Artificial Intelligence for monitoring water pollutants

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Abstract. This project aims to develop an innovative model based on neural networks and differential equations (DEs) to analyze, simulate, and predict the dynamics of pollutants in water bodies. The approach focuses on mixing problems, where the concentration of substances changes over time due to the inflow and outflow of pollutants within the system. Through mathematical modeling, the project seeks to accurately represent the physical and chemical processes affecting water quality, while neural networks provide the capability to learn complex patterns and make precise predictions based on observed data. The proposed methodology enables the identification of critical pollution peaks, predicts their evolution over time, and assesses their environmental impact, offering essential information for preventing and mitigating risks associated with water quality. By integrating advanced artificial intelligence techniques with the rigor of mathematical modeling, this project addresses the growing need for innovative tools to support sustainable water management. Moreover, the developed model can serve as a key decision-making tool for environmental authorities and water resource managers. It facilitates strategic planning and the design of public policies aimed at ensuring the sustainability of natural resources. This approach not only promotes environmental conservation but also positively impacts economic and social development by securing access to clean water for present and future generations.

Keywords: Artificial Intelligence, education, applied physics, neural network, DEs, environmental sciences

1 Introduction

Rivers, as natural streams of freshwater flowing from higher elevations to lower areas, play essential roles within the hydrological cycle by transporting water and sediments through diverse ecosystems. These fluvial systems not only serve as critical habitats for a wide range of aquatic and terrestrial species but have also been fundamental for the development of human civilizations throughout history, providing sources of water, transportation routes, and economic drivers (Ward & Tockner, 2001).

The importance of rivers spans multiple dimensions, as they are vital for supplying water for human consumption, agricultural production, and industrial activities, in addition to being key sources for hydroelectric power generation. Rivers also support

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ecosystems with remarkable biodiversity and provide essential ecosystem services, such as climate regulation and natural water purification. Several studies highlight that rivers and lakes are facing unprecedented pressures due to human activities, which jeopardize their ecological and socio-economic functions (Grill et al., 2019).

Today, rivers face significant threats stemming from pollution, the overexploitation of water resources, and the effects of climate change. Industrial and agricultural discharges have severely compromised water quality, impacting aquatic ecosystems and posing risks to human health. Additionally, interventions such as dam construction and excessive water extraction for irrigation have altered natural flow regimes, negatively affecting fluvial ecosystems. Recent research has identified the presence of heavy metals and persistent organic compounds in rivers as a serious threat to both aquatic biodiversity and human communities that rely on these resources (Tóth et al., 2016).

The degradation of rivers has far-reaching consequences. Impacts on water quality and availability directly affect food security, public health, and economic activities, especially for communities that depend on these resources for their livelihoods. Moreover, the loss of biodiversity and changes in ecosystem services linked to rivers can undermine the capacity of ecosystems to adapt and recover from future disturbances. To mitigate these effects, it is crucial to implement conservation policies and sustainable management strategies that protect the integrity of fluvial systems and promote the well-being of human communities that rely on them (Grill et al., 2019).

In the present context, the ability to anticipate and manage water quality is essential for safeguarding water resources and ensuring community well-being. The growing need for innovative tools to effectively monitor water pollution has driven the adoption of advanced approaches, such as combining mathematical modeling with artificial intelligence (AI), which offer accurate, real-time solutions to address this challenge (Pellenz et al., 2020).

This project combines the solution of differential equations (DEs) and artificial neural networks to model and predict the dynamics of pollutants in water bodies. By integrating AI techniques and mathematical modeling, the system allows for the analysis of how pollutants spread and dilute based on factors such as flow rate, pollutant load, and environmental conditions. Trained with historical water quality data, the model can identify complex patterns, predict pollution peaks, and assess environmental impacts, providing a precise tool for the management and protection of water resources.

This project not only aims to understand how pollution levels in Michoacán's rivers vary based on environmental and human factors but also seeks to generate concrete, scalable solutions that contribute to more sustainable water management.

2 Background

Artificial Intelligence (AI) has become an essential tool in environmental management, standing out for its ability to analyze large volumes of data and detect complex patterns. In pollutant dispersion modeling, AI enables the prediction of trajectories and concentrations of harmful substances in the air, water, and soil by integrating variables such as meteorological and geospatial data. These capabilities have significantly improved decision-making and the implementation of public policies, protecting both ecosystems and human communities. Additionally, AI plays a key role in responding to ecological disasters such as oil spills, wildfires, and floods. With predictive systems based on historical and real-time data, AI allows for the simulation of critical scenarios and the optimization of response and mitigation strategies. Integrated with tools like remote sensors and satellite imagery, AI facilitates constant ecosystem monitoring and early detection of environmental changes, significantly contributing to environmental protection and human well-being (Kolasa-Więcek, 2011).

Using predictive models based on machine learning, advanced simulations have been developed to understand and predict how hydrocarbons disperse in water. These simulations incorporate complex variables such as ocean currents, water temperature, winds, and other climatic conditions, enabling accurate predictions of spill trajectories and spread. This information is crucial for prioritizing response areas, identifying high-risk zones, and preventing severe damage to vulnerable ecosystems like coral reefs, mangroves, and marine habitats. AI applications have significantly optimized cleanup and mitigation strategies. By analyzing real-time data, models can suggest ideal locations for deploying containment barriers or initiating recovery operations, maximizing resource efficiency. They also assist in assessing the environmental impact post-event, facilitating the design of ecological restoration programs. These advancements not only minimize the environmental and economic consequences of oil spills but also reduce response times, protecting both biodiversity and the communities that rely on marine environments for their livelihoods. The integration of AI in this field represents a significant shift toward more precise and effective management of ecological disasters (Temitope Yekeen & Balogun, 2020).

One relevant work in this field is by Quiñones Huatangari et al. (2020), who developed a neural network to estimate the Water Quality Index using various environmental monitoring variables. Their research highlighted the benefits of neural networks in processing large volumes of data, such as pollutant concentrations, pH, temperature, and other critical parameters that determine water quality. The proposed approach not only provided an effective tool for estimating water quality but also allowed for more accurate predictions of potential changes in water conditions over time, which is essential for efficient water resource management.

Additionally, a study conducted by Flores et al. (2023) on the water quality of the Loa River in the Atacama Desert, Chile, used machine learning models to classify water quality status and predict its variations over time. This research focused on water quality classification and the identification of potential pollutants, using both historical data and specific environmental parameters of the area. The study demonstrated how AI techniques can identify and predict the effects of pollution in rivers under extreme climatic conditions, which has direct implications for other regions with similar environmental characteristics.

Similarly, the study by Conejeros Molina et al. (2021) addressed water quality monitoring in rural drinking water systems. Using an AI-based approach, this work provided effective tools for water management in rural areas, where water quality is crucial for public health and local development. A neural network model was used to predict contamination levels based on variables such as pollutant load, flow rate, and characteristics of the water distribution system. This approach demonstrates the viability of neural networks as tools for predicting water quality and optimizing available resources in rural drinking water systems.

Collectively, these studies highlight the potential of neural networks to accurately and efficiently monitor water quality. However, few studies have combined the use of differential equations (DEs) with neural networks to model and predict pollutant dynamics in water bodies, especially in regions with environmental complexities like Michoacán. This project aims to advance this field by integrating these approaches, providing a predictive tool that not only simulates pollution evolution but also supports the implementation of concrete solutions for sustainable water management.

3 Problem Statement

Research Question. How can a model based on neural networks, combined with differential equations, improve the analysis, simulation, and prediction of contaminant dynamics in water bodies, enabling the identification of critical pollution peaks, the anticipation of its future evolution, and the assessment of its environmental impact?

Clarity and Focus. The central point of the research is to design and validate a hybrid model that integrates artificial intelligence and mathematical modeling to address mixing problems in water bodies. This includes analyzing how the inflow and outflow of pollutants affect their temporal concentration, predicting future behaviors, and generating useful information to mitigate environmental risks and optimize water management. The research specifically focuses on the applicability of the model to identify critical pollution events and facilitate real-time decision-making.

Contribution to the Field. This proposal provides an innovative approach to environmental management and water monitoring systems by integrating artificial intelligence techniques with traditional mathematical models. The impact of this research lies in its ability to provide advanced predictive tools, which not only enable a more effective response to pollution events but also improve long-term planning. Additionally, by linking artificial intelligence with environmental modeling, the theoretical and methodological framework is expanded to address complex problems in natural resource conservation, positioning this research as a reference in the application of emerging technologies for environmental sustainability.

3.1 Relevance and Pertinence

Social Relevance

Water is a vital resource for life and sustainable development. In a global context where water pollution poses a significant threat to public health, ecosystems, and food security, efficient monitoring of contaminants in water bodies becomes a priority. This project addresses a critical issue by developing advanced technological tools that allow for the anticipation and management of pollution events. Ensuring water quality directly contributes to the well-being of communities, environmental sustainability, and the achievement of the Sustainable Development Goals (SDGs), particularly SDG 6: Clean Water and Sanitation.

Practical Implications

The development of a neural network-based model for pollutant analysis has immediate practical applications. It allows environmental authorities, water resource managers, and companies to identify critical pollution peaks, assess their impact in real-time, and design effective mitigation strategies. Additionally, the model's predictive capacity strengthens long-term water management and planning, reducing environmental and economic risks. The implementation of this system can be integrated into real-time monitoring platforms, optimizing resources and preventive actions.

Theoretical Value

The project combines two fundamental disciplines: mathematical modeling using DEs and artificial intelligence, specifically neural networks. This interdisciplinary approach generates new knowledge about the dynamics of pollutants in complex water systems and their behavior under different conditions. The integration of these methods not only enriches the existing theory on mixing and dispersion processes but also opens pathways for their application in other environmental systems, fostering research in related areas.

Methodological Usefulness

The proposed methodology stands out for its versatility and scalability. By modeling pollutant dynamics with DEs and neural networks, a tool adaptable to different geographical contexts and types of water bodies is developed. The ability to predict future scenarios and assess impacts strengthens the design of public policies and environmental management strategies. Furthermore, this approach can be replicated for other environmental issues, positioning it as a methodological reference for the use of artificial intelligence in natural resource conservation.

Altogether, our proposal not only addresses an urgent need that affects us all but also provides innovative and sustainable solutions that benefit both the natural environment and human communities.

3.2 Goals

General Goal

To develop a model based on neural networks and differential equations to analyze, simulate, and predict the dynamics of pollutants in water bodies, in order to identify critical pollution peaks, anticipate their evolution, and assess their environmental impact, contributing to informed decision-making and the sustainable management of water resources.

Specific Goals

- To design a mathematical model based on differential equations that describes the mixing processes and concentration variations of pollutants as a function of inflow and outflow flows in water bodies.
- To implement and train a neural network that, using data generated by the mathematical model and empirical observations, allows predicting future pollution scenarios and evaluating their impact over time.
- To validate the proposed model by comparing its predictions with real water monitoring data, to optimize its accuracy and ensure its applicability in environmental risk management and public policy planning.

4 Methodology

This project uses a non-experimental approach based on computational simulations to model and predict the dynamics of pollutants in bodies of water. The methodology focuses on the development and training of artificial neural networks designed to solve ordinary (ODE) and partial (PDE) differential equations, which describe the mixing and diffusion of pollutants in aquatic systems.

4.1 Procedure

Definition of the model

The ODE that models the inflow and outflow of pollutants in a water reservoir is:

$$\frac{dq}{dt} = r_e - r_s \tag{1}$$

where: $r_e = c * a$ represents the rate of entry of pollutants, with c being the concentration and a, the rate of water entry. Moreover, $r_s = q * v * b$ models the exit of pollutants, where q is the current flow, v is the system volume, and b is the exit rate.

On the other hand, the PDE that models the diffusion of a contaminant substance of certain density in a medium is

$$\partial u/\partial t = k\,(\partial^2 u/\partial x^2 + \partial^2 u/\partial y^2) + f(x,y) \tag{2}$$

where: u=u(x,y,t) represents the concentration of pollutants, k is the diffusion coefficient and f(x,y) is a source term dependent on the spatial coordinates.

```
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import matplotlib.pyplot as plt

# Define the neural network model
class DiffusionNet(nn.Module):
    def __init__(self):
        super(DiffusionNet, self).__init__()
        self.fc1 = nn.Linear(3, 64)  # Fewer neurons
        self.fc2 = nn.Linear(64, 64)
        self.fc3 = nn.Linear(64, 1)

    def forward(self, inputs):
        x = torch.tanh(self.fc1(inputs))
        x = torch.tanh(self.fc2(x))
        return self.fc3(x)

# Source term f(x, y), can be customized for specific problems
def f(x, y):
    return torch.cos(x/4)

# Loss function
def loss_function(model, x, y, t, alpha, Lx, Ly):
    inputs = torch.cat([x, y, t], dim=1)
    u = model(inputs)

    # Compute temporal derivative
    u_t = torch.autograd.grad(u, t, grad_outputs=torch.ones_like(u), create_graph=True)[0]

    # Compute spatial derivatives
    u_x = torch.autograd.grad(u, x, grad_outputs=torch.ones_like(u), create_graph=True)[0]
    u_y = torch.autograd.grad(u, y, grad_outputs=torch.ones_like(u), create_graph=True)[0]
    u_xx = torch.autograd.grad(u_x, x, grad_outputs=torch.ones_like(u_x), create_graph=True)[0]
    u_yy = torch.autograd.grad(u_y, y, grad_outputs=torch.ones_like(u_y), create_graph=True)[0]
```

Fig. 1. Architecture of the network to model the inflow and outflow of contaminants.

```
import torch
import torch.nn as nn
import torch.optim as optim
import numpy as np
import matplotlib.pyplot as pltplt
from torch.optim.lr_scheduler import StepLR

# Define the neural network model
class ODEModel(nn.Module):
    def __init__(self):
        super(ODEModel, self).__init__()
        self.fc1 = nn.Linear(1, 128)
        self.fc2 = nn.Linear(128, 128)
        self.fc3 = nn.Linear(128, 1)

    def forward(self, t):
        t = torch.tanh(self.fc1(t))  # Tanh for added non-linearity
        t = torch.tanh(self.fc2(t))
        t = self.fc3(t)
        return t

# Modify the model to respect the boundary condition q(0) = 100
def model_with_boundary(model, t, initial_value):
    return initial_value + t * model(t)  # Enforces q(0) = 100
```

Fig. 2. Architecture of the network with the equation that models diffusion.

Neural network architecture

In order to solve the ODE, the proposed architecture is as follows:

Input layer: Receives time (t).

Hidden layer: Three layers, each with 128 neurons and Tanh activation, introducing non-linearity.

Output layer: Returns the pollutant amount q. A specific formulation is incorporated to satisfy the boundary condition

$$q(0) = 100: q(t) = q(0) + t * NN(t), \tag{3}$$

where NN(t) is the output of the neural network.

For the PDE (DiffusionNet), the selected architecture was as follows:

Input Layer: Receives (x,y,t).

Hidden Layer: Three hidden layers with 64 neurons each and Tanh activation function.

Output Layer: Returns u(x,y,t), the concentration of pollutants.

```
# Parameters
c = 0.01  # Concentration of contaminant
a = 100   # Flow rate (m³/min)
b = 250   # Outflow rate
v = 10000 # Volume of water (m³)
initial_value = torch.tensor([100.0])  # Initial condition q(0) = 100

# Define the differential equation dq/dt = re - rs
def f(t, q):
    re = c * a
    rs = (q / v) * b
    return re - rs

# Define the loss function
def loss_function(model, t):
    q_pred = model_with_boundary(model, t, initial_value)
    q_pred_prime = torch.autograd.grad(q_pred, t, grad_outputs=torch.ones_like(q_pred), create_graph=True)[0]
    f_val = f(t, q_pred)
    loss_ode = torch.mean((q_pred_prime - f_val)**2)
    # Enforce boundary condition with a higher weight
    loss_bc = 10 * torch.mean((model_with_boundary(model, torch.tensor([[0.0]], requires_grad=True), initial_value) - initial_value)**2)
    return loss_ode + loss_bc
```

Fig. 3. Parameter definitions and the loss function that enforces boundary conditions.

```
    # PDE loss
    pde_residual = u_t - alpha * (u_xx + u_yy) - f(x, y)
    loss_pde = torch.mean(pde_residual**2)

    # Boundary condition: u = 0 on the boundary
    boundary_mask = (x == 2) | (x == Lx) | (y == 0) | (y == Ly)
    loss_bc = torch.mean(u[boundary_mask]**2)

    # Initial condition: u(x, y, 0) = I(x, y)
    initial_mask = t == 0
    u_initial = u[initial_mask]
    I = torch.sin(np.pi * x[initial_mask]) * torch.sin(np.pi * y[initial_mask])  # Example initial condition
    loss_ic = torch.mean((u_initial - I)**2)

    return loss_pde + loss_bc + loss_ic

# Parameters
Lx, Ly = 1.0, 1.0  # Spatial domain
T = 5.0  # Temporal domain
alpha = 0.02  # Diffusion coefficient
batch_size = 1000  # Subset size for minibatches

# Generate training data
n_points = 50  # Smaller mesh
x_train = torch.linspace(0, Lx, n_points).view(-1, 1).requires_grad_(True)
y_train = torch.linspace(0, Ly, n_points).view(-1, 1).requires_grad_(True)
t_train = torch.linspace(0, T, n_points).view(-1, 1).requires_grad_(True)

x_grid, y_grid, t_grid = torch.meshgrid(x_train.squeeze(), y_train.squeeze(), t_train.squeeze(), indexing='ij')
x_flat, y_flat, t_flat = x_grid.flatten(), y_grid.flatten(), t_grid.flatten()

x_train = x_flat.unsqueeze(1)
y_train = y_flat.unsqueeze(1)
t_train = t_flat.unsqueeze(1)
```

Fig. 4. Definition of the PDE loss, boundary and initial conditions, and the generation of training data using a spatial and temporal mesh.

Generation of training data

For the ODE, values of t were generated in an interval from 0 to 50 minutes, with higher point density near $t=0$ to ensure compliance with the boundary condition.

For the PDE, a uniform spatial mesh was used over the domain $[0, L_x]$ X $[0, L_y]$ and temporal $[0, T]$ with n=50 points.

The data was scaled and prepared to maximize the model accuracy.

4.2 Training the network

Loss

A loss function was used that combines: Error in solving the ODE. Penalization for violating the initial condition.

Optimization

The RAdam optimizer was used with a learning rate scheduler (StepLR) that dynamically adjusts the rate to stabilize training.

The model was trained for 2500 and 2000 epochs.

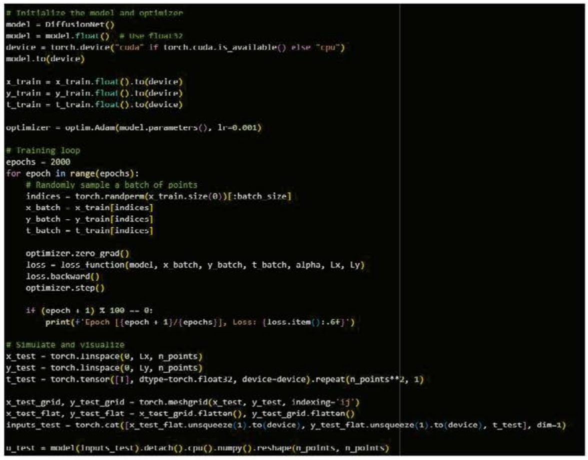
```
# Generate training data with denser points near t = 0
t_train = torch.cat([
    torch.linspace(0, 1, 200),  # More points near the initial condition
    torch.linspace(1, 50, 550) # Remaining points
]).view(-1, 1)
t_train.requires_grad = True

# Initialize the model and optimizer
model = ODEModel()
optimizer = optim.RAdam(model.parameters(), lr=0.001, weight_decay=1e-5)  # RAdam for better optimization
scheduler = StepLR(optimizer, step_size=500, gamma=0.5)

# Training loop
epochs = 2500
for epoch in range(epochs):
    optimizer.zero_grad()
    loss = loss_function(model, t_train)
    loss.backward()
    optimizer.step()
    scheduler.step()

    if (epoch + 1) % 100 == 0:
        print(f'Epoch [{epoch + 1}/{epochs}], Loss: {loss.item():.6f}')
```

Fig. 5. Training of the first network (ODE)



```python
# Initialize the model and optimizer
model = DiffusionNet()
model = model.float()  # Use float32
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
model.to(device)

x_train = x_train.float().to(device)
y_train = y_train.float().to(device)
t_train = t_train.float().to(device)

optimizer = optim.Adam(model.parameters(), lr=0.001)

# Training loop
epochs = 2000
for epoch in range(epochs):
    # Randomly sample a batch of points
    indices = torch.randperm(x_train.size(0))[:batch_size]
    x_batch = x_train[indices]
    y_batch = y_train[indices]
    t_batch = t_train[indices]

    optimizer.zero_grad()
    loss = loss_function(model, x_batch, y_batch, t_batch, alpha, Lx, Ly)
    loss.backward()
    optimizer.step()

    if (epoch + 1) % 100 == 0:
        print(f'Epoch [{epoch + 1}/{epochs}], Loss: {loss.item():.6f}')

# Simulate and visualize
x_test = torch.linspace(0, Lx, n_points)
y_test = torch.linspace(0, Ly, n_points)
t_test = torch.tensor([T], dtype=torch.float32, device=device).repeat(n_points**2, 1)

x_test_grid, y_test_grid = torch.meshgrid(x_test, y_test, indexing='ij')
x_test_flat, y_test_flat = x_test_grid.flatten(), y_test_grid.flatten()
inputs_test = torch.cat([x_test_flat.unsqueeze(1).to(device), y_test_flat.unsqueeze(1).to(device), t_test], dim=1)

u_test = model(inputs_test).detach().cpu().numpy().reshape(n_points, n_points)
```

Fig. 6. Training of the diffusion network

Model validation

After training, the model was evaluated by generating predictions over a time range *t* and comparing the results with the expected solution to verify consistency.

4.3 Equipment and Tools

Software

Python 3.9 with libraries: torch for neural network implementation, matplotlib for result visualization, numpy for mathematical operations

Data collection

Data used for training is artificially generated based on the parameters of the defined differential equations. In future applications, the model could integrate with sensor systems for real-time data collection from local rivers.

Data analysis

The mean squared error (MSE) between the derivatives calculated by the model and the theoretical derivatives was measured. Prediction graphs of pollutants were analyzed to evaluate behavior patterns and detect.

4.4 Discrepancies and Schematics

Neural Network Architecture

Diagram of the network layers, showing connections and activations.

Training Flow

Flowchart detailing the steps from data generation to model evaluation.

Result Graphs

Loss curves during training.

Network predictions compared to the theoretical solution.

With this methodology, the model is expected to predict the dynamics of contaminants with high accuracy, facilitating the monitoring and sustainable management of water in the rivers of Michoacán.

5 Results

The results obtained validate the predictive capability of both models in different scenarios.

5.1 ODE

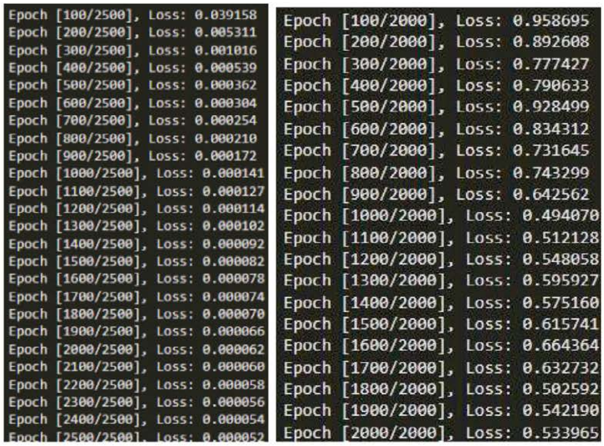
The neural network accurately predicted the temporal evolution of the contaminant quantity q(t). Stable loss curves were observed, reaching minimum values after 1500 epochs, as seen in Fig. 7. Figure 8 depicts the numerical solution and the theoretical prediction, that are on top of each other.

5.2 PDE

The DiffusionNet accurately captured diffusion and mixing patterns of contaminants across spatial and temporal domains, as can be seen in Fig. 9. Plots of the concentration u(x,y,T) at the final time showed strong alignment with expected conditions, highlighting critical areas of accumulation.

5.3 Patterns and Analysis

The models identified contamination peaks and anticipated long-term trends, demonstrating their applicability in water management. The experiment replicability offers a tool adaptable to different water bodies, validating its use in diverse contexts. These results reaffirm the feasibility of the proposed hybrid approach, combining neural networks with differential equations for monitoring and predicting contaminants in water bodies.



```
Epoch [100/2500], Loss: 0.039158
Epoch [200/2500], Loss: 0.005311
Epoch [300/2500], Loss: 0.001016
Epoch [400/2500], Loss: 0.000539
Epoch [500/2500], Loss: 0.000362
Epoch [600/2500], Loss: 0.000304
Epoch [700/2500], Loss: 0.000254
Epoch [800/2500], Loss: 0.000210
Epoch [900/2500], Loss: 0.000172
Epoch [1000/2500], Loss: 0.000141
Epoch [1100/2500], Loss: 0.000127
Epoch [1200/2500], Loss: 0.000114
Epoch [1300/2500], Loss: 0.000102
Epoch [1400/2500], Loss: 0.000092
Epoch [1500/2500], Loss: 0.000082
Epoch [1600/2500], Loss: 0.000078
Epoch [1700/2500], Loss: 0.000074
Epoch [1800/2500], Loss: 0.000070
Epoch [1900/2500], Loss: 0.000066
Epoch [2000/2500], Loss: 0.000062
Epoch [2100/2500], Loss: 0.000060
Epoch [2200/2500], Loss: 0.000058
Epoch [2300/2500], Loss: 0.000056
Epoch [2400/2500], Loss: 0.000054
Epoch [2500/2500], Loss: 0.000052
```

```
Epoch [100/2000], Loss: 0.958695
Epoch [200/2000], Loss: 0.892608
Epoch [300/2000], Loss: 0.777427
Epoch [400/2000], Loss: 0.790633
Epoch [500/2000], Loss: 0.928499
Epoch [600/2000], Loss: 0.834312
Epoch [700/2000], Loss: 0.731645
Epoch [800/2000], Loss: 0.743299
Epoch [900/2000], Loss: 0.642562
Epoch [1000/2000], Loss: 0.494070
Epoch [1100/2000], Loss: 0.512128
Epoch [1200/2000], Loss: 0.548058
Epoch [1300/2000], Loss: 0.595927
Epoch [1400/2000], Loss: 0.575160
Epoch [1500/2000], Loss: 0.615741
Epoch [1600/2000], Loss: 0.664364
Epoch [1700/2000], Loss: 0.632732
Epoch [1800/2000], Loss: 0.502592
Epoch [1900/2000], Loss: 0.542190
Epoch [2000/2000], Loss: 0.533965
```

Fig. 7. Loss Per Epoch

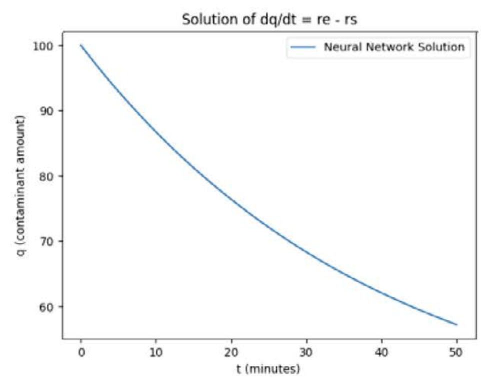


Fig. 8. Solution Plot

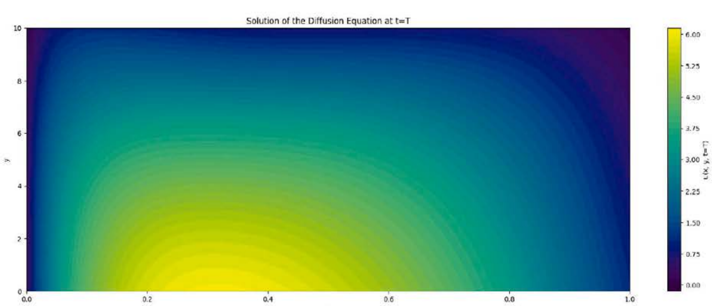


Fig. 9. Diffusion Equation Solution Plot

6 Conclusions

A hybrid model has been proposed that combines the power of neural networks with the rigor of differential equations, providing an accurate and adaptable tool for analyzing the dynamics of pollutants in bodies of water. The model has demonstrated its ability to predict the evolution of pollutants over time with high precision, making it a valuable tool for informed decision-making. The analysis of the results has allowed the identification of patterns in the evolution of pollution, facilitating the understanding of underlying processes and the anticipation of future events.

The model can be used by environmental authorities and water resource managers to design more efficient monitoring and management strategies, reducing the risks associated with pollution and ensuring the availability of clean water for future generations. By predicting and preventing pollution events, the project contributes to the protection of aquatic ecosystems and the conservation of biodiversity. The proposal has driven the development of advanced technological tools, such as neural networks, in the field of environmental management, opening new possibilities for research and innovation.

The combination of knowledge from mathematics, computer science, and environmental science has been fundamental to the success of the project, highlighting the importance of an interdisciplinary approach to address complex problems. The developed model can be adapted and applied to different types of water bodies and pollutants, demonstrating its potential to be a general tool in water management. In future research, integrating real-time water quality monitoring data will be crucial to validate and refine the model, as well as exploring the possibility of using real-time sensor data to enhance the system response capabilities. Other AI techniques, such as deep learning and reinforcement learning, can be explored to further improve the accuracy of the model and generalization capabilities.

This proposal directly contributes to ensure availability and sustainable management of water and sanitation for all. By providing tools to improve water quality and manage water resources, it contributes to public health, food security, and economic development in communities. The development of this model represents a significant advancement in the field of environmental management and the application of artificial intelligence to solve real-world problems. The results demonstrate the potential of this technology to improve water quality and protect aquatic ecosystems. However, it is essential to continue researching and developing such tools to address the complex challenges faced in water resource management in an increasingly changing world.

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