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Efficiency Prediction for Yield of Alternative Fuel from Polypropylene Waste via Catalytic Pyrolysis by Using Date Palm Seeds Derived Activated Carbon-Based Composite Catalyst: A Python Neural Network Approach

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Abstract

Effective management of refinery waste plastics is crucial to mitigating environmental impacts. Technological advancements have enabled the conversion of plastic waste, specifically polypropylene, into valuable feedstock for biodiesel production. This study focuses on the preparation of a catalyst for the catalytic pyrolysis of waste polypropylene, utilizing date palm seeds (DPS) to produce activated carbon (AC). The process involves the catalytic pyrolysis of plastic waste, wherein air must be excluded from the feedstock. In this research, environmentally friendly AC and zeolite catalysts were prepared, with AC derived from DPS and zeolite from Iraqi natural kaolin. An artificial neural network (ANN) model, implemented using Python, was developed to predict the catalytic efficiency. The model was trained and validated using experimental data from a hydrothermal autoclave reactor. The dataset was categorized based on temperature, time, and catalyst type. The predicted alternative fuel yield showed a high accuracy of approximately 97% agreement with experimental results, and the regression coefficient (R^2) was determined to be 0.99. This study demonstrates the potential of DPS-derived AC as an effective catalyst in the catalytic pyrolysis of waste polypropylene for alternative fuel production.

Keywords: *Alternative fuel; Activated carbon; Catalytic Pyrolysis; Python.*

1. Introduction

The utilization of waste plastic to produce fuel and useful chemicals has garnered significant attention due to its potential to address both environmental pollution and energy resource depletion [1]. Advances in technology have enabled the conversion of waste plastics, such as polypropylene, into valuable products through processes like catalytic pyrolysis. This method not only helps in managing plastic waste but also contributes to the production of alternative fuels and chemical feedstocks, reducing dependence on fossil fuels and lowering greenhouse gas emissions. The integration of innovative catalysts and reactors has further enhanced the efficiency and yield of these conversion processes, making them viable solutions for sustainable development. Yield here is defined as the C_{5+} hydrocarbons. Neural networks are mathematical models that use biological neuron-based processing to handle information or signals. The architecture of these networks is very intricate, since it comprises linked neurons that facilitate the resolution of difficult issues [2]. Artificial Neural Networks (ANNs) are a specific sort of artificial intelligence system that originated in the 1940s with the work of McCulloch and Pitts [3]. Updated the structure of the initial neural model. Later, as a result of the widespread interest in artificial neural networks among researchers and in various application domains, more potent networks, refined training algorithms, and enhanced hardware were developed [4]. By analyzing examples, ANNs primarily resolve the issue of inductive concept acquisition [5]. Augmenting the learning process principles across various applications is facilitated by ANNs' capacity to generalize and learn from data, thereby imitating the human ability to acquire knowledge through experience [6]. ANNs may show incredibly complex relationships

based only on input-output data, making them extremely powerful tools [7]. ANN is a computational model that mimics the functioning of the human brain [8]. It enables learning via examples by analyzing representative patterns that mirror physical phenomena or decision-making processes. The distinctive capability of ANN lies in its ability to assess empirical correlations between dependent and independent variables and extract information from representative data groupings [9]. Different movement and reaction processes happen at the same time in a phase reactor, which makes modeling and validating it very hard. The reason the model is hard is that the system is heterogeneous, with solid, liquid, and gas properties [10]. To solve the differential and algebraic equations that are part of the model, you need accurate program software. The assumptions of the model can also make it more or less complicated [11]. ANNs are often used to simulate chemical processes. Non-linear ANNs may reliably predict complicated process outcomes compared to linear statistical models. ANN has hidden layers. Each layer contains an ANN that estimates error by comparing predicted values to target values after each iteration. In the event that the variance that exists between projected and actual values exceeds the suggested threshold, the network reapplies itself with adjusted weights in an effort to minimize error [12]. Artificial neural networks are more adept at handling chaotic data than regression-based approaches [13]. As predicted by Armenise *et al.* [14], The significance of the discipline will grow in the coming years. Potentially more accurate at predicting and evaluating variables, such as the impact of contaminants and catalysts on plastic pyrolysis, are machine learning and ANN. An ANN model was initially constructed by Conesa *et al.* [15] in 2004 to forecast the kinetic parameters of the pyrolysis process of specific materials. The model utilized TGA-experimental data and varied heating rates. Abnisa *et al.* [16] This research was conducted with the intention of developing a prediction model for fuel generation by using data on a variety of plastics that were not recycled again. For the purpose of constructing the predictive model inside the framework of a feed-forward neural network, the Levenberg-Marquardt technique was successfully applied [17]. When determining the best number of hidden neurons, the number that provided the lowest sum of the mean square errors was taken into consideration [18]. The correctness and dependability of the suggested model were evaluated via the use of statistical analysis and graphical representation throughout the evaluation process [19]. The outcomes demonstrated that the model accurately predicted product yields resulting from the pyrolysis of non-recycled plastics, and there was a noteworthy correlation between the output values and those documented in the literature [20]. Furthermore, the outcomes demonstrated that the anticipated product yields were precise. The current research used the Python programming language to create an ANN model. This model was designed to forecast the efficiency of generating alternative fuel, specifically focusing on the conversion of polypropylene plastic waste, which is known to have fluctuating results. The study focused on the conversion of polypropylene into alternative fuel using a hydrothermal autoclave reactor. The experiment included varying the temperature, duration, and catalyst type.

2. Experimental work

The main aim of this project is to create an economically efficient catalytic method for converting plastic waste into liquid fuel by using plastic waste from refineries. This purpose may be accomplished by attaining the following particular goals:

- Preparation catalyst from natural materials for convert a plastic waste to energy.
- Preparation of (Co-Mo/AC-ZSM-5) catalysts with 5 wt. % cobalt chloride hexahydrate ($CoCl_2.6H_2O$), and 5 wt. % ammonium heptamolybdate $(NH_4)_6Mo_7O_{24}\bullet 4H_2O$).
- Characterization of the prepared catalyst using advance materials techniques.
- Evaluation of the prepared catalyst in a hydrothermal autoclave reactor.
- Evaluation of the optimal set of operation conditions in the reactor via modeling and simulation in Python programming language.

The study investigates the impact of several operational parameters (temperature, pressure, and catalyst type) on the kinetic variables of catalytic pyrolysis of plastic waste. The experimental design is shown in Table 1.

Table 1. Experimental variables studied in catalytic pyrolysis.

Operational parameters	Level	Values
Type of catalyst	1	Co-Mo/AC-ZSM-5
Temperature (ºC)	6	200-325
Residence time (min)	5	30-90

The feedstock in the present work is polypropylene that was obtained from North Refineries Company in Iraq after washing and crushing, as seen in Figure 1. The specifications were seen in Table 2.

Figure 1. Crushing plastic waste (polypropylene).

Table 2. Properties of the waste polypropylene.

Property	Value
Density	900 kg/cm^3
Impact resistance at 23°C	48 J/m
Tensile strength	37 MPa
Flexural modulus	1358 MPa
Deflection temperature	81°C
Specific volume	32 cm^3/Ib
Melting point	159°C

2.1. Experimental setup

A hydrothermal autoclave is a commonly used apparatus for conducting reactions under conditions of high pressure and high temperature. A wide range of high-pressure containers was produced throughout the twentieth century. Typically, any autoclave should include these crucial attributes.

- Needs great mechanical strength for long-term high-pressure and high-temperature investigations.
- Excellent acid, alkali, and oxidant resistance.
- A basic mechanical construction should make it easy to use and maintain.
- For the specified temperature gradient, its size and form must be appropriate.

When selecting an autoclave, experimental pressure, temperature, and hydrothermal solution corrosion resistance are most critical. The autoclave reactor was ordered from (Gongyi Yuhua Instrument Co., China) as shown Figure 2. It consists of a 304 stainless steel micro reactor placed inside a magnetic stirrer. The stainless-steel micro-reactor is small in size, the

structure of the whole machine is simple and reliable, the temperature setting is digital, and the speed setting is digital.

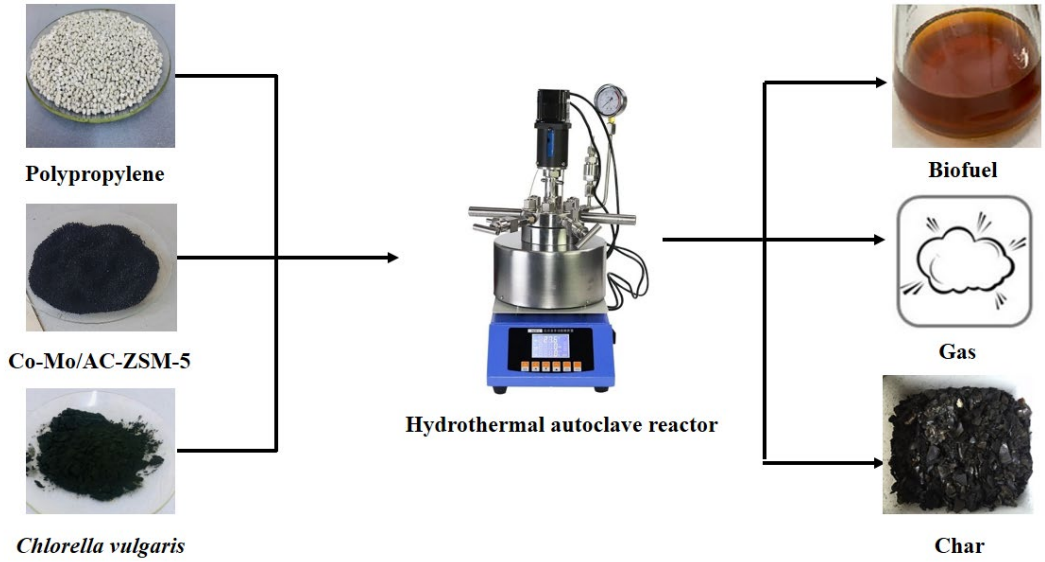

Figure 2. Graphical description of the catalytic pyrolysis.

Figure 3 shows the activated carbon prepared from the date palm seeds, the ZSM-5pre-pared from natural clay and the Co-Mo/Ac-ZSM5 catalyst.

Figure 3. Activated carbon (AC) and the catalyst prepared for the catalytic pyrolysis of waste polypropylene.

The experimental runs have been carried out into hydrothermal autoclave reactor for eval-uation of the catalyst prepared (Co-Mo/AC-ZSM-5) with and without *chlorella vulgaris* by im-plementing the following steps for each experiment:

- 20 g of the polypropylene, 5 mL of distilled water, and 2 g of the catalyst and 0.5 g of *Chlorella vulgaris,sp.* in part two of experiments were poured into the reactor vessel. Screws and plates for high temperatures and pressures were used to seal the reactor. After that, the reactor tank was put into the heating furnace room of the reactor system. All the valves were kept closed, and the reactor furnace was turned off.

- The temperature sensor was used to set the reactor heater to the right temperature for the desired time of reaction according to the matrix of the experiment.
- While the tests were being done, N_2 gas was pumped over the reactor to help mix the reaction ingredients evenly.
- The observation of the operational pressure reaching 12 MPa on the pressure gauge indicates that an increase in reaction temperature led to a natural rise in pressure. This outcome can be attributed to the synergistic effect that temperature and pressure have in hydrothermal processes.
- Each run concluded with the reactor furnace turned off in accordance with a regulating cycle that brings the temperature back down to 25°C temperature at a pace 20°C per minute.
- After the reactor vessel had come to atmospheric pressure, it was opened using a screwdriver and the products were transferred to a sample vial for examination. The vessel was then removed from the furnace chamber.
- Before the next run, the reactor vessel was cleaned with distilled water then ethanol solution. Then allowed to dry.

3. Methodology of prediction of alternative fuel yield

3.1. Data preprocessing

Data preprocessing is a systematic approach used to manipulate raw data in order to make it suitable for further processing tasks. Data preprocessing is a crucial stage in the processes of data analysis, data mining, and machine learning .Data collection methods go from manual record-keeping to the use of electronic sensors. During the process of data collection, some errors or discrepancies may occur. Excessive irrelevant and redundant information, as well as noisy data, may lead to erroneous conclusions during data analysis, resulting in inaccurate understanding of the topic at hand. Consequently, several researchers directed their attention into data preprocessing techniques [22]. The information is partitioned into three separate groups, each indicating the impact of temperature, time, and catalyst type. The dataset is organized into columns, which are listed as follows: The factors that influence alternative fuel yield include time, catalyst type, and the use of a catalyst. The target variable for prediction in the ANN model is the yield of alternative fuel. Initially, it is crucial to gather all the components of the data from the raw dataset and organize them into a CSV file to be used as input for the ANN model. Out of the total of sixty rows in the dataset, eighty percent were allocated for assessment assignments and the remaining twenty percent were used for training. The model was provided with a CSV file including the catalyst type, time, and T variables. These data were used to provide a prediction for the production of alternative fuel. Subsequently, the yield alternative fuel % was forecasted by using the raw data and an additional CSV file. All of the unprocessed data was saved in the 'data_prediction.csv' file. In order to assess the accuracy of the model, seven variables were intentionally excluded from the original dataset that was used as input for the model. The experimental results were then compared to these values.

3.2. Import necessary modules

The necessary modules have been extracted from Python packages. Numpy, referred to as (.np), and Pandas, referred to as (.pd), were used to facilitate data manipulation and analysis. Matplotlib, referred to as (.plt), and Seaborn, referred to as (.sns), were employed for data visualisation to identify any anomalies in the dataset. Furthermore, Scikit-Learn, Tensorflow, and Keras were included into the existing ANN model, in addition to the aforementioned Python libraries. Official documentation is available for Numpy, Pandas, Matplotlib, Seaborn, Scikit-Learn, Tensorflow, and Keras. The stated file included imported records. In order to construct an AI/ML model, it is necessary to import all the modules that will be used in the model. Import the biodiesel_v4.csv file. The modules in Python consist of a comprehensive standard library, as well as several third-party libraries and frameworks. By importing these modules,

you may use pre-existing functionality, which helps save time and effort throughout the development process.

3.3. Read the dataset

The complete dataset was read and loaded with Python. A dataset were used to make colab read and load the dataset. Three columns and 60 rows were created. Following training with these data, the ANN model generated a prediction for the yield alternative fuel percentage.

3.4. Split the dataset into train and test sections

The dataset was partitioned for processing. The yield column was assigned to the variable 'X', while the remaining data was placed in the field 'Y'. The yield column functions as the target variable for the present ANN model, which will be used for making predictions. We used Scikit-Learn to once again divide our dataset into separate Train and Test parts. We have a total of 60 rows and we will choose 20% of these rows, which is equal to 60 * 0.2 = 12 rows, for our testing purposes. Specifically, 30% of the data will be used for evaluating the ANN model, whereas 80% of the data was utilized for training the model. Now, let's divide the dataset into two separate pieces. The input features refer to one set of variables used to make predictions, while the target column represents the variable being predicted. The CSV file format will be used to read and load the Dataset using Pandas.

3.5. Normalization

The train and twist data were subjected to training using the MinMaxScaler function provided by Scikit-Learn. By utilizing the Fit and Transform functions, the train was scaled.

3.6. Building of ANN model

The dataset has been preprocessed thus far in preparation for its input into the ANN Model. Tensorflow and Keras were presently employed in the construction of the ANN model. In this study, an ANN model was constructed with three layers, each containing three neurons. In addition, functions for activation, optimization, and loss were incorporated to aid in the evaluation of the model's performance. Figure 4 displays the ANN model layers and neurons.

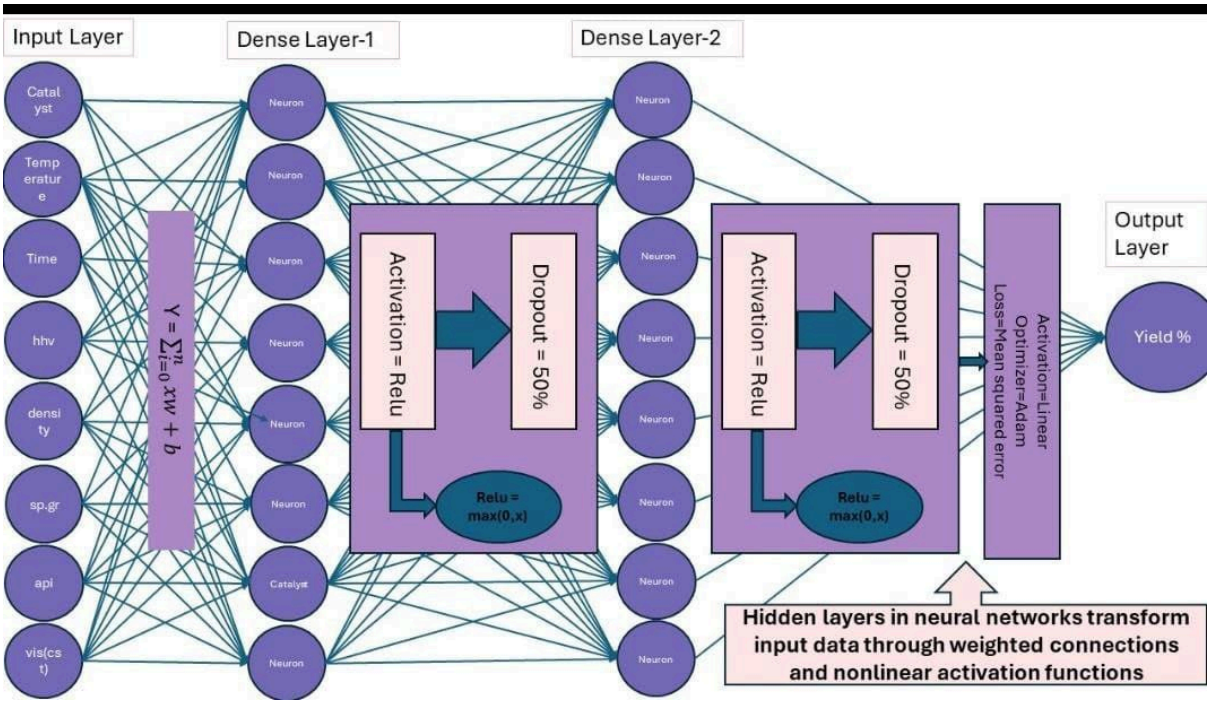

Figure 4. The ANN model layers and neurons.

The most frequently employed activations in machine learning and deep learning analysis include the step function, sigmoid function, hyperbolic tangent, and Rectified Linear Unit (ReLU), among others. The selection of an activation function is problem-dependent. In the current study, which employs a regression process, ReLU was utilised due to its superior performance in comparison to alternative functions. ReLU operates on the following principle:

$$f(x) = \max(0,z) \quad (1)$$

It indicates that if the output is negative, it is regarded as zero, and if it is positive, it can be processed. Furthermore, it was widely employed as an activation function due to its speed and simplicity. Moreover, its capacity to incorporate non-linearity into neural networks empowers them to discern intricate patterns and connections within data, rendering it an indispensable instrument in a multitude of applications [23]. In deep learning models, the Rectified Linear Unit is the most frequently employed activation function [24]. The function yields a value of 0 in response to any negative input but returns the value x if the input is positive. An unexpectedly straightforward function (consisting of only two linear components) can adequately incorporate non-linearities and interactions into a model. On the contrary, the ReLU function exhibits exceptional performance across a broad range of engineering applications. As shown in Figure (4) the test set can be used to evaluate different hyperparameter configurations and select the best-performing model.

3.7. Training of the model

In this instance, determining the collection size and number of epochs is critical. When discussing the quantity of data processed by the model during each training iteration, the term "batch size" is utilized. The effectiveness of the existing artificial neural network (ANN) model can be assessed through parameter modifications. Utilizing a Graphics Processing Unit (GPU) is crucial in order to accelerate the training procedure.

Training the model is at this moment. One hidden layer employs ReLU activation, while the output layer utilizes linear activation, making the model well-suited for regression tasks. The mean squared error is the loss function and 'adam' is the optimizer.

3.8. Loss function

A loss function, which is alternatively referred to as an objective function or cost function, measures the disparity between the predicted and actual values (ground truth) of a model within the domain of machine learning. The goal during training is to minimize this loss function, leading to a better-performing model. Different tasks, such as regression or classification, may require different types of loss functions.

3.9. Prediction

In order to estimate the percentage of yield alternative fuel production and optimize the operational parameters to increase the yield, the whole dataset that was not used for training was used to predict the percentage of sulfur conversion using the well-developed and trained artificial neural network (ANN) model. Furthermore, the predictive accuracy of the model may be assessed by evaluating the regression coefficient (R^2).

The (R^2) (R-squared) score, also referred to as the coefficient of determination, this metric is frequently employed to assess the adequacy of a regression model's fit. It provides an indication of how well the predicted values match the actual values and is expressed as a value between 0 and 1.

Additionally, mean absolute error (MAE) is another statistic used to assess the effectiveness of the model. Additionally, another statistic used is the Root Mean Squared Error (RMSE). To reuse the Python ANN model, just add fresh data ('Temp', 'time', 'type catalyst', and 'yield') to the CSV file. Then, run the Google Colab with GPU to receive the predicted yield (%).After running the cell just check the bellow cell to enter your preferred values to get the expected parameters like Time, Catalyst and Temperature Prediction yield calculate as shown in Figure 4.

The proposed ANN model was evaluated utilizing a number of statistical parameters, including the correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE), and mean bias error (MBE) [25-26]. The equations for them are shown below:

$$\text{Correlation coefficient (R)} = \frac{\sum_{i=1}^{n}(Y_{exp,i}-Y_{exp,I,avg})(Y_{est,i}-Y_{est,i,avg})}{\sqrt{\sum_{i=1}^{n}(Y_{exp,i}-Y_{exp,I,avg})^2 \sum_{m=1}^{n}(Y_{est,i}-Y_{est,i,avg})^2}} \quad (2)$$

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{1}{N}\sum(Y_{est}-Y_{exp})^2} \quad (3)$$

$$\text{Mean absolute error (MAE)} = \frac{1}{N}\sum\left|Y_{est}-Y_{exp}\right| \quad (4)$$

$$\text{Mean bias error (MBE)} = \frac{1}{N}\sum(Y_{est}-Y_{exp}) \quad (5)$$

where Y_{exp} is the experimental value of the yield; Y_{est} is the ANN-estimated value of the yield; Y_{avg} is the average value of the yield.

4. Results and discussion

4.1 Activated carbon based catalyst

4.1.1. SEM

Figure 5 presents the Scanning Electron Microscopy (SEM) images of the activated carbon (AC) prepared from date palm seeds. The SEM images reveal the porous structure of the AC, which is essential for its role as a support material in catalytic pyrolysis. The high surface area and well-developed porosity observed in the SEM images indicate that the AC can effectively disperse the Co-Mo catalyst, enhancing its catalytic activity. The preparation of AC from date palm seeds provides a sustainable and cost-effective method for producing high-quality catalyst supports, crucial for improving the efficiency of the catalytic pyrolysis process.

Figure 6 displays the SEM images of the Co-Mo/AC.ZSM-5 catalyst. The images show a uniform distribution of Co and Mo particles on the AC surface, indicating successful impregnation of the catalyst. The combination of AC with ZSM-5 enhances the catalyst's performance by providing a large surface area and acidic sites necessary for the pyrolysis reactions. The SEM analysis confirms that the Co-Mo/AC.ZSM-5 catalyst has a well-developed structure, making it suitable for converting waste polypropylene into alternative fuel. The uniform particle distribution observed in the images is critical for achieving high catalytic activity and stability during the pyrolysis process.

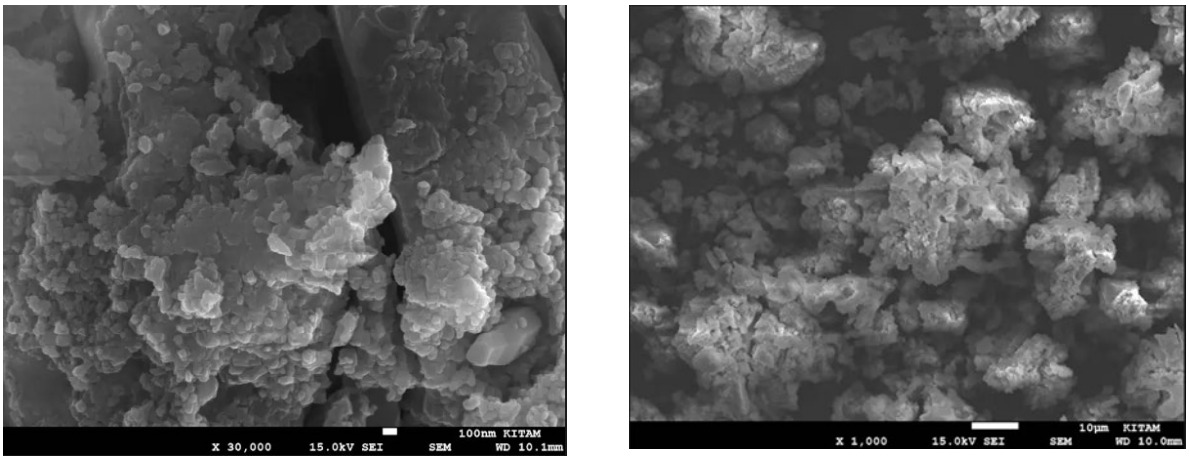

Figure 5. The AC prepared from date palm seeds as a support for the catalytic pyrolysis of waste polypropylene.

Figure 6 shows the scanning electron microscopy of the Co-Mo/ AC.ZSM-5 catalyst.

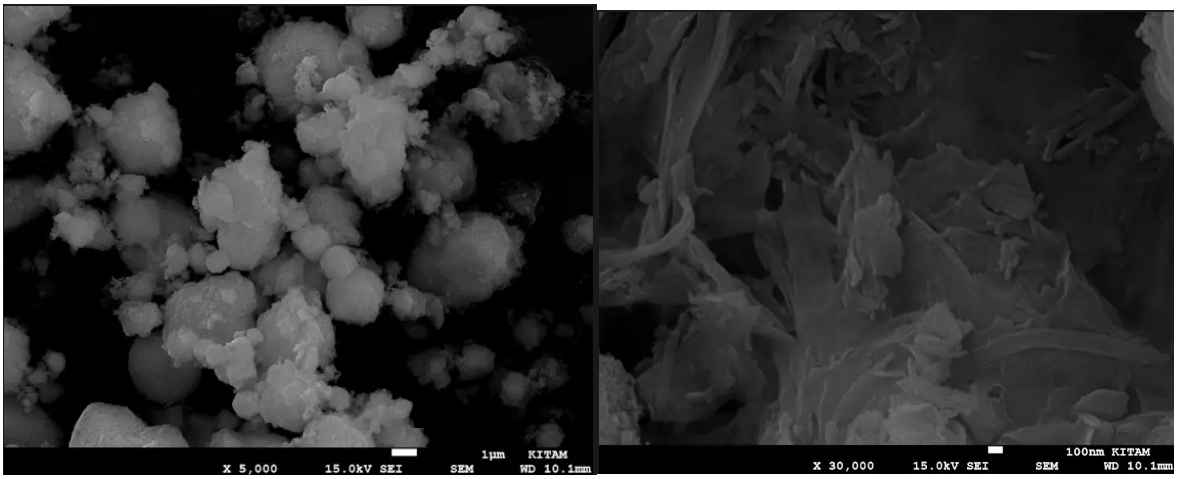

Figure 6. The AC based Co-Mo catalyst for the catalytic pyrolysis of waste polypropylene.

4.1.2. ICP

It is useful to use ICP analysis to find out how much cobalt (Co), molybdenum (Mo), and other elements are in Co-Mo/AC-ZSM-5 composite catalysts. This information is vital for understanding the catalyst composition and performance in catalytic processes. Furthermore, it used ICP analysis to monitor catalyst stability and detect any changes in elemental composition over time. This is crucial for enhancing catalytic processes in many industrial applications [27]. The inductively coupled plasma optical emission spectrometer (ICP-OES) technique investigates the loading amount of the synthesised Co-Mo/ZSM-5 and Co-Mo/AC-ZSM-5 catalysts. it can rely on it to determine the weight percentage of cobalt and molybdenum loaded on ZSM-5 and AC-ZSM-5 composites, as it provides the precise loading of metal elements on the plain support. The ICP results revealed a loading of 4.7% Co and 4.8% Mo on the ZSM-5. This result shows the weight of dried bulk powder containing various amounts of Co and Mo dissolved in the mixture. The ICP results revealed a loading of 4.75% Co and 4.86% Mo on the composite AC-ZSM-5. The ICP analysis reveals that the Co and Mo weight percentages primarily concentrate the active components in the sample on the particle surface, not within the pores.

4.2. Quality of the alternative fuel

Figure 7 displays the GC-MS spectrum of alternative fuel produced from the catalytic pyrolysis of waste polypropylene using the Co-Mo/AC-ZSM-5 catalyst derived from date palm seeds. The spectrum reveals a diverse array of hydrocarbons, including alkanes (such as hexane, heptane, and octane), which are saturated hydrocarbons contributing to the energy content of the alternative fuel. It also identifies alkenes (such as hexene, heptene, and octene), unsaturated hydrocarbons with double bonds that enhance reactivity. Additionally, the spectrum highlights the presence of aromatic hydrocarbons (such as benzene, toluene, and xylene), known for their stability and high energy content, making them valuable components in the fuel. This variety of hydrocarbons underscores the efficiency of the Co-Mo/AC-ZSM-5 catalyst in breaking down waste polypropylene into high-quality alternative fuel, showcasing the potential for sustainable fuel production. The gas chromatography-mass spectrometry (GC-MS) results shown in Figure 7 indicate that no light hydrocarbons (C1-C4) were produced from the catalytic pyrolysis of waste polypropylene. The GC-MS analysis focused on identifying and quantifying the products of the pyrolysis process. The data revealed the following:

- **Gas Yield**: The absence of C_1-C_4 hydrocarbons was confirmed by the GC-MS analysis, as illustrated in Figure 7.
- **Liquid C_{5+} fraction**: The majority of the products formed were within the C_{5+} hydrocarbon range, which aligns with the objective of producing alternative fuels.
- **Solid residue**: The solid residue primarily consisted of char and it was the leftover found in the bottom of the hydrothermal autoclave reactor at the end of each experiment.

The SEM images confirm the high-quality preparation of the catalysts, while the GC-MS spectrum validates the production of valuable alternative fuel components.

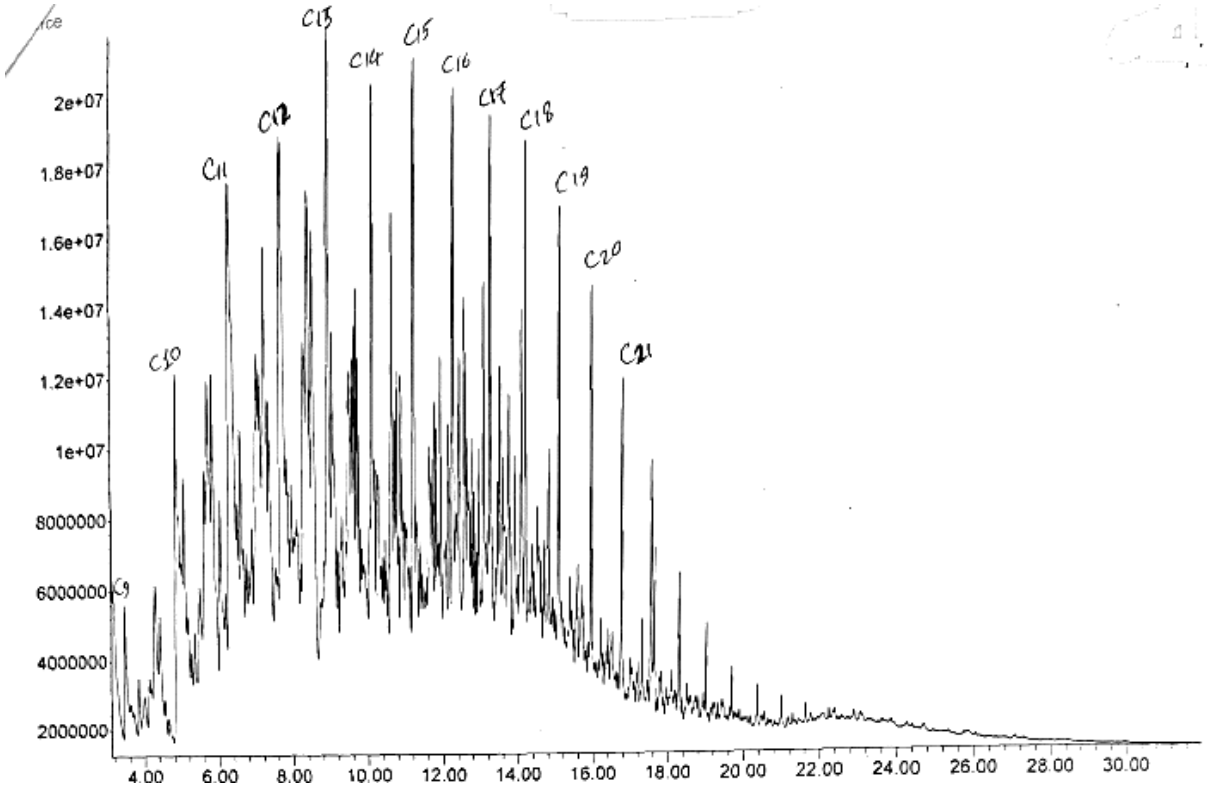

Figure 7 Alternative fuel compunds via testing in GC-MS by pyrolysis of waste polypropylene.

4.2. The ANN model

Comparing the experimental yield alternative fuel of all collected masses in accordance with the simulation results of Co-Mo/AC-ZSM-5 catalytic pyrolysis of polypropylene is shown in Table 3. This contrast makes it possible to have a deeper comprehension of the implications of the experiment's findings. It is feasible to make a comparison between the yield of alternative fuel that was achieved via testing and the yield that was originally anticipated with the assistance of this table. It is likely that the percentages of absolute error that exist between the values that were produced by simulation and those that were acquired through testing might reach 2.86%.

Table 3. Comparison between experimental & and simulated results of Co-Mo/AC-ZSM-5 catalytic pyrolysis of polypropylene.

Run	Temperature, (ºC)	Time (min)	Yield observed (%)	Yield predicted (%)	Percentage error (%)
1	200	30	61	62.1	1.77
2	200	45	64.5	65.1	1.01
3	200	60	65.2	66.7	2.3
4	200	75	69.5	70.2	1.00
5	200	90	63.75	64.7	1.54
6	225	30	74.9	75.7	1.09
7	225	45	75.6	75.9	0.42
8	225	60	77.7	77.6	0.005
9	225	75	81.5	80.4	1.34
10	225	90	78.9	79.7	1.0
11	250	30	85.5	86.5	1.2

Run	Temperature, (ºC)	Time (min)	Yield observed (%)	Yield predicted (%)	Percentage error (%)
12	250	45	84.9	83.7	1.40
13	250	60	86.65	87.3	0.77
14	250	75	89.3	90.1	0.89
15	250	90	92.05	91.6	0.39
16	275	30	87	88.8	2.07
17	275	45	88.3	89.6	1.5
18	275	60	89.75	90.3	0.62
19	275	75	91.7	93.4	1.85
20	275	90	95.7	96.0	0.32
21	300	30	85.95	86.7	0.87
22	300	45	88.2	87.3	0.91
23	300	60	90.6	88.4	2.3
24	300	75	92.05	92.0	0.01
25	300	90	96.3	95.5	0.79
26	325	30	92.55	90.6	2.1
27	325	45	94.3	93.2	1.1
28	325	60	95.15	95.0	0.07
29	325	75	97.3	96.8	0.47
30	325	90	97.55	98.1	0.63

This is a significant amount of variation. Figure 8 illustrate the disparity between the alternative fuel yield produced via the experimental approach and the alternative fuel yield acquired by the nonlinear regression methodology, respectively. The fact that these results were acquired is evidence that the strategy that was used was effective in achieving the desired results. A comparison was made, and the results of that comparison are shown in the figures that are included in the text.

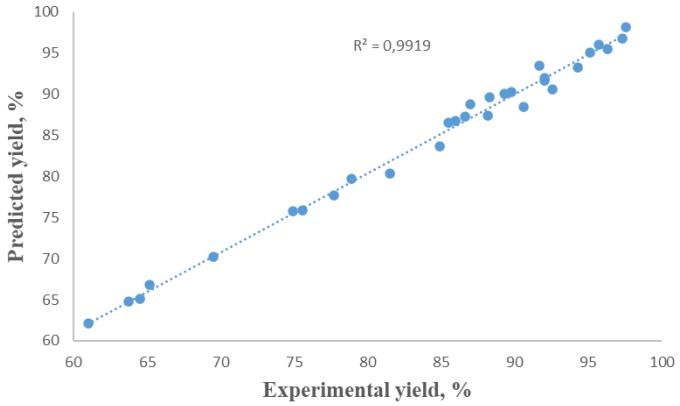

Figure 8. Comparison between experimental and predicted yield alternative fuel at different reaction conditions for Co-Mo/AC-ZSM-5 catalyst.

By running the ANN model on the Google Colab website with a graphics processing unit (GPU) and a goal objective function of yield alternative fuel percentage approaching 100%, it is possible to calculate the optimal operating parameters for the purpose of achieving the highest possible yield alternative fuel percentage. This can be accomplished by achieving the highest possible yield alternative fuel percentage. This is one approach that may be used to achieve this objective. In line with the data that is shown in Table 3, estimates have been produced about the optimal operating conditions, as well as the percentage of alternative fuel production that is yielded.

In this particular instance, the mean squared error (MSE) is found to be 1.8%, which is an extraordinarily high degree of accuracy in terms of prediction. With the help of the Python

ANN model, the present inquiry was able to create a maximum yield alternative fuel percentage of 98.34876 percent. A hydro thermal autoclave reactor was used to treat the alternative fuel that was produced by the catalytic pyrolysis of polypropylene. This was accomplished in order to get the desired result. The best working conditions were as follows: temperature = 325 °C, duration = 90 minutes, and the kind of catalyst used was Co-Mo/AC-ZSM-5. This was done in order to get the desired yield. The loss function of the ANN model is shown in Figure 9, which depicts both the training and validation processes.

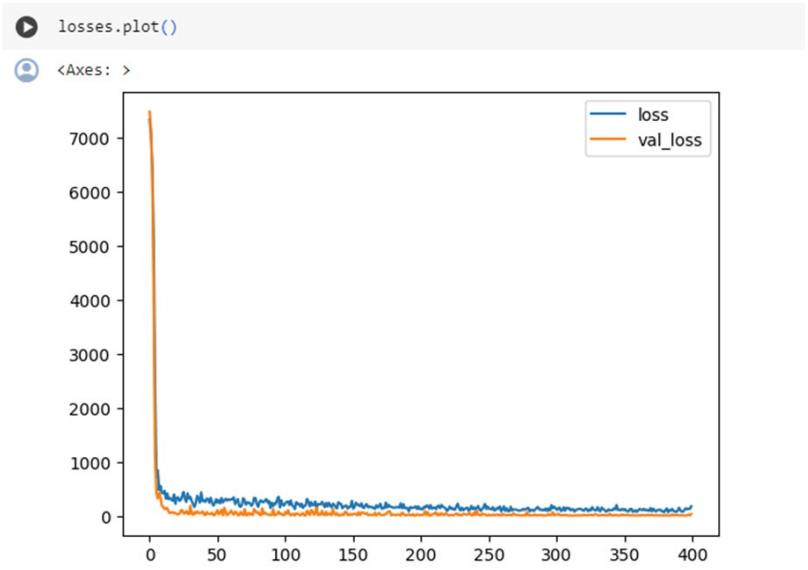

Figure 9. Dataset training and validation loss for 400 epochs.

The ANN model's architecture and performance further support the feasibility of using machine learning techniques to predict and optimize alternative fuel yields, contributing to the advancement of sustainable waste-to-fuel technologies.

5. Conclusions

The preparation of activated carbon from date palm seeds provides a sustainable and cost-effective method for producing high-quality catalyst supports. The SEM analysis revealed a well-developed porous structure in the AC, which is essential for its role in catalytic pyrolysis. The Co-Mo/AC-ZSM-5 catalyst exhibited a uniform distribution of Co and Mo particles on the AC surface, as confirmed by SEM images. This uniform particle distribution is critical for achieving high catalytic activity and stability during the pyrolysis process, making it suitable for converting waste polypropylene into alternative fuel. The catalytic pyrolysis of waste polypropylene using the Co-Mo/AC-ZSM-5 catalyst in a hydrothermal autoclave reactor resulted in a high yield of alternative fuel. The experimental results showed that the highest yield achieved was 99% at a temperature of 325°C, with a reaction duration of 90 minutes. The quality of the produced alternative fuel was analyzed using GC-MS, which revealed a diverse array of hydrocarbons, including alkanes, alkenes, and aromatic hydrocarbons. The absence of light hydrocarbons (C_1-C_4) in the gas yield suggests that the catalytic pyrolysis process efficiently converts waste polypropylene into heavier hydrocarbons (C_{5+}), which are desirable for producing liquid fuels. This is evident from the GC-MS data shown in Figure 7, which confirms the formation of primarily C_{5+} hydrocarbons and the absence of C_1-C_4 hydrocarbons.

The results underscore the effectiveness of the Co-Mo/AC-ZSM-5 catalyst in promoting the formation of liquid hydrocarbons while minimizing the production of light gases. This aligns with the intended goal of maximizing liquid fuel yield from polypropylene waste. These components contribute to the energy content and stability of the alternative fuel, showcasing the efficiency of the Co-Mo/AC-ZSM-5 catalyst in breaking down waste polypropylene into high-

quality alternative fuel. An artificial neural network (ANN) model was developed using the Python and it was successful in prediction of the yield of the alternative fuel produced.

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