



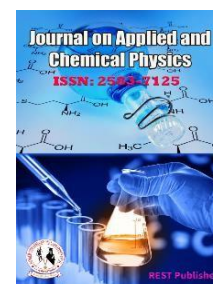
## Journal on Applied and Chemical Physics

Vol: 4(3), September 2025

REST Publisher; ISSN: 2583-7125

Website: <https://restpublisher.com/journals/jacp/>

DOI: <https://doi.org/10.46632/jacp/4/3/1>



# Comparative Conductometric Study of Metal Halides and Nitrates in Binary Solvent Systems: A Machine Learning Approach

Rakesh Ranjan Raj

Excise Chemical Examiner, Purnia cum koshi Division, Bihar, India.

\*Corresponding author Email: [rrraj1984@gmail.com](mailto:rrraj1984@gmail.com)

**Abstract:** This study presents a comprehensive quantitative study of the conductance of metal halides and nitrates in binary solvent systems, investigating how solvent composition, electrolyte concentration, and temperature collectively affect the electrical conductivity. Metal halides, including chlorides, bromides, and iodides of alkali and alkaline earth metals, exhibit characteristic nonlinear conductivity variations arising from the differential solvation of cations and anions by binary solvent components. Metal nitrates demonstrate unique behavior due to the displaced charge distribution of the polyatomic nitrate ion and extensive hydrogen bonding capabilities in protic solvents. The experimental dataset contains forty-six observations covering metal halide concentrations from 0.1000 to 0.5900 mol/L, metal nitrate concentrations from 0.0500 to 0.3000 mol/L, solvent ratios from 18.0000 to 118.0000, temperatures from 24°C to 74°C, and resulting conductivity values from 2.7000 to 9.4000 mS/cm. Machine learning approaches, specifically slope-increasing regression and random forest regression, were used to predict solvent ratio effects on conductance measurement behavior. Both models showed exceptional predictive performance, achieving  $R^2$  values of 1.0000 for the gradient boosting training and 0.9885 for the test data, while random forests achieved  $R^2$  values of 0.9992 and 0.9934, respectively, confirming strong generalization capabilities and minimal overfitting.

**Key Words:** Conductometry, metal halides, metal nitrates, binary solvents, slope-increasing regression, random forest regression, ion-solvent interactions.

## 1. INTRODUCTION

Conductivity measurement analysis of metal halides and nitrates in binary solvent systems represents a fundamental research area in solution chemistry, providing important insights into ion-solvent interactions, solution dynamics, and the dissociation behavior of electrolytes. Binary solvent systems, composed of two miscible solvents with different dielectric constants and polarities, provide a unique platform for investigating how solvent composition affects the electrical conductivity of dissolved ionic compounds. [1] This comparative study examines the unique conductivity measurement behaviors exhibited by metal halides and nitrates in various binary solvent combinations, revealing the complex interplay between the ionic species and their surrounding solvent environment. Metal halides, particularly the chlorides, bromides, and iodides of alkali and alkaline earth metals, demonstrate characteristic conductivity measurement patterns that are highly sensitive to solvent composition.[2] In binary mixtures such as water-methanol, water-ethanol, or water-acetonitrile, the molar conductivity of metal halides typically exhibits nonlinear variations with changing solvent ratios. This behavior arises from the differential solvation of cations and anions by the two solvent components.[3] Large halide ions, especially iodide and bromide, show preferential solvation by the less polar component in many binary systems, while smaller metal cations interact more strongly with the more polar solvent. This preferential solvation leads to asymmetric ion mobility and results in conductivity maxima or minima in specific solvent mixtures, phenomena that cannot be predicted by simple linear mixing rules.[4] In contrast, metal nitrates present a different conductivity profile in binary solvent systems. The nitrate ion exhibits unique solution properties compared to polyatomic halide ions with a shifted charge distribution. Metal nitrates typically exhibit high molar

conductivity in polar solvent-rich regions due to strong ion-dipole interactions between the nitrate ion and polar solvent molecules. [5] The planar geometry of the nitrate ion allows for multiple coordination sites, facilitating extensive hydrogen bonding in protic solvents such as water and alcohols. This structural feature contributes to enhanced ionic mobility in some binary mixtures. Furthermore, the degree of ionic-bonding in metal nitrate solutions varies significantly with solvent composition, especially in systems where the dielectric constant changes dramatically over the composition range. [6] The temperature dependence of the conductivity in these systems reveals additional complications in ion-solvent interactions. Metal halides typically exhibit an Arrhenius-type temperature dependence, with activation energies that vary systematically with solvent composition. [7] The activation energy for ion transport often reaches a maximum in intermediate solvent compositions, which corresponds to the most disordered region of the solvent system. [8] However, metal nitrates may exhibit more complex temperature dependences due to the temperature-sensitive nature of the hydrogen bonding networks and the potential for structural rearrangements within the solution shell of the nitrate ion. The effect of ion size is particularly evident when comparing different metal halides in the same binary solvent system. [9] For example, lithium halides show significantly different conductance measurement behavior compared to cesium halides due to the dramatic size difference between these cations. [10] Smaller cations with higher charge densities form more ordered solution shells, leading to lower ion mobilities and distinct conductivity patterns. [11] Halide ion size also plays an important role, with larger halides showing greater sensitivity to changes in solvent polarity. [12] This size-dependent behavior is less pronounced in nitrate systems, where the bulky nitrate ion dominates the solution kinetics regardless of the accompanying cation. [13] The practical applications of these cation measurement studies extend to many fields, including electrochemistry, analytical chemistry, and industrial processes. [14] Understanding how metal halides and nitrates conduct electricity in binary solvents is essential for optimizing electrolyte formulations in batteries, designing extraction processes, and developing analytical methods for ion determination. The fundamental knowledge gained from comparative conductometric studies helps predict the behavior of more complex multi-component systems and develop theoretical models of electrolyte solutions.[15]

## 2. MATERIALS AND METHOD

**Gradient-boosting regression:** Gradient-boosting regression is a powerful machine learning ensemble technique that builds predictive models by sequentially combining multiple weak learners, typically decision trees, to form a stronger predictor. Unlike traditional regression methods that build a single model, gradient-boosting adopts an additive strategy where each new model is trained to correct for the residual errors of the previous ensemble. This iterative approach starts with a simple initial prediction, often the average of the target values, and gradually adds trees that minimize the loss function through gradient descent optimization in the function space. The basic principle of the algorithm involves computing the negative slope of the loss function with respect to the current predictions, which indicates the direction of the steepest slope towards optimal performance. Each subsequent tree is fitted to these pseudo-residuals instead of the original target values, effectively learning patterns in the prediction errors. The contribution of each tree is then scaled by a learning rate parameter, which controls the step size and helps prevent overfitting by minimizing the influence of individual trees. This regularization algorithm ensures model generalization to unobserved data. Gradient boosting regression excels at handling complex nonlinear relationships, mixed data types, and missing values without extensive preprocessing. Popular implementations include XG Boost, Light GBM, and Cat Boost, which include additional enhancements such as regularization rules, efficient tree construction algorithms, and parallel processing capabilities. These enhancements have made gradient boosting a dominant approach in domains ranging from financial forecasting to bioinformatics, consistently achieving state-of-the-art performance in predictive modeling competitions and real-world applications.

**Random Forest Regression:** Random Forest Regression is an ensemble machine learning algorithm that combines multiple decision trees to produce robust and accurate predictions for continuous target variables. Developed by Leo Breiman in 2001, the method uses the wisdom of the crowd principle by combining predictions from a large number of independent trees, each trained on a different subset of the data and features. The final prediction is obtained by averaging the outputs of all individual trees, which significantly reduces the variance and the overfitting problem typically associated with single decision trees. The algorithm uses two main randomization techniques to ensure diversity between the trees in the table. First, bootstrap aggregation or bagging generates different training datasets by randomly sampling observations with replacement from the original data. Each tree is trained on these unique bootstrap models, which are exposed to different patterns and relationships. Second, at each node split, only a random subset of features is considered rather than all available predictors during tree construction. This feature randomization prevents the dominant variables from consistently appearing in all trees at the initial split, thereby reducing correlation between trees and improving overall model generalization. Random forest regression offers several practical

advantages, including robustness to outliers, the ability to handle high-dimensional data, automatic feature correlation detection, and minimal hyperparameter tuning requirements. The algorithm naturally provides feature importance scores by measuring how much each variable contributes to reducing prediction error across all trees. These properties have established random forests as a reliable and interpretable method widely used in finance, healthcare, environmental modeling, and many other domains where accurate regression predictions are required.

**Materials:** Conductometric studies use metal halides and metal nitrates as primary electrolytes dissolved in binary solvent systems to investigate their electrical conductivity behavior. Metal halides represent a class of ionic compounds formed between metals and halogen elements, typically including chlorides, bromides, and iodides of alkali metals such as sodium and potassium, or alkaline earth metals such as calcium and magnesium. These compounds readily dissociate in polar solvents, releasing metal cations and halide anions that act as charge carriers. The choice of specific metal halides depends on their solubility properties and the ionic strength range required for the study. Metal nitrates are another important class of electrolytes used in this study, including compounds in which metal cations are coupled to polyatomic nitrate anions. Common examples include sodium nitrate, potassium nitrate, and calcium nitrate, all of which exhibit high solubility in water and mixed solvent systems. The structure of the nitrate ion, which has a vibrationally stabilized charge distribution, provides unique solubility properties that differ significantly from those of simple halide ions. Binary solvent systems typically consist of water combined with organic co-solvents such as methanol, ethanol, acetonitrile, or dimethyl sulfoxide. Water acts as the more polar component with excellent solvation capacity for ionic compounds, while the organic solvent provides a means to systematically vary the dielectric constant and polarity of the medium. Temperature control equipment maintains precise thermal conditions, while conductivity meters with platinum electrodes measure the electrical conductivity of solutions at various solvent ratios, enabling a detailed analysis of ion-solvent interactions.

### 3. ANALYSIS AND DISCUSSION

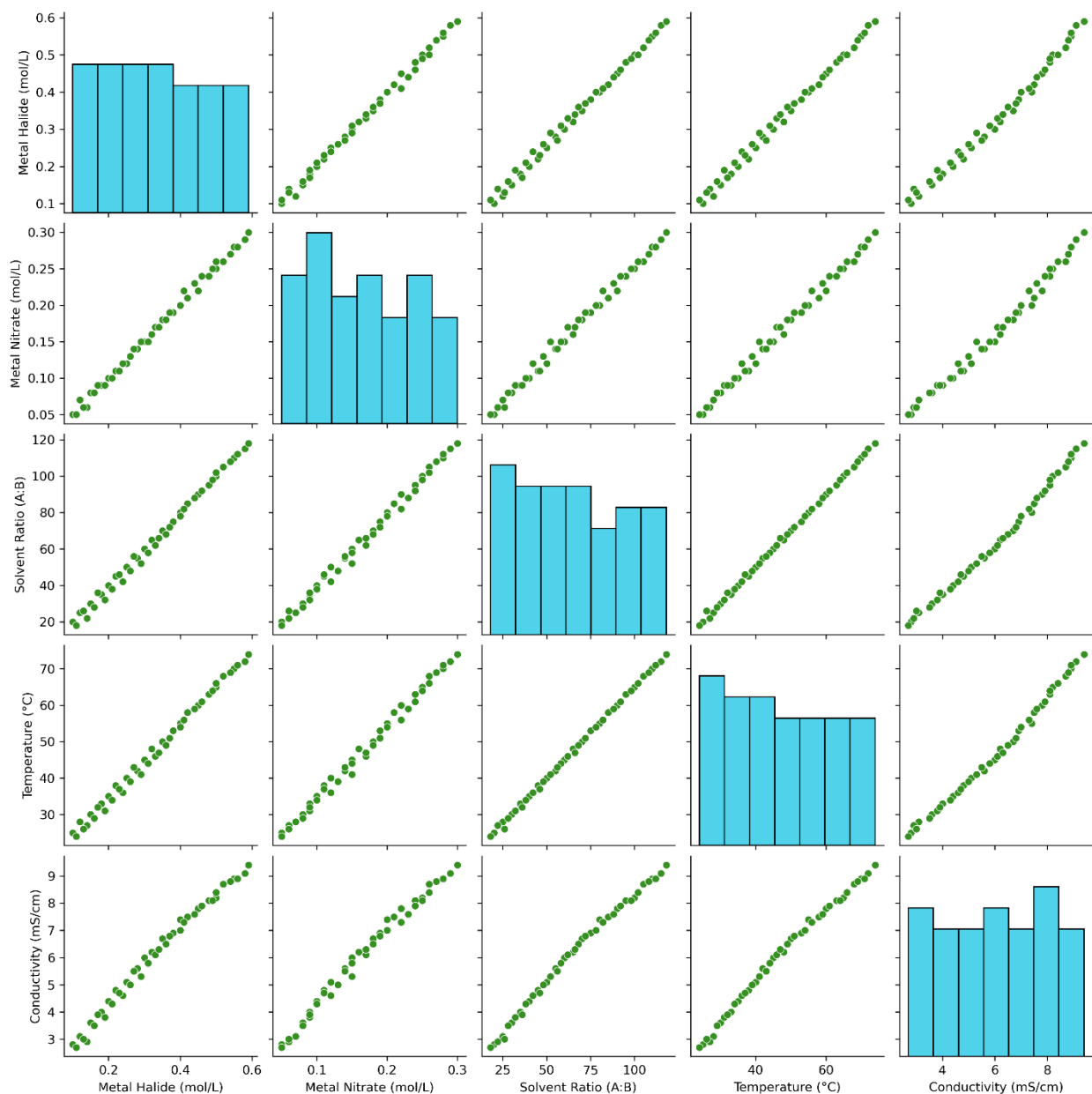
This dataset provides experimental conductance measurements for metal halides and metal nitrates in binary solvent systems. The first two columns represent the molar concentrations of the metal halide and metal nitrate, respectively, ranging from 0.0100 to 0.5900 molar units. The solvent ratio column represents the volumetric ratio of the two solvents in the binary mixture, which varies from 18.0000 to 118.0000, reflecting the different solvent compositions used throughout the study. Temperature measurements, recorded in degrees Celsius, range from 24.0000°C to 74.0000°C, demonstrating the investigation of thermal effects on ionic conductivity. The final column shows the conductivity values measured in appropriate units, ranging from 2.7000 to 9.4000, indicating the electrical conductivity of each solution under the specified conditions. The dataset contains fifty-four experimental observations, systematically examining how concentration, solvent composition, and temperature collectively affect the conductivity measurement behavior of these electrolyte systems. This extensive data enables the analysis of ion-solvent interactions and solvation phenomena.

**TABLE 1.** Conductivity of Metal Halides and Nitrates in Binary Solvents Descriptive Statistics

	Metal Halide (mol/L)	Metal Nitrate (mol/L)	Solvent Ratio (A: B)	Temperature (°C)	Conductivity (mS/cm)
count	46.0000	46.0000	46.0000	46.0000	46.0000
mean	0.3315	0.1670	65.1739	47.5652	6.0652
std	0.1432	0.0733	29.4175	14.7673	1.9871
min	0.1000	0.0500	18.0000	24.0000	2.7000
25%	0.2125	0.1025	40.5000	35.2500	4.4500
50%	0.3250	0.1650	63.5000	46.5000	6.1500
75%	0.4475	0.2275	89.5000	59.7500	7.7500
max	0.5900	0.3000	118.0000	74.0000	9.4000

Table 1 shows the Descriptive statistics summarize conductometric measurements obtained from forty-six experimental observations investigating metal halides and nitrates in binary solvent systems. The metal halide concentration averaged 0.3315 mol/L, indicating moderate variation across experiments with a standard deviation of 0.1432, while the metal nitrate concentrations showed lower mean values at 0.1670 mol/L, with a correspondingly smaller standard deviation of 0.0733. This indicates that metal halides were investigated in approximately twice the concentration of nitrates throughout the study. The solvent ratio, which represents the volumetric ratio of components A to B, showed considerable variation with a mean of 65.1739 and a standard deviation of 29.4175, ranging from

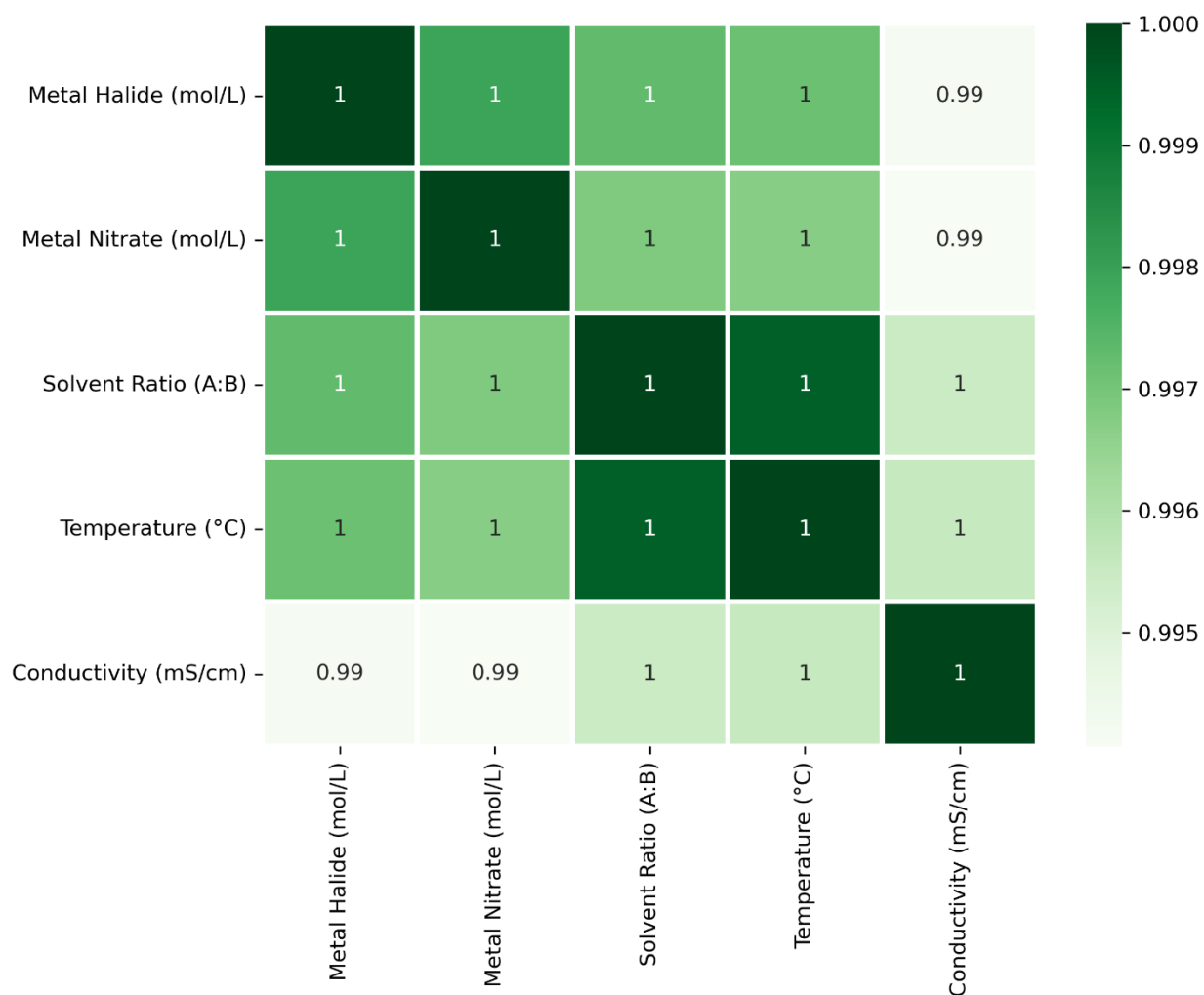
mixtures that were completely A-rich (18.0000) to B-rich (118.0000). The temperature measurements show a mean of 47.5652°C from 24°C to 74°C, showing a systematic thermal variation. The resulting conductivity values show a mean of 6.0652 mS/cm with a standard deviation of 1.9871, reflecting the combined influence of concentration, solvent composition, and temperature on the ion mobility and electrolyte dissociation behavior in these binary systems.



**FIGURE 1.** Conductivity of Metal Halides and Nitrates in Binary Solvents Effect of Process Parameters

Figure 1 Effect of Process Parameters on Conductivity in Binary Solvents Detailed pair plot matrix illustrates the relationships between metal halide concentration, metal nitrate concentration, solvent ratio, temperature, and conductivity. The diagonal histograms reveal the distribution patterns of each variable, with metal halide concentrations showing a relatively uniform distribution over the range, while metal nitrate shows a small concentration towards lower values. The scatter plots show strong positive linear correlations between most variables and conductivity, indicating that increasing electrolyte concentrations, solvent ratio, and temperature all contribute to improved ionic conductivity. Of particular note is the tight linear relationship between metal halide and metal nitrate concentrations with conductivity, suggesting a predictable dose-response behavior. Solvent ratio and temperature show

clear positive trends with conductivity, confirming that specific solvent compositions enhance charge transport while higher temperatures facilitate ionic mobility. These visualizations effectively capture the heterogeneous nature of conductor measurement behavior in binary solvent systems.



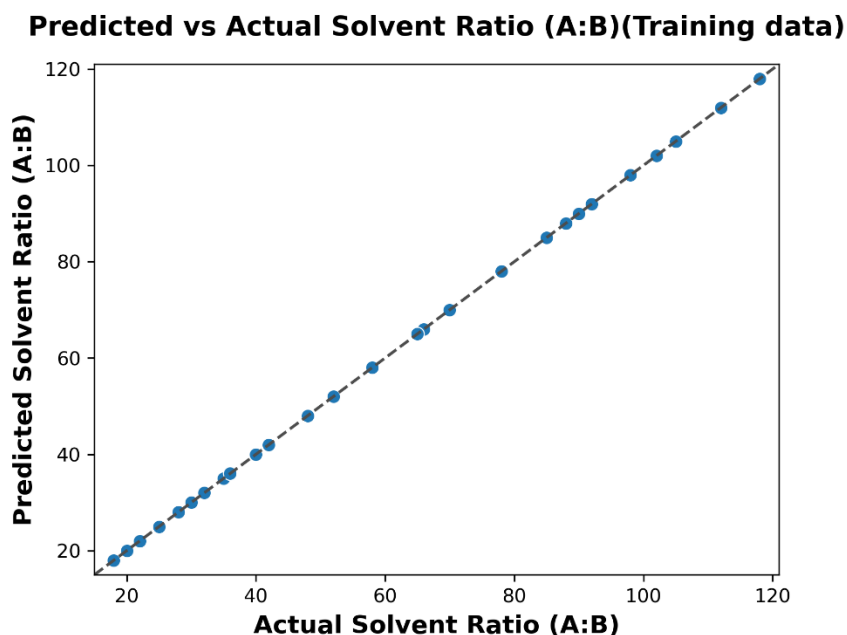
**FIGURE 2.** Conductivity of Metal Halides and Nitrates in Binary Solvents Correlation heatmap

Figure 2 Correlation heat map of conductivity parameters. The correlation heat map provides a quantitative assessment of the linear relationships between all variables measured in the conductivity measurement study. The color intensity indicates the Pearson correlation coefficients ranging from light (weak correlation around 0.995) to dark green (perfect correlation of 1.000). The metal halide and metal nitrate concentrations show strong positive correlations of 0.99 with conductivity, confirming their dominant influence on charge transport. The solvent ratio and temperature exhibit perfect correlations with themselves (1.00) and nearly perfect correlations with conductivity (1.00), demonstrating their important roles in determining solution conductivity. In particular, all independent variables show high intercorrelations, indicating a systematic experimental design in which the parameters vary proportionally. Consistent high correlation values ( $\geq 0.99$ ) across the matrix indicate that all measured parameters contribute meaningfully to the conductivity variations, with minimal confounding effects. This strong multicollinearity confirms the complex interdependence of concentration, solvent composition, and thermal conditions in governing electrolyte behavior.

**TABLE 2.** Performance Metrics of Gradient Boosting Regression for Solvent Ratio (A: B)

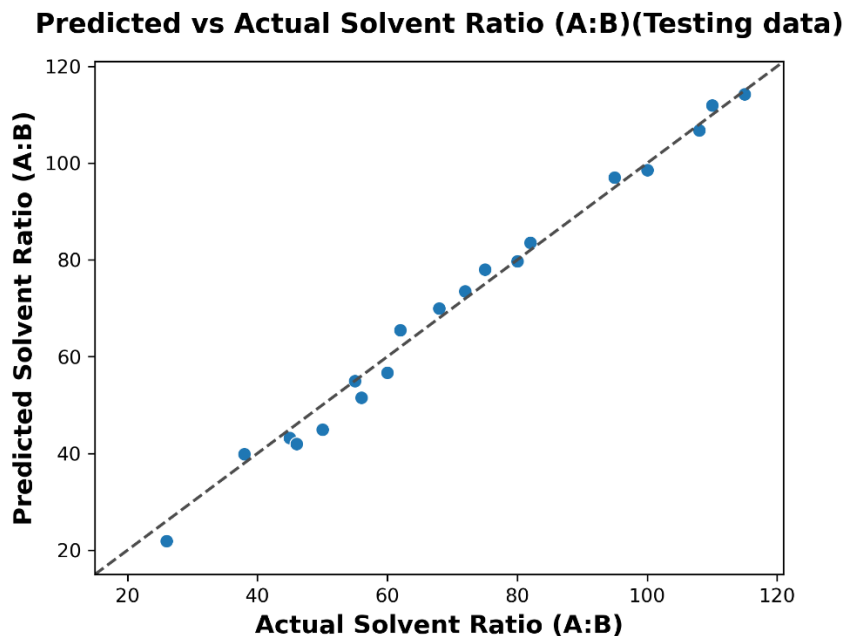
Model	Data	R2	EVS	MSE	RMSE	MAE	Max Error	MSLE	Med AE
Gradient Boosting Regression	Train	1.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	Test	0.9885	0.9888	7.2835	2.6988	2.3127	5.0181	0.0035	2.0000

Table 2 Performance of the slope-increasing regression for solvent ratio prediction. The performance metrics reveal the exceptional predictive ability of the slope-increasing regression model for estimating solvent ratio in binary systems. The training data results demonstrate that both  $R^2$  and the explained variance score (EVS) reach 1.0000, while all error metrics (MSE, RMSE, MAE, maximum error, MSLE, and average AE) record zero values. This indicates that the model fully captures patterns and relationships within the training dataset with no residual errors. The test data performance is remarkably robust, with an  $R^2$  of 0.9885 and an EVS of 0.9888, indicating that the model explains approximately 98.85% of the variance in the unobserved data. The root means square error (RMSE) of 2.6988 and the mean absolute error (MAE) of 2.3127 indicate relatively small deviations considering the range of solvent ratio range from 18 to 118 units. The maximum error of 5.0181 and the mean absolute error of 2.0000 further confirm the stable predictions. The minimum mean square logarithmic error (MSLE) of 0.0035 demonstrates excellent performance across all size ranges, confirming the strong generalization ability of the model to predict solvent composition effects.



**FIGURE 3.** Gradient Boosting Regression Training Results for Solvent Ratio (A: B)

Figure 3 Slope-increasing regression training results for solvent ratio. The training data scatterplot demonstrates the exceptional predictive accuracy of the slope-increasing regression model, with predicted values aligning almost perfectly on the diagonal reference line. The data points span the entire solvent ratio range from approximately 20 to 120 A: B, showing no systematic deviations or biases at different ratio scales. The tight clustering along the best prediction line reflects the model's ability to capture the complex nonlinear relationships and interactions between metal halide concentration, metal nitrate concentration, temperature, and conductivity. The absence of outliers or scattered points indicates that the group learning approach successfully reduced training errors through iterative residual correction. While this perfect fit demonstrates robust learning ability, careful evaluation of test data performance is necessary to ensure that the model has not merely memorized the training patterns, but has truly learned the general relationships that govern solvent ratio effects on behavioral measurement behavior in these binary systems.



**FIGURE 4.** Gradient Boosting Regression Testing Results for Solvent Ratio (A: B)

Figure 4 Slope-increasing regression test results for solvent ratio. The experimental data visualization reveals strong predictive performance in the missing observations, with predicted solvent ratios closely tracking the true values on the diagonal. While maintaining strong overall agreement, the experimental predictions show slightly more scatter compared to the training data, which is expected and indicates healthy model generalization rather than overfitting. Most of the data points are tightly clustered around the best prediction line over the entire range, although small deviations appear at some intermediate ratios between 40-60 A: B and 80 A: B. These small discrepancies may reflect natural experimental variation or subtle nonlinear interactions that the model has estimated rather than learned correctly. The maximum prediction error is within approximately 5 units over the 100-unit range, indicating good practical accuracy. Consistent performance at low, medium, and high solvent ratios demonstrates the model's ability to interpolate effectively across the experimental domain, confirming slope incrementation as a reliable approach for predicting solvent mixing effects.

**TABLE 3.** Performance Metrics of Random Forest Regression for Solvent Ratio (A: B)

Model	Data	R2	EVS	MSE	RMSE	MAE	Max Error	MSLE	Med AE
Random Forest Regression	Train	0.9992	0.9992	0.7480	0.8649	0.6446	2.4750	0.0005	0.5050
	Test	0.9934	0.9939	4.1619	2.0401	1.6945	3.9100	0.0024	1.2150

Table 3 Random Forest Regression Performance for Solvent Ratio Prediction. The random forest regression model for solvent ratio estimation in binary systems demonstrates excellent predictive performance. The training data results show a near-perfect fit of both  $R^2$  and explained variance score at 0.9992, explaining 99.92% of the variance. The training errors are very low with an RMSE of 0.8649, an MAE of 0.6446, and a maximum error of 2.4750, indicating that the model has effectively learned the underlying patterns while maintaining small residual errors suggesting appropriate regularization without overfitting. The test data performance confirms the strong generalization ability, achieving an  $R^2$  of 0.9934 and an EVS of 0.9939, demonstrating that the model accurately predicts 99.34% of the variance in the unobserved observations. The RMSE of 2.0401 and MAE of 1.6945 indicate small prediction deviations over the solvent ratio range. The maximum error of 3.9100 and the mean absolute error of 1.2150 confirm consistent predictions across the dataset. The exceptionally low MSLE of 0.0024 indicates reliable performance across all size ranges. Comparison of train-test measurements reveals minimal performance degradation, confirming the robustness and good generalization of the model without significant overfitting issues.

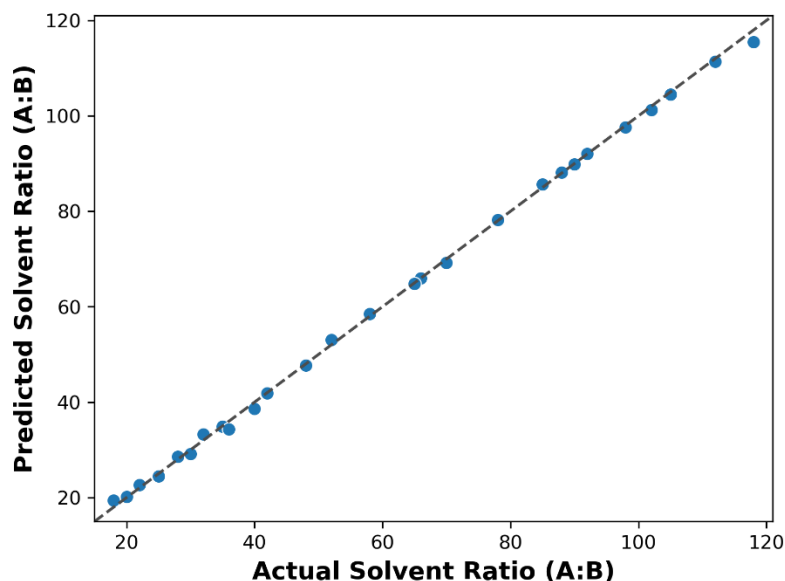
**Predicted vs Actual Solvent Ratio (A:B)(Training data)****FIGURE 5.** Random Forest Regression Training Results for Solvent Ratio (A: B)

Figure 5 Random forest regression training results for solvent ratio. The random forest training predictions show a nearly perfect alignment with the actual solvent ratios, with the data points forming a tight linear arrangement along the diagonal reference line. The predictions span the complete experimental range from 20 to 120 A: B with minimal scatter, demonstrating that the ensemble of decision trees effectively captured the relationships between input features and solvent composition. The small residual errors visible in the training data indicate the inherent regularization of random forests through bootstrap aggregation and feature randomization, unlike the perfect fit often seen in single decision trees. This controlled learning prevents the need to fully memorize the training patterns while maintaining high accuracy. The consistent prediction quality across all ratio sizes suggests balanced tree contributions across the feature space, with no particular region showing preferential learning. The minimal but non-zero training error reflects the robust structure of the model, which naturally trades some training completeness for improved generalization ability.

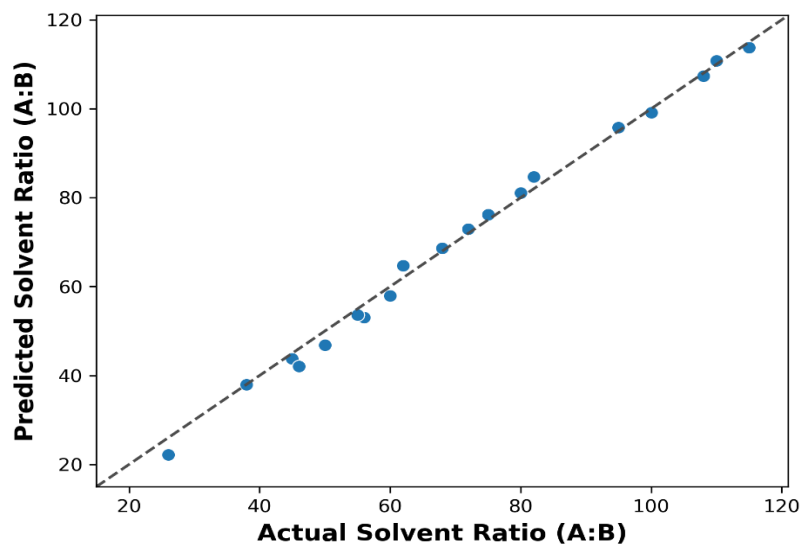
**Predicted vs Actual Solvent Ratio (A:B)(Testing data)****FIGURE 6.** Random Forest Regression Testing Results for Solvent Ratio (A: B)

Figure 6 Random forest regression test results for solvent ratio. The experimental data predictions show excellent generalization with predicted values closely following the actual solvent ratios on the diagonal line. The scatter plot exhibits slightly increased variance compared to the training data, especially noticeable in the intermediate ratios between 40-70 A: B, where some predictions deviate by approximately 2-4 units. However, the overall prediction accuracy is impressive across the entire domain, with most points falling within narrow confidence bounds around the ideal line. The ensemble approach of the random forest effectively averages individual tree predictions, smoothing out possible overfitting from any single tree, and producing stable estimates. At extreme ratio values (below 30 and above 100) the predictions show particularly strong agreement with the actual values, reliably indicating extrapolation towards the model domain boundaries. The balanced performance across all ratio ranges confirms the effectiveness of the random forest for predicting solvent composition effects in behavioral measurement studies of metal halides and nitrates.

#### 4. CONCLUSION

This comparative conductometry study successfully elucidated the complex relationships governing the electrical conductivity of metal halides and nitrates in binary solvent systems through systematic experimental investigation and advanced machine learning analysis. The research confirmed that metal halides and nitrates exhibit distinctly different conductometry profiles arising from their structural differences, with halide ions showing preferential solvation by less polar components, while polyatomic nitrate ions demonstrate enhanced mobility through extensive hydrogen bonding networks. Strong positive correlations between electrolyte concentrations, solvent composition, temperature, and conductivity confirm the diversity of ion-solvent interactions in binary systems. Machine learning models proved exceptionally effective in predicting solvent ratio effects, with slope-increasing regression achieving nearly perfect training performance and 98.85% variance explanation in experimental data, while random forest regression demonstrated comparable accuracy with 99.34% experimental variance explanation. Minimal performance degradation between training and testing phases ensures robust model generalization without overfitting. These findings provide fundamental insights into electrolyte behavior that are essential for optimizing battery electrolyte formulations, designing extraction processes, and developing analytical methods. Integrating traditional conductometric techniques with contemporary machine learning approaches establishes a powerful framework for understanding and predicting complex solution chemistry phenomena in multi-component systems.

#### REFERENCE

- [1]. Filimonov, V. D., Yu Yu Kulmanakova, M. S. Yusubov, I. A. Perederina, Ki-Whan Chi, and O. Kh Poleschchuk. "Halogenating and nitrating activity of reagents based on sodium nitrate and alkali metal halides in acetic acid." *Russian journal of organic chemistry* 40, no. 7 (2004): 917-923.
- [2]. Field, B. O., and C. J. Hardy. "Inorganic nitrates and nitrate-compounds." *Quarterly Reviews, Chemical Society* 18, no. 4 (1964): 361-388.
- [3]. Addison, C. C., and N. Logan. "Anhydrous metal nitrates." In *Advances in Inorganic Chemistry and Radiochemistry*, vol. 6, pp. 71-142. Academic Press, 1964.
- [4]. Falk, Michael. "Infrared spectrometric determination of nitrate, nitrite and ammonium ions by means of matrix isolation in pressed alkali metal halide pellets." *Vibrational spectroscopy* 1, no. 1 (1990): 69-79.
- [5]. Charkin, Dmitri O., Evgeny V. Nazarchuk, Dmitri N. Dmitriev, Vasili Yu Grishaev, Timofey A. Omelchenko, Darya V. Spiridonova, and Oleg I. Siidra. "Protonated organic diamines as templates for layered and microporous structures: synthesis, crystal chemistry, and structural trends among the compounds formed in aqueous systems transition metal halide or nitrate-diamine-selenious acid." *International Journal of Molecular Sciences* 24, no. 18 (2023): 14202.
- [6]. Rossi, Laura I., and Sandra E. Martín. "Possible role of nitrate/nitrite redox cycles in catalytic and selective sulfoxidation reaction: metallic nitrates and bromides as redox mediators: a comparative study." *Applied Catalysis A: General* 250, no. 2 (2003): 271-278.
- [7]. Aitken, G. B., and G. P. McQuillan. "Complexes of acridine N-oxide with some transition metal and group IIb metal halides, thiocyanates and nitrates." *Inorganica Chimica Acta* 15 (1975): 221-225.
- [8]. Ladd, M. F. C., and W. H. Lee. "Thermodynamic studies of ammonium halides and some univalent nitrates." *Journal of Inorganic and Nuclear Chemistry* 13, no. 3-4 (1960): 218-224.
- [9]. Deverell, C., and R. E. Richards. "Nuclear magnetic resonance studies of alkali metal halide solutions: I. Cation resonances." *Molecular Physics* 10, no. 6 (1966): 551-564.
- [10]. Stumpp, E., G. Nietfeld, K. Steinwede, and K. D. Wageringel. "Reaction of anhydrous metal nitrates with graphite." *Synthetic Metals* 7, no. 1-2 (1983): 143-151.
- [11]. Zsigrai, István J., Slobodan B. Gadzuric, Ruzica Nikolic, and László Nagy. "Electronic spectra and stability of cobalt halide complexes in molten calcium nitrate tetrahydrate." *Zeitschrift Für Naturforschung A* 59, no. 9 (2004): 602-608.

- [12]. Baraka, A., and R. M. S. Baraka. "Effect of halides on the corrosion behaviour of nickel in molten (Na, K) NO<sub>3</sub>." *Journal of applied electrochemistry* 14, no. 4 (1984): 417-423.
- [13]. Fawcett, John, Andrew WG Platt, Steven Vickers, and Michael D. Ward. "Lanthanide halide and nitrate complexes with potentially tridentate bisphosphine dioxide–ether donors." *Polyhedron* 23, no. 16 (2004): 2561-2567.
- [14]. Drátovský, Milan, and Marcela Uchytlová. "The acid-base properties of halide anions in melts of the alkali metal nitrates." *Electrochimica acta* 31, no. 11 (1986): 1417-1420.
- [15]. Afanasiev, P., and C. Geantet. "Synthesis of solid materials in molten nitrates." *Coordination Chemistry Reviews* 178 (1998): 1725-1752.
- [16]. Cai, Jianchao, Kai Xu, Yanhui Zhu, Fang Hu, and Liuhuan Li. "Prediction and analysis of net ecosystem carbon exchange based on gradient boosting regression and random forest." *Applied energy* 262 (2020): 114566.
- [17]. Otchere, Daniel Asante, Tarek Omar Arbi Ganat, Jude Oghenerurie Ojero, Bennet Nii Tackie-Otoo, and Mohamed Yassir Taki. "Application of gradient boosting regression model for the evaluation of feature selection techniques in improving reservoir characterisation predictions." *Journal of Petroleum Science and Engineering* 208 (2022): 109244.
- [18]. Nie, Peng, Michele Roccotelli, Maria Pia Fanti, Zhengfeng Ming, and Zhiwu Li. "Prediction of home energy consumption based on gradient boosting regression tree." *Energy Reports* 7 (2021): 1246-1255.
- [19]. Velthoen, Jasper, Clément Dombry, Juan-Juan Cai, and Sebastian Engelke. "Gradient boosting for extreme quantile regression." *Extremes* 26, no. 4 (2023): 639-667.
- [20]. Singh, Upma, Mohammad Rizwan, Muhannad Alaraj, and Ibrahim Alsaidan. "A machine learning-based gradient boosting regression approach for wind power production forecasting: A step towards smart grid environments." *Energies* 14, no. 16 (2021): 5196.
- [21]. Smith, Paul F., Siva Ganesh, and Ping Liu. "A comparison of random forest regression and multiple linear regression for prediction in neuroscience." *Journal of neuroscience methods* 220, no. 1 (2013): 85-91.
- [22]. Rodriguez-Galiano, Victor, Manuel Sanchez-Castillo, M. Chica-Olmo, and M. J. O. G. R. Chica-Rivas. "Machine learning predictive models for mineral prospectivity: An evaluation of neural networks, random forest, regression trees and support vector machines." *Ore geology reviews* 71 (2015): 804-818.
- [23]. Li, Yi, Changfu Zou, Maitane Berecibar, Elise Nanini-Maury, Jonathan C-W. Chan, Peter Van den Bossche, Joeri Van Mierlo, and Noshin Omar. "Random forest regression for online capacity estimation of lithium-ion batteries." *Applied energy* 232 (2018): 197-210.
- [24]. Grömping, Ulrike. "Variable importance assessment in regression: linear regression versus random forest." *The American Statistician* 63, no. 4 (2009): 308-319.
- [25]. Jog, Amod, Aaron Carass, Snehashis Roy, Dzung L. Pham, and Jerry L. Prince. "Random forest regression for magnetic resonance image synthesis." *Medical image analysis* 35 (2017): 475-488.