AI-Driven Weather Prediction System with Real-Time Data Integration and Interactive Visualization

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Abstract. Forecasters need to change their approach to weather prediction because extreme weather events keep increasing in number and strength throughout Southeast Asia which experiences extreme weather disasters. The implementation of physical-based Traditional Numerical Weather Prediction (NWP) models faces difficulties because their high computational requirements and operational delays create obstacles for issuing urgent weather alerts. The current paper presents a weather forecasting system based on artificial intelligence which addresses the existing challenges. The system uses advanced deep learning technologies to create weather prediction models that include Convolutional LSTMs (ConvLSTM) and transformers for forecasting cyclone paths and rain distribution and rapid intensification which represents the most dangerous weather phenomenon. The system uses Physics-Informed Neural Networks (PINNs) to implement atmospheric physical constraints which enhance system performance during extreme weather situations.

The implementation of Explainable AI (XAI) methods enables the model to provide clear visibility into its prediction process through the identification of critical weather elements that determine its forecasting outcomes. Our system will help make complicated meteorological data available and useful by using real-time data from various sources, including NOAA, ECMWF, and JAXA, and displaying the results on an interactive web-based visualization platform created with Next.js and Mapbox.

The suggested framework shows how AI can help reduce the prediction time by several folds and improve user interaction, which is consistent with important UN Sustainable Development Goals on climate action and disaster resilience.

Keywords: Weather Prediction, Artificial Intelligence, ConvLSTM, Transformer Models, Cyclone Forecasting, Rapid Intensification, Interactive Visualization, Numerical Weather Prediction (NWP)

1 INTRODUCTION

Hydro-meteorological hazards including tropical cyclones and flooding and extreme rainfall pose severe threats to Southeast Asia which results in serious socioeconomic disruptions. Since 1989, these disasters have resulted in economic losses exceeding USD 136 billion [1]. The system needs to establish trustworthy early warning and prediction systems according to this requirement. Numerical Weather Prediction (NWP) models serve as the foundation for traditional weather forecasting because they use physical equations to model atmospheric behavior. The models which scientists developed require high computing power because they need multiple hours to produce forecasts from advanced computing systems. The slow response time of the system prevents organizations from addressing disasters in a timely manner. Recent developments in deep learning have created data-driven solutions which can identify complex atmospheric patterns that occur over time through analysis of historical data [2]. The Convolutional LSTM

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(ConvLSTM) architecture achieves high accuracy in precipitation nowcasting because it combines spatial and temporal feature learning abilities [3]. Transformer-based models use self-attention mechanisms to improve their ability to understand long-range relationships between data points [4]. The application of data-driven models results in physically impossible results when system conditions reach extreme levels. The Physics-Informed Neural Networks (PINNs) framework uses physical laws during their training process in order to generate predictions that follow real-world physics [5]. The black-box functionality of deep learning systems creates risk factors for essential functions which include disaster prediction processes. Explainable AI (XAI) methods which include SHAP enable better understanding of predictions through their ability to measure how specific factors affect results [6].

2 LITERATURE SURVEY

Weather forecasting has continued to change at a very amazing rate, as it has moved the primitive forms of observations, which are mainly empirical, to the more complex form of computation modeling. The requirement of making precise and timely predictions has led to the creation of diverse methods, starting with the classical Numerical Weather Prediction (NWP) models and moving on to the recent deep learning models. The previous research investigates the strengths and weaknesses of these methods which require the development of artificial intelligence solutions that combine accurate prediction capabilities with practical implementation and fast response times

2.1 Numerical Weather Prediction Models

Numerical Weather Prediction has remained the foundation of operational meteorology for decades. The Global Forecast System (GFS) and the ECMWF forecasting system operate atmospheric simulations through their solution of partial differential equation systems [2]. The models demonstrate scientific validity but they depend on high-performance computing systems which create extended forecasting periods that prevent their use in real-time situations.

2.2 Deep Learning Approaches in Weather Forecasting

Deep learning has proven effective for meteorological applications according to recent studies. The combination of Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks has become the standard method for executing time-series forecasting tasks. The ConvLSTM network demonstrates effective weather prediction capabilities [3] because it integrates convolutional feature extraction with its temporal modeling function. The self-attention mechanisms of Transformer-based architectures enable advanced forecasting capabilities [4] because they track long-range dependencies. The models are valuable for analyzing atmospheric patterns that extend across large regions which affect cyclone paths and rainfall patterns over time.

2.3 Importance of Interactive Visualization

The effectiveness of accurate forecasts relies on their ability to be easily understood. Research in data visualization emphasizes the importance of interactive tools for communicating uncertainty and risk. The modern web-based platforms provide users with dynamic map-based visualizations which enhance their understanding and assist them in making choices during severe weather situations.

2.4 Physics-Informed Neural Networks in Climate Modeling

Physics-Informed Neural Networks [5] have developed into a powerful method which enables researchers to combine data driven learning with physical science models. The PINN training process uses a loss function which combines mass conservation and momentum conservation and energy conservation equations to create a training method which maintains physical accuracy in model outputs. The research demonstrates that PINNs enhance climate modeling capabilities through their ability to capture both spatial and temporal patterns which occur during extreme weather events and situations with limited data. The approach uses physical constraints as its primary input method to provide accurate cyclone intensity estimates and precipitation prediction results

2.5 Explainable AI in Meteorological Applications

Research on Explainable Artificial Intelligence (XAI) methods has become popular in weather forecasting because it provides solutions to the deep learning model interpretability problem. Professionals use SHAP [6] Integrated Gradients and attention-based visualizations to identify which atmospheric factors have the most significant effect on their predictions. XAI enhances cyclone prediction efficiency through its ability to display information clearly which helps experts validate results while increasing trust in artificial intelligence-based warning systems.

2.6 Research Gap

While recent AI-based models have significantly improved forecasting accuracy and computational efficiency, several gaps remain:

1. The previous systems do not fully integrate real-time data streams which come from multiple sources.
2. The previous systems do not provide complete integration between physics-informed learning and explainability mechanisms which need to operate through a single system.
3. The previous systems currently lack user-focused visualization systems which can convert unprocessed model results into usable business intelligence.

3 METHODOLOGY

The suggested project will take an interdisciplinary approach and will be based on both the newest techniques of artificial intelligence and the system of data collection, processing and interactive visualization on the basis of the modern web-based platform. This methodology has the main aim of making predictive efficiency, practical feasibility and interpretation of weather forecasts possible. The system will assist in ensuring timely decision-making by various stakeholders since it will convert complex meteorological data into actionable information. This section outlines how the data is going to be collected and incorporated into the system.

3.1 Data Acquisition and Integration

Weather forecasting systems rely on the quality and prompt availability of observational and numerical data on the quality and reliability of their systems. The proposed system will combine the information provided by various sources of authority in order to obtain a full picture of the state of atmospheric conditions. Organizations like the National Oceanic and Atmospheric

Administration (NOAA) which provides historical storm track data and satellite imagery, and the European Centre for Medium-Range Weather Forecasts (ECMWF) which provides gridded numerical reanalysis data provide the historical and real-time meteorological data. Moreover, Japan Aerospace Exploration Agency (JAXA) high-resolution satellite imagery is added to make the spatial detail more detailed especially in the Asia-Pacific region. In order to be responsive to the continuously evolving weather, real-time weather data are constantly obtained via OpenWeather and Meteomatics API. This multi-source integration allows the system to change dynamically with changing meteorological situations. Any incoming datasets are subjected to an intensive preprocessing pipeline that includes cleaning and normalizing data and converting it to tensors that can be fed to deep learning models. The missing values are treated with the correct methods used to impute them, the outliers are checked and spatial-temporal congruence is imposed to keep homogeneous data sources consistent. This procedure leads to a single, large dimensional expression of the state of the atmosphere, on which the basis of sound AI-based forecasting is formed.

3.2 AI-Based Forecasting Models with Physical and Explainability Constraints

The forecasting framework employs a multi-model architecture in which each artificial intelligence component is optimized for specific predictive tasks. Convolutional Long Short-Term Memory (ConvLSTM) networks are applied in short term forecasting tasks especially precipitation nowcasting and cyclone track prediction. ConvLSTMs integrate the time-based modeling ability of LSTMs and the spatial abilities to extract features of convolutional layers to achieve the capability to learn sequences of weather maps and predict future atmospheric conditions. Transformer-based models are used in doing longer range forecasting. Self-attention mechanism of Transformers is very useful in capturing the long-range dependencies in spatiotemporal data hence identifying large-scale atmospheric patterns that determine storm-tracks and precipitation trends. This is particularly useful in modeling the complex meteorological processes that are rendered by interactions between more than two atmospheric systems. Physics-Informed Neural Networks (PINNs) are introduced to the framework to make the predictions consistent physically and realistic. PINNs incorporate basic physical principles directly into the model loss. This combination helps in making sure that the forecasts produced are not only consistent with the past data but also follow the important rules of the atmosphere which would enhance their reliability during extreme weather. The prediction framework operates with multiple models because each AI component requires specific training to handle its designated forecasting tasks. ConvLSTMs use their LSTM temporal processing abilities and convolutional layer spatial feature extraction functions to learn from weather map sequences which predict upcoming atmospheric conditions. The proposed system achieves spatial awareness and temporal accuracy and physical plausibility through the integration of ConvLSTM networks and Transformer models and PINNs within a unified system. The multi-model system enables the organization to perform different meteorological forecasting operations while maintaining computational efficiency required for real-time applications.

3.3 Physics-Informed Learning (PINNs)

Physics-Informed Learning (PINNs) may be defined as a machine learning model that relies on physical laws of material behavior as a guide in the process of performing a task. Physics-Informed neural networks (PINNs) are added to the forecasting pipeline to ensure physical consistency. Besides data-driven loss, physics-based loss terms that are based on atmospheric governing equations are added in the training process. These limits punish physically unrealistic predictions, and provide a guarantee that laws of conservation are adhered to and make them more robust in cases of extreme weather such as rapid cyclone intensification.

3.4 Explainable AI Module (XAI)

A module called an Explainable AI (XAI) is introduced in order to explain how the model prediction works and to improve level of transparency and user trust. The SHAP values and attention-weight visualizations are used as feature attribution tools to determine the most influential meteorological variables and spatial areas used in the forecasts of the model. Such explanations allow qualitative and quantitative evaluation of model behavior through the aspects of factors that drive the predictions. The resulting interpretability outputs are displayed together with forecast outcomes enabling domain experts to authenticate predictions, determine reliability, and facilitate informed decision making in the event of critical weather.

4 SYSTEM ARCHITECTURE

A modern, decoupled architecture is used to implement the proposed forecasting system in order to achieve scalability, maintainability and real time performance. The system is divided into three main systems by the overall design the frontend client, the backend API layer, and the AI prediction module. This service architecture enables the different components to be developed, tested, and scaled individually which is necessitated by the handling of large scale and real time weather data. Besides, the AI prediction component integrates physics-informed learning constraints, as well as explainability mechanisms, which allow significant physical consistent predictions and transparent interpretation of model predictions.

4.1 Frontend Client

The system presents its web interface through Next.js which uses TailwindCSS for its design and implements a responsive interface that users can easily navigate. Users can see climate data through Mapbox GL JS maps which show precipitation patterns and cyclone paths and areas of uncertainty. Recharts enable the creation of interactive charts which display timeseries data and statistical information. The frontend also shows explainability overlays produced by the XAI module, e.g., attention maps and feature-attribution visualizations in addition to the forecast output to facilitate model interpretability. This visual information assists users to comprehend the most important atmospheric drivers affecting predictions. The frontend interacts with the backend via RESTful API endpoints, and thus provides the latest forecast data at real-time to be visualized. This design guarantees the ease of interaction by users with low latency data update.

4.2 Backend API Layer

The backend is a set of services, which deal with the process of retrieving, aggregating, and processing meteorological information provided by several external sources, such as NOAA, ECMWF, JAXA, and a range of real-time weather applications. Raw data of these sources are purged, normalized, and transformed into normalized forms that can be used to infer AI models and also to provide visualizations in the frontend. The RESTful endpoints expose the processed data to the frontend, which provides efficient support of low-latency access to the real-time applications. This layer is also an orchestration element, which provides the stream of data between external sources and the AI prediction module to be seamless. The backend also handles the communication with the Explainable AI (XAI) module. The AI prediction service also produces interpretability metadata as well as forecast outputs, such as feature-importance score and spatial relevance map. These results are standardized and sent to the frontend to be visualized and there is close correlation between the predictions and their justifications.

4.3 AI Prediction and Explainability Module

The AI prediction module is the heart of the system and has incorporated the data-powered learning with the physical constraints and interpretability mechanisms. ConvLSTM and Transformer networks forecasting models are trained towards physics-informed learning aims, in which loss terms of PINN based loss terms require the network to comply with fundamental atmospheric principles. After the creation of prediction, the XAI sub-module can be used to analyze the model results and generate feature attribution scores and spatial attention representations. Such descriptions will give an idea of the prevailing meteorological variables of the forecasts and will be transferred to the backend API layer to be visualized downstream. Such close association means that each of the forecasts is supported with a corresponding explanation, and the level of transparency and confidence in the AI-powered weather prediction increases.

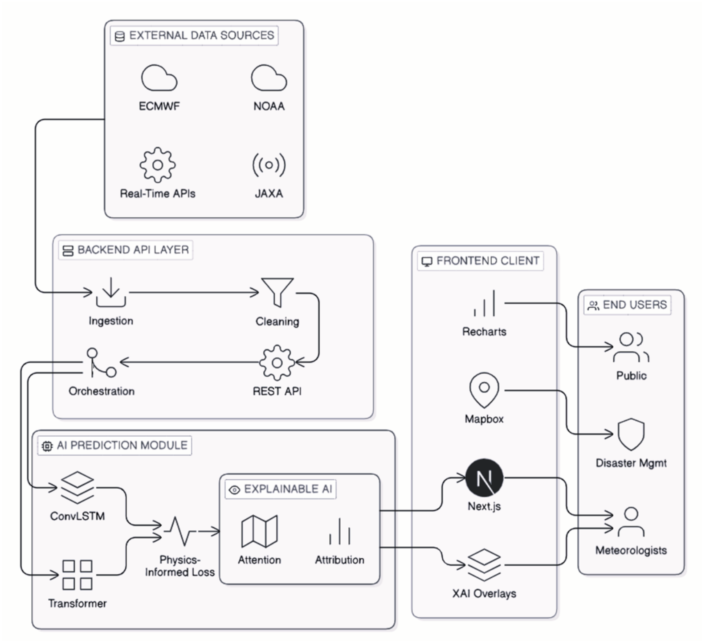

Fig. 1. System Architecture of the Proposed AI-Driven Weather Forecasting Framework

4.4 Architectural Overview

This decoupled system architecture will make sure that the computationally intensive nature of responsibilities, like AI based weather prediction, does not impact frontend responsiveness. The system is able to isolate heavy computation and lets people interact with the application and get updates in near real time. In addition, modular design makes system maintenance and scalability easier, since all the parts are able to be optimized or even deployed on other infrastructure at the point of need. This architectural design is favorable to the future growth and trusted functionality in the future against growing data and user demands. Physics-informed constraints and explainability services are additional features that increase the reliability of the system as they guarantee that predictions are physically reasonable, as well as understandable to domain experts.

5 IMPLEMENTATION

The implementation phase is a stage that converts the suggested system architecture into an operational prototype, giving evidence of the system framework feasibility. The system combines the frontend visualization component, the back-end data service component and the AI prediction component into a continuous workflow without compromising on modularity. In this way, individual components can be created, experimented, and improved separately

5.1 User Interface

User interface is the main interface between the system and the end-users. Its app is designed with two primary interfaces: a landing page and an effective visualization page. The opening page welcomes the user to the site and it uses smooth animation effects with libraries like GSAP and Anime.js to make the user interested in the site. The main functional page (/ tool) contains the interactive weather visualization capabilities. It is an interactive page that is fueled by Mapbox GL JS and allows users to view the real time weather overlays, tracks of cyclones, and the intensity of rainfall forecast. Interactive features enable the user to choose storm systems to access in-depth forecast data, and there is a time-scrubber feature that enables users to view the forecasts in various time periods. The interface would be such that it would make available complex meteorological information to both technical and non-technical people. The user interface incorporates an AI insight panel, as shown in Fig.2, that summarizes a few key model, derived indices and suggestions so that the users can quickly grasp the forecast results without being deeply familiar with meteorology. It may be equipped with explainability layers for providing insights into the contributing atmospheric factors.

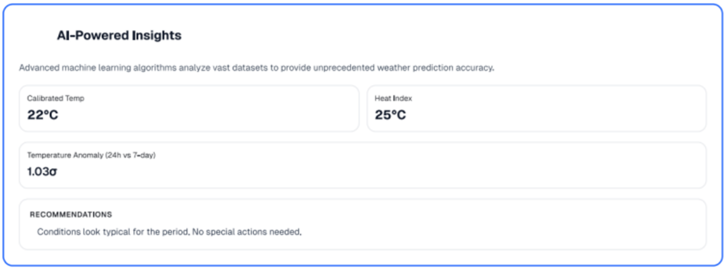

Fig. 2. AI-generated insight panel produced by the proposed system, presenting derived meteorological indicators and decision-support recommendations alongside forecast visualizations.

5.2 Backend and Data Flow

The backend acts as the focal intermediary between outside sources of data, the AI prediction engine, and the front-end client. It constantly checks and aggregates meteorological information to sources including NOAA, ECMWF, JAXA and real-time weather APIs. The incoming data is filtered and processed into formats that can be further used in visualization and model inference. The frontend is exposed to processed data via RESTful API endpoint, which guarantees low latencies to access updated forecasts. Moreover, the backend is in charge of communication with the AI module. When a forecast request is received, the corresponding data are preprocessed and sent to AI service, which in turn generates predictions which are sent back in a normalized format which can be directly displayed by the frontend. Such a modular data flow model can be easily extended with the new data sources or APIs during further development cycles.

5.3 AI Module

The AI prediction module is a proxy service that is deployed at the prototyping stage to represent the behavior of fully trained deep learning models. The module produces some forecast-like results such as cyclone paths, rainfall intensity-based maps, and precipitation maps. The simulation provides the opportunity to completely develop and test the frontend, the backend and the visualization pipeline before deploying trained ConvLSTM, Transformer, and PINN models. The system provides early-stage usability testing and optimization of user interactions without needing to rely on computationally intensive model training by using a placebo AI module. The trained models can be updated easily once the last models are ready, and the other system components will not need significant changes.

5.4 Prototype Summary

The final prototype shows on-end to end functionality of the proposed weather forecasting system which is based on AI. The interface of the frontend is easy to use to navigate through the weather information, the backend takes care of seamless integration of real-time data sources, and the AI aspect of the development phase simulates the predictive functions. This step-by-step implementation plan improves the modularity, faster development, and provides a powerful base for incorporating more advanced deep learning models in the next generation.

6 RESULT ANALYSIS

Despite the fact that active development of the AI models has not been finalized yet, the prototype system proved to have good performance and usability features.

6.1 Prediction Speed

The placeholder AI module, which is a simulation of the inference time of trained deep learning models, makes predictions in under one minute. This is better than the conventional Numerical Weather Prediction (NWP) models which usually take many hours to run. These findings underscore the efficiency potential that can be realized by AI based forecasting solutions

6.2 Interactive Visualization

The online visualization system is efficient in terms of converting the complicated meteorological information into interactive and easy to understand format. According to usability testing, the Mapbox-based visualization can be used to have a clear image of cyclone tracks and rainfall intensity. The interactive maps greatly improve the understanding of the users and situational awareness compared to the existing charts or raw numbers.

6.3 Model Interpretability and Trust Analysis

The Explainable AI module shows how atmospheric factors influence model performance which leads to better understanding of system behavior. The study found that sea surface temperature and wind shear together with pressure gradients act as major determinants for predicting cyclone intensity. The system provides interpretable results which help experts to validate AI predictions and create trust in the system.

6.4 Visualization-Driven Decision Support

Besides the accuracy of the prediction, the proposed system also highlights the importance of visualization in decision support. By combining the forecast results and the explanation layers in a single interface, users are enabled to link the predictions with their underlying causes immediately. The innovative system is especially useful in situations of early warning and disaster response where it is essential to know not only what is being predicted but also the reasons behind it. With the system, users can query information about particular areas, time, and weather events at their own initiative, hence receiving timely and well- informed responses that suit the situation. The strength of the proposed visualization layer is demonstrated through dynamic geospatial weather maps that display real-time atmospheric conditions. Fig. 3 shows a cloud coverage map created with Mapbox GL JS, allowing users to examine spatial weather patterns alongside contextual meteorological information

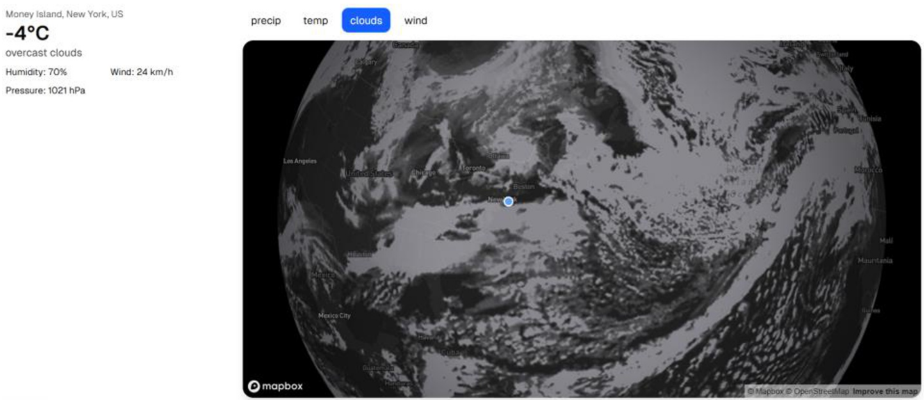

Fig. 3. Interactive cloud-coverage visualization generated by the proposed system using Mapbox GL JS, illustrating real-time spatial weather patterns and associated meteorological parameters for user-driven analysis.

6.5 System Performance and Practical Utility

The decoupled architecture ensures that computationally intensive prediction tasks do not impact frontend responsiveness. During prototype testing, the system demonstrated near real-time responsiveness for data retrieval, model inference, and visualization updates. Table 1 provides a qualitative comparison between traditional numerical weather prediction workflows and the proposed AI-based system, highlighting improvements in interpretability, interaction, and visualization capabilities.

Table 1. Comparison Of Traditional Forecasting and Proposed System

Aspect	Traditional NWP	Proposed System
Forecast Generation Time	High	Low
Visualization	Static	Interactive
Explainability	Limited	High (XAI)
Physical Consistency	Model-dependent	PINN-enforced
User Interaction	Minimal	Real-time

In general, the prototype confirms the practicality of the suggested method and forms a proper base in the implementation and assessment of superior AI models in future practice

7 CONCLUSION AND FUTURE WORK

This paper described an AI-based weather prediction system that provides prompt, precise, and accessible weather forecasts, especially to the vulnerable areas. Using contemporary deep learning models like ConvLSTM and Transformer networks and integrating them with an interactive web-based visualization application, the system provides a viable way of supplementing the conventional Numerical Weather Prediction models. The architecture of the system focuses on real-time data fusion, the modular nature, and user-friendly visualization, which is why the system can be used in disaster management, early warning distribution, and public awareness. Although the prototype that is currently being developed helps prove the effectiveness of the approach, there are still multiple opportunities to develop it in future research. The next step in work will be to train and validate the AI models with the help of large volumes of historical data to strictly check the accuracy of the forecast. Other improvements involve the use of high order multi-modes data integration, use of satellite image, radar data, and numerical forecasts to enhance functionality under various weather conditions. Moreover, the flood risk mapping will be integrated with high resolution topographical and hydrological data to determine the areas susceptible to floods. These extensions can enhance the proposed structure to become a full-scale AI-based forecasting and risk analysis application that could be used both by meteorology experts and an average citizen.

References

1. United Nations Office for Disaster Risk Reduction (UNDRR), *Economic Losses from Disasters 1989–2024*, Geneva, Switzerland, 2025 [Online]. Available: https://www.undrr.org
2. D. J. Dueben and P. Bauer, "Challenges and Design Choices for Global Weather and Climate Models Based on Machine Learning," *Geoscientific Model Development*, vol. 11, no. 10, pp. 3999–4009, 2018.
3. X. Shi, Z. Chen, H. Wang, D.-Y. Yeung, W.-K. Wong, and W.-C. Woo, "Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting," in *Proceedings of the Advances in Neural Information Processing Systems (NeurIPS)*, 2015, pp. 802–810.
4. A. Vaswani, N. Shazeer, N. Parmar, J. Uszkoreit, L. Jones, A. N. Gomez, L. Kaiser, and I. Polosukhin, "Attention Is All You Need," in *Proceedings of the Advances in Neural Information Processing Systems (NeurIPS)*, 2017, pp. 5998–6008.
5. M. Raissi, P. Perdikaris, and G. E. Karniadakis, "Physics-Informed Neural Networks: A Deep Learning Framework for Solving Forward and Inverse Problems Involving

Nonlinear Partial Differential Equations," *Journal of Computational Physics*, vol. 378, pp. 686–707, 2019.

6. S. M. Lundberg and S.-I. Lee, "A Unified Approach to Interpreting Model Predictions," in *Proceedings of the Advances in Neural Information Processing Systems (NeurIPS)*, vol. 30, 2017.