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Predicting the next decade of sea surface temperatures in the Mediterranean Sea using hybrid deep learning models

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Abstract

The Mediterranean Sea plays a crucial role in regulating regional climate, supporting biodiversity, and sustaining coastal economies, making its temperature an essential factor for environmental stability. This study presents a forecast of sea level temperatures in the Mediterranean Sea for the next 10 years using historical data from the European Centre for Medium-Range Weather Forecasts (ECMWF), spanning from 1940 to 2024. Two hybrid deep learning models, CNN-LSTM and CNN-GRU, are employed to predict future temperature trends. The models are evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) as primary accuracy metrics. The results will provide valuable insights into the potential impacts of climate change on the Mediterranean region's sea level temperatures, contributing to better understanding and future planning efforts.

Keywords: Climate Change, Forecasting, Mediterranean, Deep Learning, Hybrid Deep Learning

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1. INTRODUCTION

The Mediterranean Sea, a semi-enclosed basin situated between Europe, Africa, and Asia, is recognized as one of the most climate-sensitive regions in the world. Due to its relatively small size and enclosed nature, the Mediterranean responds rapidly to changes in both atmospheric and oceanic conditions. The region has already witnessed significant climate-related changes, including rising air and sea surface temperatures, altered precipitation patterns, and an increase in the frequency and intensity of extreme weather events such as marine heatwaves and heavy rainfall. These transformations are not only a consequence of global climate change but are also exacerbated by local anthropogenic factors, such as overfishing, pollution, and coastal development.

As global temperatures continue to rise, the Mediterranean is projected to experience warming at a rate 20% faster than the global average. This accelerated warming poses a myriad of risks. Increasing sea surface temperatures (SSTs) have been linked to marine heatwaves, which can lead to mass mortality events in marine life, including fish and coral populations (Ko,2022). The shifting of species distributions, the loss of biodiversity, and the introduction of invasive species further threaten the delicate balance of Mediterranean ecosystems. The warming atmosphere and seas fuel more intense storms, while altered precipitation patterns exacerbate drought conditions in some areas. These extreme events contribute to coastal erosion and can damage critical infrastructure and lead to high amount of death tolls, particularly in densely populated coastal cities. Furthermore, the Mediterranean is highly susceptible to sea level rise, which is another consequence of global warming driven by the thermal expansion of water and the melting of polar ice. Rising sea levels threaten to inundate low-lying coastal areas, leading to the displacement of communities, loss of coastal habitats such as wetlands, and increased salinity in freshwater resources.

In this context, predicting the future trajectory of sea surface temperatures in the Mediterranean is crucial for understanding and mitigating the long-term impacts of climate change. Traditional statistical models have been widely used for such predictions but are often limited in their ability to capture the complex, nonlinear interactions between various climatic factors influencing SST. Consequently, the use of advanced machine learning approaches, particularly hybrid deep learning models, is gaining traction in environmental science. These models can process large amounts of historical data and uncover patterns that traditional models might miss, making them powerful tools for long-term climate predictions (Patil, 2022).

In recent years, hybrid deep learning models combining Convolutional Neural Networks (CNNs) and recurrent networks like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRUs) have shown great promise in time series forecasting and environmental data analysis (Li,2021). CNNs are highly effective in capturing spatial patterns within data due to their ability to automatically learn local features through convolutional operations. In the context of sea temperature prediction, CNNs can help identify significant spatial trends and correlations across different regions of the Mediterranean, which might be indicative of broader climatic patterns. On the other hand, LSTM and GRU networks, which are designed to process sequential data, excel at capturing temporal dependencies, making them ideal for handling long-term forecasting tasks where past temperature data influences future predictions. By integrating CNNs with LSTM or GRU networks, hybrid models combine the strengths of both architectures, enabling them to capture spatial-temporal dynamics in a way that standalone models cannot. This synergy is especially valuable for predicting complex environmental phenomena like sea temperature changes, where both spatial and temporal factors are intertwined. In this study, the hybrid CNN-LSTM (Zhang, 2024) and CNN-GRU (Zheng,

2023) models are employed to improve the accuracy and reliability of long-term temperature predictions for the Mediterranean Sea, offering a robust approach to forecasting future trends in response to climate change.

Sea surface temperature (SST) is critical for understanding climate change, marine biodiversity, and environmental protection, making accurate forecasting essential for early detection of climate-related events. Recent studies highlight the effectiveness of deep learning algorithms in this domain, such as the STA-SST model proposed by (Elafi, 2024), which combines Bidirectional Long Short-Term Memory (BiLSTM) with convolutional layers and attention mechanisms, outperforming traditional models like LSTM and SVR. The Effective Attention Model (EAM) introduced by Pan,2024 enhances prediction accuracy by addressing spatiotemporal correlations, while a deep learning model utilizing convolutional gated recurrent units developed by Zu, 2023 improves SST prediction by incorporating spatial correlations in intelligent ocean data. Additionally, a hybrid model employing Variational Mode Decomposition (VMD), LSTM, and Broad Learning System (BLS) has been proposed for the East China Sea by Han, 2023, effectively reducing noise and improving accuracy. Studies using ConvLSTM and ST-ConvLSTM models in the South China Sea by Hao, 2023 explore the impact of input lengths and hidden sizes on prediction performance, emphasizing the complexity of optimal parameter settings. The DBULSTM-Adaboost model, developed by Yang, 2022, integrates Deep Bidirectional and Unidirectional LSTM with Adaboost to enhance accuracy and stability, while the Unet-LSTM model proposed by Taylor, 2022 forecasts global SST anomalies, demonstrating predictive skills for significant climate events. Despite these advancements, systematic applications of SST prediction in the Mediterranean Sea remain limited, indicating a need for further research in this area.

1.1. Purpose of the study

The primary aim of this research is to develop a robust deep learning model for accurately predicting sea surface temperature (SST) in the Mediterranean Sea over the next decade. As climate change continues to impact marine environments, precise SST forecasting becomes increasingly vital for ecological management, disaster response, and understanding climate dynamics. While numerous studies have focused on SST prediction using advanced machine learning techniques, there remains a significant literature gap specifically pertaining to the Mediterranean region. Existing models often overlook the unique climatic and oceanographic characteristics of this area, leading to potential inaccuracies in prediction outcomes.

Our research seeks to fill this gap by employing a hybrid deep learning approach that integrates temporal and spatial data, leveraging cutting-edge techniques such as LSTM and CNN. By focusing on the Mediterranean Sea, this study not only contributes to the theoretical understanding of SST dynamics in a critical region but also provides practical applications for policymakers and environmental managers.

Addressing this literature gap is essential, as it will pave the way for more accurate climate models that can adapt to the specific conditions of the Mediterranean. This research has the potential to enhance our understanding of marine heatwaves, climate change, and their broader implications for the region.

2. METHOD AND MATERIALS

2.1. Data

The monthly SST data spanning from 1940 to September, 2024 were obtained from the ERA5 project, managed by the European Centre for Medium-Range Weather Forecasts (ECMWF). This dataset integrates historical short-term weather forecasts with observational data through a process known as data assimilation.

This approach simulates the generation of monthly weather forecasts, which begin by analyzing the current state of the Earth's system. The analysis itself is a physically coherent fusion of observational data and short-term forecasts based on prior analyses.

2.2. Location

The Mediterranean region encompasses a geographically diverse area, characterized by a variety of landscapes, climates, and natural features. Central to this region is the Mediterranean Sea, which is connected to the Atlantic Ocean through the Strait of Gibraltar in the west and to the Red Sea via the Suez Canal in the east. The region is bordered by Europe to the north, Africa to the south, and Asia to the east, and is home to 21 countries with a combined population of nearly 500 million people. The Mediterranean climate, known for its hot, dry summers and mild, wet winters, is influenced by the moderating effect of the sea. The region also contains several prominent mountain ranges and plateaus, including the Pyrenees between France and Spain, the Alps along the northern coast, the Apennines in Italy, the Atlas Mountains in North Africa, and the Taurus Mountains, among others. The area that we concentrated extends between the coordinates of 30°N-46°N latitude and 0°E-30°E longitude.

2.3. Models

2.3.1. Convolution Neural Network (CNN)

Convolutional Neural Networks (CNNs) are commonly used with image data, they can also be adapted for time series prediction by treating the data as two- or three-dimensional structures. In the context of time series forecasting, CNNs use filters to identify local patterns and features in the data, which are then combined through deeper layers to generate more complex representations. This allows CNNs to effectively capture temporal hierarchies and spatial relationships within the data, making them valuable for tasks such as signal processing, sensor data analysis, and multivariate time series prediction as illustrated in Figure

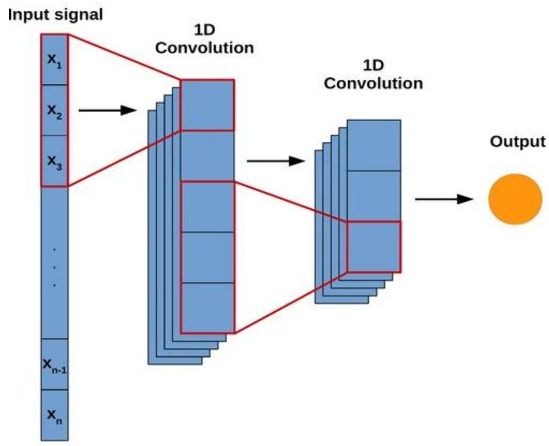

Figure 1. CNN overlay (Shenfield, 2022)

2.3.2. Long Short-Term Memory (LSTM)

Long Short-Term Memory (LSTM) networks are a specialized type of recurrent neural network (RNN) architecture, designed to address the challenges that traditional RNNs face in capturing long-range dependencies within sequential data. Central to LSTM networks are memory cells, which allow them to store information over extended periods, enabling the network to learn from sequences with long-term dependencies.

LSTMs incorporate mechanisms called gates to control the flow of information within the network. These gates, using sigmoid activation functions that produce outputs between 0 and 1, regulate how much information is retained or discarded as seen in Figure 2. During the training process, LSTM networks optimize the parameters of these gates and memory cells through techniques such as backpropagation through time (BPTT). By fine-tuning these parameters, LSTM networks are able to capture and leverage long-range dependencies in sequential data effectively. In essence, LSTMs use memory cells and gates to manage information flow, making them well-suited for modeling time series and other sequential data.

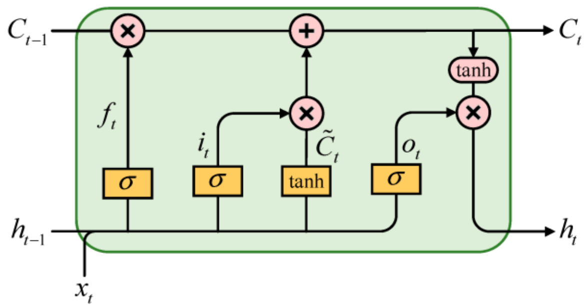

Figure 2. LSTM overlay (Liu,2024)

2.3.3. Gated Recurrent Unit (GRU)

The Gated Recurrent Unit (GRU) is a type of recurrent neural network (RNN) designed as an alternative to traditional LSTM or RNN models. GRUs have gained significant popularity in various language processing tasks. GRUs offer a simplified version of the LSTM memory cell, often delivering similar performance while being computationally more efficient. The GRU's modified gating mechanism is designed to improve the handling of long-term dependencies compared to standard RNNs, but without the computational complexity associated with LSTMs. Unlike LSTM, the GRU architecture has fewer gates, allowing for faster computation while still being highly effective in modeling long-term dependencies in sequential data such as time series.

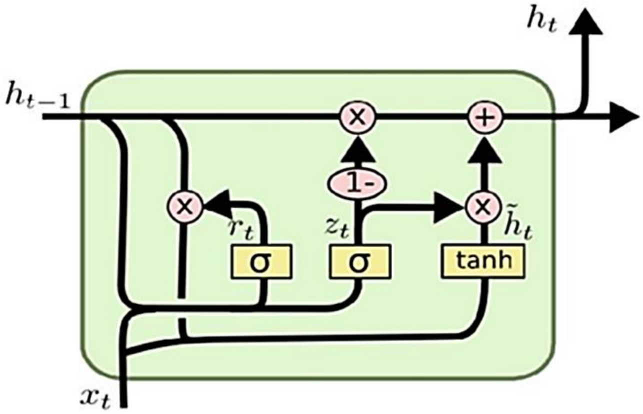

Figure 3. GRU overlay (Chang,2024)

2.3.4. Hybrid Deep Learning Models

LSTM-CNN and GRU-CNN are hybrid deep learning models that combine the strengths of Convolutional Neural Networks (CNNs) and recurrent neural networks, specifically Long Short-Term Memory (LSTM) or Gated Recurrent Units (GRUs), to effectively model time series data. CNNs are well-known for their ability to extract local patterns and features through convolutional layers, typically in spatial data like images. However, when applied to time series data, CNNs can capture short-term dependencies and local temporal patterns by treating time series as sequences, allowing the model to learn from fluctuations within a limited timeframe. In contrast, LSTMs and GRUs are recurrent architectures that excel in capturing long-term dependencies in sequential data due to their inherent memory cells and gating mechanisms, which regulate the flow of information over time.

In the LSTM-CNN model, the CNN layers first identify short-term patterns from the time series, which are then passed to the LSTM layers to capture longer-range temporal dependencies. Similarly, the GRU-CNN model employs GRUs instead of LSTMs, providing a computationally simpler yet effective mechanism to learn long-term relationships in the data as depicted on Figure 4. GRUs typically require fewer parameters than LSTMs, making them computationally more efficient while maintaining comparable performance. Both hybrid models are highly effective for time series forecasting tasks, such as predicting SST, as they capture both local variations and long-term trends in the data, providing robust predictions in complex temporal patterns.

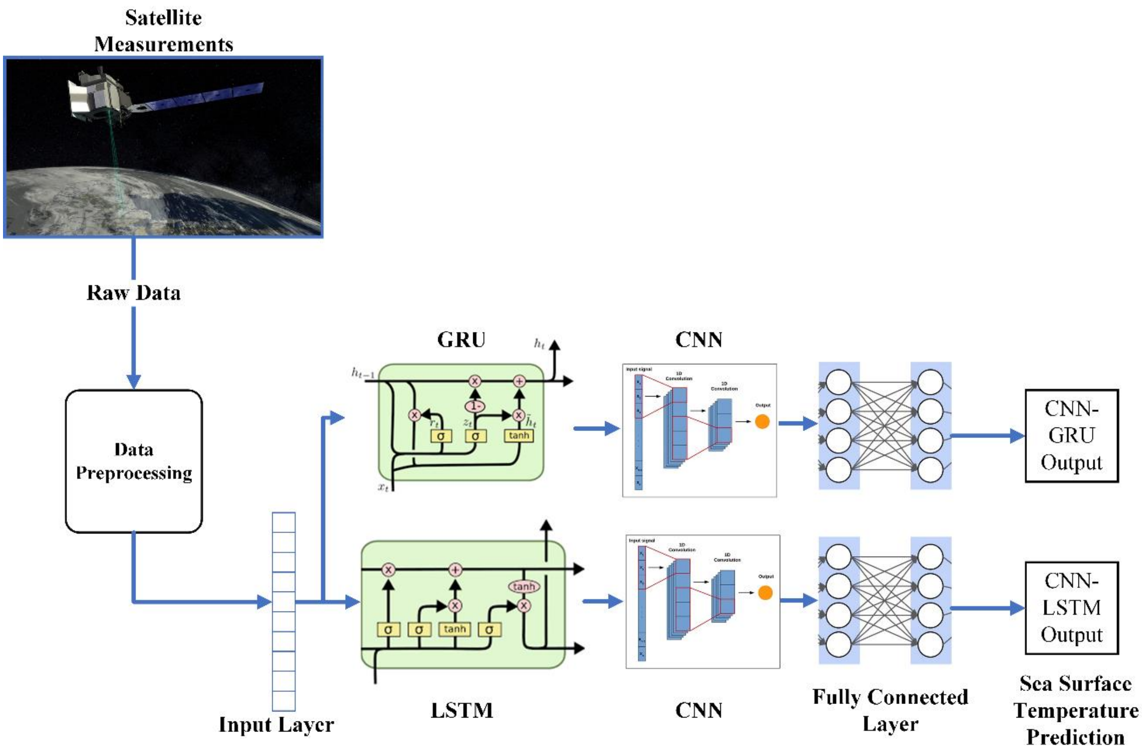

Figure 4. Hybrid Deep Learning Structure

2.4. Accuracy Metrics

2.4.1 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is a commonly used metric for evaluating the accuracy of a predictive model, particularly in regression and time series forecasting (Qu,2021). It measures the average magnitude of the error between predicted and observed values. RMSE is calculated by taking the square root of the average of the squared differences between the predicted and actual values.

Mathematically, RMSE is expressed as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

Where:
y_i represents the actual (observed) values,
$\hat{y}_i$ represents the predicted values,
n is the number of data points.

2.4.2. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a widely used metric for assessing the accuracy of a predictive model, particularly in regression and time series forecasting (Ledmaoui, 2023). It measures the average magnitude of the errors between predicted and actual values, without considering their direction (positive or negative). MAE provides an indication of how far, on average, the predictions are from the true values.

The formula for MAE is:

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

3. RESULTS&DISCUSSION

3.1. Data Preprocessing

The time series forecasting methodology utilized in this study involves applying a statistical model to predict future values of a time series based on historical data. This process entails conducting a univariate modeling study, which relies on past time series data for the variable of interest. In time series analysis, known past data serves as the input for the model, while the subsequent value of the variable represents the output. This approach emphasizes univariate modeling, which captures the inherent periodic patterns within the data. A significant advantage of univariate modeling is its capacity to leverage historical data points and their trends to forecast future values without requiring additional information or external observations.

Figure 5 presents the training (814 months) and testing (203 months) datasets, along with the observed monthly Sea Surface Temperature (SST) for the Mediterranean region, used in the GRU-CNN and LSTM-CNN models. The entire dataset, comprising 1,017 months of SST data, was divided into two subsets for training and testing. For all simulations, 80% of the dataset was allocated for training the models, while the remaining 20% was reserved for testing, serving to validate the models and mitigate overfitting. In Figure 5, the X-axis represents the data points, and the Y-axis denotes the SST values.

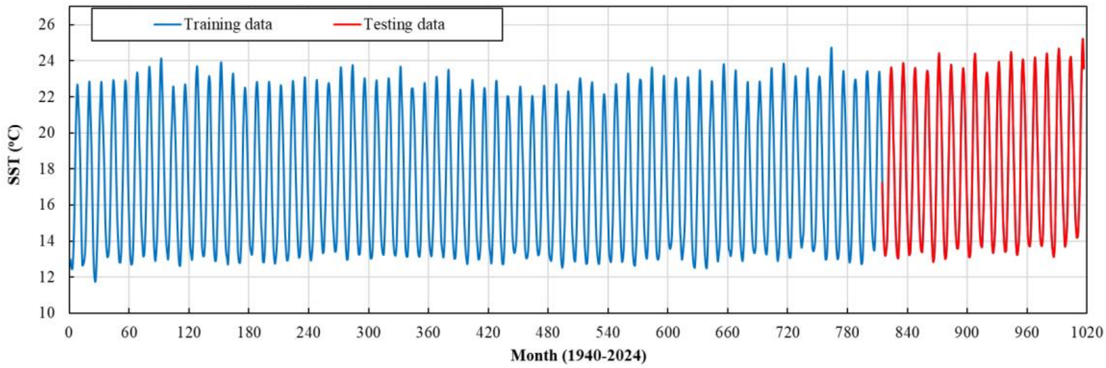

Figure 5. Training and Testing Data

The Augmented Dickey-Fuller (ADF) test is a widely used statistical test for determining whether a given time series is stationary or contains a unit root, indicating non-stationarity. Stationarity is a critical assumption in time series analysis. Before conducting the Augmented Dickey-Fuller (ADF) test, the data was subjected to a first differencing operation to achieve stationarity. This transformation was necessary to remove any trends or seasonality inherent in the original series, making the data more suitable for time series modeling. Following the differencing operation, the ADF test was applied with a significance level of 0.05. The test statistic was calculated as -22.79, which is significantly lower than the critical value of -1.94 at the 5% level. Since the test statistic is far below the critical threshold, the null hypothesis of a unit root is rejected, confirming that the differenced data is stationary. Consequently, the dataset is appropriate for use in models that assume stationarity, ensuring reliable and robust forecasting.

3.2. Hyperparameter Tuning and Testing

The hyperparameters optimized in this study were the number of hidden units and the initial learning rate. The number of hidden units was varied between 10 and 50, while the initial learning rate was adjusted within the range of 0.004 to 0.008. These values were fine-tuned using a trial-and-error approach to achieve optimal performance. By experimenting with different combinations of these parameters, the models were calibrated to better capture the underlying patterns in the time series data, improving prediction accuracy. As a result of the hyperparameter tuning process, the optimal configuration for the LSTM-CNN model was found to be an initial learning rate of 0.005 and 20 hidden units. For the GRU-CNN model, the optimal setup consisted of 30 hidden units and an initial learning rate of 0.006. These specific combinations provided the best performance for each model.

The performance of the LSTM-CNN and GRU-CNN models was evaluated using RMSE and MAE as accuracy metrics. The LSTM-CNN model achieved an RMSE of 0.3323 °C and an MAE of 0.259 °C, whereas the GRU-CNN model obtained an RMSE of 0.3370 °C and an MAE of 0.264 °C. These results indicate that while both models performed similarly, the LSTM-CNN model slightly outperformed the GRU-CNN model in terms of both RMSE and MAE, making it marginally better at capturing the time series patterns and reducing prediction errors as summarized in Table 1.

Table 1

Model Accuracy Performance Details

Model	RMSE(°C)	MAE(°C)
LSTM-CNN	0.3323	0.259
GRU-CNN	0.3370	0.264

For visual comparison, Figure 6, a boxplot was selected to illustrate the performance differences between the models and the actual data. The interquartile range (IQR) of the actual data was found to be 25.223 °C for the upper bound and 12.842 °C for the lower bound. The LSTM-CNN model produced an upper bound of

24.814 °C and a lower bound of 12.928 °C, while the GRU-CNN model yielded values of 24.834 °C for the upper bound and 12.942 °C for the lower bound. These values demonstrate that both models closely approximate the IQR of the actual data, with the LSTM-CNN model slightly more aligned with the real data distribution.

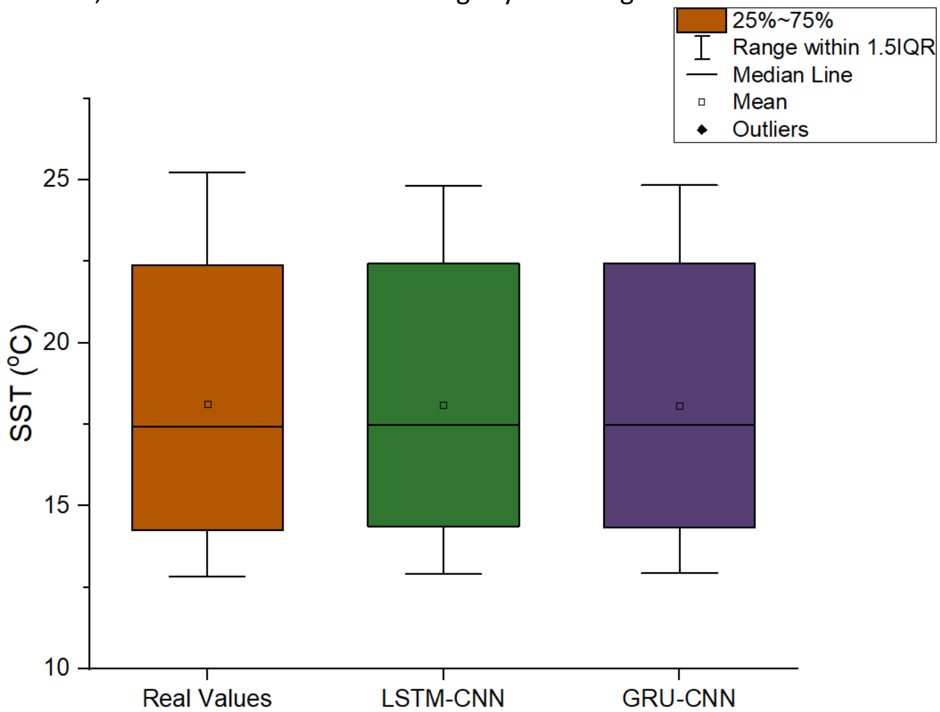

Figure 6. Boxplot Illustration

3.3. Future Forecast

The graph presents the Sea Surface Temperature (SST) trend over time, with observed data spanning from 1940 to the present and forecasted data extending up to 2034. The GRU-CNN model was used to forecast future SST values. The blue line represents the observed SST data, while the purple line indicates the forecasted SST for future periods. The proposed models proves that the late increasing trend in SST will grow which means that the yearly mean SST will increase nearly 1.1 °C for the next decade as depicted in Figure 7.

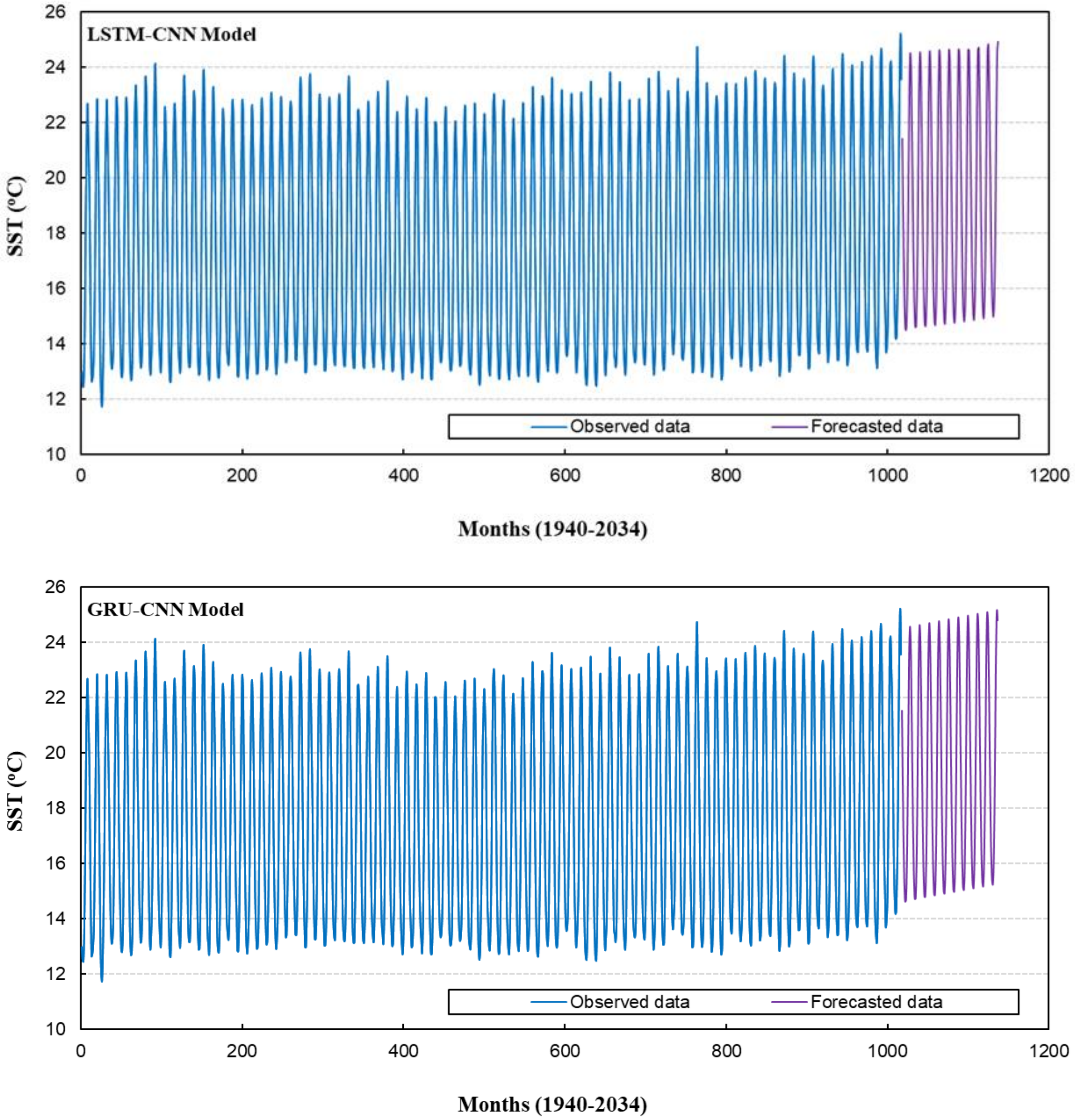

Figure 7. Hybrid Deep Learning Model Monthly SST Outputs for the Next Decade

The analysis of the yearly maximum sea surface temperature (SST) demonstrates a clear warming trend over the studied period. The yearly maximum SST is particularly important because it has direct implications for marine ecosystems, weather patterns, and the intensification of extreme events such as heatwaves and storms. Higher SSTs contribute to the disruption of marine life, including coral bleaching and shifts in species distributions, and they also influence atmospheric dynamics, potentially leading to more intense and frequent extreme weather events. In 1940, the maximum SST was recorded at 22.689°C, which increased to 24.22°C by 2023, reflecting a rise of approximately 1.53°C as seen on Figure 8. This observed warming trend continues in the forecasted period (2024–2034) based on the predictions from both the LSTM-CNN and GRU-CNN models. According to the LSTM-CNN model, the maximum SST is projected to reach 24.90°C by 2034, while the GRU-CNN model predicts a slightly higher increase, with a forecasted maximum SST of 25.22°C for the same year.

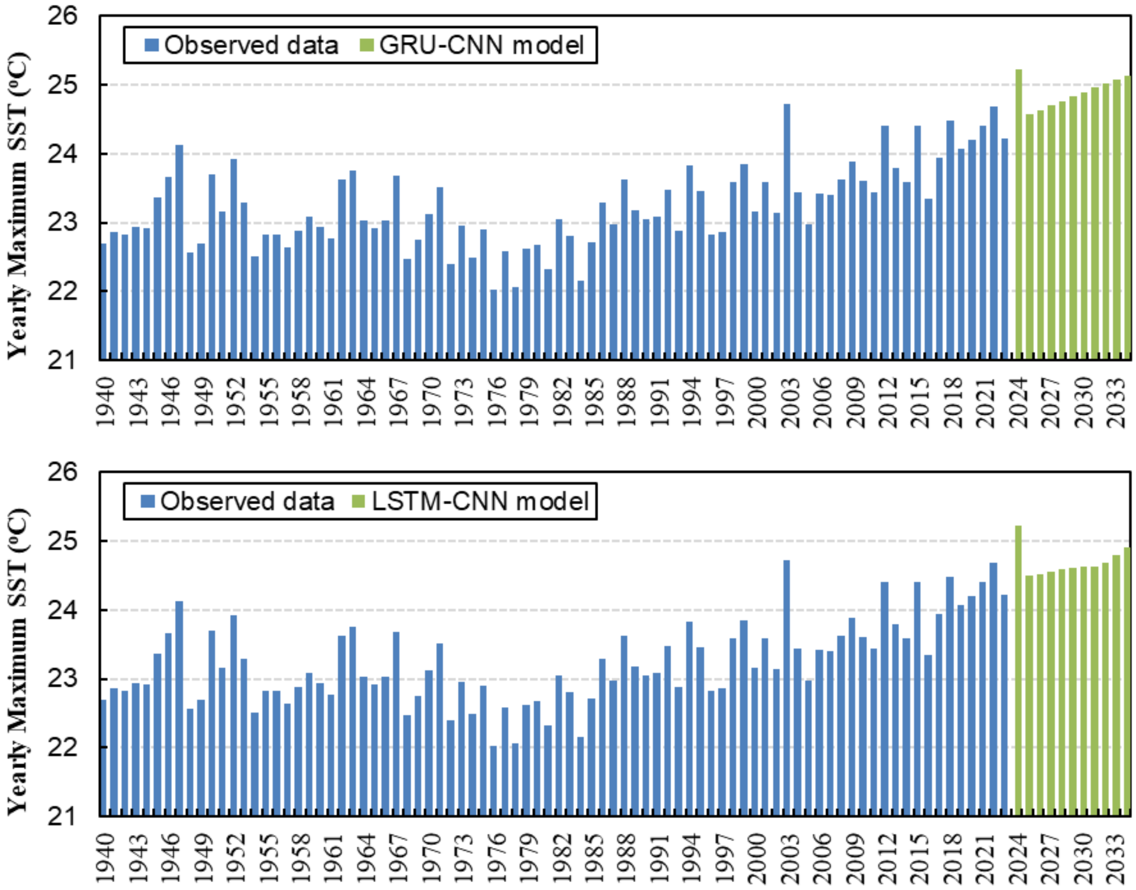

Figure 8. Yearly Maximum SST Predictions of the Hybrid Deep Learning Models

4. CONCLUSION

In this study, we applied hybrid deep learning models, LSTM-CNN and GRU-CNN, to predict sea surface temperature (SST) in the Mediterranean Sea from 1940 to 2034. By leveraging historical data and forecasting future trends, the models provide insights into the ongoing warming of the Mediterranean region. The LSTM-CNN model demonstrated slightly better performance in terms of RMSE and MAE compared to the GRU-CNN, although both models exhibited strong predictive capabilities. Notably, the projected increase in the yearly maximum SST, from 24.22°C in 2023 to as high as 25.22°C by 2034, underscores the continued warming trend.

The models employed in this research offer a reliable approach for predicting long-term climate patterns in the Mediterranean Sea, which could be further applied to other regions with similar climatic conditions. The observed warming trend and its potential ecological and environmental consequences highlight the urgency of addressing climate change and developing adaptation strategies for affected regions.

5. RECOMMENDATION AND FUTURE DIRECTIONS

Future work could enhance the predictive capabilities of the models by incorporating additional variables, such as ocean circulation patterns, atmospheric conditions, and greenhouse gas concentration levels. Moreover, extending the forecast period and analyzing other climate-sensitive regions may provide a more comprehensive understanding of global sea surface temperature dynamics in the context of climate change.

Conflict of Interest: There is no conflict of interest.

Ethical Approval: There is no need for Ethical Approval.

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