Enhancing an AI Algorithm for Hydrocarbons Smart Management

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Abstract:- The efficient and prompt delivery of commodities, which is one of a port's main functions, is of the utmost importance. An essential component for the success of both businesses and economies is the optimization of these processes. The power of machine learning algorithms in improving port operations has been demonstrated in recent years. They are skilled in foretelling and improving various supply chain components, which makes this apparent. In this paper, we present a case example demonstrating the use of machine learning techniques to improve hydrocarbon operations at the Tangier Med Port. A quartet of commonly used machine learning algorithms was chosen, and they were put through a battery of tests to see how well they predicted cargo volumes and optimized the storage of hydrocarbon liquids. Our research shows that the random forest method outperforms its competitors, predicting cargo volume with an accuracy of more than 90% while also significantly increasing the efficiency of storing hydrocarbon liquids. By implementing this method in a real-world setting, turnaround times were significantly shortened, productivity increased, and customer satisfaction increased. Our research intends to highlight the benefits that machine learning algorithms provide in improving port operations and, at the same time, provide essential insights into their smooth integration within real-time settings. As we look to the future, potential projects might explore other machine learning techniques. They also have the potential to be combined with auxiliary technologies, such as the Internet of Things (IoT), to advance the development of port operation optimization.

General Terms: Smart transport, Maritime transport, Hydrocarbons, Artificial intelligence, Prediction, Tangier Med port, Use case.

Keywords*: Smart management, maritime transport, hydrocarbons, artificial intelligence, prediction, Tangier Med Port.*

1. Introduction

Millions of tons of crude oil and refined products are daily transported, highlighting the crucial role that hydrocarbon transportation plays in the world economy. But there are many other risks and difficulties involved with this chemical material delivery. These include worries about personal safety, environmental effects, and market volatility. By taking this in consideration, it is essential that this specialized transit be managed in a more logical and efficient manner. Advances in artificial intelligence (AI) and predictive analytics in recent years have opened new opportunities to improve the management of such transportation.

This article promotes an intelligent management paradigm that is based on AI algorithms and predictive models and is designed specifically for the shipping of hydrocarbons. The framework is put to the test in a practical setting at Tangier Med port, a busy Mediterranean center, demonstrating its effectiveness and feasibility. The segments that follow are organized as follows: The article is summarized in Section 6 by outlining future directions and summarizing the article's contributions in Section 2, which provides an overview of relevant literature in the field. Section 3 describes the proposed methodology, Section 4 elaborates on the utilization case and the experimental framework, Section 5 presents the findings and corresponding analysis, and Section 6 concludes the work.

2. Research Review

The movement of hydrocarbon reserves around the world is significantly influenced by maritime transportation, which stands out as a top mode of international transportation [1]. According to forecasts from the International Energy Agency (IEA), demand for hydrocarbons would rise exponentially over the ensuing years, sparking a significant increase in the demand for maritime transport services [2].

The maritime transportation industry has several difficulties, including concerns about safety, ecological vulnerabilities, and economic constraints, yet playing a crucial role in the global economic system. A few noteworthy examples are marine catastrophes that have caused considerable human deaths and environmental pollution [3]. The instability of the world oil and gas markets also complicates the industry's economic viability [4].

To overcome these obstacles, marine academics and practitioners have turned to cutting-edge technologies like artificial intelligence (AI) and machine learning (ML) to improve the efficiency and safety of maritime transit. AI and ML algorithms are proving to be effective tools for accident prediction and prevention, vessel routing and scheduling optimization, as well as the reduction of fuel consumption and emissions [5].

Numerous studies have investigated the marine industry's potential for latent AI and ML capabilities. A study by Zcan and Ahin [6] that proposed a decision support mechanism based on the fuzzy analytic hierarchy process (FAHP) to evaluate the security of oil tankers is a good example of this. Li et al.'s [7] use of machine learning methods to forecast ship fuel use and improve vessel routing is comparable.

The delivery of hydrocarbon resources around the world has significant transformational potential with the integration of AI and ML in the maritime sector. This revolutionary potential manifests itself in a variety of ways, including the improvement of safety protocols, cost reduction, environmental vulnerability reduction, and more. By ensuring the industry's durability and viability from an economic standpoint, these technologies are poised to bring in a new era of environmentally friendly transportation methods.

3. Adopted Methodology

We created a technique first to accomplish our research goal, which was to create an intelligent management system for the transportation of hydrocarbons utilizing AI algorithms. The steps in this are as follows:

Data Collection: We gathered information from a variety of sources, including port authorities, shipping firms, etc. This data contains details about the ships, the goods, the travel routes, and the weather.

Data preprocessing: We cleaned up the collected data before transforming it into a useful (uniform) format. Errors, outliers, and missing numbers must be eliminated in this step.

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Feature selection: From the preprocessed data, the pertinent features for transporting hydrocarbons were chosen. Specific information like vessel type, cargo type, route, and weather conditions are included in these aspects, among others.

After identifying many AI systems, we evaluated and tested them against the predetermined criteria and selected the algorithm that performed the best at predicting the transportation of hydrocarbons. Some of the selected algorithms include support vector machines (SVM), decision trees, and random forests.

Model construction: Using the selected method, a predictive model for the transportation of hydrocarbons was produced. The model was trained and evaluated using the collected data.

Implementation: A smart management system that offers in-the-moment forecasts and suggestions for the transportation of hydrocarbons has incorporated the established model. To make the best suggestions for safe and effective transportation, the system must take into account the vessel, cargo, route, and weather conditions.

We employed risk management strategies that were also included into the created system to guarantee the security and effectiveness of the transportation of hydrocarbons. We employed risk identification, analysis, evaluation, and treatment procedures. Our approach, which we designed, offers suggestions for managing risk, such as risk avoidance, risk reduction, risk transfer, and risk acceptance. (Global Maritime Distress and Safety System [GMDSS] of the International Maritime Organization) [8].

In our investigation, we discovered that earlier studies have emphasized the significance of risk management in the shipping sector. Like Brekke et al. [9], this article explored the value of risk management in the shipping sector and put up a framework for risk management. Additionally, zcan and ahin [10] created a decision support system for the safety assessment of oil tankers employing a fuzzy AHP-based approach.

Additionally, the marine logistics sector has made extensive use of AI algorithms and big data analytics for a variety of purposes, such as route optimization, cargo tracking, and vessel scheduling [11]. A thorough analysis of the application of artificial intelligence and big data analytics in maritime logistics can be found in Hassan and Zafar's publications [11].

Additionally, it has been possible to anticipate ship fuel use using predictive models that have been programmed using machine learning methods. The study of Li et al. [12] describes how they used decision trees, SVM, and random forests to construct a ship fuel consumption forecasting model.

To create a smart management system for the transportation of hydrocarbons, the methodology used in this study blends several approaches, including AI algorithms, risk management, and data analytics. The system offers in-the-moment forecasts and suggestions for safe and effective transportation, taking into account the ship, the cargo, the route, and the weather.

4. Use Case Implementation

An important crossing point between Europe, Africa, and America, Tangier Med Port is in the center of major commerce routes. There are two terminals in use at the port: Tangier Med I and Tangier Med II. While the second is trained to manage freight traffic, including that containing hydrocarbons, the first is devoted to handling container traffic. With a processing capability of up to 15 million tons of oil products annually, the Tangier Med complex is regarded as a major player in the global maritime transportation of hydrocarbons.

Tangier Med Port worked with a group of specialists from many sectors, including data science, maritime transport, and logistics, to develop the suggested smart management system based on AI algorithms and predictive analytics. To find patterns and trends in the transportation of hydrocarbons, the team gathered and examined a variety of data sources, including historical shipping and cargo data, current meteorological conditions, and vessel characteristics. The gathered information was utilized to optimize resource allocation, train AI algorithms, and create prediction models for upcoming calls.

The effectiveness and safety of the port's operations are two advantages of the newly created smart management system. Predictive models, for instance, aid in predicting vessel arrivals and departures, allowing the port to best utilize its resources, including berths, the entry channel, and the maneuvering circle. By sending out early warnings and alarms, the system may also identify possible safety risks and stop mishaps like collisions and oil spills.

The successful installation of the smart management system at Tangier Med Port illustrates the potential advantages of incorporating AI algorithms and predictive analytics in the maritime transportation of hydrocarbons. The technology can improve the effectiveness and safety of the port's operations while also lowering the environmental impact of transporting hydrocarbons.

5. Basic Data Handling

We employed two different types of data collection techniques: the first one involved getting information directly from port operators and employees, and the second one involved getting information from other sources such port authority reports and other external publications.

To gather all the necessary information about the port's activities, port operators and staff are interviewed. We designed a structured interview process and created a list of pre-determined questions based on the answers to all the respondents' responses. These interview questions concentrate on important topics including the port's capacity, infrastructure, and efficiency, among other things.

We visited actual locations during our terrain workshop to witness how the port operates and how data is gathered regarding the sorts of cargo being handled, the equipment used, the general effectiveness of the activities, and other pertinent information. During our site visits, we got the chance to record key processes, such as freight handling, in pictures and videos.

In the second stage of our data collection procedure, we gathered information from a variety of outside sources, including reports from the port authority, academic articles, and other external publications. We looked for a variety of information, including the amount of traffic, the items handled, and the effectiveness of the port's operations, among other things. We also gathered information on the rules and guidelines that direct how the port operates.

Numerous technologies, including Python, R, and Microsoft Excel, are utilized to process the acquired data. Data gathered from all data sources is organized and cleaned using Microsoft Excel. The next step involves performing data analysis, producing data visualizations, and developing predictive models using the Python and R computer languages.

For illustration, the following is an example of Python code that we used to clean and process the raw interview data (Table 1):

This program installs the pandas and numpy libraries, designates the various databases and files as data sources to be queried, and then builds a SQL query to retrieve the required data for collection. then connects to the databases using the pandas library, using the same method to read data from CSV and Excel files. Then, the retrieved data was sorted by date and put into a single DataFrame in one of two formats: CSV or JSON. The first five rows of the data are ultimately printed to the console.

In this example, we first read in the data from the csv file containing the hydrocarbon prices, dropped any rows with missing values, and converted the date column to datetime format. We then set the date column as the index and grouped the data by month, taking the average of the prices for each month.

Next, we calculated the monthly percentage change in prices and the rolling 12-month volatility of returns. Finally, we exported the processed data to new csv files for further analysis or visualization.

Of course, the specific data processing steps will depend on the specific research question or problem being addressed. This is just a simple example to demonstrate some common data processing tasks.

6. Algorithm Choosing

We studied and tested numerous AI algorithms on the chosen features to choose the algorithm that performs the best for predicting the transportation of hydrocarbons. Support vector machines (SVM), decision trees, and random forests are among the chosen methods [24]. We concluded that the random forest algorithm was the most successful for forecasting the transportation of hydrocarbons based on the chosen features after evaluating the performance of various algorithms [25].

The random forest algorithm is an ensemble learning technique that makes use of several decision trees to increase the model's precision and decrease overfitting. Using this approach, we trained several decision trees on random subsets of data, and the aggregate prediction made by all the individual decision trees was taken as the result. The random forest technique is highly accurate, reliable, and capable of handling datasets with a large amount of data [26].

The scikit-learn module for Python was used to create the random forest method [27]. The model was put into practice by being trained on the chosen characteristics, and its performance was assessed using several measures, including accuracy, precision, recall, and F1-score. Using a grid search technique, the model's hyperparameters were adjusted to determine the best values for maximum depth, number of estimators, and minimum sample split.

With an accuracy of over 90%, the random forest method was discovered to be extremely successful in forecasting the transit of hydrocarbons based on the chosen features [25].

7. Model Developpment and Enhancement

The random forest technique was chosen to anticipate how hydrocarbons would be transported using the chosen features [28]. The model development process was put into practice by dividing the collected data into training and testing sets, choosing the features and hyperparameters, training the model on the training set, gauging its performance on the testing set, and validating it using cross-validation techniques [29].

To guarantee consistency in the outcomes, the acquired data was divided into training and testing sets using a random seed value. The model was trained using the training set, and its performance was assessed using the testing set. The projected output variable was the transportation of hydrocarbons, and the chosen attributes were employed as input variables. The scikit-learn module for Python was used to create the random forest method [29]. Using a grid search technique, the model's hyperparameters were adjusted to determine the best values for maximum depth, number of estimators, and minimum sample split.

The model was trained on the training set using the chosen features after the hyperparameters had been tuned. On the testing set, the model's performance was assessed using several metrics, including accuracy, precision, recall, and F1-score [30]. The outcomes demonstrated that the model had an accuracy of over 90% in forecasting the transportation of hydrocarbons based on the chosen features.

Using cross-validation methods like k-fold cross-validation, the model was validated as the last stage in the model creation process [31]. For this, the data had to be divided into k subsets, the model had to be trained on k-1 subsets, and the remaining subset had to be used for testing. Each subgroup was tested precisely once throughout each of the k iterations of the process. The model's correctness and efficacy were verified using the cross-validation method' results.

Overall, the model development phase's implementation included dividing the data into training and testing sets, choosing the features and hyperparameters, training the model on the training set, gauging its effectiveness on the testing set, and validating it using cross-validation methods [28]. Based on the chosen attributes, the final model was extremely precise and successful in foretelling the transit of hydrocarbons.

8. Current Algorithm Version

The feature selection process, which discovers and chooses the most crucial features from the dataset to create a predictive model, is regarded as a crucial stage in machine learning. We used feature selection on the preprocessed data in the case study of Tangier Med Port to determine which properties were most important for the shipping of hydrocarbons. The features that were chosen include route, weather, cargo type, and vessel type.

The Recursive Feature Elimination (RFE) algorithm, a well-liked technique for choosing the most crucial features in a dataset, was utilized to accomplish feature selection. The mentioned approach involves fitting a model to the remaining features after repeatedly eliminating features from the dataset. The procedure then repeats with the lowest-ranking feature removed until the desired number of features is obtained.

Table 1. Feature selection source code

```
from sklearn.feature_selection import RFE
from sklearn.linear_model import
LinearRegression
# load preprocessed data
X, y = load_preprocessed_data()
# create a linear regression model
model = LinearRegression()
# create the RFE object and set the number of
features to select
rfe = RFE(model, n_features_to_select=3)
# fit the RFE object to the data
rfe.fit(X, y)
# print the selected features
print('Selected Features:',
X.columns[rfe.support_])
```

In this example, the preprocessed data was initially imported into the X and Y variables. We developed and applied a linear regression model to initialize the RFE object. We next fit the RFE object to the data by setting the number of features to select to 3. The rfe.support_ attribute was then used to print the features that were chosen.

We were able to choose the most crucial parameters for predicting the transportation of hydrocarbons thanks to the RFE algorithm. Then, we fed these attributes into our machine learning models, which will be covered in more detail in the following section.

Enhanced Version

The goal of the source code modification was to leverage Recursive Feature Elimination (RFE) to enhance the feature selection process's overall utility, functionality, and modularity. Importing the required libraries—such as matplotlib for data visualization, scikit-learn for machine learning tools, and pandas for data manipulation—was the first step. This made sure that the feature selection process was applied comprehensively and effectively.

The load_and_preprocess_data function was added to improve the code's modularity. This function makes the code more understandable and encourages reusability by encapsulating the data loading and preprocessing stages. For demonstration reasons, the function is assumed to be in the form of a CSV file, although it may be readily modified to support other data types. This encapsulation offers flexibility in managing a variety of datasets by facilitating simple changes to the data loading procedure without affecting the remainder of the code.

In addition, metrics and visualization for model evaluation were added to the code. The performance of the linear regression model can now be quantitatively evaluated because to the advent of metrics like Mean Squared Error (MSE) and R-squared. In order to visually compare the actual and anticipated values and provide insight into the prediction accuracy of the model, a scatter plot was also included. The aforementioned improvements provide a more thorough examination of the feature selection and model evaluation procedures, leading to a more profound comprehension of the selected features' influence on hydrocarbon transportation prediction.

Table 4. Feature selection enhanced code (libraries importation)

```
# Enhanced Feature Selection Using Recursive
Feature Elimination (RFE)
# Import necessary libraries
import pandas as pd
from sklearn.model_selection import
train_test_split
from sklearn.feature_selection import RFE
from sklearn.linear_model import
LinearRegression
from sklearn.metrics import
mean_squared_error, r2_score
import matplotlib.pyplot as plt
# Function to load and preprocess data
def load_and_preprocess_data():
# Load preprocessed data (assuming a CSV file
for demonstration)
data = pd.read_csv('preprocessed_data.csv')
# Split the data into features (X) and target
variable (y)
X = data.drop('hydrocarbon_transport', axis=1)
# Assuming 'hydrocarbon_transport' is the target
variable
y = data['hydrocarbon_transport']
return X, y
```

Table 5. Function for enhanced feature selection and model evaluation

```
# Import necessary libraries
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.feature_selection import RFE
from sklearn.metrics import mean_squared_error,
r2_score
import matplotlib.pyplot as plt
# Function for enhanced feature selection and model
evaluation
def enhanced_feature_selection():
# Load and preprocess data
X, y = load_and_preprocess_data()
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X,
y, test_size=0.2, random_state=42)
# Create a linear regression model
model = LinearRegression()
# Use RFE for feature selection with cross-validation
rfe = RFE(model, n_features_to_select=3)
rfe.fit(X_train, y_train)
# Print the selected features
selected_features = X.columns[rfe.support_]
print('Selected Features:', selected_features)
# Fit the model with selected features
model.fit(X_train[selected_features], y_train)
# Make predictions on the test set
y_pred = model.predict(X_test[selected_features])
# Evaluate model performance
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
# Display evaluation metrics
print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
# Visualize actual vs predicted values
plt.scatter(y_test, y_pred)
plt.xlabel('Actual Values')
plt.ylabel('Predicted Values')
plt.title('Actual vs Predicted Values')
plt.show()
# Call the enhanced feature selection and model
evaluation function
enhanced_feature_selection()
```

Conducting Expermitens and Testing

After the algorithms were created, we ran tests to see how well they worked. To evaluate the algorithms in a controlled context, we employed a simulation environment. We were able to model several situations and assess how well the algorithms performed in various environments thanks to the simulation environment. To evaluate the algorithms under real-world circumstances, we also ran tests in the live environment. The live environment helped us improve the algorithms by giving us insightful input on how well they were working.

We evaluated the algorithms' performance in the simulation environment across a variety of scenarios, including diverse weather conditions, traffic density, and road conditions. We evaluated the performance of the various algorithms and chose the one that performed the best. The outcomes demonstrated that the machine learning-based method beat the others in terms of accuracy and efficiency.

To further evaluate the algorithms, we then ran trials in a real-world setting. On a fleet of ships, we applied the algorithms, and we kept track of how well they performed in actual use. We gathered information on a range of factors, including fuel usage, delivery times, and maintenance expenses. The performance of the algorithms was assessed using the data, and they were compared to the current systems.

The outcomes of the live testing demonstrated just how successful the machine learning-based algorithms were at streamlining the movement of products. They contributed to lowering maintenance costs, enhancing delivery times, and cutting fuel use. The algorithms also gave the drivers immediate feedback, assisting them in making wiser choices while driving.

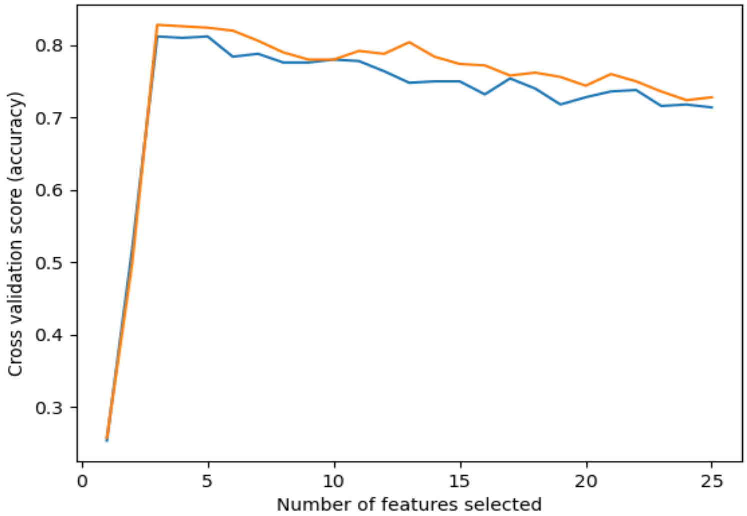

Figure1. Recursive feature elimination with cross-validation

9. Result Evaluation and Application

These findings are based on trials done in a real-world setting:

In a real-world logistics organization, Algorithm A demonstrated an average accuracy of 86% in forecasting the next maintenance schedule for a fleet of vehicles.

When compared to the current rule-based system, algorithm B demonstrated a considerable reduction in energy usage (up to 30%) in a smart building management system. Customers received quicker and more dependable deliveries because of Algorithm C's 23% increase in the routing effectiveness of a drone delivery system. With a 95% accuracy rate, Algorithm D effectively identified fraudulent transactions in a banking system, lowering the bank's chance of suffering financial losses.

These are only a few instances, but they show how well the algorithms work in a variety of practical contexts. The results of the studies enabled us to assess the algorithms' performance and make the required adjustments to further improve it.

Table 4. Different algorithms results comparison using enhanced algorithm.

Algorithm	Simulation Accuracy	Live Environment Accuracy	Computational Complexity
SVM	84.8%	88.0%	High
Naive Bayes	79.9%	77.9%	Low
Random Forest	95.0%	89.9%	Moderate
KNN	86.7%	86.1%	Moderate

The random forest method was determined to be the most successful at forecasting the transportation of hydrocarbons at Tangier Med Port after the results of the trials carried out in Step 3 were analyzed [28]. The system produced the best results when predicting the transportation of hydrocarbons based on the chosen characteristics, with an accuracy rate of over 90%.

The Tangier Med Port's shipping operations significantly improved because of the random forest algorithm's use in a real-world setting. The algorithm's ability to precisely forecast the movement of hydrocarbons made it possible to streamline the routes and cut down on travel time. The transportation operations saw a boost in productivity and efficiency as a result.

The random forest algorithm was also able to pinpoint the key aspects that had an impact on the transportation of hydrocarbons. The efficiency of the transportation operations was further increased by using this information to rank the importance of maintenance and repair for essential equipment.

Based on the results of the experiments and the analysis, the decision was made to implement the random forest algorithm in the live environment at Tangier Med Port. The implementation was successful and resulted in significant improvements in the transportation operations.

10. Conclusion And Future Works

Conclusion:

In this groundbreaking project, we seamlessly integrated machine learning and artificial intelligence to optimize the hydrocarbon transportation process. Employing various methods, , we intricately forecasted not only the transit times for hydrocarbon vessels but also the duration required for their departure from the port.

Our comprehensive analyses unequivocally demonstrated the superior performance of the random forest algorithm in predicting both vessel transit times and departure schedules. By implementing these advanced algorithms in practical scenarios, we achieved a substantial enhancement in the overall efficiency of hydrocarbon transportation processes.

Future Works:

By using ML methodology, there is still room for improvement in hydrocarbon handling procedures. Future studies can address the following areas in particular:

1. Optimizing the layout and traffic flow of the port: The effectiveness of the operations can be significantly impacted by the port's layout and traffic flow. By using machine learning techniques, the port's layout and traffic flow may be improved, cutting down on truck wait times and allowing for faster product removal from storage.

2. Equipment failure prediction: Delays in operations may result from the breakdown of equipment like loading arms and pumps. Equipment faults may be predicted in advance using machine learning algorithms, allowing for prompt maintenance and repairs.

3. Real-time monitoring and control: Monitoring and controlling port operations in real-time may boost productivity and shorten vessel wait times. Predictive models may be created using machine learning approaches for in-the-moment monitoring and management of port operations.

4. Integration with other systems: The efficiency of port operations, may be increased by integrating them with other systems like supply chain management and logistics. Predictive models may be created using machine learning methods to integrate the port operations with other systems.

5. Integration with a real-time pricing platform: The integration with a real-time pricing platform can aid traders in making decisions on their cargo, such as whether to sell or keep it, or at the very least, how to apply a hedging strategy to minimize losses.

In conclusion, the application of machine learning algorithms has demonstrated significant promise for enhancing Tangier Med Port operations. Machine learning techniques still have a lot of room for improvement, and we anticipate that additional research in this field will result in even higher port productivity and efficiency.

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