

# Optimisation of Acid Yellow Dye Decolourisation using CNS Carbon: A Response Surface Methodology Approach with Exploratory Data Analysis in Jupyter Notebook

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**Abstract:** *The current research is focused on the need to develop an efficient adsorbent with low-cost effectiveness and high potentiality for removal of dye from waste water. Cashew nut shell, a solid waste generated in the cashew nut industry is taken as the adsorbent for the decolorization of acid yellow synthetic dye solution. Batch adsorption studies were carried out with the consideration of factors/variables such as dye concentration, adsorbent dosage and contact time. A comparative decolorization study has been done with both commercial activated carbon (CAC) and Cashew nut shell carbon (CNSC). The factors were optimized statistically using Central Composite Design (CCD) in response surface methodology. The characterization of the adsorbent was analyzed in FTIR, SEM and XRD. In recent years, the use of interactive computing environments has significantly improved the efficiency of data analysis workflow. This study investigates the effectiveness using Jupyter notebooks in facilitating exploratory data analysis and reproducible research practices. Using the datasets, we conducted a comprehensive analysis involving data cleaning, visualization, and statistical exploration, leveraging Python libraries such as numpy, pandas, seaborn, and matplotlib*

**Keywords:** Acid yellow dye, Adsorption, Commercial Activated Carbon, Cashew nut Shell, Central composite design, Jupyter notebooks

## I. INTRODUCTION

Synthetic dyes are used to cause immediate visible pollution in effluent water aside from contamination by interfering with light, which may retard photosynthesis and biota growth. They increase oxidation demand and lower vital oxygen levels in waters [1, 2]. Synthetic dyes are generally resistant to biodegradation and physiochemical techniques for their removal, such as adsorption, chemical oxidation, electro-coagulation and advance oxidation processes have been recently used extensively to comply with more and more stringent legislation regarding maximum allowable dye concentration in discharged waste water [3, 4]. Adsorption by activated carbon has been proven to be a successful physiochemical technique for the treatment of dye-laden wastewater mainly for its simplicity, efficiency and ease of implementation [5-7].

The utilization of alternative low-cost materials with high adsorption activity to solve environmental problems has received considerable attention over the recent years. Adsorbents from agriculture by-products are particularly advantageous due to their low cost and high availability as many other materials, for example, clays[8], cane waste[9], wood[10], cellulosic materials [11] and fish scale [12] have been tested as adsorbent on remediation of contaminated water.

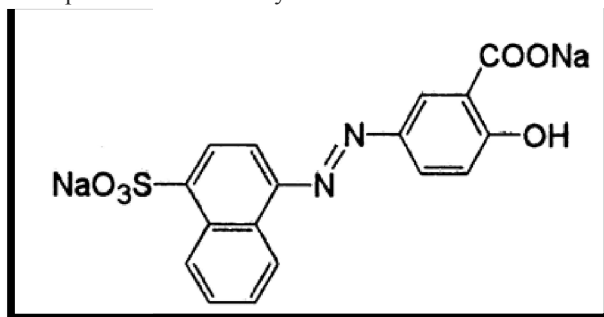


The study to be reported deals with investigating the impact of supplementing mechanically conducted preliminary treatment which includes screening with adsorption on the treatability of tannery waste water containing acid yellow dye 100.

Acid Yellow dye 100 has the IUPAC name 4-Aminonaphthalene-1-sulfonic acid di azo, coupled with 2-Hydroxybenzoic acid and then translate into chromium complex. Its structure is Single azo, metal Complexes. Molecular formula is  $C_{17}H_{10}N_2Na_2O_6S$  and Molecular weight is 416.32.

For the reduction of concentration of this dye to the environment, the natural waste material cashew nut shell generally known as CNS was used. This CNS has abundant carbon content when it is burnt, usually CNS is the waste material which used as feed instead of wood because of its ignition capacity. CNS has a thick, highly viscous liquid in it which is mostly used for engine ignition on proportions with other oil.

In this study, we have treated the acid yellow dye using CNS carbon and Activated carbon (purchased) to find the effectiveness of both carbons. Normally, activated carbons taken from market are meant to have high % of removal of concentration compared to any natural products, but due to the expensive nature of commercial activated carbon an alternate usage of CNS Carbon is preferred in this study.



**Figure 1. Structure of Acid Yellow 100 dye**

## **II. MATERIALS AND METHODS**

### **Preparation of Carbon from Cashew Shell nut**

The cashew nut shell (CNS) was collected from local agriculture fields near Tamil nadu, India. The CNS was washed thoroughly 3–4 times in tap water to remove dust and other impurities adhered to it. It was then dried in a hot air oven at 60°C for 24 h. The Commercial activated carbon (CAC) was purchased from Lobachemie ltd, India. The cashew nut shell carbon (CNSC) was used as adsorbents and analytical techniques were performed.

### **Exploratory Data Analysis**

Jupyter Notebook is an open-source web-based interactive computing platform that allows users to create and share documents containing live code, equations, visualizations, and narrative text. It supports various programming languages, most commonly Python, and is widely used in data science, machine learning, and scientific computing. In this study, Jupyter Notebook was used for exploratory data analysis (EDA), preprocessing, and visualization of the dataset. Its interactive nature facilitated iterative analysis, enabling real-time feedback on code execution and data outputs. The reproducibility and transparency of the computational workflow were enhanced by embedding code, results, and explanatory commentary in a single document.

### **Preparation of dye solution**

The Acid Yellow 100 dye (molecular formula is  $C_{17}H_{10}N_2Na_2O_6S$  and molecular weight is 416.32) was supplied by tannery. Double distilled water was used for the preparation of all the solutions with pH 6.5. A1000mg/L stock solution was prepared and 250,500,750mg/L solutions were prepared and the concentrations of the acid yellow solutions were obtained from standard calibrations curve.



### Characterization of the Cashew Nut Shell Carbon (CNSC)

The CNSC were examined using FTIR spectrum, SEM - EDS analysis and X-Ray diffractometer. FTIR was employed to determine the presence of surface functional groups in the samples (Agilent Technologies). The crystal structure was characterized by X-Ray diffractometer (XRD) with Cu, K $\alpha$  radiation (X Ray Pro powder method). The micro structure of the carbon was performed by Scanning Electron Microscope and the quantity of carbon was obtained by EDS analysis (High resolution field emission electron microscope with EDS, nano manipulation system).

### Design of Experiments (DOE)- Response surface methodology:

Design of experiments is used to systematically investigate the process variables that influence the output quality with optimization. Response surface methodology (RSM) is a tool in DOE that is widely used to assess the relationship between one or more response variables and a set of quantitative experimental variables or factors. There are three steps in RSM (a) design and experiments, (b) response surface modeling through regression, and (c) optimization. Central composite design (CCD) is often recommended for optimizing the experimental variables in the study.

Independent process parameters can be represented in quantitative form using RSM as:

$$Y = f(X_1, X_2, X_3, X_4 \dots X_n) \quad (1)$$

where, Y represents the response (yield), f is the response function,  $\epsilon$  is the experimental error, and  $X_1, X_2, X_3 \dots X_n$  are independent parameters. A surface, known as the response surface is obtained by plotting the expected response of Y.

The response surface is obtained by plotting the expected response of Y. Thus, RSM aims at approximating f by a suitable lower ordered polynomial in some region of the independent process variables. If the response can be well-suited by a linear function of the independent variables [Prem Kumaret al.2014], the function (Eq. (1)) can be written as:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \dots + \beta_n X_n \pm \epsilon \quad (2)$$

### Experimental studies

Yellow dye adsorption experiments onto CNS and CCS from aqueous solution was performed in batch scale at pH 6.5 and 50 RPM. The experiments were conducted in 250 ml conical flasks containing 100ml solution of dye solution with adsorbent concentration ranging from 1-2g/ per 100ml each, which was scaled up in g/l as shown in table 2. Interactive effects were studied between chosen variables (Adsorbent dosage, Dye Concentration and Contact time) on the maximum removal of dye.

Independent Variables	Design Variables	Range and levels		
		-1	0	1
Adsorbent dosage(g/l)	$X_1$	4	6	8
Dye concentration (mg/l)	$X_2$	50	75	100
Contact time (mins)	$X_3$	60	75	90

**Table 1 : Level of independent variables and experimental range**

Since, the independent variables is three in the present study, a full factorial CCD in this study consists of 8 factorial points, 6 axial points and 6 replicates at the centre with total of 20 sets of experiments under CCD with suitable combinations of independent variables chosen using RSM were calculated by the Eq. (3) and the details are presented in Table 3.

$$N = 2^{K-1} + 2^K + n_0 \quad (3)$$

Where N is the total number of experiments and k is the number of factors. The experiments were designed from CCD under RSM using MINITAB 16.0. Adsorbent dosage, Dye Concentration and Contact time were taken as independent variables and the carbon removal rate (%) was taken as dependent output response variable in this study. The experimental design matrices of three individual variables with regard to their uncoded and coded values are given in Table 3. Estimation of quality of fit of the model is done through coefficient determination and analysis of variances. A



mathematical model in form of second-order polynomial Eq. (4) was used to fit the experimental results as a function of independent variables involving their interactions.

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_{11} X_1^2 + \beta_{22} X_2^2 + \beta_{33} X_3^2 + \beta_{12} X_1 X_2 + \beta_{13} X_1 X_3 + \beta_{23} X_2 X_3 \quad (4)$$

Where,

Y represents the dependent variable (Dye removal (%);

$X_1, X_2, X_3$  represents the independent variable;

$\beta_0$  represents the regression coefficient at center point;

$\beta_1, \beta_2, \beta_3$  represents the linear coefficients;

$\beta_{11}, \beta_{22}, \beta_{33}$  represents the quadratic coefficients; and  $\beta_{12}, \beta_{13}, \beta_{23}$  represents the second-order interaction coefficients.

The obtained regression model was assessed by taking the regression coefficient values, analysis of variance (ANOVA), P- and F-values. The coefficient of determination  $R^2$  was used to express the goodness of fit of the polynomial model equation. To identify the experimental design and to generate a regression model to find the optimum combinations considering the effects of linear, quadratic, and interactive effects on removal of dye, the statistical software package (MINITAB 16.0) was used.

Run	$X_1$	$X_2$	$X_3$	Adsorbent Dosage (mg/l)	Dye Concentration (mg/l)	Contact time (min)
1	-1	-1	-1	4	50	60
2	1	-1	-1	8	50	60
3	-1	1	-1	4	100	60
4	1	1	-1	8	100	60
5	-1	-1	1	4	50	90
6	1	-1	1	8	50	90
7	-1	1	1	4	100	90
8	1	1	1	8	100	90
9	-1.6817	0	0	2.63	75	75
10	1.6817	0	0	9.36	75	75
11	0	-1.6817	0	6	32.95	75
12	0	1.6817	0	6	117.04	75
13	0	0	-1.6817	6	75	49.7
14	0	0	1.6817	6	75	100.22
15	0	0	0	6	75	75
16	0	0	0	6	75	75
17	0	0	0	6	75	75
18	0	0	0	6	75	75
19	0	0	0	6	75	75
20	0	0	0	6	75	75

Table 2: Full factorial design with code and real variables

### III. RESULTS AND DISCUSSION

#### Characterization of the adsorbent

The surface characteristics of carbon samples can be seen by SEM photographs analyzed at 50 $\mu$ m, in which pores on the surface confirming the carbon. The availability of pores and internal surface is necessary for an effective adsorbent and percentage of carbon from EDS analysis are performed resulting in effective carbonaceous material.

Fourier Transform Infrared Spectroscopy provides the qualitative information about the functional groups of the surface. The absorption capacity of the carbon is also studied by this surface chemical structure, it was attributed at



2283  $\text{cm}^{-1}$  and 2210  $\text{cm}^{-1}$  indicating alkyl C=C stretch bonds, 1238  $\text{cm}^{-1}$  and 1182.903  $\text{cm}^{-1}$  indicating C-C bonds. Unsaturated compounds are attributed above 3000  $\text{cm}^{-1}$ .

The X-Ray diffractometer analysis are performed, the peaks are found around  $2\theta = 26^\circ$  and  $43^\circ$ , the anode material used was Cu having broad peaks similar to crystalline carbonaceous structure such as graphite (JCPDS).

### Regression Equation Development

The dye removal results of various design variables (Adsorbent dosage, Dye concentration, and Contact time) are shown in the Table 4. The experimental results of maximum dye removal (%) from the calculated regression coefficients shown in Table 4 and Table 6 are fitted to second order polynomial Eq.4. The Eq.4 with regression coefficient for removal of dye by CNSC and CAC is given in the Equation 5 and Equation 6 respectively

$$Y = 92.1646 + 10.9846X_1 - 7.7342X_2 + 3.7066X_3 - 4.6386X_1^2 - 3.5508X_2^2 - 13.4527X_3^2 - 0.49X_1X_2 + 1.015150X_1X_3 + 1.0125X_2X_3 \quad (5)$$

$$Y = 99.2692 + 0.3008X_1 + 0.18X_2 - 0.3497X_3 - 0.1381X_1^2 - 0.2608X_2^2 - 0.0098X_3^2 + 0.0778X_1X_2 + 0.1647X_1X_3 + 0.5047X_2X_3 \quad (6)$$

The predicted output responses by CCD were correlated with experimental data with help of regression coefficient  $R^2$ . Furthermore, the proportion of variation in the outcome is given by the model and is denoted by  $R^2$  and adjusted  $R^2$  values, where  $R$  denotes the variation in the observed responses. The measure of fit of the model is also given by the value of  $R^2$ , and the model is compared with different independent variables by the adjusted  $R^2$  values. The  $R^2$  evaluates correlation between experimental and predicted values [premkumar].

The  $R^2$  value for CNSC and CAC were 0.91 and 0.87 obtained is closer to 1, which indicates the perfect fit of the data presented in Table 4 and 5. The obtained  $R^2$  value indicates that 91% and 87% of variability in dye removal by both the adsorbents (CNSC and CAC) could be explained by the model.

### Proximate and ultimate analysis

#### Proximate analysis of CNS and its char

Proximate analysis of CNS and its Char for determination of moisture content and volatile matter,

	Moisture content	Volatile matter
CNS	10-11%	65-70%
Char	5-6%	25-30%

#### Ultimate analysis of CNS and its char

The Ultimate analysis of CNS and its Char was carried out in order to determine its carbon, hydrogen, oxygen and nitrogen percentage.

	Carbon	Hydrogen	Oxygen	Nitrogen
Percentage	60-62%	6 to 7%	29-31%	0.7-0.75%

### Ordinary Least Squares (OLS) Regression

OLS is a statistical method used to model the relationship between one or more independent variables (predictors) and a dependent variable (outcome). It is the most common form of linear regression.

OLS estimates the best-fitting line (or hyperplane, in higher dimensions) through the data by minimizing the sum of the squared differences between the actual values and the predicted values—these differences are called residuals.



Run	X <sub>1</sub>	X <sub>2</sub>	X <sub>3</sub>	Ad. Dos (mg/l)	Dye Con. (mg/l)	Contact Time (mins)	CNSC-1	CAC	CNSC-1 Pred.	CAC Expt.
1	-1	-1	-1	4	50	60	64.8000	99.760	65.1029	99.4766
2	1	-1	-1	8	50	60	85.1500	99.980	86.0222	99.5933
3	-1	1	-1	4	100	60	56.7000	98.810	48.5896	98.6716
4	1	1	-1	8	100	60	72.1400	99.400	67.5489	99.0992
5	-1	-1	1	4	50	90	70.7000	97.322	68.4610	97.4382
6	1	-1	1	8	50	90	92.1600	98.260	93.4403	98.2139
7	-1	1	1	4	100	90	63.7000	98.450	55.9978	98.6522
8	1	1	1	8	100	90	86.1500	99.640	79.0171	99.7388
9	-1.68	0	0	2.63	75	75	53.3100	98.400	60.5707	98.3726
10	1.6817	0	0	9.36	75	75	95.1200	99.096	97.5185	99.3845
11	0	-1.6817	0	6	32.95	75	98.5501	97.961	95.1286	98.2288
12	0	1.6817	0	6	117.04	75	56.0336	98.841	69.1142	98.8342
13	0	0	-1.6817	6	75	49.7	44.3200	99.259	47.8809	99.8296
14	0	0	1.6817	6	75	100.22	54.2500	98.963	60.3483	98.6534
15	0	0	0	6	75	75	92.4408	99.120	92.1646	99.2692
16	0	0	0	6	75	75	92.4408	99.340	92.1646	99.2692
17	0	0	0	6	75	75	92.4408	99.300	92.1646	99.2692
18	0	0	0	6	75	75	92.4408	99.300	92.1646	99.2692
19	0	0	0	6	75	75	92.4408	99.300	92.1646	99.2692
20	0	0	0	6	75	75	92.4408	99.300	92.1646	99.2692

**Table 3 : Full factorial design with experimental and predicted results of adsorbents**

Fischer's test (F-test) is used to calculate the ratio of mean square of regression (MRR) to error (MRE). The smaller the extent of the F-value yields more significant is the corresponding coefficient. Moreover, if the model has high degree of adequacy for predicting the experimental results, the computed F-value from the model should be greater than the tabulated F-value. From Table 4&6, it can be noted that the obtained F-value for dye removal by ACS and CCS is 12.3 and 7.48, which is greater than the tabulated F-value.

The calculated regression coefficient for dye removal is given in Table 5 and Table 7 for ACS and CCS together with their corresponding p-value and T-value. From the table 5, the coefficient for single effect of Adsorbent dosage ( $\beta_1$ ), and Dye concentration ( $\beta_2$ ), square effects of adsorbent dosage ( $\beta_{11}$ ) and contact time ( $\beta_{33}$ ) are significant ( $p < 0.050$ ). Similarly, From the table 7, the coefficient for single effect of Adsorbent dosage ( $\beta_1$ ), and Contact time ( $\beta_3$ ), interactive effects of dye concentration and contact time ( $\beta_{23}$ ) are significant ( $p < 0.050$ ).

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	5491.55	491.55	510.17	2.30	.000
Residual Error	10	496.17	496.17	49.62		
Total	19	5987.72				

R-Sq = 91.71% ; R-Sq(adj) = 84.26%

**Table 4 Analysis of variance CNSC**

Term	Coefficient	SE Coefficient	T	P
$\beta_0$	92.1646	2.873	32.081	0.000
$\beta_1$	10.9846	1.906	5.763	0.000
$\beta_2$	-7.7341	1.906	-4.058	0.002
$\beta_3$	3.7066	1.906	1.945	0.080





$\beta_{11}$	-4.6386	1.856	2.500	0.031
$\beta_{22}$	-3.5508	1.856	1.914	0.085
$\beta_{33}$	-13.4527	1.856	7.250	0.000
$\beta_{12}$	-0.4900	2.490	-0.197	0.848
$\beta_{13}$	1.0150	2.490	0.408	0.692
$\beta_{23}$	1.0125	2.490	0.407	0.693

**Table 5 Estimated Regression coefficient for CNSC**

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	6.82594	6.82594	0.75844	7.48	0.002
Residual Error	10	1.01405	1.01405	0.10140		
		7.8399				

**R-Sq = 87.07% ; R-Sq(adj) = 75.42%**

**Table 6 Analysis of Variance for CAC**

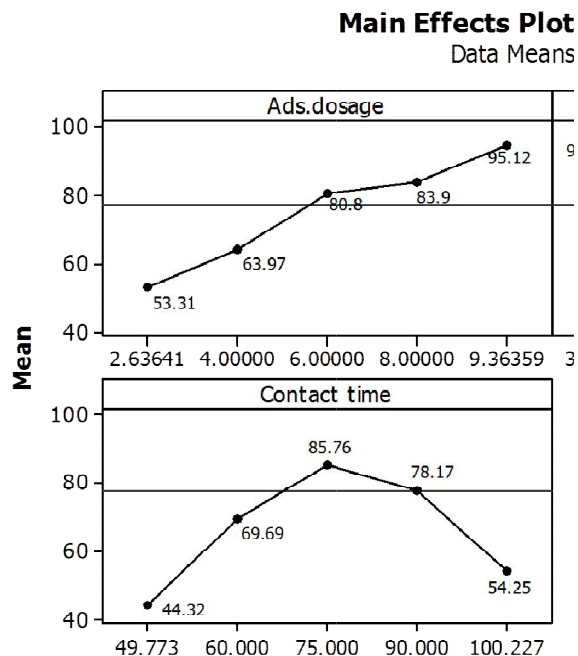
Term	Coefficient	SE Coefficient	T	P
$\beta_0$	99.2692	0.12988	764.340	0.000
$\beta_1$	0.3008	0.08617	3.491	0.006
$\beta_2$	0.1800	0.08617	2.089	0.063
$\beta_3$	-0.3497	0.08617	-4.058	0.002
$\beta_{11}$	-0.1381	0.08388	-1.647	0.131
$\beta_{22}$	-0.2608	0.08388	-3.109	0.011
$\beta_{33}$	-0.0098	0.08388	-0.117	0.909
$\beta_{12}$	0.0778	0.11259	0.691	0.506
$\beta_{13}$	0.1647	0.11259	1.463	0.174
$\beta_{23}$	0.5047	0.11259	4.483	0.001

**Table 7 Estimated Regression Coefficients for CAC**

### Main Effect Plots

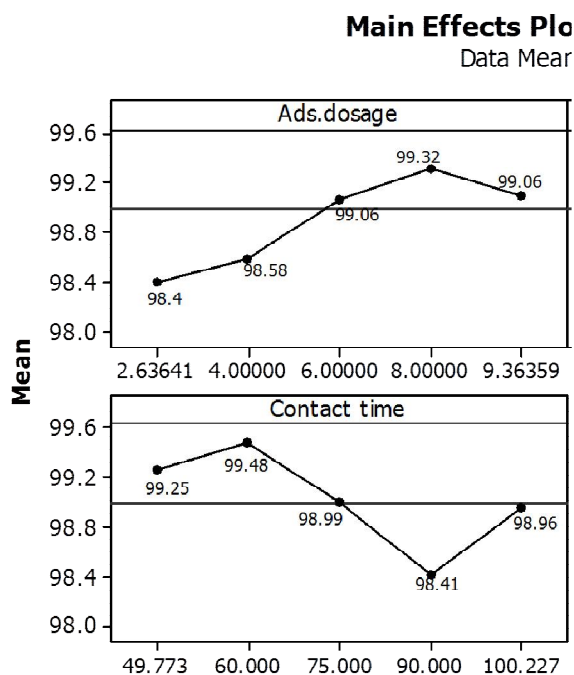
These plots are used to calculate data means when several factors are involved in the process and to compare magnitudes of marginal means. The points in the plot represent the means of the response variables at various levels of each factor, with a reference line drawn at the grand mean of the response data. The MEP of ACS adsorbent on dye removal with effect of process variables is shown in figure 2. It can be noted that maximum dye removal was of 95.12%, 98.5%, and 85.76% were observed at 9.36(g/l), 32.95(mg/l), and 75mins. Furthermore, it can also be observed that lower dye concentration (32.955mg/l) yielded maximum removal (98.5%) and higher dye concentration (117.045mg/l) resulted in less removal (56.03%). Similarly, in 75mins of Contact time 85.75% of dye removal has been achieved, beyond that desorption process occurs.





**Figure 2 : Main effect plots on Adsorbent dosage, Concentration and Contact time for ACS**

In the case of CAC which is shown in figure 3. It is observed at adsorbent dosage 8(g/l); Dye concentration of 75mg/l with contact time 60mins resulted in 99.13%, 99.32 % and 99.48% of dye removal .On the other hand, at very high concentrations of Adsorbent dosage (9.36mg/l) and Dye concentration (117.045mg/l) , there is decrease in the dye removal was observed.



**Figure 3 : Main effect plots on Adsorbent dosage, Concentration and Contact time on CAC**





From the MEP, it can be noted that at high adsorbent dosage, >90% of dye removal has been observed, this may be due to the fact that as the increase in availability of surface sites which is resulted from the increase dosage and conglomeration of the adsorbent [13]. With high concentration of the dye both adsorbents exhibited less removal which may be due to the lack of available sites in the surface of the adsorbent. Also, it can be noted that as the contact time increases, viz., after 75mins the average mean data of dye removal of both adsorbents did not show much significant in dye removal rate [14].

### Response surface plots

The response surface plot for the carbon prepared from activated cashew shell (ACS) on dye removal is shown in the figure 4. It can be noted from the figure a. that increases in adsorbent dosage increases dye removal. However, as the dye concentration increases, after 75mg/l of dye concentration there was decrease in the reduction of dye removal respective of increase in adsorbent dosage. Similar trends were observed in figure b. On the other hand, it can be noted from the figure c, that higher dye concentration showed less removal at lower contact time, but as the contact time increases, increase in dye removal was observed till 75mins after which desorption starts. This shows that increase in dye concentration decrease the rate of external diffusion and enhancing stationary phase collision of adsorbed particles takes place as a result sorption is reduced.

Similarly, the response surface plots for CAC as shown in figure 5. It can be observed from figure a, that as the higher adsorbent dosage showed slight lower trend than initial dosage. Meantime, from figure b, it can be noted that at higher dosage, there was not much significant change in the dye removal at increasing contact time. However, at lower adsorbent dosage the dye removal was less as the contact time increases. This condition was similarly observed in figure c. This shows that at initial contact maximum sites in the adsorbent is filled at higher adsorbent dosage. At same time, initial adsorbent dosage there was decrease in dye removal as the contact time increase may be due to the fact that increase in the movement of adsorbed particles causes decrease in the film resistance to mass transfer in the adsorbent [15].

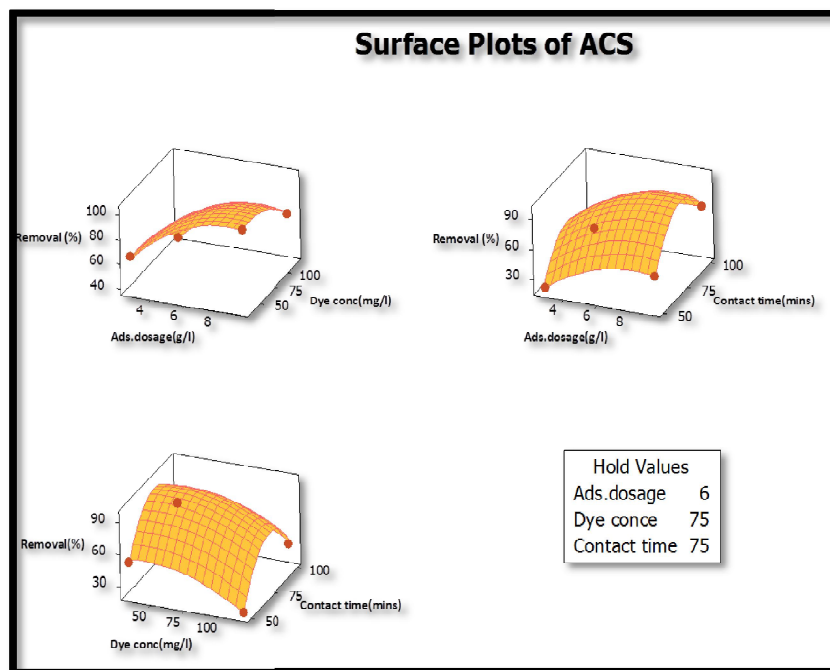


Figure 4: Response Surface plots of CNSC



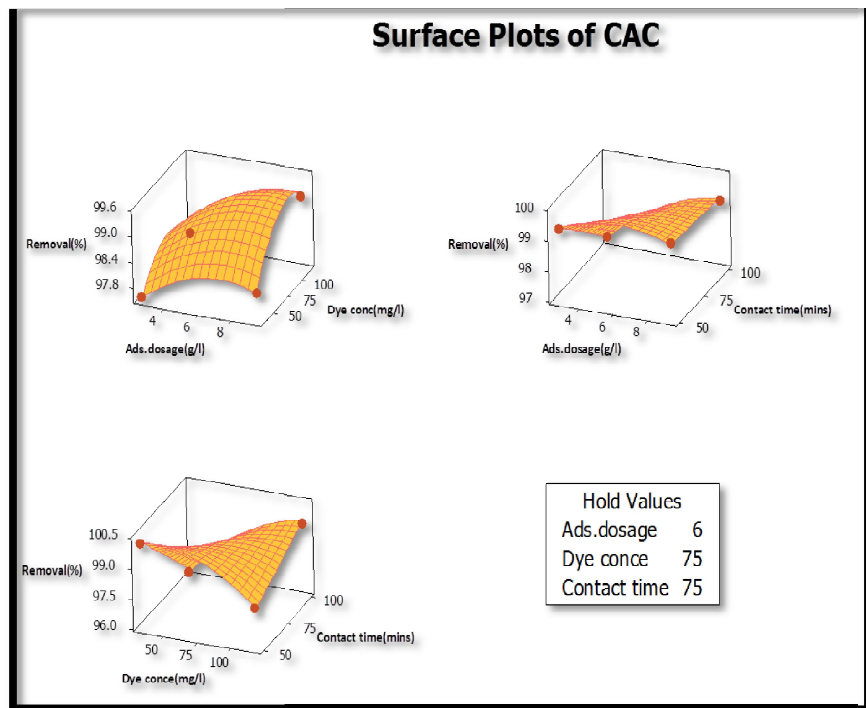


Figure 5: Response Surface plots of CAC

### Exploratory Data Analysis

#### Program to import libraries

```
import pandas as pd
import statsmodels.api as sm
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
```

### EDA for CNSC Experiment Vs Prediction

#### Data frame creation and OLS regression



```
data = {
    'X1': [-1, 1, -1, 1, -1, 1, -1, 1, -1.68, 1.6817, 0, 0, 0, 0, 0, 0, 0, 0],
    'X2': [-1, -1, 1, 1, -1, -1, 1, 1, 0, 0, -1.6817, 1.6817, 0, 0, 0, 0, 0, 0],
    'X3': [-1, -1, -1, -1, 1, 1, 1, 1, 0, 0, 0, 0, -1.6817, 1.6817, 0, 0, 0, 0],
    'Ad.Dos(mg/l)': [4, 8, 4, 8, 4, 8, 4, 8, 2.63, 9.36, 6, 6, 6, 6, 6, 6, 6, 6],
    'Dye Con.(mg/l)': [50, 50, 100, 100, 50, 50, 100, 100, 75, 75, 32.95, 117.04, 75, 75, 75, 75, 75, 75],
    'Contact time(min)': [60, 60, 60, 60, 90, 90, 90, 90, 75, 75, 75, 75, 75, 75, 75, 75, 75, 75],
    'CNSC-1 Exp.': [64.8, 85.15, 56.7, 72.14, 70.7, 92.16, 63.7, 86.15, 53.31, 95.12, 98.5901, 56.0336, 44.32, 54.25, 92.44, 92.44, 92.44],
    'CAC Exp.': [99.76, 99.98, 98.81, 99.4, 97.32, 98.26, 98.45, 99.64, 98.4, 99.096, 97.861, 98.841, 99.259, 98.963, 99.12, 99.34, 99.3, 99.3],
    'CNSC-1 Pred.': [65.1029, 86.0222, 48.5896, 67.5489, 68.4610, 93.4403, 55.9978, 79.0171, 60.5707, 97.5185, 95.1286, 69.1142, 47.8809, 60.3483, 92.16, 99.4766, 99.5933, 98.6716, 99.0992, 97.4382, 98.2139, 98.6522, 99.7388, 98.3726, 99.3845, 98.2288, 98.8342, 99.8296, 98.6534, 99.2692,
}

df = pd.DataFrame(data)

# Independent variables (X1, X2, X3)
X = df[['X1', 'X2', 'X3']]
X = sm.add_constant(X) # Adds a constant term for the intercept

# Dependent variable for CNSC-1 (Experimental vs Predicted)
y_cns = df['CNSC-1 Exp.'].

# Regression model for CNSC-1
model_cns = sm.OLS(y_cns, X).fit()

# Predicted CNSC-1 values from the model
df['CNSC-1 Pred. Model'] = model_cns.predict(X)

# Model Summary
print("CNSC-1 Model Summary:")
print(model_cns.summary())

# Evaluate the model for CNSC-1 (R-squared, MAE, MSE, RMSE)
mae_cns = mean_absolute_error(y_cns, df['CNSC-1 Pred. Model'])
mse_cns = mean_squared_error(y_cns, df['CNSC-1 Pred. Model'])
rmse_cns = np.sqrt(mse_cns)
r2_cns = r2_score(y_cns, df['CNSC-1 Pred. Model'])

print(f"CNSC-1 Model Evaluation:\nMAE: {mae_cns}\nMSE: {mse_cns}\nRMSE: {rmse_cns}\nR-squared: {r2_cns}")

# Plot the experimental vs predicted for CNSC-1
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_cns, y=df['CNSC-1 Pred. Model'])
plt.plot([y_cns.min(), y_cns.max()], [y_cns.min(), y_cns.max()], color='red', linestyle='--')
plt.xlabel('Experimental CNSC-1')
plt.ylabel('Predicted CNSC-1')
plt.title('Experimental vs Predicted CNSC-1')
plt.show()
```

## Output Model Summary

CNSC-1 Model Summary:

OLS Regression Results

Dep. Variable:	CNSC-1 Exp.	R-squared:	0.443
Model:	OLS	Adj. R-squared:	0.338
Method:	Least Squares	F-statistic:	4.241
Date:	Sun, 20 Apr 2025	Prob (F-statistic):	0.0220
Time:	16:42:24	Log-Likelihood:	-79.545
No. Observations:	20	AIC:	167.1
Df Residuals:	16	BIC:	171.1
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P> t	[0.025	0.975]
const	77.3853	3.228	23.969	0.000	70.541	84.229
X1	10.9865	3.908	2.811	0.013	2.702	19.271
X2	-7.7342	3.907	-1.980	0.065	-16.017	0.540
X3	3.7067	3.907	0.949	0.357	-4.576	11.989

Omnibus:	1.890	Durbin-Watson:	0.889
Prob(Omnibus):	0.389	Jarque-Bera (JB):	1.218
Skew:	-0.600	Prob(JB):	0.544
Kurtosis:	2.860	Cond. No.	1.21

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

CNSC-1 Model Evaluation:

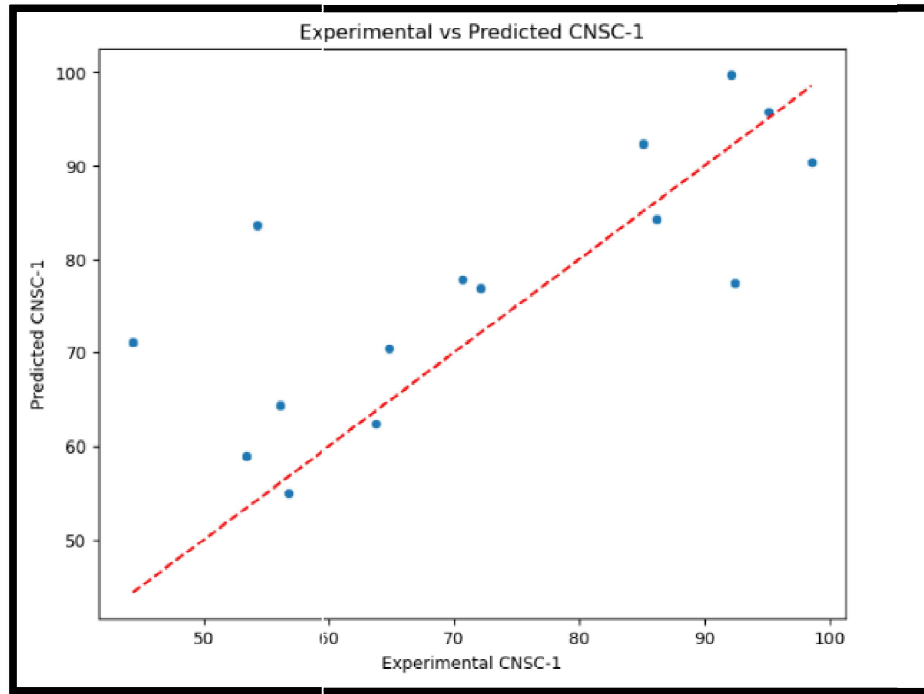
MAE: 10.336337074577624

MSE: 166.7702260258126

RMSE: 12.913954701245185

R-squared: 0.44294532728467476





#### EDA for CAC Experiment Vs Prediction

```
y_cac = df['CAC Exp.']
model_cac = sm.OLS(y_cac, X).fit()
df['CAC Pred. Model'] = model_cac.predict(X)

# Evaluate the model for CAC
mae_cac = mean_absolute_error(y_cac, df['CAC Pred. Model'])
mse_cac = mean_squared_error(y_cac, df['CAC Pred. Model'])
rmse_cac = np.sqrt(mse_cac)
r2_cac = r2_score(y_cac, df['CAC Pred. Model'])

print("CAC Model Summary:")
print(model_cac.summary())

print(f"CAC Model Evaluation:\nMAE: {mae_cac}\nMSE: {mse_cac}\nRMSE: {rmse_cac}\nR-squared: {r2_cac}")

# Plot the experimental vs predicted for CAC
plt.figure(figsize=(8, 6))
sns.scatterplot(x=y_cac, y=df['CAC Pred. Model'])
plt.plot([y_cac.min(), y_cac.max()], [y_cac.min(), y_cac.max()], color='red', linestyle='--')
plt.xlabel('Experimental CAC')
plt.ylabel('Predicted CAC')
plt.title('Experimental vs Predicted CAC')
plt.show()
```



### Output Model Summary

CAC Model Summary:

OLS regression Results

Dep. Variable:	CAC Exp.	R-squared:	0.427			
Model:	OLS	Adj. R-squared:	0.320			
Method:	Least Squares	F-statistic:	3.977			
Date:	Sun, 20 Apr 2025	Prob (F-statistic):	0.0271			
Time:	16:45:55	Log-Likelihood:	-13.451			
No. Observations:	20	AIC:	34.90			
Df Residuals:	16	BIC:	38.08			
Df Model:	3					
Covariance Type:	nonrobust					

	coef	std err	t	P> t	[0.025	0.975]
const	98.9900	0.119	835.234	0.000	98.739	99.241
X1	0.3010	0.143	2.099	0.052	-0.003	0.605
X2	0.1801	0.143	1.256	0.227	-0.124	0.484
X3	-0.3499	0.143	-2.439	0.027	-0.654	-0.046

Omnibus:	1.850	Durbin-Watson:	0.779			
Prob(Omnibus):	0.396	Jarque-Bera (JB):	0.993			
Skew:	-0.037	Prob(JB):	0.609			
Kurtosis:	1.911	Cond. No.	1.21			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

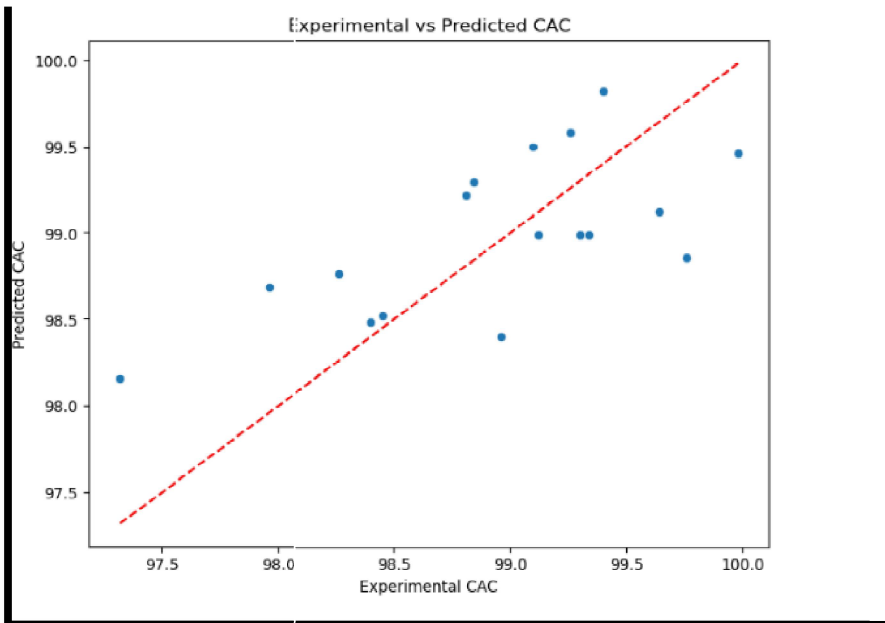
CAC Model Evaluation:

MAE: 0.4220838132283767

MSE: 0.22474309566663261

RMSE: 0.47407077073642984

R-squared: 0.42716298009134124



#### IV. CONCLUSION

The objective is to use the efficacy of low-cost adsorbent over commercial adsorbent for tannery dye removal from aqueous solutions. In this study the effects of variables, such as adsorbent dosage, dye concentration and contact time on dye removal by CNSC and CAC powder using CCD under RSM with statistical analysis were performed. From the results, the dye removal by CNSC was 98.5% attained at adsorbent dosage 6g/l, dye concentration 32.95mg/l with contact time 75mins. Similarly for ACS, 99.980% of dye removal was achieved at adsorbent dosage of 8g/l, dye concentration of 50mg/l with contact time 60mins for CAS. The regression coefficient ( $R^2$ ) value of 0.91 and 0.87 for CNSC and CAC, shows that experiments are statistically significant. The OLS regression analysis of the experimental data reveals that both CNSC-1 and CAC adsorbents are effective in removing dye from aqueous solutions, but their performance characteristics differ notably. CNSC-1 exhibits a strong dependency on process variables, particularly adsorbent dosage ( $X_1$ ) and contact time ( $X_3$ ), with higher values leading to significantly improved adsorption. The efficiency for CNSC-1 ranges more widely, indicating that careful optimization is necessary to achieve maximum performance. In contrast, CAC demonstrates consistently high adsorption efficiency (above 97%) across all experimental conditions, indicating a more stable and robust behavior with minimal sensitivity to variations in dye concentration, dosage, or contact time. The regression models for both materials show a good fit, with CAC having a slightly higher predictive accuracy ( $R^2 \approx 0.99$ ). Overall, CAC is recommended for applications requiring high and stable dye removal efficiency under varying conditions, while CNSC-1 may be a suitable and cost-effective alternative when operating parameters can be tightly controlled and optimized

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## APPENDIX

### SEM & EDS Analysis

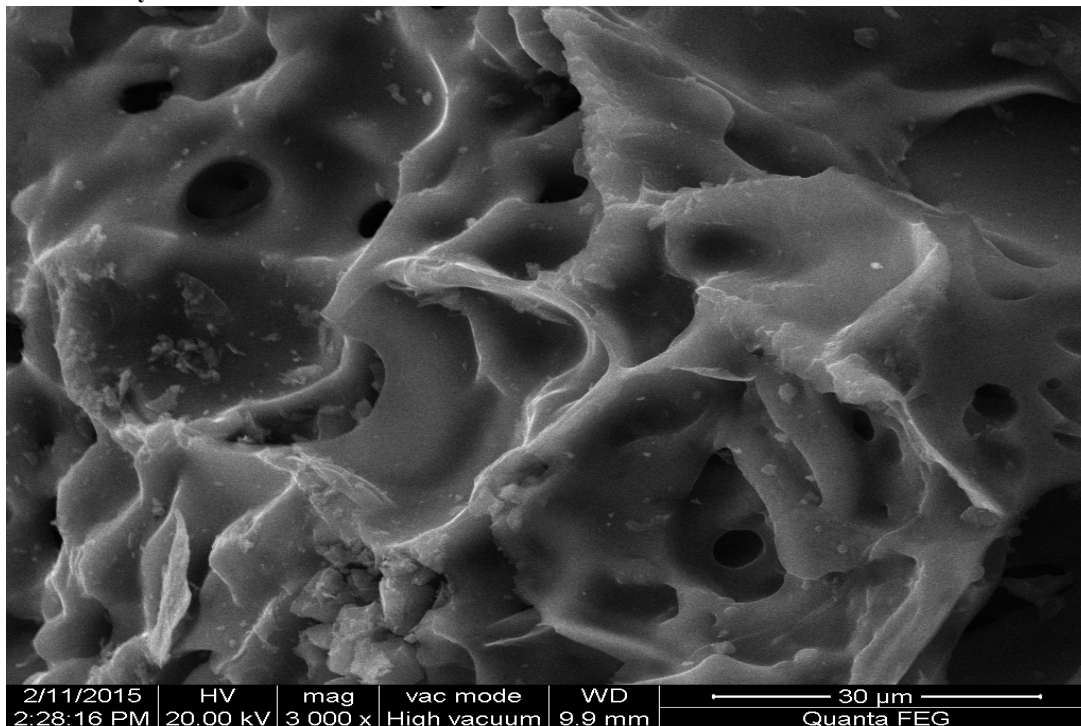


Figure 7 SEM analysis of CNSC before treatment

EDS Chart

Spectrum: training

El AN Series unn. C norm. C Atom. C Error (1 Sigma)

[wt. %] [wt. %] [at. %] [wt. %]

C 6 K-series 100.00 100.00 100.00 17.21

Total: 100.00 100.00 100.00



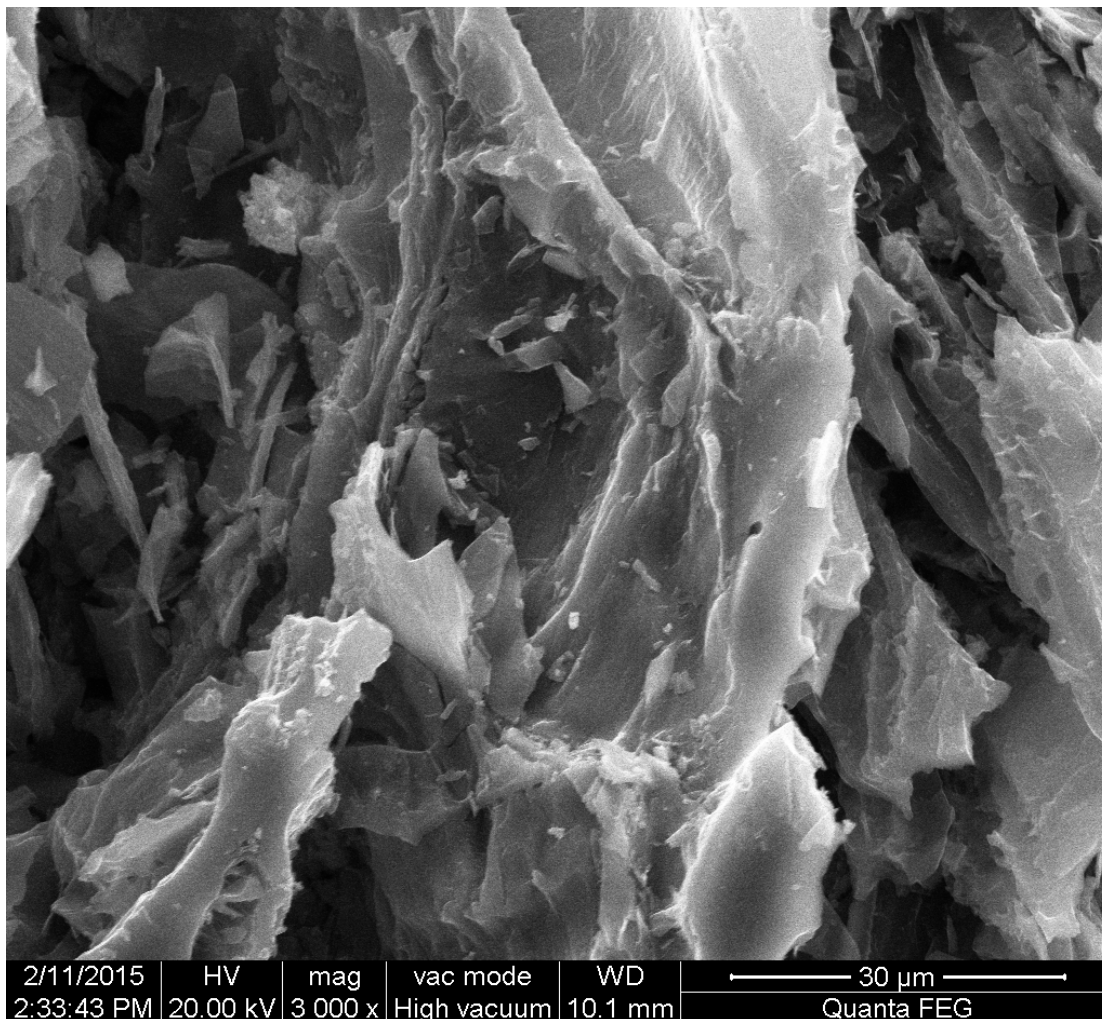


Figure 8 SEM analysis of CNSC after Dye treatment

EDS Chart

Spectrum: training

El AN Series un. C norm. C Atom. C Error (1 Sigma)

[wt. %] [wt. %] [at. %] [wt. %]

C 6 K-series 100.00 100.00 100.00 14.98

Total: 100.00 100.00 100.00





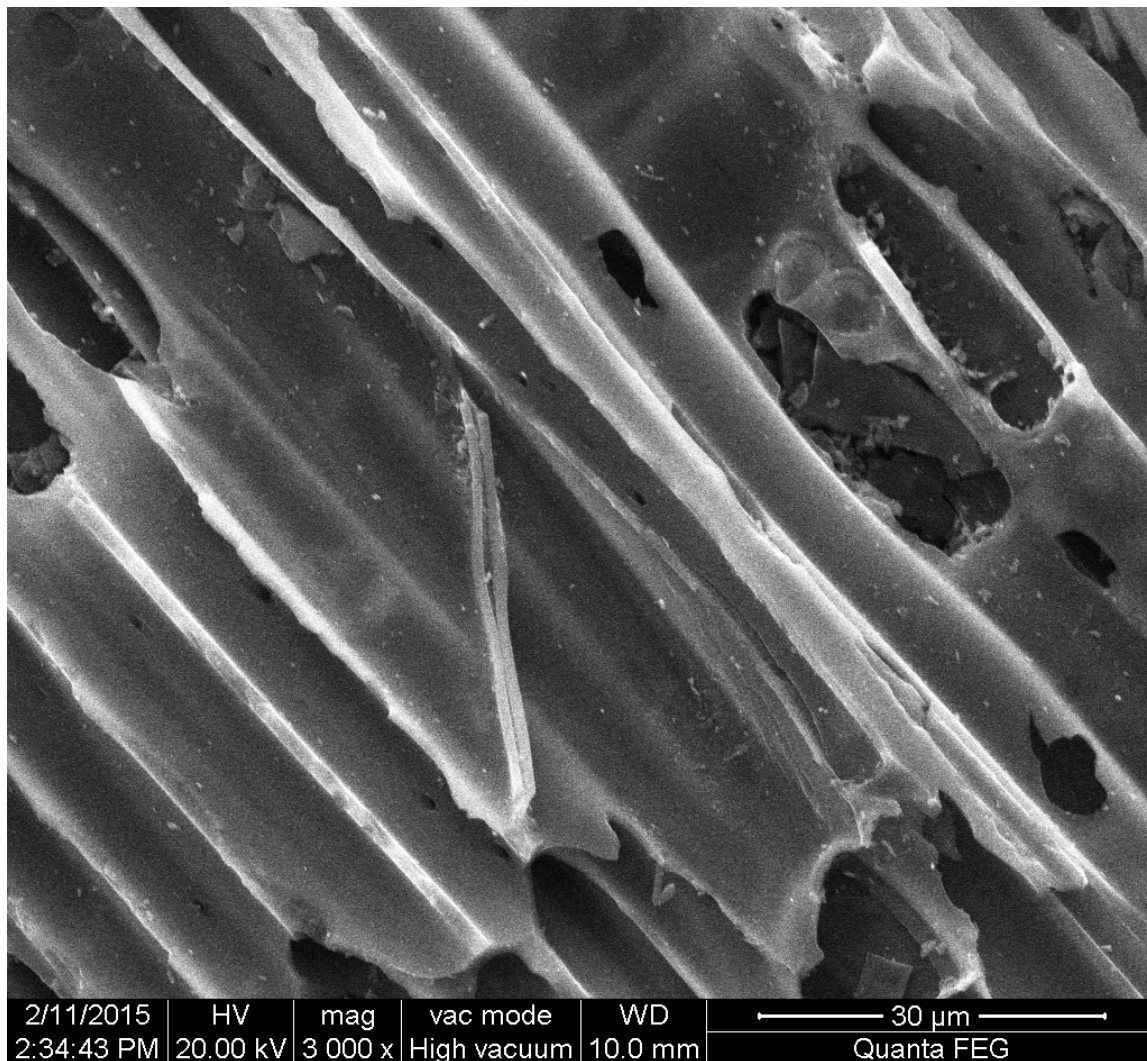


Figure 9 SEM analysis of CAC before Dye treatment

Table EDS Chart

Spectrum: training

El AN Series un. C norm. C Atom. C Error (1 Sigma)

[wt.%) [wt.%) [at.%) [wt.%)

-----  
C 6 K-series 100.00 100.00 100.00 14.88  
-----

Total: 100.00 100.00 100.00



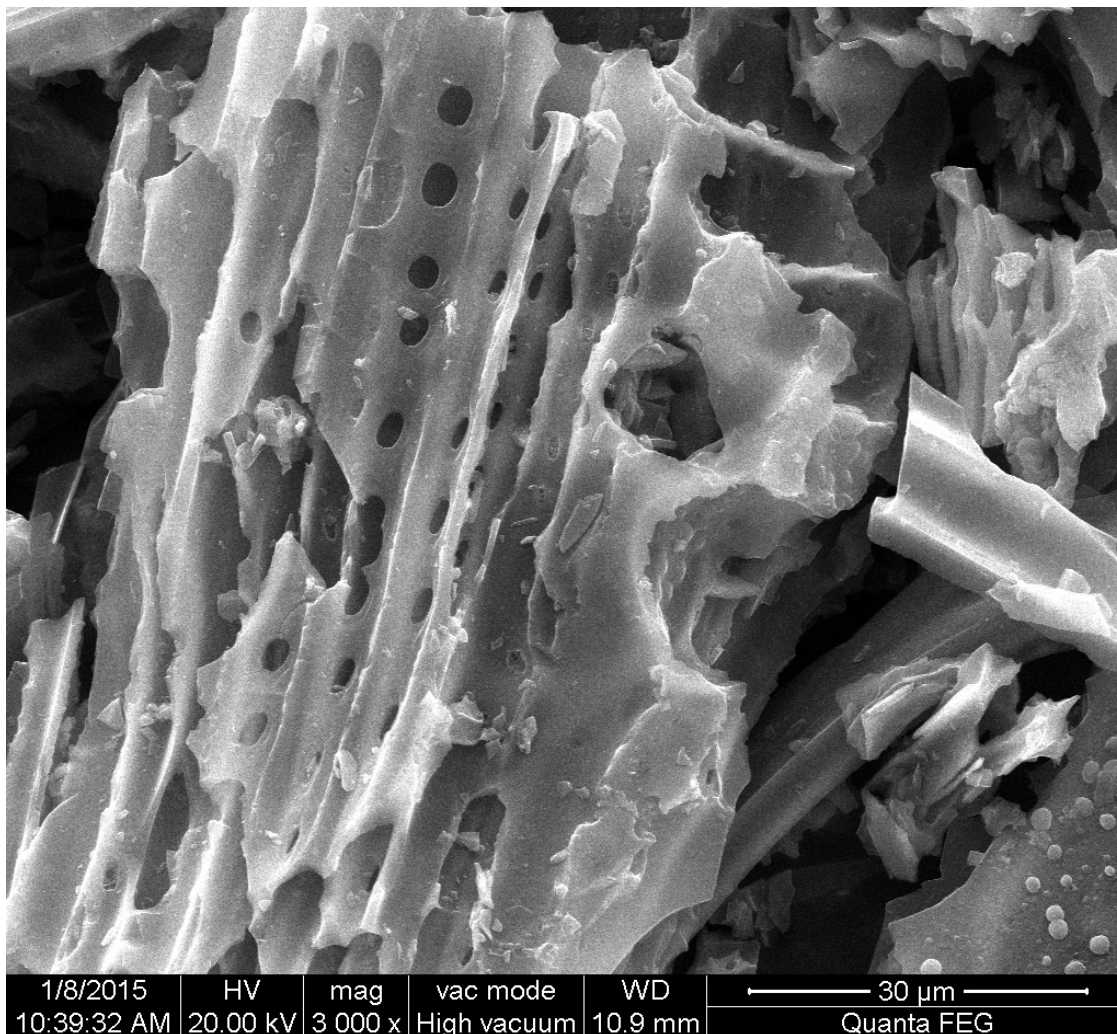


Figure 10 is the SEM analysis of CAC after treated with the dye.

#### EDS CHART

Spectrum: training

El AN Series unn. C norm. C Atom. C Error (1 Sigma)

[wt.%) [wt.%) [at.%) [wt.%)

C 6 K-series 100.00 100.00 100.00 13.89

Total: 100.00 100.00 100.00



### XRD Analysis

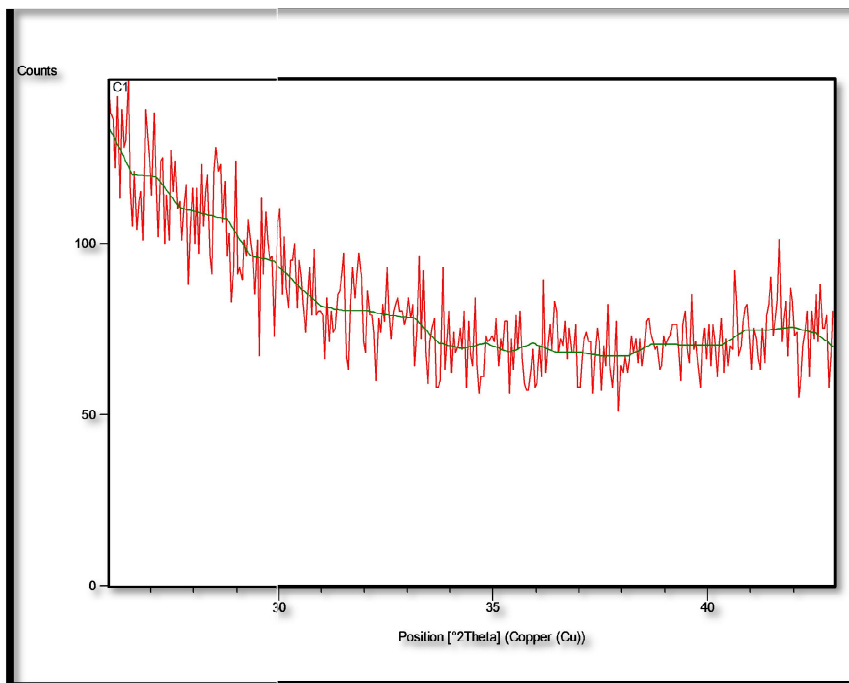


Figure 11 represents the XRD analysis of CNSC

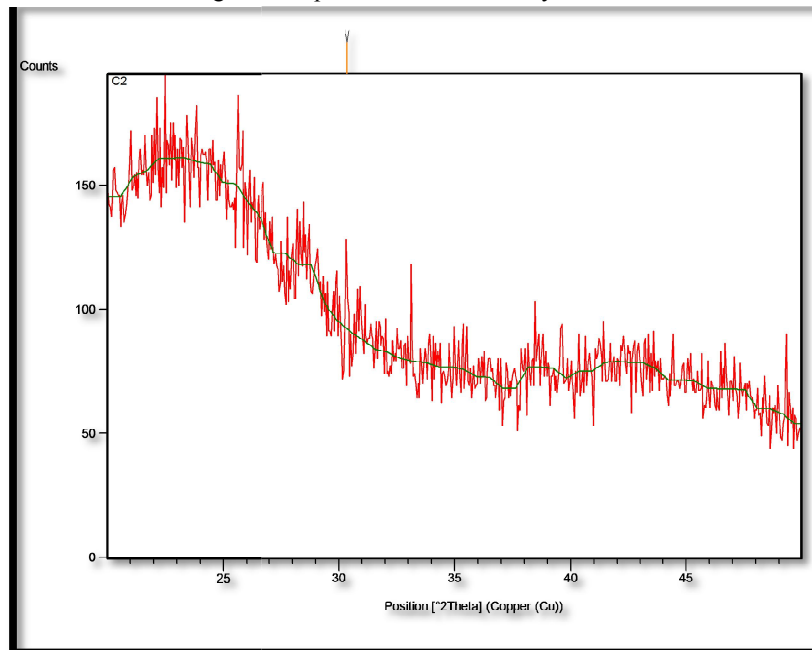


Figure 12 represents the XRD analysis of CNSC -Treated





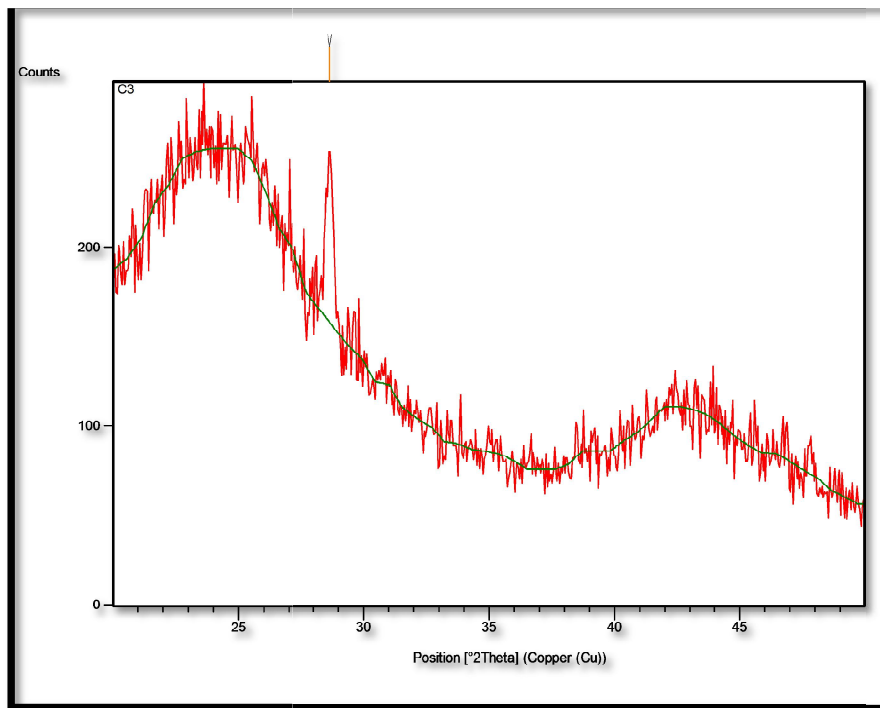


Figure 13 represents the XRD analysis of CAC

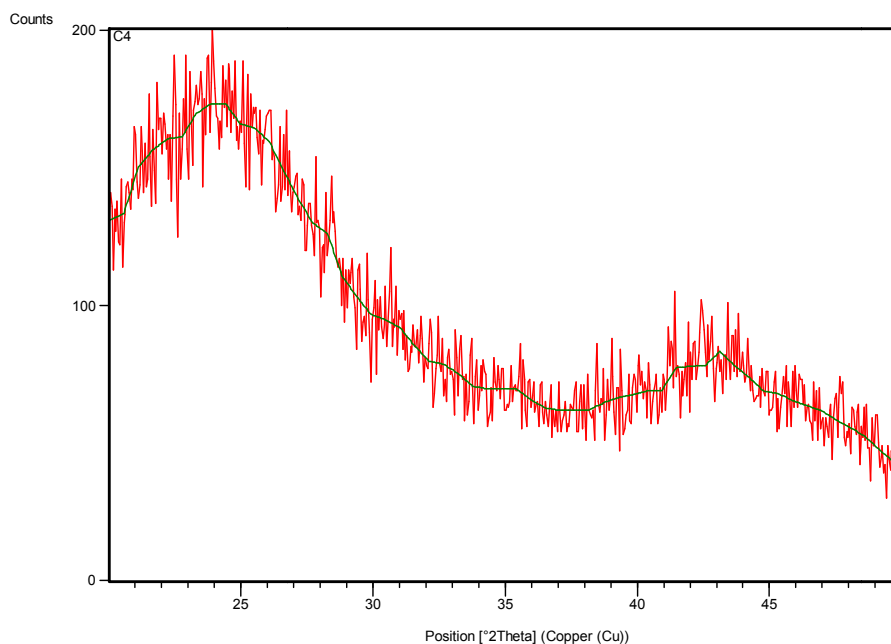


Figure 14 represents the XRD analysis of CAC –Treated





# FTIR ANALYSIS

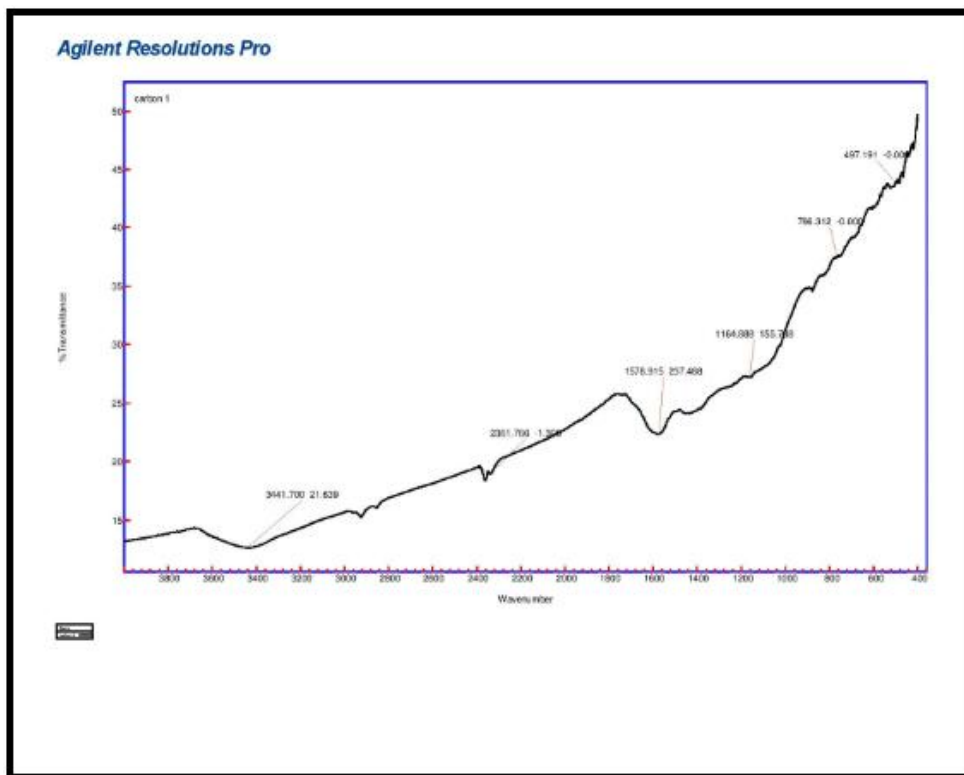


Figure 15 FTIR analysis of CNSC before treatment

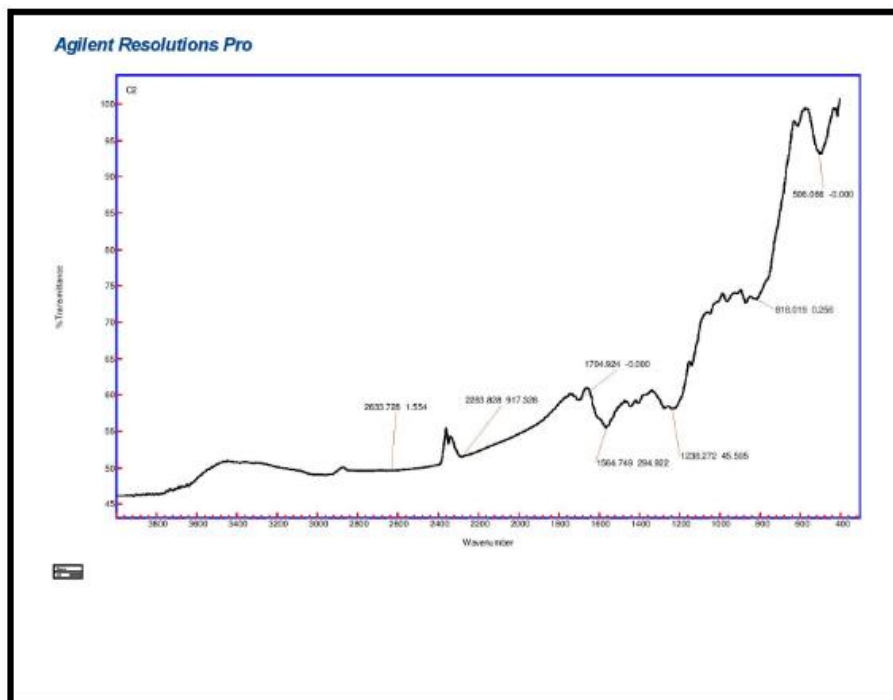


Figure 16 represents CNSC after dye treatment



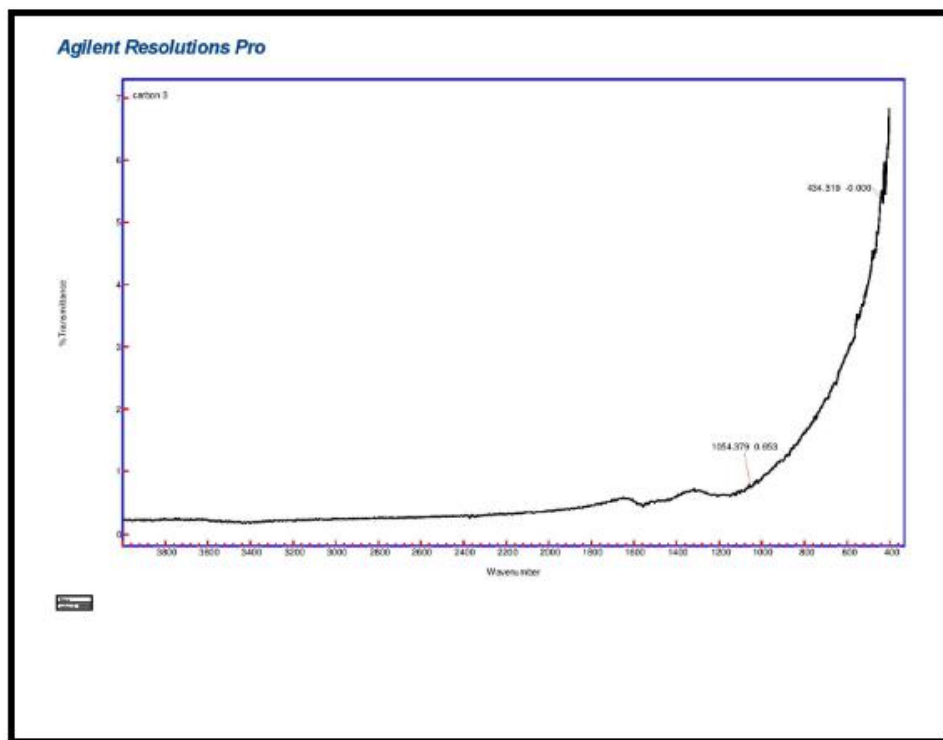


Figure 17 represents FTIR for CAC before treatment

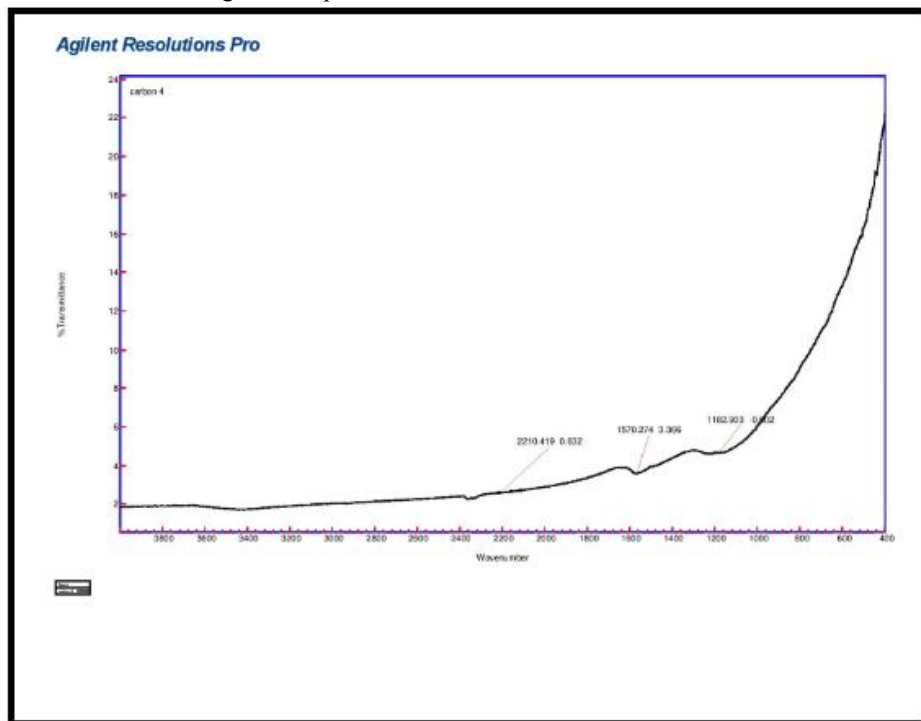


Figure 18 represents FTIR for CAC treated with the dye

