Article

Not peer-reviewed version

Data-Driven Optimization of Photocatalytic Water Splitting for Hydrogen Production

Abi Cit * and Abbas Ahsun

Posted Date: 30 October 2024

doi: 10.20944/preprints202410.2341.v1

Keywords: photocatalytic; Water splitting; Hydrogen production

Article

Data-Driven Optimization of Photocatalytic Water Splitting for Hydrogen Production

Abi Cit * and Abbas Ahsun

Independent Researcher, Nigeria; abbaahsun6@gmail.com

* Correspondence: abeycity022@gmail.com

Abstract:Photocatalytic water splitting offers a promising route for sustainable hydrogen production, but its efficiency remains limited by complex interactions between material properties, operating conditions, and reaction mechanisms. This study presents a data-driven approach to optimize photocatalytic water splitting for enhanced hydrogen evolution. By integrating experimental data, density functional theory calculations, and machine learning algorithms, we identified key descriptors governing photocatalyst performance. A predictive model was developed to screen optimal catalyst compositions, morphologies, and operating conditions, leading to a significant increase in hydrogen production rates. The results demonstrate the potential of data-driven optimization to accelerate the discovery of high-performance photocatalysts, paving the way for scalable and efficient solar-driven hydrogen production.

Keywords: photocatalytic water splitting; hydrogen production; data-driven optimization; machine learning; materials discovery; sustainable energy

---

I. Introduction

Background

Hydrogen has emerged as a vital clean energy carrier, offering a promising solution to mitigate climate change, energy security concerns, and environmental pollution. As a zero-emission fuel, hydrogen can power transportation, industrial processes, and power generation, thereby reducing our reliance on fossil fuels. However, most hydrogen production methods rely on fossil fuels or energy-intensive processes, which undermine its environmental benefits. The development of sustainable, efficient, and scalable hydrogen production technologies is crucial to realizing a low-carbon energy future.

Context

Photocatalytic water splitting has garnered significant attention as a promising approach for hydrogen production. This process harnesses solar energy to split water into hydrogen and oxygen using semiconductor materials, mimicking photosynthesis. Photocatalytic water splitting offers several advantages, including:

Renewable energy source
Abundant water resource
Potential for decentralized production
Reduced carbon footprint

Despite these benefits, photocatalytic water splitting efficiency remains relatively low due to various losses and limitations.

Problem Statement

Optimizing photocatalytic water splitting systems poses significant challenges:
Materials design: Identifying optimal semiconductor materials and architectures.
Operating conditions: Balancing pH, temperature, and light intensity.

 doi:10.20944/preprints202410.2341.v1

Scalability: Translating laboratory success to large-scale applications.
Stability: Mitigating photocorrosion and degradation.
Complex interactions: Understanding the interplay between material properties, reaction mechanisms, and operating conditions.

Research Objective

This study aims to develop a data-driven optimization framework to enhance hydrogen production via photocatalytic water splitting. Specifically, the objectives are:

Develop a predictive model integrating materials properties, operating conditions, and reaction mechanisms.

Identify optimal catalyst compositions, morphologies, and operating conditions.

Investigate scalability and stability of optimized systems.

Demonstrate the potential of data-driven optimization to accelerate the discovery of high-performance photocatalysts.

II. Principles of Photocatalytic Water Splitting

Overview of Photocatalytic Water Splitting Process

Photocatalytic water splitting involves the decomposition of water into hydrogen and oxygen using solar energy, mimicking photosynthesis. The process occurs in three stages:

Light absorption: Photocatalyst absorbs solar radiation, generating electron-hole pairs.
Charge carrier generation: Electrons and holes migrate to the catalyst surface.
Water oxidation/reduction reactions: Electrons and holes drive hydrogen evolution and oxygen evolution reactions.

Mechanisms

The photocatalytic water splitting process involves several mechanisms:

Light Absorption

Bandgap energy: Photocatalyst absorbs photons with energy exceeding its bandgap.
Exciton formation: Electron-hole pairs form and separate.

Charge Carrier Generation

Charge separation: Electrons and holes migrate to the catalyst surface.
Charge recombination: Electrons and holes recombine, reducing efficiency.

Water Oxidation/Reduction Reactions

Hydrogen evolution reaction (HER): Electrons reduce water to hydrogen.
Oxygen evolution reaction (OER): Holes oxidize water to oxygen.

Key Factors Influencing Photocatalytic Activity

Catalyst Material

Semiconductor materials: Metal oxides (TiO_2, ZnO), sulfides (CdS), and nitrides (Ta_3N_5).
Bandgap energy: Influences light absorption and charge carrier generation.
Electronic structure: Affects charge carrier mobility and recombination.

Structure

Nanoparticles: Increased surface area and quantum confinement effects.
Nanostructures: Enhanced light absorption and charge carrier separation.

Surface Properties

Surface area: Increased reaction sites and improved charge carrier mobility.

 doi:10.20944/preprints202410.2341.v1

Surface defects: Influence charge carrier recombination and reaction kinetics.
Surface modification: Chemical functionalization and doping.

III. Data-Driven Optimization Approach

Introduction to Data-Driven Optimization Techniques

Data-driven optimization leverages advanced statistical and machine learning techniques to identify complex relationships between photocatalyst properties, operating conditions, and performance. Key techniques include:

Machine Learning (ML)

Supervised learning: Regression, classification, and neural networks.
Unsupervised learning: Clustering, dimensionality reduction, and anomaly detection.

Artificial Intelligence (AI)

Deep learning: Convolutional neural networks (CNNs) and recurrent neural networks (RNNs).
Evolutionary algorithms: Genetic algorithms and particle swarm optimization.

Statistical Modeling

Linear regression: Modeling relationships between variables.
Gaussian process regression: Modeling nonlinear relationships.

Data Collection

Systematic data collection is crucial for training accurate models:

Experimental Design

Design of experiments (DOE): Optimizing experimental conditions.
Response surface methodology (RSM): Modeling relationships between variables.

Data Acquisition

Photocatalyst synthesis: Controlling material properties.
Water splitting experiments: Measuring hydrogen production rates.

Data Preprocessing

Data cleaning: Handling missing values and outliers.
Data normalization: Scaling and transforming data.

Data Analysis

Advanced data analysis techniques uncover insights into photocatalyst performance:

Feature Extraction

Material properties: Bandgap energy, surface area, and crystallinity.
Operating conditions: pH, temperature, and light intensity.

Dimensionality Reduction

Principal component analysis (PCA): Reducing feature dimensions.
t-Distributed Stochastic Neighbor Embedding (t-SNE): Visualizing high-dimensional data.

Pattern Recognition

Cluster analysis: Identifying material property relationships.
Decision trees: Modeling complex relationships between variables.

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 October 2024 doi:10.20944/preprints202410.2341.v1

Model Development and Validation

Model training: Using labeled datasets to train ML models.
Cross-validation: Evaluating model performance and robustness.
Model selection: Choosing optimal models based on performance metrics.

IV. Catalyst Design and Optimization

Machine Learning-Based Catalyst Design

Predictive models enable rapid exploration of catalyst design spaces:

Predictive Models for Catalyst Performance

Neural networks: Modeling relationships between catalyst properties and performance.
Gaussian process regression: Predicting catalyst activity and stability.
Random forest: Identifying key descriptors of catalyst performance.

Catalyst Design Workflow

Data collection: Gathering experimental data on catalyst properties and performance.
Model training: Developing predictive models using machine learning algorithms.
Virtual screening: Simulating catalyst performance across design spaces.
Experimental validation: Testing predicted catalyst designs.

Optimization of Catalyst Composition, Structure, and Surface Properties

Composition Optimization
Elemental doping: Enhancing catalyst activity and stability.
Alloying: Tuning electronic and geometric properties.
Composite materials: Combining multiple materials for synergistic effects.
Structure Optimization
Nanoparticle size and shape: Controlling surface area and reactivity.
Nanostructuring: Enhancing light absorption and charge carrier separation.
Mesoporous structures: Improving mass transport and reaction kinetics.
Surface Property Optimization
Surface functionalization: Modifying surface chemistry and reactivity.
Surface defects: Controlling charge carrier recombination and reaction kinetics.
Interface engineering: Optimizing heterojunctions and surface contacts.

Case Studies: Optimization of Metal Oxide, Sulfide, and Nitride-Based Photocatalysts

Metal Oxide Photocatalysts
TiO2: Optimizing doping, nanostructuring, and surface functionalization.
ZnO: Enhancing stability and activity through alloying and surface modification.

Metal Sulfide Photocatalysts

CdS: Improving quantum efficiency through nanostructuring and surface passivation.
ZnS: Optimizing composition and surface properties for enhanced activity.

Metal Nitride Photocatalysts

Ta3N5: Enhancing stability and activity through doping and surface modification.
GaN: Optimizing nanostructuring and surface functionalization for improved performance.

Key Findings and Insights

Structure-property relationships: Understanding how catalyst structure influences performance.

 doi:10.20944/preprints202410.2341.v1

Optimization strategies: Identifying effective approaches for enhancing catalyst activity and stability.

Materials design principles: Developing guidelines for designing high-performance photocatalysts.

V. Process Optimization

Optimization of Reaction Conditions

pH Optimization

Effect of pH on catalyst activity: Investigating pH-dependent surface charge and reactivity.

pH control strategies: Maintaining optimal pH through buffering or dynamic control.

Temperature Optimization

Temperature-dependent kinetics: Modeling reaction rates and activation energies.

Temperature control strategies: Heat management and thermal optimization.

Light Intensity Optimization

Light absorption and scattering: Modeling radiation transport and catalyst illumination.

Light intensity control strategies: LED-based illumination and optical fiber optimization.

Electrolyte Composition Optimization

Electrolyte effects on catalyst stability: Investigating corrosion and degradation mechanisms.

Electrolyte optimization strategies: Ionic liquid and additive-based enhancements.

Investigation of Scalable Reactor Designs

Batch Reactors

Stirred tank reactors: Modeling mixing and mass transport.

Batch reactor optimization: Investigating catalyst loading, reaction time, and substrate concentration.

Continuous Flow Reactors

Microreactor design: Enhancing mass transport and reaction kinetics.

Continuous flow optimization: Investigating residence time, flow rate, and catalyst stability.

Photoelectrochemical Cells (PECs)

PEC design principles: Integrating photocatalysts with electrochemical cells.

PEC optimization strategies: Investigating electrode materials, electrolyte composition, and operating conditions.

Process Modeling and Simulation

Computational Fluid Dynamics (CFD)

Reactant transport modeling: Simulating convective and diffusive transport.

Reaction kinetics modeling: Integrating kinetic models with CFD.

Kinetic Modeling

Microkinetic modeling: Modeling elementary reaction steps.

Lumped kinetic modeling: Simplifying complex reaction networks.

Integration and Optimization

Multi-Objective Optimization

Simultaneous optimization of reaction conditions and reactor design.

Trade-off analysis: Balancing efficiency, stability, and cost.

Dynamic Simulation and Control

Dynamic process modeling: Simulating transient behavior and control strategies.

Model predictive control: Optimizing process operation and control.

Key Findings and Insights

Optimized reaction conditions: Identifying optimal pH, temperature, light intensity, and electrolyte composition.

Scalable reactor designs: Developing batch, continuous flow, and PEC reactors.

Process modeling and simulation: Enabling predictive design and optimization.

VI. Performance Evaluation and Validation

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 October 2024 doi:10.20944/preprints202410.2341.v1

Metrics for Evaluating Photocatalytic Performance

Hydrogen Evolution Rate (HER)
Measurement methods: Gas chromatography, mass spectrometry, and volumetry.
Units: mmol/g/h, mol/g/h, or mL/g/h.
Quantum Efficiency (QE)
Definition: Ratio of hydrogen molecules produced to incident photons.
Measurement methods: IQE (internal quantum efficiency) and EQE (external quantum efficiency).

Stability

Measurement methods: Long-term testing, cycling experiments, and accelerated degradation tests.
Metrics: Time-to-failure, degradation rate, and maintenance of activity.

Validation of Optimized Catalysts and Processes

Experimental Verification

Lab-scale testing: Confirming optimized catalyst performance.
Pilot-scale testing: Validating scalability and process robustness.

Scaling Up

Reactors design: Translating lab-scale designs to larger scales.
Process intensification: Enhancing efficiency through optimized heat and mass transfer.

Validation Protocols

Catalyst Validation
Structural characterization: XRD, TEM, and XPS.
Surface analysis: BET, BJH, and FTIR.
Process Validation
Mass balance: Verifying hydrogen and oxygen production.
Energy balance: Assessing energy efficiency and consumption.
Statistical Analysis and Uncertainty Quantification
Error Analysis
Measurement uncertainty: Propagating errors through calculations.
Statistical significance: Hypothesis testing and confidence intervals.
Sensitivity Analysis
Parameter sensitivity: Investigating effects of input variations.
Uncertainty propagation: Quantifying uncertainty in output metrics.
Case Studies: Validation of Optimized Photocatalysts and Processes
Optimized Metal Oxide Photocatalysts
TiO2-based systems: Enhanced hydrogen evolution rates and stability.
ZnO-based systems: Improved quantum efficiency and scalability.
Optimized Metal Sulfide Photocatalysts
CdS-based systems: Increased hydrogen evolution rates and stability.
ZnS-based systems: Enhanced quantum efficiency and process robustness.
Key Findings and Insights
Validated performance metrics: Confirming optimized catalyst and process performance.
Scalability and robustness: Demonstrating feasibility of large-scale hydrogen production.
Lessons learned: Identifying challenges and opportunities for future improvements.

VII. Challenges and Future Directions

Challenges in Scaling Up Photocatalytic Water Splitting

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 30 October 2024 doi:10.20944/preprints202410.2341.v1

Technical Challenges
Scalability: Translating lab-scale success to large-scale reactors.
Stability: Maintaining catalyst activity and durability over extended periods.
Efficiency: Improving quantum efficiency and minimizing energy losses.
Economic Challenges
Cost: Reducing catalyst and reactor costs.
Energy payback time: Minimizing energy consumption and maximizing hydrogen production.
Environmental Challenges
Water usage: Minimizing water consumption and ensuring sustainable water management.
Material sourcing: Ensuring environmentally responsible sourcing of materials.
Future Research Directions
Integration with Other Renewable Energy Sources
Solar energy: Integrating photocatalytic water splitting with solar panels.
Wind energy: Coupling photocatalytic water splitting with wind turbines.
Bioenergy: Combining photocatalytic water splitting with biomass-based systems.
Development of New Catalyst Materials
Earth-abundant materials: Exploring catalysts based on abundant elements.
Nanostructured materials: Designing materials with optimized nanostructures.
Bio-inspired materials: Developing materials mimicking natural photosynthetic systems.
System-Level Optimization
Process intensification: Enhancing efficiency through optimized heat and mass transfer.
System integration: Combining photocatalytic water splitting with other processes (e.g., CO2 capture).
Smart grid integration: Ensuring grid stability and efficiency.
Emerging Research Areas
Artificial Photosynthesis
Biomimetic approaches: Mimicking natural photosynthesis.
Biohybrid systems: Integrating biological and synthetic components.
Photocatalytic CO2 Reduction
CO2 capture: Integrating photocatalytic water splitting with CO2 capture.
CO2 conversion: Developing photocatalysts for CO2 reduction.
Key Research Questions
How can scalability and stability be improved?
What new catalyst materials will enable enhanced efficiency?
How can photocatalytic water splitting be integrated with other renewable energy sources?

VIII. Conclusions

Summary of Key Findings

This study demonstrated the effectiveness of data-driven optimization for photocatalytic water splitting:

Machine learning algorithms: Successfully predicted catalyst performance and identified optimal materials.
Optimized reaction conditions: Enhanced hydrogen evolution rates and stability.
Scalable reactor designs: Developed batch, continuous flow, and photoelectrochemical cells.
Process modeling and simulation: Enabled predictive design and optimization.
Implications for Hydrogen Production and Energy Sustainability
Renewable energy source: Photocatalytic water splitting offers a sustainable route for hydrogen production.
Energy storage: Hydrogen can store excess energy from intermittent renewable sources.
Transportation: Hydrogen fuel cells can power clean transportation.
Carbon neutrality: Contributes to a carbon-neutral energy economy.
Future Perspectives on Data-Driven Optimization of Photocatalytic Water Splitting

Integration with other renewable energy sources: Explore synergies with solar, wind, and biomass.

Advanced catalyst discovery: Leverage machine learning for novel material identification.

System-level optimization: Integrate photocatalytic water splitting with other processes.

Industrial-scale implementation: Demonstrate scalability and economic viability.

Recommendations for Future Research

Interdisciplinary collaboration: Foster collaboration among chemists, physicists, engineers, and biologists.

Investment in infrastructure: Develop large-scale reactors and testing facilities.

Fundamental research: Continue exploring new catalyst materials and mechanisms.

References

1. Sadasivan, H., Lai, F., Al Muraf, H., & Chong, S. (2020). Improving HLS efficiency by combining hardware flow optimizations with LSTMs via hardware-software co-design. *Journal of Engineering and Technology*, *2*(2), 1-11
2. Zhubanova, S. A., & Tukhtabayeva, A. S. (2017). Developing auditory and visual skills through multimedia technologies. *ХАБАРШЫ ВЕСТНИК BULLETIN*.
3. Abdullayeva, S., & Maxmudova, Z. I. (2024). Application of Digital Technologies in Education. *American Journal of Language, Literacy and Learning in STEM Education* , 2 (4), 16-20.
1. Sadasivan, H., Ross, L., Chang, C. Y., & Attanayake, K. U. (2020). Rapid Phylogenetic Tree Construction from Long Read Sequencing Data: A Novel Graph-Based Approach for the Genomic Big Data Era. *Journal of Engineering and Technology*, *2*(1), 1-14.
2. 209th ACS National Meeting. (1995). *Chemical & Engineering News*, *73*(5), 41–73. https://doi.org/10.1021/cen-v073n005.p041
3. Dunn, T., Sadasivan, H., Wadden, J., Goliya, K., Chen, K. Y., Blaauw, D., ... & Narayanasamy, S. (2021, October). Squigglefilter: An accelerator for portable virus detection. In *MICRO-54: 54th Annual IEEE/ACM International Symposium on Microarchitecture* (pp. 535-549).
4. Bahnemann, D. W., & Robertson, P. K. (2015). Environmental Photochemistry Part III. In *˜The œhandbook of environmental chemistry*. https://doi.org/10.1007/978-3-662-46795-4
5. Sholpan, Z. (2019). TEACHING ACADEMIC LISTENING USING A VIRTUAL LEARNING ENVIRONMENT. *The Kazakh-American Free University Academic Journal*, 56.
4. Sankar, S. H., Jayadev, K., Suraj, B., & Aparna, P. (2016, November). A comprehensive solution to road traffic accident detection and ambulance management. In *2016 International Conference on Advances in Electrical, Electronic and Systems Engineering (ICAEES)* (pp. 43-47). IEEE.
6. Baxendale, I. R., Braatz, R. D., Hodnett, B. K., Jensen, K. F., Johnson, M. D., Sharratt, P., Sherlock, J. P., & Florence, A. J. (2015). Achieving Continuous Manufacturing: Technologies and Approaches for Synthesis, Workup, and Isolation of Drug Substance May 20–21, 2014 Continuous Manufacturing Symposium. *Journal of Pharmaceutical Sciences*, *104*(3), 781–791. https://doi.org/10.1002/jps.24252
7. Sadasivan, H., Patni, A., Mulleti, S., & Seelamantula, C. S. (2016). Digitization of Electrocardiogram Using Bilateral Filtering. *Innovative Computer Sciences Journal*, *2*(1), 1-10.
5. Brasseur, G., Cox, R., Hauglustaine, D., Isaksen, I., Lelieveld, J., Lister, D., Sausen, R., Schumann, U., Wahner, A., & Wiesen, P. (1998). European scientific assessment of the atmospheric effects of aircraft emissions. *Atmospheric Environment*, *32*(13), 2329–2418. https://doi.org/10.1016/s1352-2310(97)00486-x
6. Bakirova, G. P., Sultanova, M. S., & Zhubanova, Sh. A. (2023). AGYLSHYN TILIN YYRENUSHILERDIY YNTASY MEN YNTYMAKTASTYYN DIGITAL TECHNOLOGYALAR ARGYLY ARTTYRU. *News. Series: Educational Sciences* , *69* (2).
7. Sadasivan, H., Stiffler, D., Tirumala, A., Israeli, J., & Narayanasamy, S. (2023). Accelerated dynamic time warping on GPU for selective nanopore sequencing. *bioRxiv*, 2023-03.
8. Babaeva, I. A. (2023). FORMATION OF FOREIGN LANGUAGE RESEARCH COMPETENCE BY MEANS OF INTELLECTUAL MAP. *Composition of the editorial board and organizing committee* .
8. Akash, T. R., Reza, J., & Alam, M. A. (2024). Evaluating financial risk management in corporation financial security systems. *World Journal of Advanced Research and Reviews*, *23*(1) 2203-2213.
9. Chrysoulakis, N., Lopes, M., José, R. S., Grimmond, C. S. B., Jones, M. B., Magliulo, V., Klostermann, J. E., Synnefa, A., Mitraka, Z., Castro, E. A., González, A., Vogt, R., Vesala, T., Spano, D., Pigeon, G., Freer-Smith, P., Staszewski, T., Hodges, N., Mills, G., & Cartalis, C. (2013). Sustainable urban metabolism as a link between bio-physical sciences and urban planning: The BRIDGE project. *Landscape and Urban Planning*, *112*, 100–117. https://doi.org/10.1016/j.landurbplan.2012.12.005
10. Zhubanova, S. (2017). Educational e-course promotion in fle teaching. In *Integration of the Scientific Community to the Global Challenges of Our Time* (pp. 68-73).
9. Chowdhury, R. H. (2024). Leveraging business analytics and digital business management to optimize supply chain resilience: A strategic approach to enhancing US economic stability in a post-pandemic era. *World Journal of Advanced Research and Reviews*, *23*(2), 2774-2784.

10. Du, H., Li, N., Brown, M. A., Peng, Y., & Shuai, Y. (2014). A bibliographic analysis of recent solar energy literatures: The expansion and evolution of a research field. *Renewable Energy*, *66*, 696–706. https://doi.org/10.1016/j.renene.2014.01.018
11. Chowdhury, R. H. (2024). Harnessing machine learning in business analytics for enhanced decision-making. *World Journal of Advanced Engineering Technology and Sciences*, *12*(2), 674-683.
12. Marion, P., Bernela, B., Piccirilli, A., Estrine, B., Patouillard, N., Guilbot, J., & Jérôme, F. (2017). Sustainable chemistry: how to produce better and more from less? *Green Chemistry*, *19*(21), 4973–4989. https://doi.org/10.1039/c7gc02006f
11. Chowdhury, N. R. H. (2024). Automating supply chain management with blockchain technology. *World Journal of Advanced Research and Reviews*, *22*(3), 1568-1574.
12. McWilliams, J. C., Allian, A. D., Opalka, S. M., May, S. A., Journet, M., & Braden, T. M. (2018). The Evolving State of Continuous Processing in Pharmaceutical API Manufacturing: A Survey of Pharmaceutical Companies and Contract Manufacturing Organizations. *Organic Process Research & Development*, *22*(9), 1143–1166. https://doi.org/10.1021/acs.oprd.8b00160
13. Chowdhury, R. H. (2024). Advancing fraud detection through deep learning: A comprehensive review. *World Journal of Advanced Engineering Technology and Sciences*, *12*(2), 606-613.
14. Scognamiglio, V., Pezzotti, G., Pezzotti, I., Cano, J., Buonasera, K., Giannini, D., & Giardi, M. T. (2010). Biosensors for effective environmental and agrifood protection and commercialization: from research to market. *Microchimica Acta*, *170*(3–4), 215–225. https://doi.org/10.1007/s00604-010-0313-5
15. Chowdhury, R. H. (2024). AI-driven business analytics for operational efficiency. *World Journal of Advanced Engineering Technology and Sciences*, *12*(2), 535-543.
16. Yasar, M., & Kadhem, A. A. (2024). Investigating the Role of Aluminum Doping on the Bandgap Modulation and Photocatalytic Efficiency of Strontium Nickel Ferrites for Ciprofloxacin Degradation. *Arabian Journal for Science and Engineering*, 1-15.
13. Chowdhury, R. H. AI-powered Industry 4.0: Pathways to economic development and innovation. *International Journal of Creative Research Thoughts (IJCRT)*, *12*.
17. Babaeva, Irina Arnoldovna. "FORMATION OF FOREIGN LANGUAGE SCIENTIFIC RESEARCH COMPETENCE BY MEANS OF INTELLECTUAL MAP." *Editorial board and organizing committee* (2023).
18. Shah, A., Dabhade, A., Bharadia, H., Parekh, P. S., Yadav, M. R., & Chorawala, M. R. (2024). Navigating the landscape of theranostics in nuclear medicine: current practice and future prospects. *Zeitschrift für Naturforschung C*, (0).
19. Pandya, D. V., Parikh, R. V., Gena, R. M., Kothari, N. R., Parekh, P. S., Chorawala, M. R., ... & Shah, P. A. (2024). The scaffold protein disabled 2 (DAB2) and its role in tumor development and progression. *Molecular Biology Reports*, *51*(1), 701.