In the second test, a light-weight MLP was created for 6-hour intensity forecasts, and when combined with a fictitious TC track model, it generated accurate TC intensity patterns within the Atlantic basin. According to these results, the MLP-based technique shows potential for improving operational TC intensity estimates and can be a useful resource for creating synthetic TCs for climate study. The complexity and computational demands that may be introduced by expanding the deep learning architecture past five hidden layers for greater model depth must be carefully managed. The effectiveness of the framework may be constrained by relying entirely on SHIPS indicators, and its precision might be improved by adding additional variables from additional data sources.

Estimating the path and strength of tropical cyclones (TCs) is crucial for protecting infrastructure and people, especially during the crucial 24-hour warning window. Accurate estimates of TC intensity are frequently difficult to come by using typical forecasting techniques, which depend on observational linkages and conventional numerical projections based on physical equations. With an emphasis on the complicated spatial aspects of three-dimensional (3D) environmental circumstances that include meteorological and oceanographic variables, this study proposed a novel approach by Wang, Wang, and Yan to TC intensity change prediction using deep learning techniques [27]. different qualities effectively sum up the traits and interactions of different environmental influences. The underlying correlations between the spatial distribution attributes and TC intensity variations are captured in order to do this using a 3D convolutional neural network (3D-CNN). A small dataset from TC samples is also expanded using algorithms for image processing to enable better learning. The algorithm extracts complex hybrid features from TC image patterns to anticipate variations in strength over a 24-hour timescale while taking into consideration the immediate 3D state of a TC, which could lead to a significant improvement in TC forecasting skills. The suggested approach for predicting TC intensity change is promising, but it also offers room for improvement and evolution in the future. One drawback is the necessity for more research into fine-grained characteristics and the precise ranges of these features related to TC intensity fluctuations.

Considering the enormous hazards, they represent to human life, infrastructure, and the economy, identifying extreme weather events—particularly hurricanes—has always been a difficult task in climate science. Accurate prediction models are crucial to reducing these disasters' catastrophic effects. Even though many deep learning techniques, including recurrent neural networks (RNNs), convolutional auto-encoders, and convolutional neural networks (CNNs), have been used to estimate tropical cyclone intensity, difficulties persist in making accurate predictions. For the purpose of classifying cyclones and assisting with post-disaster management, this study focuses on precisely measuring tropical cyclone intensity. It was developed by Devaraj et al. [28]. The model improves accuracy by including batch normalisation and dropout layers. The work further broadens its scope to include post-disaster evaluation by optimising a pre-trained VGG 19 model to forecast damage extent and automatically annotate satellite imagery data. In order to categorise different severe weather events and automatically label them, VGG 19 was additionally trained on video datasets. These models have the potential to help scientists and meteorologists better understand how storms occur because of their great accuracy in predicting hurricane damage and classifying severe weather events. The research's importance in improving our capacity to successfully manage and respond to these catastrophic weather occurrences is highlighted by its discussion of mitigation measures for lowering hurricane risks. Although deep learning algorithms have showed potential in properly predicting cyclone intensity, estimating the likelihood of storm damage and its impact on susceptible locations faces natural challenges and constraints. The complexity of estimating damage caused by hurricanes depends upon the specific susceptibility of the afflicted area, encompassing essential facilities like water and sewage systems, flood control measures, and transportation routes, in addition to the storm's ferocity.

Roy et al. [29] presented a method for forecasting the intensity of tropical cyclones in the Bay of Bengal (BoB) using a biologically inspired computational model. Despite difficulties in predicting TC intensity due to a lack of understanding of related mechanisms and data restrictions, the model produced promising results. The model effectively anticipated TC intensity 12 and 24 hours in advance using both supervised and unsupervised learning, achieving over 90% accuracy when tested with existing TC data. When using fully new TC data, predicting accuracy declined to 36–48%. These findings show that the biologically inspired computer model for TC intensity forecasting could be further developed with additional training using more TC data from the BoB region. The study's shortcomings include a reliance on data from a single region (the Bay of Bengal), which may limit generalizability to other places. Furthermore, the model's efficiency declined when applied to completely new TC data, indicating possible difficulties in extrapolating findings to previously unknown incidents. The study's emphasis on TC intensity forecasting may obscure other critical components of TC prediction, such as track and rainfall forecasting. Furthermore, the model's accuracy may be altered by elements not considered in the study, such as quick intensification episodes or interactions with land masses. These limitations highlight the need for more refining and validation of the proposed model.

Kumar et al. [30] recommended using machine learning (ML) techniques to reduce errors in tropical cyclone (TC) intensity estimates produced by the NCMRWF Ensemble Prediction System (NEPS) over the North Indian Ocean. Four machine learning (ML) methods such as Multivariate Linear Regression (MLR), Support Vector Regression (SVR), Random Forest (RF), and eXtreme Gradient Boost (XGB) were used for bias correction (BC) of mean maximum sustained winds (MSW) and central pressure (CP) while maintaining ensemble spread. The study examined 20 TC cases between 2018 and 2021, using best track (BT) data from the India Meteorological Department (IMD) for ML training and verification. The results showed that RF and XGB outperformed CP and MSW, respectively, with statistically significant decreases in mean absolute error (MAE) and root mean square error. Correlation coefficients significantly improved, and probabilistic testing revealed improved reliability and Receiver Operating Characteristic (ROC) for RF and XGB models when compared to raw and other ML approaches. The study's limitations include a focus on TC cases from the North Indian Ocean (NIO), which may restrict generalizability to other regions. The research is based on a relatively limited sample size of 20 TC cases from a specified time period (2018–2021), which may not represent the full spectrum of TC variations. The study's use of best track (BT) data from the India Meteorological Department (IMD) for machine learning training and verification may introduce biases inherent in observational datasets. Elements not considered in the study, such as quick intensification events or complicated atmospheric interactions, may have an impact on the performance of ML approaches.

The reviewed papers present new approaches that use deep learning, convolutional neural networks (CNNs), and generative adversarial networks (GANs) to enhance the prediction of tropical cyclone strength. These methods consider elements such as the integration of many environmental variables, infrared satellite imaging, and spatiotemporal interactions. Notwithstanding the models' encouraging accuracy in predicting cyclone severity, issues with datasets, computational complexity, and the requirement for wider applications point to areas in which cyclone forecasting research and development is still needed.

3. Problem statement

The earlier literature reviews focus on the challenge of accurately predicting and assessing tropical cyclone intensity, which is critical for mitigating the potentially devastating effects of these weather-related calamities. Researchers propose a number of deep learning models and approaches to improve the accuracy and reliability of tropical cyclone intensity forecasts. To increase forecast accuracy, these algorithms usually incorporate physical qualities, spatiotemporal correlations, and environmental variables from several data sources, such as previous track data and satellite imagery. Despite the fact that these models show promise for forecasting and understanding cyclone activity, the search for more precise tropical cyclone intensity estimation and damage assessment continues. These issues include dataset limitations, model complexity, and the need for fine-grained features [28,24].

4. Cyclone intensity prediction using GA enhanced fruit fly optimized hybrid CNN-Bi-LSTM model

Cyclone intensity is predicted using a thorough methodology that utilises a Hybrid CNN-Bi-LSTM model that has been optimized using a Genetic Algorithm (GA) enhanced Fruit Fly Optimizer. Data preparation is the first step in the procedure, which includes data resizing and normalisation to guarantee consistency and stability across the dataset. The model is then given the tools it needs to grasp the intricate spatiotemporal patterns present in cyclone data using a Hybrid CNN-Bi-LSTM architecture for feature extraction. Following that, model parameters are fine-tuned using the Genetic Algorithm and Fruit Fly Optimizer, improving the model's generalisation and predictive accuracy. The final optimized model is thoroughly assessed and contrasted with previous techniques, demonstrating its superiority in cyclone intensity forecast accuracy. This methodology offers a comprehensive and innovative method for predicting cyclone strength, with the potential to greatly increase forecasting accuracy and support efforts to prepare for and mitigate disasters. Fig. 1. shows the block illustration of the proposed method.

4.1. Novelty of the work

This study's novelty comes from the establishment of a novel predictive model for cyclone strength prediction that addresses significant shortcomings in existing methodologies. This framework considerably improves cyclone intensity forecasting accuracy by using a hybrid CNN and Bi-LSTM architecture modified with a Genetic Algorithm (GA) enhanced Fruit Fly Optimizer (FFO). Unlike previous approaches, this method easily captures the complex spatial-temporal patterns inherent in cyclone evolution, resulting in increased forecasting skills critical for

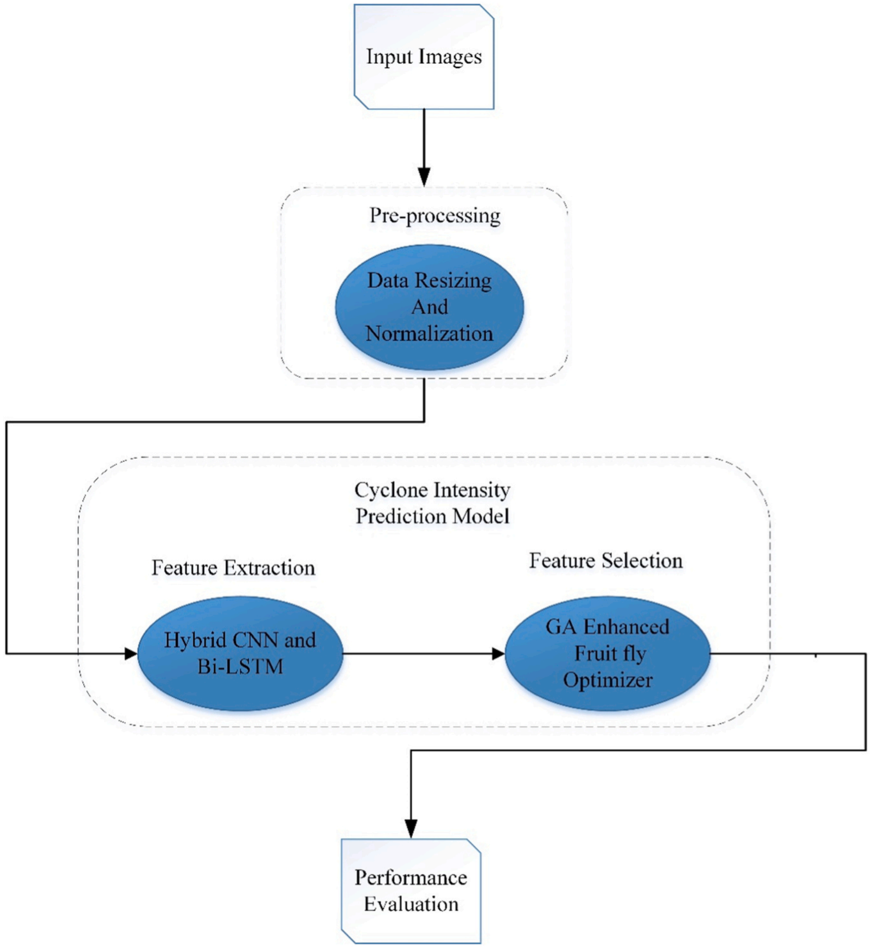

Fig. 1. Block illustration of GA enhanced fruit fly optimized hybrid CNN-Bi-LSTM model.

disaster preparedness and risk reduction efforts. The use of Python software for implementation improves the suggested model's accessibility and applicability. This novel approach presents a possible avenue for improving cyclone intensity prediction, hence improving disaster preparedness and mitigation strategies in areas of risk.

4.2. Data collection

The dataset used in this study was methodically gathered from 2012 to 2021, and includes a wide range of INFRARED and RAW cyclone pictures recorded by the INSAT-3D satellite across the Indian Ocean region. To create this excellent resource, raw data from the MOSDAC server was rigorously collected and processed. Each image in the dataset was meticulously annotated with the relevant KNOTS intensity value, which is an important parameter for cyclone monitoring and prediction. The labelling method required giving an expiration date to each image, which was exactly aligned with its position on the intensity-time graph for each cyclone [31]. This rigorous tagging procedure increases the dataset's usability by allowing the linking of cyclone images to their changing intensity over time. Despite the extensive data collection method, there may have been limitations or biases that influenced the outcomes. For example, the dataset's reliance on imagery acquired by a single satellite could generate biases due to satellite-specific traits or constraints. While the labelling process is rigorous, it may still be prone to human mistake or subjective interpretation, which may alter the accuracy of intensity values provided to individual images. The dataset's coverage may be restricted to the Indian Ocean region, limiting its applicability to cyclones in other regions. These limitations should be observed when evaluating the study's results. Fig. 2. shows the sample images of dataset.

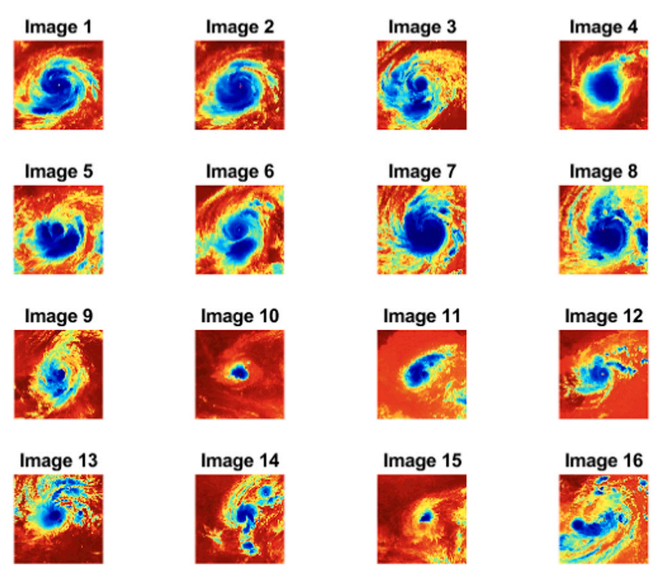

Fig. 2. Sample images of dataset.

4.3. Pre-processing using data resizing and normalization

To achieve consistency in image dimensions, which is necessary for the majority of image categorization jobs, the pre-processing step of scaling images to a standard resolution while keeping their aspect ratio is the main goal. By altering the width and height of each image to the same value, potential computational problems are avoided, and the method is compatible with the model architecture of choice. The resolution to use—such as 256×256 pixels or 128×128 pixels—is determined by the computational capabilities at hand as well as the particular specifications of the model being utilized. Resizing an image while keeping the aspect ratio ensures that the proportions of the image are maintained, eliminating distortion. The model being trained may now concentrate on important patterns, which enhances its capacity to generalize from the dataset.

The input information must be normalized in order to keep the cyclone intensity forecast models simple to learn and to produce accurate forecasting outcomes because various prediction components have different dimensions and size ranges. Eq. (1) describes the data normalization method:

$$Z(j) = \frac{(0.1 \times (\max - z(j)) + 0.9 \times (z(j) - \min))}{(\max - \min)} \tag{1}$$

The original value of a data point before to normalization is represented by $Z(j)$. The changed value of the same data point after normalization is shown by the symbol $z(j)$. The term "min" designates the smallest value within the group, which includes $z(j)$and maybe other data points. “max” denotes the largest value inside the same group, including $z(j)$ and any additional pertinent data points.

Cyclone strength may be predicted as a time sequence problem using historical cyclone cases and LSTM since cyclones change during their life cycles and because there are only few samples from a single cyclone case. For instance, the time sequence of one cyclone case is $Z(1), Z(2), \ldots\ldots, Z(n)$, while the time series of another cyclone case is $X(1), X(2), \ldots\ldots, X(m)$; as a result, the processed time series of these cyclone cases is $Z(1), Z(2), \ldots\ldots, Z(n)$, $X(1), X(2), \ldots\ldots, X(m)$ [32].

Data must be reverse normalized as follows after model training in Eq. (2):

$$z(j) = \frac{(Z(j) \times (\max - \min) + 0.9 \times \min - o.1 \times \max)}{0.8} \tag{2}$$

4.4. Feature extraction using hybrid CNN and Bi-LSTM

The Bi-LSTM turns into the best method to create artificial cyclone intensity curves when the measurements of the cyclone intensity along depth are thought of as structured sequences because it can spread information from adjacent depths with depth-term dependencies in addition to capturing details from a sequence of data. At the same time, the benefits of CNN for extracting abstract features are described. Fig. 3 depicts the suggested CNN and Bi-LSTM approach’s conceptual layout. This architecture consists of two branches, one of which uses CNN to gather the characteristics of cyclone intensities and the other of which implements the feature selections using a two-layer Bi-LSTM. For the last dense layer to produce the goal predictions, the features from two branches are combined and mixed together.

The CNN’s convolution layer is a crucial component. Every convolutional layer contains a number of convolutional kernels, which are organized using the input information to identify hidden characteristics and create feature maps. Convolutional layer output is produced using feature maps and a non-linear activation function. Following are several ways to express the convolutional layer:

$$C_j = F(W_j \times z_j + b_j) \tag{3}$$

In Eq. (3), the convolution layer’s input is represented byz_j. C_j uses the j^{th} output feature map as its reference. W_j represents the convolution operation’s weight matrix. The dot product operation between the weight matrix and the input is represented by the $'' \times ''$ symbol. b_j the bias vector that was applied to the outcome of the dot product is represented. The function used for activation is represented by $F(.)$. The activation function for CNNs is frequently selected to be the rectified linear unit (ReLU) function. ReLU is defined mathematically in Eq. (4):

$$C_j = F(h_j) = \max(0, h_j) \tag{4}$$

Where, h_j is a feature map component that was created by convolutional operations.

The pooling procedure has two goals: it decreases feature maps’ dimensions and acts as a safeguard against overfitting. Max pooling is the most often used pooling technique. According to Eqs. (5) and (6), max pooling achieves this goal by locating the maximum value within a predetermined area of the feature maps.

$$\Delta(C_j, C_{j-1}) = \max(C_j, C_{j-1}) \tag{5}$$

$$\wp_j = \Delta(C_j, C_{j-1}) + \gamma_j \tag{6}$$

Where, γ_j denotes the bias, $\wp_j$ is the output of the max-pooling layer, and $\Delta(.)$ denotes the max pooling sub-sampling function. The feature maps are then sent into the fully connected layer after the convolutional and pooling procedures. The model calculates the ultimate output vector in

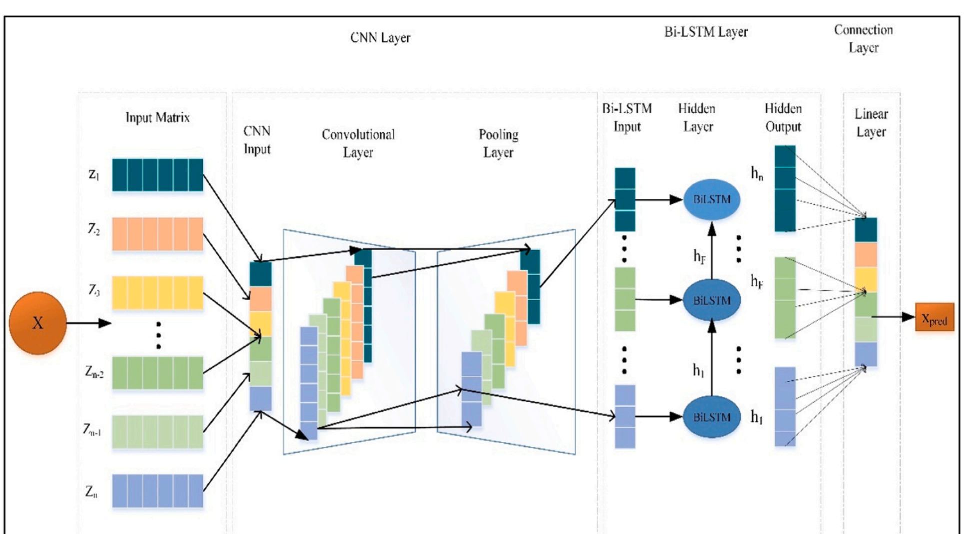

Fig. 3. Architecture of hybrid CNN and Bi-LSTM.

this layer, as shown in Eq. (7):

$$y_j = F(t_j \wp_j + \gamma_j) \tag{7}$$

Here, y_j stands for the final output vector, γ_j stands for the bias, and t_j stands for the weight matrix.

The only context that conventional LSTMs may use is the past with forward hidden layers and backward hidden layers, bidirectional architecture was able to simultaneously extract contextual information from both ways.

Fig. 2 shows that the forward and backward hidden layers' respective outputs, $\overrightarrow{h_{T'}}$ and $\overleftarrow{h_{T'}}$, are shown. The outputs and hidden sequences of the forward layer are computed sequentially, starting at step 1 and continuing up to step T'. The output and hidden sequences of the backward layer, however, move from step T' back to step 1 in the opposite direction. The forward layer and backward layer outputs, $\overrightarrow{h_{T'}}$ and $\overleftarrow{h_{T'}}$, are computed using the conventional LSTM. A vector, y, with each element generated using Eq. (8) is the result of the Bi-LSTM layer.

$$y_{T'} = \alpha\left(\overrightarrow{h_{T'}}, \overleftarrow{h_{T'}}\right) \tag{8}$$

The two sequences, $\overrightarrow{h_{T'}}$ and $\overleftarrow{h_{T'}}$, are integrated within the Bi-LSTM model using a function. This function may be expressed as a summation function, multiplication function, concatenation function, or average function, among other variations. When a Bi-LSTM layer is used to do cyclone intensity prediction, the final output can be written as a vector, $y = [y_1, y_2, \ldots\ldots, y_{T'}]$, where the last element, $y_{T'}$, represents the anticipated value for the following depth.

4.5. *Optimizing cyclone intensity prediction through GA enhanced fruit fly optimizer*

With the help of the Fruit Fly Optimizer, it is possible to estimate cyclone intensity more accurately by combining a genetic algorithm (GA) with the features of fruit flies. GA is an adaptable approach that can handle a variety of optimisation issues, both confined and uncontrolled. The purpose of using GA in this situation is to increase a network's durability and speed. In particular, it helps in choosing sensor nodes with the highest energy and storage capacity, increasing the network's lifetime and improving the effectiveness of sensor nodes inside a wireless sensor network [33]. This optimisation strategy is based on the eating habits of fruit flies, which are renowned for their keen vision and ability to detect smell. Every fruit fly in a group keeps track of where it is in relation to the amount of food present in the surrounding area as it seeks for nourishment. They assess the number of smells and travel towards the area with the greatest amount of nourishment, ultimately optimising their foraging technique. An objective function that has the inverse of the smell intensity as its optimisation goal can be used to mathematically convey this behaviour.

$$\begin{array}{c} \min Fitness(y) \\ s.t.y \in [Lb_j, Ub_j] j = 1, 2, \ldots\ldots, n* \end{array} \tag{9}$$

In Eq. (9), the fruit fly optimisation algorithm's fitness function, or fitness(y), represents the objective function that is equal to the reciprocal of the scent concentration. $y = (y_1, y_2, \ldots., y_n)$ represents the fruit fly vector for the parameters under optimisation. Lb_j (Lower bound) and Ub_j (Upper bound) is the values within the search image.

Four major steps make up the optimisation algorithm:

Step 1: Set the upper (Ub) and lower (Lb) boundaries for the search range, the total number of iterations (*maxgen*), the total population size of the fruit fly swarm (*popsize*), and the index of each individual fly (n)as starting algorithm variables. Under the predetermined parameters, a random location is chosen for the swarm at first.

$$\begin{cases} Y_{ini*} = Lb + (Ub - Lb) \times rand() \\ Z_{ini*} = Lb + (Ub - Lb) \times rand() \end{cases} \tag{10}$$

Where Eq. (10), a random number between 0 and 1 is produced using the function rand ().

Step 2: Each fruit fly searches for food by assessing smell concentrations and communicating its location with others.

Step 2.1: Calculate a new position for each fruit fly with Eq. (11) and measure its separation from the original location with Eq. (12).

$$\begin{cases} y_j = y_{ini*} + rand() \\ Z_j = z_{ini*} + rand() \end{cases} \tag{11}$$

$$Dist_j = \sqrt{y_j^2 + z_j^2} \tag{12}$$

Step 2.2: Determine the fruit fly's smell concentration judgement value (S_j) by taking the reciprocal of its distance, and then plug that value into the fitness equation as stated in Eq. (13) to get the smell concentration ($Smell_j$):

$$\begin{cases} S_j = \dfrac{1}{Dist_j} \\ Smell_j = fitness(S_j) \end{cases} \tag{13}$$

Step 3: Then, relocate the swarm to the area where there is the least amount of fruit fly odour present by using Eq. (14).

$$\begin{cases} [best \quad smell, best \quad index] = \min(smell) \\ y_{ini*} = y(best \quad index) \\ z_{ini*} = z(best \quad index) \end{cases} \tag{14}$$

Step 4: Continuously iterate through Steps 2 and 3 until either the desired cyclone intensity prediction has been achieved or the maximum number of iterations has been reached. This iterative process mimics the search and adaptation behaviour inspired by fruit flies, aiding in the optimization of cyclone intensity prediction [34].

By using this optimisation strategy, Cyclone Intensity Prediction can have access to improved search capabilities motivated by the cooperative foraging behaviour of fruit flies, ultimately producing forecasts that are more precise and effective.

GA Enhanced Fruit Fly Optimized Hybrid CNN-Bi-LSTM Algorithm	
Input: INFRARED and RAW cyclone imagery dataset	
Output: Cyclone Intensity Prediction	
Load the input image	
Perform preprocessing process	*//Data Resizing and Normalization*
Feature extraction using Hybrid CNN-Bi-LSTM	*//CNN layers extract spatial characteristics. LSTM layers record temporal dependencies.*
Feature Selection	*//GA enhanced FFO*
	// Initialization of a parameter
1. Set population size and maximum iteration	*// Combining visual and smell indicators to predict cyclone severity.*
2. Initialization of swarm location	*//Adaptive value Calculation*
3. Repeat	
4. (Best smell, best index) =fitness	
5. If best smell< smell best,	
Then, $y_{ini} = y$(best index)	
$z_{ini} = z$(best index) And then, best smell=smell best	
6. t=t+1	
until t=maximum iteration or find food	
End	

5. Results and discussion

This section discusses the outcome of the suggested model's efficiency in cyclone intensity prediction. By utilizing an extensive dataset that included both RAW and INFRARED cyclone pictures, the model was able to attain an astounding 99.4% accuracy rate. The implementation was carried out in Python and involved a number of steps, including feature extraction, normalization, and data downsizing using a hybrid CNN and Bi-LSTM architecture. The model's great precision was largely due to the optimization step, which included a GA augmented Fruit fly Optimizer. These results highlight the robustness of the suggested method and show that it has the capacity to accurately anticipate cyclone strength, which is important for risk reduction and disaster preparedness.

5.1. Aspect ratio distribution

The statistical distribution of aspect ratios within a dataset of cyclones is referred to as the "aspect ratio distribution" in cyclone intensity prediction. Aspect ratio, which is commonly expressed as the ratio of the major axis to the minor axis of the storm system, is an indicator of how circular or elongated the cloud pattern of a cyclone is. Analyzing the aspect ratio distribution in the context of cyclone strength prediction sheds light on cyclone shape aspects. Meteorologists and climate scientists can better forecast the strength of cyclones by knowing how these ratios change between various cyclones. This will help them analyze the severity and possible evolution of cyclonic systems.

Fig. 4. provides important information on the form properties of these meteorological systems. The aspect ratio values are plotted on the x-axis, which shows the proportion of the major to minor axes of the cyclones. A visual depiction of the distribution throughout the dataset is given by the y-axis, which measures the frequency of occurrence for each aspect ratio. Trends in cyclone forms in the dataset are explained by the graph's peaks and patterns, which display common aspect ratios. This kind of visualization is helpful in recognizing the differences and similarities among cyclone structures, providing vital data for models that predict cyclone intensity, and assisting meteorologists in identifying the various shapes that cyclonic systems might take in the dataset.

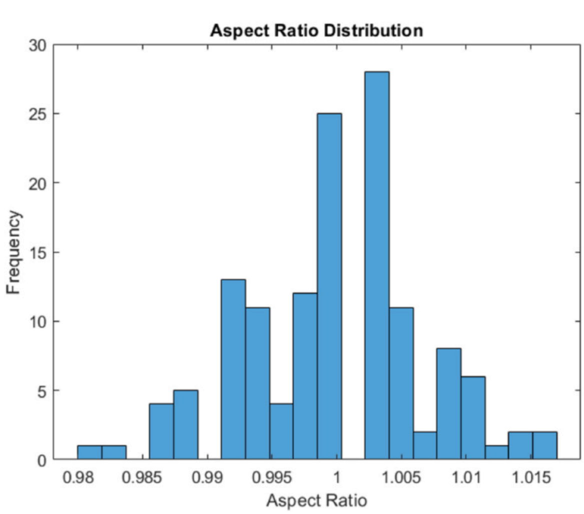

Fig. 4. Aspect ratio distribution.

5.2. Cyclone intensity

A graph that shows the fluctuations in the strength or intensity of cyclonic systems over a given time span is called a cyclone intensity graph. The graphic illustrates the variations in cyclone intensity categories, which can vary by location and range from tropical depressions to hurricanes or typhoons. These categories are typically quantified on a scale like the Saffir-Simpson Hurricane Wind Scale. Fig. 5. shows the cyclone intensity.

Fig. 6. shows how different cyclone intensity prediction measures are distributed within a certain dataset. Cyclone frequency is plotted on the x-axis, and various metrics are plotted on the y-axis, such as hurricane wind radius, maximum wind speed, rainfall rate, storm surge height, forward speed, tornado potential, sea surface temperature, eyewall replacement cycle, and duration. A metric's frequency within the dataset is indicated by each data point on the graph. With its ability to display trends and variances in the frequency of several metrics connected to cyclones, this visual representation offers a thorough summary of the dataset's attributes. By gaining knowledge about how storm features are distributed, analysts can spot patterns and connections that lead to a more complex comprehension of cyclone activity.

5.3. Error metrics

Error metrics are quantitative measurements used to assess the precision and efficacy of prediction models. Examples of these metrics are Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R-squared (R^2). The mean absolute error (MAE), which is given in Eq. (15) measures the difference between the expected and actual outcomes and gives a clear picture of prediction mistake. The average squared difference (MSE) between the actual and anticipated values highlights bigger mistakes, which is represented in Eq. (16). The square root of the average squared differences, or RMSE, is a statistic that provides information in the original measurements of the projected values. It is derived from MSE. A greater value denotes better predictive accuracy. R^2, or the coefficient of determination, measures the percentage of variance in the dependent variable explained by the model. Together with each other, these metrics help to thoroughly evaluate the accuracy and dependability of prediction models, enabling well-informed choices across a range of fields, such as data analysis, statistics, and machine learning.

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}| \tag{15}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y})^2 \tag{16}$$

Fig. 7, which shows the metrics MAE, MSE, RMSE, and R2 on the x-axis, offers a thorough summary of the model evaluation metrics. The y-axis displays the predictive model's efficacy by quantifying the associated values for every metric. Interestingly, the average absolute difference between the expected and actual values is represented by the Mean Absolute Error (MAE), which is recorded at 5. Because of its low value of 2.1, the Mean Squared Error (MSE) highlights the squared discrepancies between the actual and anticipated values. The square root of the average squared discrepancies in the original units of the predicted values is represented by the Root Mean Squared Error (RMSE), which is 5.1%. A high R2 score of 0.99 suggests that the model accounts for a sizable amount of the variance in the dependent variable. The decreased error metrics and high coefficient of determination in this graph demonstrate the predictive model's effectiveness in addition to providing a visual depiction of its performance across these important measures. Table1 refers the comparison of error metrics.

5.4. Scatter plot for predicted vs actual

A scatter diagram for a graphical representation of the relationship between the anticipated intensity values and the corresponding actual intensity values of cyclones is called "Predicted vs. Actual" in cyclone intensity prediction. The x-axis in this map shows the anticipated intensity values produced by a predictive model, while the y-axis shows the actual observed intensity values. Each point in this plot represents a distinct cyclonic event. By displaying the alignment or divergence between anticipated and actual values, the scatter plot offers a visual way to evaluate the predictive model's accuracy and precision. Points along a diagonal line that are tightly clustered indicate a strong connection and accurate forecasts, whereas dispersed points show differences between the actual and expected intensities.

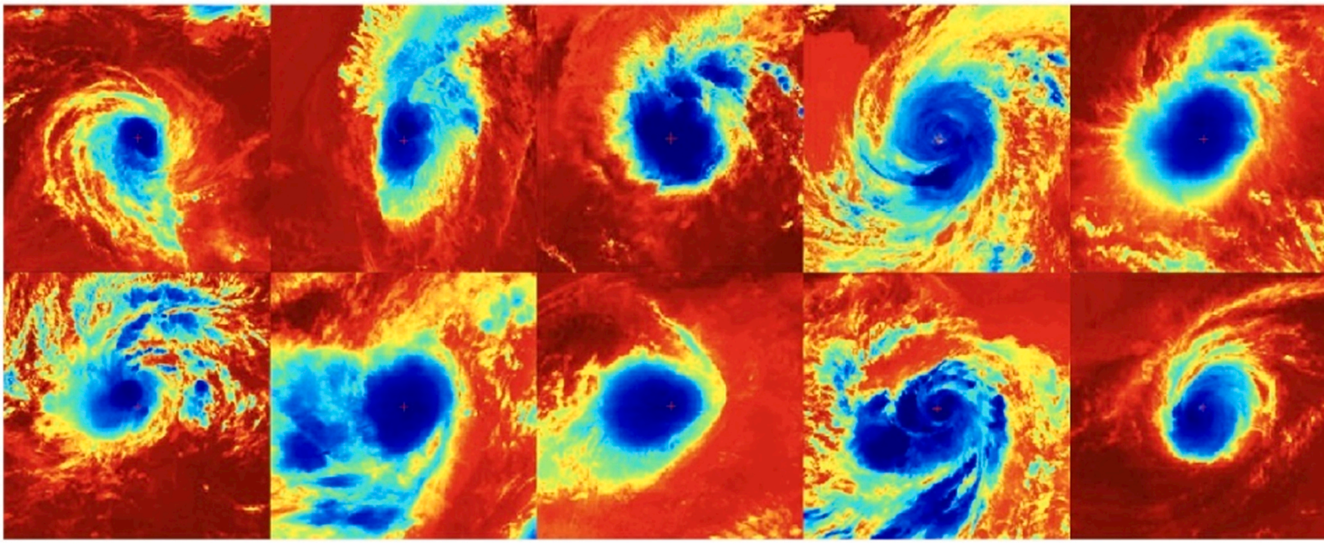

Fig. 5. Intensity of cyclone.

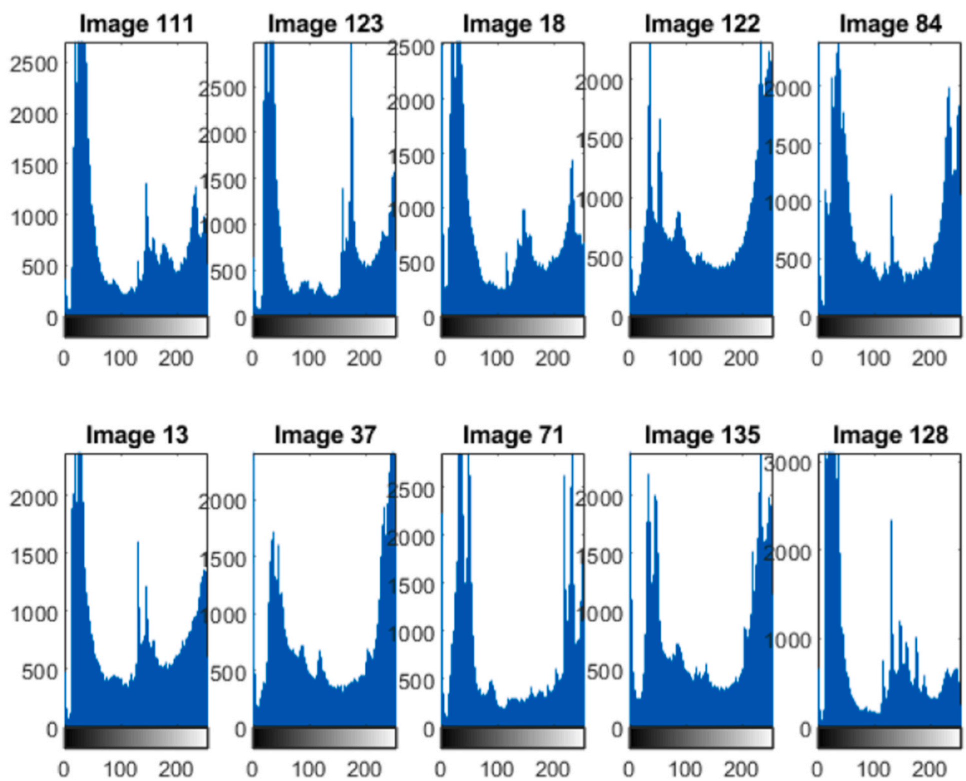

Fig. 6. Distribution of various cyclone intensity metrics in the dataset.

The correlation between the appropriate expected performance index and the actual performance index is visually represented in Fig. 8. The real performance index values are plotted on the x-axis, which shows the observed intensities of the cyclones. The predictive model simultaneously generates expected performance index values, which are quantified on the y-axis. Every data point represents a distinct cyclonic event on the scatter plot, and the position of the point indicates how well the model predicted the strength. Precise predictions are indicated by a tight clustering along the diagonal line, which indicates a strong agreement between expected and actual values. On the other hand, disparities are indicated by dispersed points, which draw attention to situations in which the predicted model differs from the measured intensities.

5.5. *Actual vs predicted performance*

Actual vs Predicted Performance is a quantitative assessment that contrasts the actual or observed results with the related expectations produced by a system or model. Numerous industries, including data analytics, forecasting, and machine learning, frequently use this performance evaluation. For example, Actual vs. Predicted Performance in the context of cyclone intensity prediction measures the degree of agreement between the actual cyclone intensity values and the intensity values predicted by a predictive model. This comparison reveals any

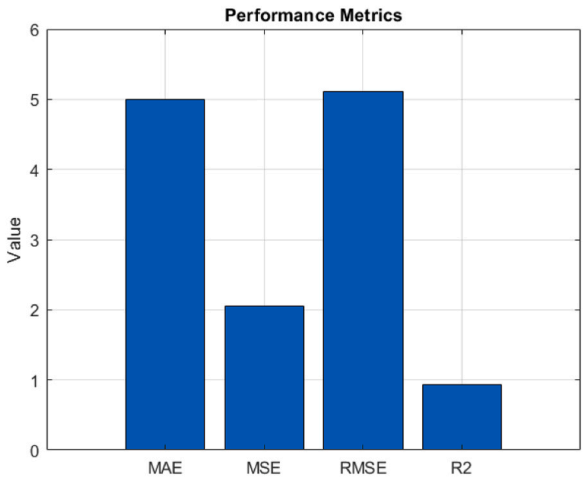

Fig. 7. Performance metrics.

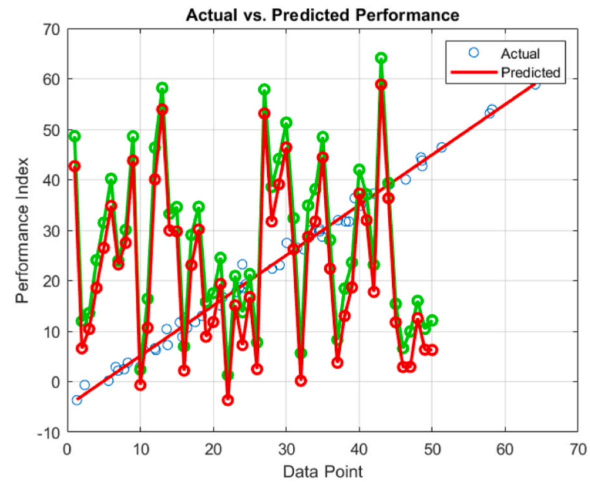

Fig. 9. Actual vs predicted performance.

Table1
Comparison of error metrics.

Methods	MAE	MSE	RMSE	R2 Score
VGG-16	15	5.3	10	7.55
Ty 5- CNN	8.76	4	9	4.22
Proposed CNN-Bi-LSTM Model	5	2.1	5.1	0.99

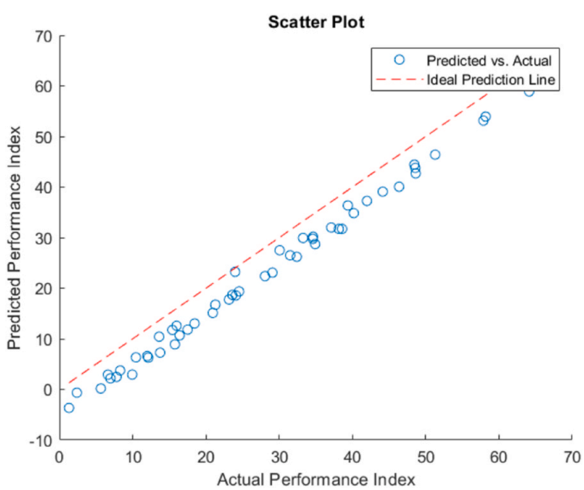

Fig. 8. Scatter plot.

discrepancies or consistency between expected and observed outcomes, offering insights into the model's accuracy and dependability.

Visual representation of the alignment between observed data points and related anticipated performance indices is provided by Fig. 9. The y-axis measures the performance index, which is produced by a predictive model and spans from −10–70. On the x-axis, data points from 0 to 70 indicate particular cases or events. It is intuitive to compare the actual results with the forecasts because each plotted point on the graph represents a unique observation. The points' distance from the diagonal line represents the model's accuracy; a tighter clustering suggests more accurate predictions. Disturbances between the actual and anticipated performance indices, on the other hand, are indicated by deviations from the diagonal line.

5.6. Fitness improvement over GA enhanced fruit-fly optimization

Fitness Improvement Over GA Enhanced Fruit-fly Optimization is an enhanced optimization technique used in cyclone intensity prediction that combines Fruit-fly Optimization Algorithm (FOA) and Genetic Algorithm (GA) to improve and optimize a predictive model's fitness function. In order to guarantee that the predictive model converges to more ideal solutions, the integration of GA and FOA attempts to enhance the overall performance and accuracy of the optimization process. The resultant Fitness Improvement Over GA Enhanced Fruit-fly Optimization method successfully utilizes the complementary strengths of GA and FOA inside the optimization framework in an effort to attain improved accuracy in cyclone intensity prediction.

The optimization process across multiple iterations in the context of cyclone intensity prediction is visually shown by Fig. 10. The x-axis shows the number of iterations (from 0 to 100) that represent the various actions that were done to improve the predictive model. In addition, the y-axis quantifies the fitness values, which span 0.01–0.1 and show how accurate and successful the model is at each iteration. The graph shows the evolution of the fitness values as the iterations go on, indicating the convergence towards more ideal solutions. The model's predictive performance keeps becoming better, as seen by a declining trend in the fitness values.

5.7. Comparison of the performance metrics with other methods

A comparison of the suggested CNN-Bi-LSTM model, Ty 5-CNN, and VGG-16 are among the methods for predicting cyclone strength that are shown in Table 2 and Fig. 11. The accuracy percentages show how

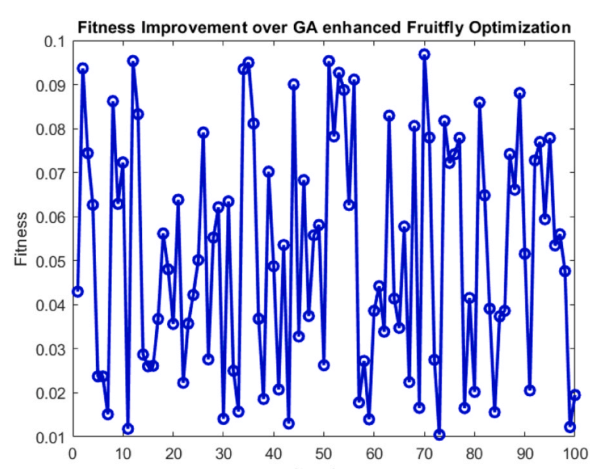

Fig. 10. Fitness improvement Over GA enhanced fruit-fly optimization.

Table2
Comparison of the performance metrics with other methods.

Methods	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
VGG-16 [35]	78	96	76	81
Ty 5- CNN [36]	95.23	95.25	95.23	94.12
Proposed CNN-Bi-LSTM model	**99.4**	**99**	**98.12**	**99.1**

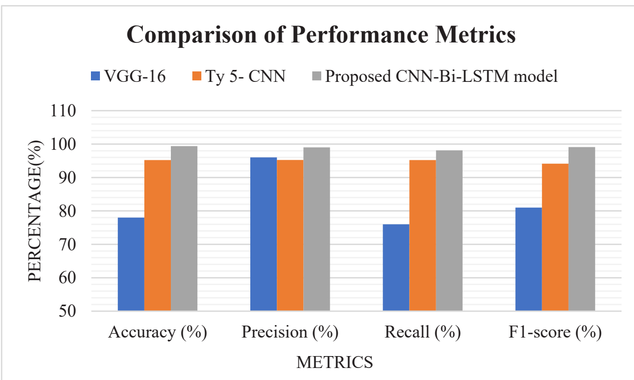

Fig. 11. Comparison of performance metrics.

accurate the models are overall. The CNN-Bi-LSTM model that has been suggested has an astounding accuracy of 99.4%, which is higher than both the VGG-16 (78%) and Ty 5-CNN (95.23%) models combined. The precision percentages show how well the models can detect positive cases; at 99%, the suggested model performs better than the other models. Recall percentages show how well the models capture all positive cases; the suggested model outperforms VGG-16 and Ty 5-CNN in this regard, obtaining an astounding 98.12% recall. The proposed CNN-Bi-LSTM model's balanced performance of 99.1% is further highlighted by the F1-score, which is a harmonic mean of precision and recall. In comparison to the evaluated techniques, these results collectively demonstrate the improved predictive capabilities of the proposed model, indicating its potential as a highly accurate and dependable tool for cyclone intensity forecasting.

5.8. Discussion

The outcomes of the extended research provide vital insights into the performance of the GA-enhanced Fruit-fly Optimized Hybrid CNN-Bi-LSTM model in predicting cyclone intensity, which is closely related to the research objective of enhancing cyclone intensity forecasting [37, 38]. Cyclone strength prediction is critical for effective disaster preparedness and response, considering its direct impact on coastal areas and inhabitants. This study tackles the urgent need for more accurate cyclone intensity prediction by providing a novel predictive model that incorporates a hybrid CNN and Bi-LSTM architecture optimized using a Genetic Algorithm (GA) enhanced Fruit Fly Optimizer (FFO) [39,40].

The data presented, which include Aspect Ratio Distribution, Cyclone Intensity, Performance Metrics, and Scatter Plots, provide a thorough assessment of the model's predicting capacity. The aspect ratio distribution sheds information on cyclone shape properties, which may influence their strength [41]. Cyclone intensity results provide significant information on the distribution of storm strength across the dataset. Performance indicators such as R2, RMSE, MAE, and MSE assess the model's accuracy, whereas scatter plots show the alignment of projected and actual cyclone intensities, providing a visual picture of the model's performance. The comparison of actual and anticipated performance confirms the model's efficacy. The CNN-Bi-LSTM model outperforms Ty 5-CNN [36] and VGG-16 [35] in accuracy (99.4%), precision (99%), recall (98.12%), and F1-score (99.1%), highlighting its superior predictive capabilities for cyclone intensity forecasting.

The supporting data of Fitness Improvement Over GA Enhanced Fruit-fly Optimization emphasizes the efficiency of the optimization technique, demonstrating the model's resilience and ability for exact forecasting. This framework significantly improves cyclone intensity prediction capabilities by resolving inadequacies in traditional machine learning models and meteorological data use, resulting in improved catastrophe preparedness and response methods.

6. Conclusion and future work

This study proposes an effective method for improving cyclone strength prediction by incorporating a Fruit Fly Optimized Hybrid CNN-Bi-LSTM model augmented by GA. Rigorous pre-processing procedures, such as data reduction and normalization, are used, along with a thorough data gathering plan that includes both INFRARED and RAW cyclone images. The suggested model is built on a novel feature extraction method that uses a hybrid CNN and Bi-LSTM architecture, which is then upgraded with a GA-enhanced Fruit Fly Optimizer. The results highlight the usefulness of this integrated technique, with enhanced prediction accuracy and dependability for cyclone strength forecasts. By applying complex optimization approaches, the study highlights the potential for improving forecast models for critical weather events, ultimately advancing meteorology. The findings contribute by demonstrating the superiority of the proposed hybrid CNN-Bi-LSTM model over existing methods, challenging traditional methodologies, and greatly improving cyclone intensity forecast accuracy.

The study's limitations include its reliance on retrospective data, which may limit its applicability to real-time forecasting scenarios. The suggested model's performance may change between geographical locations and meteorological conditions, necessitating additional validation across multiple datasets. The computational complexity of the model and optimization procedure may provide difficulties for real-time implementation, necessitating efficient computing resources. While the hybrid CNN-Bi-LSTM architecture produces promising results, its interpretability and robustness to outliers or noise in the data need to be thoroughly investigated. Additional study is required to address these shortcomings and improve the model's dependability for operational application in cyclone strength prediction. Future research directions include looking into other optimization approaches and incorporating diverse datasets to help refine the model. Investigating the effects of various meteorological variables on cyclone strength may potentially improve forecasting capabilities. Extending the study to include real-time data integration and analysing model performance across multiple geographic areas would improve its application and resilience in a variety of environmental circumstances.

Declaration of Competing Interest

The authors declare that the research was conducted without any commercial or financial relationships construed as a potential conflict of interest.

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