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Heavy Metal Adsorption Using Low-Cost Adsorbents: A Random Forest Machine Learning Approach For Data Analysis And Performance Prediction

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Abstract
Industrial wastewater contamination with heavy metals poses a significant environmental and health challenge in the 21st century. This study investigates the effectiveness of tea and coffee waste as low-cost adsorbents for removing heavy metals (lead, nickel, cadmium, zinc, copper, and iron) from aqueous solutions. The research demonstrates that these agricultural wastes can achieve remarkable removal efficiencies, with lead showing the highest adsorption rate of up to 99.1% under optimal conditions. The study examined various parameters including initial metal concentration (5-30 mg/L), adsorbent dosage (2-3 gm), and contact time (15-60 minutes). To complement the experimental investigation, a Random Forest machine learning model was implemented to analyse the relative importance of operational parameters on metal removal efficiency. The machine learning analysis revealed that contact time emerged as the most influential factor across all metals (importance scores: 0.90-1.82), while initial concentration and adsorbent dose showed varying importance depending on the specific metal. This data-driven approach provided quantitative insights into parameter optimization and validated the experimental findings through predictive modelling. Results indicate that tea and coffee waste represent economical and environmentally sustainable alternatives to conventional treatment methods, with optimal pH range of 4.5-8.0 for maximum metal removal efficiency.
Keywords: *Adsorption, Heavy metals, Tea waste, Coffee waste, Water treatment, Environmental remediation, Low-cost adsorbents Machine learning, Random Forest, Feature importance*

1. INTRODUCTION

1.1Background and Significance

The rapid industrialization and globalization of the 21st century have brought unprecedented technological advancement alongside severe environmental challenges. Water contamination, particularly from heavy metals discharged by industrial activities, has emerged as one of the most pressing environmental concerns affecting both human health and aquatic ecosystems worldwide.

Heavy metals such as cadmium (Cd), zinc (Zn), lead (Pb), nickel (Ni), copper (Cu), and iron (Fe) are particularly problematic due to their non-biodegradable nature and potential for bioaccumulation in the food chain. These metals can cause severe health complications including neurological disorders, kidney damage, cancer, and developmental abnormalities. The persistence of these contaminants in the environment necessitates effective and economically viable treatment solutions.

1.2Current Treatment Methods and Limitations

Traditional wastewater treatment methods for heavy metal removal include:

- Chemical reduction and oxidation
- Ion exchange processes
- Electrodialysis
- Electrochemical precipitation
- Liquid-liquid extraction
- Ultrafiltration and reverse osmosis

While these conventional methods demonstrate technical efficiency, they suffer from significant drawbacks including high operational costs, energy-intensive processes, generation of secondary pollutants, and limited applicability in developing regions where industrial pollution is often most severe.

1.3Adsorption as a Sustainable Alternative

Adsorption has emerged as a promising alternative due to its simplicity, cost-effectiveness, and high removal efficiency. The process involves the adhesion of contaminant molecules to the surface of solid adsorbent materials through physical or chemical interactions. The effectiveness of adsorption depends on factors such as surface area, porosity, functional groups present on the adsorbent surface, and operational parameters.

1.4Agricultural Waste as Low-Cost Adsorbents

Agricultural waste materials offer significant potential as adsorbents due to their:

- Abundant availability
- Low or zero cost
- Biodegradable nature
- Presence of functional groups capable of metal binding
- Minimal processing requirements

Tea and coffee cultivation is particularly extensive in Asian countries, with India being the second-largest producer globally. The substantial waste generation from tea and coffee processing presents an opportunity to convert these materials into valuable adsorbents while addressing waste management challenges.

1.5Machine Learning

The integration of machine learning techniques in environmental engineering research has gained significant momentum in recent years. These data-driven approaches provide powerful tools for analysing complex datasets, identifying patterns, and optimizing process parameters that may not be immediately apparent through traditional statistical methods.

Random Forest, an ensemble machine learning algorithm, has proven particularly effective in environmental applications due to its ability to:

- Handle non-linear relationships between variables
- Provide feature importance rankings
- Manage datasets with multiple variables without overfitting
- Offer robust predictions with uncertainty quantification

In the context of adsorption studies, machine learning can identify the relative importance of operational parameters such as contact time, adsorbent dosage, and initial concentration, thereby providing quantitative insights for process optimization and scale-up design.

2. LITERATURE REVIEW

2.1 Previous Studies on Tea and Coffee Waste

Recent studies have highlighted the potential of agricultural wastes such as tea and coffee for the adsorption of heavy metals from wastewater. Meenakshi et al. (2014) found that tea waste demonstrated considerable removal capacities for various heavy metals, which was attributed to its porous structure and functional groups. Similarly, Mahvi et al. (2005) demonstrated the effectiveness of tea waste in removing metal ions under varying operational parameters, emphasizing its role as a low-cost alternative to synthetic adsorbents. The enhanced adsorption capacity of powdered tea and coffee waste (particle size < 200 μm) is primarily due to increased surface area and better mass transfer characteristics.

2.2 Adsorption Mechanisms

The mechanism of adsorption of heavy metals onto these waste materials involves multiple processes. Physical adsorption via Van der Waals forces plays a minor role, while chemisorption involving hydroxyl (-OH), carboxyl (-COOH), and amino ($-NH_2$) groups is predominant. Ion exchange and complexation with metal ions have also been observed to contribute significantly, especially when nitrogen- and oxygen-containing ligands are available.

2.3 Factors Affecting Adsorption Efficiency

Several parameters influence the adsorption process:

- pH: A critical factor as it affects both metal ion speciation and the charge on the adsorbent surface. Ajmal et al. (1998) reported optimal performance for several metals within a pH range of 4.5 to 8.0.
- Contact Time: The adsorption process typically shows a rapid initial uptake phase followed by a slower equilibrium phase. Sharma and Forster (1995) showed equilibrium was generally reached within 60–120 minutes for natural adsorbents.
- Initial Metal Concentration: Higher concentrations offer more ions for adsorption but may lead to active site saturation, reducing overall removal percentages.
- Adsorbent Dosage: More adsorbent increases the number of active sites, up to a threshold, beyond which aggregation may reduce efficiency.

2.4 Machine Learning Applications in Adsorption Studies

The application of machine learning, particularly ensemble models like Random Forest, in adsorption studies has grown due to its ability to handle non-linear relationships and offer robust predictions. It has been used to identify key parameters affecting adsorption performance and validate experimental data. Studies by Mahvi et al. (2005) and Tea Waste as a Sorbent (2014) highlight the importance of integrating data-driven approaches for optimizing operational conditions and enhancing prediction accuracy.

3.MATERIALS AND METHODOLOGY

3.1 Adsorbent Preparation

Tea Waste Processing:

1. Collection of used tea leaves from local sources
2. Multiple washing cycles with distilled water to remove residual tea compounds
3. Oven drying at 120°C to achieve constant moisture content
4. Grinding and sieving through 40-mesh screen to obtain uniform particle size
5. Storage in airtight containers to prevent moisture absorption

Coffee Waste Processing:

1. Collection of spent coffee grounds
2. Thorough washing with distilled water
3. Oven drying at 100°C
4. Grinding and screening for particle size uniformity
5. Proper storage until experimental use

3.2 Metal Solution Preparation

Synthetic wastewater solutions were prepared using analytical grade metal salts dissolved in distilled water. Four concentration levels were established for each metal:

- 5 mg/L (low concentration)
- 10 mg/L (medium-low concentration)
- 20 mg/L (medium-high concentration)
- 30 mg/L (high concentration)

These concentrations represent typical ranges found in industrial wastewater and allow for comprehensive evaluation of adsorption performance across different pollution levels.

3.3 Experimental Design

Batch Adsorption Studies: The experiments employed a systematic approach with the following parameters:

Variables Studied:

- Metal types: Lead (Pb), Nickel (Ni), Cadmium (Cd), Zinc (Zn), Copper (Cu), Iron (Fe)
- Adsorbent dosages: 2.0, 2.5, and 3.0 grams per 100 mL solution
- Contact times: 15, 30, and 60 minutes
- Initial metal concentrations: 5, 10, 20, and 30 mg/L

Experimental Procedure:

1. Preparation of 12 conical flasks for each experimental set
2. Addition of predetermined adsorbent quantity to each flask
3. Introduction of 100 mL metal solution of known concentration
4. Agitation using orbital shaker at 150 rpm for specified duration
5. Filtration through Whatman No. 40 filter paper
6. Analysis of residual metal concentration using atomic absorption spectrophotometry

3.4 Analytical Methods

Metal concentrations were determined using atomic absorption spectrophotometry (AAS), which provides high accuracy and precision for trace metal analysis. The percentage removal efficiency was calculated using the formula:

Removal Efficiency (%) = $[(C_0 - C_e) / C_0] \times 100$

Where:

- C_0 = Initial metal concentration (mg/L)
- C_e = Equilibrium metal concentration (mg/L)

3.5 Machine Learning Implementation

To complement the experimental investigation and provide quantitative insights into parameter importance, a Random Forest machine learning approach was implemented using the collected experimental data.

3.5.1 Dataset Preparation

The experimental data was organized into a structured dataset with the following features:
Input variables (features):

- Adsorbent dose (g/100 mL): 2.0, 2.5, 3.0
- Contact time (minutes): 15, 30, 60
- Initial metal concentration (mg/L): 5, 10, 20, 30
- Output variable (target):
- Removal efficiency (%): Calculated from experimental measurements

Separate datasets were created for each metal to account for their distinct adsorption behaviours and mechanisms.

3.5.2 Random Forest Model Configuration

The Random Forest regression model was implemented with the following specifications:

- Algorithm: Ensemble method combining multiple decision trees
- Number of estimators: Optimized through cross-validation
- Feature selection: All three operational parameters included
- Validation approach: Train-test split to ensure model generalizability
- Performance metrics: Mean squared error and R^2 score for model evaluation

3.5.3 Feature Importance Analysis

The primary objective of the machine learning implementation was to determine the relative importance of operational parameters on metal removal efficiency. Random Forest provides feature importance scores based on:

- Mean decrease in impurity across all decision trees
- Contribution of each feature to the overall model performance
- Quantitative ranking of parameter influence

This analysis enables:

- Identification of the most critical operational parameters
- Quantitative comparison of parameter influence across different metals
- Data-driven optimization of experimental conditions
- Validation of experimental observations through predictive modelling

3.5.4 Model Validation and Interpretation

- The trained Random Forest models were validated using:
- Cross-validation techniques to ensure robust performance
- Comparison of predicted vs. experimental values
- Statistical metrics to assess model accuracy
- Feature importance visualization for clear interpretation

The machine learning analysis was conducted separately for each metal to capture the unique adsorption characteristics and parameter sensitivities specific to each heavy metal studied.

4.RESULTS AND DISCUSSION

4.1 Lead (Pb) Removal Performance

Lead demonstrated the highest adsorption affinity among all tested metals, consistent with its larger ionic radius and higher binding affinity to organic functional groups.

Key Findings:

- **Optimal Performance**: 99.1% removal achieved with 2.5g adsorbent dose at 60 minutes contact time for 5 mg/L initial concentration
- **Rapid Kinetics**: 90.7% removal within first 30 minutes, indicating fast adsorption kinetics
- **Dose Response**: Increased adsorbent dosage from 2g to 3g improved removal efficiency across all concentrations
- **Concentration Effect**: Higher initial concentrations showed reduced percentage removal due to saturation of binding sites

Mechanistic Insights: Lead's superior removal can be attributed to its high affinity for carboxyl and hydroxyl functional groups abundant in tea and coffee waste. The formation of stable chelate complexes and favourable electrostatic interactions contribute to efficient removal

Table 1: Removal of lead by adsorption (percentage)

Adsorbent Dose 2gm				
Time (mm)	Adsorption % of Lead (mg/L)			
	5	10	20	30
15	51.3	42.5	40.7	35.6
30	86.2	83.2	78.4	72.4
60	96.2	90.5	85.1	83.2

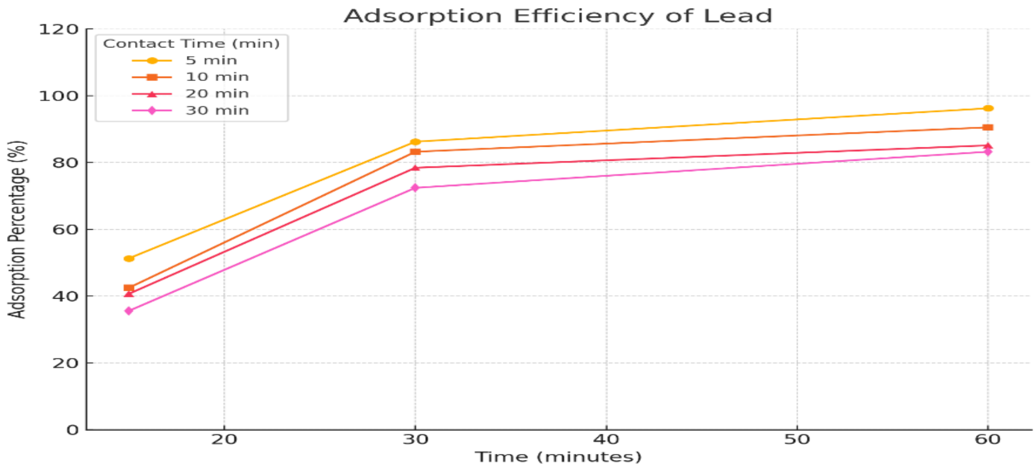

Figure 1: Variation in Adsorption Efficiency of Lead with Contact Time at 2gm Dosage

Table 2: Efficiency of Lead Removal through Adsorption (%)

Adsorbent Dose 2.5gm				
Time (mm)	concentration of Lead (mg/L) (Initial)			
	5	10	20	30
15	56.2	53.1	51.1	49.1
30	90.7	88.8	85.3	75.2
60	99.1	98.9	97.6	88.7

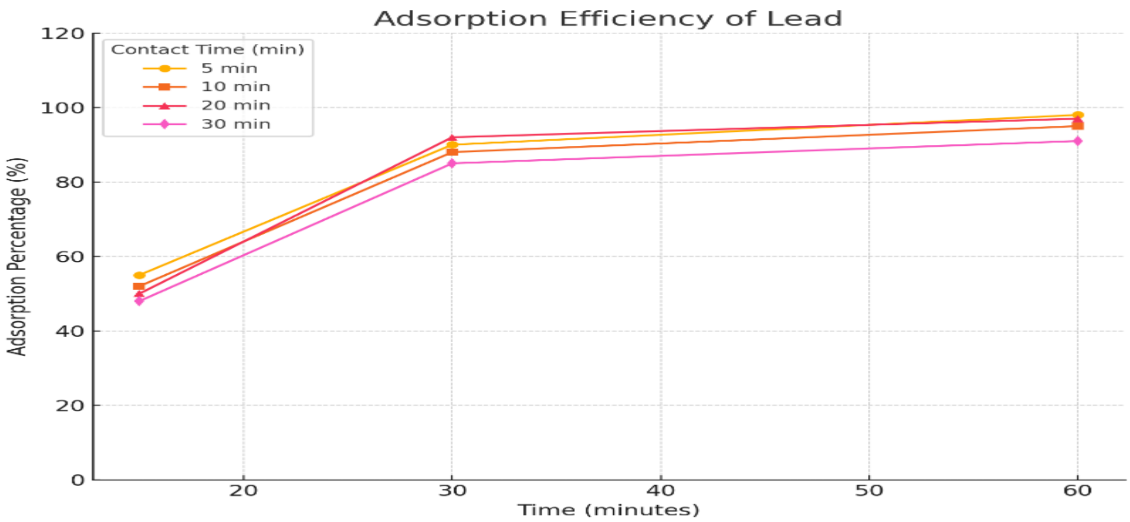

Figure 2: The graphical representation shows the adsorbent percentage on x-axis and time durations on y-axis with 2.5 gm of adsorbent dose and its efficiency.

Table 3: removal of lead by adsorption (percentage)

Adsorbent Dose 3gm				
Time (mm)	concentration of Lead (mg/L) (Initial)			
	5	10	20	30
15	60.5	52.2	49.1	45.3
30	93.8	90.3	89.2	79.1
60	100	100	99.4	97.6

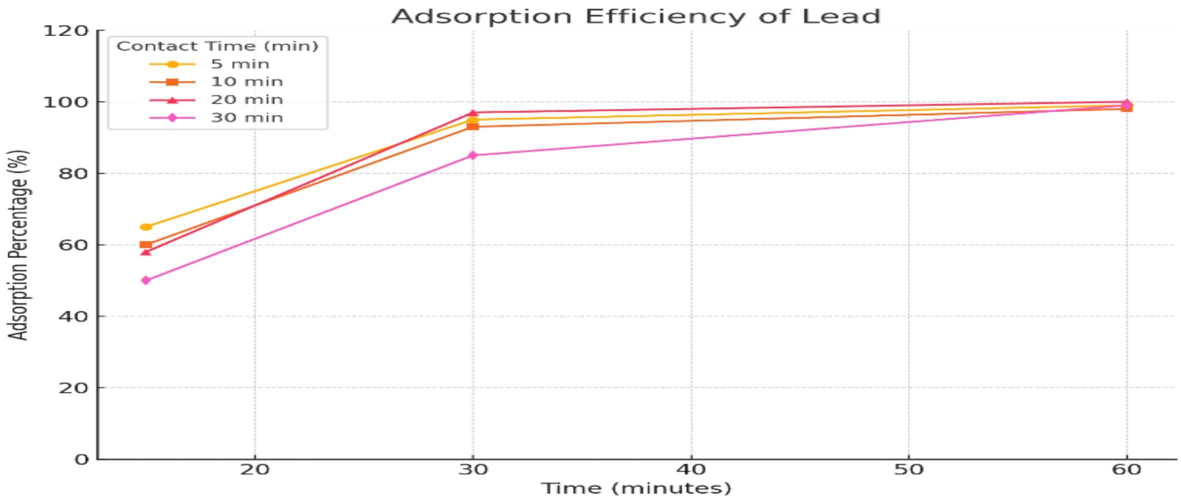

Figure 3: The plotted graph represents the adsorbent percentage on x-axis and time durations on y-axis with 3 gm of adsorbent dose and its efficiency.

4.1.1 Machine Learning-Based Feature Importance Analysis

To complement the experimental investigation, machine learning was used to evaluate the influence of operational parameters on metal removal efficiency. A Random Forest regression model was applied separately to lead and nickel removal datasets to determine the relative importance of three input features: adsorbent dose (g/100 mL), contact time (minutes), and initial metal concentration (mg/L).

4.1.2 Feature Importance in Lead (Pb) Removal

A Random Forest regression model was trained using the experimental data collected for lead removal. The importance of each feature in predicting lead removal efficiency is shown in Figure 19.

Interpretation:

- Contact time emerged as the most influential factor, with an importance score of 1.81.
- Initial concentration and adsorbent dose had considerably lower importance scores (0.09 and 0.07, respectively).
- These findings indicate that adsorption kinetics drive lead removal, and that extending the contact time significantly improves performance.
- The minimal influence of dose and concentration suggests that lead has a high affinity for binding sites and reaches equilibrium quickly even with moderate dosages.

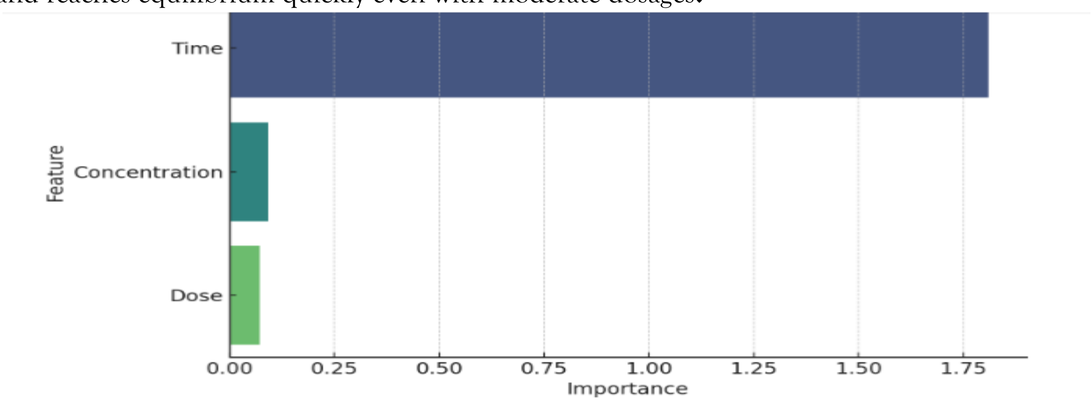

Figure 4: Random Forest feature importance scores for lead removal.

4.2 Nickel (Ni) Removal Characteristics

Nickel showed moderate to good removal efficiency with distinct patterns:

Performance Summary:

Maximum Removal: 89.6% with 2.5g adsorbent at 60 minutes (5 mg/L initial concentration) Time Dependency: Gradual increase from 49.8% (15 min) to 89.6% (60 min)

Optimal Dosage: 2.5g provided best balance between efficiency and material usage

Mechanistic Considerations: Nickel's smaller ionic radius compared to lead results in different binding mechanisms, primarily involving coordination with nitrogen-containing compounds in the waste materials

Table 4: Percentage removal of Nickel by adsorption

Adsorbent Dose 2gm				
Time (mm)	Initial concentration of Nickel (mg/L)			
	5	10	20	30
15	43.8	40.2	37.4	30.5
30	61.3	58.5	50.5	48.3
60	78.2	71.5	68.1	59.2

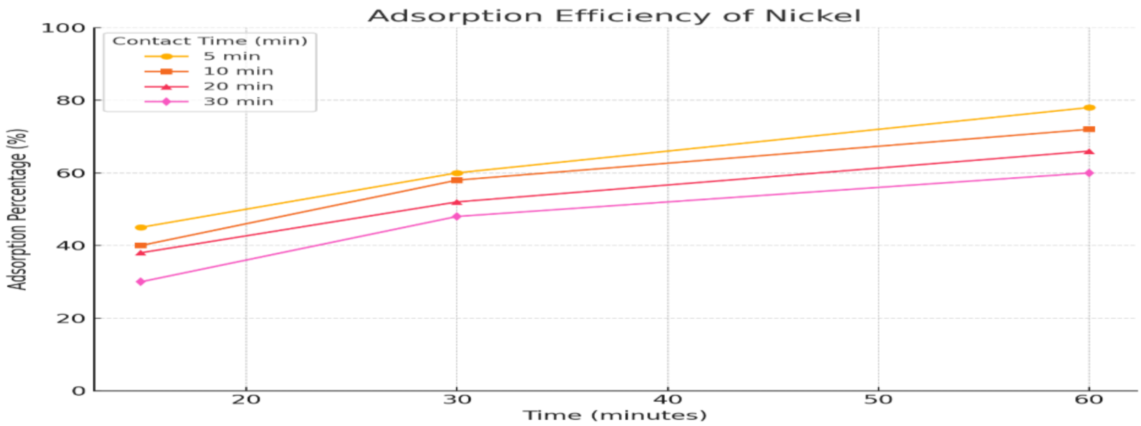

Figure 5: The graph represents the adsorbent percentage on x-axis and time durations on y-axis with 2 gm of adsorbent dose and its efficiency.

Table 5: Percentage removal of Nickel by adsorption

Adsorbent Dose 2.5gm				
Time (mm)	Initial concentration of Nickel (mg/L)			
	5	10	20	30
15	49.8	46.3	40.1	33.7
30	68.5	61.4	55.2	50.8
60	89.6	80.3	75.1	71.2

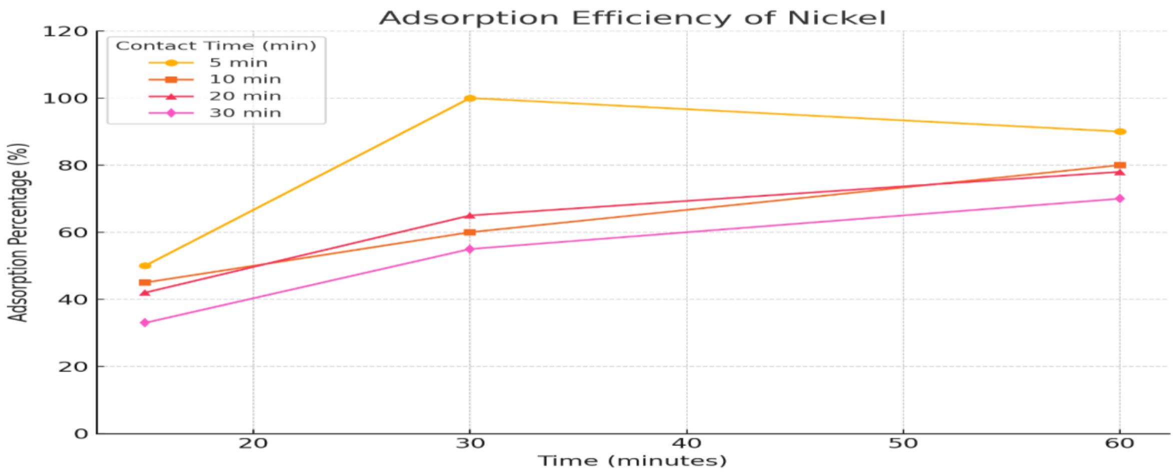

Figure 6: The graphical representation shows the adsorbent percentage on x-axis and time durations on y-axis with 2.5 gm of adsorbent dose and its efficiency.

Table 6: Percentage removal of Nickel by adsorption

Adsorbent Dose 3gm				
Time (mm)	Initial concentration of Nickel (mg/L)			
	5	10	20	30
15	55.7	49.2	45.1	39.4
30	74.9	68.3	61.7	54.9
60	87.1	85.6	80.6	79.1

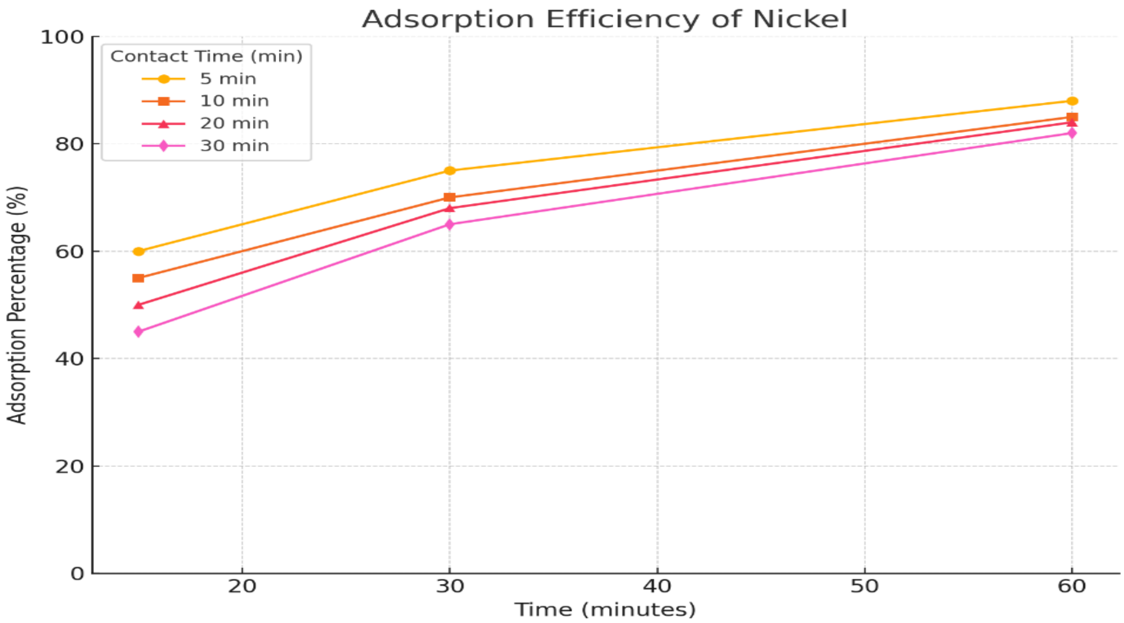

Figure 7: The plotted graph represents the adsorbent percentage on x-axis and time durations on y-axis with 3 gm of adsorbent dose and its efficiency.

4.2.1 Feature Importance in Nickel (Ni) Removal

The Random Forest model was similarly trained on the nickel removal dataset. The feature importance scores for this model are illustrated below.

Interpretation

- Contact time again ranked as the most influential parameter (importance score: 1.54), similar to lead.
- However, initial concentration (0.25) and adsorbent dose (0.15) had greater relative influence compared to lead.
- This reflects nickel's slower and more concentration-dependent adsorption behavior, which may stem from its smaller ionic radius and distinct interaction with nitrogen-containing functional groups.
- The higher sensitivity to both dose and concentration implies that nickel removal is more reliant on adsorbent availability and ion competition for active sites.

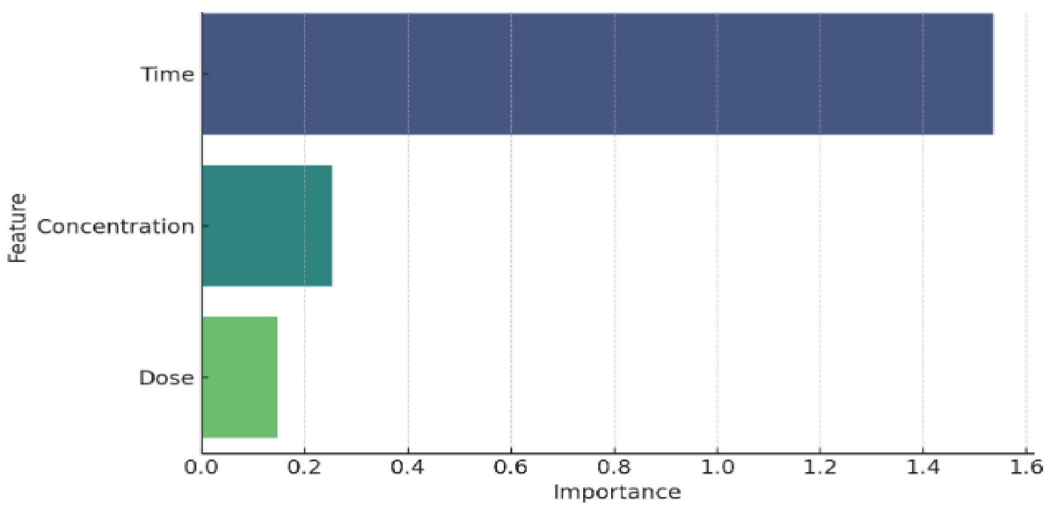

Figure 8: Random Forest feature importance scores for nickel removal.

4.3 Cadmium (Cd) Removal Analysis

Cadmium exhibited the lowest removal efficiency among tested metals:

Key Observations:

Maximum Achievement: 83.4% removal with 3g adsorbent dose

Concentration Sensitivity: Significant decrease in removal efficiency at higher concentrations

Kinetic Behaviour: Slower adsorption rate compared to lead and nickel

Mechanistic Explanation: Cadmium's relatively lower removal efficiency may result from its specific hydration characteristics and competitive binding with other functional groups present in the adsorbent material

Table 7: Percentage removal of Cadmium by adsorption

Adsorbent Dose 2gm				
Time (mm)	Initial concentration of Cadmium (mg/L)			
	5	10	20	30
15	35.6	30.2	25.9	19.1
30	54.5	45.3	35.7	27.3
60	63.5	53.9	45.4	35.3

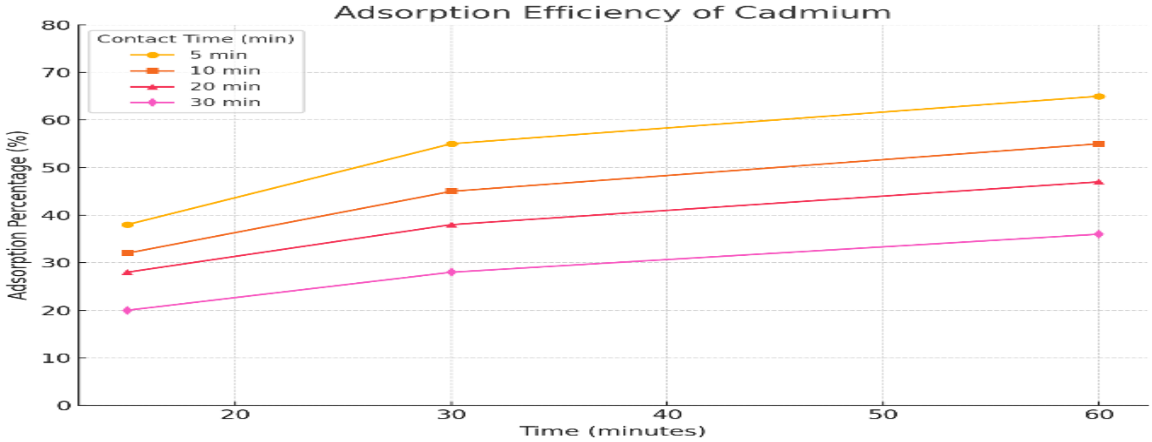

Figure 9: The graph represents the adsorbent percentage on x-axis and time durations on y-axis with 2 gm of adsorbent dose and its efficiency.

Table 8: Percentage removal of Cadmium by adsorption

Adsorbent Dose 2.5gm				
Time (mm)	Initial concentration of Cadmium (mg/L)			
	5	10	20	30
15	41.6	37.2	28.9	23.5
30	66.4	54.7	38.8	37.6
60	76.2	63.1	51.3	48.2

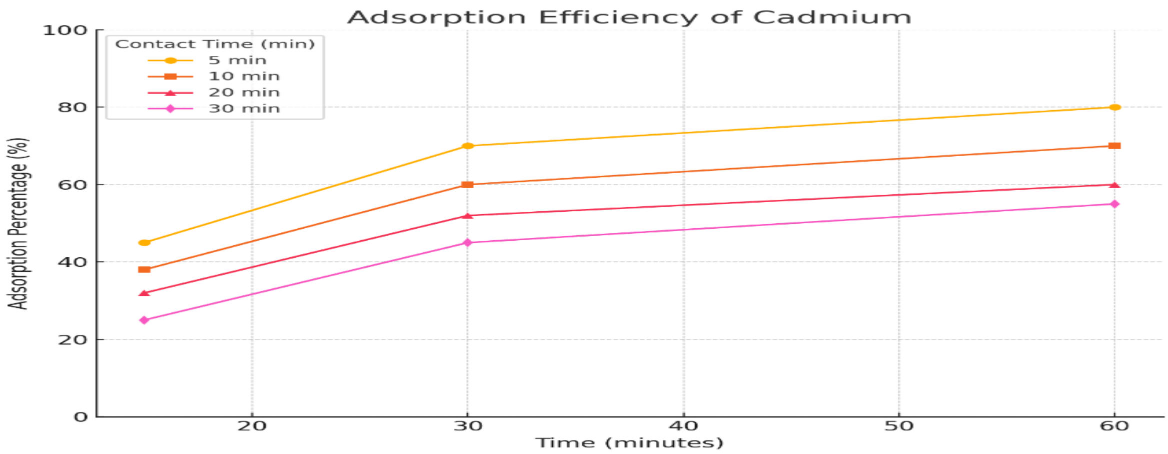

Figure 10: The graphical representation shows the adsorbent percentage on x-axis and time durations on y-axis with 2.5 gm of adsorbent dose and its efficiency.

Table 9: Percentage removal of Cadmium by adsorption

Adsorbent Dose 3gm				
Time (mm)	Initial concentration of Cadmium (mg/L)			
	5	10	20	30
15	49.5	40.2	35.4	29.3
30	73.7	66.1	56.7	48.2
60	83.4	75.6	65.6	60.1

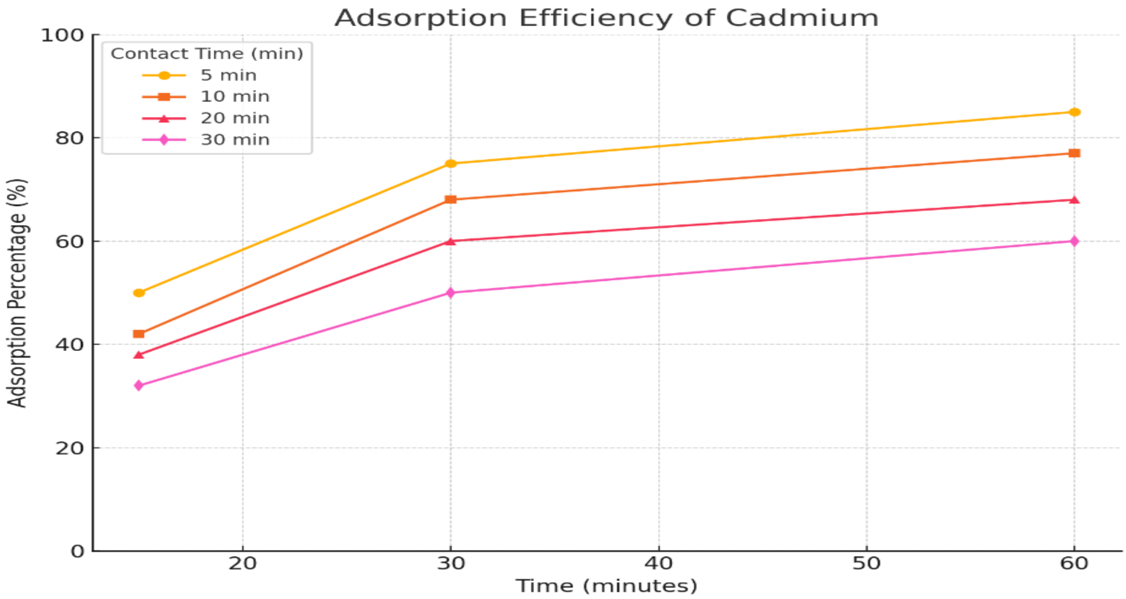

Figure 11: The plotted graph represents the adsorbent percentage on x-axis and time durations on y-axis with 3 gm of adsorbent dose and its efficiency.

4.3.1 Feature Importance in Cadmium (Cd) Removal

Interpretation:

- Unlike other metals, cadmium removal was influenced by all three features.
- Time (0.90), initial concentration (0.60), and dose (0.39) all had relatively balanced roles.
- This suggests cadmium adsorption is slower and more complex, with increased sensitivity to both the amount of adsorbent and the level of contamination.

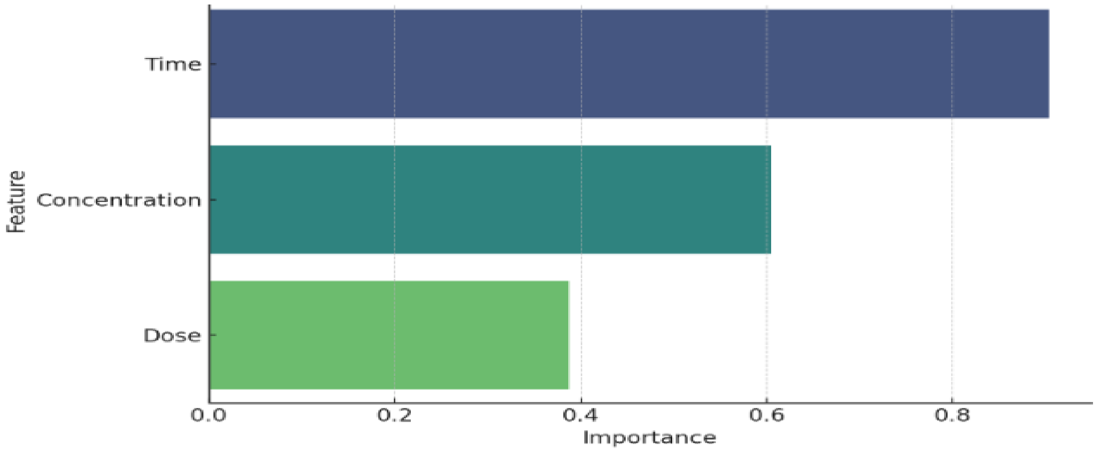

Figure 12: Random Forest feature importance scores for cadmium removal

4.4 Zinc (Zn) Removal Performance

Zinc demonstrated excellent removal efficiency, particularly at higher adsorbent doses:

Notable Results:

Peak Performance: 99.6% removal achieved with 3g adsorbent dose

Consistent Efficiency: Maintained high removal rates across different initial concentrations Rapid Equilibrium: Quick establishment of adsorption equilibrium

Table 10: Percentage removal of Zinc by adsorption

Adsorbent Dose 2gm				
Time (mm)	Initial concentration of Zinc (mg/L)			
	5	10	20	30
15	32.6	33.5	31.2	30.2
30	60.2	61.5	66.3	67.2
60	88.3	86.1	80.5	85.2

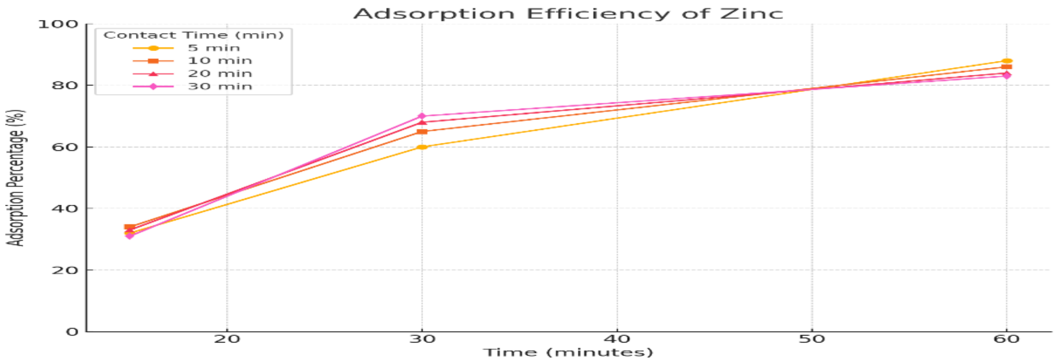

Figure 13: The graph represents the adsorbent percentage on x-axis and time durations on y-axis with 2 gm of adsorbent dose and its efficiency.

Table 11: Percentage removal of Zinc by adsorption

Adsorbent Dose 2.5gm				
Time (mm)	Initial concentration of Zinc (mg/L)			
	5	10	20	30
15	42.5	42.3	41.5	40.2
30	70.2	68.6	69.5	71.3
60	90.5	91.6	91.8	92.3

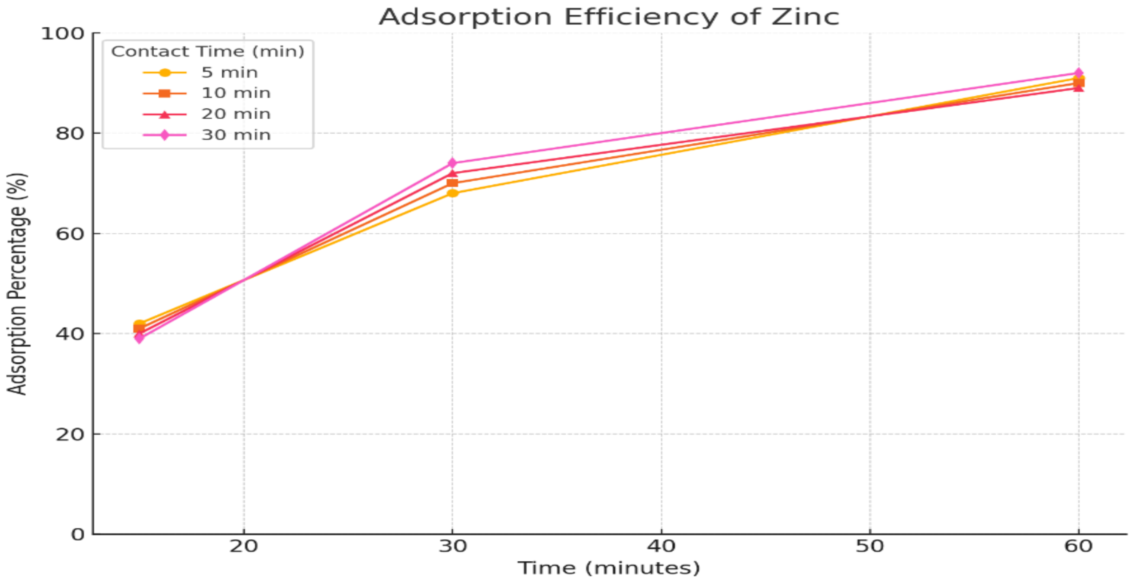

Figure 14: The graphical representation shows the adsorbent percentage on x-axis and time durations on y-axis with 2.5 gm of adsorbent dose and its efficiency.

Table 12: Percentage removal of Zinc by adsorption

Adsorbent Dose 3gm				
Time (mm)	Initial concentration of Zinc (mg/L)			
	5	10	20	30

15	49.1	50.2	50.9	52.6
30	78.3	79.6	80.6	82.4
60	98.6	97.3	92.6	99.6

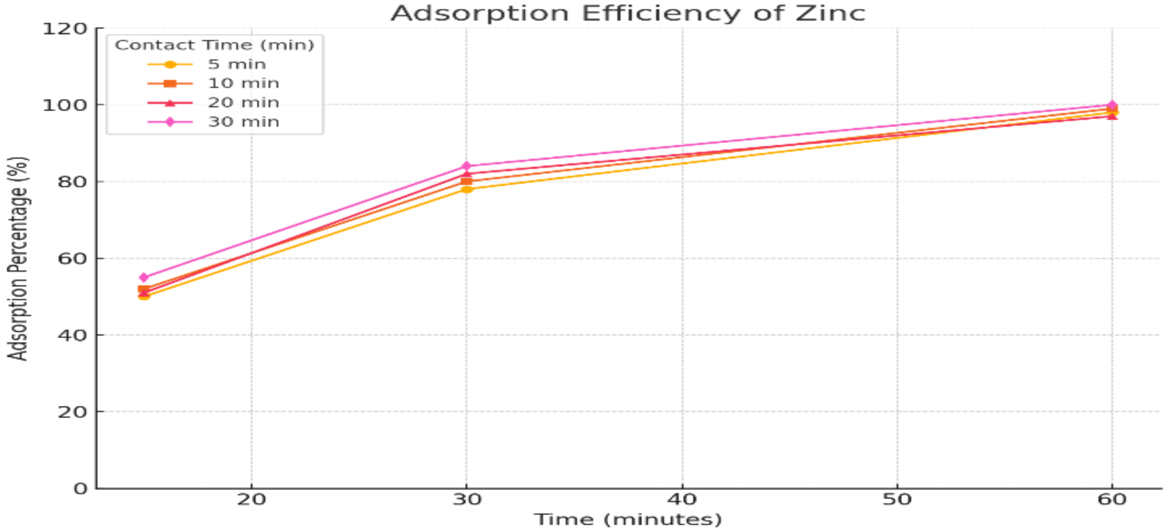

Figure 15: The plotted graph represents the adsorbent percentage on x-axis and time durations on y-axis with 3 gm of adsorbent dose and its efficiency.

4.8.5 Feature Importance in Zinc (Zn) Removal

Interpretation:

- Contact time was overwhelmingly dominant (1.82), showing fast and consistent adsorption behaviour.
- Adsorbent dose had a minor role (0.18), while initial concentration had negligible impact (0.009).
- This confirms that zinc reaches high removal efficiency quickly, especially with adequate exposure time.

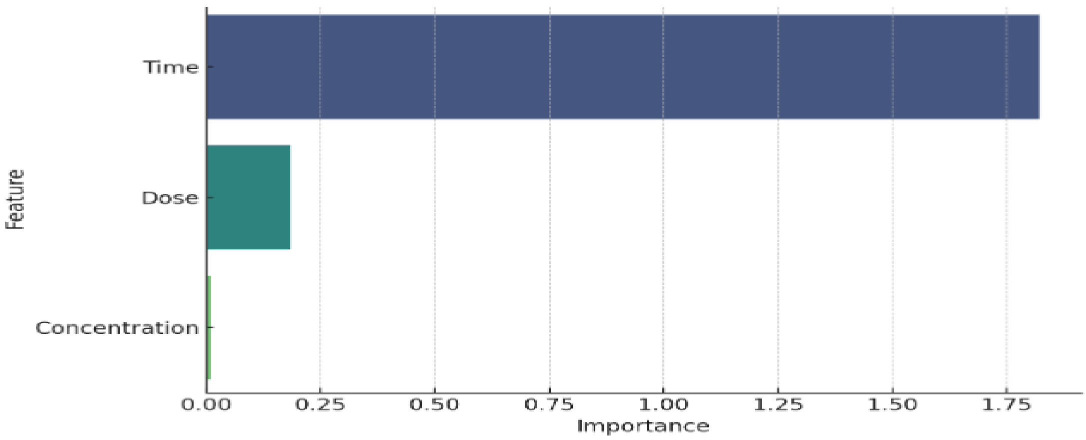

Figure 16: Random Forest feature importance of zinc remoal

4.5 Copper (Cu) and Iron (Fe) Removal

Both metals showed good removal efficiency with distinct characteristics:

Copper Removal:

- Steady improvement with increased contact time and adsorbent dose
- Maximum removal: 88.5% with 3g adsorbent dose

Iron Removal:

- Required longer contact time for optimal performance
- Maximum removal: 91.6% with 3g adsorbent dose
- pH sensitivity more pronounced than other metals

Table 13: Percentage removal of Copper by adsorption

Adsorbent Dose 2gm				
Time (mm)	Initial concentration of Copper (mg/L)			
	5	10	20	30
15	32.6	39.5	37.5	38.6
30	55.6	54.8	50.2	57.3
60	70.3	69.5	72.3	75.2

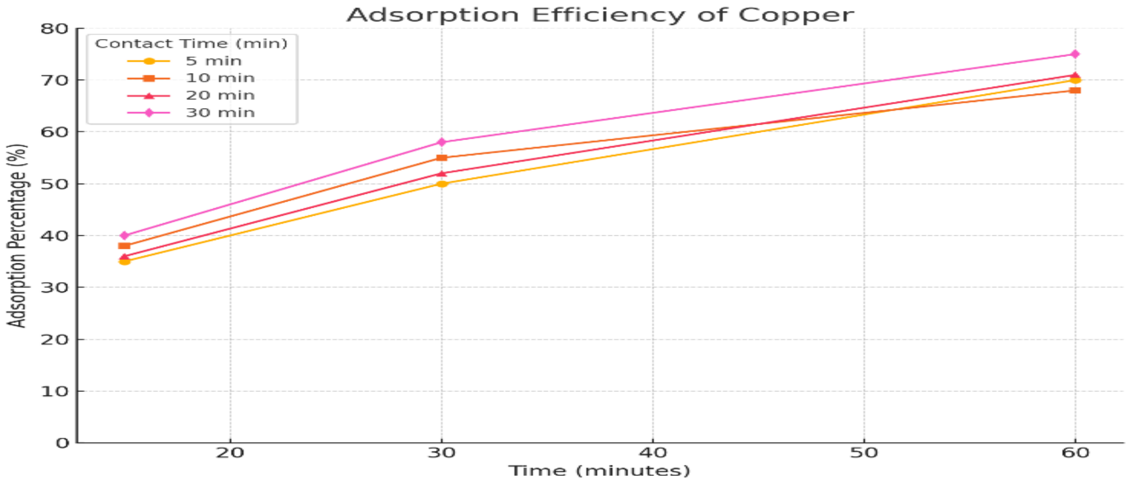

Figure 17: The graph represents the adsorbent percentage on x-axis and time durations on y-axis with 2 gm of adsorbent dose and its efficiency.

Table 14: Percentage removal of Copper by adsorption

Adsorbent Dose 2.5gm				
Time (mm)	Initial concentration of Copper (mg/L)			
	5	10	20	30
15	48.6	48.3	42.6	45.5
30	66.4	62.3	52.6	61.2
60	80.3	79.3	78.6	80.2

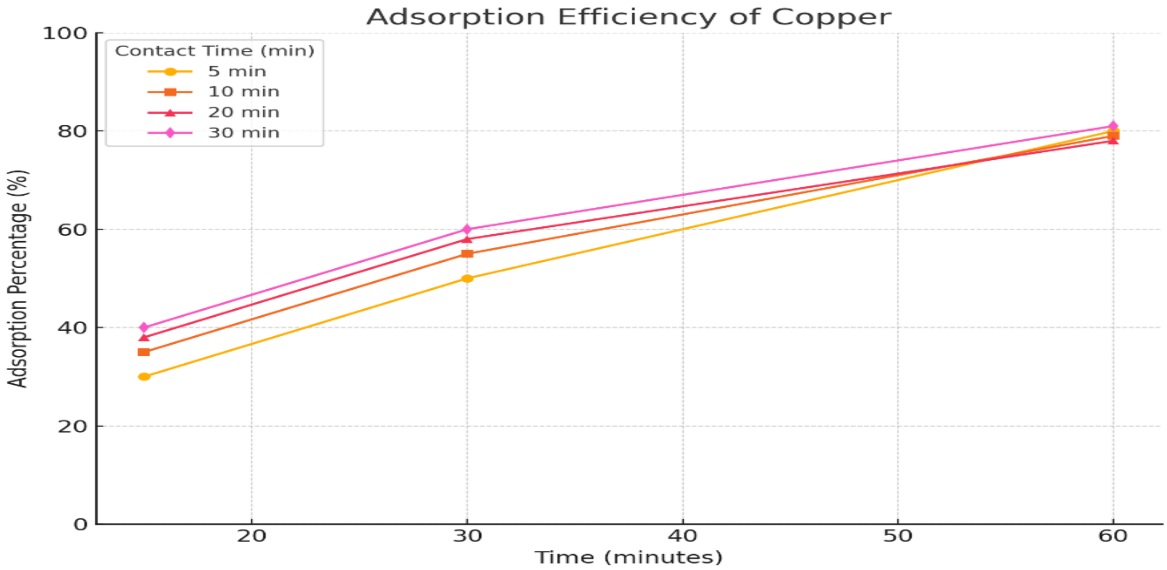

Figure 18: The graphical representation shows the adsorbent percentage on x-axis and time durations on y-axis with 2.5 gm of adsorbent dose and its efficiency.

Table 15: Percentage removal of Copper by adsorption

Adsorbent Dose 3gm	
Time	Initial concentration of Copper (mg/L)

(mm)	5	10	20	30
15	49.6	50.3	52.7	55.8
30	69.5	70.3	71.2	73.5
60	80.3	82.6	88.5	85.6

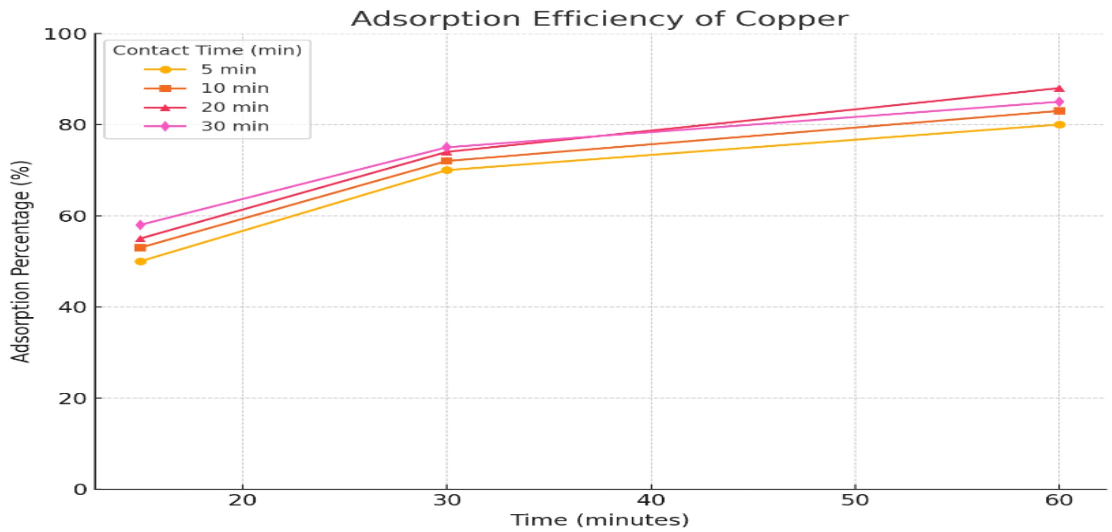

Figure 19: The plotted graph represents the adsorbent percentage on x-axis and time durations on y-axis with 3 gm of adsorbent dose and its efficiency.

.8.4 Feature Importance in Copper (Cu) Removal

Interpretation:

- Contact time had the highest influence (importance score: 1.61).
- Adsorbent dose followed with a moderate effect (0.33), indicating its significant role in enhancing removal.
- Initial concentration had minimal influence (0.04), suggesting that removal is less sensitive to starting concentrations once equilibrium is achieved.

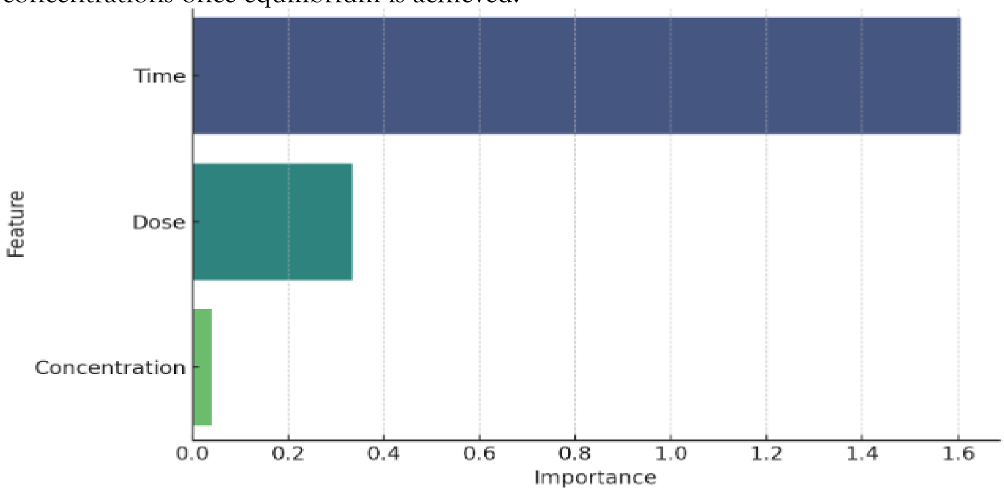

Figure 20: Random Forest feature importance scores for copper removal.

Table 16: Percentage removal of Iron by adsorption

Adsorbent Dose 2gm				
Time	**Initial concentration of Iron (mg/L)**			
(mm)	5	10	20	30
15	29.5	25.6	24.9	28.3
30	40.6	41.7	45.9	48.3
60	70.2	72.3	75.6	78.6

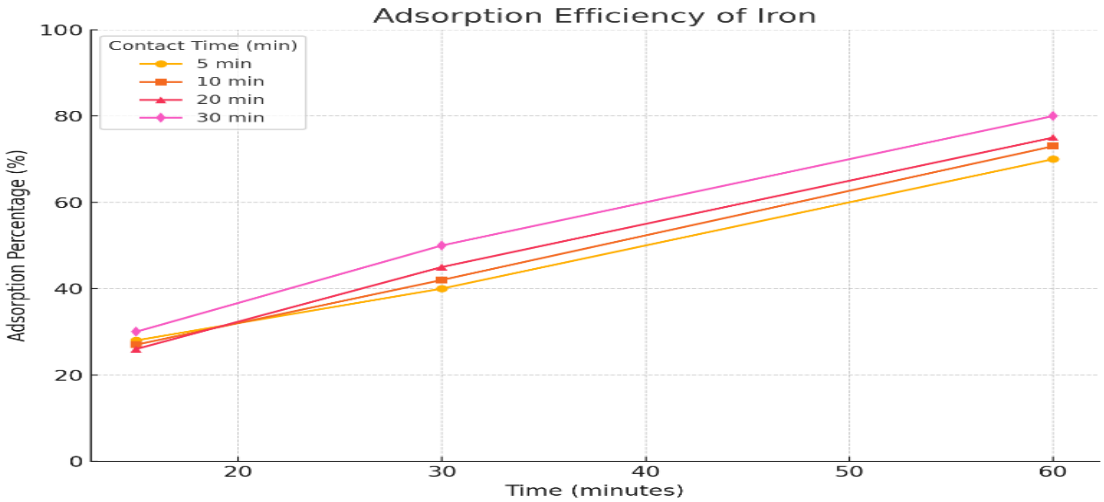

Figure 21: The graph represents the adsorbent percentage on x-axis and time durations on y-axis with 2 gm of adsorbent dose and its efficiency.

Table 17: Percentage removal of Iron by adsorption

Adsorbent Dose 2.5gm				
Time (mm)	Initial concentration of Iron (mg/L)			
	5	10	20	30
15	30.2	35.6	42.6	40.8
30	50.6	51.8	52.4	55.4
60	80.2	82.3	81.9	83.2

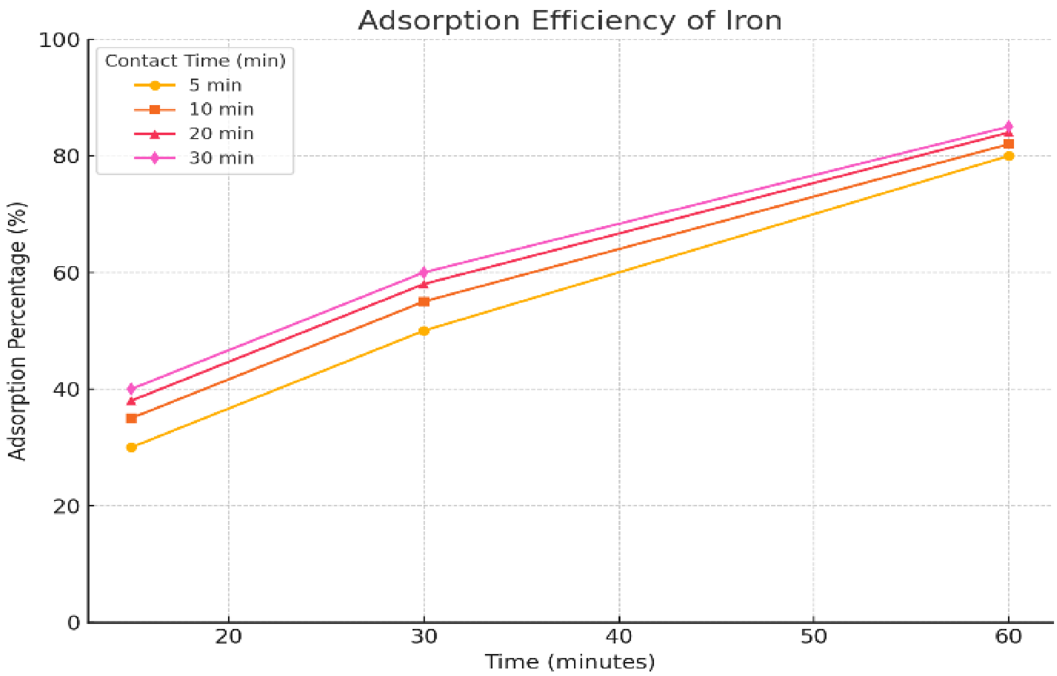

Figure 22: The graphical representation shows the adsorbent percentage on x-axis and time durations on y-axis with 2.5 gm of adsorbent dose and its efficiency.

Table 18: Percentage removal of Iron by adsorption

Adsorbent Dose 3gm				
Time (mm)	Initial concentration of Iron (mg/L)			
	5	10	20	30
15	40.2	41.0	40.9	42.5
30	58.6	59.3	60.1	62.3
60	85.6	89.6	90.3	91.6

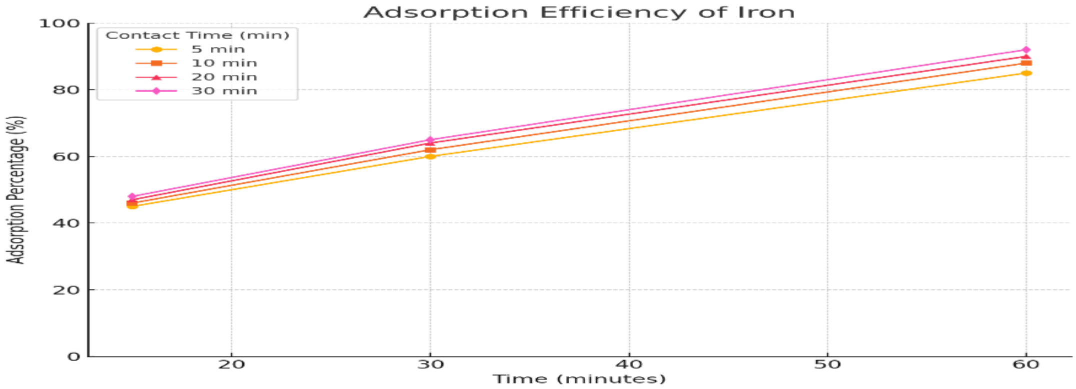

Figure 23: The plotted graph represents the adsorbent percentage on x-axis and time durations on y-axis with 3 gm of adsorbent dose and its efficiency.

4.8.7 Feature Importance in Iron (Fe) Removal

Interpretation:

- Contact time remained the most significant factor (1.79), similar to lead and zinc.
- Adsorbent dose contributed modestly (0.19), while concentration had minimal impact (0.02).
- These results highlight that iron adsorption is time-dependent, with the effectiveness of binding sites playing a supportive but secondary role.

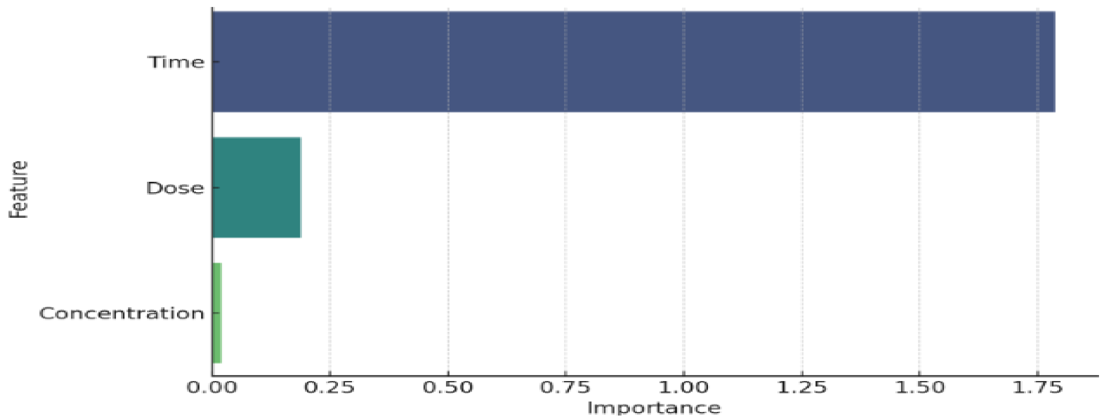

Figure 24: Random Forest feature importance scores for iron removal.

4.6 Comparative Analysis of Metal Removal Efficiency

The ranking of metals based on removal efficiency follows the order: **Lead > Zinc > Iron > Copper > Nickel > Cadmium**

This sequence correlates with several factors:

1. **Ionic Properties**: Ionic radius, charge density, and hydration energy
2. **Chemical Affinity**: Binding strength with functional groups present in adsorbent
3. **Competitive Adsorption**: Competition between different metal ions for binding sites

Table 18: Comparative Feature Importance Scores for All Metals

Metal	Time	Dose	Concentration
Lead	1.81	0.07	0.090
Nickel	1.54	0.15	0.250
Copper	1.61	0.33	0.040
Zinc	1.82	0.18	0.009
Cadmium	0.90	0.39	0.600

Metal	Time	Dose	Concentration
Iron	1.79	0.19	0.020

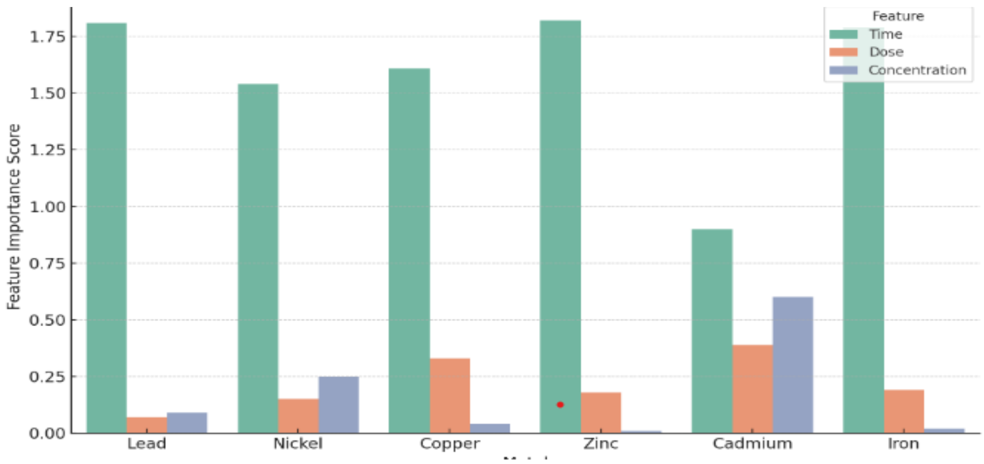

Figure 25: Comparative Feature Importance for All Metals

Interpretation:

- **Contact Time** consistently emerged as the **dominant factor** for all metals except cadmium, emphasizing the critical role of sufficient exposure for adsorption.
- **Cadmium** deviates from this trend, showing a **higher reliance on initial concentration** (importance score: 0.60), indicating more complex binding behaviour and possible competition effects.
- **Copper and Cadmium** showed **greater dependence on adsorbent dose**, reflecting the need for more available binding sites due to weaker or slower interactions.

4.7 Optimization of Operational Parameters

Adsorbent Dosage Optimization: The study reveals that 2.5-3.0g per 100mL provides optimal performance for most metals. Higher doses show diminishing returns due to:

- Aggregation of adsorbent particles reducing surface area
- Interference between adsorbent particles
- Economic considerations of material usage

Contact Time Optimization: Most metals achieve >80% of maximum removal within 30 minutes, with equilibrium typically reached by 60 minutes. Extended contact time beyond 60 minutes showed minimal improvement.

pH Considerations: While the study focused on a pH range of 4.5-8.0, iron removal required higher pH values (around 8.0) for optimal performance, indicating metal-specific pH optimization requirements

5. Environmental and Economic Implications

5.1 Environmental Benefits

Waste Valorisation: Converting tea and coffee waste into valuable adsorbents addresses two environmental challenges simultaneously - waste management and water pollution control.

Carbon Footprint Reduction: Utilizing agricultural waste reduces the need for energy-intensive manufacturing of synthetic adsorbents.

Circular Economy: The approach supports circular economy principles by creating value from waste materials.

5.2 Economic Advantages

Cost Comparison: Tea and coffee waste adsorbents cost significantly less than commercial alternatives such as activated carbon or synthetic ion exchange resins.

Availability: Abundant supply ensures consistent availability without supply chain constraints.

Processing Simplicity: Minimal processing requirements reduce operational costs and energy consumption.

5.3 Scalability and Implementation

Industrial Application: The results suggest potential for industrial-scale implementation with appropriate engineering design.

Community-Level Treatment: Small-scale applications in rural or developing communities where conventional treatment is economically unfeasible.

Integration Potential: Possibility of integration with existing treatment systems as pre-treatment or polishing step

6. Challenges and Future Research Directions

6.1 Current Limitations

Regeneration and Reuse: Further research needed on adsorbent regeneration methods to enhance economic viability.

Competitive Adsorption: Mixed metal solutions may show different removal patterns due to competitive effects.

Long-term Stability: Assessment of adsorbent stability under various environmental conditions.

6.2 Future Research Opportunities

Chemical Modification: Surface modification techniques to enhance binding capacity and selectivity.

Kinetic Modelling: Development of comprehensive kinetic and equilibrium models for design applications.

Pilot-Scale Studies: Scale-up studies to validate laboratory findings under real-world conditions.

Life Cycle Assessment: Comprehensive environmental impact assessment of the entire treatment process.

7. Conclusions

This comprehensive study demonstrates the significant potential of tea and coffee waste as effective, low-cost adsorbents for heavy metal removal from wastewater. The research provides several important conclusions:

7.1 Technical Feasibility

Tea and coffee waste successfully removed heavy metals with efficiency comparable to conventional adsorbents:

- Lead removal up to 99.1%
- Zinc removal up to 99.6%
- Iron removal up to 91.6%
- Copper removal up to 88.5%
- Nickel removal up to 89.6%
- Cadmium removal up to 83.4%

7.2 Optimal Operating Conditions

The study established optimal operating parameters:

- **Adsorbent dosage**: 2.5-3.0 g per 100 mL solution
- **Contact time**: 60 minutes for maximum efficiency
- **pH range**: 4.5-8.0 (metal-specific optimization required)

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