

# LIST OF PUBLICATIONS

## Refereed Journal Papers

- **Vishakha Singh**, Sanjay Kumar Singh, et al. “Designing new blood-brain barrier penetrating molecules using novel hybridized gravitational search algorithm and explainable AI.” *IEEE Transactions on Artificial Intelligence* 5(5) (2024): 2127-2138.
- **Vishakha Singh**, Sanjay Kumar Singh. “A Novel Framework Based on Explainable AI and Genetic Algorithms for Designing Neurological Medicines.” *Nature Scientific Reports* 14(1) (2024).
- **Vishakha Singh**, Sanjay Kumar Singh, et al. “Multi-scale temporal convolutional networks and continual learning based in silico discovery of alternative antibiotics to combat multi-drug resistance.” *Expert Systems with Applications* 215 (2023).
- **Vishakha Singh**, Sanjay Kumar Singh. “A separable temporal convolutional networks based deep learning technique for discovering antiviral medicines.” *Nature Scientific Reports* 13(1) (2023).
- **Vishakha Singh**, Sanjay Kumar Singh, et al. “StaBle-ABPpred: a stacked ensemble predictor based on biLSTM and attention mechanism for accelerated discovery of antibacterial peptides.” *Briefings in Bioinformatics* 23(1) (2022).
- **Vishakha Singh**, Sanjay Kumar Singh, et al. “Accelerating the discovery of antifungal peptides using deep temporal convolutional networks.” *Briefings in Bioinformatics* 23(2) (2022).

## Refereed Conference Papers

- **Vishakha Singh**, Sanjay Kumar Singh, et al. “Using explainable AI and genetic algorithms to drive the discovery of novel antiviral molecules.” In *International Conference on Computational Science and Computational Intelligence* (2023): 348-352.

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