Using Neural Net
Launch a Preim
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Advisor: Kevin Cr

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Research Question

Can neural networks be used to conduct a preimage attack?

Hypothesis

Linking together neural networks that are individually trained on data from each round of the cryptographic hash SHA-1 will reduce the complexity each network needs to model, allowing deduction of the preimage.

Knowledge Gap

- Previous work using neuro-cryptanalysis for preimage attacks against modern, non-lightweight hashes has been mostly ineffective (Goncharov, 2019; Liu et al., 2021)
    - Attacked the entire hash with a single neural network
- Failed to take into account the internal structure of the algorithm

Analysis

- Accuracy remained at 0 regardless of any modifications to hyperparameters or training data
- Fundamental issue: some information is lost in each round, so all candidate previous rounds are equally plausible
- Major limitation: lack of computing power resulted in datasets insufficient to train for a modern hash effectively

Conclusion

- Aimed to leverage machine learning advancements for preimage attacks, but all tested neural network architectures were completely ineffective in reversing single rounds
- Future research may explore combining neural network chains with meet-in-the-middle attacks, which have similar strategic paradigms

- Clarified an approach that does not work; research in classical or differential-neural cryptanalysis may be more fruitful

References

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Sharma, N., & Bhatt, R. (2018). Privacy preservation in WSN for healthcare application. *Procedia Computer Science*, *132*, 1243–1252. https://doi.org/10.1016/j.procs.2018.05.040

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Main Ta

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networks nor recurrent neural
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Therefore, neural network chains
a preimage attack on a reduced
such as SHA-1.

modern hash s

Layer Amount	Learning Rate	Round	Epochs	Batch Size	Loss	Train Accuracy	Test Accuracy	Datase
3	0.001	2	11	32	377.5233	0	0	
3	0.001	2	11	64	377.6703	0	0	
7	0.01	2	11	64	377.4963	0	0	
3	0.001	2	11	64	377.5508	0	0	
3	0.001	16	11	64	405.3415	0	0	
3	0.01	16	11	64	405.2192	0	0	
3	0.01	2	11	64	379.9132	0	0	
3	0.01	3	11	64	428.5194	0	0	
3	0.01	3	50	64	428.6604	0	0	
3	0.01	3	11	64	438.9447	0	0	restricte
3	0.01	3	11	64	399.1621	0	0	1 millio
3	0.01	3	11	64	468.2508	0	0	fuzzy d

Layer Amount	Learning Rate	Round	Epochs	Batch Size	Loss	Train Accuracy	Test Accuracy	Dataset
3	0.01	3	11	64	428.6908	0	0	
3	0.01	3	11	64	439.0123	0	0	restricte
3	0.01	3	11	64	399.1277	0	0	1 million
3	0.01	3	11	64	468.1121	0	0	fuzzy da

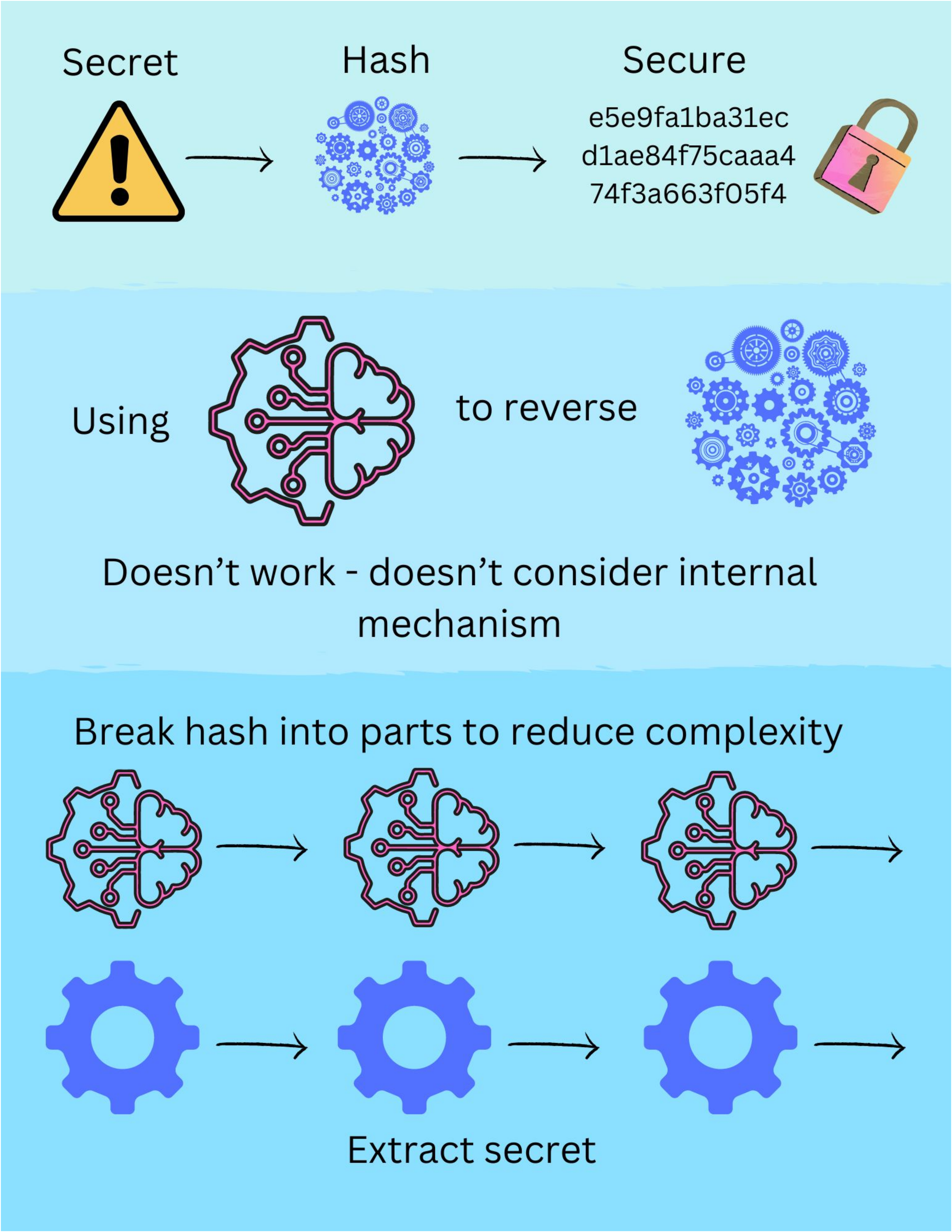
uch as SHA-1.

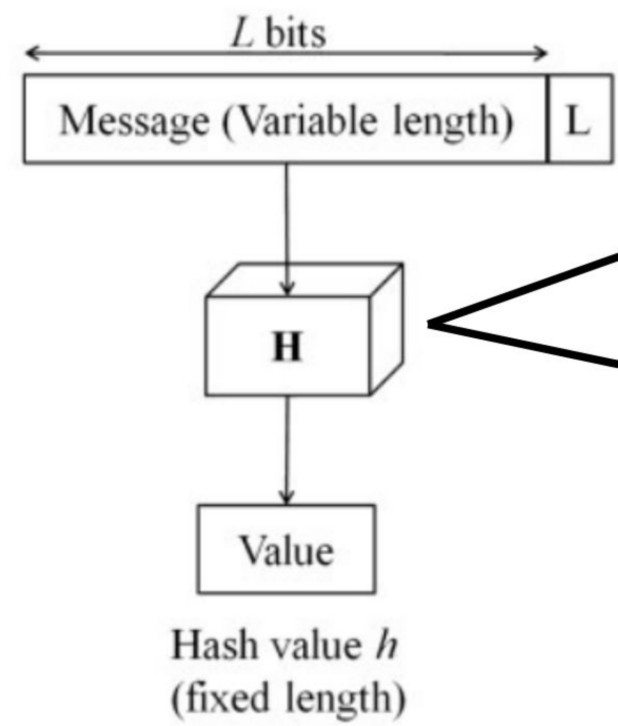
	Bit Accuracy
	0.49
	0.49
	0.49
	0.49
	0.49
	0.49
	0.49
	0.49
	0.49
d input	0.46
dataset	0.51
ta	0.48

Table 1: Accuracies and loss for multilayer feed-forward neural networks with varying hyperparameters and training datasets

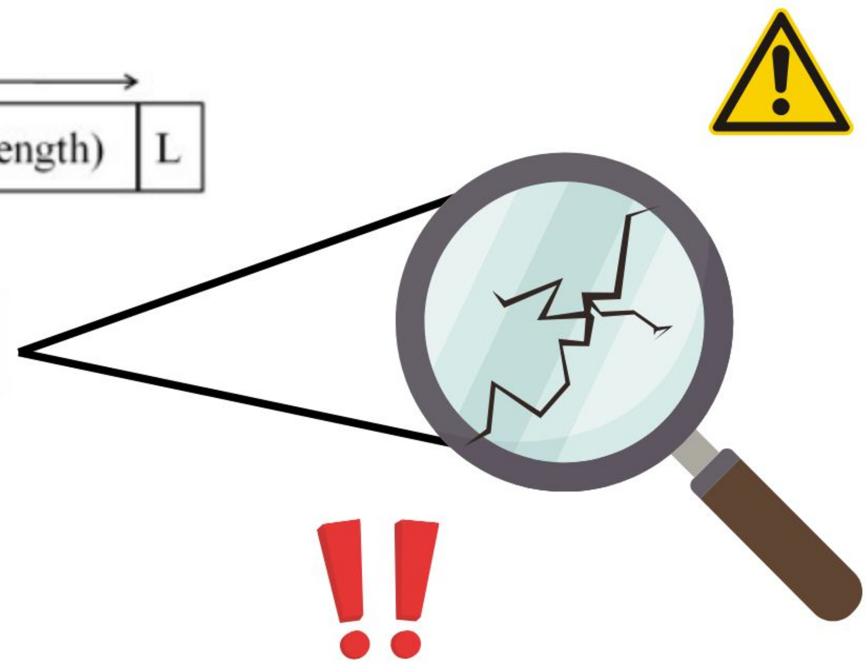
	Bit Accuracy
	0.49
d input	0.46
	0.51
ta	0.48

Table 2: Accuracies and loss for recurrent neural networks with varying hyperparameters and training datasets


Secret
Hash
Secure
e5e9fa1ba31ec
d1ae84f75caaa4
74f3a663f05f4
Using
to reverse
Doesn’t work - doesn’t consider internal mechanism
Break hash into parts to reduce complexity
Extract secret



Structure of a hash function (Sharma & Bhatt, 2018)



Cryptanalysis identifies the issues within these functions.

- **Cryptanalysis:** the process of analyzing systems of information to deduce secret parts of those systems
- Cryptanalysis ensures digital security by identifying weaknesses in critical systems
- Cryptographic hashes: deterministic functions that map the plaintext to the ciphertext approximately randomly
  - Operate in rounds
- Neuro-cryptanalysis can be used for preimage attacks

Proce

Generate Data

Inputs were randomly generated and hashed with a custom implementation of the SHA-1 hash (both normal and fuzzy) in Java that returns internal states for each round.

Single Layer Learning

Feed-forward and recurrent neural networks were programmed in PyTorch and trained to reverse single layers from the data.

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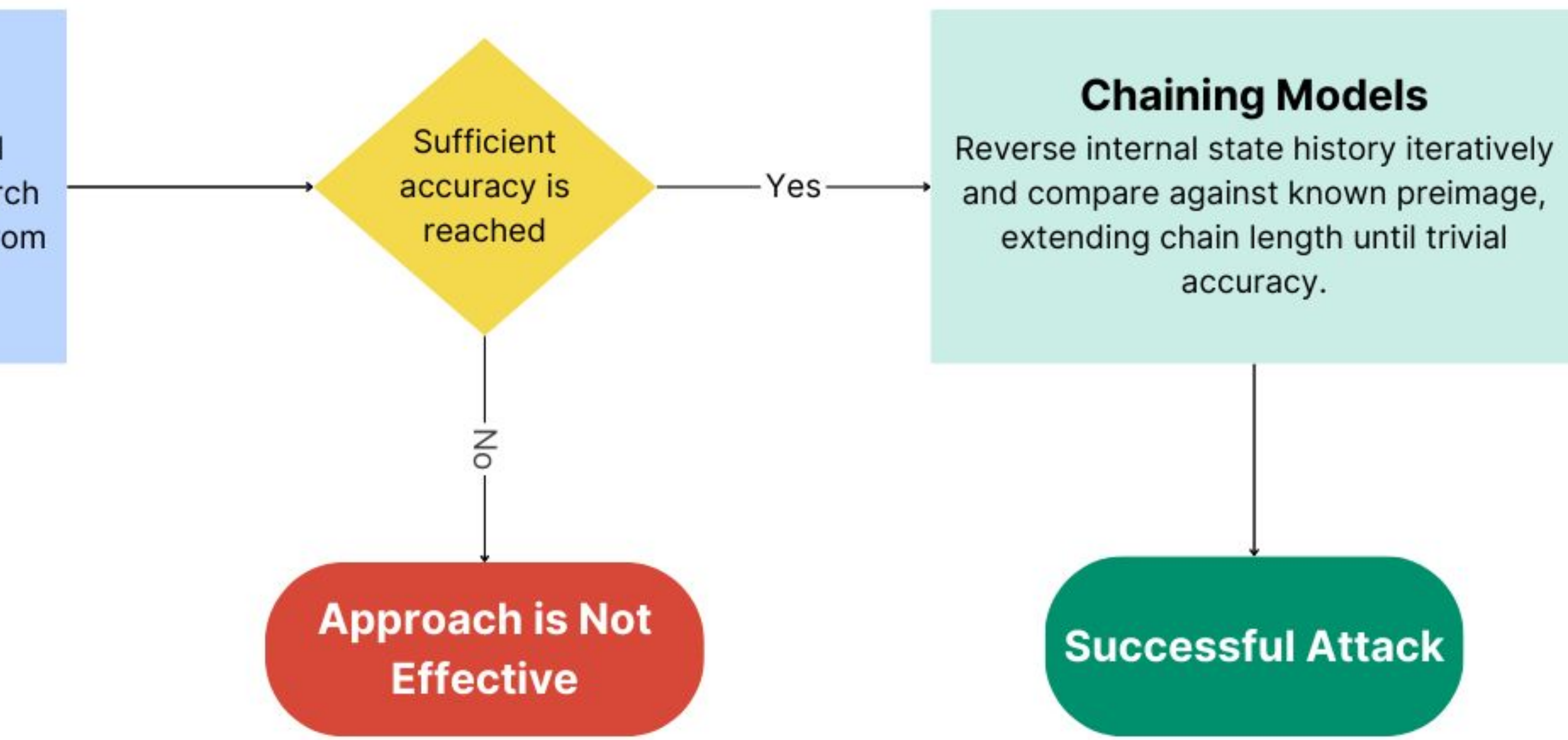

Sufficient accuracy is reached
Yes
No
Chaining Models
Reverse internal state history iteratively and compare against known preimage, extending chain length until trivial accuracy.
Approach is Not Effective
Successful Attack