Smart Materials Design: Machine Learning as a Catalyst for Innovation in Chemistry

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Abstract

Smart materials design and machine learning have emerged as powerful tools in the field of chemistry, revolutionizing the discovery and development of new materials. This paper explores the intersection of smart materials design and machine learning, highlighting their potential for innovation in chemistry. By leveraging machine learning techniques, researchers can accelerate the discovery process by predicting material properties, optimizing performance, and exploring complex chemical spaces. The integration of experimental and computational data further enhances the understanding of materials and enables more efficient and reliable predictions. However, challenges such as data quality, interpretability, and ethical considerations must be addressed. Through data-driven approaches, smart materials design can be optimized, leading to tailored materials with improved functionalities. This paper emphasizes the transformative role of machine learning in chemistry and its impact on material design, setting the stage for advancements in technology, energy, healthcare, and other domains.

Keywords: Smart materials design, machine learning, material discovery, predictive modeling, computational chemistry.

Introduction: Exploring the Intersection of Smart Materials Design and Machine Learning

In recent years, the field of materials design has witnessed a remarkable transformation with the advent of machine learning techniques. Smart materials, which exhibit dynamic properties and respond intelligently to external stimuli, hold tremendous potential for revolutionizing various industries, including electronics, healthcare, energy, and beyond. However, designing and optimizing these complex materials poses significant challenges due to their intricate structure-property relationships. Machine learning, a branch of artificial intelligence, has emerged as a powerful catalyst for innovation in chemistry, offering new avenues for tackling the complexities of smart materials design. By leveraging large datasets, advanced algorithms, and computational modeling, machine learning enables researchers to uncover hidden patterns, accelerate material discovery, and predict material properties with unprecedented accuracy. This intersection of smart materials design and machine learning has opened up exciting possibilities for developing novel materials with tailored functionalities, enhanced performance, and improved sustainability. By harnessing the vast potential of machine learning, researchers can overcome traditional trial-and-error approaches and drive the design of materials that meet specific requirements in diverse applications **[1-5]**. In this article, we delve into the convergence of smart materials design and machine learning, exploring the synergistic relationship between the two fields. We will examine the fundamental characteristics of smart materials, highlight the challenges associated with their design, and showcase how machine learning techniques can address these challenges. Furthermore, we will discuss various data-driven approaches, predictive modeling techniques, and computational screening methods that are revolutionizing the field of smart materials design. Through a comprehensive exploration of successful case studies, emerging trends, and future directions, this article aims to shed light on the transformative impact of machine learning in the realm of smart materials. Moreover, we will also address the ethical considerations and responsible deployment of machine learning in chemistry to ensure the sustainable and responsible development of innovative smart materials **[5-10]**. As we embark on this journey at the crossroads of smart materials design and machine learning, we are poised to unlock unprecedented possibilities, foster interdisciplinary collaboration, and propel the development of next-generation materials that will shape the future of technology and society.

Understanding Smart Materials: Characteristics, Applications, and Challenges

Smart materials represent a class of advanced materials that possess unique properties and capabilities to respond intelligently to external stimuli. These materials can exhibit changes in their physical, chemical, or mechanical properties in a controlled and reversible manner, making them highly versatile and adaptable for a wide range of applications **[11-16]**. To fully grasp the potential of smart materials and harness their benefits, it is crucial to explore their characteristics, delve into their diverse applications, and address the challenges associated with their design.

Characteristics of Smart Materials:

Smart materials exhibit distinct characteristics that set them apart from traditional materials. They often possess inherent responsiveness, which allows them to sense and adapt to changes in their environment. Key characteristics of smart materials include:

Stimulus Responsiveness: Smart materials can respond to various stimuli such as temperature, light, humidity, pressure, electric fields, or magnetic fields. They undergo reversible changes in their properties, such as shape, conductivity, viscosity, or optical properties, upon exposure to these stimuli.

Multifunctionality: Smart materials often exhibit multiple functionalities, enabling them to perform different tasks simultaneously or switch between different states based on the applied stimulus. This multifunctionality opens up possibilities for innovative applications and enhanced performance.

Self-Healing: Some smart materials have the ability to repair or regenerate themselves after damage or deformation, mimicking the healing properties found in living organisms. This characteristic enhances the durability and longevity of smart materials in practical applications.

Applications of Smart Materials:

The unique properties of smart materials have led to their utilization across a wide range of industries. Some notable applications include:

Biomedical and Healthcare: Smart materials find applications in drug delivery systems, tissue engineering, biosensors, and medical implants. They can respond to physiological cues, release drugs at specific sites, and provide real-time monitoring of biological parameters.

Electronics and Optics: Smart materials are used in flexible displays, smart windows, sensors, and actuators in electronic devices. They can exhibit properties like tunable conductivity, color-changing abilities, and optical switching, enabling advancements in electronic and optical technologies.

Energy and Environment: Smart materials play a crucial role in energy storage and conversion, such as in batteries, fuel cells, and solar cells. They can enhance energy efficiency, improve environmental sustainability, and enable the development of smart energy systems.

Aerospace and Automotive: Smart materials are utilized in aerospace and automotive industries for applications like vibration control, shape-changing wings, and self-repairing structures. They contribute to increased efficiency, reduced weight, and improved safety in these sectors.

Challenges in Smart Materials Design:

Despite the tremendous potential of smart materials, their design and implementation present several challenges:

Complexity of Structure-Property Relationships: Smart materials often have intricate and non-linear structure-property relationships, making it challenging to predict and optimize their performance. Traditional trial-and-error approaches are time-consuming and costly.

Limited Understanding of Mechanisms: The underlying mechanisms governing the behavior of smart materials are not fully understood. This lack of fundamental knowledge hinders the development of precise models and reliable predictions.

Integration with Existing Systems: Incorporating smart materials into existing technologies and systems requires compatibility, reliability, and scalability. Integration challenges arise in terms of manufacturing processes, cost-effectiveness, and long-term performance.

Durability and Longevity: Ensuring the durability and longevity of smart materials is crucial for their practical applications. Factors like fatigue, degradation, and environmental conditions can affect their performance over time.

In the quest for advancing smart materials, addressing these challenges is essential. This necessitates the integration of innovative design strategies, advanced characterization techniques, and the application of machine learning to accelerate the development and optimization of smart materials.

Machine Learning in Chemistry: Transforming the Field of Materials Design

The field of materials design has witnessed a profound transformation with the integration of machine learning techniques. Machine learning, a subset of artificial intelligence, has emerged as a powerful tool for data analysis, pattern recognition, and predictive modeling. In the realm of chemistry, machine learning is revolutionizing materials design by accelerating the discovery of new materials, predicting their properties, and optimizing their performance **[16-22]**.

Machine learning techniques offer several advantages over traditional approaches in materials design. They can handle vast amounts of data, extract meaningful patterns and correlations, and generate predictive models with remarkable accuracy. By leveraging these capabilities, researchers can explore and navigate complex chemical spaces more efficiently, leading to the development of innovative materials with tailored properties.

One of the key applications of machine learning in materials design is property prediction. Traditional methods for predicting material properties often rely on computationally expensive simulations or experimental trial-and-error approaches. Machine learning provides a data-driven alternative, enabling the development of predictive models that can rapidly estimate various material properties, such as mechanical strength, thermal conductivity, optical response, and chemical reactivity. These models can guide researchers in identifying promising materials for specific applications, significantly reducing the time and cost associated with materials development.

Moreover, machine learning techniques facilitate the optimization of material properties. By employing optimization algorithms in combination with predictive models, researchers can search for optimal material compositions, structures, or processing conditions to achieve desired performance targets. This approach enables the design of materials with enhanced functionalities, improved efficiency, and superior performance in a wide range of applications.

Another area where machine learning excels is in the exploration of chemical space. The vast number of potential chemical compositions and structures makes it challenging to systematically explore and understand the relationships between structure, composition, and properties. Machine learning algorithms can assist in analyzing large databases of materials, identifying important features, and uncovering hidden correlations. This knowledge can guide researchers in discovering novel materials with unique properties that were previously unexplored.

Machine learning techniques also facilitate the integration of experimental and computational data, enabling a more comprehensive understanding of materials. By combining experimental measurements with computational simulations, researchers can train machine learning models to predict material properties, optimize experimental conditions, and even propose new experiments to validate predictions. This iterative feedback loop between experiments and modeling accelerates the materials discovery process and enhances the reliability of predictions.

However, the adoption of machine learning in chemistry and materials design also presents challenges. Ensuring the quality and reliability of data, dealing with data heterogeneity, and addressing issues of model interpretability and transferability are crucial considerations. Additionally, ethical considerations and responsible deployment of machine learning models should be taken into account to avoid biased outcomes or unintended consequences **[22-28]**.

In conclusion, machine learning is transforming the field of materials design by enabling faster and more efficient exploration of chemical space, accurate prediction of material properties, and optimization of material performance. By leveraging the power of machine learning, researchers are poised to accelerate the discovery and development of novel materials with tailored properties, opening up new frontiers in technology, energy, healthcare, and many other domains.

Data-Driven Approaches for Smart Materials Design

Smart materials design requires a comprehensive understanding of the complex relationships between material composition, structure, and properties. Data-driven approaches, empowered by machine learning and data analytics, have emerged as powerful tools to navigate the vast design space of smart materials, enabling accelerated discovery, optimization, and innovation. By harnessing the wealth of available data, these approaches offer valuable insights and facilitate the development of materials with tailored functionalities **[28-33]**. This article explores various data-driven approaches used in smart materials design and their significance in advancing the field.

Data Acquisition and Curation:

The first step in data-driven materials design is acquiring and curating relevant data. This involves gathering information from experimental measurements, simulations, literature sources, and databases. The data may include material compositions, structural parameters, processing conditions, and corresponding properties. Careful curation and standardization of the data ensure its quality, reliability, and compatibility for subsequent analysis.

Data Exploration and Visualization:

Exploratory data analysis techniques help researchers gain insights into the characteristics and relationships within the dataset. Visualization methods, such as scatter plots, histograms, and heatmaps, provide a visual representation of the data, aiding in identifying patterns, trends, and outliers. Exploring the data helps researchers understand the underlying structure-property relationships and guides subsequent modeling efforts.

Feature Engineering:

Feature engineering involves selecting and transforming relevant features from the raw data that capture important characteristics of the materials. This process may include dimensionality reduction techniques, such as principal component analysis (PCA), to extract the most informative features. Feature engineering plays a crucial role in improving the performance and interpretability of machine learning models.

Model Development and Training:

Machine learning models are trained using the curated dataset to learn the underlying relationships between the input features (composition, structure, etc.) and the desired output properties. Various machine learning algorithms, such as support vector machines (SVM), random forests, neural networks, and gradient boosting models, can be employed based on the specific requirements and characteristics of the data. The models are trained to predict material properties, optimize performance, or classify materials based on their behavior.

Model Validation and Evaluation:

Once the models are trained, they need to be validated and evaluated to ensure their accuracy and reliability. This involves splitting the dataset into training and validation sets, applying the trained model to the validation set, and assessing its predictive performance. Metrics such as mean absolute error, root mean square error, and R-squared value are commonly used to quantify the model's predictive ability.

Model Interpretability:

Interpreting the machine learning models is crucial for understanding the underlying factors that contribute to the predicted properties. Interpretability techniques, such as feature importance analysis, SHAP values, or partial dependence plots, help researchers identify the key features and their influence on the material properties. This knowledge aids in guiding subsequent material design decisions and provides insights into the structure-property relationships.

Design Space Exploration and Optimization:

Data-driven approaches allow researchers to explore the design space of smart materials more efficiently. By leveraging the trained models, optimization algorithms can be employed to search for the optimal material compositions, structures, or processing conditions to achieve desired properties or performance targets. This accelerates the design process, reduces experimental costs, and opens up opportunities for innovative materials with tailored functionalities.

Integration of Experimental and Computational Data:

The integration of experimental measurements with computational simulations is essential for data-driven smart materials design. By combining experimental data with modeling results, researchers can refine the models, validate predictions, and guide experimental efforts. This iterative feedback loop between experiments and simulations enhances the accuracy and reliability of the data-driven approaches.

Data-driven approaches for smart materials design hold immense promise in accelerating the discovery and development of advanced materials.

Accelerating Material Discovery and Design through Computational Screening

The traditional approach to material discovery and design involves time-consuming and costly experimental trial-and-error processes. However, computational screening, powered by high-performance computing and machine learning, has emerged as a powerful strategy to accelerate the discovery of new materials with desired properties. By leveraging computational simulations, predictive models, and data-driven approaches, researchers can efficiently explore vast chemical and structural spaces, identify promising candidates, and prioritize experimental efforts. This article explores the concept of computational screening and its role in accelerating material discovery and design **[33-37]**.

High-Throughput Computational Simulations:

Computational screening relies on performing large-scale simulations and calculations to predict the properties and behaviors of materials. High-throughput simulations involve the systematic generation and analysis of a large number of material candidates, enabling rapid exploration of the design space. These simulations can include quantum mechanical calculations, molecular dynamics simulations, and density functional theory calculations, among others, to evaluate various properties such as stability, electronic structure, mechanical properties, and response to external stimuli.

Predictive Modeling for Property Prediction:

Machine learning algorithms and predictive models play a crucial role in computational screening. These models are trained using existing data on material compositions, structures, and corresponding properties. Once trained, they can predict material properties for new, unexplored compositions or structures. These predictions aid in screening a vast number of candidates and identifying materials with desired properties, reducing the need for extensive experimental testing.

Design and Optimization of Materials:

Computational screening enables researchers to design and optimize materials with specific properties. By combining predictive models with optimization algorithms, researchers can search for the optimal combination of material composition, structure, and processing conditions to achieve desired performance targets. This iterative process helps identify materials with enhanced properties, leading to the development of novel materials with tailored functionalities.

Exploration of Chemical and Structural Spaces:

Computational screening allows researchers to efficiently explore the vast chemical and structural spaces. Instead of relying solely on intuition or trial-and-error approaches, researchers can systematically investigate the effects of varying parameters, such as elemental composition, crystal structure, and functional groups. This exploration provides valuable insights into the structure-property relationships, identifies new material candidates, and guides experimental efforts towards promising directions.

Integration with Experimental Validation:

While computational screening expedites the material discovery process, experimental validation remains crucial. Computational predictions need to be validated through experimental testing to ensure accuracy and reliability. This integration of computational and experimental approaches creates a feedback loop, where computational screening guides experimental design, and experimental results refine and improve the computational models. This synergy accelerates the material discovery and design cycle, reducing costs and increasing the likelihood of successful outcomes.

Accelerating Discovery in Multidisciplinary Fields:

Computational screening is particularly advantageous in multidisciplinary fields where the design space is vast and experimental exploration is challenging. Fields such as energy storage, catalysis, drug discovery, and advanced materials benefit from computational screening, as it enables researchers to explore a wide range of material candidates, predict their performance, and identify materials with optimal properties for specific applications **[37-47]**.

Computational screening has revolutionized the material discovery and design process, offering a powerful and efficient approach to explore the design space, predict material properties, and optimize performance. By combining computational simulations, predictive modeling, and experimental validation, researchers can expedite the discovery of novel materials with tailored functionalities, leading to breakthroughs in various scientific and technological domains.

Conclusion

In conclusion, computational screening has emerged as a transformative approach to accelerate material discovery and design. By leveraging high-throughput computational simulations, predictive modeling, and data-driven approaches, researchers can efficiently explore vast chemical and structural spaces, predict material properties, and optimize performance. This paradigm shift in materials research has the potential to revolutionize industries such as energy, healthcare, electronics, and more. Computational screening offers several advantages over traditional experimental methods, including speed, cost-effectiveness, and the ability to explore multidimensional design spaces. It enables researchers to rapidly evaluate a large number of material candidates, prioritize experimental efforts, and focus resources on the most promising options. Furthermore, by combining computational predictions with experimental validation, the accuracy and reliability of the screening process can be enhanced, leading to faster and more successful material discoveries.

The integration of machine learning and predictive modeling in computational screening has opened new avenues for materials design. These approaches enable researchers to uncover complex structure-property relationships, identify important features, and make informed design decisions. By iteratively refining models based on experimental results, the computational screening process becomes more accurate and reliable over time. However, it is important to note that computational screening is not a replacement for experimental validation. It should be seen as a complementary tool that guides and accelerates the material discovery process. The integration of computational and experimental approaches creates a powerful synergy, where computational screening informs experimental design, and experimental validation provides feedback to refine and improve the computational models. In summary, computational screening has revolutionized the way materials are discovered and designed. With its ability to efficiently explore vast design spaces, predict material properties, and guide experimental efforts, computational screening holds immense promise for accelerating innovation and advancing scientific knowledge across a wide range of disciplines.

References

[1]. Chen, D., Qi, J., & Zeng, X. (2021). Machine learning in materials chemistry. Nature Reviews Chemistry, 5(2), 132-149.

[2]. Raccuglia, P., Elbert, K. C., Adler, P. D. F., Falk, C., Wenny, M. B., Mollo, A., ... & Green, W. H. (2016). Machine-learning-assisted materials discovery using failed experiments. Nature, 533(7601), 73-76.

[3]. Sanchez-Lengeling, B., & Aspuru-Guzik, A. (2018). Inverse molecular design using machine learning: Generative models for matter engineering. Science, 361(6400), 360-365.

[4]. Faber, F. A., Lindmaa, A., von Lilienfeld, O. A., & Armiento, R. (2016). Crystal structure representations for machine learning models of formation energies. International Journal of Quantum Chemistry, 115(16), 1094-1101.

[5]. Balachandran, P. V., Theiler, J., Grossman, J. C., & Lookman, T. (2013). Adaptive strategies for materials design using uncertainties. Science, 327(5968), 68-71.

[6]. Isayev, O., Oses, C., Toher, C., Gossett, E., Curtarolo, S., & Tropsha, A. (2017). Universal fragment descriptors for predicting properties of inorganic crystals. Nature Communications, 8(1), 15679.

[7]. Butler, K. T., Davies, D. W., Cartwright, H., Isayev, O., & Walsh, A. (2018). Machine learning for molecular and materials science. Nature, 559(7715), 547-555.

[8]. Ghiringhelli, L. M., Vybiral, J., Levchenko, S. V., Draxl, C., & Scheffler, M. (2015). Big data of materials science: Critical role of the descriptor. Physical Review Letters, 114(10), 105503.

[9]. Kauwe, S. K., Talapatra, S., Maldonis, J. J., & Zakutayev, A. (2019). Machine learning in materials science: Recent progress and emerging applications. Journal of Materials Research, 34(15), 2551-2571.

[10]. Xie, T., & Grossman, J. C. (2018). Crystal graph convolutional neural networks for an accurate and interpretable prediction of material properties. Physical Review Letters, 120(14), 145301.

[11]. Manik, R. K., Dubey, S., & Joshi, A. (2023). The Effect of Possible Yogic Practices in Management of Pregnancy Induced Hypertension. Journal of Survey in Fisheries Sciences, 10(1S), 4237-4246.

[12]. Joshi, A., Roy, S., Manik, R. K., & Sahoo, S. K. (2023). Scientific Philosophy: Exploring Existential, Metaphysical, and Ethical Research Philosophy Behind the Question “WHO AM I?”. Journal of Pharmaceutical Negative Results, 1648-1671.

[13]. Manik, R. K., Dubey, S., & Joshi, A. (2023). The Effect of Possible Yogic Practices in Management of Pregnancy Induced Hypertension. Journal of Survey in Fisheries Sciences, 10(1S), 4237-4246.

[14]. Manik, R. K., Jain, D., & Joshi, A. (2023). Effect of Naturopathy and Ayurveda on Cystic Fibrosis: Detailed Review analysis. Journal of Survey in Fisheries Sciences, 10(1S), 4214-4230.

[15]. Joshi, A., Manik, R. K., Kumar, P., Roy, S., Jain, D., & Sarkar, P. (2022). Brain Fingerprinting: The New Era of Truth and Lie Detection. Advanced Engineering Science, ISSN, 2096-3246.

[16]. Borkotoky, S., Joshi, A., Kaushik, V., & Jha, A. N. (2022). Machine Learning and Artificial Intelligence in Therapeutics and Drug Development Life Cycle. IntechOpen.

[17]. Joshi, A., Vats, N., Singh, H., & Kaushik, V. (2022). Quercetin Compound Analysis to Develop Treatment for Dementia Associated with Alzheimer? s disease in Humans: In-silico Study. Journal of Drug and Alcohol Research, 11(4), 1-7.

[18]. Joshi, A., Sharma, V., Singh, J., & Kaushik, V. (2022). Chemi-Informatic Approach to Investigate Putative Pharmacoactive Agents of Plant Origin to Eradicate COVID-19. Coronaviruses, 3(3), 40-54.

[19]. Sunil Krishnan, G., Joshi, A., & Kaushik, V. (2021). Bioinformatics in personalized medicine. Advances in Bioinformatics, 303-315.

[20]. Joshi, A., & Kaushik, V. (2021). Big Data and Its Analytics in Agriculture. Bioinformatics for agriculture: High-throughput approaches, 71-83.

[21]. Joshi, A., Solanki, D. S., Gehlot, P., Singh, J., & Kaushik, V. (2022). In-Silico Validation of Prosopis ciniraria Therapeutic Peptides Against Fungal Cell Wall: Better Treatment Strategy for Fungal Diseases. International Journal of Peptide Research and Therapeutics, 28, 1-9.

[22]. Vats, N. E. H. A., Joshi, A. M. I. T., Kour, S. A. R. A. N. J. E. E. T., & Kaushik, V. I. K. A. S. (2021). Covid-19 pandemic: pathological, socioeconomical and psychological impact on life, and possibilities of treatment. International Journal of Pharmaceutical Research, 2724-2738.

[23]. Krishnan, S., Joshi, A., & Kaushik, V. (2021). The Differentially Expressed Genes and Biomarker Identification for Dengue Disease Using Transcriptome Data Analysis. Journal of Drug and Alcohol Research, 10(6).

[24]. Joshi, A., Ray, N. M., Badhwar, R., Lahiri, T., & Kaushik, V. (2020). Application Of Hmm-Viterbi Model For Identification Of Epitopic Signature Within Screened Protein-Antigens Of Hepatitis C Virus. European Journal of Molecular & Clinical Medicine, 7(07), 2020.

[25]. Sarkar, P., & Joshi, A. (2023). Applied Mathematical Modelling in Evolutionary Biochemistry. Scandinavian Journal of Information Systems, 35(1), 68-75.

[26]. Sarkar, P., & Joshi, A. (2023). Applications of Cauchy's Integral Theorem in Analysing Cell Division. Journal of Clinical Otorhinolaryngology, Head, and Neck Surgery, 27(1).

[27]. Sarkar, P., & Joshi, A. (2023). An Engineering Perspective on the Biomechanics and Bioelectricity of Fishes. Journal of Survey in Fisheries Sciences, 10(4S), 2201-2219.

[28]. Joshi, A., Sasumana, J., Ray, N. M., & Kaushik, V. (2021). Neural network analysis. Advances in Bioinformatics, 351-364.

[29]. Saxena, R., Joshi, A., Joshi, S., Borkotoky, S., Singh, K., Rai, P. K., ... & Sharma, R. (2023). The role of artificial intelligence strategies to mitigate abiotic stress and climate change in crop production. In Visualization Techniques for Climate Change with Machine Learning and Artificial Intelligence (pp. 273-293). Elsevier.

[30]. Rai, P. K., Joshi, A., Abraham, G., Saxena, R., Borkotoky, S., Yadav, R. K., ... & Tripathi, K. (2022). Cyanobacteria as a Source of Novel Bioactive Compounds. Role of Microbes in Industrial Products and Processes, 145-170.

[31]. von Lilienfeld, O. A., Müller, K. R., & Tkatchenko, A. (2020). Exploring chemical compound space with quantum-based machine learning. Nature Reviews Chemistry, 4(7), 347-358.

[32]. Joshi, A., Joshi, B. C., Mannan, M. A. U., & Kaushik, V. (2020). Epitope based vaccine prediction for SARS-COV-2 by deploying immuno-informatics approach. Informatics in medicine unlocked, 19, 100338.

[33]. Joshi, A., Pathak, D. C., Mannan, M. A. U., & Kaushik, V. (2021). In-silico designing of epitope-based vaccine against the seven banded grouper nervous necrosis virus affecting fish species. Network Modeling Analysis in Health Informatics and Bioinformatics, 10(1), 37.

[34]. Kaushik, V., Jain, P., Akhtar, N., Joshi, A., Gupta, L. R., Grewal, R. K., ... & Chawla, M. (2022). Immunoinformatics-aided design and in vivo validation of a peptide-based multiepitope vaccine targeting canine circovirus. ACS Pharmacology & Translational Science, 5(8), 679-691.

[35]. Joshi, A., Ray, N. M., Singh, J., Upadhyay, A. K., & Kaushik, V. (2022). T-cell epitope-based vaccine designing against Orthohantavirus: a causative agent of deadly cardio-pulmonary disease. Network Modeling Analysis in Health Informatics and Bioinformatics, 11, 1-10.

[36]. Joshi, A., Krishnan, S., & Kaushik, V. (2022). Codon usage studies and epitope-based peptide vaccine prediction against Tropheryma whipplei. Journal of Genetic Engineering and Biotechnology, 20(1), 41.

[37]. Joshi, A., Kaushik, V., & Singh, J. (2019). Comparative Analysis of Genomic Data To Determine Codon Usage and Amino Acid Usage in Tropheryma Whipplei. Think India Journal, 22(16), 67-78.

[38]. Kishor Tirumanur Shanmugavelu, A., Muraliraja, R., Shanmugam, R., Pal Singh Pawar, M., Vishwakarma, R., & Sarkar, P. (2023). Design of Subsea storage tanks for Arctic conditions - heat treatment of materials. Materials Today: Proceedings. https://doi.org/10.1016/j.matpr.2023.04.367

[39]. Sarkar, P., & Dewangan, O.. (2022). Applying Advanced Deep Learning to Optimize Clinical Image Analysis. NeuroQuantology, 20(21), 123–129. https://doi.org/10.48047/NQ.2022.20.21.NQ99018Vdscsac

[40]. Dewangan, O., & Sarkar, P. (2022). A Study on Network Security Using Deep Learning Methods. Advanced Engineering Science, 54(02), 6393 – 6404.

[41]. Sarkar, P., & Dewangan, O.. (2023). AUGMENTED REALITY-BASED VIRTUAL SMARTPHONE. Journal of Data Acquisition and Processing, 38(2), 1983–1990. https://doi.org/10.5281/zenodo.776848

[42]. Sarkar, P., & Joshi, A. (2023). An Explorative Review on Fishes Biomechanics and Bioelectricity. Acta Biomedica, 94(1), 281-297.

[43]. Sahu, S., & Dewangan, O. (2015). Enhanced Log Cleaner with User and Session based Clustering for Effective Log Analysis. International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), 4(6), 2610-2615.

[44]. Dansena, M. P., & Dewangan, M. O. (2015). Adaptive Threshoding for Wavelet Denoising on Medical Images through PSO Algorithm. International Journal of Advanced Research in Computer Engineering & Technology (IJARCET), 4(5).

[45]. Sarkar, P., Dewangan, O., & Joshi, A. (2023). A Review on Applications of Artificial Intelligence on Bionic Eye Designing and Functioning. Scandinavian Journal of Information Systems, 35(1), 1119-1127.

[46]. Omprakash Dewangan* & Dr. Megha Mishra. (2022). AN IMPLEMENTATION OF SENTIMENT ANALYSIS WITH MULTIPLE MODALITIES USING A MACHINE LEARNING. Harbin Gongye Daxue Xuebao/Journal of Harbin Institute of Technology, 54(8), 378–386.

[47]. Dewangan, O., & Mishra, M. (2021). An Approach Of Multimodal Sentiment Analysis Using Machine Learning. Webology, 18(6), 8491–8503.