

# LIST OF PUBLICATIONS

## Refereed Journal Papers

- **Ritesh Sharma**, Sanjay Kumar Singh, et al. “Deep-AVPpred: Artificial intelligence driven discovery of peptide drugs for viral infections.” IEEE Journal of Biomedical and Health Informatics 26.10 (2021): 5067-5074. (**SCIE, Q1, IF 7.021**)
- **Ritesh Sharma**, Sanjay Kumar Singh, et al. “Deep-AFPpred: identifying novel antifungal peptides using pretrained embeddings from seq2vec with 1DCNN-BiLSTM.” Briefings in Bioinformatics 23.1 (2022): bbab422. (**SCIE, Q1, IF 13.994**)
- **Ritesh Sharma**, Sanjay Kumar Singh, et al. “EnDL-HemoLyt: Ensemble Deep Learning-based Tool for Identifying Therapeutic Peptides with Low Hemolytic Activity.” IEEE Journal of Biomedical and Health Informatics (2023) : DOI-10.1109/JBHI.2023.3264941 (**SCIE, Q1, IF 7.021**)
- **Ritesh Sharma**, Sanjay Kumar Singh, et al. “Artificial intelligence-based model for predicting the minimum inhibitory concentration of antibacterial peptides against ESKAPEE pathogens” IEEE Journal of Biomedical and Health Informatics (2023) : Accepted for Publication (**SCIE, Q1, IF 7.021**)
- **Ritesh Sharma**, Sanjay Kumar Singh, et al. “XAI-INVENT: An explainable artificial intelligence based framework for rapid discovery of novel peptide antibiotics.” Briefings in Bioinformatics (Under Review) (**SCIE, Q1, IF 13.994**)

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