WhiteNet: Phishing Website Detection by Visual Whitelists

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Abstract
Phishing websites aiming at stealing users’ information by claiming fake identities and impersonating visual profiles belonging to trustworthy websites are still a major threat for today’s Internet thread. Therefore, detecting visual similarity to a set of whitelisted legitimate websites was often used in phishing detection literature. Despite numerous previous efforts, these methods are either evaluated on datasets with severe limitations or assume a close copy of the targeted legitimate webpages, which makes them easy to be bypassed.

This paper contributes WhiteNet, a new similarity-based phishing detection framework, i.e., a triplet network with three shared Convolutional Neural Networks (CNNs). We furthermore present WhitePhish, an improved dataset to evaluate WhiteNet and other frameworks in an ecologically valid manner.

WhiteNet learns profiles for websites in order to detect zero-day phishing websites and achieves an area of 0.9879 under the ROC curve of legitimate versus phishing binary classification which outperforms re-implemented state-of-the-art methods.

1 Introduction
Phishing pages impersonate legitimate websites without permission [37] to steal sensitive data from users causing major financial losses and privacy violations [8, 15, 16, 36].

Phishing attacks have increased due to the advances in creating phishing kits that enabled the deployment of phishing pages on larger scales [8, 29]. According to the Anti-Phishing Working Group (APWG) [2], an international association aiming at fighting phishing attacks, 180,768 attempts have been reported in the first quarter of 2019 which is higher than the total number of phishing attempts in the third and fourth quarters of 2018, indicating that phishing attacks are continuously increasing.

There have been numerous attempts to combat the threats imposed by phishing attacks by automatically detecting phishing pages. One solution is using heuristics based on monitored phishing pages [16]. These heuristics can be extracted from URL strings [4, 28, 39] or HTML [7, 21] to detect anomalies between the claimed identity of a webpage and its features [30]. However, since phishing attacks are continuously evolving, these heuristics are subject to continuous change and might not be effective in detecting future attacks (e.g. the use of "HTTPS" is now more common in phishing webpages [2], its absence formerly was used as features to detect phishing pages [30]).

Since the key factor in deceiving users is the high visual similarity between phishing webpages and their corresponding legitimate ones, detecting such similarity was used in many previous detection studies [15]. In these methods, a whitelist of websites is maintained (domain names and screenshots), and whenever a user visits a page that is not in the whitelist, its content is compared against the whitelist’s ones. If a high visual similarity is detected, then this page is classified as a phishing page as it impersonates one of the whitelist’s websites. Similarity-based methods have the advantage of not
relying on handcrafted features and instead they rely on the strong incentive of the adversary to design pages that are similar to trustworthy websites. This makes them less prone in an arms race between defenders and attackers. Similarity can be detected from rendered screenshots of webpages which allows the detection of webpages composed entirely of images or embedded objects that attackers might use to hide textual information and avoid detection by HTML methods [15].

These efforts still have limitations. First, their whitelists are too small (e.g. 4-14 websites in [9, 26, 27]) which makes them able to detect attacks against these few websites only. Second, existing approaches fall short in detecting zero-day phishing webpages as they only protect certain webpages of the legitimate websites such as login forms where phishing pages are assumed to have a close copy of them [5, 12, 15, 20, 31]. Consequently, attackers can bypass detection by crafting phishing pages that show differences from the corresponding legitimate webpages (e.g. by obfuscation using advertisement banners and changed layout [6]), in addition to using other webpages from the targeted websites.

Our work targets the limitations mentioned above. First, we present a new similarity-based dataset (WhitePhish) covering 155 websites from previous phishing reports. We include unique screenshots of phishing pages, while the legitimate whitelisted pages cover pages with different designs and views for each website. Also, we collected a legitimate test set of websites that are not included in the whitelist. Furthermore, we performed an in-depth analysis of the collected dataset; in addition to the whitelist we manually collected from phishing reports, we inspected different sources of potential whitelists. We aim at finding strategies to build a sustainable whitelist that also contains websites that might be targeted in future attacks. This serves as a proactive step since attackers might mitigate detection by targeting new websites.

Second, we propose WhiteNet, a similarity-based detection model utilizing triplet convolutional neural networks to learn a more robust visual similarity metric between different designs and webpages of the same website. Hence, a phishing attempt targeting a certain website can be detected albeit partially copied or obfuscated, or even different in design from training webpages (i.e. zero-day phishing pages). To the best of our knowledge, this is the first end-to-end approach using triplet networks or deep learning for phishing detection using screenshots. We aim to capture each website visual profile by learning a feature representation such that pages belonging to the same website will be closer in the new feature space than screenshots from different websites. A conceptual overview of our method is depicted in Figure 1 in which we show a potential whitelist of websites. The figure shows a learned feature space in which whitelist webpages belonging to the same website have high proximity. Additionally, phishing webpages embeddings have a high visual similarity to the whitelist and thus would be classified as phishing. Finally, websites that are outside the whitelist have a genuine identity and relatively different features.

### Key Contributions:

- **WhitePhish**, an extended dataset which we constructed to mitigate limitations of previous datasets to improve ecological validity when evaluating phishing detection frameworks.
- **WhiteNet**, a similarity-based detection model utilizing triplet convolutional neural networks with a more robust visual similarity metric between different designs and webpages of the same website. The concept is shown in Figure 1

## 2 Related Work

The similarity between phishing and whitelisted websites can be inferred by extracting features that represent text content (e.g. most frequent words) and style information (e.g. font name and color, etc.), which then can be compared against whitelisted identities [14, 23]. Also, Document Object Model (DOM) comparison between two webpages can be used to detect similarity as DOM represents the logical structure of HTML or XML files [32]. However, these methods fail if attackers used images to represent the webpage instead of HTML text [12]. Additionally, they are vulnerable to code obfuscation techniques where different code produces similar rendered images [12].

Therefore, another line of work infers similarity directly from rendered screenshots. As an example, layout similarity that is deduced from the matching of screenshots’ segmentation blocks was used in [20]. Also, Earth Mover’s Distance (EMD) was used to compute the similarity between low-resolution screenshots in [12]. Besides, discriminative keypoint features were often used to match screenshots, such as the use of Scale-Invariant Feature Transform (SIFT) in [1], Speeded-Up Robust Features (SURF) in [31], Histogram of Oriented Gradients (HOG) in [5], and Oriented FAST and rotated BRIEF (ORB) in [25] to detect mobile applications spoofing.

Despite these efforts, we believe that our work explores new territory in phishing detection research with no similar precedence; most of these previous methods assume a close similarity in layout and content of the phishing and the legitimate images pair, while we aim to learn a more general similarity between any pages of the same website albeit different in design. Also, none of these previous methods utilized deep learning models to detect the similarity between screenshots. An approach similar in spirit was recently proposed in [38], but only to detect the visual similarity between URL pairs using Siamese CNNs. In contrast, we propose a visual similarity metric based on screenshots as a general approach, with further optimizations adapting to the harder problem, to
potentially detect more phishing pages which goes beyond homoglyph attacks.

3 Datasets

In this section, we discuss previously published datasets and their limitations and present how we constructed and analyzed WhitePhish.

3.1 Previous Datasets Analysis

Unfortunately, only a small number of datasets for the phishing detection task using screenshots are publicly available. One of these is DeltaPhish [8] for detecting phishing pages in compromised legitimate websites. The dataset consists of phishing pages along with legitimate pages from the corresponding compromised website. Hence, this dataset cannot be used for similarity-based detection as it does not contain the legitimate examples of the targets found in the phishing pages. We observed that a large percentage of phishing pages’ screenshots in this dataset are duplicates since PhishTank1 reports unique URLs which do not necessarily contain unique screenshots. We also found that the legitimate and phishing examples had different designs as phishing examples generally consisted of login forms with few page elements, while legitimate examples contained more details. This could cause the trained model to be biased to these design changes and, therefore, could fail when tested with legitimate pages with login forms.

The Phish-IRIS dataset [9] for similarity-based detection consists of phishing pages collected from PhishTank targeting 14 websites and an “other” class collected from the Alexa top 300 websites2 representing legitimate examples outside the whitelist. However, this dataset has a limited number of whitelisted websites, and the screenshots of the whitelisted websites were taken only from phishing reports which skewed the dataset towards poorly designed phishing pages.

3.2 WhitePhish Dataset

Based on the previously mentioned limitations, we collected the WhitePhish dataset for similarity-based detection to whitelisted websites aiming to cover the following gaps: 1) we extended the number of whitelisted websites to cover more targets, and consequently, detect more phishing attacks. 2) we collected a phishing webpage corpus with removing duplicity in screenshots. 3) instead of only training on phishing pages, we also collected legitimate pages of the targeted websites with different page designs and views. 4) we collected a legitimate test set of websites outside the whitelist that limits bias as far as possible (e.g. login forms should also be well represented in this test set).

\footnotetext[1]{https://www.phishtank.com/}
\footnotetext[2]{https://www.alexa.com}

![Figure 2: A histogram of the 23 most frequent websites that were found in the unique phishing set.](image)

**Phishing Webpages.** To collect the phishing examples, we crawled and saved the screenshots of the active verified phishing pages from PhishTank which yielded 10250 pages. We observed that the same phishing screenshot design could be found with multiple URLs, therefore, we manually inspected the saved screenshots to remove duplicates in addition to removing not found and broken URLs. Having an uncorrelated phishing set is important to have an accurate error estimate and not to have duplicates in training and test splits. After filtering, the phishing set contained 1195 phishing pages targeting 155 websites. However, we observed that the majority of these phishing pages belonged to a small subset of these 155 websites, as we show in Figure 2. Also, the most frequent websites belonged to categories such as social media platforms, Software as a Service (SaaS) websites, and banking websites, which is consistent with the APWG reported statistics [2] and previous studies [9].

**Legitimate Training Webpages.** Besides collecting phishing webpages, we collected legitimate pages from those 155 targeted websites. Using the same web crawler, we crawled all internal links that were parsed from the HTML file of the homepage and saved the corresponding screenshots. We saved all webpages from the website to get different page designs, possible login forms, and different languages to make the similarity model trained with this dataset robust against these differences. For the 155 websites in the whitelist, we collected 9363 screenshots, where the number of collected screenshots for each website depends on the number of hyperlinks found in the homepage.

**Legitimate Test Webpages.** In addition to these targets that were collected from the phishing pages from PhishTank, we also queried the top 500 ranked websites from Alexa, the top 100 websites from SimilarWeb3, in addition to the

\footnotetext[3]{https://www.similarweb.com/}
top 100 websites in categories most prone to phishing such as banking, finance, and governmental services. In total, we collected a list of 400 websites from SimilarWeb. From these lists, we downloaded the screenshots of a set of 57 unique websites from SimilarWeb (1612 screenshots) and 59 unique and different websites from Alexa (844 screenshots). These two sets are not overlapping with the whitelist we built from PhishTank.

We utilized these sets of websites in two ways, first, we added a subset of them to the training whitelist as we illustrate later in our experimental results. Second, we used them to build the legitimate test set of websites that the model should identify as dissimilar to the whitelist.

To collect our test set, we selected a total of 683 screenshots from Alexa and SimilarWeb websites. Unlike the legitimate whitelist training where we wanted to train on all variations of a website to have robustness against different potential phishing designs, we here wanted to collect an uncorrelated set to have an accurate error estimate. Also, we wanted the benign examples to simulate a general user’s browsing session spanning many websites with different categories not only multiple webpages from the same website, therefore, we selected 3-7 non-redundant screenshots from each website to form our legitimate test set.

In order not to have a biased dataset that might give optimistic results only because the legitimate and phishing test sets have different designs, our legitimate test set should contain an adequate number of forms, and have a similar distribution of categories as phishing pages’ ones (e.g. banks or payment). With a well-balanced test set, we can accurately evaluate the similarity model performance and whether it can find the website identity instead of relying on other unrelated features such as the page layout (e.g. having forms). Therefore, we inspected the categories in the legitimate test set in a qualitative analysis which we show in Figure 3. As can be observed, we found that nearly 41% of the screenshots contain forms; we believe that these are the most challenging pages to be classified as different from the phishing pages since the latter usually contain forms. We also found that categories most prone to phishing are well represented in the legitimate set which makes our test set unbiased. Finally, the test set has high coverage of possible categories a user might face in browsing.

**Whitelist Analysis.** In addition to the whitelist we built from PhishTank, we also examined alternative sources for building whitelists without needing to crawl phishing data. This could help in taking proactive steps to protect websites that might be attacked in the future if the adversary decided to avoid detection by targeting other websites than the ones which have been already known to be vulnerable. In order for the attacks to succeed, attackers have an incentive to target websites that are trusted and known for a large percentage of users, therefore, top-ranked websites have a high potential to be useful in building alternative whitelists.

Based on that, we built our analysis on the top 500 websites from Alexa, and the top 400 websites from SimilarWeb in categories most prone to phishing. To evaluate whether or not these lists can represent the targets that might be susceptible to attacks, we found the intersection between those lists and the PhishTank whitelist. To visualize our analysis, Figure 4 shows cumulative percentages of phishing instances whose targets are included in ascending percentiles of the Alexa, SimilarWeb, and the concatenation of both lists. We found that including both lists covered around 88% of the phishing instances we collected from PhishTank, which indicates that the top-ranked websites are relevant for constructing whitelists. We also observed that the SimilarWeb list covered more instances than the Alexa list, we accounted that for the

![Figure 3: A histogram of the categories in the legitimate test set.](http://example.com/figure3)

![Figure 4: Percentage of phishing instances whose targets are covered by ascending percentiles of Alexa, SimilarWeb and by the concatenation of both lists.](http://example.com/figure4)
fact that the former was built from categories such as banks, SaaS and payment, in addition to the general top websites. We, therefore, conclude that this categorization approach is more effective in forming potential whitelists since important categories are less likely to change in future phishing attacks.

4 Method

As we presented in Figure 1, similarity-based phishing detection is based on whether there is a high visual similarity between a visited webpage to any of the whitelisted websites, while having a different domain. If the visited page was found to be not similar enough to the whitelist, it would be classified as a legitimate page with a genuine identity. Therefore, our objective can be considered as a similarity learning problem rather than a multi-class classification between whitelist’s websites and an “other” class. Including a subset of “other” websites in training with a multi-class classification method could cause the model to fail at test time when testing with new websites. Motivated by these reasons and adapting to the harder problem of the whitelist size in the dataset, we treated the problem as a similarity learning problem with deep learning using Siamese or triplet networks which have been successfully used in applications such as face verification [35], signature verification [10], and character recognition [18]. In each of these applications, the identity of an image is compared against a database and the model verifies if this identity is matched with any of those in the database. They have been also used in the tasks of few-shots learning or one-shot learning [18] by learning a good representation that encapsulates the identity with few learning examples. These reasons make this deep learning paradigm suitable for similarity-based phishing detection.

Our network, WhiteNet, adopts the triplet network paradigm with three shared convolutional networks. We show an overview of the training of WhiteNet in Figure 5 which consists of two stages: in the first stage, training is performed on all database screenshots with a random sampling of examples. The second training stage fine-tunes the model weights by iteratively training on hard examples that were wrongly classified by the model last checkpoint according to the distance between the learned embeddings. By learning these deep embeddings, we build a profile for each website that encapsulates its identity, which would enable us to detect zero-day webpages that are not necessarily contained in the whitelist database. The rest of this section illustrates in more detail each aspect of the WhiteNet model.

4.1 Triplet Networks

The Siamese networks are two networks with shared weights trained with the goal of learning a feature representation of the input such that similar images have higher proximity in the new feature space than different images. The sub-networks shares weights and parameters and the weight updates are mirrored for each of them, the sub-networks are then joined with a loss function that minimizes the distance of similar objects’ embeddings while maximizing the distance of dissimilar objects’ ones [10].

The triplet network, which we used in WhiteNet, extends this approach; it was initially used in the FaceNet system [33] to learn an embedding for the face verification task. This type of architectures performs the training on three images, an anchor image, a positive image whose identity is the same as the anchor, and a negative image with a different identity than the anchor. The overall objective of the network is to learn a feature space in which the distance between the positive and anchor images’ embeddings is smaller than the distance between the anchor and negative images’ ones. This is achieved by minimizing the loss function that is

![Figure 5: An overview of WhiteNet. Our model utilizes triplet networks with convolutional sub-networks to simultaneously learn visual similarity between screenshots from the same website (denoted by same shaped symbols), and dissimilarity between screenshots belonging to different websites. Our network has two training stages; first, training is performed with uniform random sampling from all screenshots. Second, training is performed by iteratively finding hard examples according to the model’s latest checkpoint.](image-url)
With the latest model checkpoint, we compute the L2 distance, and any screenshot from the same website have the same probability of selection. Therefore, mining of triplets instead of forming all combinations. However, this paradigm would not scale well with the number of websites in the whitelist, and therefore it is not tractable in our case as a single training example would have 155 pairs (whitelist websites). The used paradigm, on the other hand, finds the most violating examples across all training data each defined number of iterations and then continues the regular triplet training on them, which does not suffer from these computational complexities.

4.2 Triplet Sampling

Since there are a large number of possible combinations of triplets, the training is usually done based on sampling or mining of triplets instead of forming all combinations. However, random sampling could produce a large number of triplets that easily satisfy the condition due to having zero or small loss which would not contribute to training. Therefore, mining of hard examples was previously used in FaceNet to speed-up convergence [33].

Therefore, as we show in Figure 5, our training process has two training stages. In the first stage, we used a random sampling of triplets to cover all combinations. In this stage, each website has the same probability of being selected in either the anchor image or the negative image to uniformly cover all websites. Also, all screenshots belonging to one website have the same probability of selection.

After training the network with random sampling, we then fine-tuned the model by iteratively finding the hard examples to form a new training subset. We first randomly sample a query set representing one screenshot from each website, then with the latest model checkpoint, we compute the L2 distance between embeddings of the query set and all the rest of training screenshots. In this feature space, the distance between a query image and any screenshot from the same website should ideally be closer than the distance from the same query image to any image from different websites. Based on this, we can find the examples that have the largest error in distance. Hence, we retrieve the one example from the same website that had the largest distance to the query (hard positive example), and the one example from a different website that had the smallest distance to the query (hard negative example). We then form a new training subset by taking the hard examples along with the sampled query set altogether, and we continue the training process with triplet sampling on this new subset.

For the same query set, we repeat the process of finding a new subset of hard examples for a defined number of iterations for further fine-tuning. Finally, we repeat the overall process by sampling a new query set and selecting the training subsets for this new query set accordingly. Sampling different query sets is motivated by avoiding overtraining to a fixed query set which might have outliers or might not be the strongest representation of each website.

This hard example mining framework can be considered as an approximation to a training scheme where a query image is paired with screenshots from all websites and a Softmin function is then applied on top of the pairwise distances with a supervised label indicating that the distance between the query and the same website’s screenshot has a label 0 (denoting minimum distance). However, this paradigm would not scale well with the number of websites in the whitelist, and therefore it is not tractable in our case as a single training example would have 155 pairs (whitelist websites). The used paradigm, on the other hand, finds the most violating examples across all training data each defined number of iterations and then continues the regular triplet training on them, which does not suffer from these computational complexities.

4.3 Prediction

At test time, the closest screenshot in distance to a phishing test page targeting a website should ideally be a screenshot of the same website. Therefore, the decision is not done based on all triplets comparison but it can be done by finding the screenshot with the minimum distance to the query image. To this end, we use the shared network to compute the embeddings then we compute the L2 distance between the embeddings of the test screenshot and all training screenshots. After computing the pairwise distances, the test screenshot is assigned to the website of the screenshot that has the minimum distance. This step could identify the website targeted if the test page is a phishing page.

As depicted in Figure 1, if the minimum distance between a page and the whitelist is smaller than a defined threshold, the page would be classified as a phishing page that tries to impersonate one of the whitelisted websites by having a high visual similarity. On the other hand, if the distance is not small enough, the page would be classified as a legitimate page with a genuine identity that is not similar to any of the whitelisted websites.
websites. Therefore, after computing the minimum distance, we apply a threshold for classification.

Our system does not require storing all screenshots of the whitelist, as it suffices to store the embedding vectors of screenshots (512-dimensional vectors). In addition, the system is computationally feasible since the training whitelisted embeddings can be pre-computed, which only leaves at test time the relatively smaller computations of the query image embedding and the L2 distances.

5 Experimental Results

In this section, we present our main experiments along with their results. First, we show the implementation details of WhiteNet and its performance as our finally used model, then we present the results of an ablation study and further experiments.

5.1 WhiteNet: Final Model

Evaluation Metrics. Since our method is based on the visual similarity of a phishing page to websites in the whitelist, we computed the percentage of correct matches between a phishing page and its targeted website. However, this is only an intermediate task since the end task is to identify phishing from legitimate webpages. Hence, we also calculated the overall accuracy of the binary classification between legitimate test pages and phishing pages at different distance thresholds to calculate the Receiver Operating Characteristic (ROC) curve area.

Implementation Details. To train the network, we used Adam optimizer [17] with momentum values of $\beta_1 = 0.9$, $\beta_2 = 0.999$ and a learning rate of 0.00002 with a decay of 1% every 300 mini-batches where we used a batch size of 32 triplets. We set the margin ($\alpha$) in the triplet loss to 2.2. The first stage of triplet sampling had 21,000 mini-batches, followed by hard examples fine-tuning, which had 18,000 mini-batches divided as follows: we sampled 75 random query sets, for each, we find a training subset which will be used for 30 minibatches, then we repeat this step 8 times. We used 40% of the phishing examples in training and used the rest of the 60% for the test set. We used the same training/test split in the two phases of training. We tested the model with the legitimate set consisting of 683 screenshots that we collected; this set were only used in testing and were not included in training the model. We used Keras with TensorFlow backend for our implementation and all the following experiments.

Performance. Using WhiteNet, 81% of the phishing test pages were matched to their correct website using the top-1 closest screenshot. After computing the correct matches, we computed the false positives and true positives at different thresholds (where the positive class is phishing) which yielded a ROC curve area of 0.9879 outperforming all the other examined models and re-implemented state-of-the-art approaches which we show in the following sections.

5.2 Ablation Study

Given the results of WhiteNet, this sub-section investigates the effects of different parameters in the model, we summarize our experiments in Table 1 which shows the top-1 match and the ROC area for each model in comparison with WhiteNet. We also show the corresponding ROC curve for each model in Figure 6.

We first evaluated the triplet network by experimenting with Siamese network as an alternative. We used a similar architecture to the one used in [18] with two convolutional networks and a supervised label of 1 if the two sampled screenshots are from the same website, and 0 otherwise. The network was then trained with binary cross-entropy loss. We also examined both L1 and L2 as the distance function used in the triplet loss.

| Sub-network | Added layer | Last layer | Network type | Distance | Sampling | %Phishing | Top-1 Match | ROC Area |
|-------------|-------------|------------|--------------|----------|----------|-----------|-------------|----------|
| VGG16       | Core 3x3(512) | GAP        | Siamese      | L2       | 2 stages | 40%       | 91.03%      | 0.9879   |
|             |             |            |              |          |          |           |             |          |
| Siamese     | FC (1024)   | GAP        | Siamese      | L1       |          |           | 75.31%      | 0.8871   |
|             |             |            |              |          |          |           | 64.8%       | 0.655    |
|             |             | GAP        | Siamese      | L1       |          |           | 73.91%      | 0.9739   |
|             |             | Flattening | Siamese      | L1       |          |           | 66.61%      | 0.6449   |
|             |             | FC (1024)  | Siamese      | L1       |          |           | 78.94%      | 0.8517   |
|             |             |            |              |          |          |           | 80.05%      | 0.8721   |
| ResNet      | Conv 3x3(512) | GAP        | Siamese      | L1       |          |           | 80.19%      | 0.9174   |
|             |             |            |              |          |          |           | 79.91%      | 0.8703   |
|             |             | Flattening | Siamese      | L1       |          |           | 78.52%      | 0.8526   |
|             |             |            |              |          |          |           | 75.3%       | 0.9477   |
|             |             |            |              |          | Random   |           | 74.37%      | 0.9899   |

Table 1: A summary of the ablation study. Row 1 is the finally used model, cells indicated by **"*"** denotes the same cell value of row 1 (WhiteNet).

Figure 6: ROC curves for the experiments in Table 1. The legend follows the same order of rows in Table 1.
Besides, we inspected different architecture parameters regarding the shared sub-network including the added convolution layer, and the final layer that is used as the embedding vector where we experimented with Global Average Pooling (GAP) [22], fully connected layer, and taking all spatial locations by flattening the final feature map. In addition to VGG16, we evaluated ResNet50 as well. We also studied the effect of the second training phase of hard examples mining by comparing it to a model that was only trained by random sampling.

As can be seen from Table 1 and Figure 6, the triplet network outperformed the Siamese network with an increase of 5.72% in matching accuracy and 10 in ROC area. Also, the second training phase of hard examples increased both the top-1 match and the ROC area with 5.73% and 4 respectively, which indicates the importance of this step to reach convergence as previously reported in [33]. We also show that the used parameters in WhiteNet outperform the other studied parameters.

Motivated by the observation that some phishing pages had bad quality designs and were different from their corresponding legitimate websites, we studied the robustness of WhiteNet to the ratio of phishing examples seen in training. We, therefore, reduced the training phishing set to only 20% and tested with the other 80%. Although the top-1 match decreased, the ROC area of the binary classification was similar to the model trained with 40%, which suggests the model ability to generalize to potential future phishing pages without overfitting to specific designs.

### 5.3 Robustness with Whitelist Expansion

In addition to the PhishTank whitelist gathered from phishing reports, we studied other sources of whitelists as per the analysis presented earlier in our dataset collection procedure. We then studied the robustness of WhiteNet’s performance when adding new websites to the training whitelist. To that end, we categorized the training websites to three lists (as shown in Figure 7), the PhishTank whitelist, a subset containing 32 websites from SimilarWeb top 400 list (418 screenshots), a subset containing 38 websites (576 screenshots) from Alexa top 500 list. Since we have phishing pages for the websites in the PhishTank whitelist only, the other two lists can be used in training as distractors to the classification performance of the phishing and legitimate examples. When training on one of these additional lists, its websites will not be used in the legitimate test set which will be formed from the rest of the websites yielding test sets of 562 and 573 screenshots in the case of adding SimilarWeb and Alexa lists respectively.

As shown in Table 2, when adding new websites to the training whitelist, the performance of the classification (indicated by the ROC area and the top-1 match) decreased. However, this decrease in performance was relatively slight. Interestingly, in case of training with Alexa list and testing mainly with SimilarWeb list, we can think of the performance as a pessimistic case scenario, since SimilarWeb set was collected to have similar categories and forms as the phishing set, and therefore, detecting dissimilarity could be harder.

### 5.4 Comparison with Prior Work

Furthermore, we compared WhiteNet to alternative approaches we re-implemented on the WhitePhish dataset. As we discussed in WhitePhish collection procedure, the collected whitelist training websites pages do not necessarily contain the same designs and layout of the phishing pages targeting the same websites. This makes methods based on layout similarity and segmentation not suitable for our prob-

| Method   | Top-1 Match | ROC Area |
|----------|-------------|----------|
| SIFT     | 6.55%       | 0.488    |
| HOG      | 27.61%      | 0.58     |
| ORB      | 24.9%       | 0.6922   |
| VGG16    | 51.32%      | 0.8134   |
| **WhiteNet** | **81.03%** | **0.9879** |

Table 3: A summary of our experiments comparing WhiteNet with alternative approaches.
lem. Therefore, we compared WhiteNet to image matching with feature descriptors (SIFT, HOG, and ORB) that have been previously used in phishing detection literature. Since deep learning methods have not been used in previous visual similarity detection studies, we compared WhiteNet to a baseline of using the features of VGG16 network pre-trained on ImageNet. A summary of our experiments with these alternative approaches is demonstrated in Table 3. In all of these experiments, similar to WhiteNet training, 40% of the phishing set was included in the training, and the prediction was performed based on the minimum distance to the training set. As shown in Table 3, the use of VGG16 outperformed the other features, however, WhiteNet achieves the higher ROC curve area and top-1 correct match with a significant performance gain.

5.5 Embeddings Visualization

WhiteNet produces a feature vector (dimensions: 512) for each screenshot that represents an encoding that resulted from minimizing the triplet loss. In this learned feature space, screenshots belonging to the same website should be in close proximity compared to screenshots belonging to different websites. To verify this, we used t-Distributed Stochastic Neighbor Embedding (t-SNE) [24] to reduce the dimensions of the embeddings vectors to a two-dimensional set. We show the visualization results in Figure 8 in which we compare the embeddings of WhiteNet to a baseline of pre-trained VGG16 ones. We first visualized the embeddings of the training whitelist webpages categorized by websites as demonstrated in Figure 8a and Figure 8c for WhiteNet and VGG16 respectively. As can be observed from the figure, the learned embeddings show higher inter-class separation between websites in the case of WhiteNet when compared to VGG16.

More importantly, Figure 8b and Figure 8d show the training whitelist pages in comparison with phishing and legitimate test for WhiteNet and VGG16 respectively. For successful phishing detection, phishing pages should have smaller distances to whitelist pages than legitimate test pages, which is clearly more satisfied in WhiteNet than VGG16. Not only does this experiment demonstrate the efficacy of WhiteNet, but it shows that using a pre-trained baseline is not adequate for the problem and further optimization, as done in WhiteNet, is needed.

Furthermore, Figure 9 demonstrates the applicability of using a distance threshold to perform the binary classification between phishing and legitimate test. In this figure, we show a histogram of the minimum distance values between the

![Figure 8: t-SNE visualizations of WhiteNet embeddings (first row) compared to VGG16 ones as a baseline (second row). Figures (a) and (c) show whitelist webpages color-coded by websites. Figures (b) and (d) show whitelist webpages (blue) and their phishing pages (red and orange) in comparison with legitimate test pages outside the whitelist (green).](image-url)
WhiteNet embeddings of test pages (legitimate and phishing) and the training set. As can be observed, phishing pages are generally closer to the training whitelist and high recall of phishing pages could be achieved at a relatively low false positives rate (e.g. true positive rate is 95.81% at a false positive rate of 6.88%).

6 Discussion

We discuss the implications of the efficacy of WhiteNet by showcasing examples of phishing pages that were correctly detected, and failure modes with both false positive and false negatives examples. We also discuss further improvements and future directions to overcome the current limitations.

6.1 Evaluating Successful Cases

We categorize the successfully classified phishing pages into three main categories. The first one is the easily classified ones consisting of exact or very close copying of a corresponding legitimate webpage that is contained in the training whitelist. However, our model still showed robustness to small variations such as the addition or removal of elements in the page or the text language of login forms which shows an advantage over text-similarity methods. The second category, which is relatively harder than the first one, is the phishing webpages that look similar in style (e.g. location of elements and layout of the page) to training pages, however, they are different in content (e.g. images and colors). We show examples of this second category in Table 4. Finally, the hardest category is the phishing pages showing disparities in design when compared to the training examples as shown in Table 5. For example, the company logo in the first phishing page has a different location, as well as having a different overall design when compared to the matched legitimate page. Also, the second phishing page has a pop-up window that partially occludes information and changes the page’s colors. The third phishing page is challenging as it does not show the company logo, yet it was correctly matched to the targeted website due to having other similar features. This suggests that WhiteNet captures the look and feel of websites, which makes it have an advantage over previous methods that relied only on logo matching such as [1, 11]. The last two pages are highly dissimilar to the legitimate page except having the same logo. Even though these examples could arguably be easily recognized as phishing pages by users, they are more challenging to be detected based on similarity and therefore they were excluded in previous studies such as [27]. However, in our study, we included all found phishing examples as the human decision could be subject to different factors [25]. This analysis shows the ability of WhiteNet to detect the similarity of phishing pages that are partially copied or created with poor quality in addition to phishing pages with no corresponding similar pages in the training whitelist which simulate possible attempts to evade detection.

Another direction for evasion attacks is crafting adversarial perturbations with imperceptible noise that would change the model decision when added to the input test points [19]. There is a lot of work towards fixing the evasion problem [3] which is beyond the scope of this paper, however, adversarial perturbations are well-known for classification models. In contrast, WhiteNet is based on a metric learning approach that, at test time, is used to compute distances to the training points, and we are not aware of existing techniques that would attack such setup.

6.2 Evaluating Failure Modes

We also inspected and analysed the failure modes of the model. We first present our results regarding targeted website matching. To this end, we computed a histogram of the wrong
matches per website for the top 19 websites with the largest numbers of phishing pages as we show in Figure 10 where the highest mismatches are for phishing examples belonging to Facebook, Dropbox, Microsoft one drive, Microsoft Office, and Adobe. We found that these websites have many phishing pages that have little similarity to the targeted legitimate websites, such as the first two phishing pages targeting Facebook and Microsoft Excel in Table 6. We also found a number of phishing pages that used outdated designs or earlier versions of certain login forms such as the third example in Table 6 and were, therefore, matched to a wrong website. On the other hand, phishing pages targeting banks had higher quality in copying and appeared similar to the targeted websites making them have fewer mismatch rate. Moreover, the last three examples in Table 6 show some of the main limitations. Since our whitelist contains a large number of screenshots per website, we have many distractors of potentially similar pages to each query screenshot, such as the fourth and fifth examples in Table 6 that were matched to similar screenshots from different websites. We also found that some phishing pages have pop-up windows that completely covered the logo and the page’s colors and structure, and were then matched to pages with darker colors such as the last examples in Table 6.

However, since phishing and legitimate pages were classified based on a threshold on the minimum distance to the whitelist, some of these wrong matches could still be classified as phishing examples if they have distances that were less than than the considered threshold. As we previously showed in the embeddings visualizations in Figure 8b and the distances in Figure 9, phishing pages were generally mapped to closer locations in the learned manifold to the training whitelist when compared to legitimate test pages. Therefore, we quantify the final classification performance using the ROC area (shown in Table 1 and Figure 6) instead of the correct match rate only.

We also show some examples of legitimate test pages that had high similarity to pages from the training set in Table 7 and could be falsely classified as phishing pages based on the set threshold (e.g. at a false positive rate of 6.88%). We observed that pages with forms were harder to identify as dissimilar to other pages with forms in the whitelist since they contain few distinguishable and salient elements and they are otherwise similar. However, since forms constitute around 40% of the legitimate test set (Figure 3), the high classification performance of WhiteNet indicates the ability of the model to correctly classify these form pages.

### 6.3 Future Directions

Our work sheds light on unexplored research areas in visual similarity phishing detection and takes the next steps towards expanding the protected websites and detecting zero-day phishing pages. In addition, we here provide insights that we believe are important for future research directions.

**Covered Whitelist.** We believe that future efforts should focus on improving the current framework by further expand-
ing the whitelist; instead of mainly training on the whitelist collected from previously reported phishing pages, we plan to expand the whitelist by training on the full top websites list retrieved from websites ranking lists (e.g. top 500 websites from Alexa or SimilarWeb ranking websites). This aims to cover future phishing attacks against websites that were not previously targeted, in addition to not relying on previous phishing pages. Instead of only using websites that do not have previous phishing pages as distractors to our classification of phishing and legitimate sets, we also plan to create proxy phishing pages to be used as a test set for these websites to evaluate the model’s performance. This proxy set could contain legitimate pages that are most likely to be copied in potential phishing attacks, such as login forms.

**Simulating Complex Spoofing.** Similar to a previous study on the simpler task of mobile application spoofing [25], another direction is to craft phishing pages that simulate complex spoofing attempts with perturbed pages that make modifications to the webpage (e.g. colors, small changes in logos, omission or occlusions of logos, elements rearrangement, and advertisement banners). This could be followed by a study of failure modes and possible optimizations to detect such attempts in order to make the model less prone to be tricked or evaded. These examples could then be included in training to provide robustness against these possible attempts.

**Deployment.** In addition, we plan to study the feasibility of training on a smaller dataset that contains fewer screenshots per website. This aims at developing a framework that can easily and automatically be expanded and fine-tuned as a browser plug-in with an updatable whitelist. To take further steps to deploy our method as a real-time browser plug-in, we plan to effectively compute the distance/similarity threshold needed to issue alarms by taking into consideration the prior probabilities and weights of both phishing and legitimate classes.

**Beyond Screenshots Comparison.** Finally, we plan to further optimize our network to make it more suitable for the logo detection task, for example, by using region-based convolution, or by including text information possibly extracted by Optical Character Recognition (OCR) tools as a second modality input to the network. We believe that including text information could reduce the false positives of legitimate pages that are visually very close to the whitelist (as in Table 7), in addition to detecting perturbed phishing pages crafted with bad quality or relatively low visual similarity to the whitelist.

### 7 Conclusion

In this work, we presented a new framework for phishing detection using visual similarity. As previous works have only considered a small number of websites and a few protected pages per website, these approaches fall short in detecting zero-day phishing pages. To address these limitations, we collected the new WhitePhish dataset that spans a whitelist of 155 websites and includes both phishing and legitimate pages for each website as well as a legitimate test set for benign pages outside the whitelist. Besides, we performed an analysis of different whitelist sources that provides valuable insights.
To detect zero-day phishing pages, the developed model should be able to identify visual similarity with any two web-pages belonging to the same website despite having different designs or layouts. To that end, we proposed WhiteNet which to the best of our knowledge is the first approach to use triplet neural networks to learn distinctive profiles of websites. We performed a qualitative analysis of the successful cases of WhiteNet and we found that our network identified easy phishing pages (with similar designs to their corresponding legitimate ones), and phishing pages that were partially copied, obfuscated, or different in layout and content from the training ones, which makes our model less prone to the fierce arms race between attackers and detection methods.

In conclusion, our work introduces important contributions to phishing detection research to learn a robust visual similarity metric that demonstrates a leap in performance over the state-of-the-art and outperforms prior work with an increase of 56% in matching accuracy and 30 in the ROC area under the curve in phishing website detection. This work paves the way for phishing detection frameworks with further extension of the covered whitelist and real-time deployment and maintenance. In addition, it enables further proactive enhancements to preempt possible evasion attacks.

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