Department of Artificial Intelligence

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Project Report

DATA DRIVEN ANALYSIS OF PYROLYTIC LIQUEFICATION OF POLYMERS USING AI & ML TECHNIQUES

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Date of Submission: 20/12/2023

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Coimbatore

CERTIFICATE

This is to certify that we, the student of Amrita School of Artificial Intelligence, has completed the data analysis of pyrolysis of the liquefication of polymers as part of their ***"DATA DRIVEN ANALYSIS OF PYROLYTIC LIQUEFICATION OF POLYMERS USING AI & ML TECHNIQUES".***

The project work was carried out under the guidance and supervision of Dr. Akhil Mohan, Assistant Professor, Centre for Computational Engineering and Networking, Amrita School of Artificial Intelligence, Coimbatore. To the best of our knowledge this work has not formed the basis for the aware of any degree/diploma/ associate ship/fellowship/ or a similar award to any candidate in any University.

Date:

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ACKNOWLEDGEMENT

We would like to make this an opportunity to transfuse our appreciation to everyone who was behind the successful completion of this design. First and foremost, we would like to thank "Department of Artificial Intelligence" for accepting our project.

Kindest regard goes to **Dr. Soman KP**, Head of the Department of Artificial Intelligence for allowing us to accomplish the design project.

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Last but not the least, we are thankful to our group members and friends of our department for their friendly support given to accomplish this project successfully and our family members for always providing the best guidance possible.

A big thanks to you all.

ABSTRACT

Pyrolysis, a thermochemical conversion process, holds significant promise in the sustainable utilization of biomass and coal for energy production and material synthesis. This study presents a comprehensive data analysis of the pyrolysis process applied to biomass and coal, aiming to understand the fundamental mechanisms, optimize product yields, and evaluate the potential environmental impact. Previous research has indicated that the biomass co-pyrolysis with other feedstock can not only enhance physiochemical properties of pyrolysis products but also effectively realize recycling of wastes. Thus, an in-depth discussion of recent advances in biomass co-pyrolysis with coal is covered in this Review.

The experimentation involved the pyrolysis of various biomass feedstocks, such as wood, agriculture residues, plant cellulose, alongside different coal types, under controlled temperature, pressure, and time conditions. The focus was on investing the influence of key parameters on the pyrolysis product's composition, including bio-oils, gases(syngas), and char. Kinetic models were also employed to understand the reaction pathways and kinetics during pyrolysis. We have also included the graphs for different methods use to find the output of the given parameters using the ML code which is also described below. Among the four methods mention, which is having least mean square error will be performed and output will be produced. The data-driven analysis provides valuable insights into optimizing the pyrolysis process for both biomass and coal, highlighting its potential as a variable and sustainable pathway for energy production, bio-based chemicals, carbonization, contributing to a more sustainable and diversified energy portfolio.

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1. INTRODUCTION

General

At the beginning of the 20th century, crude petroleum fuels covered only 4% of the world's energy demand. However, nowadays, petroleum fuels are the most important energy source and covers about 40% of the world's energy demand. It also produces 96% of the transportation fuels [1]. Nevertheless, petroleum fuels are non-renewable and the reserves of fossil fuel are depleting fast. In addition, the use of petroleum fuels influences environment by generating huge amounts of net carbon dioxide emission and other pollutants such as NO_x and SO_x. Therefore, there is an urgent need to find renewable and environmentally benign feedstocks for sustainable supply of fuels and energy.

Pyrolytic liquefaction of polymers involves the thermal degradation of polymers in the presence of a liquefying agent, typically at elevated temperatures. The process generates liquid products, which can be further analysed through data analysis techniques. Here are some key points on data analysis for the pyrolytic liquefaction of polymers:

1. Product Composition Analysis.

2. Reaction Kinetics.

3. Pyrolysis Solid Characterization and Analysis.

4. Pyrolysis Gas Analysis.

5. Characterization of Liquid Products.

6. Molecular Weight Distribution.

7. Yield Optimization.

8. Economic Analysis.

9. Environmental Impact Assessment.

10. Data Visualization and Reporting.

Scope of our project

Data Analysis of pyrolysis of coal and biomass offers valuable insights and aspects of this process. There is broad scope for this:

1) Analysis of Chemical Composition: Understanding the breakdown of different compounds present in the coal and biomass during pyrolysis. This involves identifying and quantifying the gases (CO, CO2, CH4, etc), liquid(bio-oil), and solids (char) produced at different temperatures and conditions.
2) Reaction Kinetics: Investing the kinetics of pyrolysis reactions, including the determination of reaction rates, activation energies and rate-controlling steps.
3) Product Characterization: Analysing the properties of the products obtained from the pyrolysis, such as the heating value, viscosity, density, elemental composition, calorific value, and chemical structure of bio-oil, char, and gas fractions.
4) Economic Analysis: Assessing the economic viability of the pyrolysis process by evaluating the costs associated with feedstock, equipment, energy consumption, product yield, and market value of end products.
5) Model Development: Developing mathematical models and simulations b used in experimental data to predict and optimize the pyrolysis process. These models could involve kinetic models, computational fluid dynamics (CFD), and process simulation tools.

2. PROBLEM STATEMENT

Data analysis of pyrolysis of polymers can help address various challenges and answer specific questions related to the thermal degradation of polymers. Here are some problems that can be tackled through data analysis in the context of polymer pyrolysis:

- **Kinetic Modelling of Plastic Pyrolysis**:
  Investigate the kinetics of polymer pyrolysis using computational approaches such as machine learning and quantum mechanics. Machine learning coupled with quantum mechanics can enhance predictions of product compositions and reactor design.

- **Waste Management and Recycling:**
  Pyrolysis can be used to convert various types of organic waste, including plastics, biomass, and rubber, into valuable products such as bio-oil, syngas, and biochar. This helps in reducing the environmental impact of waste disposal and contributes to a more sustainable approach to managing waste.

- **Reaction Mechanism Identification:**
  Machine learning can aid in identifying and understanding complex reaction mechanisms involved in pyrolysis. By analysing large datasets, ML algorithms can reveal patterns and relationships that might be challenging for traditional methods to discern.

3. RELATED WORK

The chemical process of pyrolysis is the thermal breakdown of organic compounds at high temperatures without the presence of oxygen or in a regulated environment. It is a type of thermolysis that is commonly employed to convert more complex organic compounds into less complex ones.

Organic materials, such as biomass, plastics, or polymers, are heated at high temperatures during the pyrolysis process, which causes chemical changes in them. When there is not enough oxygen present, combustion cannot occur, and gases, liquids, and solid wastes are frequently produced as a result.

Pyrolysis is employed in various industries and applications, including waste management, bioenergy production, and the conversion of biomass or waste plastics into valuable products.

The process is of particular interest in the context of sustainable practices and resource recovery, as it provides a means to convert organic materials into useful substances while minimizing environmental impact.

Pyrolytic liquefaction of polymers involves the thermal degradation of polymers in the presence of a liquefying agent, typically at elevated temperatures. The process generates liquid products, which can be further analysed through data analysis techniques. Here are some key points on data analysis for the pyrolytic liquefaction of polymers:

1. Analysis of Product Composition:

- Recognize and measure the different liquid products that the pyrolytic liquefaction process produces. This could involve char, oils, and gasses.
- Use analytical methods to ascertain the liquid products' composition, such as nuclear magnetic resonance (NMR), mass spectrometry (MS), and gas chromatography (GC).

2. Reaction Kinetics: - Examine the pyrolytic liquefaction process's reaction kinetics. Find the activation energies and reaction rates linked to the breakdown of the various polymer components.

- Create kinetic models to explain how goods change with temperature and time.

4. Pyrolysis Gas Analysis:

- Analyse the gases evolved during pyrolysis, such as carbon dioxide, methane, and other volatile compounds.

- Use techniques like Fourier-transform infrared spectroscopy (FTIR) or mass spectrometry to identify and quantify the gas-phase products.

5. Liquid Product Characterization:

- Describe the characteristics and chemical makeup of the liquid products that result during pyrolytic liquefaction.

Utilize methods such as NMR, GC-MS, and liquid chromatography (LC) to analyse the molecular makeup and structure of the liquid products.

6. Molecular Weight Distribution: To ascertain the degree of polymer degradation, ascertain the molecular weight distribution of the liquid products.

Molecular weight analysis can be performed using gel permeation chromatography (GPC) or size-exclusion chromatography (SEC).

7. Yield Optimization: - Adjust process parameters in accordance with the intended yield of liquid products. This could entail changing the liquefying agent kind, residence time, and temperature.

- To find the ideal settings, apply statistical methods and experimental design strategies.

8. Economic Analysis: - Examine the viability of large-scale pyrolytic liquefaction technologies through economic analysis.

- Take into account elements like energy usage, the price of raw materials, and product yields when assessing the economic feasibility.

9. Environmental Impact Assessment: - Examine how the pyrolytic liquefaction method affects the environment, taking into account things like energy use, emissions, and waste production.

10. Data Visualization and Reporting: - Use charts and graphical representations to convey the data analysis results visually.

- Write in-depth summaries of the main conclusions and lessons learned from the pyrolytic liquefaction tests in reports.

4. LITERARTURE REVIEW

Nowadays, increasing population, widespread urbanization, rise in living standards together with versatile use of polymers have caused non-biodegradable polymeric wastes affecting the environment a chronic global problem, simultaneously, the existing high energy demand in our society is a matter of great concern. Pyrolysis of waste non-biodegradable polymer materials involves controlled thermal decomposition in the absence of oxygen, cracking their macromolecules into lower molecular weight ones, resulting into the formation of a wide range of products from hydrogen, hydrocarbons to coke. Noncatalyzed pyrolysis is a recommended solution to the low thermal conductivity of polymers, promoting faster reactions in breaking the C-C bonds at lower temperatures, denoting less energy consumption and enabling enhancement in the process selectivity, whereby higher value-added products are generated with increased yield. [1]

Nanotechnology plays an indispensable role in academic research as well as in industrial applications. Existing reviews illustrate that one of the oldest application field of nanotechnology is in the arena of nano catalysis. Nano catalysis closes the gap between homo and heterogeneous catalyses while combines their advantageous characteristics and positive aspects, reducing the respective drawbacks. During the current nano hype, nanostructured catalysts are esteemed materials and their exploration provide promising solutions for challenges from the perspective of cost and factors influencing catalytic activity, due to their featured high surface area to volume ratio which render enhanced properties with respect to the bulk catalyst. [2]

Viable technologies and investigations towards this direction, for conversion of waste non-biodegradable polymers to potent chemical feedstocks and ultimately fuels, are rapidly growing through pyrolysis. Pyrolysis being a simple thermal process, involves the controlled thermal degradation of materials in an oxygen starved chamber, heating and cracking the polymers to lower molecular weight, *i.e.* breaking down polymers to smaller molecules, also into oligomers and monomers, as mixed products of gaseous, liquid along with solid hydrocarbons. However, pyrolysis suffers from few hindrances, requiring high temperatures typically above 500 °C because of low thermal conductivity of polymers and endothermic reaction of degradation, together with that the products obtained are in a broad range, also not as good fuels due to their poor quality. [3]

HDPE, LDPE, PP, PS, PVC, and PET are reported as the most common municipal solid wastes in Europe. However, PE plastics (HDPE and LDPE) are the most popular and make up over 40 % of the total content of municipal solid wastes. The chemical processes such as thermal and catalytic methods of converting the waste into energy and value-added fuels/chemicals are promising techniques to eliminate the plastic refuse, which otherwise is a major cause of environmental contamination. Extracting fuel oils from waste plastics can also decrease the dependence on fossil fuel since the plastic manufacturing industry uses nearly 6 % of petroleum produced worldwide. Therefore, it is like 'killing two birds with one stone' in terms of saving the supply of energy and alleviating environmental concerns. [4]

Waste plastics are resources that open many opportunities like job-creating, growth, innovation, and sustainability and have multiple effects on society and the economy. Some countries banned landfill and incineration; therefore, energy recovery from the waste resources through pyrolysis is the best choice for waste management. Having all the environmental risks of the non-degradable waste plastics, it is timely and urgent to review their conversions to energy fuels through thermal or catalytic pyrolysis. [5]

Waste minimization through pyrolysis is an auspicious method that involves the thermochemical decomposition of the plastics at an elevated temperature (usually at 300–900 °C). It is carried in the absence of oxygen to ensure that no oxidation reaction is taking place to extract the fuels. Basically, four different mechanisms may occur during the plastic waste pyrolysis, namely, random-chain scission, end-chain scission or depolymerization, cross-linking, and chain stripping. It is important to conduct proximate analyses of the waste plastic compositions based on their moisture content, fixed carbon, volatile matter, and ash content. Thus, the volatile matter and ash contents are the major factors influencing pyrolysis yields. The amount of volatile matter favoured oil production while high ash content decreased the amount of liquid oil, and, consequently, increased the gas yield and char formation. [6]

5. BENEFITS OF USING PYROLYSIS AND AI & ML MODEL

Benefits of pyrolysis:

- **Resource Efficiency**: By converting organic materials into useful products like syngas, biochar, and bio-oil through pyrolysis, biomass resources can be used as efficiently as possible.
- **Waste Reduction:** It helps to lessen environmental pollution by offering a sustainable method of managing and reducing different kinds of organic waste, such as wood, plastic, and agricultural wastes.
- **Biochar for Soil Improvement:** A byproduct of pyrolysis, biochar can improve soil fertility, water retention, and carbon sequestration, which will help to mitigate climate change and support sustainable agriculture.
- **Reduced Greenhouse Gas Emissions:** Pyrolysis, especially when compared to conventional waste disposal techniques, can help reduce overall greenhouse gas emissions by turning organic waste into valuable products and bioenergy.

Benefits of using AI and ML model in data analysis of pyrolysis:

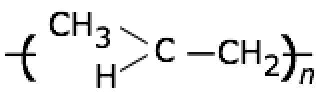
- **Pattern Recognition**: Researchers and engineers can better understand the parameters driving the process and adjust conditions for increased efficiency by using AI and ML models to find complex patterns and relationships among pyrolysis data.
- **Automation:** AI and ML can reduce the time and effort needed for manual data interpretation by automating the processing of massive datasets. This facilitates expedited decision-making and expedites the process of research and development.
- **Optimization:** By examining data, machine learning algorithms can optimize pyrolysis settings to determine the best circumstances for achieving targeted product yields or quality. This may result in pyrolysis procedures that are more economical and efficient.
- **Data Fusion:** Artificial Intelligence systems have the ability to combine data from multiple sources, including as literature, sensor data, and experimental results, to provide a comprehensive and all-encompassing picture of the pyrolysis process.
- **Energy Efficiency:** By optimizing process parameters based on AI analysis, energy consumption in pyrolysis can be minimized, contributing to sustainability and cost-effectiveness.

6. METHODOLOGY

We have provided a Python Script that performs data analysis using various regression models (Linear Regression, SVM, Decision Tree, and Artificial Neural Network) on a dataset related to Pyrolysis of Polymers. This process generates liquid products, which can be further analysed through data analysis techniques.

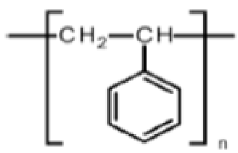
The input parameters which are entered by the user are shown below. According to that values the output is generated through the best model according to the value of Mean Squared Error. The model which is having least Mean Squared error value will be performed. The inputs are:

- ✓ PE (wt.%) – Polyethylene
- ✓ PP (wt.%) – Polypropylene
- ✓ PS (wt.%) – Polystyrene
- ✓ PVC (wt.%) – Poly vinyl Chloride
- ✓ Size (mm) – Size of particle
- ✓ C (wt.%) – Carbon weight
- ✓ H (wt.%) – Hydrogen weight
- ✓ N (wt.%) – Nitrogen weight
- ✓ O (wt.%) – Oxygen weight
- ✓ Cl (wt.%) – Chlorine weight
- ✓ Feed Intake (kg/h) – Amount of Input added per hour
- ✓ Reaction Temperature (°C) – Temperature od reaction
- ✓ Vapour Residence time (s) – Time that gaseous products, including vapours, spend within the high-temperature environment.



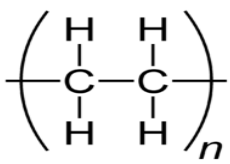
PP

FIG 6.1



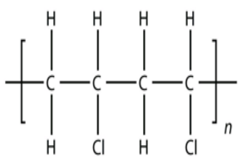
PS

FIG 6.2



PE

FIG 6.3



PVC

FIG 6.4

7. PYTHON CODE

We have used different libraries in the code for storing data, data preprocessing, data manipulation, and for evaluation metrics(mean_squared_error). Including regression models **(‘Linear Regression’, ‘SVR’, ‘DecisionTreeRegressor’, Multioutput Regressor’**).

```
#prediction using plastic type, ultimate analysis, Reactor conditions
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.multioutput import MultiOutputRegressor
from sklearn.metrics import r2_score, mean_squared_error
from sklearn.model_selection import train_test_split
from keras.models import Sequential
from keras.layers import Dense

def evaluate_model(model, X, Y_true, model_name):
    Y_pred = model.predict(X)
    r2 = r2_score(Y_true, Y_pred)
    rmse = mean_squared_error(Y_true, Y_pred, squared=False)
    print(f"{model_name} - R-squared: {r2}, RMSE: {rmse}")
    return r2, rmse

# Load data from Excel file
file_path = '/content/pyrolysisdataset_3.xlsx'
df = pd.read_excel(file_path, sheet_name="Set-3")

# Separate input (X) and output (Y) parameters
X = df.iloc[:, :13]  # Input parameters
Y = df.iloc[:, 13:]  # Output parameters

# Standardize the features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Split the data into training and testing sets for ANN
X_train, X_test, Y_train, Y_test = train_test_split(X_scaled, Y,
test_size=0.2, random_state=42)

# Build and train Linear Regression model
linear_model = MultiOutputRegressor(LinearRegression())
linear_model.fit(X_scaled, Y)
```

```
# Build and train SVM Regression model
svm_model = MultiOutputRegressor(SVR())
svm_model.fit(X_scaled, Y)

# Build and train Decision Tree Regression model
dt_model = MultiOutputRegressor(DecisionTreeRegressor())
dt_model.fit(X, Y)

# Build and train ANN model
ann_model = Sequential()
ann_model.add(Dense(Y.shape[1], input_dim=13, activation='linear'))
ann_model.compile(optimizer='adam', loss='mean_squared_error')
ann_model.fit(X_train, Y_train, epochs=50, batch_size=32, verbose=0)

# Model evaluation
linear_r2, linear_rmse = evaluate_model(linear_model, X_scaled, Y,
'Linear Regression')
svm_r2, svm_rmse = evaluate_model(svm_model, X_scaled, Y, 'SVM')
dt_r2, dt_rmse = evaluate_model(dt_model, X, Y, 'Decision Tree')
ann_r2, ann_rmse = evaluate_model(ann_model, X_test, Y_test, 'ANN')

# Choose the best model based on R-squared
best_model_name, best_model_r2 = max([('Linear Regression', linear_r2),
                                       ('SVM', svm_r2),
                                       ('Decision Tree', dt_r2),
                                       ('ANN', ann_r2)],
                                      key=lambda x: x[1])

# Display the best model name
print(f"\nBest Model: {best_model_name}")

# Predict using the best model
input_values_best_model = {}
for column in X.columns:
    while True:
        try:
            value = float(input(f"Enter value for {column}: "))
            input_values_best_model[column] = value
            break
        except ValueError:
            print("Invalid input. Please enter a numeric value.")

# Standardize the input parameters for the best model
input_parameters_scaled_best_model =
scaler.transform([list(input_values_best_model.values())])

# Make predictions using the best model
```

```
predictions_best_model = None
if best_model_name == 'Linear Regression':
    predictions_best_model =
linear_model.predict(input_parameters_scaled_best_model)
elif best_model_name == 'SVM':
    predictions_best_model =
svm_model.predict(input_parameters_scaled_best_model)
elif best_model_name == 'Decision Tree':
    predictions_best_model =
dt_model.predict([list(input_values_best_model.values())])
elif best_model_name == 'ANN':
    predictions_best_model =
ann_model.predict(input_parameters_scaled_best_model)

# Display the predicted values with column names for the best model
print(f"\nPredicted Output Values using {best_model_name}:")
for i, column in enumerate(Y.columns):
    print(f"{column}: {predictions_best_model[0, i]}")

while True:
    # Ask if the user wants to try another model
    another_model = input("\nDo you want to try another model?
(yes/no): ")
    if another_model.lower() != 'yes':
        break

    # Display the four models
    print("\nChoose a model:")
    print("1) Linear Regression")
    print("2) SVM")
    print("3) Decision Tree")
    print("4) Artificial Neural Network")

    # Ask the user to choose a model
    chosen_model = input("Enter the number of the model you want to
use: ")

    # Select the chosen model
    if chosen_model == '1':
        selected_model = linear_model
        selected_model_name = 'Linear Regression'
    elif chosen_model == '2':
        selected_model = svm_model
        selected_model_name = 'SVM'
    elif chosen_model == '3':
        selected_model = dt_model
        selected_model_name = 'Decision Tree'
    elif chosen_model == '4':
```

```
        selected_model = ann_model
        selected_model_name = 'Artificial Neural Network'
    else:
        print("Invalid choice. Please enter a number between 1 and 4.")
        continue

    # Ask for input parameters
    input_values = {}
    for column in X.columns:
        while True:
            try:
                value = float(input(f"Enter value for {column}: "))
                input_values[column] = value
                break
            except ValueError:
                print("Invalid input. Please enter a numeric value.")

    # Standardize the input parameters
    input_parameters_scaled =
scaler.transform([list(input_values.values())])

    # Make predictions using the chosen model
    predictions = selected_model.predict(input_parameters_scaled)

    # Display the predicted values with column names
    print(f"\nPredicted Output Values using {selected_model_name}:")
    for i, column in enumerate(Y.columns):
        print(f"{column}: {predictions[0, i]}")
```

Code Explanation:

- The evaluate_model function takes a regression model (‘model’), input features(‘X’), true output values(‘Y_true’), and a model name (‘model_name’). It calculated R-squared and root mean squared error (RMSE) between predicted and true values, the predicts and return these metrics.
- The code loads dataset from an Excel file (‘pyrolysisdata.xlsx’) into a Pandas Dataframe (‘df’). The dataset is assumed to have 13 input features and multiple output columns.
- The input features (‘X’) and the output values (‘Y’) are extracted from Dataframe and then standardized using ‘StandardScalar’.
- The standardized data is split into training and testing sets, specifically for training the artificial neural network (ANN).
- Four different regression models are instantiated, trained, and fitted to the data: Linear Regression, Support Vector Machine (SVM), Decision Tree, and an Artificial Neural Network (ANN).
- The code selects the best model based on the highest R-squared value. It then prompts the user to input values for the input features and predicts the output using the chosen model.
- The code allows the user to try other models by entering input values and selecting a model and according to the user’s choice it will give output in the form of graph, and numerical solutions.

8. LIMITATIONS OF AI MODELS

While pyrolysis data analysis can benefit greatly from AI and ML models, there are definite drawbacks and difficulties with them as well.

- **Data Quality:** The quality of input data has a major impact on the accuracy and dependability of AI and ML models. A noisy, incomplete, or biased set of training data could negatively impact the model's performance.
- **Quantity of Data:** In order to train machine learning models to their best potential, a lot of data is frequently needed. It might be difficult to get enough different data for pyrolysis processes, particularly for uncommon or specialized situations.
- **Overfitting:** When a model is trained very well on the training set, it may capture noise or outliers and perform badly on fresh, untrained data. It can be difficult to find the ideal balance between generalization and model complexity.
- **Model Generalization:** When applied to diverse operating circumstances, feedstocks, or differences in pyrolysis processes, models that were trained on particular datasets may find it difficult to generalize. In order for the model to be applicable to a variety of contexts, generalization is essential.
- **Absence of Causation:** Machine learning models are good at finding connections in data, but they might not be able to tell what causes what. Effective process optimization in pyrolysis processes requires an understanding of the cause-and-effect linkages.
- **Human Expertise:** AI and ML models are powerful tools, but they should complement, not replace, human expertise. Subject matter experts are still crucial for interpreting results, validating findings, and making informed decisions based on the model's outputs.

9. FUTURE SCOPE

1) Optimization of Process Conditions:

- ML algorithms can analyze complex relationships between input parameters (temperature, pressure, residence time) and output variables (product composition, yields). By identifying optimal conditions, ML can assist in maximizing desired product yields or minimizing undesirable by-products.

2) Quality Control and Fault Detection:

- ML can be applied for real-time quality control during pyrolysis processes. By monitoring key parameters, machine learning algorithms can detect deviations from expected outcomes, helping to identify and rectify issues before they affect product quality.

3) Data-driven Decision Making:

- Machine learning facilitates data-driven decision-making by extracting meaningful insights from large datasets. This can guide researchers and engineers in making informed choices regarding process optimization, parameter adjustments, and overall system design.

10. CONCLUSION

In conclusion, the application of Artificial Intelligence (AI) and Machine Learning (ML) models for data-driven analysis of pyrolytic liquefaction of polymers holds great promise but also comes with challenges. The integration of AI and ML in this context provides opportunities for enhanced process optimization, predictive modeling, and data-driven decision-making. The ability to uncover complex patterns, predict outcomes, and automate analysis contributes to advancements in polymer pyrolysis research and applications. The benefits include increased efficiency, reduced waste, and the potential for economic and environmental sustainability.

However, it's essential to acknowledge the limitations, such as the dependence on data quality and quantity, the challenge of interpretability in complex models, and the necessity for careful consideration of biases. Additionally, the need for collaboration between domain experts and data scientists is emphasized to ensure that the models are grounded in a deep understanding of the underlying chemistry and physics of polymer pyrolysis.

Despite these challenges, the ongoing evolution of AI and ML technologies, coupled with advancements in data collection and processing, provides a solid foundation for continued progress in the data-driven analysis of pyrolytic liquefaction of polymers. By addressing these challenges responsibly and iteratively refining models based on emerging data, researchers and engineers can harness the full potential of AI and ML to unlock insights, optimize processes, and contribute to sustainable and innovative solutions in the field of polymer pyrolysis.

11. CONTRIBUTIONS

- Data Collection and Preprocessing:
  - **Responsibility:** Aditya Santosh

    Collect relevant datasets from experimental setups or literature sources.

    Ensure data integrity and completeness.

    Preprocess raw data, including cleaning, normalization, and handling missing values.
- Literature Review and Background Research:
  - **Responsibility:** Adityan PV

    Summarize key findings and identify gaps in existing research.

    Provide a theoretical foundation for the project and explain the relevance of AI and ML techniques in polymer pyrolysis data analysis.
- Algorithm Selection and Implementation:
  - **Responsibility:** C Vishnuvardhan Chowdary

    Implement linear regression and support vector machine algorithms using programming language Python.

    Optimize and fine-tune the algorithms for efficient data analysis and predictive modeling.
- Algorithm Selection and Implementation:
  - **Responsibility:** G Harsha Vardhan

    Research and select appropriate machine learning algorithms like decision tree and artificial neural networks for the analysis of pyrolysis data.

    Optimize and fine-tune the algorithms for efficient data analysis and predictive modeling.
- Model Evaluation and Validation:
  - **Responsibility:** Abhishek pandey

    Implement cross-validation techniques to ensure model generalization.

    Evaluate model accuracy, precision, recall, and other relevant metrics.

    Validate the models using independent datasets or experimental results.

12. REFERENCES

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