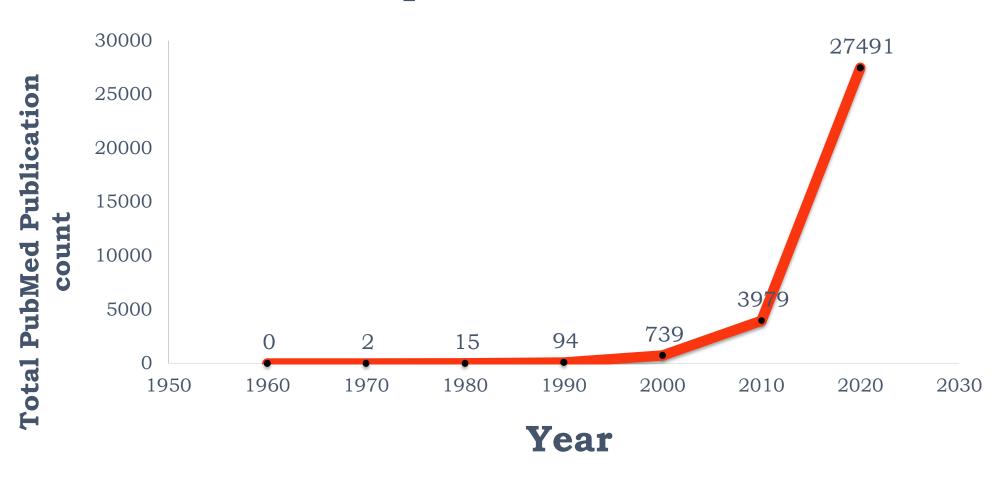
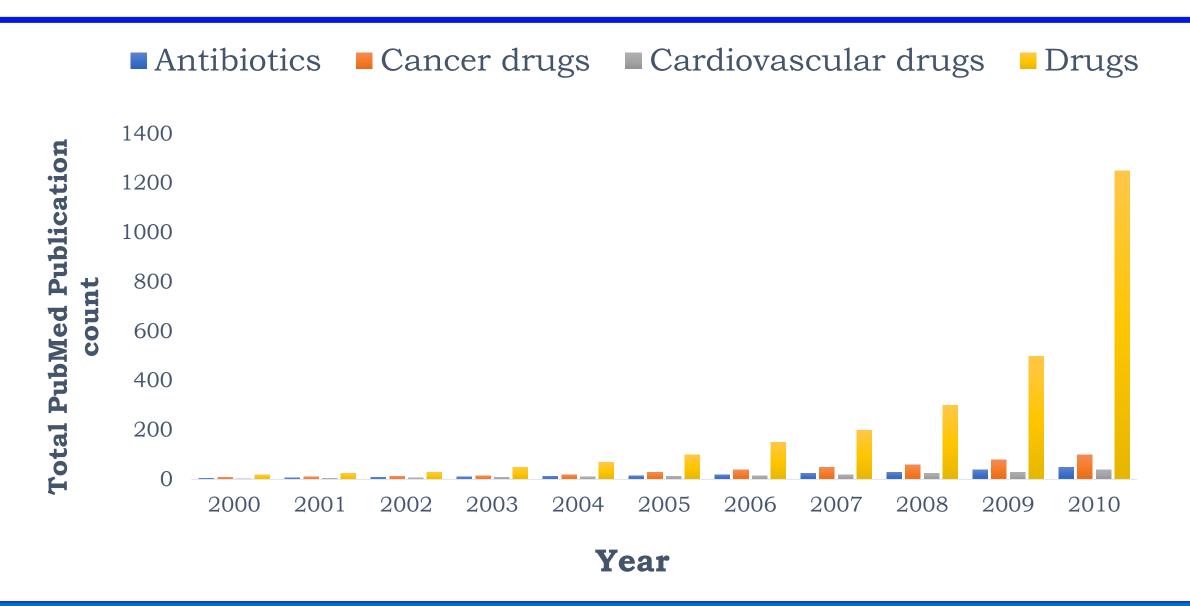


Trends in AI/ML research over Time

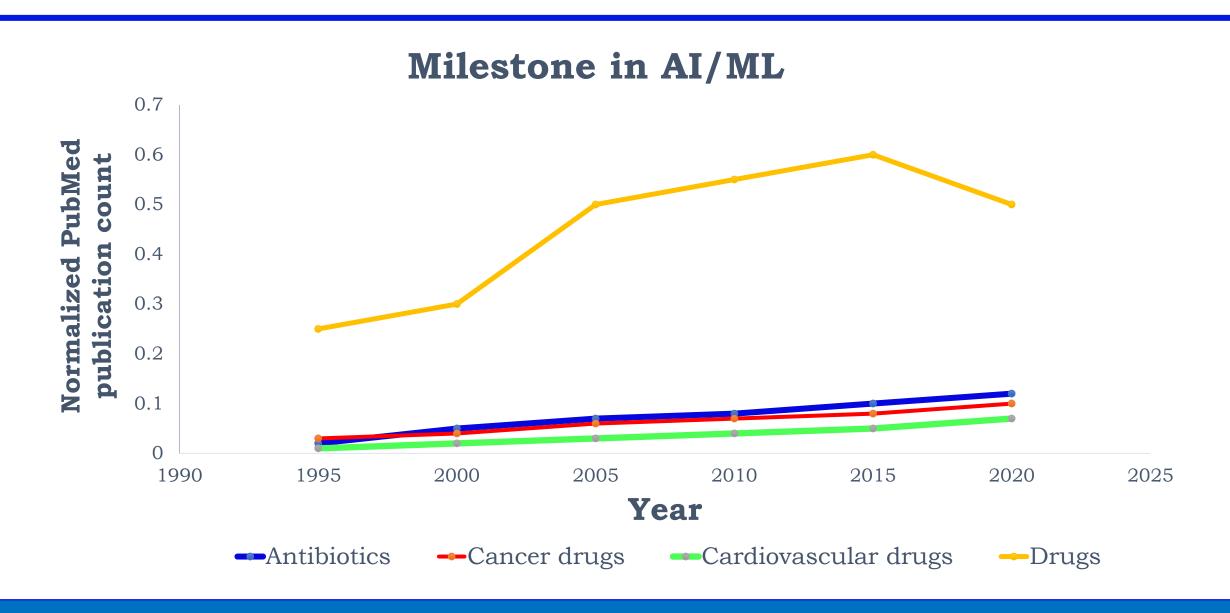




AI/ML in drug discovery research

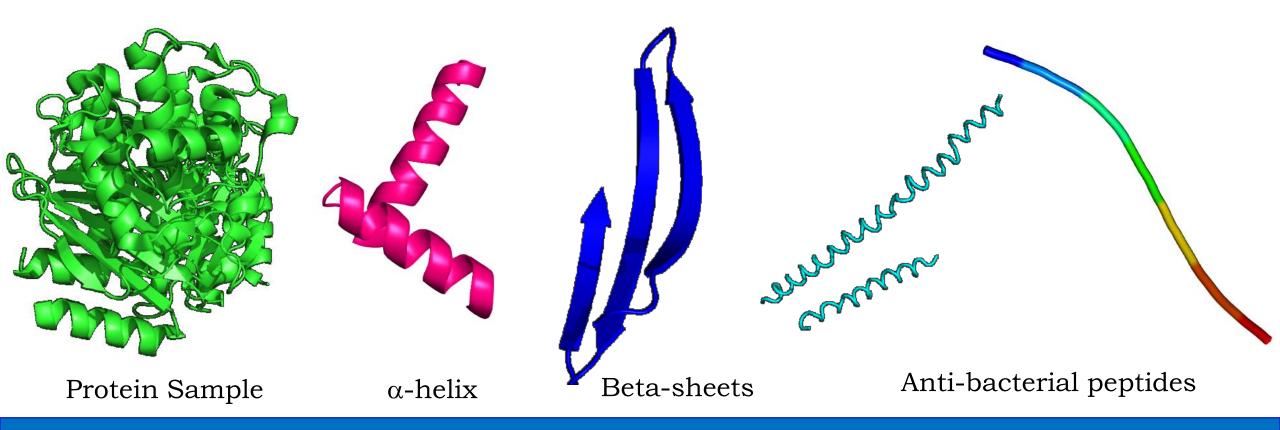


Trends in AI/ML research



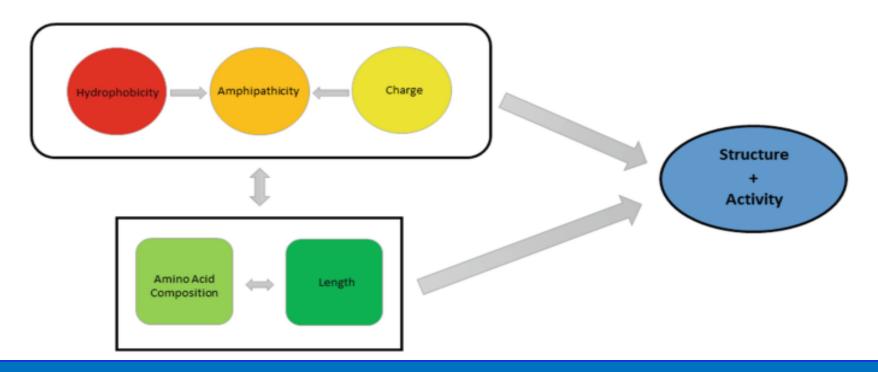
Anti-Bacterial Peptides

- Anti-Bacterial peptides (ABPs) are a class of small peptides, usually 10-50 amino acids long, that exhibit broad-spectrum Anti-Bacterial activity.
- Transforming peptides into small molecules as peptide-based molecules often present poorer bioavailability and lower metabolic stability.



Peptidomimetic compounds

- Peptidomimetic compounds are non-peptidic analog, synthetic molecules that mimic the structure and function of peptides.
- Improved stability, bioavailability, and pharmacological properties (such as resistant to enzymatic degradation, can more easily cross cellular membranes)
- AMP sequences can be used as templates for designing peptidomimetics.



The problem we are looking upto?

Development of Peptidomimetic Compounds with Antibacterial Properties to Overcome Antibacterial Resistance (ABR)

- Mimic AMP structural motifs amphipathic helices, β -sheets, & positively charged.
- Show antibacterial activity against resistant bacterial strains
- Improve stability resistance to enzymatic degradation
- **Reduce cytotoxicity** to human cells & improved specificity towards pathogens.



Machine learning prediction of Antimicrobial peptides

Tool name	URL	Algorithms	Features	Year	Ref
AntiBP	http://crdd.osdd.net/raghava/antibp2 🖸	SVM,QM,ANN	Single label	2007	[17]
CAMP	http://www.bicnirrh.res.in/antimicrobial	SVM, RF, DA	Single label	2010	[<u>18</u> , <u>53</u>]
	http://amp.biosino.org/ 🖸	BLASTP, NNA	Single label	2011	[54]
AMPA	http://tcoffee.crg.cat/apps/ampa 🖸		AMP region scan	2012	[<u>55</u>]
ANFIS		ANFIS	Single label	2012	[<u>56</u>]
Peptide Locator	http://bioware.ucd.ie/ 🗹	BRNN	Single label	2013	[<u>57</u>]
iAMP-2L	http://www.jci-bioinfo.cn/iAMP-2L ☑	FKNN	Two-level, Multi-label	2013	[<u>52</u>]
DBAASP	https://dbaasp.org/prediction/general 🗷	thresholds		2014	[33]
SVM-LZ	NG (BioMed Research International)	SVM	Single label	2015	[<u>58</u>]
ADAM	http://bioinformatics.cs.ntou.edu.tw/ADAM/	SVM, HMM	Single label	2015	[<u>59</u>]
MLAMP	http://www.jci-bioinfo.cn/MLAMP	RF - ML-SMOTE	Multi-label	2016	[60]
<i>i</i> AMPpred	http://cabgrid.res.in:8080/amppred/ 🖸	SVM	Single label	2017	[<u>61</u>]
AmPEP	http://cbbio.cis.umac.mo/software/AmPEP/	RF	Single label	2018	[62]
AMP scanner	www.ampscanner.com 🗹	DNN	Single label, Large scale	2018	[63]
AntiMPmod	https://webs.iiitd.edu.in/raghava/antimpmod/	SVM	Single label, PTM/3D	2018	[64]
dbAMP	http://csb.cse.yzu.edu.tw/dbAMP/ 🖸	RF	Single label	2019	[65]

Table: Lists of some major machine learning prediction programs

Approach to solution?







Generation of Novel AMPs Design of Peptidomimetic Compounds

Testing and Validation

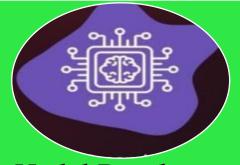
Train Al model to generate AMP candidates Modify AMP sequences for stability and synthesis

Conduct in vitro tests for efficacy and toxicity

Future Directions in Antibacterial Resistance Research Using Machine Learning



- 1. Accomplished Work in ML and Antibacterial Resistance
- 2. Developed **ML models** for analysing existing Antimicrobial Peptides (AMPs).
- 3. Investigated **patterns in AMP sequences** and their mechanisms of action.



- 1. **ML Model Development**: Train an ML model to generate novel AMPs.
- 2. **Peptide Synthesis**: Synthesize peptides in-vitro for validation.
- 3. **Iterative Validation**: Evaluate generated peptides for binding affinity.
- 4. **Selection for Synthesis**: Top 10 peptides are finalized for synthesis based on performance.



- 1. ML model is unable to predict the peptides that contains **non-natural amino acids**, hence complicating ML training and prediction.
- 2. **Lack of Repository**: No centralized, comprehensive AMP repository for training datasets.

Target protein: BLIP-I

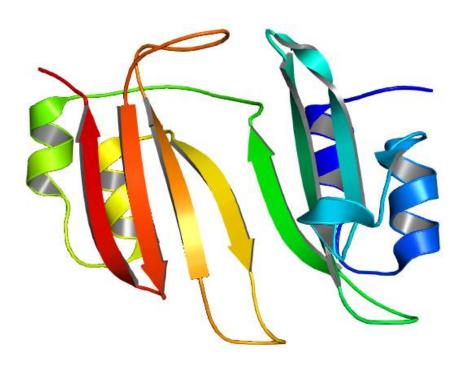


Fig: Structure of Beta-Lactamase Inhibitory Protein (BLIP-1) under PDB accession ID 3GMU

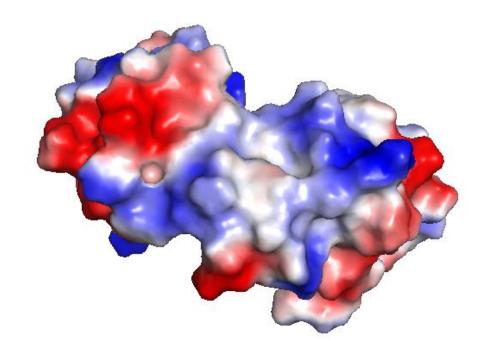
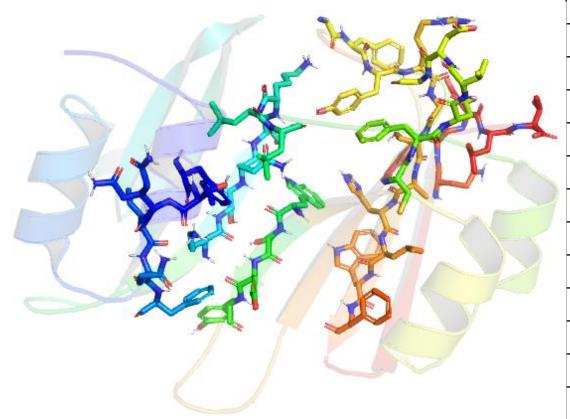


Fig: Electrostatic Potential of BLIP PDB-ID 3GMU (50.530 kcal/mol)

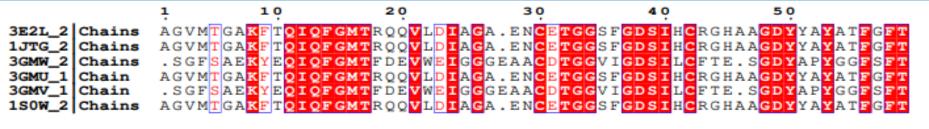
Binding site prediction for BLIP-1

• Fixed regions for binding are: [9-14, 70-76, 111-114, 130-135, 140-150, 160-165]



S.No.	Amino acid Residues	Residue Position	Residue Name
1	F	9	Phenylalanine
2	Т	10	Threonine
3	I	12	Isoleucine
4	Q	13	Glutamine
5	F	14	Phenylalanine
6	K	70	Lysine
7	E	73	Glutamic acid
8	L	76	Leucine
9	Т	111	Threonine
10	E	114	Glutamic acid
11	S	130	Serine
12	F	132	Phenylalanine
13	F	142	Phenylalanine
14	Y	143	Tyrosine
15	S	146	Serine
16	Н	148	Histidine
17	W	162	Tryptophan

Multiple sequence alignment



		e ö	70	8 ö	9 O	100	110
3E2L_2	Chains						GQGSCTTWSEYYPAY
1JTG_2	Chains						GQGSCTTWSEYYPAY
3GMW_2	Chains	DEG	ELWSKRNEYL	YKAKTPSVKI	SHYNRTALGM	TEAQLWAAV	PKDSCVSQGESYPNW
3GMU_1	Chain						GQGSCTTWSEYYPAY
3GMV_1							PKDSCVSQGESYPNW
1S0W_2	Chains	SAAADA	KVD <mark>SK</mark> SQEKI	LAPSAPTLTI	AKFNQVTV G M	TRAQVLATV	GQG <mark>SC</mark> TTWSEY YP AY

		120	130	140	150	160
3E2L_2	Chains			YSS <mark>TG</mark> FYRG <mark>SA</mark>		
1JTG_2	Chains	PSTAGVT	LSLSCFDVDG	YSSTGFYRGSA	HLWFTDGVL	QGKROWDLV
3GMW_2	Chains			TGLFPPSA		
3GMU_1	Chain	PSTAGVT	LSLSCFDVDG	YSS <mark>TG</mark> FYRG <mark>SA</mark>	HLWF TDGVL	QGKRQWDLV
3GMV_1	Chain			TGLFPPSA		
1S0W_2	Chains	PSTAGVT	LSLS <mark>C</mark> FD <mark>V</mark> DG	YSS <mark>TG</mark> AYR <mark>GSA</mark>	HLWF TDGVL	QGKRQWDLV

S.No.	PDB ID	Class of Beta lactamase
1	3E2L	BLIP (KPC)
2	1JTG	BLIP (TEM-1)
3	3GMW	BLIP-I (TEM-1)
4	3GMU	BLIP (Apo form)
5	3GMV	BLIP-I (Apo form)
6	1SOW	BLIP (TEM)

Target for OMEGA Loop

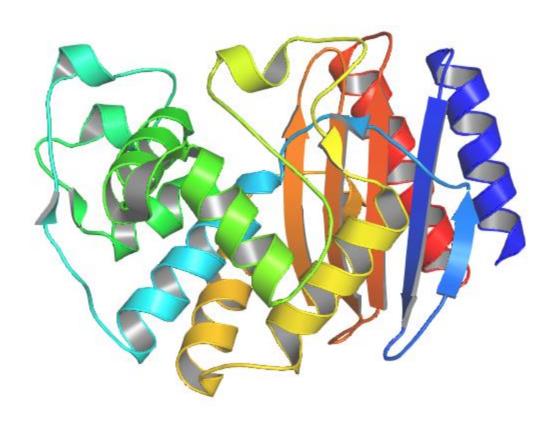


Fig. SHV-14 (Homology modeling with SwissModel)

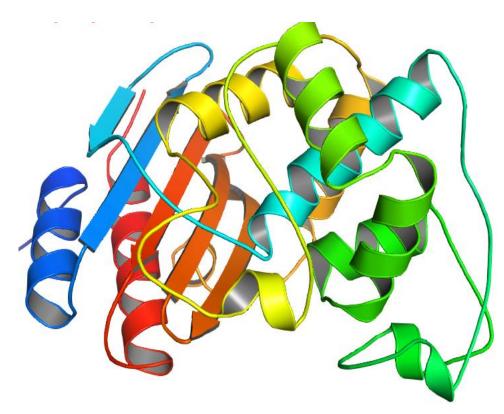
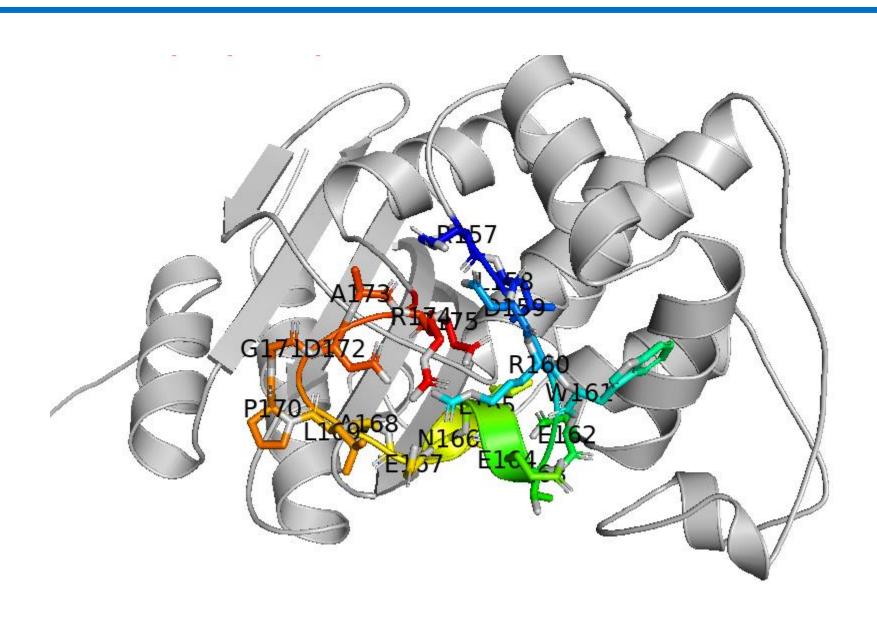
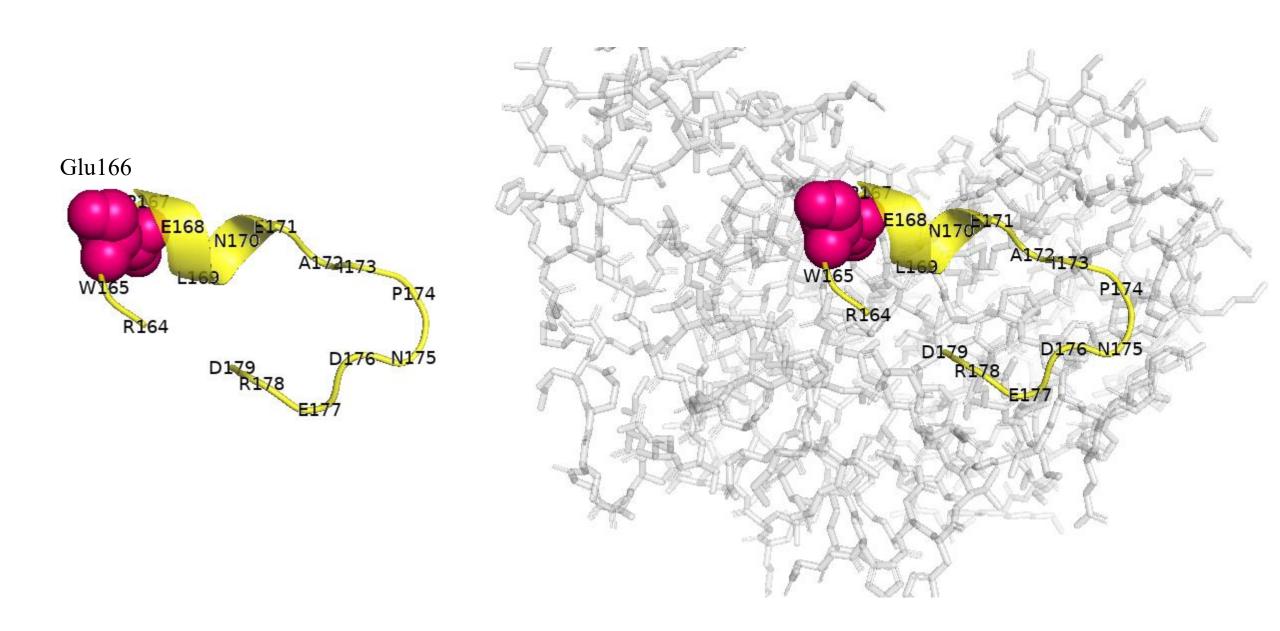


Fig. TEM-1

OMEGA loop in SHV-14

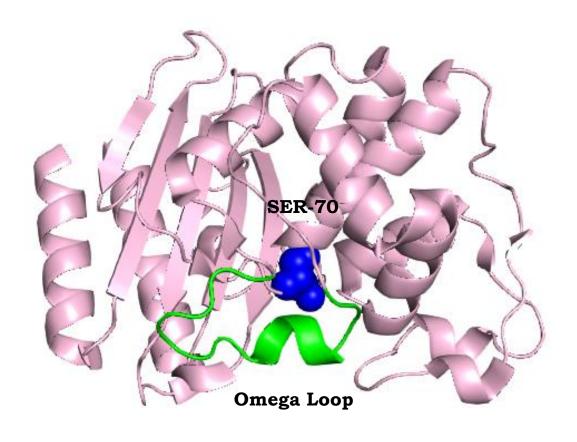


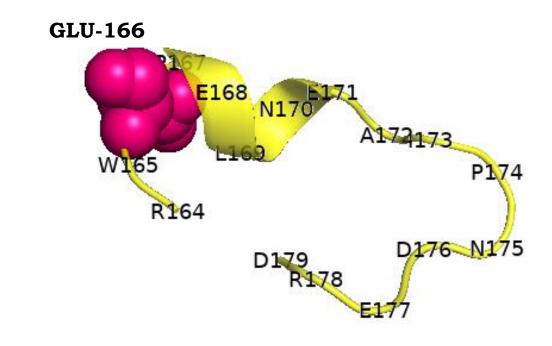
OMEGA loop in TEM-1



OMEGA loop of Class-A β -Lactamase

- Ω -loop of TEM-type β Ls contains **16 residues** (from Arg164 to Asp179)
- Glu 166, highly conserved in class A β Ls, plays a crucial role in the hydrolysis of β -lactams.





(PDB ID: 8GIJ) Resolution: 1.59 A°

Class-A β -lactamase variants

Methodology

- 1. performed Multiple sequence alignment using Clustal omega
- 2. Visualize it using Espript 3.0 web server
- 3. Manually identified conserved regions
- 4. Found 12 conserved sequences.

Conserved motifs in Class-A β -lactamase



Conserved motifs in Class-A β -lactamase

• Essential structural motifs common to subclasses of Class A beta-lactamase

S.No.	Position	Conserved Regions	Length	Shorthand
1	41-44	RLGV	4	C1
2	59-62	DERF	4	C2
3	103-106	VSPL	4	C3
4	136-139	NLLL	4	C4
5	143-146	LGGP	4	C5
6	178-183	RDTTTP	6	C6
7	251-258	NDVAILWP	8	C7
8	262-269	PLLVVIY	7	C8
9	130-132	SDN	3	C9
10	234-237	DKTG	4	C10
11	70-73	STFK	4	C11
12	166-170	EPELN	5	C12

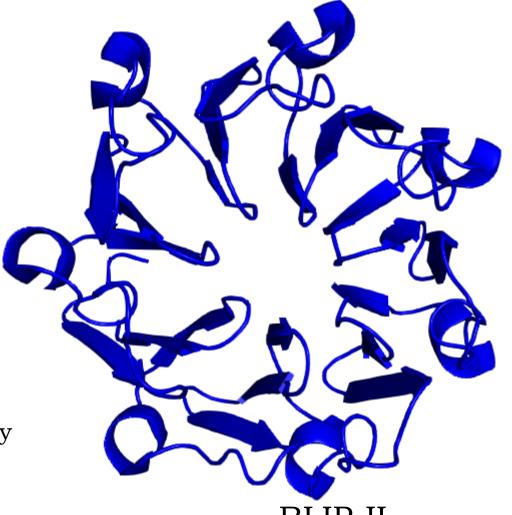
BLIP-II

• Mol wt. 28KDa

• Source organism: *Streptomyces exfoliates*

• It has motif seven bladed beta-propeller contains 3anti-parallel beta-sheets

 Blocks the beta-lactamase active site (S-70) sterically and inhibit its activity.



BLIP-II

PDB ID: 1JTD

De-novo peptides against BLIP-I

S.No.	Reference PDB Structure	Backbone structure	Sequence Length	Predicted sequences	Predicted 3D structure	Charge (Kcal/mol)
1	BLIP_3GMU.pdb	BLIP_B0.pdb	7	TEEERRE	BLIP_P0.pdb	63.309
2	BLIP_3GMU.pdb	BLIP_B1.pdb	7	GENLSLL	BLIP_P1.pdb	66.844
3	BLIP_3GMU.pdb	BLIP_B2.pdb	7	ELEKLLS	BLIP_P2.pdb	82.123
4	BLIP_3GMU.pdb	BLIP_B3.pdb	7	ISEEALT	BLIP_P3.pdb	76.202
5	BLIP_3GMU.pdb	BLIP_B4.pdb	7	GLAEKLA	BLIP_P4.pdb	71.297
6	BLIP_3GMU.pdb	BLIP_B5.pdb	7	LEDLTEA	BLIP_P5.pdb	85.967
7	BLIP_3GMU.pdb	BLIP_B6.pdb	7	DVDLSAG	BLIP_P6.pdb	69.418
8	BLIP_3GMU.pdb	BLIP_B7.pdb	7	SELNIIE	BLIP_P7.pdb	80.723
9	BLIP_3GMU.pdb	BLIP_B8.pdb	7	RNRLNIT	BLIP_P8.pdb	81.029
10	BLIP_3GMU.pdb	BLIP_B9.pdb	7	IPSLLSP	BLIP_P9.pdb	59.061

De-novo peptides against OMEGA loop

S.No	Backbone Structure	Ref OMEGA Sequence	Predicted Sequence Length	Predicted Sequence	Predicted 3D structure	Charge (kcal/mol)
1	OM_0.pdb	RWEPELNEAIPNDERD	7	LSREYIV	OM_P0.pdb	66.768
2	OM_1.pdb	RWEPELNEAIPNDERD	7	GLAELIG	OM_P1.pdb	48.636
3	OM_2.pdb	RWEPELNEAIPNDERD	7	EEALLAG	OM_P2.pdb	62.497
4	OM_3.pdb	RWEPELNEAIPNDERD	7	LEEELRG	OM_P3.pdb	78.201
5	OM_4.pdb	RWEPELNEAIPNDERD	7	AERLEIS	OM_P4.pdb	77.06
6	OM_5.pdb	RWEPELNEAIPNDERD	7	SSGVLAP	OM_P5.pdb	46.841
7	OM_6.pdb	RWEPELNEAIPNDERD	7	AEAVLAA	OM_P6.pdb	61.965
8	OM_7.pdb	RWEPELNEAIPNDERD	7	GEIRLGG	OM_P7.pdb	64.568
9	OM_8.pdb	RWEPELNEAIPNDERD	7	NTAVNTA	OM_P8.pdb	52.656
10	OM_9.pdb	RWEPELNEAIPNDERD	7	DEALLAG	OM_P9.pdb	79.412

OMEGA loop peptide generation

S.No.	Reference sequence	Peptide Name	Peptide Sequence	Length
1	RWEPELNEAIPNDERD	P1	EYRIR	5
2	RWEPELNEAIPNDERD	P2	TYRLR	5
3	RWEPELNEAIPNDERD	Р3	TSHLR	5
4	RWEPELNEAIPNDERD	P4	TTHIR	5
5	RWEPELNEAIPNDERD	P5	ETHIH	5
6	RWEPELNEAIPNDERD	Р6	TSHLH	5
7	RWEPELNEAIPNDERD	P7	ESRLH	5
8	RWEPELNEAIPNDERD	P8	ESHIH	5
9	RWEPELNEAIPNDERD	P9	ESRIH	5
10	RWEPELNEAIPNDERD	P10	TYHLH	5

Source: Biswal et al. (2023)

OMEGA loop peptide generation

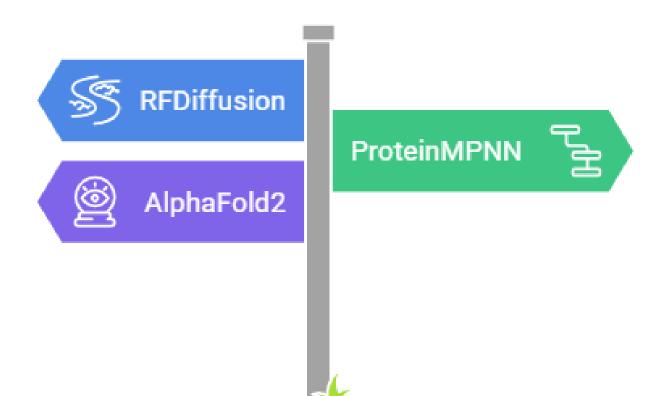
s.no	Ref P7 Sequence	Generated Backbone	Length of generated peptide	Generated AA sequence	Generate 3D structure
1	ESRLH	OM_PP7_0.pdb	7	RERELLS	OM_PAP7_0.pdb
2	ESRLH	OM_PP7_1.pdb	7	NLEELLS	OM_PAP7_1.pdb
3	ESRLH	OM_PP7_2.pdb	7	EEALRRA	OM_PAP7_2.pdb
4	ESRLH	OM_PP7_3.pdb	7	ALNEREA	OM_PAP7_3.pdb
5	ESRLH	OM_PP7_4.pdb	7	NLRELLE	OM_PAP7_4.pdb
6	ESRLH	OM_PP7_5.pdb	7	EGIEERG	OM_PAP7_5.pdb
7	ESRLH	OM_PP7_6.pdb	7	EEALIIE	OM_PAP7_6.pdb
8	ESRLH	OM_PP7_7.pdb	7	ADATERA	OM_PAP7_7.pdb
9	ESRLH	OM_PP7_8.pdb	7	TEAERLG	OM_PAP7_8.pdb
10	ESRLH	OM_PP7_9.pdb	7	SEALEKA	OM_PAP7_9.pdb

Template motifs for peptide design

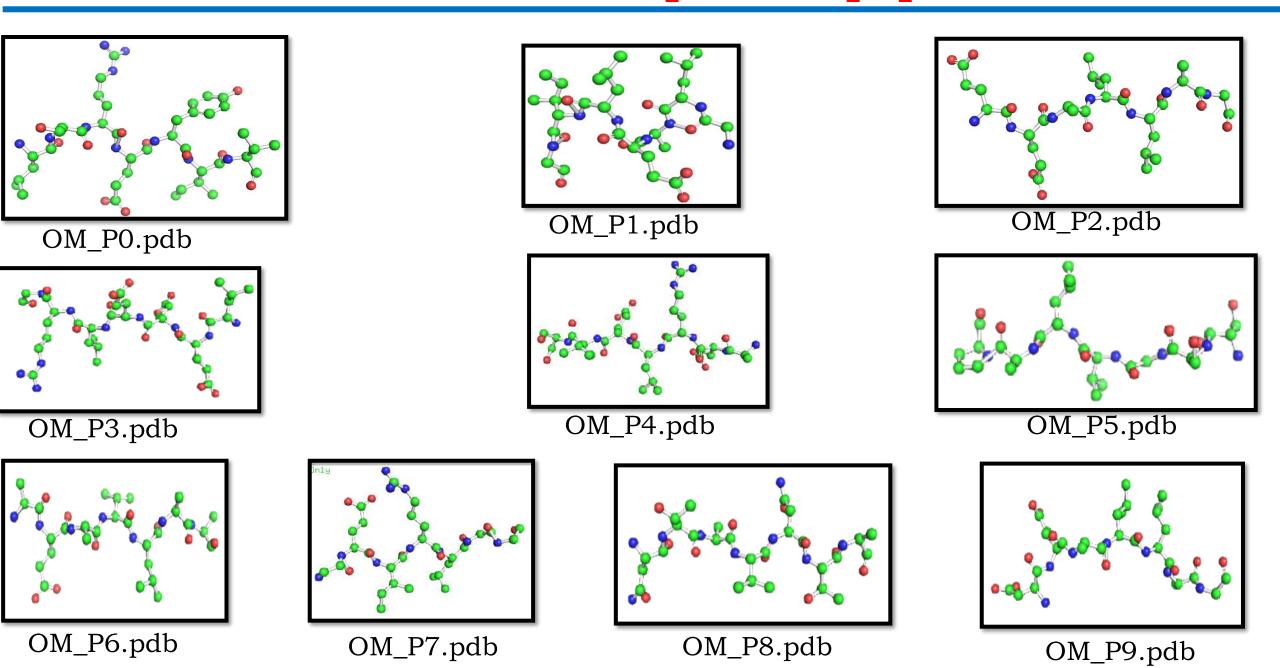
S.No	Ref. peptide sequence	Backbone generation	Length of generated peptide	Generated AA sequence	Generate 3D structure
1	NDVAILWP	C7_0.pdb	7	TEAERLG	VAR_C7_0.pdb
2	NDVAILWP	C7_1.pdb	7	TLEELLK	VAR_C7_1.pdb
3	NDVAILWP	C7_2.pdb	7	ELEKLLA	VAR_C7_2.pdb
4	NDVAILWP	C7_3.pdb	7	RLAELLG	VAR_C7_3.pdb
5	NDVAILWP	C7_4.pdb	7	GEALRRA	VAR_C7_4.pdb
6	NDVAILWP	C7_5.pdb	7	EPASLTA	VAR_C7_5.pdb
7	NDVAILWP	C7_6.pdb	7	ELAKLTK	VAR_C7_6.pdb
8	NDVAILWP	C7_7.pdb	7	VLGLEKG	VAR_C7_7.pdb
9	NDVAILWP	C7_8.pdb	7	NLADLLA	VAR_C7_8.pdb
10	NDVAILWP	C7_9.pdb	7	DEAAIIP	VAR_C7_9.pdb

Computational techniques used for peptide design

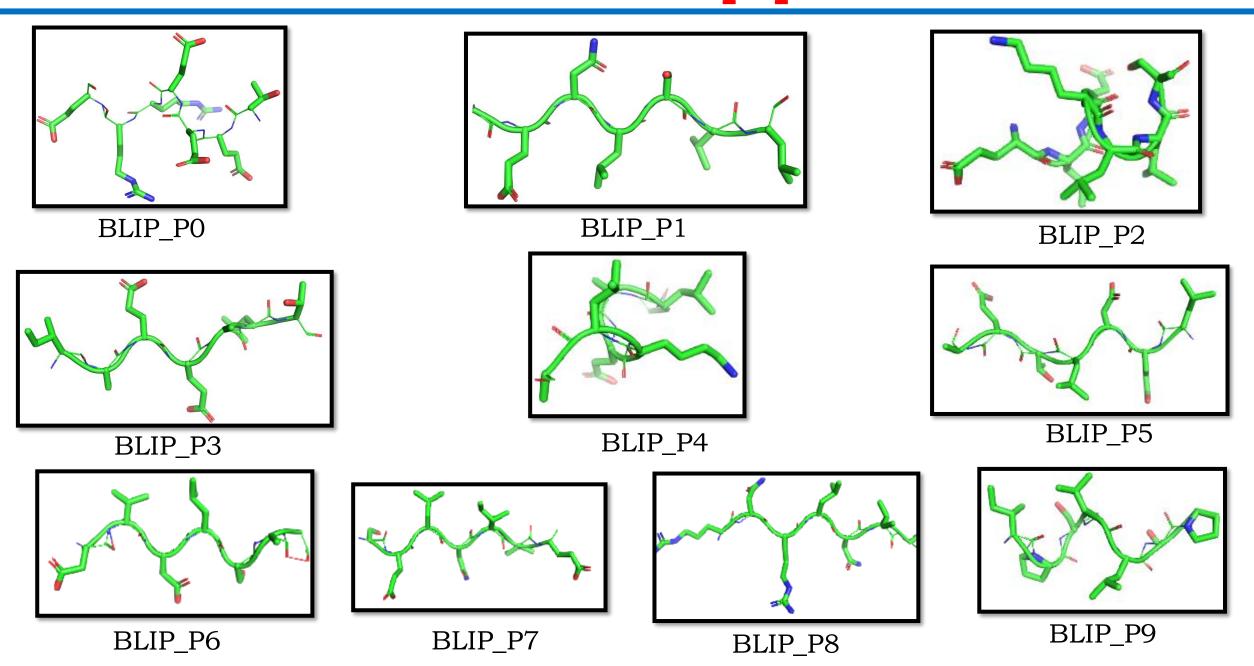
- RFDiffusion: De novo peptide generation based on protein diffusion models.
- ProteinMPNN: Optimizing sequences for structural stability and target affinity.
- AlphaFold2: Predicting peptide-target interactions and validating stability.



OMEGA loop based peptides



BLIP-I based peptides



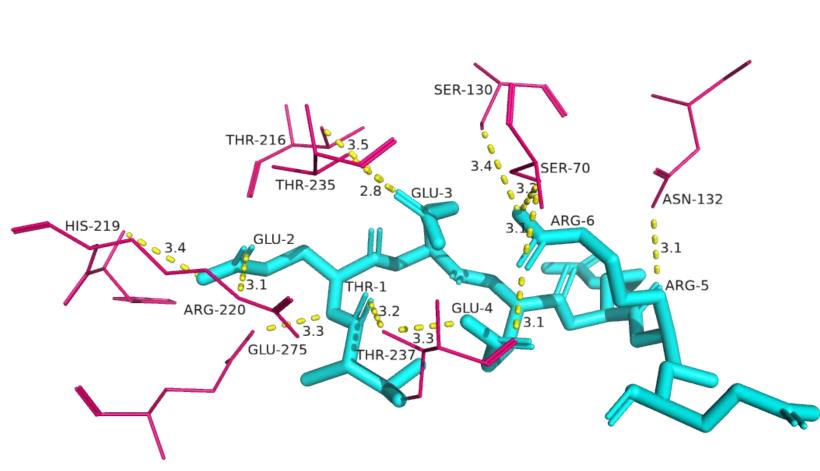
Number of generated peptides

Target	Number of peptides generated
BLIP-I	10
Omega Loop	110
Class A beta lactamase	120
Total	240

Number of peptides generated for each target.

Docked BLIP_P0 with KPC-2

BLIP-P0	KPC-2	Distance	
THR-1	THR-237 3.2		
GLU-2	HIS-219 3.4		
GLU-2	ARG-220 3.1		
GLU-2	GLU-275	3.3	
GLU-3	THR-216	3.5	
GLU-3	THr-235	2.8	
GLU-4	THR-237	3.3	
ARG-5	ASN-132	3.1	
ARG-6	SER-70 3.2		
ARG-6	THR-237	3.1	
ARG-6	SER-130 3.4		



PRODIGY analysis

Binding Score (△G) kcal/mol					
	BLIP_P0	OM_PO	OM_PAP1_0	VAR_C1_0	VAR_C12_0
CTX-M-1	-7.5	-8.6	-8.4	-8.5	-7.7
KPC-2	-7.5	-11.2	-9.2	-8.5	-6.6
SME-1	-8.2	-9.3	-8.6	-7.4	-7.6
TEM-1	-8.3	-7.2	-7.6	-6.7	-8.1
SHV-1	-7.5	-9.1	-8.9	-7.9	-10.3

Summary

- Successfully designed novel peptides targeting BLIP proteins, Omega loop, and conserved motifs.
- Computational approaches (RFDiffusion, ProteinMPNN, AlphaFold2) have successfully predicted stable and high-affinity peptide inhibitors.

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THANK YOU!