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Recent Advances in Tropical Cyclone Forecasting

Abstract: - Tropical cyclones (TCs) are low-pressure weather phenomena characterized by a revolving circulation of high winds, heavy rain, and thunderstorms. TCs cause catastrophic damage if they make landfall in populated areas. Therefore, it is essential to monitor and prepare for potential disasters in the form of emergency responses or evacuations. For decades, predicting the intensity of tropical cyclones has been a challenging problem. The use of machine learning techniques to predict TCs is still challenging due to the number of parameters used for prediction and the availability of historical data. This paper highlights the techniques and parameters used to estimate TCs. This paper focuses on significant parameters such as ocean indices, sea surface temperature, and many others that have a greater impact on the formation of TCs. This paper discusses various opportunities and challenges in forecasting TCs in advance and the factors influencing the formation of TCs. The challenge is obtaining long amounts of historical data to analyse all ocean indices. Although many researchers have utilized ML techniques, the accuracy of TCs is still a more significant issue. Our survey focused on the importance of data fusion in accurately predicting TCs and their intensities.

Keywords: Data Fusion, Indian Ocean Dipole (IOD), Machine Learning Techniques, Ocean Indices, Sea Surface Temperature (SST), Tropical Cyclones (TC), Wind Shear (WS).

I. INTRODUCTION

The warm waters of the Bay of Bengal and Arabian Sea basins generate cyclones during the summer and fall, bringing heavy rain, high winds, and large waves. The damage they cause can be severe. In recent years, tropical cyclones have become more frequent and intense due to climate change. It is, therefore, essential to understand their formation process to better prepare for future events. Solid winds converge towards the center by an inwards spiral convergence of low pressure [1]. Tropical cyclones are significant natural hazards in India because they cause socioeconomic and human loss to a large extent. Sea surface temperature (SST), sea level pressure (SLP), wind speed and direction, and other ocean indices are believed to be the factors that drive TCs.

Forecasting the intensity of tropical cyclones has always been challenging for both researchers and cyclone prediction teams. Various studies have been conducted on the internal dynamics, wind shear (WS), and other dry dynamics of tropical cyclones [2], [3], [4], [5], [6], [7]. However, few studies have explored whether the impact of vertical wind shear on the evolution of TCs is also very high [8], [9], [10], [11] or vice versa.

The extent of deep shear was estimated to calculate differences between winds at standard pressure levels of 200–850 hPa [10]. Several investigations have shown that low-level sensible and heat flumes are critical for TCs in tropical seas [12]. [13] A relationship has been observed between the SST and the maximum intensification rate of TCs in the North Atlantic Ocean. However, the impact of the wind shear magnitude on TC formation remains an unsolved problem [3].

Although there are various parameters to be considered with varied impact levels, most researchers have considered one or two parameters, or very few were considered in estimating TCs. In addition to considering many parameters, such as wind speed, shear, and SST, meteorologists need to consider the ocean index, which has a greater impact on TC formation and intensity. There are different ocean indices, such as the Indian Ocean Dipole (IOD), El Nino-Southern Oscillation (ENSO), North Atlantic Oscillation (NAO), quasibiennial oscillation (QBO), Atlantic Multidecadal Oscillation (AMO) and Madden–Julian Oscillation (MJO). Every ocean index has an impact on tropical cyclones at various locations. Various studies have demonstrated the impact of one ocean index on the other.

These TCs have been predicted until recently based on specific statistical/numerical models [14]. However, although various models are available, some metrological cyclone prediction stations still utilize manual estimation. Nevertheless, the accuracy of prediction is of primary concern. Hence, to overcome the issues about the accuracy of prediction, the advent of computing technological advancements has made these calculations much more manageable with increased accuracy.

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Considering the advantages of computing power and its prediction accuracy, in addition to the statistical models adopted, large amounts of historical data on TCs globally paved the path for utilizing machine learning techniques in handling large-scale datasets [15], [16]. In some experiments, researchers have utilized many advanced techniques, such as CNNs, RNNs, and long short-term memory (LSTM) networks [14] [15], [16]. As a result, studies have proven such models to have some improved accuracy. However, the accuracy of longevity prediction is challenging. Hence, this paper focuses on various aspects of TC prediction with better accuracy.

The paper is structured as follows: Section I introduces TC prediction and highlights issues related to TC forecasts. Section II elaborates on the SST, wind speed, sea level pressure, and ocean index, and Section III demonstrates the impact of the shutdown of the thermohaline circulation. Section IV explores various machine learning techniques utilized by various researchers and their advantages and disadvantages. Section V addresses prediction accuracy challenges, and Section VI concludes the paper.

II. Related Work

A. Sea Surface Temperature (SST), Sea Level Pressure, and Wind Speed.

The sea surface temperature, or SST, measures the average temperature in the uppermost layer of seawater (the top millimeter). It varies depending on location and time but typically ranges from 2 to 30°C°C (29–86 °F). Measurements are primarily collected through satellite imagery and drifting buoys that detect local changes in seawater temperatures over time. SSTs are essential for understanding the Earth's climate, as they help to regulate temperatures and weather patterns. They also affect ocean currents and marine life, making them an essential part of monitoring the health of our planet's oceans.

Sun et al. [3] conducted a study on the effects of outer and inner sea surface temperatures (SSTs) on tropical cyclone (TC) intensity. Researchers have used a high-resolution Weather Research and Forecasting (WRF) model to conduct a series of sensitivity experiments and investigate how changes in SST at different radial extents affect TC intensity. The study revealed that the inner and outer SSTs impose opposite effects on the TC intensity. Specifically, inner SSTs negatively affect TC intensity, while outer SSTs have a positive impact. The study also revealed that understanding the mechanisms behind these effects is crucial for predicting variations in TC intensity and inner core size when a tropical cyclone encounters a cold or warm ocean pool. This study provides insights into the complex relationship between SST and TC intensity, which could help improve our understanding and forecasting of tropical cyclones, a crucial area of research given their potential for catastrophic impacts.

Jing Xu et al. [13] established a relationship between the maximum potential intensification rate (MPIR) and sea surface temperature of tropical cyclones utilizing best-track TC data and SSTs over 27 years from 1988–2014 in the North Atlantic. Consequently, the authors' findings support intensity prediction based on the optimized dynamical system model from several viewpoints.

Yuan et al. [16] conducted a study on the relationship between tropical cyclone genesis (TCG) over the Indian Ocean and sea surface temperature anomalies (SSTAs) in the tropical Indo-Pacific Ocean. They analysed datasets from the Joint Typhoon Warning Center from 1981–2015. They found a strong dependence between TCG in the Indian Ocean and SSTAs in the tropical Indo-Pacific Ocean. This study also investigated the impact of tropical Indo-Pacific Ocean SSTAs on the TCG environment in the Indian Ocean. The authors found that the Indian Ocean zonal dipole pattern had a more substantial effect on TCG than did the exclusive El-Nino (ENSO) or Indian Ocean dipole (IOD) modes. This study emphasizes the intricate interaction of oceanic and atmospheric elements that leads to the formation of tropical cyclones across the Indian Ocean. Understanding these links is critical for enhancing our capacity to forecast and minimize the effects of tropical cyclones, which may be catastrophic for residents in impacted regions.

M A K Mallik et al. [17] conducted an intensive study to identify the monotonic seasonal and annual trends of monsoon depressions that formed across the Bay of Bengal basin for 33 years, from 1981 to 2014. They utilized the Mann–Kendall test and Sen's method. The observations revealed that the SST showed an increasing trend over the Bay of Bengal and a negative trend over Bangladesh. The findings also revealed that the mean easterly wind prevailed over the lower latitudes at 850 hPa.

Maneesha Sabastian and Manasa Ranjan Behra [18] have attempted to identify the correlation between cyclonic activities and climatic change in the North Indian Ocean (NIO) basin. The power dissipative index (PDI) over the NIO, along with the Arabian Sea and the Bay of Bengal basins, was calculated individually along with the SSTs over the temporal periods. Their results proved that more than the SST is needed to establish the changing climate in the NIO region for cyclonic activities in the future.

Yuan Sun et al. [19] studied this topic based on gaps in previous research, ignoring the effect of changes in the size of tropical cyclones on global warming. The insufficient historical data led to the underestimation of TC destructive potential and the linkage between SST and TC size due to global warming. Their study also revealed that TCs should become more prominent, stronger, and unexpectedly more destructive due to global warming.

B. Ocean indices:

The ocean is a dynamic system, and its behavior is constantly changing. Ocean oscillations are one of the essential components of this change and have been studied extensively in recent years. These oscillations refer to periodic fluctuations in sea level, temperature, salinity, and other ocean properties that affect global climate systems. Ocean oscillations influence the world's climate by influencing global weather patterns and temperatures. They also play a role in catastrophic weather conditions, including storms, floods, droughts, and rising sea levels. Therefore, understanding these oscillations is crucial for predicting future climate changes and developing effective strategies to manage them. These oscillations also determine the intensity of TCs at different locations at different times.

i. Indian Ocean Dipole (IOD):

IOD produces different effects in the Bay of Bengal and Arabian Sea. IOD has two phases: the negative IOD phase and the positive IOD phase. A positive IOD has warmer SSTs than regular SSTs in the western and eastern basins, while a negative IOD has cooler SSTs than regular SSTs. The Arabian Sea has a greater SST during positive IOD events than does the Bay of Bengal basin, which is the opposite of what occurs during adverse IOD events. A positive IOD influences African coastal areas with floods and Australian areas such as Droughts; a negative IOD influences floods and hurricanes in Australia and droughts in Africa [20]. Both positive and negative events influence India's ISMR [21]. Table 1 lists the negative and positive IoD years, and Table 2 displays the effect of the IOD on the ISMR. During the neutral IOD, the anomalous SST ranges between -0.4°C and +0.4°C. According to [22], the IOD is independent of ENSO in the Pacific Ocean. The number of cyclones originating in either the Arabian Sea or Bay of Bengal basin is determined by whether the year is a positive IOD year or a negative IOD year. From Table 2 and Figure 1 to Figure 3, it can be observed that the number of TCs formed during negative IoDs is high and consistent. In contrast, it is highly less common and varies during positive IoD years. The dataset was collected from the Indian Meteorological Department.

TABLE I

POSITIVE AND NEGATIVE IOD YEARS AND THE CORRESPONDING CYCLONE COUNT AND IMD [23], [24]

Positive IOD Years	**1961, 1963, 1972, 1982, 1983, 1994, 1997, 2002, 2006, 2012, 2015**
Negative IOD Years	**1960, 1964, 1974, 1981, 1989, 1992, 1996, 1998, 2010, 2014, 2016**

TABLE II

NUMBER OF CYCLONES DURING POSITIVE AND NEGATIVE YEARS. DATA COLLECTED FROM THE INDIAN METEOROLOGICAL DEPARTMENT, INDIA

Year	Positive IOD/Negative IOD	Basin	# Count	Total	Intensified Cyclones
1982	Positive IOD	Bob	12		
		Arabian Basin	4	19	3
		Land	3		
1983	Positive IOD	Bob	2		
		Arabian Basin	2	7	2
		Land	3		
1994	Positive IOD	Bob	3		
		Arabian Basin	2	5	5
		Land	0		
1997	Positive IOD	Bob	8		
		Arabian Basin	1	9	2
		Land	0		
2002	Positive IOD	Bob	1		
		Arabian Basin	5	6	
		Land	0		
2006	Positive IOD	Bob	9		
		Arabian Basin	2	12	

		Land	1		
2012	Positive IOD	Bob	2		
		Arabian Basin	3	5	All are DD (Deep Depression)
		Land	0		
2015	Positive IOD	Bob	2		
		Arabian Basin	4	10	1
		Land	4		
1989	Negative IOD	BOB	9		
		Arabian Basin	1	10	2
		LAND	0		
1992	Negative IOD	BOB	8		
		Arabian Basin	4	12	2
		LAND	0		
1996	Negative IOD	BOB	8		
		Arabian Basin	2	11	3
		LAND	1		
1998	Negative IOD	BOB	6		
		Arabian Basin	4	10	4
		LAND	0		
2010	Negative IOD	BOB	6		
		Arabian Basin	2	8	3
		LAND	0		
2014	Negative IOD	BOB	5		
		Arabian Basin	2	8	2
		LAND	1		
2016	Negative IOD	BOB	6		
		Arabian Basin	2	10	4 are CS (Cyclonic Storm)
		LAND	2		

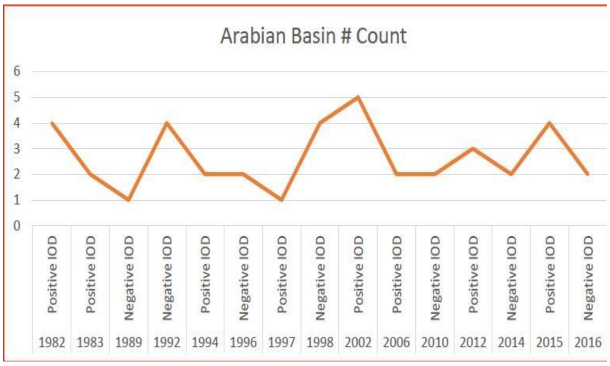

FIGURE 1: Graph displaying the number of cyclones that formed in the Arabian Basin during 1982–2016

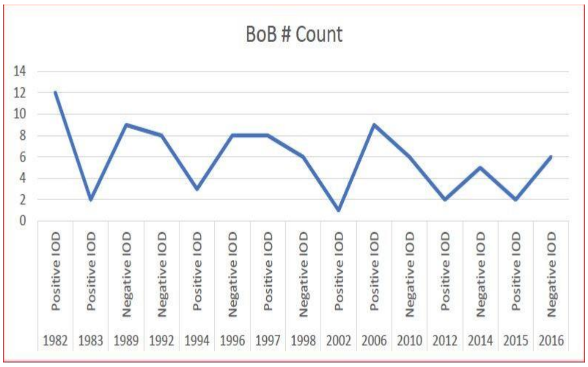

FIGURE 2: Graph showing the number of cyclones that formed in the Bay of Bengal Basin during 1982–2016

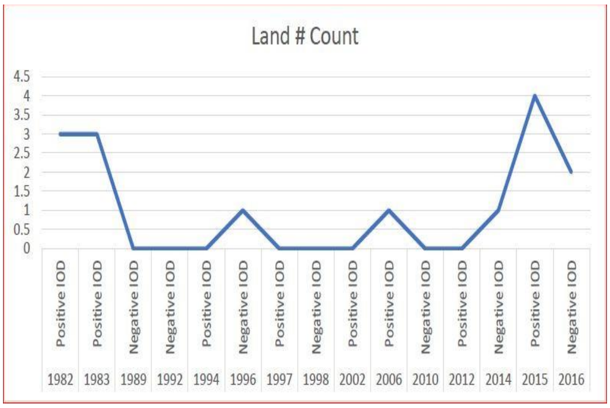

FIGURE 3: Graph showing the number of cyclones that formed on land during 1982-2016

ii. El Nino–Southern Oscillation (ENSO)

ENSO is a type of oscillation that occurs in the Pacific Ocean. It is a tropical climatic phenomenon that significantly impacts worldwide climatic conditions [25]. For example, in 1995 and 1998, mega-heatwaves and excessive rainfall during the summer monsoons devastated 20% and 8% of India, respectively [26]. As the two significant tropical climatic phenomena have both positive and negative occurrences, the effect on the ISMR is determined by the phase and amplitude of the IOD and ENSO. Although some IOD events may be connected to ENSO events, the present technique of considering the IOD as one of the critical coupled modes in the tropics successfully analyses the effects of the IOD on the ISMR [27]. According to specific research, ENSO teleconnections considerably influence tropical SSTs in the Indian Ocean during the spring but not throughout the summer [28]. IOD events independent of ENSO events showed less intense rainfall in northern India and more substantial rainfall in central India than did individual Nino events [21]. At the same time, another study showed that ENSO El Nino years strongly influence precipitation, evapotranspiration, and temperature in most districts of India compared with La Nina and neutral years [29]. Differences in the regional distribution and amplitude of SST anomalies and the associated atmospheric circulation are primarily responsible for ISM rainfall asymmetry [30]. India experiences a temperature of approximately 42°C and even a high, increased sea surface temperature (SST) (Sea et al.), with sea level pressure values of approximately 500 hPa during pre- and post-ENSO events [31]. The equatorial Atlantic SSTA (also known as Atlantic NINO) may also have an impact on ENSO evolution in future seasons [32], [33]. SST can influence the variability of the ISMR over the Atlantic Ocean (AO) in two ways: an "indirect pathway" in which the AO forces ENSO and alters the ENSO-ISMR teleconnection and a “direct pathway” in which the AO may directly force the ISMR in the absence of interactions with other vital aspects such as ENSO [34]. Tropical western Indian Ocean warming caused by the Atlantic NINO can also reduce India's rainfall [35]. During an El Nino event, cold waters in the North Pacific, cold waters in the western North Pacific, warm waters in the Indian Ocean, and a warm sea in the North Atlantic all coincide. Cold SST anomalies in the eastern Indian Ocean fade when El Nino winds form. As winter approaches, IOB basin-side warming accelerates quickly and peaks in spring [35].

iii. Madden–Julian Oscillation (MJO):

MJO and Boral simmer seasonal oscillations play a significant role in Indian Ocean climate change. Therefore, these two modes occur most frequently. The theoretical approach states that BSISO is symmetric about the equator, but practical observations state that BSISO is highly active and non-symmetric in the Northern Hemisphere [36]. During the Northern Hemisphere summer and early autumn, the MJO’s travel across the globe can periodically pause or stall, resulting in consistently increased rainfall on one side of the globe and consistently decreased rainfall on the other, which is also possible early in the year. The MJO can also fall silent for a while resulting in non-anomalous storm activity in any part of the world. The Madden–Julian oscillation activity varies significantly yearly, with extended periods of high activity followed by low or no activity periods. The MJO’s interannual inconstancy is partly connected to the ENSO cycle. Intense MJO events are frequently recorded in the Pacific approximately 6-12 months before an El Nino episode begins. However, it is almost absent at the maxima of specific El Nino episodes, whereas MJO activity is generally more significant during a La Nina event. Intense occurrences in the MJO in the Western Pacific over months might hasten the formation of an El Nino or La Nina but do not generally result in the commencement of a warm or cool ENSO event.

iv. Quasi-Biennial Oscillation QBO

The ENSO strongly influences the QBO, and less evidence is available because the availability of data on the QBO and corresponding cyclonic genesis is low. However, many past studies have shown that teleconnections between the QBO and ENSO were more frequent from 1953 to 1980. After 1985, the relationships between the ENSO and the QBO indices became increasingly positive, and the positive IOD frequently exhibited a QBOW phase, while the negative IOD frequently exhibited a QBOE [37]. The QBO is a cycle of winds in the tropical stratosphere oscillating between the easterly and westerly directions approximately every 28 months. Although the QBO can strongly influence atmospheric circulation and weather patterns, its behavior is difficult to predict, and reliable forecasts of its timing or strength are currently needed. The QBO affects the North Atlantic Oscillation (NAO). The NAO is a large-scale atmospheric circulation pattern influencing weather in the North Atlantic region, including Europe. The QBO can influence the NAO by affecting the position and strength of the jet stream. However, the need for reliable QBO cycle forecasts makes using this information for seasonal weather forecasts challenging. For example, while scientists may speculate that the coming winter could be warmer and stormier in the northern European region based on the potential influence of the QBO on the NAO, there still needs to be more certainty in these predictions. Overall, while the QBO and its potential influence on weather patterns are areas of ongoing research, it is vital to recognize the limitations of our current understanding and forecasting abilities.

v. The Atlantic Multidecadal Oscillation (AMO)

The Atlantic Multidecadal Oscillation (AMO) is a natural pattern of ocean temperature oscillations that have occurred over many decades to a century in the North Atlantic Ocean. Sea surface temperature variations in the AMO can substantially affect regional weather patterns, ocean currents, and marine ecosystems. During an AMO-positive phase, the SST in the North Atlantic is greater than usual, resulting in more frequent and severe storms in the Atlantic basin and changes in rainfall patterns and ocean circulation. In contrast, during an AMO-negative phase, sea surface temperatures in the North Atlantic are lower than usual. They can result in lower storm activity and changes in other climate and ocean conditions. Both natural climatic cycles and exogenous causes, such as variations in solar radiation and volcanic activity, influence the AMO. However, the precise mechanisms behind the AMO remain unknown, and research is being conducted to identify the drivers and implications of this crucial ocean oscillation. The AMO has an estimated 60-80-year period in the North Atlantic Ocean, which occurs coherently. The indicator is based on sea surface temperature (SST) anomalies from 0 to 80°N in the North Atlantic basin. The SST-based definition of the AMO index frequently leads to an insufficient understanding of the AMO in terms of North Atlantic SST anomalies. The AMO, on the other hand, reflects coherent multivariate low-frequency variability in the Atlantic, such as correlated changes in subpolar North Atlantic heat content and salt content, turbulent heat fluxes driven by the ocean, and anticorrelated changes in tropical North Atlantic subsurface temperature. The suggested AMO processes should explain the observed coherent multivariate low-frequency variability and low-frequency SST changes in the North Atlantic. Therefore, employing multivariate measures to comprehend the mechanisms underlying AMO is critical. However, in comparison to the multidecadal length of the AMO, the available SST data are short. The SST-based AMO does not adequately represent AMO characteristics such as subsurface temperature, coherent fluctuations in salinity, and turbulent heat fluxes in the ocean. The relative role of large-scale ocean circulation vs. external radiative forcing in generating the AMO is challenging to define.

III. Global Thermohaline Or Conveyor Belt

Global thermohaline circulation or variable sea currents and the flow of sea currents play vital roles in global climate change. The Indian Ocean is connected to 3 major ocean regions, and changes in the Indian Ocean affect the other two regions. Due to IOD events, anomalous wind events drive ocean circulation [38]. Internal variability is one factor for IOD, and ENSO is another. Global thermohaline causes internal variability.

Impact Due To Shutdown of the Thermohaline Circulation

The consequences of global warming on thermohaline circulation in the North Atlantic Ocean might be catastrophic. Climate change might be severe if global warming disrupts the thermohaline circulation in the North Atlantic Ocean. According to calculations, whether the shutdown is reversible or irreversible impacts the environmental consequences. Changes in the temperature and salinity of seawater lead to thermohaline circulation. The circulation pattern acts like a vast conveyor belt, transporting warm surface water from the Southern Hemisphere to the North Pole. After cooling, the water dips into the deep ocean and flows south between Greenland and Norway. According to Michael Schlesinger, an atmospheric sciences professor at the University of Illinois at Urbana-Champaign, this movement carries massive heat northwards. It plays a crucial role in maintaining the current climate. It is believed that while its closure due to global warming would not cause an ice age, an ambient temperature change throughout eastern North America and Western Europe could be caused by it. Palaeoclimate data from Greenland ice cores show that once the thermohaline circulation stopped, it caused regional climate change. When the massive ice sheet that covered much of North America during the previous ice age was retreated, meltwater poured down the St. Lawrence River and into the North Atlantic. The addition of fresh water was said by Schlesinger to have made the ocean surface less dense, and its sinking was stopped, effectively shutting down the thermohaline circulation. He explained that, as a result, Greenland experienced a cooling of approximately 7 degrees Celsius over several decades. When the meltwater flow stopped, the circulation pattern restarted, and Greenland began to experience warming.

Schlesinger added that, referring to the system's self-shutdown, it is not unlikely that it will be done again, especially with our help of pouring greenhouse gases into the atmosphere. Higher temperatures due to global warming may cause increased precipitation and melting of nearby sea ice, mountain glaciers, and the Greenland ice sheet, contributing fresh water to the northern North Atlantic. This freshwater intake may reduce the surface salinity and density, halting the thermohaline circulation.

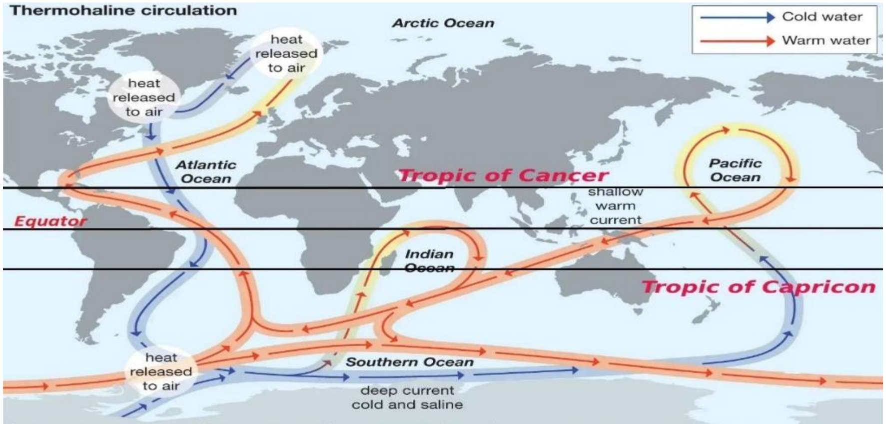

FIGURE 4: Thermohaline circulation

IV. Review Of Machine Learning Models

Although promising research has been conducted on the meteorological aspects of cyclone genesis in different ocean basins, deep learning and machine learning models also contribute to predicting and forecasting cyclone genesis, intensity estimation, and intensity identification.

Using Machine Learning Models

One study showed that by using ensemble deep 2D deep convolution neural networks on image datasets of ocean basins and outgoing longwave radiation (OLR) as features, we can identify the precursors and formation of cyclones 2 to 7 days ahead. However, this study must consider other vital cyclone genesis factors [39], as explained in [40], about the relationship between the IoD and ENSO. According to [41], the interior, i.e., the 700-meter-deep water column, influences the sea surface temperature. LSTM with the RNN technique was used to model the changes in coastal sea level variability as the sea level changed. Sea circulation patterns are critical in identifying storms, rainfall, and other climatic situations. Alternatively, the Gaussian process was also used to predict sea level and temperature. In [15], the authors proposed different deep CNN models to estimate hurricane intensity, and these models achieved good accuracy. Whereas [42] used Coupled TCNN (Tensor-based Convolution Neural Networks) and Tucker TCNN to estimate the Tropical cyclone intensity and MSI imagery as an input dataset, the proposed models gave promising results and provided an excellent breakthrough to the research, as there is a need for considering other parameters related to cyclone genesis and improvement in the construction of CNN architectures to identify unsupervised data.

Other research has shown that graph convolution neural networks can also be used to identify the spatial features of cloud and wind patterns, especially when cyclone states are transformed from one state to another, such as deep depressions to cyclonic storms and severe cyclonic storms [43]. By using graph convolution networks along with LSTM [44], TC precipitation patterns can be examined, which in turn leads to the identification and estimation of TC intensity; over the decades, TC precipitation patterns have usually been identified by using numerical weather prediction models in some countries and a combination of ML and NWP models in other countries.

TABLE III: Detailed Related Work In Machine Learning To Identify Tropical Cyclone Estimations

Citation/Reference	Method/Model used	Estimated Parameter	67Dataset used\ ] =	Meteorological Parameters
[4]	MTL-NET	Precursors of IOD	Monthly mean SST from GODAS and Centennial historical simulations from Coupled Model Intercomparison Project phases 5 and 6 (CMIP5 and CMIP6) and reconstructed historical observation data.	Temporal features and spatial features of the North Indian Ocean and Pacific Ocean

[10]	Cascaded CNN Inception-ResNet-V2 Improved AlexNet	TC Estimation TC classification	Satellite images	
[29]	Deep Micro net based on Alex's net	TC intensity estimation	Microwave imagery from the MINT collection	Temperature
[36]	Combination of NWP and ML	Current TC precipitation and weather conditions in the next 24-hrs	Samples obtained from the European Centre for Medium-Range Weather Forecast (ECMWF)	Sea level Pressure, wind speed, wind direction, Temperature
[37]	2D-CNN and 3D – CNN	TC intensity estimation	COMS - KOREAN Geo Stationary Imagery Data	TC eyewall, vertical and wind shear, spiral rain bands
[41]	PCA and Quantile Regression	Wind uncertainty	Aircraft reconnaissance data available at North Atlantic and North PacificPacific basins and Satellite IR images	IC Intensity and Wind Field Structure
[45]	VGG-16 CNN ensembled in cloud	Wind speed estimation	Satellite GOES-IR images From HURSAT	
[46]	VGG Net with 13 layers	TC intensity and size Estimation in terms of Mean Wind speed, Sea Level Pressure	HURSAT- B1, Gridsat-B1, IBTrAcs	1-min maximum sustained surface winds (MSW), minimum sea level pressure (MSLP), radius of maximum wind (RMW), and radii of 64-, 50-, and 34-kt winds
[47]	Improved DCNN -VGG19	TC intensity estimation	Satellite IR images from HURSAT in Net CDF Format and HURDAT2	Wind Speed
[48]	convLSTM	IOD Prediction	https://psl.noaa.gov/data/gridded/	Atmospheric temperature, east–west wind speed, north–south of different wind speeds.
[49]	TC Detector- R-CNN, Wind Speed-CNN, Classifier-CNN	TC prediction	The investigation used level 1.5 Meteosat visible, infrared imager (MVIRI) IR satellite pictures from Meteosat 5 and Meteosat 7 Indian Ocean Data Coverage (IODC) at a six-hourly frequency from 2001 to 2007 2007 to 2016.	TC structure from satellite IR images
[50]	Deep Micro net based on Alex's net	TC intensity estimation	Microwave imagery from the MINT collection	Temperature
[51]		TC intensity Estimation	Tropical Cyclone Dataset for Image-to-Intensity Regression (TCIR)	TC structure from IR images and microwave channels, Water Vapour.
[52]	2D-CNN and 3D – CNN	TC intensity estimation	COMS - KOREAN Geo Stationary Imagery Data	TC eyewall, vertical and wind shear, spiral rain bands
[53]	VGG-16 CNN ensembled in cloud	Wind speed estimation	Satellite GOES-IR images From HURSAT	
[54]	Combination of NWP and ML	Current TC precipitation and weather conditions in the next 24-hrs	The European Centre for Medium-Range Weather Forecast (ECMWF) provided the sample datasets.	Pressure at sea, wind speed, wind direction, and temperature.
[55]	VGG Net with 13 layers	TC intensity and size Estimation in terms of Mean Wind speed, Sea Level Pressure	HURSAT- B1, Gridsat-B1, IBTrAcs	1-minute maximum sustained surface winds (MSW), minimum sea level pressure (MSLP), maximum wind radius (RMW), and 64-, 50-, and 34-kt wind radii
[56]	convLSTM	IOD Prediction	https://psl.noaa.gov/data/gridded/	Atmospheric temperature, north–south wind speed, and east–west wind speed.

V. Future Research And Scope

A. Opportunities

- This experimentation has yet to be performed using a multiscale/multisource dataset.
- There are differences in estimating rainfall intensity, and wind field forecasts need to be more accurate.
- The operational cost of forecasting is inappreciable
- It is essential to fuse both numerical models and ML models to obtain better accuracy
- Developing models that accept more parameters and global temperatures at all slots is essential for higher forecasting accuracy.
- Mathematical or statistical models are highly efficient but require substantial computational capabilities. Therefore, developing new models that accept data from various sources is essential.

B. Challenges

- Designing learning-based prediction models is the greatest challenge.
- Machine learning can provide only short lead-time predictions, so it is essential to devise long-lead time-based prediction models with increased accuracy.
- As TCs are highly dynamic, their formation and behavior depend on the atmospheric conditions on the ocean's surface; acquiring as many features as possible from the available data is essential. Hence, more observations and a massive number of experiments are also essential.
- Most machine learning algorithms are supervised learning methods, but in real time, no labelled data that can achieve high accuracy are available.
- Most of the research on TC prediction has considered only a few parameters confined to a specific region or index. However, any region with certain weather conditions should have an impact on another region under inverse conditions. Hence, in prediction, it is essential to consider global conditions, which makes it challenging to obtain the region's weather conditions.

The development of machine learning/deep learning models that use numerical and image data by fusion is a greater challenge.

VI. Conclusion

Tropical cyclones have long been a source of concern during the last century. Many scholars have studied essential topics such as structure, dynamics, and forecasting approaches. Machine learning is based on statistical algorithms that may automatically find appropriate rules from massive volumes of data for detection, analysis, prediction, and other applications. Using machine learning to solve critical TC problems provides a novel approach for overcoming many industrial challenges. Many studies have shown that strategies relying on data and incorporating machine learning to improve numerical models may significantly improve TC forecasts.

Similarly, the Indian Ocean Dipole (IOD), El Nino-Southern Oscillation (ENSO), Madden–Julian Oscillation (MJO), quasibiennial oscillation (QBO), and Southern Oscillation Index (SOI) have little influence on tropical cyclones in the Indian Ocean. As a result, the Indian Ocean, which includes the Arabian Sea and the Bay of Bengal, generates 6% of all cyclones globally.

We can conclude that machine learning in TC forecasts is both promising and challenging, which means that researchers must have a strong understanding of TC dynamics as well as machine learning to identify critical problems and solve them by developing appropriate machine learning models while also taking into account the impact of the global ocean index and global warming.

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