Supporting Information

De novo **synthetic antimicrobial peptide design with a recurrent neural network**

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Supplementary Figures

Figure S1: Amino acid compositions of sequences generated by different AMP sequence generation methods. For each AMP sequence generation method (Nagarajan et al. 2018; Van Oort et al. 2021; Szymczak et al. 2022), the average proportions of different amino acid residues per peptide sequence were calculated. The amino acid compositions of the AMPd-Up training sequences were also analyzed for comparison.

Figure S2: Sequence similarity distribution of the AMPd-Up-generated sequences to known AMPs. The known AMP sequence set comprises 4,538 distinct sequences downloaded from Antimicrobial Peptide Database (APD3) (Wang et al. 2016) and Database of Anuran Defense Peptides (DADP) (Novković et al. 2012). The sequence similarity distribution, with a mean of 51.03% and a standard deviation of 9.38%, was calculated based on the 2,000 sequences generated by AMPd-Up. The sequence similarity of each generated sequence to known AMPs was considered as the similarity of that sequence to its most similar known AMP sequence, based on which the distribution was plotted.

Figure S3: Distributions of pairwise sequence similarities between different sequence sets of AMPd-Up. The pairwise sequence similarities between two different sets of sequences were calculated as the similarities of all sequence pairs between the two sets (e.g., Generated vs. Training), while the pairwise sequence similarities of the same set of sequences (i.e., sequence diversity measurements) were defined as the similarities of sequences to each other in the set (e.g., Generated vs. Generated). The intra-model sequence similarities were calculated as the similarities of sequences generated by the same model instance to each other, while inter-model sequence similarities were calculated as pairwise sequence similarities between sets of sequences generated by different model instances. A set of 2,000 random sequences matching the length distribution of the 2,000 generated sequences were added for comparison, in addition to the training and generated sequence sets. Mean (μ) and standard deviation (σ) values of each distribution are as follows: Random vs. Random (μ = 13.71%, σ = 5.09%), Random vs. Generated (μ = 10.34%, σ = 5.28%), Random vs. Training (μ = 13.76%, σ = 4.91%), Training vs. Training (μ = 18.06%, σ = 7.92%), Generated vs. Training (μ = 18.80%, σ = 8.94%), Generated vs. Generated (μ = 33.61%, σ = 16.18%), Intra-model (μ = 39.14%, σ = 19.79%), and Inter-model $(\mu = 33.56\%, \sigma = 16.14\%)$. Two-sided Kolmogorov-Smirnov tests reveal that the difference between any two of the distributions is significant ($p < 0.0018$), except that between Generated vs. Generated and Inter-model ($p = 0.0519$). We note that 0.0018 is an adjusted alpha level calculated with Šidák correction (Šidák 1967) from a family-wise alpha level of 0.05 for the multiple comparisons.

Supplementary Tables

Table S1: Antimicrobial susceptibility testing and hemolysis experiment results of the 58 selected peptides *in vitro***.** Peptides were tested for their antimicrobial activity against *Escherichia coli* ATCC 25922 and *Staphylococcus aureus* ATCC 29213 for their minimum inhibitory concentration (MIC) and minimum bactericidal concentration (MBC) values. Porcine red blood cells (RBCs) were used to test the hemolytic activity of the selected peptides for their hemolytic concentration (HC50) values. Data are presented as the lowest effective peptide concentration range (μg/mL) observed in three independent experiments performed in duplicate, with one maximum data point and one minimum data point dropped for each measurement. Ranateurin-4 (Goraya et al. 1998) and OT15 were used as the positive and negative control peptides, respectively.

	DeNo1038	64	$64 - 128$	>128	>128	>128
\bf{B}	DeNo1039	>128	>128	>128	>128	$32 - 64$
	DeNo1040	$64 - 128$	\geq 128	64	$64 - 128$	>128
	DeNo1041	>128	>128	>128	>128	>128
	DeNo1042	>128	>128	>128	>128	>128
$\mathbf C$	DeNo1043	>128	>128	>128	>128	>128
	DeNo1044	\geq 128	\geq 128	>128	>128	>128
	DeNo1045	64	$64 - 128$	>128	>128	>128
	DeNo1046	$16 - 64$	$16 - 64$	128	128	>128
	DeNo1047	\geq 128	\geq 128	>128	>128	>128
	DeNo1048	128	128	>128	>128	>128
	DeNo1049	$4 - 8$	$4 - 16$	>128	>128	>128
	DeNo1050	>128	>128	>128	>128	>128
	DeNo1051	$16 - 32$	$16 - 64$	>128	>128	>128
	DeNo1052	\geq 128	\geq 128	>128	>128	>128
	DeNo1053	>128	>128	>128	>128	>128
	DeNo1054	>128	>128	>128	>128	>128
	DeNo1055	\geq 128	\geq 128	>128	>128	>128
	DeNo1056	$32 - >128$	$32 - >128$	>128	>128	>128
	DeNo1057	$8 - 16$	$8 - 32$	32	$32 - 128$	>128
	DeNo1058	>128	>128	>128	>128	>128
Controls	Ranateurin-4	$8 - 16$	$8 - 16$	$2 - 4$	$\overline{4}$	$64 - 128$
	OT15 ^a	>128	>128	>128	>128	>128

^a OT15 (TKPKGTKPKGTKPKG) is a truncated form of a negative control peptide OT20 (Horváti et al. 2017) used in previous studies.

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