Predictive Modelling and Simulation of Marine Debris Dispersion in Maltese Territorial Waters

Progress Report

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ABSTRACT

The accumulation of surface marine debris in the territorial waters of Malta presents a severe ecological and environmental challenge, negatively impacting marine life and human activities. This project focuses on the application of a practical system integrating a physics based Lagrangian dispersion model with a Machine Learning enhanced predictive model. Utilizing historical wind and surface ocean current datasets, the system utilizes a Lagrangian model to simulate and visualize historical dispersal paths of marine debris, enabling the visualization of past dynamics. Concurrently, an AI model is developed and trained on the same dataset. This model is tasked with predicting key environmental parameters, essential for simulating future conditions. These resultant predictions are integrated into the Lagrangian framework, enabling the model to extend its simulations into the future, thus offering a predictive view of marine debris dispersion trajectories. Hosted on a web platform, this approach offers a significant advancement in marine debris management by facilitating real-time data visualization and predictive analytics. This project not only demonstrates a method for enhancing marine conservation efforts through accurate predictions of marine debris movement but also underlines its vital role in planning and executing effective cleanup operations, thus contributing to a more comprehensive understanding of marine pollution.

1. INTRODUCTION

In this section, we establish the project's context, focusing on the ecological challenge posed by marine debris in Malta's territorial waters. The introduction also highlights the project's different aims and objectives.

1.1 Problem Definition/Motivation

Surface marine debris around Malta's territorial waters presents a significant environmental challenge. Consisting largely of plastics and other non-biodegradable materials, this debris poses a direct threat to marine ecosystems, endangering aquatic life, and disrupting the natural balance. The presence of marine debris also compromises the ecological value of coastal areas adversely impacting recreational activities. This project seeks to address these challenges by developing an integrated system that aims to track and predict the movement of marine debris. The goal is to provide accurate predictions that can guide effective cleanup operations and inform strategies for long-term marine conservation in Maltese waters.

1.2 Aims and Objectives

The aim of this project is to create a system enhanced with Machine Learning for simulating and predicting the movement of marine debris in the territorial waters of Malta, thereby supporting marine conservation efforts.

To achieve this aim, the following objectives have been identified:

01. **Data integration:** To preprocess and integrate the datasets, which include wind and sea surface currents. This will be used for both models.

02. **Lagrangian model development:** To utilize the Ocean Parcels Python toolkit [1] for simulating the movement of surface marine debris, employing historical data to ensure accurate simulations.

03. **AI model development:** To develop a predictive model that can predict future wind and sea surface currents. While a CNN-LSTM architecture is likely, we maintain flexibility in our choice to accommodate evolving project requirements and new insights as the project develops.

04. **Integrating the AI model with the Lagrangian model:** To integrate the AI model's predictions into the Lagrangian model. This integration aims to create future simulations of marine debris movement, enhancing the project's predictive capabilities for marine conservation.

05. **Web-based visualisations:** To develop a web-based platform that facilitates the visualization of both past data and predicted future simulations, providing essential tools for marine conservation and debris management.

1.3 Document Structure

This report is organized into eight main sections, each focusing on a different aspect of the project:

1. **Introduction:** This section sets the context of the project, defining the problem of surface marine debris in Malta's

territorial waters and outlining the motivation behind the study. It also presents the aims and objectives of the project.

2. **Background:** Here, the foundational elements of the project are discussed. It includes detailed descriptions of the datasets used, the principles and functionalities of the Lagrangian model, and the AI model.

3. **Literature Review:** This section delves into existing research and findings relevant to marine debris, the use of Lagrangian models, and the application of different AI models in environmental forecasting. It establishes the scientific grounding for the project's methodologies.

4. **Proposed Solution & Methodology:** This section details the methodologies and processes undertaken to achieve the project's objectives. It includes the steps involved in data integration, the development and integration of the Lagrangian and AI models, and the creation of web-based visualizations.

5. **Testing and Evaluation:** A comprehensive outline of the strategies employed to test and evaluate the effectiveness and reliability of both the Lagrangian model, and the AI model is presented in this section. It covers the evaluation metrics, and real-world scenario testing.

6. **Conclusion:** The final section summarizes the progress made in the project, highlighting key achievements, challenges faced, and future steps.

7. **References:** This section will catalogue all the scholarly resources, articles, papers, and other citations referenced throughout the report to support the research and findings.

8. **Appendices:** The report includes appendices, such as a Gantt chart (Appendix A), which provide supplementary information and visual representations of the project's timeline and milestones.

2. BACKGROUND

In this section, we provide a comprehensive background for the project, detailing the different datasets as well as the different models that will be used.

2.1 The Datasets

The datasets form the backbone of any research project, and their careful selection and processing are critical in producing accurate models. In this project, two essential types of datasets are utilized, both provided by the Department of Geosciences of the University of Malta.

The first dataset is the Sea surface currents dataset, derived from a model generated by high frequency radars [2] located around the islands of Malta and southern Sicily. This dataset is formatted in NetCDF, a standard format for weather data and the most accepted format for the Lagrangian Model [3] . This dataset includes longitude, latitude, time, eastern Ocean Current Velocity, and Northern Ocean Current Velocity. It offers data in hourly increments over three years, from 2020 to 2023. The second dataset is from the Copernicus atmosphere monitoring service, also in NetCDF format. This dataset encompasses longitude, latitude, time, and the northern and eastern wind components. The data is provided in 12-hour increments, centred at 00:00 and 12:00 over three years, from 2020 to 2023 like the previous dataset.

Both datasets are integral to the project, providing comprehensive environmental parameters essential for the subsequent development of predictive models and simulations. The precise and systematic handling of these datasets lays the groundwork for the project's success, ensuring that the modelling efforts are based on accurate and reliable data.

2.2 The Lagrangian Model

The Lagrangian model [3] , a critical component in environmental simulation, offers a dynamic method for tracing the movement of particles through fluid mediums. This model is central to studying phenomena such as marine debris dispersion, as it allows for precise tracking of individual particles over time. The Lagrangian approach incorporates several key functions:

- **Custom Kernels:** Can be defined and executed, allowing for specific, tailored simulation scenarios.

- **Advection [4] :** This process describes how particles are transported by fluid currents, typically modelled by the equation $v = u \cdot \Delta t$, where v is the particle's velocity, u is the current's velocity, and Δt is the time increment.

- **Diffusion [4] :** Representing the random motion of particles, diffusion is often modelled using algorithms like random walks or Gaussian distributions, simulating the effects of molecular diffusion and turbulence.

- **Initial Particles:** These represent the starting locations of simulated particles, crucial for accurately modelling the dispersal of marine debris based on likely origin points.

The Ocean Parcels toolkit [1], the chosen tool for this project, is a set of Python classes and methods specifically designed for simulating the movement of particles in the ocean. It provides the ability to customize and execute particle tracking simulations using data on ocean currents, wind fields, and other environmental factors. Furthermore, it provides functionalities like starting and removing particles during execution. While other projects like PyGnome [5] and Flexpart [6] also offer similar functionalities, Ocean Parcels is particularly suited for this project due to its flexibility and ease of integration with various data formats, including NetCDF. By using OceanParcles [1], we can obtain detailed trajectories of each particle, enabling the visualization of their movement over time. This output is crucial in understanding the dispersal patterns of marine debris, aiding in the development of effective conservation strategies.

2.3 The AI Model

In this project, initial research suggests that a hybrid CNN-LSTM model is a strong contender for predicting future sea currents and wind conditions, due to its proficiency in handling complex, multi-dimensional data sets, such as those in NetCDF file format. CNNs excel in identifying spatial patterns, while LSTMs are effective for sequential data and

long-term dependencies. However, this choice is subject to change based on ongoing research and project requirements. By learning from these parameters, the model will be able to predict future weather conditions. These predictions, once processed, can be inputted into the Lagrangian model, enabling it to simulate future scenarios of marine debris movement. This approach not only utilizes the strengths of both CNNs and LSTMs but also aligns perfectly with the project's aim of integrating predictive modelling with environmental simulations.

3. LITERATURE REVIEW

In this section, we conduct a thorough literature review to underpin the project's scientific foundations.

3.1 Impact of marine debris on ecosystems

The environmental and ecological impact of marine debris, particularly in coastal and marine ecosystems, has been extensively researched, as seen in [7] and [8]. Studies in this area reveal significant negative effects, ranging from harm to marine wildlife due to ingestion and entanglement [9], to the disruption of natural habitats [10]. The impact on coastal ecosystems extends beyond the environment, affecting economic sectors reliant on marine health, such as tourism and fishing as discussed in [10]. Further research delves into the long-term ecological consequences, highlighting the urgent need for effective management and mitigation strategies as evidenced by [11]. These studies collectively emphasize the critical nature of addressing marine debris for ecosystem sustainability and conservation.

3.2 Physics based Lagrangian model

The physics based Lagrangian model [12], a common model used for oceanic debris dispersion simulation, acclaimed for its effectiveness, as detailed in studies [13], [14]. Its implementation through Ocean Parcels [1], a set of Python-based tools, is particularly noteworthy for leveraging the Lagrangian method in particle tracking, a choice corroborated by its robustness in marine simulations [15]. Further research like [7] and [8] delves into the model's adaptability and precision across varied oceanographic scenarios, from localized studies to larger, intricate systems. Its versatility is highlighted in applications ranging from tracking pollutant spread to studying biological entities in marine ecosystems [12]. This underscores the model's integral role in environmental research, offering insights and fostering advancements in marine conservation methodologies.

3.3 AI model for environmental forecasting

The CNN-LSTM hybrid model has emerged as a leading approach in environmental forecasting as seen in [16] and [17]. Hence our implementation will adopt this hybrid model for predicting the sea currents and wind conditions. Its combination of Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTMs) networks makes it highly adept at processing complex time-series data, crucial for environmental variables [18]. CNNs excel in identifying spatial patterns, while LSTMs effectively capture temporal dependencies, making this hybrid model especially suitable for forecasting environmental phenomena [18]. Studies have demonstrated its efficacy in scenarios similar to marine debris dispersion like in [19]. The model's compatibility would allow us to work with NetCDF files as seen in [20]. Its adaptability

to diverse forecasting scenarios further validates its utility. This versatility positions the CNN-LSTM model as an ideal candidate for integration with the Lagrangian model in the subsequent phases of this project, although this decision will be guided by ongoing assessments and findings.

3.4 Feasibility of integrating AI with Lagrangian modelling

Integrating the Lagrangian model with an AI weather forecasting model, akin to the approach seen in [21], is both feasible and advantageous for predicting future marine debris movement. The AI model's ability to accurately predict environmental conditions, in this case, sea currents and wind, will be crucial. These predictions enhance the Lagrangian model's capability to simulate future debris dispersion scenarios, offering a more comprehensive tool for marine conservation efforts. This approach, combining an AI-driven weather forecasting model with particle dispersion modelling, promises to provide deeper insights and more effective strategies for addressing marine debris challenges.

3.5 Visualization Techniques for Lagrangian Model Analysis

The visualization of Lagrangian models in marine environments plays a crucial role in understanding and communicating complex data. Studies [14], [15], and [22] highlight various techniques and tools developed for visualizing particle movements for Lagrangian models, emphasizing their importance in conveying the dynamics of phenomena like marine debris dispersion. Advanced visualization technologies, including interactive maps and 3D simulations [23], have been instrumental in providing clearer insights into marine ecosystems. Research in this field also focuses on enhancing user interfaces for broader accessibility, ensuring that these visualizations can be effectively used for educational and decision-making purposes, as demonstrated in [24].

3.6 The Role of Web-based Platforms

Developing a web-based platform to host simulations of marine debris movement, both past and future, represents a positive step in marine conservation and education. This platform will make it easier for users to access and interpret the simulated data. This will enhance user understanding and engagement. Studies [25], and [26] show the effectiveness of web-based tools in aiding users to interact and understand complex scientific data. It also enables sharing information to a wider audience. As discussed earlier, the integration of visualizations into this platform will further aid in conveying the intricacies of surface marine debris dynamics [24]. Such accessibility is crucial for informed decision-making in conservation efforts and provides an educational resource for understanding marine ecosystems.

4. PROPOSED SOLUTION & METHODOLOGY

The Python programming language was selected for implementing and achieving all the objectives of this project.

4.1 Objective 01: Data Integration

The Data Integration process commences with Panoply [27], which is used for its capability to visualize NetCDF formatted files. This application enables an initial review of the

data's structure and content, providing an overview of variables like wind speed, direction, and ocean currents. Once the data's characteristics are understood, Python scripts will be utilized to open and process the NetCDF files. This involves reading the data into a Python-friendly format, typically using libraries like xarray or NumPy, which are adept at handling multi-dimensional arrays common in environmental data.

Temporal alignment is a pivotal step, particularly for the Copernicus Atmosphere Monitoring Service Wind Data. This step is achieved through spline interpolation [28]. This technique adjusts the 12-hour interval data to an hourly scale, ensuring alignment with the sea surface currents data. This interpolation not only fills in the gaps but also maintains the data's integrity and continuity. Spatial alignment then aligns the datasets across the same geographical grid, ensuring that the wind and sea current data correspond to the same spatial locations. Data cleaning involves going through the data to identify and remove anomalies, like missing values or statistical outliers. This step may involve imputation strategies for missing data or statistical methods to identify and handle outliers.

Finally, additional preprocessing needs to be done for the AI model. Feature engineering enhances the AI model's predictive capability. This process includes generating new variables that might better capture environmental dynamics and applying techniques like normalization or standardization. Normalization adjusts the data to a common scale without distorting differences in the ranges of values, while standardization involves rescaling data to have a mean of zero and a standard deviation of one. These processes are crucial for preparing the data for effective AI modelling.

4.2 Objective 02: Lagrangian Model Development

The process begins with the previous pre-processed wind and sea surface current datasets, ensuring compatibility with Ocean Parcels [1] in terms of format and resolution. The next steps involve developing a custom kernel and defining the computational rules for particle movement within the simulation, including interactions with environmental factors. Particular attention is paid to selecting the initial particle locations, focusing on areas around Malta that align with the datasets and are significant for marine debris studies. Configuring the simulation parameters is a critical step, involving the setup of duration, time steps, and output time intervals to match the objectives and computational constraints. Once these parameters are established, the model is executed, simulating particle movement based on the environmental data and the kernel rules. Post-simulation, the output data is analysed to distinguish particle movement patterns, with visualization tools employed to create illustrative maps and animations, enhancing the understanding of marine debris dispersion in Malta's territorial waters.

4.2.1 Setting the Initial Coordinates

In the development of the Lagrangian model, setting the initial coordinates for particle release is a critical step. For this project the initial particles will be strategically placed along the most common marine traffic routes around Malta's territorial waters, utilizing data provided by Spire. This approach is grounded in the understanding that marine traffic areas are hotspots for marine debris accumulation, thus providing a realistic and relevant starting point for the simulation [29]. By aligning the particle release points with these high-traffic marine routes, the simulation aims to accurately represent the initial conditions leading to marine debris dispersion in the region, enhancing the model's applicability and effectiveness in analysing debris movement patterns.

4.3 Objective 03: AI Model Development

The development of the AI model in this project is centred around constructing a CNN-LSTM architecture, utilizing either the PyTorch or TensorFlow library. This model is designed for time series forecasting, aiming to predict future sea surface currents and wind conditions. The initial phase involves organizing pre-processed data into distinct training, validation, and testing sets, to ensure a robust learning framework.

The model's architecture is a combination of Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) layers. The CNN component is responsible for detecting spatial patterns within the environmental data, while the LSTM layers are tasked with capturing temporal dependencies. This hybrid approach facilitates a comprehensive analysis of both spatial and temporal elements, enhancing the accuracy of predictions regarding marine weather conditions.

An important step involves the selection and iterative testing of model parameters. This process is crucial to refine the model's performance and accuracy. Additionally, a key requirement is to format the output data in NetCDF (Network Common Data Form). This specific format is necessary to seamlessly integrate the AI model's output with the Lagrangian model, as discussed in the subsequent section. The integration is intended for advanced simulations of debris movement, leveraging the predictive insights gained from the AI model.

4.4 Objective 04: Integrating the AI model with the Lagrangian model

Ensuring that the AI model's output precisely matches the input requirements of the Lagrangian model is a critical technical focus in the integration of the AI and Lagrangian models. This entails converting the predicted wind and sea current data into a format that the Lagrangian model can interpret and use. The process involves adjustment and testing for data compatibility, ensuring that the two models are combined seamlessly. This integration is pivotal, as it equips the Lagrangian model with the capability to simulate future scenarios of marine debris movement, a feature that the standalone physics based Lagrangian model lacks. This enhancement is crucial for advancing marine conservation efforts by providing foresight into future debris dispersion patterns and simulations.

4.5 Objective 05: Web-based Visualisations

The development of a web-based platform under *Objective 05* involves creating an intuitive interface using HTML, CSS, and JavaScript. This platform is designed to display visualizations from the Lagrangian model, depicting both his-

torical data and predicted future scenarios. A key feature will be an interactive system allowing users to select a date for which they wish to see a prediction. Upon selection, the platform will display the corresponding Lagrangian model output, offering insights into future marine debris movement. The technical challenge lies in seamlessly integrating the simulation data with the web interface to provide a user-friendly and informative experience.

5. TESTING & EVALUATION

This section outlines comprehensive strategies to assess the effectiveness and reliability of both the Lagrangian and the AI models. This is critical to ensure that the models perform accurately and can also be applied to practical marine conservation scenarios.

5.1 Lagrangian Model

The evaluation of the Lagrangian model will be conducted through comparative tests against other established Lagrangian models found in [12], [13], and [14]. These analyses will focus on assessing the consistency and accuracy of debris movement simulations. A key aspect of the testing will involve scenario-based approaches, where the model's predictions are compared under a variety of environmental conditions against outcomes from the models mentioned in the literature review. This method allows for a comprehensive assessment of the model's predictive abilities and its reliability in different scenarios, ensuring a robust evaluation of its performance.

5.2 AI Model

The AI model, designed for predictive accuracy in time series forecasting, will undergo a comprehensive evaluation process. The primary focus will be on its performance on the testing dataset, which has not been exposed to the model during the training phase. Key metrics for the evaluation of the AI model, as detailed in [30], and [31] will include:

- **Precision:** Measuring the model's accuracy in predicting positive occurrences.

- **Recall:** Assessing the model's ability to identify all actual positive cases.

- **Confusion Matrix:** Providing a detailed breakdown of the model's predictions in terms of true positives, false positives, true negatives, and false negatives.

These metrics will offer a comprehensive view of the model's predictive performance, encompassing aspects of accuracy, sensitivity, and specificity. Additionally, the F1 Score, which is the harmonic mean of precision and recall, will be used to balance the trade-offs between these two metrics.

To further ensure the robustness and generalisability of the AI model, cross-validation techniques will be employed, particularly K-Fold Cross-Validation. This approach involves dividing the dataset into K subsets and iteratively using each subset as a testing set while training the model on the remaining subsets. This method provides a thorough assessment of the model's performance across various subsets of the data, safeguarding against overfitting and ensuring its applicability to diverse datasets as seen in [32].

5.3 Real-World Scenario Testing

In the final phase of testing, the integrated system combining the AI and Lagrangian model will undergo extensive evaluation to validate its accuracy in forecasting future marine debris movement. This important step will involve back testing the model with historical data, analysing its predictive capabilities, and comparing its forecasts against actual outcomes, as demonstrated in [33]. Additionally, the functionality of the web-based platform, particularly the feature allowing users to request future scenario visualizations, will be evaluated. This ensures that the system not only provides accurate predictions but also operates seamlessly when interacted with by users, enhancing its practical application.

6. CONCLUSION

This report outlines the comprehensive steps undertaken in developing an integrated system for predicting and simulating marine debris dispersion in Malta's territorial waters. It has highlighted the process of combining a physics based Lagrangian model with a Machine Learning driven model, resulting in the development of a user-friendly web platform for data visualization. Challenges such as data preprocessing, model integration, and the selection of effective parameters were addressed. Future steps include the completion of model integration and extensive testing, ensuring the system's effectiveness in real-world scenarios. The project's progress aligns with the planned timeline, as detailed in the accompanying Gantt chart in Appendix A. This approach contributes to integrating technological solutions for environmental conservation.

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APPENDIX A

FYP GANTT CHART   AUGUST 2023 - MAY 2024

	AUG	SEP	OCT	NOV	DEC	JAN	FEB	MAR	APR	MAY
BACKGROUND RESEARCH	1 AUG - 31 SEP									
DATA GATHERING		25 AUG - 30 OCT								
PROGRESS REPORT				15 NOV - 15 DEC						
DATA INTEGRATION						31 JAN - 7 FEB				
DEVELOP THE LAGRANGIAN MODEL							7 FEB - 21 FEB			
DEVELOP CNN-LSTM							21 FEB - 7 MAR			
INTEGRATE THE MODELS								7 MAR - 14 MAR		
CREATE WEB BASED PLATFORM								14 MAR - 21 MAR		
EVALUATION & TESTING							7 FEB - 21 MAR			
REPORT WRITING								22 MAR - 15 MAY		