

Arctic and Antarctic Sea Ice Extent Forecasting using Hybrid LSTM Technique

Spandan Sureja

Department of Computer Engineering, Government Engineering College, Gandhinagar, India

E-mail: spandan.sureja@gmail.com

Abstract

Recent changes in global climate patterns have triggered the accelerated melting of polar sea ice, especially in Arctic regions. A much faster rate of decrease in the sea ice extent (SIE) is observed at than previously expected. The Antarctic region, on the other hand, has shown a stable sea ice pattern throughout the last few decades. However, the southern polar region is not completely unaffected. Recent studies of the Bellingshausen and Amundsen Seas have shown a downward trend in sea ice. The SIE is crucial for regulating global climate patterns, ocean circulation, and human activities, including shipping and fishing. Hence, forecasting sea ice extent is vital for global economic planning and climatological studies. In this proposed study, time-series forecasting of five Antarctic and Arctic regions are evaluated using a hybrid convolutional long short-term memory (ConvLSTM) and a bidirectional long short-term memory (BiLSTM) and compared with a standalone long short-term memory (LSTM). This study uses regional sea ice extent data rather than considering the extent across entire hemispheres. With lower and stable RMSE scores across all lead times, the proposed hybrid BiLSTM model shows better performance in regional sea ice forecasting than does the standalone and ConvLSTM. The study also indicated that the climatic conditions of a particular region play a crucial role in forecasting efficiency, especially at longer lead times.

Keywords: Sea Ice Extent, Time Series Forecasting, Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (BiLSTM), Arctic SIE, Antarctic SIE.

1. Introduction

The increase in greenhouse gases, which has resulted in an increase in global temperature, has eventually caused notable changes in polar regions. The Arctic ice cover is declining at an accelerated rate, along with a significant reduction in its thickness [1]. Over the past few decades, an increase in the near-surface air temperature called the 'Arctic Amplification' has been observed [2]. The temperature increase and continuous melting have led to a feedback mechanism in the Arctic. This will result in additional ice melting. The Arctic is expected to be 'seasonally ice-free' once all layers of its multilayered ice are lost [3]. On the other hand, in contrast to its gradual increase in ice cover since the 1970s, Antarctica experienced a remarkable decline between 2014 and 2017. Over these four years, the reduction in the extent of Antarctic Sea ice exceeded the total Arctic Sea ice loss observed in the four decades from 1979 to 2018 [4]. However, after 2017, several recoveries were noted, but they have yet to reach the peak achieved in 2014, indicating a decreasing trend. The reason behind the irregular pattern of Antarctic ice remains a subject of debate. The climate change has a direct effect on polar sea ice extent.

The sea ice extent (SIE) is defined as the area of the ocean with a minimum of 15% ice concentration [5]. The reduction in the SIE commonly occurs during the summer because of melting, followed by a rise in the SIE during the winter due to ice formation. The Antarctic SIE follows a seasonal pattern, with February as the month of minimum coverage and September as the month of maximum coverage [6]. Similarly, for the Arctic extent, March and September are the months with the maximum and minimum coverage, respectively [7]. The Arctic Sea ice is more sensitive to climate change than the Antarctic Sea ice [8].

As defined by [9], the Arctic is divided into 14 regions. As the entire Arctic region has experienced melting since the 1970s, these regions have shown a strong negative trend. A maximum negative slope is observed for the Kara and Barents Seas, Baffin Bay, Bering Sea, and Greenland Sea [7] (Figure 1). While the Antarctic regions showed a positive trend until 2014, the trends during the decline were very different. A steep negative trend was observed for all regions except the Indian Ocean and a few parts of the Ross Sea [10], resulting in an overall negative trend (Figure 2).

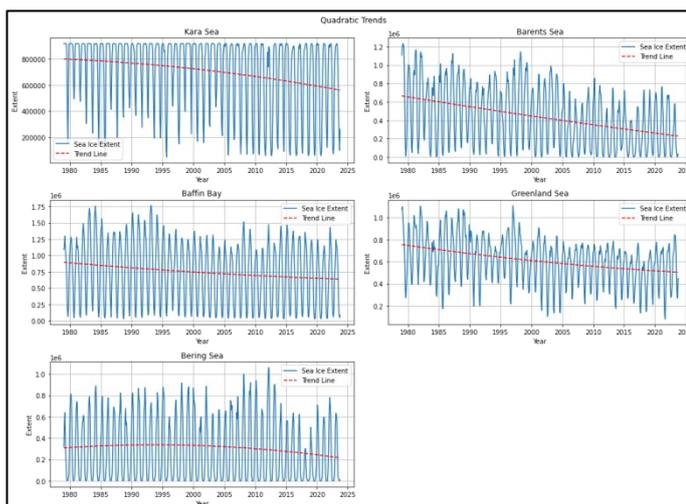


Figure 1. Time-Series Plots of the SIE (in km²) from 1979 to 2023 for Five Arctic Regions Along with a Quadratic Regression Trend Line

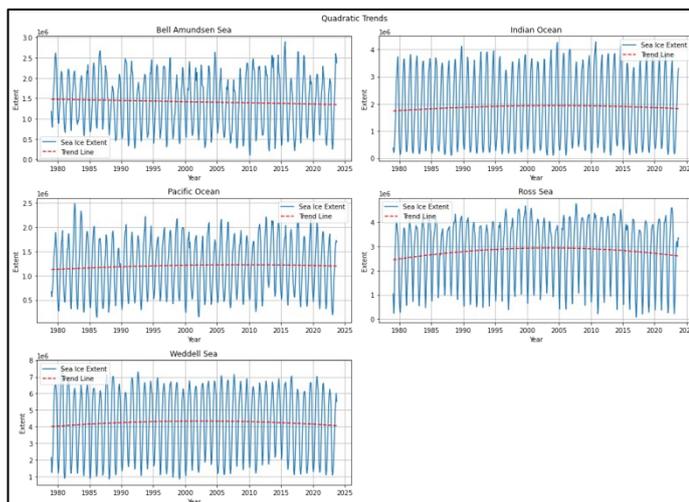


Figure 2. Time-Series Plots of the SIE (in m) from 1979 to 2023 for Five Antarctic Regions Along with a Quadratic Regression Trend Line

The Arctic SIE is closely monitored because it affects weather patterns and has economic impacts, such as opening new summer marine routes between the Atlantic and Pacific Oceans through the Northwest Passage [11] and Northeast Passage [12]. This affects the Northern Hemisphere population in several ways. Although the Antarctic SIE does not have the same effect on the global economy or population, its melting plays a crucial role in global ocean circulation and climate patterns. Melting Antarctic ice is also expected to influence temperature, sea level, and storm frequency in multiple regions, especially within the Southern

Hemisphere. The Arctic has always been a center of study, and very few models have been applied for Antarctic sea ice forecasting.

The remainder of this study is organized as follows: Section 2 discusses various ML approaches previously implemented to forecast SIE. Section 3 describes the dataset and the LSTM models along with error metrics used in the study. Section 4 discusses the results obtained from proposed models. Section 5 summarizes the findings of the study and outlines possible directions for further research.

2. Related Work

SIE forecasting is important for daily marine activities, as well as for research in future climate modeling. In the past few decades various statistical models were developed for predicting SIE. The models were based on the interaction of sea ice with atmospheric or oceanic conditions, and sea ice variables such as thickness and concentration [13],[14]. However, these methods are computationally expensive, and their accuracy depends largely on the initial ice state [15]. These models had limited flexibility and faced difficulty in handling nonstationary data.

To overcome the limitations of statistical models, a new class of nonlinear models, such as neural networks, were developed. With the recent development of artificial intelligence, machine learning techniques can now perform data learning and make predictions. With the help of techniques such as regression, sea ice prediction can be done without having any additional predictors. Linear regression was first applied by [16] to predict Beaufort Sea ice, Gaussian regression by [17] for Arctic regions' SIE, and Bayesian logistic regression by [18] for September SIE in the Arctic. These models had better prediction accuracy compared to the previous statistical models. The most recent development with deep learning models, specifically RNNs [19], including LSTM, made time series forecasting more accurate in dealing with large complex nonstationary data.

An LSTM architecture was applied for the Arctic by [20], and it outperformed traditional statistical models. [21] introduced an LSTM architecture with an attention layer to further improve the forecasting accuracy. A hybrid CNN+LSTM was introduced by [22] for forecasting Arctic SIE at longer time scales.

Although these models were developed primarily for the Arctic, they may not operate in the case of the Antarctic SIE. Furthermore, the accuracy of the SIE forecasting model is primarily determined by the time series plot peaks and troughs, which represent the periods of maximum and minimum melting, respectively. The proposed methods take advantage of the Arctic and Antarctic regional SIE time-series properties to accurately predict ice extent over a longer time scale, particularly during the highest and lowest melting periods. To the best of current knowledge, the proposed work is the first to use a bidirectional LSTM architecture for regional Arctic and Antarctic SIE prediction. The bidirectional model performed better than the standalone LSTM and the CNN+LSTM models for longer lead times.

3. Proposed Work

3.1 Data and Pre-processing

The NSIDC (National Snow and Ice Data Center) sea ice index data are used for the study. The dataset has monthly SIE values from 1979 to 2023 for both the southern and the northern hemispheres. The 5 Arctic regions used for the analysis are the Barents Sea, Baffin Bay, Bering Sea, Greenland Sea, and Kara Sea (Figure 3). These regions experienced noticeable melting and played a vital role in the Northeast and Northwest Passages. The Barents and Bering Seas are of economic importance owing to widespread fishing and other maritime activities. The five Antarctic regions are the Pacific Ocean, Indian Ocean, Bell-Amundsen Sea, Weddell Sea, and Ross Sea (Figure 4). The Bell-Amundsen Sea and the Ross Sea are regions of concern due to the recent increase in ice melting.



Figure 3. The Arctic Regions used in Study

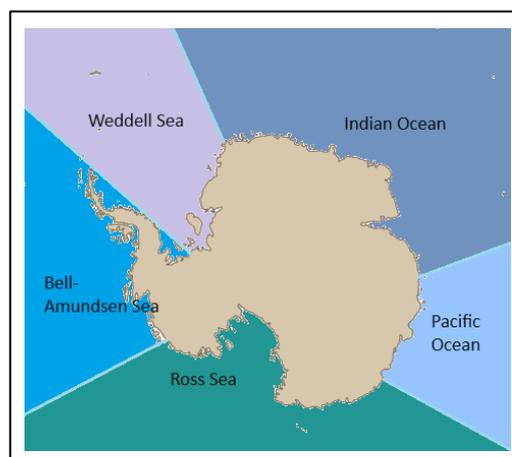


Figure 4. The Antarctic Regions used in Study.

The dataset is divided into 80:20:20 partitions for training, validation, and testing. A sliding window approach with a window size of 12 and a lead time of up to 12 months is used for all the LSTM models. As shown in Figure 5, the prediction at any time-step will be derived from the SIE values of the past 12 months. This allows the model to capture long-term dependencies, eventually assisting in better forecasts, especially for regions with high seasonal variability.



Figure 5. Prediction using a Sliding Window of size 12. The Red Box Shows a Window while the Blue Box Represents the Target Value

3.2 Standalone and Bidirectional (Bidir) LSTM

The RNN encounters a ‘vanishing gradient problem’ where gradients diminish as they back-propagate through time. The LSTM architecture was first explained by [23] to solve the backpropagation problems of RNNs while enabling long-term memory capabilities. Typically, an LSTM cell contains four layers, including three sigmoid functions and one hyperbolic tan function, which act as activation functions (Figure 6). The cell state (C_t) flows the information through a cell, and the hidden state (h_t) is the output of the current cell. LSTM controls the flow and loss of information using three gates (red boxes). The forget gate decides which information to discard from previous cells, the input gate adds new information from the current cell to the cell state, and the output gate decides the output of the current cell.

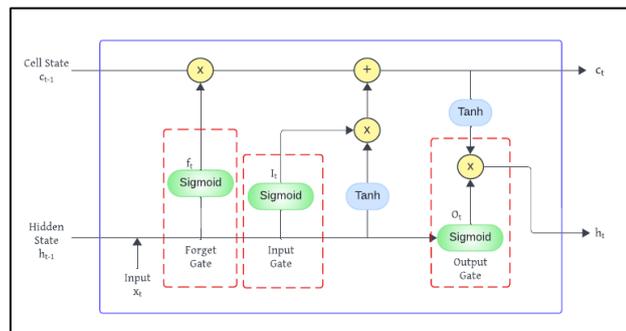


Figure 6. A Single LSTM Cell with Three Gates

Let x_t and h_{t-1} denote the input and the previous cell hidden state respectively. Then, the output of each LSTM gate is as follows:

$$\text{forget gate: } f_t = \sigma(x_t * u_f + h_{t-1} * w_f) \quad (1)$$

$$\text{candidate layer: } \bar{C}_t = \tanh(x_t * u_c + h_{t-1} * w_c) \quad (2)$$

$$\text{input gate: } I_t = \sigma(x_t * u_i + h_{t-1} * w_i) \quad (3)$$

$$\text{output gate: } O_t = \sigma(x_t * u_o + h_{t-1} * w_o) \quad (4)$$

Here (u_f, u_c, u_i, u_o) and (w_f, w_c, w_i, w_o) are all weight metrics for respective gates and layer. The cell state and hidden state for the next cell are as follows:

$$C_t = f_t * C_{t-1} + \bar{C}_t I_t \quad (5)$$

$$h_t = O_t * \tanh(C_t) \quad (6)$$

While the standalone (unidirectional) LSTM processes the input sequence in a single direction, the bidirectional LSTM works in both directions: forward processing (from the start to the end) and backward processing (from the end to the start) for the same sequence (Figure 7). The outputs of these two processing layers are concatenated at each time step, resulting in a combined output that captures the bidirectional context. The simultaneous input sequence processing from two directions improves the model's flexibility in learning complex patterns and reduces information loss.

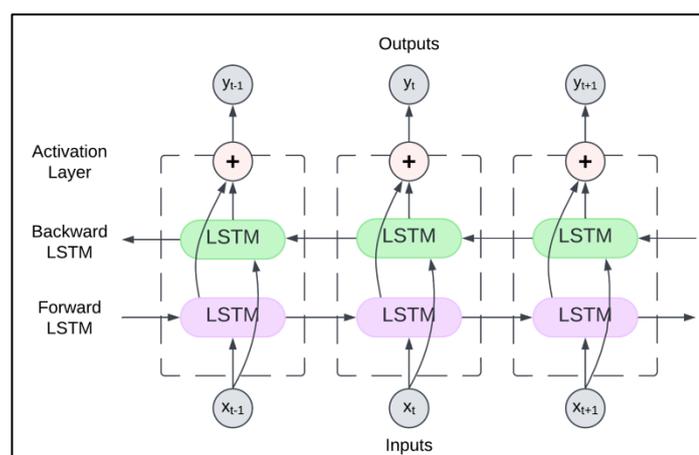


Figure 7. A Bidirectional LSTM with Forward and Backward Processing Layers

3.3 ConvLSTM

The convolution LSTM model uses CNNs as the initial layers to capture patterns and relevant features of the time-series data. CNNs are capable of processing multidimensional data. The core components of a CNN architecture are convolutional and pooling layers. The convolutional layer extracts features using a set of filters (kernels), while the pooling layer downsamples these features, reducing the number of dimensions. Consider an input at the l^{th} convolutional layer of size $H^l \times W^l \times D^l$ and let f represent the kernels used, each of size . Then, the convolution process can be expressed mathematically as

$$y_{i^{l+1},j^{l+1},d^l} = \sum_{i=0}^H \sum_{j=0}^W \sum_{d=0}^{D^l} f_{i,j,d^l} \times x_{i^{l+1}+i,j^{l+1}+j,d^l}^l \tag{7}$$

where $x_{i^{l+1}+i,j^{l+1}+j,d^l}^l$ is an element of input x^l and y is x^{l+1}

The pooling layer operates independently on x^l channels. It divides each channel into subregions of size $H \times W$. Then, a pooling operator maps each subregion to a single number, thus reducing the dimensions. A max pooling operator, which maps the subregion to its maximum value, was used in this study. Mathematically, max pooling can be expressed as

$$y_{i^{l+1},j^{l+1},d} = \max x_{i^{l+1} \times H+i,j^{l+1} \times W+j,d}^l \tag{8}$$

As shown in Figure 8, the architecture used in this study has a convolutional layer with 64 filters, followed by a pooling layer. The output of the CNN will be passed to the LSTM with 32 units, followed by a normalization layer that ensures training stability. The final output is produced by a fully connected (dense) layer.

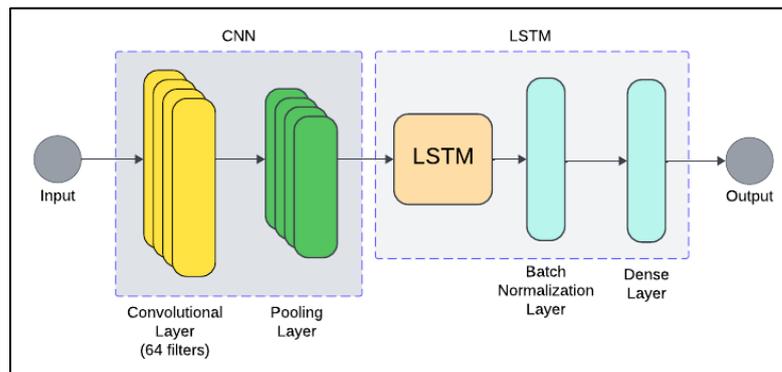


Figure 8. A CNN+LSTM Architecture used in the Study

These models were trained with a batch-wise processing approach and compiled using an Adam optimizer with a learning rate of 0.0001. During BPTT (back propagation through time), Adam will optimize parameters and minimize the loss function for the entire sequence. Adaptive moment estimation (Adam) is a better choice for time-series forecasting models because it has a minimum memory requirement as it computes only the first-order gradients [24].

3.4 Evolution Metrics

The performance of the three models is evaluated using standard accuracy metrics: root mean square error (RMSE) and mean absolute error (MAE). These metrics are widely used for measuring the performance of time series forecasting models [25]. The RMSE indicates the overall error that occurred during forecasting, while the MAE measures the absolute deviation of the predicted values from the original data [26]. $SIE^{observed}$ is the true value of the ice extent, and $SIE^{predicted}$ is the extent value predicted by the model. The RMSE penalizes large errors, while the MAE penalizes all errors regardless of their magnitude.

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (SIE_i^{observed} - SIE_i^{predicted})^2} \quad (9)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |SIE_i^{observed} - SIE_i^{predicted}| \quad (10)$$

4. Results and Discussion

4.1 Forecasting the Arctic SIE

Figure 9 presents the lead times with their RMSE scores for CNN+LSTM, Bidir LSTM, and standalone LSTM. For the lower lead times for all regions, CNN+LSTM was found to be best. Again, with increasing lead time, these error scores fluctuate because of regional climatic dynamics and variability. Climate patterns and ocean currents make LSTM models less predictable at longer lead times. One important factor of SIE is wind direction, for it not only affects the SST but also determines the movement of the sea ice [27], which causes compression or divergence of the sea ice cover.

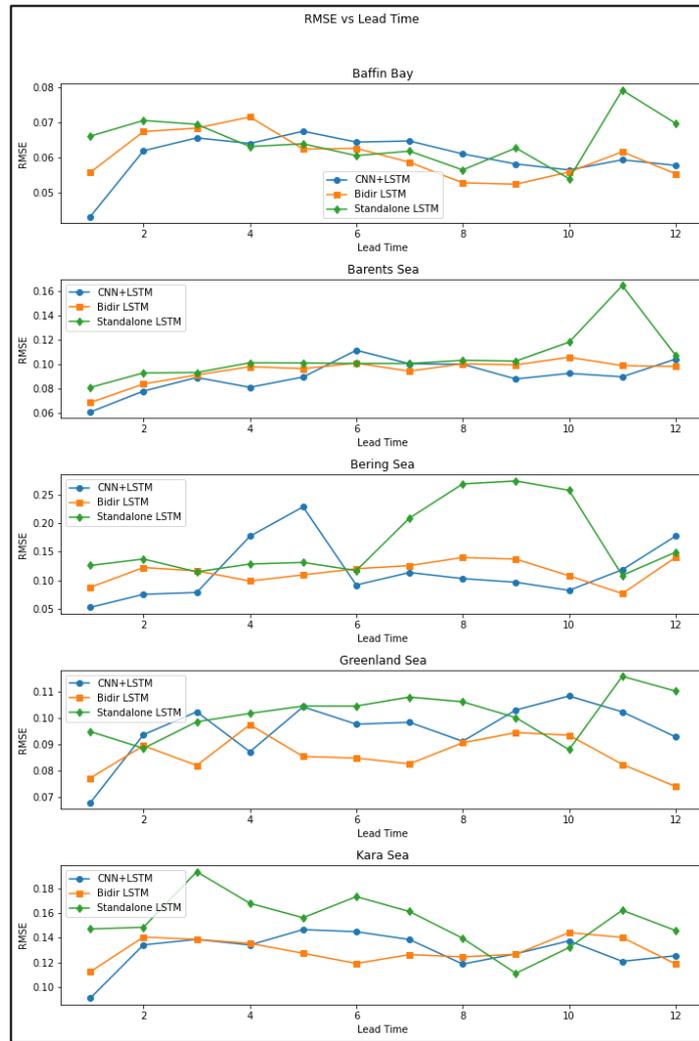


Figure 9. RMSE vs Lead Time Plots for five Arctic Regions

The Bering Sea experiences strong winds and frequent storms due to the Aleutian low-pressure system. The deepening of the Aleutian Low and increased penetration of warmer Pacific streams after the mid-1970s resulted in the gradual warming of the Bering Sea [28]. This eventually affects the SIE and its forecasting. The high variability of the Bering Sea leads to fluctuations in the forecasting efficiency of CNN+LSTM. The bidirectional LSTM has shown stable RMSE scores throughout the lead times and slightly improved performance compared with CNN+LSTM at higher lead times. Table 1 shows the average error scores of the three models across the 12-month lead period.

Table 1. RMSE and MAE Scores of Arctic Regions Averaged Over a 12-Month Lead Time for the Three Models used in the Study.

| Regions | CNN+LSTM | | Bidirectional (Bidir) LSTM | | Standalone LSTM | |
|---------------|----------|-------|----------------------------|-------|-----------------|-------|
| | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| Bering Sea | 0.016 | 0.095 | 0.015 | 0.086 | 0.168 | 0.136 |
| Barents Sea | 0.090 | 0.731 | 0.094 | 0.074 | 0.105 | 0.086 |
| Baffin Bay | 0.060 | 0.046 | 0.060 | 0.046 | 0.064 | 0.051 |
| Kara Sea | 0.129 | 0.091 | 0.129 | 0.091 | 0.153 | 0.119 |
| Greenland Sea | 0.095 | 0.079 | 0.086 | 0.066 | 0.101 | 0.079 |

The Barents Sea is comparatively more stable than the Bering Sea. Due to its proximity to the Arctic Ocean, the northern part of the Barents Sea is permanently covered by ice [29]. However, it has contributed the most to Arctic sea ice loss. A large part of Arctic sea ice loss can be traced back to the missing Barents Sea winter ice [30]. The influence of warmer Atlantic water has warmed the Barents Sea, resulting in a large volume of sea ice melting annually. The Barents Sea is expected to be completely ice-free by 2050 if the warming continues. Hence, these recent climatic developments in the past few decades have increased variability in the winter and summer ice cover of the Barents Sea, eventually affecting forecasting. In summer, there is a significant north-south temperature gradient. CNN+LSTM predicts the Barents Sea SIE more efficiently than does bidirectional and standalone LSTM.

The Baffin Bay had shown minimal errors in the initial lead months using the CNN+LSTM model, likely because the area has a reduced influence from complex ocean currents compared to areas like the Barents and Kara Seas [31]. As a relatively enclosed water body, forecasting its SIE is easier, and its hybrid models perform equally well due to the climatic stability of the region. During the winter, the Kara Sea's sea ice experiences significant expansion, and by February and March, almost the entire sea is covered under the ice. The Kara Sea has high summer sea ice variability, and winter sea ice is also affected by strong winds and storms. This may lead to fluctuations in the performance of CNN+LSTM and bidirectional LSTM, as seen in the above regions.

The Greenland Sea has also shown high sea ice variability over the past few decades. Similar to the Barents Sea, the influence of warmer Atlantic water has warmed the Greenland Sea. This process is subject to a significant feedback mechanism that accelerates ice melting. This instability is observed in the performance of the three models at higher lead times. Although all the models achieved significant rises and falls in the error scores, the bidirectional LSTM model noticeably outperformed the CNN+LSTM and standalone LSTM models for the Greenland Sea.

4.2 Forecasting the Antarctic SIE

The RMSE vs. lead time plots for the Antarctic regions are shown in Figure 10. The Antarctic climate plays a major role in SIE forecasting. Like in Arctic regions, global warming is now also affecting the Antarctic climate, eventually leading to ice melting. The climate of the Bell-Amundsen Sea is influenced by circumpolar westerlies, resulting in strong winds in the region. The region is consistently frigid throughout the year, and the winter is marked by strong winds and sea ice drifting. Ice movement and formation are also influenced by the Antarctic Circumpolar Current (ACC). However, the change in ocean currents due to the warming of deep ocean water has triggered basal melting in the region, making the Bell-Amundsen Sea one of the most affected Antarctic regions.

The sea ice distribution between the Antarctic Peninsula and the Ross Sea is affected by El Niño and La Niña phases [32], where the former leads to a less dynamic environment, allowing sea ice to extend further northward, and the latter results in increased sea ice advection, leading to potentially less sea ice cover. The rapid melting of Ross Sea ice is observed throughout the spring [33]. The sea ice dynamics related to the El Niño Southern Oscillation (ENSO) also affect the Pacific Ocean SIE. These events account for the high seasonal variability in the Bellingshausen-Amundsen Sea, the Ross Sea, and the Pacific Ocean, eventually leading to comparatively higher error scores in forecasting among the Antarctic regions.

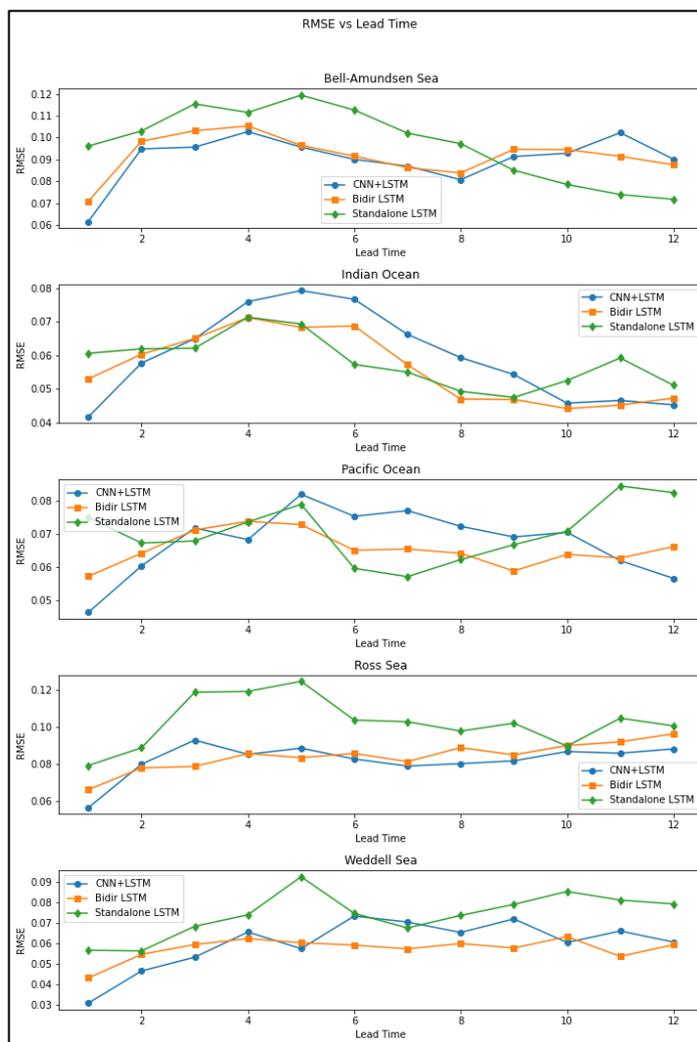


Figure 10. RMSE vs Lead Time Plots for Five Antarctic Regions

Table 2 shows the average error scores across the 12-month lead period for five Antarctic regions. Overall, the CNN+LSTM model performed better than did the other two models for the Bell-Amundsen Sea; however, a rather unexpected outcome was observed with the standalone LSTM model, where it outperformed the hybrid models for longer lead months. The CNN+LSTM showed minimum average error scores for the Ross Sea, and the Bidir LSTM outperformed in Pacific Ocean SIE forecasting.

Table 2. RMSE and MAE Scores of Antarctic Regions Averaged Over a 12-Month Lead Time for the Three Models used in the Study.

| Regions | CNN+LSTM | | Bidirectional (Bidir) LSTM | | Standalone LSTM | |
|-------------------|----------|-------|----------------------------|-------|-----------------|-------|
| | RMSE | MAE | RMSE | MAE | RMSE | MAE |
| Bell-Amundsen Sea | 0.090 | 0.072 | 0.091 | 0.074 | 0.097 | 0.080 |
| Indian Ocean | 0.059 | 0.049 | 0.056 | 0.046 | 0.058 | 0.047 |
| Pacific Ocean | 0.067 | 0.053 | 0.065 | 0.052 | 0.070 | 0.056 |
| Ross Sea | 0.082 | 0.061 | 0.084 | 0.063 | 0.102 | 0.083 |
| Weddell Sea | 0.060 | 0.048 | 0.057 | 0.047 | 0.073 | 0.057 |

The Indian Ocean is a relatively more stable region with no direct effects of ENSO, leading to minimum error scores. The limited fluctuations in the Indian Ocean and the Weddell Sea enable the model to predict values closer to the original SIE values. Bidir LSTM showed a noticeably improved performance compared with the other two models for comparatively stable regions such as the Indian Ocean and the Weddell Sea.

5. Conclusion

Considering the significance of sea ice in the operation of polar maritime routes, climate regulation, sea level rise, and global ocean circulation, the precise forecasting of Sea Ice Extent (SIE) is crucial. Particularly, regional SIE forecasting will enable better understanding and planning given the importance and unique climatic conditions of each region surrounding the Arctic and the Antarctic. This study explores the potential of employing hybrid LSTM models (CNN+LSTM and bidirectional LSTM) for SIE forecasting of five Arctic and Antarctic regions. RMSE and MAE were used to compare the models' performance for a lead time of up to 12 months. The results highlight complex interactions between climate variables and sea ice dynamics.

The Arctic region is particularly sensitive to the climate change and has exhibited significant ice loss in regions like the Barents Sea, the Bering Sea, and the Greenland Sea. The

study demonstrates that the CNN+LSTM model excels in short-term predictions across most Arctic regions, but the bidirectional LSTM provides more stable and accurate forecasts at longer lead times. In contrast, Antarctic Sea ice is influenced by different climatic drivers, including circumpolar westerlies and the Antarctic Circumpolar Current (ACC). The study shows that the CNN+LSTM model generally performs better in Antarctic regions, particularly for the Bell-Amundsen Sea and the Ross Sea. However, the bidirectional LSTM model outperforms in other regions, suggesting its robustness in handling more dynamic environments.

The utilization of a bidirectional LSTM architecture represents a novel approach in the field of sea ice extent forecasting, particularly for capturing long-term dependencies and complex patterns influenced by various climatic variables. Its improved and stable performance in several regions indicates its potential for improving prediction accuracy over extended periods. As climate dynamics continue to evolve, further improvement of these models and the incorporation of additional climatic variables will be essential for enhancing prediction accuracy and supporting decision-making. For instance, the RMSE of the CNN+LSTM model fluctuates as the lead time increases, which can be addressed in future research by integrating atmospheric variables to enhance stability. Future studies will also include Arctic regions not covered in this analysis. Overall, the proposed models offer significant advancements in precise SIE forecasting, benefiting climatology research and facilitating economic planning in polar regions.

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Author's biography

Spandan Sureja recently completed under-graduation in Computer Engineering from Gujarat Technological University (State University), Gujarat, India. He has worked on various projects comprising neural networks and machine learning. His previous research was application of neural networks in pulsar candidate selection. His primary areas of interest is application of deep learning techniques in various scientific domains including astrophysics and earth science. He has successfully led various teams to national and state level events.