**Development of an AI-Driven Phishing Detection System Using Advanced NLP and ML Techniques**

CSI 4900 – Honours Project

2024

University of Ottawa

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# 1. Introduction

# 2. Methodology

## c. Explainable AI (XAI)

Explainable AI or XAI “is a set of processes and methods that allows human users to comprehend and trust the results and output created by machine learning algorithms” [1]. Models in artificial intelligence are often considered a black box, where information is given as input, and a prediction is made after some time. This lack of explainability, interpretability, and reproducibility poses a challenge for us. As humans, when we explain a phenomenon or a concept, we usually try our best to accompany our conclusion with explanations to help others understand how we came to a given decision. However, with AI models, is hard to understand how they come up with their results. To avoid this problem, models need to be explainable in the sense that the underlying workings of a machine-learning model are described in human language. It must also be interpretable. This means it must show the capacity to recognize how inputs and outputs relate to one another and estimate how the inputs will react when they change. Models must be reproducible as well by indicating their capacity to consistently replicate a model’s output using the same inputs [2].

Knowing how impactful XAI can be, it should come as no surprise that it could be a powerful tool to use for phishing detection. Many of the currently available products marketed to detect phishing emails and phishing links simply take in an input, and give an output of phishing or not phishing. We, therefore, believed that it would be important to incorporate XAI into our product to promote a better understanding of why any email or link is labeled the way it is. Explainability in phishing detection is beneficial for many other reasons. Namely, when a system explains its choices, users are more inclined to trust it. The ability of a phishing detection model to explain why an email is deemed suspicious increases the trust in the technology. It can also assist in detecting biases and mistakes in the model’s prediction, which enables constant improvements to the detection methods, and it promotes AI transparency as laws regarding data protection become stricter [3].

Of the many different XAI tools, SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) are some of the most popular and most useful for phishing detection. At its core, SHAP is a technique for providing context for machine learning models by giving each feature a value that corresponds to a specific prediction. It evaluates every potential feature subset to determine a feature’s contribution by comparing predictions made with and without that feature. It also ensures that every prediction is covered, and it will favor features that increase the model’s accuracy and relevance, which aligns with how the model behaves at a global and local level [4]. To better understand, let’s imagine we want to understand why a friend chose a specific restaurant. SHAP will look at all past dining decisions and calculate how much each factor such as cuisine, location, and price contributed to the choice.

LIME, on the other hand, provides local explanations that help users understand why a model makes specific predictions. It works by randomly modifying features of the input data and observing how the model's predictions change. By comparing the modified predictions with the original, LIME determines the relative importance of each feature to the final decision. These modifications are weighted by their similarity to the original input to ensure that the explanation is relevant to that specific instance [4]. Going back to the example of understanding why a friend chose a specific restaurant, LIME will only look at the current decision and explore how modifying factors such as lowering the price, or changing the location would affect the choice.

Another technique to enhance the explainability of models is the use of case-based reasoning (CBR). This technique aims to evaluate new instances by comparing them with previously known cases stored in a database. Instead of relying on a defined model such as Logistic Regression, CBR works on the idea that similar problems should have similar solutions. This is particularly useful in link analysis, where we can compute the cosine similarity of a link to a database of phishing and benign links. This solution contributes to explainable predictions by showing the most similar cases and their labels.

# 3. Related Studies

# 3. Model Testing and Comparison

# 5. Application Development

# 6. Conclusion

# 7.

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