



Taipei – October 17th, 2025

ACM Workshop on Artificial Intelligence Security (AISec)

E-PhishGen: Unlocking Novel Research in Phishing Email Detection

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TWO (2)

Takeaways

First:
Phishing Email Detection
is (still) an Open Problem

First:
Phishing Email Detection
is (still) an Open Problem,
especially in Research

Phishing Emails in the Real World

Threat landscape by the numbers

68%*	80-95%	\$4.88 million	4,151%
Breaches contain the human element	Of cyber-attacks begin with a phish	Avg. cost of a phishing breach	Increase in phishing attacks since ChatGPT in November 2022
Verizon DBIR	Comcast Business Cybersecurity Threat Report	IBM/Ponemon Cost of a Data Breach Report	SlashNext State of Phishing Report

DBIR: *2024 would have been 74%, not 68%, using previous criteria

<https://hoxhunt.com/guide/phishing-trends-report>

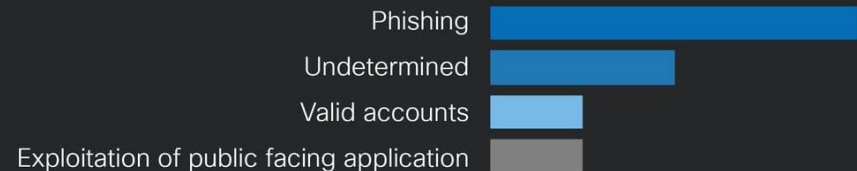
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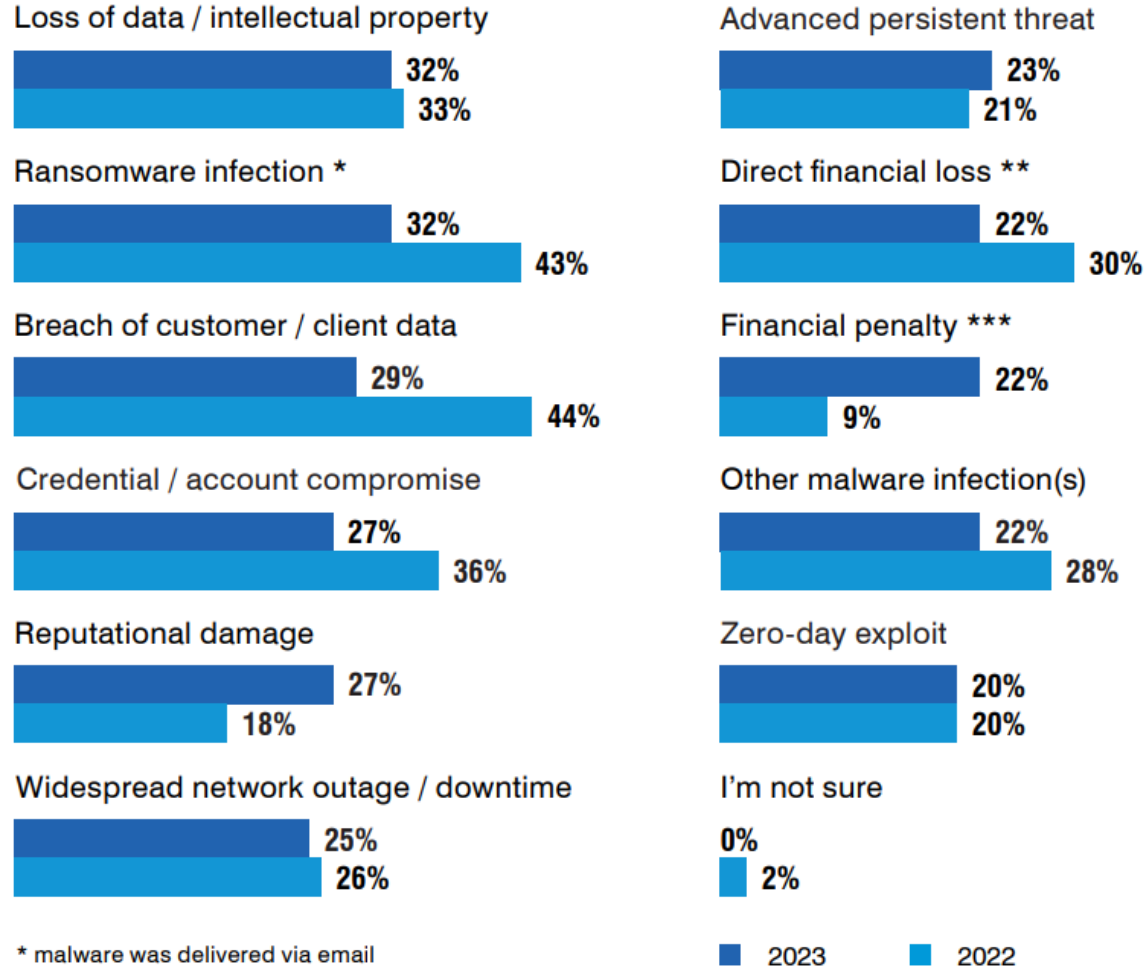
Phishing was the
top infection vector
in Q1



CISCO
TALOS

Phishing Emails in the Real World

Results of Successful Phishing Attacks



Phishing Emails in Research

Phishing Emails in Research

processing (NLP) techniques. The proposed deep learning model was trained and tested using the dataset, and it was found that it can achieve high accuracy in detecting email phishing compared to other state-of-the-art research, where the best performance was seen when using BERT and LSTM with an accuracy of 99.61%. The results demonstrate the potential of deep learning for improving email phishing detection and protecting against this pervasive threat.

Phishing Emails in Research

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Experimental tests verified that the classifier was effective in detecting phishing emails using body text among the existing detection methods, and it took short time and produced a high accuracy rate of 98.2% and a low false-positive rate of 0.015.

Phishing Emails in Research

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the proposed architecture employs models like Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN). Experimental evaluation demonstrates the approach's remarkable accuracy, recall, precision, and F1-score, achieving 99.51%, 99.68%, 99.5%, and 99.52%, respectively. This signifies its high efficacy in detecting and classifying malicious emails with minimal

Phishing Emails in Research



Why?

On what data are (ML-based) phishing email detectors evaluated?

[Subject] Help!

You have been specially selected to qualify for the following:

Premium Vacation Package and Pentium PC Giveaway

To review the details, please click on the link below using the confirmation number:

<http://www.1chn.net/wintrip>

Confirmation Number: **Lh340**

Please confirm your entry within 24 hours of receiving this confirmation.

Wishing you a fun-filled vacation!

If you have any additional questions or cannot connect to the site, do not hesitate to contact me:

vacation@btamail.net.cn

Email 1. An email in the popular dataset SpamAssassin [39] (from 2005).



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A shortlist of (arguably old) datasets

*SpamAssassin, Enron, TREC,
LingSpam, CEAS, Nazario*,
SpamBase, NigerianFraud*

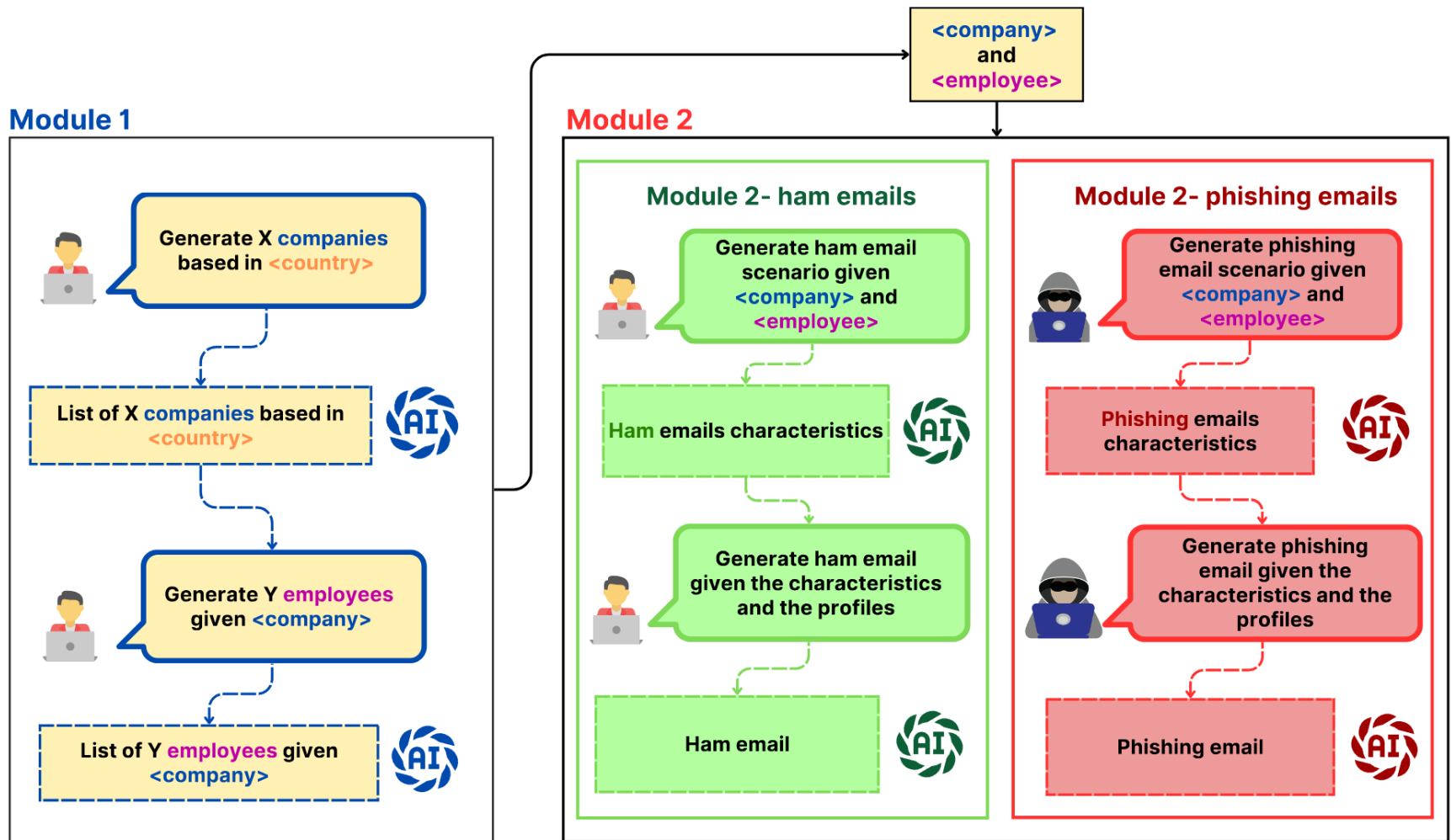
A shortlist of (arguably old) datasets

*SpamAssassin, Enron, TREC,
LingSpam, CEAS, Nazario*,
SpamBase, NigerianFraud*

**All containing real-world emails...
but mostly (*) from before 2010!**

Second:
We (try to) “unlock”
research in Phishing
Email Detection

E-PhishGen: an email-generation framework



E-PhishLLM: dataset of 16k LLM-written emails

[Subject] Scheduling a Call for Supply Chain Adjustments

Dear Marco, I hope this message finds you well. We need to schedule a video call to discuss some adjustments and potential delays in the supply chain affecting our current project components. Could you please inform me of your availability this week? Looking forward to hearing from you. Best regards, TomJohnson

Email 2. Illustrative example of a benign email in E-PhishLLM.

[Subject] Urgente: Verifica delle Credenziali dell'Account

Ciao Marco, Ti scrivo per conto del tuo manager per richiedere un'urgenteverifica delle tue credenziali aziendali. È molto importante che tu proceda al controllo immediato della correttezza delle informazioni d'accesso personali. Si prega di seguire il link di verifica di seguito e aggiornare qualsiasi informazione necessaria quanto prima:«link» Grazieperla tua collaborazione. Cordiali saluti, Federica Rossi Responsabile IT Fabbri Tech Automazione

Email 3. Illustrative example of a malicious email in E-PhishLLM.

We re-assess prior methods on “old” datasets

Model	Trained On	CEAS	Enron-v1	Ling-v1	SpamAssassin	TREC	Chatuat	Enron-v2	Ling-v2	Average Drop
Logistic Regression	CEAS	0.98	0.57	0.29	0.32	0.68	0.57	0.58	0.27	0.51
	Enron-v1	0.74	0.96	0.43	0.51	0.77	0.83	0.96	0.44	0.30
	Ling-v1	0.45	0.62	0.91	0.73	0.54	0.35	0.62	0.92	0.31
	SpamAssassin	0.42	0.65	0.74	0.91	0.55	0.40	0.66	0.71	0.32
	TREC	0.83	0.92	0.68	0.73	0.94	0.59	0.92	0.65	0.18
	Chatuat	0.72	0.63	0.25	0.45	0.62	1.00	0.65	0.26	0.49
	Enron-v2	0.72	0.95	0.41	0.47	0.65	0.87	0.95	0.42	0.31
	Ling-v2	0.49	0.65	0.93	0.73	0.56	0.39	0.66	0.93	0.30
Naive Bayes	CEAS	0.83	0.14	0.01	0.05	0.25	0.35	0.15	0.01	0.69
	Enron-v1	0.79	0.95	0.60	0.58	0.78	0.75	0.96	0.62	0.23
	Ling-v1	0.70	0.71	0.97	0.54	0.67	0.71	0.72	0.96	0.25
	SpamAssassin	0.67	0.70	0.62	0.95	0.68	0.45	0.71	0.63	0.31
	TREC	0.79	0.90	0.83	0.79	0.88	0.51	0.90	0.82	0.08
	Chatuat	0.69	0.62	0.27	0.45	0.60	0.98	0.64	0.28	0.48
	Enron-v2	0.79	0.96	0.59	0.58	0.78	0.75	0.96	0.62	0.23
	Ling-v2	0.70	0.71	0.97	0.54	0.68	0.71	0.73	0.96	0.24
Random Forest	CEAS	0.99	0.52	0.23	0.12	0.58	0.51	0.53	0.21	0.60
	Enron-v1	0.73	0.98	0.44	0.54	0.80	0.78	0.99	0.46	0.30
	Ling-v1	0.47	0.72	0.98	0.71	0.59	0.42	0.72	0.99	0.32
	SpamAssassin	0.46	0.69	0.68	0.97	0.63	0.40	0.70	0.67	0.36
	TREC	0.84	0.94	0.58	0.77	0.97	0.54	0.94	0.57	0.23
	Chatuat	0.72	0.64	0.28	0.45	0.62	1.00	0.66	0.28	0.48
	Enron-v2	0.71	0.97	0.41	0.52	0.79	0.80	0.97	0.43	0.31
	Ling-v2	0.50	0.72	0.99	0.71	0.60	0.44	0.73	0.98	0.31

Support Vector Machine	CEAS	0.99	0.61	0.28	0.30	0.72	0.55	0.62	0.28	0.50
	Enron-v1	0.77	0.97	0.44	0.51	0.78	0.83	0.97	0.45	0.29
	Ling-v1	0.42	0.70	0.96	0.77	0.60	0.38	0.70	0.94	0.32
	SpamAssassin	0.47	0.68	0.72	0.94	0.59	0.41	0.69	0.68	0.34
	TREC	0.84	0.94	0.70	0.74	0.95	0.60	0.94	0.67	0.18
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	Enron-v2	0.73	0.97	0.40	0.48	0.72	0.87	0.96	0.41	0.31
	Ling-v2	0.44	0.70	0.98	0.77	0.62	0.40	0.71	0.97	0.31
Multi-Layer Perceptron	CEAS	0.99	0.69	0.40	0.46	0.77	0.54	0.69	0.41	0.43
	Enron-v1	0.76	0.98	0.60	0.60	0.83	0.74	0.98	0.61	0.25
	Ling-v1	0.54	0.66	0.97	0.79	0.61	0.42	0.67	0.97	0.30
	SpamAssassin	0.64	0.70	0.75	0.97	0.68	0.43	0.71	0.73	0.31
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	Ling-v2	0.53	0.66	0.98	0.79	0.61	0.41	0.67	0.96	0.30
DistilBERT	CEAS	1.00	0.83	0.62	0.67	0.83	0.56	0.84	0.57	0.30
	Enron-v1	0.80	0.99	0.58	0.60	0.88	0.77	1.00	0.55	0.26
	Ling-v1	0.81	0.71	1.00	0.52	0.69	0.75	0.72	1.00	0.25
	SpamAssassin	0.84	0.81	0.74	0.98	0.80	0.56	0.81	0.77	0.22
	TREC	0.86	0.98	0.89	0.84	0.99	0.56	0.98	0.87	0.14
	Chatuat	0.71	0.64	0.28	0.45	0.62	1.00	0.66	0.28	0.48
	Enron-v2	0.83	0.99	0.52	0.56	0.84	0.80	0.99	0.49	0.27
	Ling-v2	0.81	0.69	1.00	0.52	0.68	0.74	0.69	0.98	0.25

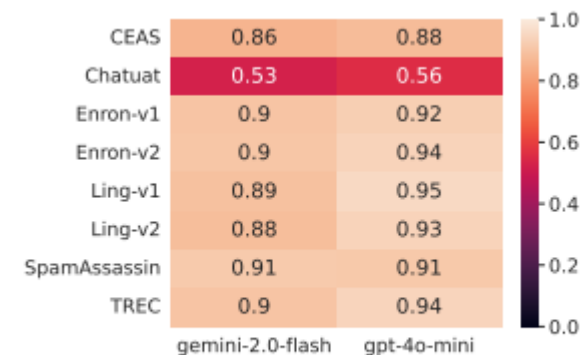
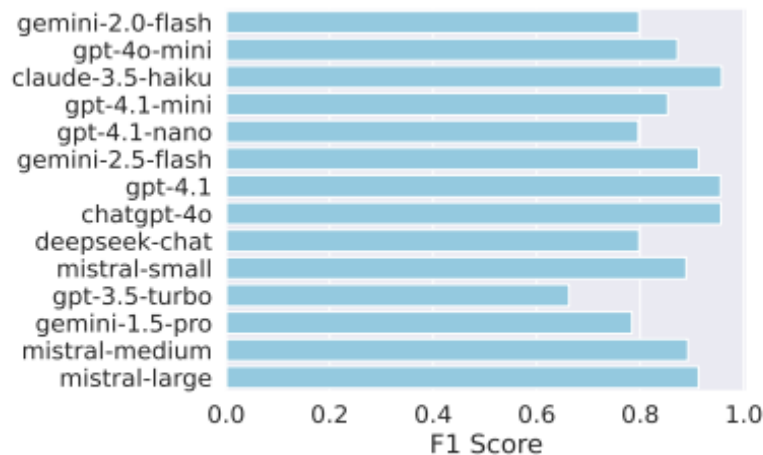
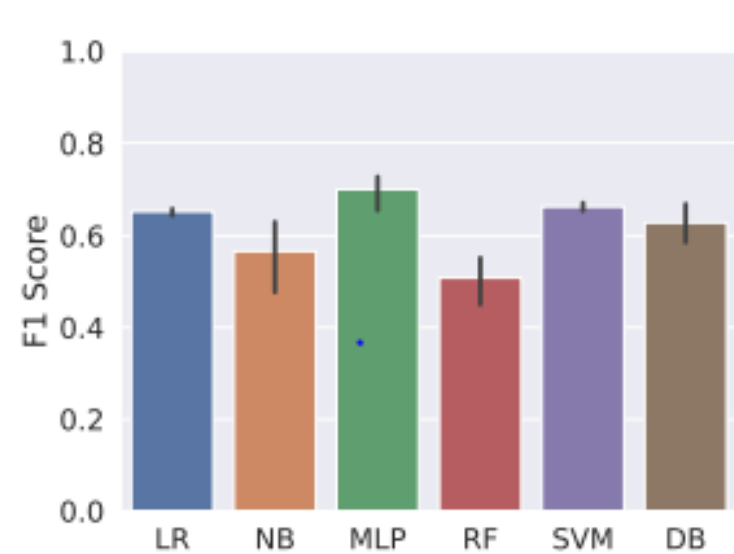
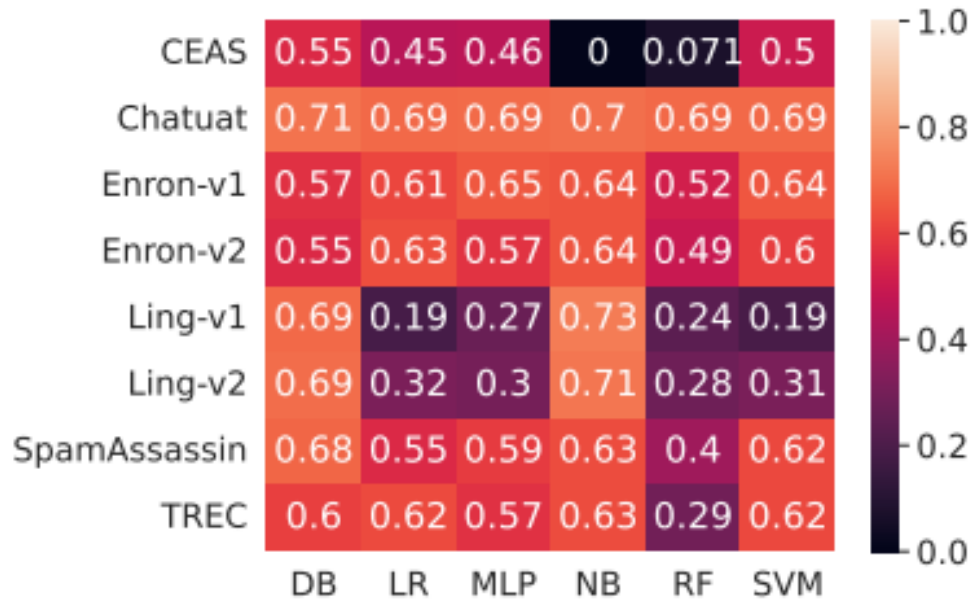


Fig. 2: LLM performance (Experiment-3).

We test prior methods on E-PhishLLM



We test various methods on F1, Precision, Recall

CEAS	0.5
Chatuat	0.7
Enron-v1	0.5
Enron-v2	0.5
Ling-v1	0.6
Ling-v2	0.6
SpamAssassin	0.6
TREC	0.5
D	

(a) Experiment-1





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