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Abbreviations

Abbreviation	Description
ABPs	Antibacterial Peptides
AI	Artificial Intelligence
ANOVA	Analysis of Variance
AVPs	Antiviral Peptides
AUC	Area under the receiver operating characteristic curve
B3P2s	Blood-Brain Barrier Penetrating Peptides
BERT	Bidirectional Representations from Transformers
BiLSTM	Bidirectional Long Short-Term Memory
ESKAPEE	Enterococcus faecium, Staphylococcus aureus, Klebsiella pneumoniae, Acinetobacter baumannii, Pseudomonas aeruginosa, Enterobacter spp. and Escherichia coli
GSA	Gravitational Search Algorithm
NP	Neurological Peptides
ReLU	Rectified Linear Unit
RFs	Random Forests
SHAP	Shapley Additive explanations
SVM	Support Vector Machine
TCNs	Temporal Convolutional Networks

List of Symbols

Symbol	Description
a_t	attention vector
$\alpha_{t,t'}$	attention weight
\tilde{c}_t	candidate state
c_t	cell state
cv_t	context vector
fit	fitness value
f_t	forget gate
h_t	hidden state
i_t	input gate
o_t	output gate
Pop	population of peptides
r_t	reset gate
z_t	update gate