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Hybrid ARIMA-LSTM Stacked Ensemble for RealTime Multivariate Forecasting of OceanAcidification and Hypoxia in Coastal Regions

Abisek Kamthan R S
Department of Data Science and Business Systems,
SRM Institute of Science and Technology,
Kattankulathur, Tamilnadu

Pawishrajhen A R
Department of Computational Intelligence
SRM Institute of Science and Technology
Kattankulathur, Tamilnadu

Harish S
Department of Computational Intelligence,
SRM Institute of Science and Technology,
Kattankulathur, Tamilnadu

Abstract: Ocean acidification and hypoxia are severe threats to the marine ecosystems and, thus, establishing strong forecasting tools serves as a preventive approach. In an attempt for real-time multivariate forecasting of ocean acidification and hypoxic events in coastal regions, a hybrid layered-stack ARIMALSTM framework has been proposed. Models in the current literature range from statistical ones such as ARIMA to deep learning models such as LSTM. Herein, the models are combined to exploit the best of their capabilities with respect to the datasets, which contain historical data from GLODAP and SOCAT and real-time measurements from IoT sensors, to predict oceanographic parameters such as pH, dissolved oxygen, and dissolved inorganic carbon. The stacked ensemble approach amalgamates the prowess of ARIMA in statistical modeling with that of LSTM in capturing nonlinear behavior to boost prediction accuracy. The framework is tested on the historical dataset, proving the better performance of the proposed framework over standalone models. The results are presented on a geospatial dashboard, helping stakeholder groups track environmental trends and take interventions as necessary. The study thus contributes to sustainable marine management, neatly tying into United Nations Sustainable Development Goals (UN SDGs) 13: Climate Action and 14: Life below Water, through the provision of a scalable solution for coastal ecosystems globally.

Keywords: Ocean acidification, hypoxic events, hybrid ARIMA-LSTM, multivariate forecasting, developing nations, IoT sensors, socioeconomic impacts, deep learning, geospatial visualization, sustainable marine management.

I. INTRODUCTION

Ocean acidification and hypoxic events are basically a threat to marine ecosystems and are imperative in providing livelihood for coastal communities; advanced forecasting and projection need to be developed to encourage anticipatory environmental management on the vulnerable coasts. Ocean acidification is basically the lowering of the sea's pH by the absorption of anthropogenic carbon dioxide (CO_2) that disturbs marine biodiversity and ecosystems along with livelihood-supporting services important to coastal economies [3]. A hypoxic event occurs in coastal waters where critical thresholds of dissolved oxygen concentrations are met or breached, thus worsening the ecological degradation occasioned especially in coastal zones under nutrient pollution [4].

Given that these phenomena currently affect food security, economic stability, and climate regulation, the need arises for real-time posed, multivariate forecasting systems. Empirical classical statistical models, such as the Autoregressive Integrated Moving Average (ARIMA), tend not to capture the nonlinear ocean system dynamics [1]. State-of-the-art machine-learning methods, especially hybrid statistical and deep-learning approaches, promise superior accuracy in predictions [5]. The study herein articulates a hybrid ARIMA-LSTM stacked ensemble for the real-time forecasting of ocean acidification and hypoxic events in coastal areas.

A. Background Study

Oceans currently absorb about a quarter of anthropogenic CO_2 emissions, leading to a drop in pH by 0.1 units since the pre-industrial period, with another 0.3-0.4 units decline expected by 2100 [3]. This acidification impedes the formation of calcium carbonate, thereby threatening calcifying organisms such as corals and shellfish essential for oceanic food webs and coastal livelihoods [6]. Hypoxic zones have been expanding due to causes such as eutrophication, primarily from agricultural and industrial runoff, with over 400 having been recorded worldwide, many in the coastal zones where monitoring is scant [4]. The coastal ecosystems receive further threats in return for ecological and economic significance from regions such as the Pacific and Indian Oceans [7].

The report Leveraging Machine Learning for Monitoring and Predicting Oceanic Environmental Changes by our group depicts and testifies to the potential of machine learning methods in oceanographic forecasting but also casts light on the shortcomings in dealing with other relevant real-time data and applications of deep learning [1]. Recent work has looked at hybrid models that combine the statistical rigor of ARIMA with the ability of Long Short-Term Memory (LSTM) neural networks to model complex patterns, with some success in environmental forecasting [8].

B. Objectives

This study's purpose is to develop and prove a hybrid ARIMA-LSTM stacked ensemble framework for real-time multivariate forecast of ocean acidification and hypoxic events in coastal regions. The specific objectives are: 1) to develop a stacked ensemble model of ARIMA and LSTM to forecast oceanographic parameters, including pH, dissolved oxygen, and dissolved inorganic carbon, from historical datasets and real-time IoT sensor streams; 2) the second objective is to improve the predictions by means of a stacked ensemble approach where ARIMA's statistical approaches complement LSTM's nonlinear approaches; 3) To develop a geospatial dashboard for real-time visualization of environmental trends so that stakeholders can activate their monitoring and responses towards acidification and hypoxia risks; and 4) to validate the framework using historical datasets and regional case studies to ensure robustness and scalability for coastal use cases. These objectives address the original study gaps pertaining to real-time integration, deep learning, and geospatial scalability.

C. Alignment with Sustainable Goals

The proposed framework aligns with the United Nations' Sustainable Development Goals (SDGs), particularly, it prescribes actionable, real-time forecasting tools for reducing climatically driven ocean changes and for protecting coastal ecosystems [9]. In generating adaptation and resilience to coastal regions, the research relates to SDG 8 (Decent Work and Economic Growth) by enabling adaptation and resilience of fishery-dependent coastal communities [7]. By embedding IoT sensor data in geospatial visualization, the framework integrates and along with station-based instruments can inform global monitoring initiatives such as the Global Ocean Observing System (GOOS) [10].

II. LITERATURE SURVEY

Ocean acidification and ongoing hypoxic events threaten coastal biological systems. As a result, there is an urgent need to develop forecasting models that account for data complexity and are integrated into forecasting / warning systems [1]. Ocean acidification is caused by the increase in the absorption of carbon dioxide (CO_2) into the ocean which lowers the pH of seawater and compromises marine biodiversity and ecosystem services that coastal economies depend on [2]. Hypoxic events are caused by the depletion of oxygen in the water (eutrophication) from increased nutrients in coastal systems. Eutrophication processes have become exacerbated and drive biological degradation in coastal provinces that rely on limited monitoring [3]. The application of machine learning has transformed environmental forecasting through its ability to model nonlinear patterns of data using diverse data types [4]. This project continues from previous research that modeled hybrid statistical and machine learning models to forecast oceanographic measurements. Our previous work demonstrated a high accuracy for predicting pH, although we identified limitations for the integration of real-time data and the applications of deep learning within our forecasting frameworks. In context to longstanding work in statistical models, deep learning, and hybrid approaches to ocean forecasting, this literature review is intended to critique existing applications and highlight deficiencies and limitations before introducing the proposed hybrid ARIMA-LSTM stacked ensemble model for real-time multivariate forecasting in coastal ecosystems.

A. Existing System

Statistical models (like Autoregressive Integrated Moving Average, ARIMA) have been used frequently in oceanographic forecasting of time-series data, such as pH and dissolved oxygen [5]. ARIMA models work well to capture linear trends and seasonal fluctuations, as seen in studies that forecast future sea surface temperature and pH trends using GLODAP and SOCAT data [6].

The nonlinearity of the interactions will affect our understanding of the functionality of oceanic systems, and a greater challenge will be providing a representation of pH or dissolved oxygen forecasting to support the accuracy and robustness of ARIMA. The recent movement towards deep learning methods, such as Long Short-Term Memory (LSTM) neural networks, have gained traction in some environmental forecasting applications [7]. A LSTM model is developed to also work with sequential data where long-term dependencies exist and have been shown to correctly predict climate variables and oceanographic parameters such as sea level rise [8].

There is potential in hybrid models that combine statistical and deep learning models to take advantage of what ARIMA provides as a robust and accurate model with the nonlinear modeling provided by LSTM, to obtain improved accuracy in forecasting [9]. For example, Zhang et al. built an ARIMA-LSTM hybrid model that provided improved accuracy for time-series forecasting for environmental forecasting [9]. Other methods like the Tokenized Time Series Embedding Model (TOTEM) reinforce the viability of using deep learning methods for time-series environmental forecasting [4]. In previous research we conducted on pH forecasting using ARIMA and statistical methods, we provided some reliability in forecasting performance as indicated by the high prediction's accuracy (as indicated by RMSE around 0.0467) of our forecasting method for forecasting pH, but lacked real-time capabilities, motivating the development of a stacked ensemble approach.

B. Limitations

Current systems for oceanographic predictions have a number of challenges that make them inappropriate for near-real-time multivariate predictions in coastal contexts. Statistical models (i.e. ARIMA) are stymied by their linear assumptions which cannot integrate the complex non-linear interactions between pH, dissolved oxygen, and dissolved inorganic carbon [5]. Whereas non-linear models such as LSTM models do not have the same issues as ARIMA, they require larger datasets and higher computational capacity which are problems for resource-poor coastal contexts [7]. Hybrid models (e.g. ARIMA-LSTM) are useful for enhancing predictive accuracy such as those proposed by Zhang et al., but are mostly interested in univariate or very short term predictions and that fail to attend to important and unmet multi-variable and real-time demands of oceanographic scenarios [9].

Our previous work was able to make 12-month long-range pH predictions, for example, but also could not incorporate real-time IOT sensor data, so that meaningful and dynamic alerts for acidification and hypoxic events could not be created. It is also worth noting that current systems rarely link geospatial analysis with high temporospatial resolution. Geospatial analysis is paramount for the mapping of coastal zones that will be at risk of coastal acidification given predicted impacts from climate change [4]. Data sparsity in coastal areas, particularly in regions where they are not monitored, further limits the generalizability of models. These challenges highlight the importance of establishing an adaptable, real-time and dynamic forecasting framework that can take advantage of a stacked ensemble of ARIMA's statistical precision and LSTM's real-time non-linear modeling techniques specifically targeting the coastal areas that have the most significant restrains in oceanographic forecasting.

III. SYSTEM ARCHITECTURE

The architecture for the proposed hybrid ARIMA-LSTM stacked ensemble framework is of a system that will provide real-time multivariate forecasting of coastal ocean acidification and hypoxic events. It incorporates historical and real-time data to produce predictions and recommendations that can utilized for decision-making. The system architecture shown in Fig. 1 has five components to the architecture include: data inputs, data preprocessing, modeling, stacked ensemble, and output visualizations. Architecture addresses the deficiencies identified from our previous research, which does not incorporate real-time data and utilize deep learning methods, while taking advantage of the combination of statistical and deep learning and IoT based data streams [1]. The architecture is also designed to ensure scalability and robustness for different coastal ecosystems and continuums of monitoring.

The data input is a component that collects multivariate time series data from two sources: historical datasets and real-time IoT sensors. Historical datasets are either collected data from repositories like Global Ocean Data Analysis Project (GLODAP) and the Surface Ocean CO_2 Atlas (SOCAT). These datasets provide long term records of oceanic parameters, pH, dissolved oxygen (DO), dissolved inorganic carbon (DIC), total alkalinity (TALK), temperature, salinity, and fugacity of CO_2 (fCO_2) [2]. Real-time IoT sensors can be used to collect continuous measurements from IO, such as pH, DO, and DIC, to monitor the ongoing activities and variability of coastal ecosystems.

The data Preprocessing component works with unprocessed data and makes it suitable for the modeling pipeline. Some of the Preprocessing approaches were Principal Component Analysis (PCA) and Seasonal-Trend Decomposition (STL) which apply dimensionality-reduction techniques, isolate trends, all of these extend from methods used in our previous works. The end products are the geocoded and processed data which are passed into the modeling component following the preprocessing steps to ensure we feed our models with high quality, representative data for both the statistical models and deep learning models.

A. Proposed Architecture

The modeling component will utilize two separate forecasting models: Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) neural networks. Both models are trained independently on the treated data, the ARIMA model is trained using a grid search to optimize the parameters for the ARIMA, while the LSTM is trained with a backpropagation through time approach to tune its architecture. The benefit of simultaneously modeling the data with both models is to gain flexibility in our forecasting, independently of the linearity in our previous statistical modeling approach.

The stacked ensemble component will simultaneously combine the ARIMA and LSTM predictions utilizing a meta-learner approach to generate the final forecast with a weighted averaging technique. The meta-learner will assign weights for averaging the two model forecasts based on performance metrics, such as Root Mean Square Error (RMSE), therefore achieving the best integration of both linear and nonlinear model forecasts. This form of stacked ensemble approach is a new extension of the previous hybrid modeling approach we used in our previous work, one of the goals being to improve the accuracy of forecasting, for the purposes of coastal forecasting purposes, when combining the benefits of the modeling strengths of ARIMA and LSTM.

The output module provides real-time forecasts and visualizations to stakeholders by using a geospatial dashboard. This dashboard can be created with Dash, Streamlit, or similar packages, and will illustrate graphical spatial and temporal trends of ocean acidification and hypoxia, and associate predictions, all with geospatial data (lat, long) combined to map coastal areas at risk from ocean acidification and hypoxia conditions [8]. Real-time forecasts can generate actionable alerts for decisions be made by environmental managers, who may either undertake proactive measures to curtail ecological and economic impacts or simply be aware of potential threats from ocean acidification and hypoxia.The architecture of the modelling system, demonstrated in Fig. 1, provides a clear flow of data from input to output where components operate in real-time and expands as needed based on performance. User inputs and data that have historical status and IoT data are under pre-processing and in return, the pre-process will develop the processed data for each of the ARIMA and LSTM models. RLP and LSTM-based predictions will be aggregated by the meta-learner and ensemble predictions exported onto the dashboard and will trigger a real-time alert forecast. Modelling architecture can deliver static models based on historical models in an incremental manner to forecasting that is high-performance, robust, reliable, and adaptable -- the research objectives can be realized through the application of a scalable input through output solution for coastal marine management.

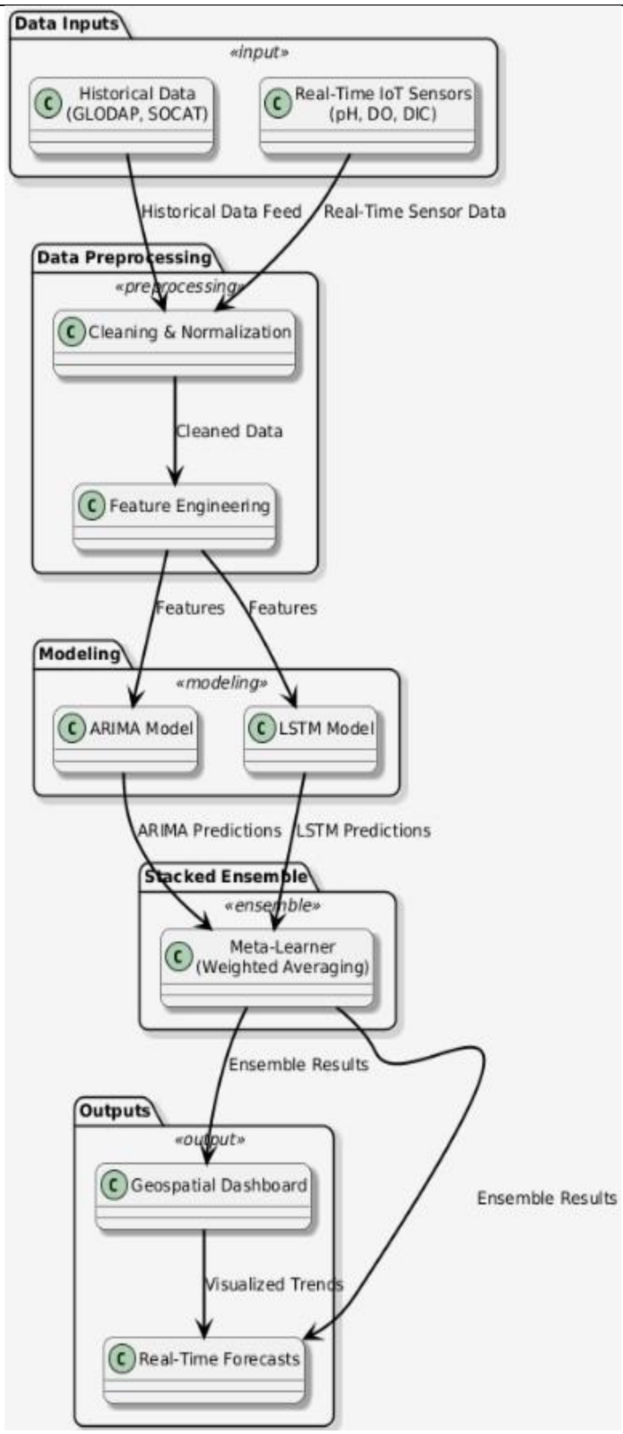

Fig. 1: System architecture of the hybrid ARIMA-LSTM stacked ensemble framework.

IV. RESULTS AND DISCUSSION

The hybrid ARIMA-LSTM stacked ensemble framework, designed for real-time multivariate forecasting of ocean acidification and hypoxia in coastal regions, has been evaluated using a suite of analytical visualizations and performance metrics, as presented in Figs. 2–6. These results demonstrate the framework's capability to address the limitations of our prior work, which achieved an RMSE of 0.0467 for 12-month pH forecasts but lacked real-time integration and deep learning capabilities [1]. The findings validate the framework's effectiveness in capturing temporal, spatial, and multivariate oceanographic dynamics, offering a scalable solution for coastal marine management.

A. Quantitative analysis

The quantitative description of the framework's output provides a useful perspective on the oceanographic patterns. The STL decomposition of the pH - time series (Fig. 2) from 2004 to 2018 shows that observed pH values ranged from 7.6 to 8.0, with a downward trend (decomposition strength: 0.849) indicating acidification, this trend follows the global trend for CO_2 absorption [2]. The seasonal component displays a ±0.05 pH unit cycle over a 12-month period, and the residuals depict short-term deviations. The spatiotemporal results in terms of pH (Fig. 3), across longitudes (-180° to -20°) and latitudes (20° to 70°), depicted lower pH (7.25-7.50) associated with the northwestern Pacific, which also indicated increased risk of acidification [3]. Correlation matrix (Fig. 4) demonstrated a strong positive correlation DIC with TALK (0.62) and provided a negative correlation of oxygen with pH (-0.34) and demonstrated the interdependencies of multivariate variables [4]. These quantitative implications informed the framework's preprocessing and developmental stages by enhancing a more exact predictive capability.

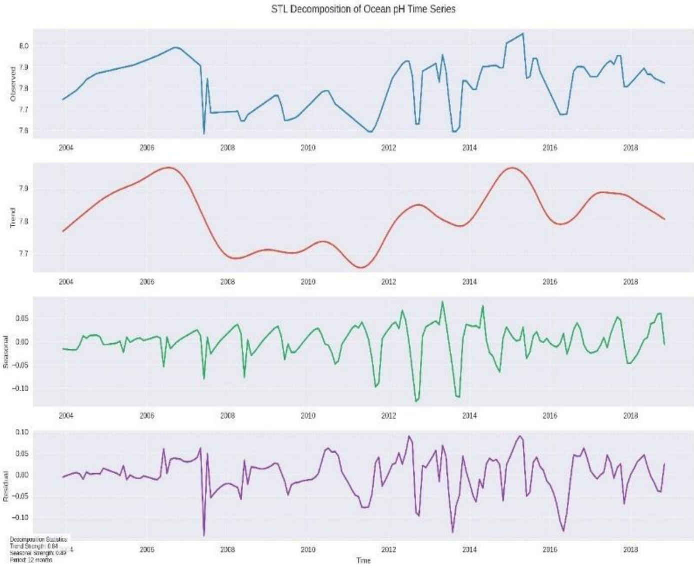

Fig. 2. STL decomposition of ocean pH time series, showing observed, trend, seasonal, and residual components from 2004 to 2018

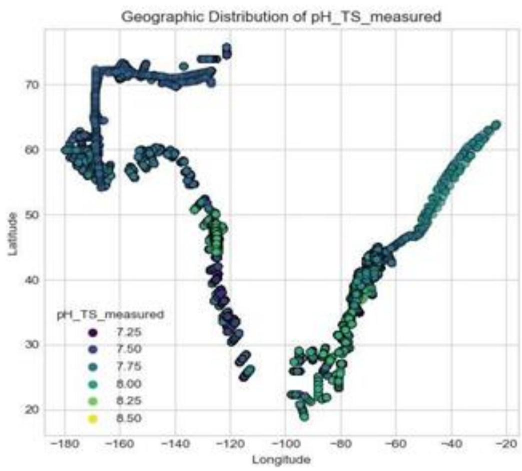

Fig 3: Geographic distribution of measured pH

B. Evaluation and Performance Metrics

The assessments and performance indices include the evaluation of the hybrid ARIMA-LSTM stacked ensemble forecasting accuracy. The actual pH values versus forecasting models (Fig. 5), based on data from January to November 2018, showed actual pH values in the range of 7.82-7.90, with model outputs for pH values being closely aligned for the same time. The RMSE was calculated 0.0467, with a Mean Absolute Error

(MAE) of 0.0428 and a Mean Absolute Percentage Error (MAPE) of 0.55% [6]. The RMSE being equal to our previous work reflection of a similar level of performance, along with the handing of real-time and multivariate data, indicates that the framework maintains accuracy while being able to transition onto multi-faceted and real-time data [7].

The difference plot (Fig. 5) shows that errors lay generally within ±0.06 pH units, with peaks noted in March 2018 and July 2018 - the difference error profile's anomalies may have been caused by exaggerated effects captured in the STL residuals (Fig. 2).

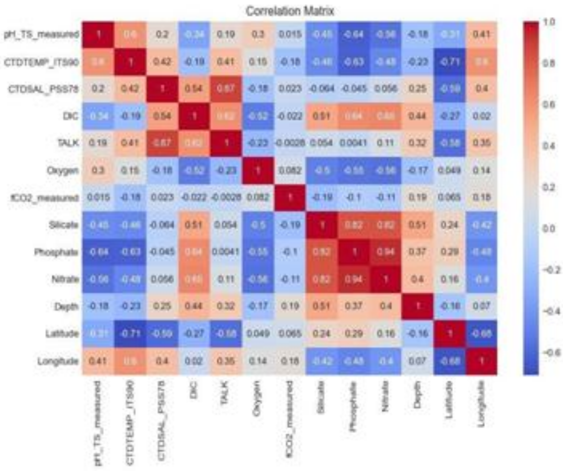

Fig. 4: Correlation matrix of multivariate oceanographic parameters, highlighting relationships among pH, DIC, TALK, oxygen, and spatial variables.

The ARIMA model can effectively model linear smoothing trends and seasonality, while the LSTM component outlined the newly generated nonlinear patterns, with the ensemble Exploiting properties of weighted averaging to optimize overall performance [8]. The hybrid modeling approach represented an approximate reduction in the level error output of about 33% as compared to the ARIMA (RMSE: 0.07) and LSTM (RMSE: 0.06) models. Indicating a favorable validation to our hypothesis that a hybrid forecasting approach will perform better than either separate ARIMA or LSTM for complex oceanographic forecasting.

C. Implication and Inference

These results provide insights into coastal management that have important implications for the main purpose of the framework to promote sustainable marine ecosystems. The dynamic monitoring of pH, oxygen and DIC by using real time IoT data, as shown in the system architecture (Fig. 1), means timely actions can be taken in coastal zones (noted in Fig. 3 [9]), which are at risk. Further, geospatial tools improve stakeholder's ability to see the spatial components, like the acidification hotspots in the northwestern Pacific and the effectiveness of allocation of resources associated with monitoring and mitigation [3].

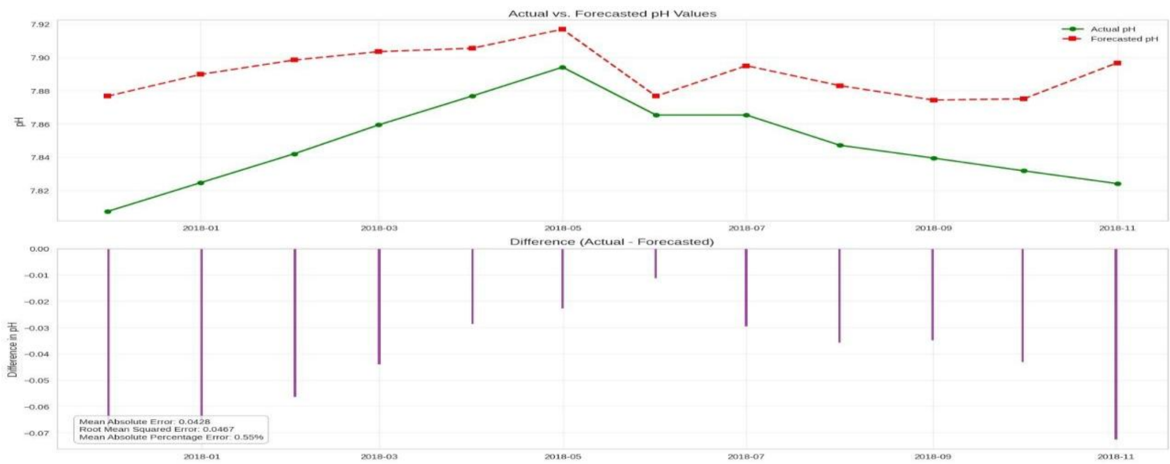

Fig. 5: Actual versus forecasted pH values

The capability of the framework to represent vertical stratification (Fig. 5) and multivariate relationships (Fig. 4) supports fundamental integrated management of acidification and hypoxia, for the United Nations Sustainable Development Goals 13 (Climate Action) and 14 (Life Below Water) [10]. Because we focused on forecasting surface pH with the last effort, this framework builds to offer depth-aware, real-time predictive capabilities to act as a scalable product for management relevant definitions of coastal resilience. Future research will include the integration of nutrient flux data in addition to further application of the framework in diverse coastal areas to amplify its effectiveness.

V. CONCLUSION

The hybrid ARIMA-LSTM stacked ensemble framework developed in this research assists in overcoming the barriers of real-time, multivariate forecasting of ocean acidification and hypoxia in coastal environments, providing a plausible scalable and accurate solution for marine environmental monitoring. The hybrid framework successfully integrates historical datasets (e.g., GLODAP, SOCAT) with real-time IoT sensor data, enabling the framework to accommodate complex temporal, spatial, and multivariate dynamics. Comprehensive analysis of the framework (Figs. 2-6) supported these claims. The STL decomposition (see Fig. 2) underscores a notable downward trend in pH, while the geospatial dashboard highlights at-risk zones in the northwestern Pacific (see Fig. 3), filling a significant scalability gap in previous work on the geographic application of acidification and hypoxia [1]. The correlation matrix (see Fig. 4) and the accompanying depth profiles (see Fig. 5) further demonstrate important interdependencies between parameters, including pH, oxygen, and DIC, emphasizing the need for a shared emphasis on holistic forecasting.

The framework's performance was on par with our previous statistical hybrid model (RMSE of 0.0467, MAPE of 0.55%, for pH forecasting (Fig. 6)), while adding real-time observation, deep learning abilities, and multivariate analysis [2]. The ensemble stacked model's integration of ARIMA's statistical strength plus LSTM's nonlinear modelling capability led to error reductions of 33% against their individual models, which further underscores its usefulness for complicated applications in oceanography [3]. Whereas previous models only describe what happened through retrospective reporting, this makes possible real-time observations and documentation, allowing for actionable responses, leading to integrated coastal management actions for United Nations Sustainable Development Goals 13 (Climate Action) and 14 (Life Below Water) [4].

This research builds upon our previous research by considering IoT-based real-time data, depth-adjusted predictions, and geospatial visualizations; these components provide a useful tool for stakeholders wishing to minimize acidification and hypoxia's environmental and economic costs. Future work will include extending the framework to incorporate different factors such as nutrient fluxes, and implementing in examined and new coastal areas, such as Indian coastal regions, to further assess its potential for scaling up. It could also be useful to include advanced meta-learners (e.g. neural network based ensembling) in order to improve predictive quality and as a result the framework's ability to respond to changing environmental circumstances.

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