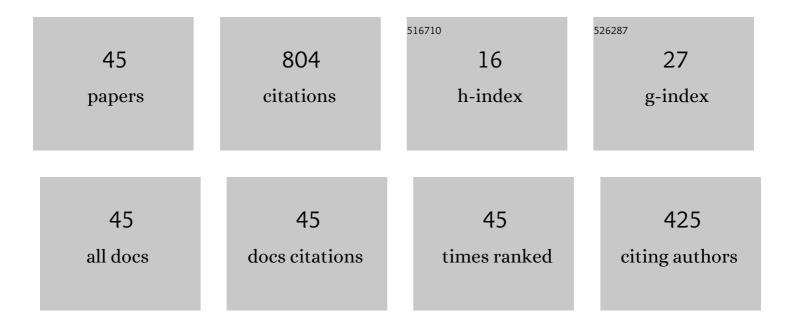
Shengli Zhang

List of Publications by Year in descending order

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#	Article	IF	CITATIONS
1	M6A-GSMS: Computational identification of N ⁶ -methyladenosine sites with GBDT and stacking learning in multiple species. Journal of Biomolecular Structure and Dynamics, 2022, 40, 12380-12391.	3.5	5
2	Pep-CNN: An improved convolutional neural network for predicting therapeutic peptides. Chemometrics and Intelligent Laboratory Systems, 2022, 221, 104490.	3.5	12
3	iPro-GAN: A novel model based on generative adversarial learning for identifying promoters and their strength. Computer Methods and Programs in Biomedicine, 2022, 215, 106625.	4.7	7
4	Integrating LASSO Feature Selection and Soft Voting Classifier to Identify Origins of Replication Sites. Current Genomics, 2022, 23, 83-93.	1.6	1
5	Accurate Prediction of Anti-hypertensive Peptides Based on Convolutional Neural Network and Gated Recurrent unit. Interdisciplinary Sciences, Computational Life Sciences, 2022, 14, 879-894.	3.6	8
6	Identification of DNA N4-methylcytosine sites based on multi-source features and gradient boosting decision tree. Analytical Biochemistry, 2022, 652, 114746.	2.4	3
7	iDHS-DASTS: identifying DNase I hypersensitive sites based on LASSO and stacking learning. Molecular Omics, 2021, 17, 130-141.	2.8	6
8	ldentifying <scp>DNA</scp> â€binding proteins based on multiâ€features and <scp>LASSO</scp> feature selection. Biopolymers, 2021, 112, e23419.	2.4	21
9	PA-PseU: An incremental passive-aggressive based method for identifying RNA pseudouridine sites via Chou's 5-steps rule. Chemometrics and Intelligent Laboratory Systems, 2021, 210, 104250.	3.5	13
10	iORI-ENST: identifying origin of replication sites based on elastic net and stacking learning. SAR and QSAR in Environmental Research, 2021, 32, 317-331.	2.2	7
11	i6mA-VC: A Multi-Classifier Voting Method for the Computational Identification of DNA N6-methyladenine Sites. Interdisciplinary Sciences, Computational Life Sciences, 2021, 13, 413-425.	3.6	10
12	UMAP-DBP: An Improved DNA-Binding Proteins Prediction Method Based on Uniform Manifold Approximation and Projection. Protein Journal, 2021, 40, 562-575.	1.6	12
13	Application of Machine Learning Techniques in Drug-target Interactions Prediction. Current Pharmaceutical Design, 2021, 27, 2076-2087.	1.9	4
14	iPromoter-ET: Identifying promoters and their strength by extremely randomized trees-based feature selection. Analytical Biochemistry, 2021, 630, 114335.	2.4	11
15	iR5hmcSC: Identifying RNA 5-hydroxymethylcytosine with multiple features based on stacking learning. Computational Biology and Chemistry, 2021, 95, 107583.	2.3	6
16	iEnhancer-MFGBDT: Identifying enhancers and their strength by fusing multiple features and gradient boosting decision tree. Mathematical Biosciences and Engineering, 2021, 18, 8797-8814.	1.9	9
17	iDHS-DSAMS: Identifying DNase I hypersensitive sites based on the dinucleotide property matrix and ensemble bagged tree. Genomics, 2020, 112, 1282-1289.	2.9	12
18	KD-KLNMF: Identification of IncRNAs subcellular localization with multiple features and nonnegative matrix factorization. Analytical Biochemistry, 2020, 610, 113995.	2.4	16

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#	Article	IF	CITATIONS
19	Use Chou's 5-steps rule to identify DNase I hypersensitive sites via dinucleotide property matrix and extreme gradient boosting. Molecular Genetics and Genomics, 2020, 295, 1431-1442.	2.1	19
20	Integrating Second-order Moving Average and Over-sampling Algorithm to Predict Apoptosis Protein Subcellular Localization. Current Bioinformatics, 2020, 15, 517-527.	1.5	3
21	Identifying DNase I hypersensitive sites using multi-features fusion and F-score features selection via Chou's 5-steps rule. Biophysical Chemistry, 2019, 253, 106227.	2.8	40
22	Identification of amyloidogenic peptides via optimized integrated features space based on physicochemical properties and PSSM. Analytical Biochemistry, 2019, 583, 113362.	2.4	9
23	iDHS-DMCAC: identifying DNase I hypersensitive sites with balanced dinucleotide-based detrending moving-average cross-correlation coefficient. SAR and QSAR in Environmental Research, 2019, 30, 429-445.	2.2	7
24	Prediction of apoptosis protein subcellular localization via heterogeneous features and hierarchical extreme learning machine. SAR and QSAR in Environmental Research, 2019, 30, 209-228.	2.2	16
25	iRSpot-DTS: Predict recombination spots by incorporating the dinucleotide-based spare-cross covariance information into Chou's pseudo components. Genomics, 2019, 111, 1760-1770.	2.9	27
26	Application of Machine Learning Techniques to Predict Protein Phosphorylation Sites. Letters in Organic Chemistry, 2019, 16, 247-257.	0.5	1
27	Pathogenic Genes Selection Model of Genetic Disease based on Network Motifs Slicing Feedback. Current Proteomics, 2019, 16, 392-401.	0.3	0
28	Accurate prediction of Gram-negative bacterial secreted protein types by fusing multiple statistical features from PSI-BLAST profile. SAR and QSAR in Environmental Research, 2018, 29, 469-481.	2.2	4
29	Prediction of Apoptosis Protein's Subcellular Localization by Fusing Two Different Descriptors Based on Evolutionary Information. Acta Biotheoretica, 2018, 66, 61-78.	1.5	11
30	Prediction of protein subcellular localization with oversampling approach and Chou's general PseAAC. Journal of Theoretical Biology, 2018, 437, 239-250.	1.7	81
31	Predicting apoptosis protein subcellular localization by integrating auto-cross correlation and PSSM into Chou's PseAAC. Journal of Theoretical Biology, 2018, 457, 163-169.	1.7	53
32	Identify Gram-negative bacterial secreted protein types by incorporating different modes of PSSM into Chou's general PseAAC via Kullback–Leibler divergence. Journal of Theoretical Biology, 2018, 454, 22-29.	1.7	36
33	Predict protein structural class by incorporating two different modes of evolutionary information into Chou's general pseudo amino acid composition. Journal of Molecular Graphics and Modelling, 2017, 78, 110-117.	2.4	33
34	Prediction of Protein Subcellular Localization by Using ?-Order Factor and Principal Component Analysis. Letters in Organic Chemistry, 2017, 14, .	0.5	1
35	A Gram-Negative Bacterial Secreted Protein Types Prediction Method Based on PSI-BLAST Profile. BioMed Research International, 2016, 2016, 1-5.	1.9	1
36	Detrended cross-correlation coefficient: Application to predict apoptosis protein subcellular localization. Mathematical Biosciences, 2016, 282, 61-67.	1.9	7

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#	Article	IF	CITATIONS
37	Prediction of Protein Structural Classes for Low-Similarity Sequences Based on Consensus Sequence and Segmented PSSM. Computational and Mathematical Methods in Medicine, 2015, 2015, 1-9.	1.3	16
38	Accurate prediction of protein structural classes by incorporating PSSS and PSSM into Chou's general PseAAC. Chemometrics and Intelligent Laboratory Systems, 2015, 142, 28-35.	3.5	45
39	Improving the prediction accuracy of protein structural class: Approached with alternating word frequency and normalized Lempel–Ziv complexity. Journal of Theoretical Biology, 2014, 341, 71-77.	1.7	20
40	Using principal component analysis and support vector machine to predict protein structural class for low-similarity sequences via PSSM. Journal of Biomolecular Structure and Dynamics, 2012, 29, 1138-1146.	3.5	55
41	A novel protein structural classes prediction method based on predicted secondary structure. Biochimie, 2012, 94, 1166-1171.	2.6	57
42	High-accuracy prediction of protein structural class for low-similarity sequences based on predicted secondary structure. Biochimie, 2011, 93, 710-714.	2.6	56
43	A Complexity-based Method to Compare RNA Secondary Structures and its Application. Journal of Biomolecular Structure and Dynamics, 2010, 28, 247-258.	3.5	14
44	Use of information discrepancy measure to compare protein secondary structures. Computational and Theoretical Chemistry, 2009, 909, 102-106.	1.5	21
45	Feature analysis of protein structure by using discrete Fourier transform and continuous wavelet transform. Journal of Mathematical Chemistry, 2009, 46, 562-568.	1.5	8