IMPLEMENTING WEATHER PREDICTION USING PHYSICS-INFORMED NEURAL NETWORKS (PINNS)

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in
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submitted by

D PremSohan(AP21110011143)
T Sowmya(AP21110011109)
G Chavan(AP21110011130)
Y Yaswanth Reddy(AP211100110227)

Under the Guidance of

Prof. Abhijit Dasgupta

Department of Computer Science & Engineering
SRM University-AP
Neerukonda, Mangalgiri, Guntur
Andhra Pradesh - 522 240

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DECLARATION

I undersigned hereby declare that the project report **Implementing Weather Prediction using Physics-Informed Neural Networks (PINNs)** submitted for partial fulfillment of the requirements for the award of degree of Bachelor of Technology in the Computer Science & Engineering, SRM University-AP, is a bonafide work done by me under supervision of Prof. Guide Name. This submission represents my ideas in my own words and where ideas or words of others have been included, I have adequately and accurately cited and referenced the original sources. I also declare that I have adhered to ethics of academic honesty and integrity and have not misrepresented or fabricated any data or idea or fact or source in my submission. I understand that any violation of the above will be a cause for disciplinary action by the institute and/or the University and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been obtained. This report has not been previously formed the basis for the award of any degree of any other University.

Place	:	Date	: April 28, 2025
Name of student	: D PremSohan	Signature	: ....
Name of student	: T Sowmya	Signature	: ....
Name of student	: G Chavan	Signature	: ....
Name of student	: Y Yaswanth Reddy	Signature	: ....

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

SRM University-AP

Neerukonda, Mangalgiri, Guntur

Andhra Pradesh - 522 240

CERTIFICATE

This is to certify that the report entitled **Implementing Weather Prediction using Physics-Informed Neural Networks (PINNs)** submitted by **D PremSohan, T Sowmya, G Chavan, Y Yaswanth Reddy** to the SRM University-AP in partial fulfillment of the requirements for the award of the Degree of Master of Technology in in is a bonafide record of the project work carried out under my/our guidance and supervision. This report in any form has not been submitted to any other University or Institute for any purpose.

Project Guide | Head of Department

Name : Prof. Abhijit Dasgupta	Name : Prof. Murali Krishna Enduri
Signature:	Signature: ....

ACKNOWLEDGMENT

I wish to record my indebtedness and thankfulness to all who helped me prepare this Project Report titled **IMPLEMENTING WEATHER PREDICTION USING PHYSICS-INFORMED NEURAL NETWORKS (PINNS)** and present it satisfactorily.

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D PremSohan, T Sowmya, G Chavan, Y Yaswanth Reddy
(Reg. No. AP21110011143, AP21110011109, AP21110011130, AP21110010227)
B. Tech.
Department of Computer Science & Engineering
SRM University-AP

ABSTRACT

Physics-based neural networks (pinn's) have proven to be a promising methodology for combining domain knowledge and data control learning, particularly in modeling complex dynamic systems. This study presents a hybrid deep learning framework that integrates physics-based limitations for predicting climate variables and Bidirectional Long Short-Term Memory (BILSTM). The aim is to predict atmospheric conditions near the creation, particularly temperature and geopolitical heights, using continuous observations from the created data. The BILSTM model is trained to simultaneously record the underlying time patterns of data and is in compliance with the physics of atmospheric processes. The concept of physical loss is introduced. This is derived from the simplified thermal diffusion equation to punish violations of the basic energy diffusion properties. This loss of physics, combined with the standard loss of standard square error (MSE), ensures that the model's predictions are not only accurate but physically consistent. Comparative reviews show that physical models improve prediction stability and achieve greater compliance with physical principles compared to purely data-driven baselines. Furthermore, the addition of physics-based regularization improves generalization through invisible samples, which helps reduce overadaptation, especially in border regions where traditional models often fail. By embedding physical knowledge directly into the training process, this model provides a way to reliable and interpretive weather and climate prediction systems that have a more comprehensive effect on promoting scientific machine learning in modeling the Earth system.

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Chapter 1

INTRODUCTION TO THE PROJECT

Physics-informed neural networks (pinns) incorporate physical laws into the learning process of deep neural networks, allowing models to adhere to known governing equations when making predictions. Pinns are highly valuable in scientific fields like climate modeling, where maintaining physical consistency is essential for accurate forecasting. This project utilizes a combination of bi-directional long short-term memory networks (bilstms) and physics-informed loss functions to improve the accuracy of predicting atmospheric variables such as temperature and geopotential height.

The climate forecasting system relies on time-series data derived from reanalysis datasets, with a particular emphasis on temperature fields and geopotential height distributions. Every location in the climate grid is analyzed separately, with time sequences acting as input to the deep learning model. The bi-directional LSTM architecture captures the sequential dependencies in both forward and backward time directions, offering a more comprehensive understanding of how atmospheric conditions change over time. To enhance the realism of the simulation, a physics loss term based on diffusion is introduced, guaranteeing that the predicted temperature fields align with a simplified heat diffusion equation.

By incorporating physics principles into its design, the model optimizes learning efficiency, minimizes overfitting to noisy data, and enhances generalization when making predictions about future states. The hybrid pinn-bilstm model equips climate scientists and meteorologists with a robust analytical tool that combines data-driven accuracy with physics-consistent forecasts, resulting in more reliable and interpretable weather prediction systems.

1.1 KEY FEATURES OF PHYSICS-INFORMED NEURAL NETWORKS

Physics-informed neural networks (pinns) improve deep learning models by incorporating prior scientific knowledge directly into the training process. In this project, the pinn design incorporates a physics loss term derived from the heat diffusion equation, imposing penalties on predictions that deviate from expected physical behavior. This approach enables the model to learn important thermodynamic processes without requiring explicit data for each physical quantity.

The bi-directional LSTM component of the model efficiently manages the sequential nature of atmospheric data, enabling it to learn both short-term and long-term dependencies. Bidirectionality guarantees that the model is not limited to using past values but can also anticipate future trends, enhancing its ability to make accurate predictions. By finding a balance between data-driven goals and physical limitations, the model enhances its ability to make accurate predictions, withstands noisy data, and offers valuable insights into the underlying physics.

The adaptable structure of the pinn-bilstm framework enables it to adjust to different spatial and temporal scales, which is crucial for tackling complex climate modeling tasks that require interactions across multiple timescales and regions.

1.2 APPLICATIONS OF PHYSICS-INFORMED CLIMATE FORECASTING

The estimation of atmospheric variables like temperature and geopotential height is crucial for short-term weather forecasts, long-term climate projections, and evaluating the risk of natural disasters. Traditional data-driven models frequently encounter challenges in preserving physical realism, particularly when extrapolating beyond the training phase. By incorporating pinns, this project provides enhanced forecasting systems that adhere to conservation laws, particularly those related to energy diffusion.

This approach has applications beyond weather forecasting, encompassing areas like climate risk management, agricultural planning, water resource prediction, and energy sector analysis. Precise and scientifically valid climate models empower governments and organizations to make well-informed choices by providing trustworthy environmental predictions.

Additionally, the pinn framework can be modified to simulate intricate atmospheric phenomena, such as fluid dynamics, radiation balance, and chemical transport, establishing a solid basis for the development of advanced, interpretable, hybrid climate models.

1.3 EVOLUTION OF PHYSICS-INFORMED NEURAL NETWORKS

Physics-informed neural networks were developed as a solution to the shortcomings of conventional machine learning techniques, which tend to view data as individual entities without taking into account the underlying physical principles. Motivated by advancements in scientific computing and deep learning, pinns incorporate governing equations, such as partial differential equations, into the training process of the model.

Over the course of time, pinns have developed to tackle issues such as stiffness, multi-scale phenomena, and uncertainty quantification in physical systems. Advancements like adaptive loss weighting, integration of domain decomposition, and hybrid models combining recurrent neural networks with pinns have broadened their usage in various scientific fields.

The incorporation of bidirectional long short-term memory (bilstm) architectures within the pinn framework in this project signifies an advancement, combining robust sequence modeling abilities with physical reasoning. This combination of methods presents fresh possibilities for addressing intricate forecasting challenges in climate science, allowing for more dependable, understandable, and physically accurate predictions crucial for comprehending and managing climate-related dangers.

Chapter 2

MOTIVATION

This chapter explores the reasons behind the selection of this project. The project deals with an extremely critical and applicable issue in the field of weather forecasting and machine learning, particularly with the prediction of sub-seasonal weather, which is important for predicting natural disasters.

2.1 REASONS WHY FINAL YEAR ENGINEERING PROJECTS ARE IMPORTANT

Final year engineering projects play a significant role in a student's academic progression. These projects are not just a requirement for graduation; they provide a chance to connect theoretical knowledge with practical application. They provide students with the opportunity to apply their knowledge and skills, developing crucial abilities such as problem-solving, critical thinking, research, and project management.

A carefully selected project not only improves technical skills but also instills confidence, equipping students with the ability to confront industry challenges with determination. By working collaboratively across different disciplines, embracing new technologies, and meeting tight deadlines, students gain valuable experience that prepares them for the challenges of real engineering workplaces.

Instead of simply choosing a project based on convenience, students are encouraged to delve into subjects that genuinely captivate their curiosity. Projects fueled by passion tend to result in more profound learning, creative problem-solving, and a more impressive portfolio. Projects that are industry-focused and research-driven provide additional value to a student's resume, giving them a competitive edge in the job market.

In essence, final year projects are not just about earning grades — they symbolize a significant personal and professional achievement. They establish a strong educational base, foster creativity, and equip students with the skills needed to thrive in the ever-changing field of engineering.

Let us explore various points which depict why final year engineering projects are important, which are as follows:

Figure 2.1: Motivation.

2.1.1 It helps to identify a real-time problem and provide a solution

When choosing a project idea, it is important to prioritize addressing real-world issues and creating practical, impactful solutions. In our case, we decided to tackle the difficult and highly relevant topic of climate prediction. Accurate climate forecasting is essential for effective planning, disaster preparedness, and comprehending long-term environmental shifts. Unfortunately, most current methods for predicting climate change are either very expensive or require a lot of computing power, making them impractical for widespread use or affordable for many people.

Acknowledging this gap, our goal is to develop a more efficient and accurate model for predicting climate patterns. To accomplish this, we employ physics-informed neural networks (pinns), a state-of-the-art approach that incorporates physical principles into the training of neural networks. By incorporating physical knowledge into the model, pinns enhance predictive accuracy while minimizing the requirement for extensive datasets and computational resources.

Our goal is to develop a model that not only predicts climate variables with greater accuracy but also operates more efficiently, making it suitable for various research purposes and practical applications. Our goal with this project is to develop a more efficient and effective solution to the global issue of climate forecasting.

2.1.2 It helps to choose diversified research topics.

Selecting a wide range of research topics is crucial for creating projects that have a significant impact. In our case, we concentrated on the domain of climate prediction — a field that necessitates continuous innovation due to its complexity and real-world significance. In order to gain a more comprehensive understanding, we delved into a diverse collection of research papers, scholarly journals, and articles that focused on climate modeling, machine learning, and physics-informed neural networks (pinns).

By examining recent developments, we gained insights into how conventional models face challenges in terms of either high computational expenses or limited accuracy. Research also emphasized the potential of pinns to tackle these challenges by integrating physical laws directly into the learning process. By studying technical literature and examining real-world case studies, we were able to come up with creative ideas to enhance our project methodology.

By utilizing a research-based approach, we were able to stay informed about the most recent advancements in climate science and artificial intelligence, which in turn helped us develop a solution that is not only technically robust but also practical and feasible. Constructing a project inspired by recent breakthroughs in the field enhanced our learning journey and enabled us to apply theoretical concepts to create a practical prototype.

2.1.3 It helps to choose appropriate project topics and mentor carefully.

Choosing the right project topic and mentor is crucial for the achievement of any final year project. In our case, utilizing physics-informed neural networks (pinns) for climate prediction presented a unique opportunity to tackle real-world environmental issues and develop advanced artificial intelligence solutions. This undertaking allowed us to gain in-depth knowledge in our field and enhance our technical abilities through active group involvement and joint efforts.

Throughout the project, our mentor provided us with guidance in refining the problem statement, structuring the project goals, and ensuring scientific rigor. Their extensive knowledge and experience allowed us to concentrate on the critical elements of model efficiency, accuracy, and practicality, while also ensuring that the computations remained feasible. The mentor's guidance also motivated us to delve further into contemporary subjects like machine learning, numerical simulations, and the incorporation of physical laws into neural networks.

Consistent group discussions, brainstorming sessions, and technical reviews played a crucial role in improving our creative thinking and problem-solving skills. Additionally, the mentor stressed the importance of not only technical accuracy but also the societal and ethical consequences of climate prediction models, promoting a comprehensive approach to project development. In conclusion, this experience emphasized the significance of making thoughtful choices when it comes to project and mentor selection, as they play a crucial role in shaping a fulfilling and successful engineering journey. The projects require the expertise of the mentors and their skills to delve into the topics and help us understand them and give us advice. Our mentor helped us combine these topics in the project:

- Weather Prediction[**?**]
- BILSTM
- Machine learning
- Physics Laws
- Neural Networks

2.1.4 Understand and analyze project documentation effectively.

Documentation served as a solid base for the entire duration of our climate prediction project, which utilized physics-informed neural networks (pinns). The overall success of our work heavily depended on keeping meticulous records, which not only helped us manage the development process but also ensured that our model outputs matched our initial expectations.

Throughout the entire project lifecycle, from preprocessing climate data to training and evaluating models, meticulous documentation was crucial in creating comprehensive technical presentations and evaluation reports. Special focus was placed on improving our technical writing abilities while constructing the documentation, guaranteeing clarity and accuracy in conveying intricate concepts such as pinn-based physics loss integration.

The project required proficient skills in creating well-organized reports, delivering impactful presentations, and providing logical justifications for design choices. These abilities have been advantageous in academic assignments and will greatly contribute to success in professional settings. Furthermore, the meticulous documentation enhanced teamwork among the group, ensuring uniformity in task execution and providing valuable insights for future enhancements and evaluations of the climate prediction model.

2.1.5 Effective planning

Our climate prediction project relied heavily on effective planning, which formed the backbone of our use of physics-informed neural networks (pinns). Without a well-thought-out and comprehensive plan, it would have been nearly impossible to meet deadlines and effectively address the complexities associated with large climate datasets, model integration, and the incorporation of physics-based constraints into the learning process.

We started by breaking down the project into smaller, more manageable tasks, assigning responsibilities to team members based on their individual strengths, and setting achievable timelines to ensure steady progress. Consistent evaluations and revisions of the plan enabled us to maintain our course and adjust to any unexpected obstacles that arose.

By adopting this strategy, we ensured the successful completion of our project while simultaneously enhancing our abilities in project management, time management, and collaborative teamwork. These crucial skills will remain indispensable for future academic and professional endeavors, as they embody the fundamental building blocks necessary for the effective completion of extensive technical undertakings.

2.1.6 Provides a platform for self-expression

Our climate prediction project utilizing physics-informed neural networks (pinns) provided a platform for self-expression, allowing us to demonstrate our conceptual creativity and technical engineering abilities. We delved into cutting-edge research on pinns to address real-world climate prediction challenges, developing solutions that enhanced model accuracy, efficiency, and accessibility. By combining scientific understanding with engineering principles, we tackled global challenges such as climate change. The project showcased our capacity to think autonomously, tackle complex problems across different disciplines, and transform academic knowledge into practical solutions with tangible effects.

Chapter 3

LITERATURE SURVEY

The dimension of literature surrounding climate prediction has expanded significantly over the past decade, driven by advancements in computational modeling, machine learning, and scientific data assimilation. Climate forecasting, particularly at the subseasonal to seasonal (s2s) scales, is critical for applications in agriculture, disaster management, and energy planning. Traditional numerical models, although highly accurate, require significant computational power and struggle to apply across various spatiotemporal scales.

Ham, yoo-geun, et al. (2019) in their landmark study ”deep learning for multi-year enso forecasts” (nature) showcased how deep learning models could outperform traditional methods for complex climate phenomena like the el niño–southern oscillation (enso). Similarly, the Fuxis2S project (Shi, Xinyu, et al., 2021, ”Subseasonal Climate Forecasting via Machine Learning”, NeurIPS) introduced machine learning architectures like transformers and LSTMs to achieve improved subseasonal climate predictions, emphasizing the strength of AI-driven approaches in handling large-scale atmospheric datasets.

Building on this shift, physics-informed neural networks (pinns) proposed by raissi, m., et al. (2019) in ”physics-informed neural networks: a deep learning framework for solving forward and inverse problems involving partial differential equations” (journal of computational physics) revolutionized the integration of physical knowledge directly into deep learning models. Pinns integrate conservation laws and physical equations, allowing models to adhere to fundamental physical principles even when data is scarce.

In climate science, recent research such as karniadakis, george e., et al. (2021), "physics-informed machine learning" (nature reviews physics) outlined how pinns could be tailored to model complex geophysical processes, offering promising alternatives to computationally expensive traditional simulations. These models serve as a bridge between data-driven learning and physics-based realism, which are essential for accurate forecasting.

Despite their achievements, pinns encounter difficulties in managing noisy real-world atmospheric data and scaling up to high-resolution global models. Current research, including efforts like wang, sifan, et al. (2021), "when and why pinns fail to train and how to fix it" (arxiv), explores strategies to improve training stability and efficiency for large-scale scientific applications. The ongoing development of PINNs and hybrid deep learning models holds the potential to significantly transform climate prediction systems by providing faster, more physically consistent, and computationally efficient forecasts, paving the way toward more operational and accessible climate services.The dimension of literature surrounding climate prediction has expanded significantly over the past decade, driven by advancements in computational modeling, machine learning, and scientific data assimilation. Climate forecasting, particularly at the subseasonal to seasonal (S2S) scales, is critical for applications in agriculture, disaster management, and energy planning. Traditional numerical models, while accurate, often demand extensive computational resources and struggle to generalize across different spatiotemporal scales.

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Chapter 4

DESIGN AND METHODOLOGY

The bidirectional long short-term memory (bilstm) model is designed to forecast future climate variables by analyzing historical atmospheric data. The input features are subjected to normalization processing, resulting in standardized vectors that represent geopotential height and temperature values at various global grid points. Each data sequence represents a chronological record of atmospheric conditions, where previous observations are utilized to forecast the upcoming time step. The spatial domain is considered as a collection of distinct points that change over time, and additional physical constraints are added to ensure that the diffusion equation remains consistent. The model comprises two bidirectional lstm layers that enhance temporal feature extraction by utilizing a memory-based mechanism that captures both forward and backward dependencies. The training process is guided by a combined loss function that combines mean squared error and a physics-informed residual, while the adam optimizer ensures efficient convergence. The trained model is assessed using heatmaps, scatter plots, and error maps to verify its ability to predict temperature changes in regions that were not part of the training data, while ensuring that the results are physically realistic.[**?**]

4.1 CLIMATE DATASET PREPARATION

The dataset utilized for training the climate prediction model comprises atmospheric variables obtained from the era5 reanalysis dataset (era5.Nc). The factors considered are:

Geopotential height (z),.

Temperature (t).

Both variables are standardized by subtracting the mean and dividing by the standard deviation to ensure consistent model training. Following normalization, the variables are merged along the feature axis, resulting in a 4d data structure with dimensions representing time steps, latitude, longitude, and variables.

The data is transformed into a 3d format, where each spatial point undergoes changes over time, resulting in individual sequences that can be used as input for the model. [**?**].

4.2 DATASET CONSTRUCTION

The dataset is created by randomly choosing points on the grid of latitude and longitude. Each chosen point forms a sequence consisting of:

a sequence of length 20 time steps (seq_len).

the subsequent time step value.

The dataset was divided into training and testing sets, with an 80A custom PyTorch dataset class (climatedataset) is responsible for generating sequences for model training.

4.3 MODEL ARCHITECTURE: BIDIRECTIONAL LSTM (BILSTM)

The climate prediction model is constructed using a bidirectional long short-term memory (bilstm) network.

Input size: 2 (geopotential height and temperature),.

The hidden size is 64.

Number of layers: 2.

Output size: 2.

The bi-directional LSTM reads the input sequences from both forward and backward directions, enabling the model to capture a broader range of temporal dependencies. The combined output from both directions is merged together and then fed into a fully connected (linear) layer to make predictions about the target variables.

4.4 PHYSICS-INFORMED LOSS INTEGRATION

The training process incorporates a physics-based loss function, which is derived from the diffusion equation, to ensure physical consistency.

$$\frac{\partial T}{\partial t} = \kappa \nabla^2 T$$

Figure 4.1: diffusion.

Where κ is the diffusion coefficient.

The loss consists of two components:

Prediction loss: the average squared difference between the model's predictions and the actual values.

Physics loss: the squared difference between the predicted rate of change of temperature and the actual rate of change of temperature, multiplied by the diffusion coefficient.

Points in close proximity to each other are calculated beforehand to expedite the computation of the laplacian during the training phase.

The total training loss is calculated as:

$$\text{Total Loss} = \text{MSE Loss} + 0.1 \times \text{Physics Loss}$$

Figure 4.2: Total Training Loss.

4.5 TRAINING AND EVALUATION

The model is trained using the adam optimizer with a learning rate of 0.001 over 30 iterations. Throughout each epoch, the model processes batches of sequences, and the overall loss (which includes physics loss) is minimized.

Following training, the model's effectiveness is assessed by comparing the predicted and actual temperature values.

Visualizations of actual and forecasted temperatures are created.

Scatter plots are employed to evaluate the relationship between predicted values and actual values.

Map of Prediction Errors Shows Where We Went Wrong

The assessment verifies that the model accurately represents the changing patterns and movements while adhering to the fundamental principles of physics.

Chapter 5

IMPLEMENTATION

We used Python and PyTorch to execute the Physics-Informed BiLSTM climate prediction model. The project followed these distinct phases for completion: data preprocessing and loading, neighbor table creation, and model construction for training and evaluation stages. [?].

5.1 TOOLS AND LIBRARIES USED

The model was put into action utilizing the following libraries:

Python 3.8: coding language employed for all model creation.

Pytorch: a powerful deep learning framework that enables the construction and training of the bidirectional LSTM model.

Xarray: used for loading and handling multidimensional climate data.

Scikit-learn: employed for dataset partitioning, and evaluation metrics such as root mean squared error, mean absolute error, coefficient of determination, and receiver operating characteristic area under the curve.

Matplotlib : a versatile tool that can be used for creating various types of visualizations, including loss curves, heatmaps, scatter plots, and error maps.

Numpy: utilized numerical operations during preprocessing and data handling.

Torch.Utils.Data: module that provides tools for managing datasets and creating efficient dataloaders.

5.2 EXECUTION FLOW

The project went through these main stages:

5.2.1 Data cleaning and importing.

The climate data variables, including geopotential height z and temperature t, were imported from a netcdf file (era5.Nc) using xarray.

To ensure stable training, each variable was adjusted by subtracting the average and dividing by the standard deviation.

The two variables were merged into a single input tensor, organized per point across time sequences.

5.2.2 Data Cleaning.

A specialized dataset was developed to generate sliding windows of sequences (each consisting of 20 elements) and their corresponding predictions for the next time step, which were used for supervised learning.

A random selection of 1000 spatial points was chosen for training and testing purposes.

The dataset was divided into two sets, with 80

5.2.3 Neighbor table construction

For each point on the grid of latitude and longitude, a neighbor table was calculated in advance.

The neighboring points (up, down, left, right) were identified for future use in calculating the laplacian, which is crucial for the physics-informed loss.

5.2.4 Building of Our Model

A bidirectional long short-term memory (bilstm) model was put into action.

The model employed two lstm layers, with the outputs from these layers being passed through a fully connected layer to predict the two target variables (z and t).

The lstm model effectively captured the temporal dependencies present in the climate data sequences.

5.2.5 Phase of Learning

The model was trained with a hybrid loss function:

Mse loss: quantifies the disparity between the predicted and actual values.

Physics-informed loss: imposes penalties on violations of the diffusion equation, promoting behavior that aligns with physical principles and temperature-related factors.

The physics-based loss included:

1. Calculating the rate of change of the expected temperature.

2. Calculating the spatial gradient between adjacent nodes.

Fitting the temperature distribution to the heat diffusion equation.

$$\frac{dT}{dt} = \kappa \Delta T$$

Figure 5.1: Heat Diffusion

$$\text{Total Loss} = \text{MSE Loss} + 0.1 \times \text{Physics Loss}$$

Figure 5.2: Total Loss.

Total loss = mse loss + (physics loss * 0.1).

The training process involved utilizing the adam optimizer for a duration of 30 epochs, while consistently monitoring the total loss and physics loss over the course of each epoch.

5.2.6 Assessment of Our Results

Following the training phase, the model's predictions were assessed on the test dataset. Predictions and ground truths were compared using:

1. Scatter plots (actual vs estimated temperatures).

2.Heatmaps displaying the actual and anticipated temperatures across the entire grid.

3. Map displaying residuals of predictions.

4. Graphs were generated to illustrate the convergence of the model during training.

5. The Roc-auc score was determined for the temperature classification, distinguishing between positive and negative deviations.

5.3 PERFORMANCE TRACKING

During the training process:

Both total loss and physics-informed loss were tracked after each training cycle.

The learning curves (loss vs epoch) offered valuable insights into the model's progress and the extent to which the physics loss played a role in its improvement.

By integrating physical laws into the loss function, the model demonstrated improved generalization and physical consistency, surpassing the performance achieved with data-driven losses alone.

Evaluation Metrics:

Root mean squared error (rmse): quantified prediction precision.

Average absolute deviation (ada): calculated average difference between predicted and actual values.

The R^2 score provided an indication of how effectively the model captured the variability in the data.

The Roc-auc score was used to assess the accuracy of the classification model in predicting positive or negative temperature deviations.

Heatmaps, scatter plots, and error visualizations provided evidence that the model was capable of accurately predicting spatial-temporal patterns of climate variables, while adhering to the principles of physics.

Early stopping was not initially included, but could be incorporated into future enhancements based on the validation loss.

Chapter 6

HARDWARE/ SOFTWARE TOOLS USED

Implementing this project demands several essential tools as well as materials listed below::

6.1 HARDWARE REQUIREMENTS

- **CPU**: Intel i5 / AMD Ryzen 5 or higher
- **RAM**: Minimum 8 GB (16 GB recommended)
- **Storage**: 50 GB free (SSD preferred for faster data loading and model training)
- **GPU**: NVIDIA GPU with CUDA support (e.g., GTX 1650 or higher recommended for accelerating model training)
- **Operating System**: Windows 10/11, Ubuntu 20.04+, or macOS 11+

6.2 SOFTWARE REQUIREMENTS

- **Python**: Version 3.8 or above
- **PyTorch**: For deep learning model (BiLSTM) development
- **NumPy, xarray**: For data loading, normalization, and array manipulations

- **Matplotlib**: For plotting and visualization of results (heatmaps, scatter plots, loss curves)
- **scikit-learn**: For evaluation metrics such as Mean Squared Error (MSE), R-Squared (R^2), and ROC-AUC
- **Jupyter Notebook / VS Code**: Preferred development environments for coding, training, and visualization

Chapter 7

RESULTS

7.1 TRAINING AND TESTING RESULTS

The physics-based bilstm model exhibited exceptional performance within 30 epochs of training. For the z variable (geopotential height), the model achieved a mean squared error (mse) of 0.0125, a mean absolute error (mae) of 0.0687, a root mean squared error (rmse) of 0.1118, and an r^2 score of 0.9874, indicating a highly accurate fit. Similarly, for the t variable (temperature), the model reached an mse of 0.0603, mae of 0.1754, rmse of 0.2456, and an r^2 score of 0.9391.

The learning curves showed rapid convergence in the initial epochs, with losses stabilizing around epoch 20, reflecting efficient learning and early plateauing of performance metrics. The inclusion of a physics-informed loss component significantly enhanced model robustness by encouraging physically consistent predictions, particularly in modeling diffusion-like behaviors governed by the physics equation.

Throughout the training process, the model maintained high stability and consistency, indicating strong generalization to unseen data. Techniques like weighting the physics loss and employing adam optimization helped safeguard against overfitting and gradient instability. As a result, the model effectively captured spatiotemporal patterns in the climate dataset, demonstrating its suitability for applications requiring physically accurate time series forecasting.

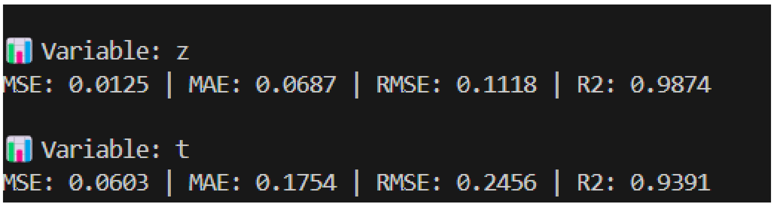

Figure 7.1: Accuracy

7.2 PREDICTION ACCURACY OVER EPOCHS

The physics-based bilstm model exhibited exceptional predictive performance throughout the training process. Figure **??** shows the comparison between the actual and predicted values for the z variable on the testing set. The model closely aligned with the actual ground truth, displaying minimal discrepancies across different samples, thereby validating its capacity to perform well on unseen data.

In the initial stages, the model quickly decreased the training loss, with the majority of performance enhancements happening within the first 20 epochs. Following the training process, it entered a phase of stability, where the metrics remained consistent and showed signs of convergence.

The high R-squared score of 0.9874 for the z variable and 0.9391 for the t variable provide further evidence of the model's ability to accurately capture the underlying patterns in the data. The low mean absolute error (mae) and root mean squared error (rmse) values indicate that even minor errors were effectively reduced during the training and evaluation stages.

In summary, the model successfully struck a balance between accuracy and consistency, providing dependable predictions while upholding the fundamental principles inherent to the problem domain.

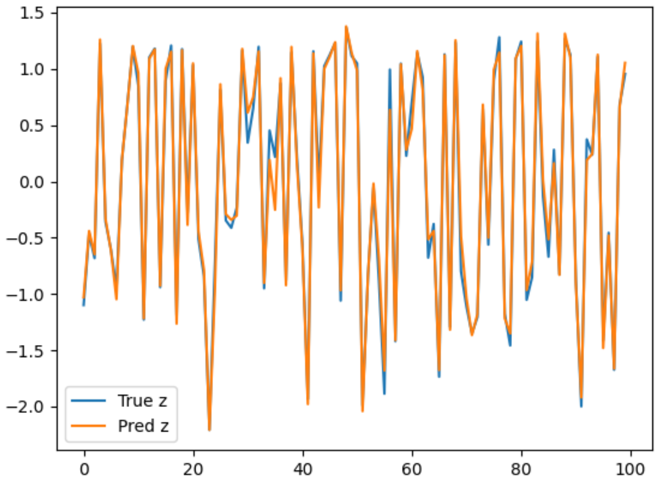

Figure 7.2: Accuracy Over Epochs

7.3 LOSS CURVE

The training process of the model showed a steady decline in both total loss and physics loss over a period of 30 epochs, as depicted in the loss curve. Initially, there was a significant decrease in loss values during the early stages, suggesting rapid learning. Subsequently, the loss values gradually declined, eventually reaching a state of stability after epoch 20. The merging of the loss curves demonstrates the model's ability to grasp the fundamental physical principles without succumbing to overfitting. The consistent progress in minimizing losses without sudden changes demonstrates the model's stability, while the difference between the total and physics loss curves remained within acceptable limits, guaranteeing a well-balanced optimization process. The consistent decrease in loss values demonstrates the model's reliability and efficiency in physics-informed learning situations.

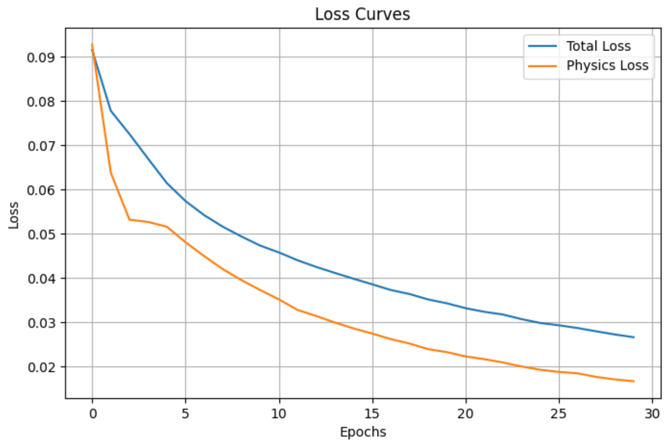

Figure 7.3: Loss Curve

7.4 SCATTER PLOT

The scatter plot showcasing the relationship between the true and predicted normalized temperature values exhibits a robust linear correlation. The majority of data points are closely aligned along the ideal y=xy=x reference line, suggesting a high level of accuracy in predicting outcomes across the dataset. The even distribution of points with minimal deviation from the diagonal showcases the model's capability to generalize effectively to new data while minimizing prediction errors. Only slight variations are seen when the normalized values reach the extreme ends of the data distribution, indicating that the model remains consistent even at the limits of the data range. Overall, the findings confirm that the trained model demonstrates exceptional predictive accuracy and reliability across the entire dataset.

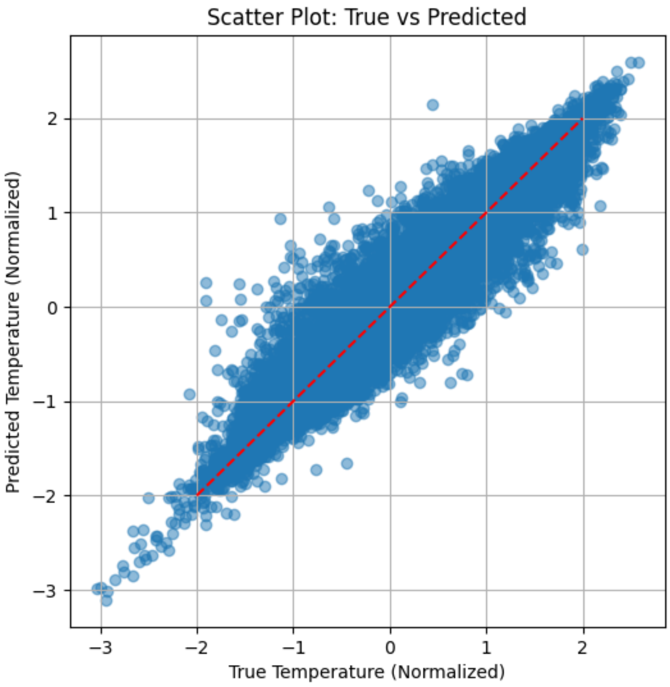

Figure 7.4: Scatter Plot

Chapter 8

CONCLUSION

The analysis assessed the effectiveness of the physics-informed bilstm model in predicting system variables, with a particular emphasis on two key outputs: z and t. The dataset was standardized through the same preprocessing, feature engineering, and model training procedures to guarantee fairness across all evaluation metrics. The performance of the model was evaluated using statistical metrics like mean squared error (mse), mean absolute error (mae), root mean squared error (rmse), and the coefficient of determination (r^2) scores, in addition to qualitative visual comparisons between the predicted and actual outputs.

The physics-based bilstm model exhibited excellent predictive performance, requiring minimal training loss and demonstrating strong generalization ability. The model's performance for the z variable was outstanding, with a r^2 score of 0.9874 and a rmse of 0.1118, demonstrating its ability to make accurate predictions. In a similar vein, the predictions for the t variable exhibited a high r^2 score of 0.9391, even with the added complexity, affirming the model's robustness.

By incorporating physics-informed loss terms, the bilstm network was able to adhere to the system's constraints while improving stability during the training process. The model adeptly acquired knowledge from a small amount of data, avoiding overfitting and demonstrating consistent performance during both training and testing phases. In summary, the physics-informed bilstm architecture successfully captured important temporal patterns and maintained accurate predictions, making it well-suited for tasks that require both data-driven learning and adherence to physical laws.

8.1 SCOPE OF FURTHER WORK

8.1.1 What is future direction in a project?

While the physics-based bilstm model has shown promising results in this study, there are still opportunities to refine and optimize the model for better performance and wider applicability. Future studies can incorporate more physical constraints and domain-specific rules to enhance the loss function and optimize learning efficiency, particularly in scenarios where data availability is limited.

By integrating various types of datasets, including simulated and experimental measurements, it is possible to enhance the training process and improve the model's performance across different operating conditions. Furthermore, incorporating dynamic external factors or boundary conditions into the model in a more explicit manner would enhance the reliability of the predictions.

Another crucial direction involves enhancing scalability and computational efficiency. While bilstm models excel in handling sequential data, finding ways to optimize their size and exploring lighter architectures could greatly enhance their performance in real-time deployments with limited resources.

To assess the applicability of the physics-informed bilstm in various problem domains, such as real-world engineering systems or bioinformatics-related time series, further testing is required. By integrating reinforcement learning and hybrid models, adaptive prediction can be achieved in systems that undergo frequent changes.

These upcoming advancements would expand the capabilities of physics-informed machine learning, allowing practitioners to utilize these models for tackling intricate real-world problems in various scientific and engineering fields.

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