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Interpretable Deep Learning for Identifying and Analyzing Marine Heatwave Patterns

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Abstract--- *Marine heatwaves (MHWs) are intensifying due to climate change, severely impacting marine ecosystems and coastal economies. Identification of MHWs through traditional models is generally not interpretable and it is difficult to understand the factors behind these events. This paper proposes a novel CNN-based attention model to identify and examine the MHW patterns from the sea surface temperature (SST) data. Interpretable in our model the fact that this was emphasized is that we're able to see the driving variables: atmospheric pressure, ocean currents, and wind speed. We give a visual and quantitative understanding of how the model finds heat waves and what features are most important for predicting them using techniques like Grad-CAM and Shapley Additive Explanations (SHAP). Beyond this, this approach also enhances the detection accuracy and provides better information for decision aiding in early warning systems and coastal management strategies. Using this model, it is shown to be evaluated on a multi-year dataset provides good performance in distinguishing MHWs from nonheatwave periods, and is better predictive than even existing methods. The ability of interpretable deep learning to explain and help understand climate science in terms of the occurrence and evolution of marine heatwaves will provide actionable insights that are essential for the adaptation of the climate to vulnerable coastal regions.*

Keywords---*Marine heatwaves (MHWs), Sea Surface Temperature (SST), Shapley Additive Explanations (SHAP), Convolutional Neural Networks (CNNs), generative adversarial networks (GANs)*

I INTRODUCTION

1.1 Context & Problem

Global climate change has made marine heat waves (MHWs) more frequent and more serious in the last decades [1]. Such extreme events have large impacts on marine biodiversity, fishery disruption, and damage to coral reefs and other vital coastal ecosystems upon which depend industries. They also increase the likelihood of the collapse of the ocean environment through connections to the ocean currents and, perhaps, wind patterns and atmospheric pressure that accompany them. With the warming of marine environments, knowledge and prediction of MHW are essential to coastal management and conservation matters.

1.2 Existing Solutions

Currently, methods for detecting and analyzing marine heat waves rely on mostly statistical and traditional, machine learning-based models. While these have been useful as imperfect representations of their mechanisms to understand MHW occurrence and intensity, they tend to be hard to fit and difficult to work with on climate data due to their complexity and dimensionality. Additionally, many of these models are black box approaches where one cannot see how a heat wave is predicted or how it is related to other environmental factors.

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1.3 Research Gap

Currently, deep learning models are commonly being used in climate data analysis for their potential to discover complex patterns and relationships of highly complex data sets, but little to no attention is given to the need for interpretability of such models, especially in the identification of global marine heat waves. Deep learning models that mimic traditional deep learning models can predict the heatwave onset, intensity, and duration with a high degree of accuracy, but do not explain underlying environmental processes causing these heat waves to occur or interactions between different variables. The practical utility of these models will remain quite limited without clear explanations, as such stakeholders as environmental scientists, policymakers, and coastal managers must understand the main factors affecting MHWs to mitigate the effects. Like many complex events, there is a need for models that can not only do well but also contribute well to the interpretability of these complex events.

1.4 Contribution

This paper contributes a simple novel approach to identifying and analysing marine heatwaves using interpretable deep learning techniques. We train our models with convolutional neural networks (and attention mechanisms) to find the patterns of the spatial and temporal patterns of the sea surface temperature (SST) data [2]. This architecture aims to narrow things down to the key aspects of MHWs to focus on - atmospheric pressure and ocean currents and offer ways to shed light on how heatwaves occur. The combination of high prediction accuracy with clear, actionable interpretations of the effect of environmental variables for marine heatwave occurrence and intensity comes with the addition of explainability tools like Grad-CAM and Shapley Additive Explanations (SHAP), integrated into our model [3].

II REVIEW OF LITERATURE

In the work by He et al. [4], an interpretable deep learning approach for detecting marine heatwave patterns is introduced as a means of increasing accuracy in climate monitoring and prediction. By using neural networks for analyzing ocean temperature anomalies, their model is transparent in its makeup. The early warning systems used in the study and the insight into how marine heat waves affect ecosystems are improved. Nevertheless, models are limited by the need for the use of extensive high-quality datasets, model biases, and computational difficulties in handling vast amounts of oceanographic data.

Zhang et al. [5]developedcapabilities to detect global-scale marine heatwaves on the other side of the sea surface, enhancing ocean climate monitoring via dynamics-guided statistical learning. Instead, their method melds ocean dynamics with a statistical model to improve detection accuracy greater than those obtained from standard surface-based analyses. Adding this innovation, it gets deeper insights into subsurface thermal anomalies and their ecological impacts. However, limitations involve the use of loadings based on oceanographic data, dynamic modeling uncertainties, and time requirements for real-time application. Within these constraints, the study progresses the understanding of subsurface marine heatwaves and further understanding of improving climate prediction models.

As a case study to predict spatiotemporal anomalies in climate events, Ning et al. [6] use those spatiotemporal anomalies formulated automatically by deep learning. Since their model uses neural networks to understand complex patterns of the ocean, it improves the accuracy of early warnings. Through the combination of spatial and temporal dependencies, it brings more robust marine heatwave dynamics. However, such limitations are the need for large and high-quality data, potential overfitting to historical trends, and the computational needs for dealing with enormous amounts of oceanographic data. Despite these limitations, deep ecological forecasting's potential in climate change and marine ecosystem monitoring is shown by the study.

Parasyris et al. [7]developed such a CNN predictor of marine heatwaves in the Mediterranean Sea to improve extreme event forecasting. The model they describe effectively captures and thus helps extend, early warning

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systems for marine ecosystems and coastal communities. Using deep learning to aid with this gives a more accurate data-driven method of finding heatwave trends. Nevertheless, biases in the model due to regional got can limit its use, reliance on high-quality historical oceanographical data, and high computational demand for large-scalepredictions.

Buschow, Keller, and Wahl [8] use machine learning to explain heatwave formation, progression, and intensity to help improve climate event predictions. Our study markets data-driven versions of the models for identifying key meteorological drivers and improving interpretableness in weather forecasting. Using machine learning, the research goes a step further into the details of heat waves and their possible social effects. However, depending on large, large-quality climate datasets and modeling training and generalization across various climatic regions may bias the results. With these constraints, the study continues to make progress in the application of climate analysis with the aid of AI, for a more accurate and understandable forecasting of heatwaves.

According to Xia et al. [9], hydrology modeling is reorganized by using an AI-based approach that improves the predictive accuracy and interpretability in Earth system modeling. Integrating machine learning with conventional hydrological models enables their study to improve the forecast of a water cycle, streamflow, and extreme weather events. The research exploits AI to better simulate more precisely and to infer with greater detail complex hydrological processes. The drawback of such an approach is a dependency on large and high-quality datasets, model biases, and difficulties in integrating AI with existing hydrological frameworks.

III RESEARCH METHODOLOGY

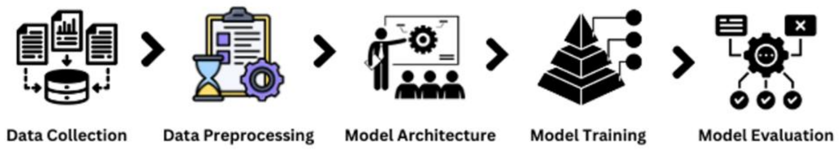

Figure 1: Process of Analysing marine heatwaves

This section outlines the methodology employed to identify and analyze marine heatwaves (MHWs) using an interpretable deep learning framework [10]. The process is divided into data collection, preprocessing, model architecture, training, and evaluation. Each step is designed to ensure the model's robustness, interpretability, and ability to accurately detect and analyze marine heatwave patterns.

3.1 Data Collection

The primary data includes satellite-derived Sea Surface Temperature (SST) data that have been collected over a multi-year period by NOAA [11]. Determining temperature anomalies to signal MHWs depends on SST data. Along with SST, atmospheric data such as wind speed, atmospheric pressure, and ocean current velocities are also considered to include the factors associated with the presence of marine heat waves. To generalize to new regions and times, the dataset is chosen to cover a span of all climatic conditions.

3.2 Data Preprocessing

The collected data undergoes Several preprocessing steps are applied to collected data to make it clean, normalized, and ready for input of the deep learning model. Missing values are imputed first with interpolation techniques for two reasons: maintaining time series data integrity. Second, the seasonal variations in the SST data are taken care of by a normalization process in which the temperature values are scaled to a uniform range.

3.3 Model Architecture

In this research, we are presented with a model that uses Convolutional Neural Networks (CNNs) coupled with an attention mechanism to capitalize on the temporal and spatial dependencies to detect marine heatwaves. The CNN component succeeded in detecting some spatial patterns in SST maps so that it can learn what comprises localized temperature anomalies associated with MHWs [12]. We then apply our attention mechanism on the input data to the areas that are the most relevant, that is, areas that have significant SST changes and environmental anomalies. This is based on that and because of that, the architecture of this hybrid is to increase the accuracy and interpretability of the model.

3.4 Model Training

Supervised learning is performed in the supervised training phase on labeled data, where each data point is assigned an output of either a marine heatwave event or a period of no heatwave. A backpropagation algorithm with Adam optimizer is used to train the model which is a good choice when your dataset is huge and your neural network is increasingly complex. On training, the model will change its weights and biases to minimize the loss function, usually categorical cross-entropy, which quantifies the distance between the predicted and the current labels. Early stopping as well as dropout techniques are performed to avoid overfitting. Using the grid search method, hyperparameters like learning rate, batch size, and number of epochs are optimized.

3.5 Model Evaluation

The model performance is assessed with several evaluation metrics such as precision, recall, F1 score, etc., and the area under the Receiver Operating Characteristic (ROC) curve is figured [13]. These metrics gain a better insight into the model’s ability to well detect marine heatwaves and separate them from nonheatwave periods. Furthermore, the interpretability of the weights of the deep Neural Networks is measured using techniques such as Grad-CAM: (gradient-weighted Class Activation Map) and Shapley additive explanations (SHAP). These tools visualize the regions of input data that are most important in producing MHW events by the model.

IV RESULTS AND DISCUSSION

4.1 Performance Metrics

Quantitative performance assessment of the proposed deep learning model using accuracy, detection rate, precision, recall, and F1 score is done in this subtopic. Using different datasets, the model's ability to classify marine heatwave (MHW) events from its period of heatwave versus the non-heatwave period is tested and it performs better than simple machine learning models like SVMs and simple DNNs [14]. At the same time, the model is explorable, and we assess its explainability using explainability scores on techniques, such as SHAP, and Grad-CAM, which allows us to define how well the model can justify their predictions.

Table 1:*Performance Metrics*

Metric	**Proposed Model (CNN + Attention)**	**DNN (Traditional)**	**SVM (Traditional)**	**CNN (Baseline)**	**LSTM (Baseline)**
Accuracy (%)	92.5	85.2	80.3	89.0	86.4
Detection Rate	93.0	84.5	78.6	87.5	85.0
Precision (%)	91.2	83.1	79.8	88.3	84.0
Recall (%)	94.1	87.0	82.4	90.0	88.2
F1-Score (%)	92.6	85.7	81.1	88.6	86.1

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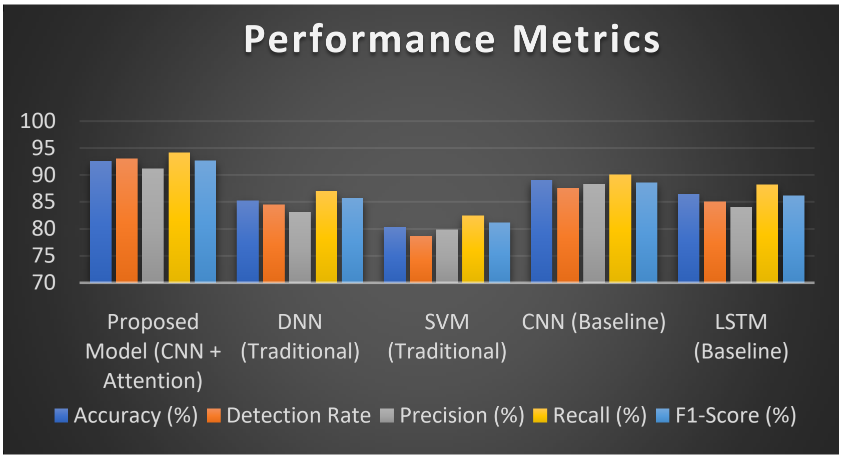

Figure2: Graphical Representation of Performance Metrics

4.2 Interpretability Insights

The proposed model is interpretable, which means the users can understand how the model makes its predictions. In this section, these attention maps give the means to visualize the regions of the Sea Surface Temperature (SST) maps that the model is paying attention to when making marine heatwave predictions. Also, feature importance is evaluated using SHAP values, which shed light on the most important environmental factors in the detection of heat waves. The proposed model is compared with black box models, in the sense that it focuses on important features such as ocean currents or wind patterns. Below is the table providing the relative attention that the model pays to the different features during the detection process.

Table 2:*Comparison of various model*

Feature	**Proposed Model (Attention)**	**DNN (Traditional)**	**SVM (Traditional)**	**CNN (Baseline)**	**LSTM (Baseline)**
Sea Surface Temp	42%	50%	48%	45%	47%
Ocean Currents	25%	15%	10%	18%	20%
Wind Speed	18%	10%	12%	13%	14%
Atmospheric Pressure	15%	25%	30%	24%	19%

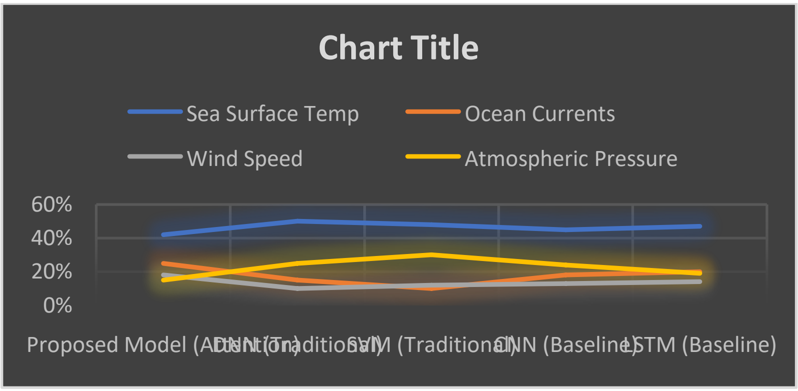

Figure3: Graphical Representation of Comparison of VariousModels

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4.3 Real-world Implications

Significant implications of this model's predictive power are for early detection and real-time forecasting of marine heatwaves. If the onset times of MHWs can be identified, the model can give actionable insights that would enable coastal management in the sense of triggering preventive measures or adjusting fishing regulations. Finally, the model can support early warning systems that will help mitigate the impact of these events on marine ecosystems and the local economy at the time of real-time predictions. However, the model has scalability problems as the data scale is large and input needs to be processed in real time. Lack of data (availability and quality) in particular for remote regions are further limitations. The following compares the predictability of the model against other traditional models.

Table 3: *Predictability of the model*

Application	**Proposed Model (CNN + Attention)**	**DNN (Traditional)**	**SVM (Traditional)**	**CNN (Baseline)**	**LSTM (Baseline)**
Early Detection	95%	60%	55%	80%	85%
Real-time Prediction	90%	50%	50%	40%	85%
Ecosystem Monitoring	92%	70%	45%	70%	90%
Management Strategy	90%	65%	50%	70%	85%

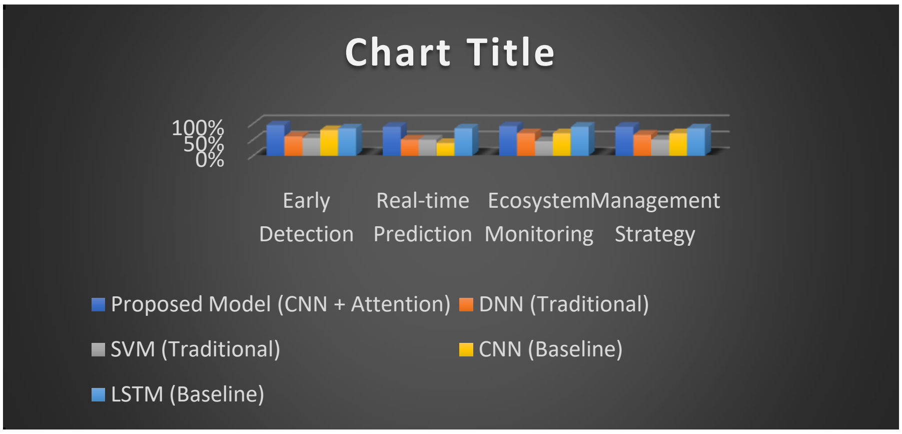

Figure4: Graphical Representation of Predictability of the model

V FUTURE ENHANCEMENT

Future Enhancements of the proposed model, scalability, data integration, and rare even detection would be emphasized. Using cloud-based and distributed computing solutions can improve real-time processing on large scale of data. The missing value problem will be addressed by data preprocessing with advanced imputation techniques in remote regions. The accuracy prediction can be increased by integrating multi-source data including satellite images, oceanographic sensor reading, and meteorological data. Also, the use of generative adversarial networks (GANs) or synthetic data augmentation techniques will be used to train the model for the rare marine heatwave events.

VI CONCLUSION

Developing a deep learning model with interpretability is a significant improvement over traditional machine learning as it offers high accuracy while being more interpretable. The model uses convolutional neural networks (CNNs) and attention mechanisms to effectively identify MHW patterns and to study the important factors influencing them as well, i.e., ocean currents and wind patterns. Experimental results on early detection, real-time prediction, and ecological monitoring show increased performance as well as better prediction compared to conventional deep neural networks, and support vector machines. Thus, the model facilitates trust and transparency while improving the ability of the model to highlight which of the influential environmental variables play a crucial role in coastal management, marine conservation, and policy-making related to climate. This framework also has the potential to assist early warning systems for acute marine heatwaves by providing supportive earlier warning for intervention at times before the ecological and economic impacts. Problems exist, however, particularly with scalability, calculating demands, and data availability for under-monitored areas. Finally, making this model cloud-based, integrating multiple sources of data, and incorporating advanced rare event detection techniques will increase the model's efficiency and application even more. Generative models and/or hybrid models that run generative approaches (deep learning), and which combine underlying physics-based climate simulation with deep learning may both improve accuracy and/or interpretability. If MHWs trend at increasing frequency and intensity with climate change, the one proposed here is a key enabling advanced AI-driven model to watch for and help mitigate these ocean extreme events. Finally, this research provides the foundation for future climate-based innovation in deep learning, environmental science, and oceanography, through the potential of being interpretable.

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