Gaurav Singh al. International Journal of Recent Research Aspects ISSN: 2349-7688, Vol. 12, Issue 3, Sept. 2025, pp. 21-28

Fostering Analytical Proficiency and Critical Thinking in First-Year Engineering Students: A Project-Based Learning Approach to Comprehensive Water Quality Assessment

Dr. Gaurav Singh[1], Prashant Singh[2]

Assistant Professor, Department of Chemistry, Anurag University, Hyderabad
Founder & CEO, DN Technology

Abstract- **Project-Based Learning (PBL) was implemented in a first-year engineering chemistry laboratory to replace traditional 'cookbook' experiments with an authentic, problem-driven water-quality investigation. Teams of students conducted comprehensive analyses of local water samples, measuring key physicochemical parameters (pH, electrical conductivity, hardness, chloride, total dissolved solids, and alkalinity) and interpreting their data in context. All results were benchmarked against national drinking-water standards and the operational criteria of various engineering uses (from domestic supply to high-pressure boiler feed). This approach shifted the focus from obtaining 'correct' values to evaluating each water source's fitness-for-purpose in real applications. The structured two-week module, beginning with a scaffolded introduction to core techniques and followed by an open-ended team project, fostered collaborative problem-solving and data-driven analysis. Students demonstrated the ability to obtain reliable, reproducible measurements and to contextualise findings in professional terms—offering nuanced recommendations rather than binary conclusions. Preliminary educational outcomes indicate that the PBL approach enhanced conceptual understanding of water chemistry and its engineering implications while cultivating analytical proficiency, critical thinking, and transferable skills in teamwork and technical communication. These results highlight that even at the introductory level, a well-designed PBL module can effectively integrate chemistry and engineering education, leading to deeper learning and improved student engagement.**

***Keywords*—PBL, TDS, Water hardness, Conductivity, Alkalinity**

I. INTRODUCTION

Project-Based Learning (PBL) offers a purposeful bridge between chemistry and engineering by replacing "cookbook" laboratory routines with authentic, problem-led inquiry that cultivates critical thinking, collaborative problem-solving, and data-driven judgement under uncertainty(Carbonell et al., 2021; Crippen et al., n.d.). In a first-year Engineering Chemistry context, a comprehensive water-quality investigation(Das et al., 2022) is an ideal PBL nucleus: students design and execute experiments to quantify core physicochemical parameters—pH, electrical conductivity, hardness, chloride, Total Dissolved Solids (TDS), and alkalinity—then interpret results against regulatory benchmarks (for example, BIS IS 10500:2012 and WHO guidelines)(Sayato, 1989) and the operational demands of real systems. This shifts the learning objective from merely producing a "correct" value to evaluating fitness-for-purpose: potable water that satisfies public-health standards may still be unsuitable for industrial assets, where Ca^{2+}/Mg^{2+}-driven scaling can undermine heat-transfer efficiency in boilers (Uwem Ekwere Inyang & Chidiebere Orji Olughu, 2025) and exchangers, while elevated TDS and chloride accelerate corrosion, shorten equipment life, and raise risk (Nielsen et al., 2000; Xu et al., 2020). Students therefore must contextualise findings—judging acceptability and proposing mitigation—by, for instance, relating conductivity to cycles of concentration in cooling towers (Rahmani, 2017), or justifying why high-pressure boilers require near-demineralised feedwater. The project compels end-to-end engineering practice: framing the problem; selecting methods and calibrating instruments; implementing controls and replicates; propagating measurement uncertainty; integrating theory with evidence; and communicating outcomes in professional artefacts (technical memos, design notes, and decision briefs). In short, PBL transforms laboratory work into genuine engineering design and analysis—replacing binary "good/bad" lab verdicts with nuanced, application-specific recommendations that balance compliance, performance, cost, and safety.

II. STUDY RATIONALE AND OBJECTIVES

This work was designed to meet clear pedagogical needs within the first-year Engineering Chemistry laboratory at Anurag University, Hyderabad, by replacing a sequence of disconnected practicals with a single, cohesive project that is engaging, rigorous, and professionally relevant. Implemented with cohort ECE-B (roll numbers 24EG104B01–24EG104B66), the study positions water-quality analysis as the central vehicle for building scientific literacy, engineering judgement, and team-based problem-solving. The paper therefore (i) articulates the design logic, scaffolding, and delivery of a Project-Based Learning (PBL) module centred on comprehensive physicochemical characterisation of water; (ii) consolidates the core analytical methodologies—complexometry, potentiometry, conductometry, precipitation titrimetry, gravimetry, and acid–base titrimetry—in a manner suitable for an undergraduate setting without prescribing stepwise 'recipes'; (iii) illustrates realistic, datasets to demonstrate expected outcomes and enable comparative interpretation; (iv) evaluates learning gains in conceptual understanding, critical thinking, and collaboration attributable to the PBL approach; and (v) distils challenges and evidence-based recommendations for colleagues seeking to deliver similar, large-scale project laboratories.

I. Pedagogical Framework and Design

A) PBL Model and Scaffolding

The instructional architecture employs a two-week arc that deliberately builds from foundational competence to independent application (Hung, 2006). In the first phase, students consolidate fundamental skills—measurement discipline, solution preparation, endpoint discernment, and stoichiometric reasoning—through a guided exploration of total hardness by EDTA complexometry, chosen for its conceptual centrality to water quality. The subsequent phase pivots to an ill-structured brief that requires teams to design and execute an integrated analytical plan across multiple parameters, drawing on provided method notes and their newly consolidated skills. Academic staff operate as facilitators—probing assumptions, surfacing uncertainty, and steering reflection—rather than as directors. This progression normalises professional practice: framing the problem, making defensible methodological choices, applying quality assurance/quality control (QA/QC), and translating data into decisions.

B) Experimental Scenario and Task Context

Students act as consulting chemists advising a new mixed-use development on the city outskirts. They evaluate the suitability of several candidate water sources from across Hyderabad—such as Jodimetla, Singaram, Venkatapur, Ghatkesar, and Uppal—for three distinct uses: potable supply for residential units, make-up water for evaporative cooling towers, and high-pressure boiler feed. The scenario forces context-dependent analysis: a sample that is acceptable for drinking may be unfit for thermal plant due to scaling risk or chloride-driven corrosion. Teams therefore benchmark measurements against relevant standards and operational envelopes, justify treatment recommendations (for example, softening, demineralisation, or blending), and quantify trade-offs in cost, performance, and risk.

III. Result and Data Analysis

The engineering chemistry lab collected water samples from five locations around Hyderabad—Jodimetla, Singaram, Venkatapur, Ghatkesar and Uppal—and measured a suite of physicochemical parameters. Each parameter has recommended limits defined by the Bureau of Indian Standards (BIS) and the World Health Organization. For example, ideal drinking water should have a pH between 6.5 and 8.5, total dissolved solids (TDS) below 500 mg L^{-1}, and hardness under 200–300 mg/l. BIS guidelines prescribe maximum allowable values for common ions such as chloride (250 mg L^{-1}) and limit alkalinity to 200 mg/l as $CaCO_3$. Understanding how our samples compare with these standards helps evaluate potability and identify areas needing treatment. The dataset contains 50 observations (10 Batches of students). Parameters recorded are:

Table 1 Water quality parameters analysed

Parameter	Description
Total Hardness (ppm)	Measures calcium and magnesium salts. High values cause scaling and affect soap efficiency (WHO et al., 2022)
TDS	Sum of all dissolved ions; affects taste and palatability. BIS recommends <500 mg/l
pH	Indicates acidity/basicity; acceptable drinking water range is 6.5–8.5
Chloride (mg/l)	Excess chloride (>250 mg L^{-1}) imparts salty taste
Alkalinity (mg/l as $CaCO_3$)	Capacity of water to neutralise acids; BIS recommends ≤200 mg/l
Acidity (mg/l as $CaCO_3$)	Opposite of alkalinity; measures H^+ content.
Conductivity ($\mu S\ cm^{-1}$)	Measures water's ability to conduct electricity; correlated with TDS.
Student Groups	(Alpha, Beta, Theta, Gama, Sigma and their "01" counterparts) recorded measurements.

Figure 1 shows the mean TDS for each location. Jodimetla (170 mg/l) and Singaram/ Uppal (300 mg/l) fall well below the 500 mg/l guideline, while Ghatkesar is at the guideline (500 mg/l) and Venkatapur exceeds it (850 mg/l), indicating potential palatability issues.

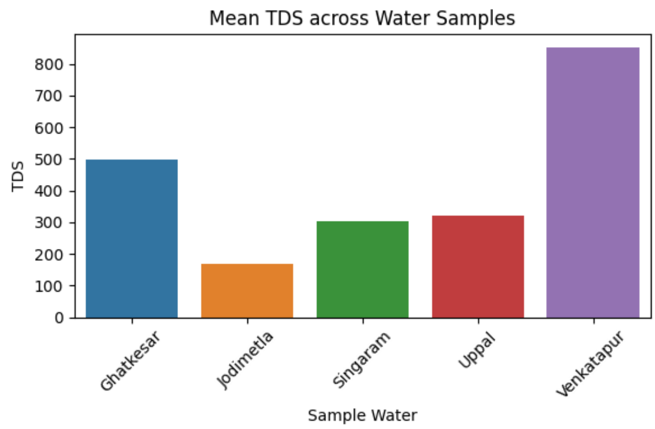

Figure 1 Mean TDS across water samples

Total hardness follows a similar trend (Table 1). Venkatapur and Uppal exhibit hardness values (400 ppm and 330 ppm, respectively) above the recommended ceiling of 200–300 mg/l. Ghatkesar (180 ppm) and Jodimetla/Singaram (150 ppm) comply with guidelines. Chloride concentrations range from 45 mg/l (Jodimetla) to 145 mg/l (Venkatapur), all below the 250 mg/l limit. Alkalinity is elevated for Ghatkesar (210 mg/l) and particularly Venkatapur (280 mg/l), surpassing the 200 mg/l limit, suggesting high buffering capacity and potential taste issues. pH across all samples ranges from 7.0 to 7.8, safely within the BIS window (6.5–8.5).

Table 2 Summary of mean water quality parameters (units in mg/l except pH and conductivity)

Sample	Total hardness	TDS	pH	Chloride	Alkalinity	Acidity	Conductivity (µS cm^{-1})
Jodimetla	150	170	7.5	45	120	5	270
Singaram	150	300	7.7	80	180	8	460
Uppal	330	320	7.1	95	165	7	480
Ghatkesar	180	500	7.2	110	210	10	750
Venkatapur	400	850	7.5	145	280	12	1 270

The correlation heat-map **Figure 2** highlights strong positive correlations among TDS, chloride, alkalinity, acidity and conductivity (coefficients >0.94). These findings are expected: higher dissolved ions simultaneously elevate conductivity and other ionic metrics. Total hardness correlates moderately with TDS and conductivity (r≈0.74), while pH exhibits weak negative correlations with most parameters (−0.1 to −0.2), implying that acidity/alkalinity variations are largely independent of ionic strength.

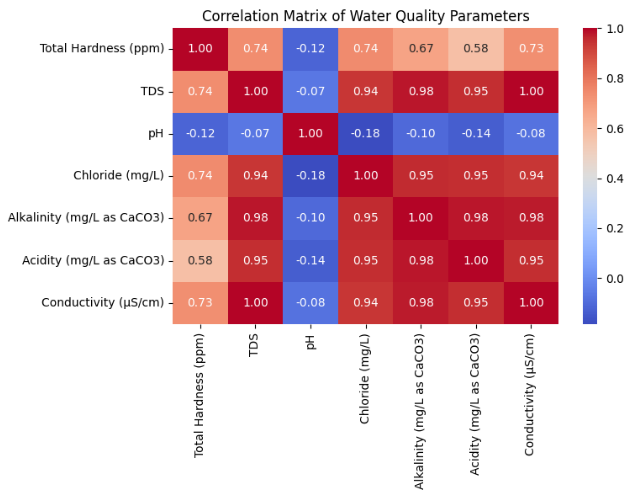

Figure 2 Correlation matrix of water quality parameters

Figure 3 plots TDS against conductivity for each sample. The strong linear clusters illustrate that conductivity is an effective surrogate for TDS, with Venkatapur forming a high-TDS/high-conductivity cluster and Jodimetla showing the lowest values. The near-linear pattern supports using conductivity sensors to estimate dissolved solids quickly in the field.

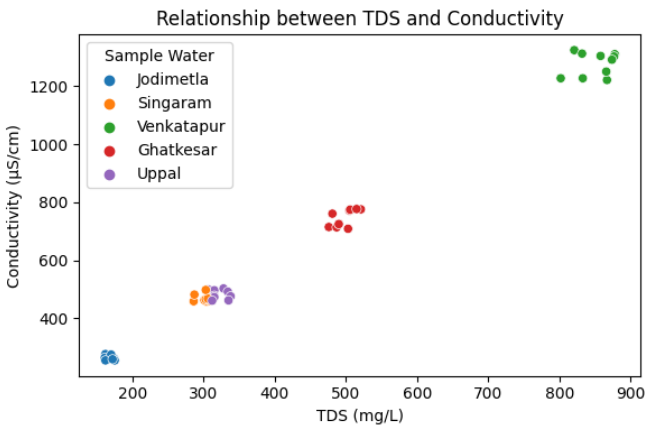

Figure 3 Relationship between TDS and conductivity across water samples

Although pH values lie within the permissible 6.5–8.5 window. Jodimetla and Singaram trend slightly alkaline (7.7), whereas Uppal and Ghatkesar lean closer to neutral (7.2). Such small variations could stem from carbonate buffering differences associated with each location's geological profile.

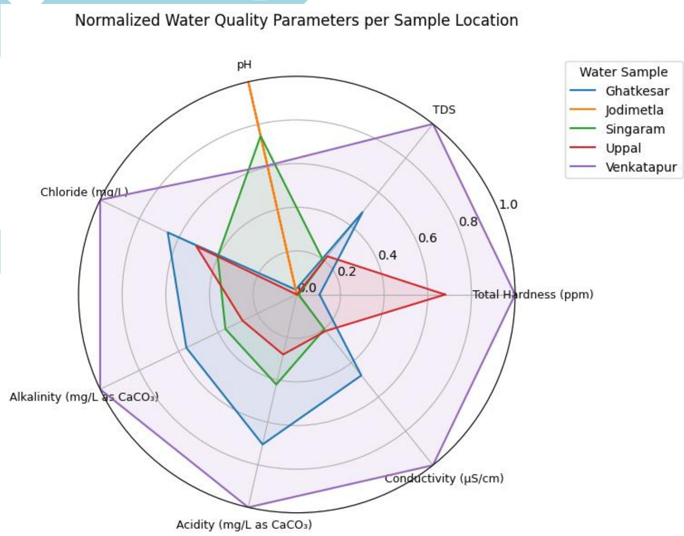

Figure 4 Normalized water quality parameters across locations

The Venkatapur (**Figure 4**) presents the most pronounced mineralization across the study area. When the mean values for total hardness, total dissolved solids, chloride, alkalinity, acidity and electrical conductivity are normalized, Venkatapur consistently attains values near unity, indicating that it contains the greatest ionic and dissolved–solid load among the five sites. Interestingly, its pH remains near the midpoint of the observed range, implying that the elevated solute concentrations do not translate to marked acidification or alkalization. At the opposite end of the spectrum lies Jodimetla, which is characterized by a relatively high pH coupled with minimal mineral content. The normalized plot shows that Jodimetla exhibits the most alkaline condition of the five locations, while contributing the lowest values for hardness, chloride, alkalinity, acidity and conductivity.

Chemically, this points to a soft, low-salinity water with a dominant basic character. Such a profile suggests a different hydrogeochemical regime—possibly flow through basaltic or siliceous strata with limited interaction with soluble evaporite minerals—and may have implications for water treatment processes sensitive to alkalinity. The Singaram occupies an intermediate position but trends toward salinity. Its normalized total dissolved solids reach unity and its pH is moderately high, while chloride, alkalinity, acidity and conductivity fall within mid-range values. This indicates a moderately saline water body that, while enriched in dissolved solids relative to Jodimetla and Ghatkesar, is less mineralized than Venkatapur.

Uppal displays a distinct combination of elevated hardness and comparatively low pH. The normalized data reveal high values for total hardness and moderate values for chloride and alkalinity, juxtaposed against the lowest pH among the sites. Such a composition reflects harder, more acidic water, conditions that are often associated with scaling and corrosive tendencies in distribution systems and plumbing. Ghatkesar occupies a central position across the measured parameters. Its normalized radar profile is fairly balanced, with acidity and alkalinity in the upper mid-range and total dissolved solids, chloride and conductivity around the median. This suggests a moderate degree of mineralization without extreme deviations in any single parameter.

IV. Analysis of the Project-Based Learning Experience

The dataset compiled herein encapsulates more than just numbers—it reflects the learning journey of first-year ECE-B students engaging in project-based enquiry. Each of the ten student teams carried out replicate determinations of key water-quality parameters across five sampling sites, providing a rich canvas for assessing both technical performance and educational outcomes. From a statistical perspective, intra-group consistency was high: when the results are aggregated by location, the standard deviation of each parameter across the ten teams remains small relative to the mean, such as Jodimetla's total hardness averaging 149.8 ppm with a standard deviation of only 4.9 ppm and its TDS averaging 192.5 mg/l with a 12 mg/l spread, with similar low variability observed for Ghatkesar, Singaram and Venkatapur; this tight clustering suggests that the students adhered closely to standard operating procedures, achieving reproducible measurements despite working independently, while modest variations of 3–6 % likely stem from normal instrumental precision and the inherent complexity of gravimetric and titrimetric assays. Comparing sites, the collective results delineate clear hydrochemical gradients: Venkatapur consistently exhibited the highest solute loads, with mean values for total hardness, TDS, chloride, alkalinity, acidity and conductivity topping the group and minimal dispersion across teams, whereas Jodimetla displayed the lowest mineralization and the highest pH, and Singaram, Ghatkesar and Uppal occupied intermediate positions; that students from all teams captured these site-specific signatures reinforces the reliability of their methods and demonstrates an ability to interpret field variability.

Pedagogically, this project underscores the power of collaborative, hands-on experimentation—dividing the cohort into small teams fostered accountability and peer learning, while replicating the same analyses across groups provided an internal quality-control mechanism and a basis for statistical comparison; the act of collecting, normalizing and visualizing the data, culminating in radar charts and quantitative summaries, encouraged students to think like chemists, interrogating their results for patterns and sources of error, and future iterations could build on this by introducing hypothesis testing or uncertainty analysis, though the current dataset already evidences a successful integration of laboratory technique, data analysis and teamwork.

V. Challenges and Recommendations for Implementation in Large Undergraduate Labs

Implementing problem-based learning (PBL) in large, foundational laboratory courses—such as the cohort in this study offers clear pedagogical value but poses practical challenges that require deliberate design and facilitation. Resource constraints are common: limited pH and conductivity meters or analytical balances can create bottlenecks and idle time. Assessment is also more complex and harder to standardise than for conventional labs, particularly when multiple graders are involved; maintaining fairness across open-ended submissions demands careful calibration. First-year students, often accustomed to tightly structured tasks, may initially resist the ambiguity inherent to ill-structured problems, while the shift in staff workload—from demonstrator to active facilitator engaging multiple teams—adds further pressure. These issues are tractable with targeted strategies. A structured two-week scaffold is recommended: a preparatory skills week builds competence and confidence before students tackle the open-ended brief, thereby reducing anxiety and improving performance. Equipment pressure can be mitigated through station-based scheduling or round-robin rotations—for example, half the teams begin with titrimetric analyses (hardness, alkalinity, chloride) that rely mainly on glassware while the others use instrumentation (pH, conductivity), switching mid-session. Rigorous, transparent rubrics should be shared from the outset and assess not only data accuracy but also data presentation (e.g., clear tabulation), depth of interpretation, evidence-based recommendations, and professional quality of writing. Team functioning should be intentionally engineered via structured formation, role assignment, task lists, and light-touch peer assessment to promote equitable contribution and accountability. Finally, instructors and TAs should be trained to facilitate rather than direct, using Socratic prompts—such as "What standard will you benchmark that value against?", "What does high hardness imply for this application?", and "How confident are you in that measurement, and why?"—to develop students' independent problem-solving. When these measures are adopted proactively, PBL can be delivered at scale in undergraduate laboratories with high levels of engagement, equitable assessment, and robust learning outcomes despite the typical constraints of large enrolments.

VI. Conclusion

This project-based learning intervention transformed a traditional first-year engineering chemistry laboratory into a holistic learning experience that bridges disciplinary boundaries and emphasises critical analysis. By centring the course on a comprehensive water-quality project, the module integrated chemical fundamentals with an engineering context and moved students beyond rote procedures to genuine problem-solving. Students emerged with strengthened analytical proficiency and deeper conceptual understanding: they not only mastered standard laboratory techniques but also learned to interpret data against real-world criteria and make informed recommendations suited to each context. The collaborative, team-based format further developed transferable skills such as communication, teamwork, and self-directed problem-solving. Notably, the consistency and depth of results achieved across independent teams demonstrated that even novice students can deliver professional-quality outcomes when given ownership of a meaningful, context-rich task.

The positive educational outcomes of this PBL approach have significant implications for engineering education. This study illustrates that active, context-driven learning can be successfully implemented at scale in early undergraduate laboratories, provided that careful scaffolding and support are in place. Key enablers of success included an initial skills-building phase to boost students' confidence, clear and rigorous assessment rubrics aligned with the learning objectives, and a shift in instructor role from demonstrator to facilitator. Anticipating and addressing practical challenges—such as limited equipment and variability in team dynamics—was also essential. For example, station rotations, structured team roles, and Socratic questioning by instructors helped ensure equitable participation and steady progress for all teams. Consequently, with these measures in place, the PBL model delivered high student engagement, equitable assessment, and robust learning outcomes even in a large cohort.

Future iterations of the project could be enriched by integrating explicit hypothesis testing, quantitative uncertainty analysis, or broader interdisciplinary elements to further sharpen students' critical thinking and data literacy. Additionally, longitudinal studies tracking students beyond the course would be valuable to determine the lasting impact of early PBL exposure on their approach to complex problems in later years. Overall, this work demonstrates that reimagining introductory laboratories as project-driven, authentic experiences can profoundly enhance engineering education. By situating chemistry learning in a realistic engineering context, the approach equips students with a stronger conceptual foundation and versatile, transferable skills that extend well beyond the chemistry laboratory.

References

[1] Carbonell, C., Cardona, S., Dominguez-Candela, I., Fombuena, V., López-Pérez, M. F., Lora, J., & Sanchis, R. (2021). PROJECT-BASED LEARNING AS A COORDINATION METHODOLOGY BETWEEN SUBJECTS IN A CHEMICAL ENGINEERING DEGREE. 5965–5974.https://doi.org/10.21125/inted.2021.1193

[2] Crippen, K., Wu, C.-Y., Boyer, T., de Torres, T., Korolev, M., & Brucat, P. (n.d.). A Pilot Study of Project-Based Learning in General Chemistry for Engineers. 2016 ASEE Annual Conference & Exposition Proceedings. https://doi.org/10.18260/p.26396

[3] Das, R., Nath, H., Das, J., & Nag, S. (2022). WATER QUALITY ASSESSMENT OF DIFFERENT SAMPLES COLLECTED FROM VARIOUS LOCATIONS OF TRIPURA UNIVERSITY CAMPUS AND SELECTION OF SARASWAT : The Tripura University Research Journal WATER QUALITY ASSESSMENT OF DIFFERENT SAMPLES COLLECTED FROM VARIOUS LOCATIONS . June.

[4] Hung, W. (2006). The 3C3R Model: A Conceptual Framework for Designing Problems in PBL. Interdisciplinary Journal of Problem-Based Learning, 1(1), 5–22. https://doi.org/10.7771/1541-5015.1006.

[5] Nielsen, H. P., Frandsen, F. J., Dam-Johansen, K., & Baxter, L. L. (2000). The implications of chlorine-associated corrosion on the operation of biomass-fired boilers. Progress in Energy and Combustion Science, 26(3), 283–298. https://doi.org/10.1016/S0360-1285(00)00003-4.

[6] Rahmani, K. (2017). Reducing water consumption by increasing the cycles of concentration and Considerations of corrosion and scaling in a cooling system. Applied Thermal Engineering, 114, 849–856.https://doi.org/10.1016/j.applthermaleng.2016.12.075

[7] Sayato, Y. (1989). WHO Guidelines for Drinking-Water Quality. Eisei Kagaku, 35(5), 307312.https://doi.org/10.1248/jhs1956.35.307

[8] Uwem Ekwere Inyang, & Chidiebere Orji Olughu. (2025). The importance of boiler feed water and its treatment in a chemical

plant. World Journal of Advanced Research and Reviews, 27(1), 1624–1632. https://doi.org/10.30574/wjarr.2025.27.1.2705

[9] WHO, Brown, L., Caracci, K., Cox, B., Jordan, F., Kratz, K., Anderson, B. a, Industry, E., Union, E., Product, T., Directive, L., Product, T., Directive, L., Ganti, A., Systems, G. E. M., Specifically, A., Its, A., Overview, A., Typical, S., … Linkages, F. (2022). Guidelines for. In ReVision (Vol. 21, Issue 6).

[10] Xu, X., Liu, S., Liu, Y., Smith, K., Wang, X., Li, J., Ma, Z., Wang, Z., & Cui, Y. (2020). Water quality induced corrosion of stainless steel valves during long-term service in a reverse osmosis system. Journal of Environmental Sciences, 89, 218–226. https://doi.org/10.1016/j.jes.2019.10.008.

[11] Abel KD, Misra S, Agrawal A, Maskeliunas R, Damasevicius R. Data security using cryptography and steganography technique on the cloud. InComputational Intelligence in Machine Learning: Select Proceedings of ICCIML 2021 2022 Mar 3 (pp. 475-481). Singapore: Springer Nature Singapore.

[12] Vijarania M, Gupta S, Agrawal A, Misra S. Achieving sustainable development goals in cyber security using aiot for healthcare application. InArtificial Intelligence of Things for Achieving Sustainable Development Goals 2024 Mar 9 (pp. 207-231). Cham: Springer Nature Switzerland.

[13] Vijarania M, Agrawal A, Sharma MM. Task scheduling and load balancing techniques using genetic algorithm in cloud computing. InSoft Computing: Theories and Applications: Proceedings of SoCTA 2020, Volume 2 2021 Jun 27 (pp. 97-105). Singapore: Springer Singapore.

[14] Sharma MM, Agrawal A. Test case design and test case prioritization using machine learning. International Journal of Engineering and Advanced Technology. 2019 Oct;9(1):2742-8.

[15] Agrawal A, Arora R, Arora R, Agrawal P. Applications of artificial intelligence and internet of things for detection and future directions to fight against COVID-19. InEmerging Technologies for Battling Covid-19: Applications and Innovations 2021 Feb 16 (pp. 107-119). Cham: Springer International Publishing.

[16] Dalal S, Jaglan V, Agrawal A, Kumar A, Joshi SJ, Dahiya M. Navigating urban congestion: Optimizing LSTM with RNN in traffic prediction. InAIP Conference Proceedings 2024 Dec 20 (Vol. 3217, No. 1, p. 030005). AIP Publishing LLC.

[17] Dalal S, Lilhore UK, Faujdar N, Simaiya S, Agrawal A, Rani U, Mohan A. Enhancing thyroid disease prediction with improved XGBoost model and bias management techniques. Multimedia Tools and Applications. 2025 May;84(16):16757-88.

[18] Naphtali JH, Misra S, Wejin J, Agrawal A, Oluranti J. An intelligent hydroponic farm monitoring system using IoT. InData, Engineering and Applications: Select Proceedings of IDEA 2021 2022 Oct 12 (pp. 409-420). Singapore: Springer Nature Singapore.

[19] Joaquim MM, Kamble AW, Misra S, Badejo J, Agrawal A. IoT and machine learning based anomaly detection in WSN for a smart greenhouse. InData, Engineering and Applications: Select Proceedings of IDEA 2021 2022 Oct 12 (pp. 421-431). Singapore: Springer Nature Singapore.

[20] Vijarania M, Udbhav M, Gupta S, Kumar R, Agarwal A. Global cost of living in different geographical areas using the concept of NLP. InHandbook of Research on Applications of AI, Digital Twin, and Internet of Things for Sustainable Development 2023 (pp. 419-436). IGI Global.

[21] Gupta, S., Vijarania, M., Agarwal, A., Yadav, A., Mandadi, R. R., & Panday, S. (2024). Big Data Analytics in Healthcare Sector: Potential Strength and Challenges. In Advancement of Data Processing Methods for Artificial and Computing Intelligence (pp. 41-67). River Publishers.

[22] Afah, D., Gautam, A., Misra, S., Agrawal, A., Damaševičius, R., & Maskeliūnas, R. (2021, February). Smartphones verification and identification by the use of fingerprint. In International Conference on Emerging Applications of Information Technology (pp. 365-373). Singapore: Springer Singapore.

[23] Deore, H., Agrawal, A., Jaglan, V., Nagpal, P., & Sharma, M. M. (2020). A new approach for navigation and traffic signs

indication using map integrated augmented reality for self-driving cars. Scalable Computing: Practice and Experience, 21(3), 441-450.

[24] Jain, V., Raman, M., Agrawal, A., Hans, M., & Gupta, S. (Eds.). (2024). Convergence Strategies for Green Computing and Sustainable Development. IGI Global.

[25] Agrawal, A., & Jain, A. (2020). Speech emotion recognition of Hindi speech using statistical and machine learning techniques. Journal of Interdisciplinary Mathematics, 23(1), 311-319.

[26] Anand, A., Dalal, S., & Dubey, P. (2023). Designing Efficient model for ModelNet10 Database and Keras for 3D Object Recognition by PointNet Architecture. Journal of Data Science and Cyber Security, 1.0(1), 88-97.

[27] Anand, A., Dalal, S., & Dubey, P. (2023). Using ModelNet10 Database for Contactless Medical Treatment Robotics: Advancing 3D Object Recognition and Autonomous Navigation. Journal of Data Science and Cyber Security, 1.0(1), 76-87.

[28] Bishnoi, A., Bharadwaj, S., & Dalal, S. (2023). Disease Detection in Crop's using Transfer Learning: An analysis on Detection through Computer. 2023 International Conference on Communication, Security and Artificial Intelligence (ICCSAI), 475-480.

[29] Dalal, S., Goel, P., Onyema, E. M., Alharbi, A., Mahmoud, A., Algarni, M. A., & Awal, H. (2023). Application of machine learning for cardiovascular disease risk prediction. Computational Intelligence and Neuroscience, 2023.0(1), 9418666.

[30] Dalal, S., Goel, P., Onyema, E. M., Alharbi, A., Mahmoud, A., Algarni, M. A., & Awal, H. (2023). Research Article Application of Machine Learning for Cardiovascular Disease Risk Prediction.

[31] Dalal, S., Lilhore, U. K., Faujdar, N., Simaiya, S., Ayadi, M., Almujally, N. A., & Ksibi, A. (2023). Next-generation cyber attack prediction for IoT systems: leveraging multi-class SVM and optimized CHAID decision tree. Journal of Cloud Computing, 12.0(1), 137.

[32] Dalal, S., Lilhore, U. K., Manoharan, P., Rani, U., Dahan, F., Hajjej, F., Keshta, I., Sharma, A., Simaiya, S., & Raahemifar, K. (2023). An efficient brain tumor segmentation method based on adaptive moving self-organizing map and fuzzy K-mean clustering. Sensors, 23.0(18), 7816.

[33] Dalal, S., Lilhore, U. K., Simaiya, S., Jaglan, V., Mohan, A., Ahuja, S., Agrawal, A., Margala, M., & Chakrabarti, P. (2023). A precise coronary artery disease prediction using Boosted C5. 0 decision tree model. Journal of Autonomous Intelligence, 6.0(3).

[34] Dalal, S., Lilhore, U. K., Simaiya, S., Sharma, A., Jaglan, V., Kumar, M., Jangra, M., Goyal, N., & Rana, A. K. (2023). A Blockchain-based secure Internet of Medical Things framework for smart healthcare. Journal of Autonomous Intelligence, 6.0(3).

[35] Dalal, S., Manoharan, P., Lilhore, U. K., Seth, B., Simaiya, S., Hamdi, M., & Raahemifar, K. (2023). Extremely boosted neural network for more accurate multi-stage Cyber attack prediction in cloud computing environment. Journal of Cloud Computing, 12.0(1), 1-22.

[36] Dalal, S., Onyema, E. M., Kumar, P., Maryann, D. C., Roselyn, A. O., & Obichili, M. I. (2023). A hybrid machine learning model for timely prediction of breast cancer. International Journal of Modeling, Simulation, and Scientific Computing, 14.0(04), 2341023.

[37] Dalal, S., Poongodi, M., Lilhore, U. K., Dahan, F., Vaiyapuri, T., Keshta, I., Aldossary, S. M., Mahmoud, A., & Simaiya, S. (2023). Optimized LightGBM model for security and privacy issues in cyber-physical systems. Transactions on Emerging Telecommunications Technologies, e4771.

[38] Dalal, S., Seth, B., & Radulescu, M. (2023). Driving technologies of Industry 5.0 in the medical field. Digitalization, sustainable development, and Industry 5.0: An organizational model for twin transitions, 267-292.

[39] Dalal, S., Seth, B., Radulescu, M., Cilan, T. F., & Serbanescu, L. (2023). Optimized deep learning with learning without forgetting (LwF) for weather classification for sustainable transportation and traffic safety. Sustainability, 15.0(7), 6070.

[40] Deshwal, D., Sangwan, P., Dahiya, N.,

Lilhore, U. K., Dalal, S., & Simaiya, S. (2023). COVID-19 Detection using Hybrid CNN-RNN Architecture with Transfer Learning from X-Rays. Current medical imaging, 20.0.

[41] Jaiswal, V., Saurabh, P., Lilhore, U. K., Pathak, M., Simaiya, S., & Dalal, S. (2023). A breast cancer risk predication and classification model with ensemble learning and big data fusion. Decision Analytics Journal, 8.0, 100298.

[42] Lilhore, U. K., Dalal, S., Faujdar, N., Margala, M., Chakrabarti, P., Chakrabarti, T., Simaiya, S., Kumar, P., Thangaraju, P., & Velmurugan, H. (2023). Hybrid CNN-LSTM model with efficient hyperparameter tuning for prediction of Parkinson's disease. Scientific Reports, 13.0(1), 14605.

[43] Lilhore, U. K., Manoharan, P., Sandhu, J. K., Simaiya, S., Dalal, S., Baqasah, A. M., Alsafyani, M., Alroobaea, R., Keshta, I., & Raahemifar, K. (2023). Hybrid model for precise hepatitis-C classification using improved random forest and SVM method. Scientific Reports, 13.0(1), 12473.

[44] Lilhore, U. K., Manoharan, P., Simaiya, S., Alroobaea, R., Alsafyani, M., Baqasah, A. M., Dalal, S., Sharma, A., & Raahemifar, K. (2023). Hidm: Hybrid intrusion detection model for industry 4.0 networks using an optimized cnn-lstm with transfer learning. Sensors, 23.0(18), 7856.

[45] Malik, A., Onyema, E. M., Dalal, S., Lilhore, U. K., Anand, D., Sharma, A., & Simaiya, S. (2023). Forecasting students' adaptability in online entrepreneurship education using modified ensemble machine learning model. Array, 19.0, 100303.

[46] Nikhil, Arpna, & Dalal, S. (2023). Machine learning model for Water Quality evaluation: Systematic Review. 2023 Second International Conference On Smart Technologies For Smart Nation (SmartTechCon), 1013-1018.

[47] Singh A, Prakash N, Jain A. A review on prevalence of worldwide COPD situation. Proceedings of Data Analytics and Management: ICDAM 2022. 2023 Mar 25:391-405.

[48] Singh A, Payal A. CAD diagnosis by predicting stenosis in arteries using data mining process. Intelligent Decision Technologies. 2021 Feb;15(1):59-68.

[49] Singh A, Prakash N, Jain A. A comparative study of metaheuristic-based machine learning classifiers using non-parametric tests for the detection of COPD severity grade.

[50] Dalal, S., Onyema, E. M., & Malik, A. (2022). Hybrid XGBoost model with hyperparameter tuning for prediction of liver disease with better accuracy. World Journal of Gastroenterology, 28.0(46), 6551.

[51] Dalal, S., Onyema, E. M., Romero, C. A. T., Ndufeiya-Kumasi, L. C., Maryann, D. C., Nnedimkpa, A. J., & Bhatia, T. K. (2022). Machine learning-based forecasting of potability of drinking water through adaptive boosting model. Open Chemistry, 20.0(1), 816-828.

[52] Dalal, S., Seth, B., Jaglan, V., Malik, M., Surbhi, Dahiya, N., Rani, U., Le, D. N., & Hu, Y. C. (2022). An adaptive traffic routing approach toward load balancing and congestion control in Cloud–MANET ad hoc networks. Soft Computing, 26.0(11), 5377-5388.

[53] Dalal, S., Seth, B., Radulescu, M., Secara, C., & Tolea, C. (2022). Predicting fraud in financial payment services through optimized hyper-parameter-tuned XGBoost model. Mathematics, 10.0(24), 4679.

[54] Edeh, M. O., Dalal, S., Dhaou, I. B., Agubosim, C. C., Umoke, C. C., Richard-Nnabu, N. E., & Dahiya, N. (2022). Artificial intelligence-based ensemble learning model for prediction of hepatitis C disease. Frontiers in public health, 10.0, 892371.

[55] Singh A, Prakash N, Jain A. Chronic Diseases Prediction using two different pipelines TPOT and Genetic Algorithm based models: A Comparative analysis. InProceedings of the 2024 9th International Conference on Machine Learning Technologies 2024 May 24 (pp. 175-180).