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Publications based on the Thesis Works

Journals

1. Patowary, Pallabi, Dhruba K. Bhattacharyya, and Pankaj Barah. "SNMRS: An advanced measure for Co-expression network analysis." Computers in Biology and Medicine (2022): 105222.

2. Patowary, Pallabi, Dhruba K. Bhattacharyya, and Pankaj Barah. "Identifying critical genes in esophageal squamous cell carcinoma using an ensemble approach." Informatics in Medicine Unlocked 18 (2020): 100277.

3. Patowary, Pallabi, and Dhruba K. Bhattacharyya. "PD_BiBIM: Biclustering-based biomarker identification in ESCC microarray data." Journal of biosciences 46.3 (2021): 1-18.

4. Patowary, Pallabi, Rosy Sarmah, and Dhruba K. Bhattacharyya. "Developing an effective biclustering technique using an enhanced proximity measure." Network Modeling Analysis in Health Informatics and Bioinformatics 9.1 (2020): 1-17.

5. Patowary, Pallabi, Dhruba K. Bhattacharyya, Jugal Kalita and Pankaj Barah. "A Comprehensive Survey on GCN Analysis: Methods, Techniques, Tools and Measures." Under Review.

Conferences

1. Patowary, Pallabi, Dhruba K. Bhattacharyya, and Pankaj Barah. "Identification of Potential Prognostic Biomarkers for ESCC Using Single-Cell RNA Sequencing Data Analysis." International Conference on Pattern Recognition and Machine Intelligence. Cham: Springer Nature Switzerland, 2023.

2. Patowary, Pallabi, and Dhruba K. Bhattacharyya. "Crucial Gene Identification for Esophageal Squamous Cell Carcinoma Using Differential Expression Analysis." International Conference on Machine Learning, Image Processing, Network Security and Data Sciences. Springer, Singapore, 2020.

3. Patowary, Pallabi, Dhruba K. Bhattacharyya, and Pankaj Barah. "Biomarker identification for escc using integrative dea." International Conference on Pattern Recognition and Machine Intelligence. Springer, Cham, 2019.