Abstract

Insider threats are costly, hard to detect, and unfortunately rising in occurrence. Seeking to improve detection of such threats, we develop novel techniques to enable us to extract powerful features, generate high quality image encodings, and augment attack vectors for greater classification power. Combined, they form Computer Vision User and Entity Behavior Analytics, a detection system designed from the ground up to improve upon advancements in academia and mitigate the issues that prevent the usage of advanced models in industry. The proposed system beats state-of-art methods used in academia and as well as in industry.

Contributions: Our contributions are as follows:

• We define File Path Variance, a metric that measures the degree a user searches an organization files.
• We utilize Natural Language Processing techniques to extract novel features from email and website access data such as indications of a disgruntled employee.
• We represent behavior indicators as novel image representations designed such that color is an indicator of malicious behavior, allowing identification of behavioral changes at a glance.
• We propose a novel context changing data augmentation that addresses data imbalance issues while preserving the unique composition of image encodings.
• We use a dual input classifier architecture, feeding in non-dynamic information to reduce the number of false positive behavior classifications.

Together, these allow CVUEBA to outperform state-of-the-art insider threat models found in both industry as well as academia on a gold standard benchmarking dataset.

1. Introduction

As we move further into an ever more digital age, newer and more complex attack vectors are appearing everyday. Insiders pose a unique threat to corporations and organizations of all scales due to their access to proprietary systems and their ability to circumvent security protocols and blind spots the public is not privy to. Close to 30% of confirmed breaches today involve insiders [93]. In total, over 2,560 internal security breaches occur in United States businesses every day [87] with a year-over-year increase in insider attack rates of 21.4% [82]. Each such attack costs an organization on average 11.45 million USD annually [36].

Unfortunately, these attacks are extremely difficult to detect from within. Third party entities detect the vast majority of most data breaches that occur within an organization; famous examples include the breaches in TJX Companies, VeriSign, Adobe and LinkedIn [21,55,69,100]. These failures can be attributed to the simplicity of insider threat detection systems used in industry today. While solutions proposed by academia boast higher predictive power, interpretability concerns prevent their usage as industry models.

It is crucial to accurately detect insider attacks before they incur and address the issues plaguing solutions from academia. To this end, we develop Computer Vision User and Entity Behavior Analytics (CVUEBA). CVUEBA is an insider threat detection system designed from the ground up to take advantage of Computer Vision techniques.

2. Related Works

Academia: Researchers have worked on a plethora of solutions for insider threat detection, the vast majority of which utilize machine learning [95].

The most popular approach is framing insider threat detection as an anomaly detection problem [7]. Chandola et al. [13] provide a detailed overview of the state of anomaly detection. Machine learning methods have been shown to effectively handle the anomaly detection problem; there is a plethora of research that has been published regarding this avenue [4,14,23,32,45,47,49,57,60,76,98,101].

Despite academia on the topic of insider detection dating as far back as 1987 with Denning’s anomaly detection regime [18], very little has reached the industry. There are numerous reasons for this discrepancy. For example, Gates et al. illustrate that academia has relied on the assumption
that attacks are easily separable from benign data [22], however work from Tan et al. has identified that insiders try to identify blind spots in detection regimes and utilize those to perform malicious activities [85]. Rieck et al. [68] cites reasons why current research in academia is not well-aligned with industry requirements such as the high cost of false positives, the semantic gap between results and their operational interpretation, and difficulty in performing sound evaluation. These requirements are sometimes in direct opposition to assumptions made in academia; for example, academic insider threat systems frequently seek to improve recall and the cost of precision [99].

**Industry:** Thus, while numerous User and Entity Behavior Analytics systems (UEBA), systems built in the security industry to detect insider threats, have been created, most rely on their own datasets and experience rather than using discoveries found in academia.

Examples of companies providing industry implementations include Niara, which utilizes Mahalanobis distance outlier detection [77], Fortinet, which uses Naive Bayes to categorize activity by an anomaly score [27], Exabeam who uses a second order Factorization Machine to improve first-time access malicious activity reporting [86], and Aruba Networks who proposes models using Support Vector Machines, and Logistic Regression [52].

Unfortunately, while there are numerous UEBA systems to be found in industry, most are rudimentary in nature. Bussa et al. in Gartner’s market analysis report for UEBA states that most vendors still rely at least partially on rule based implementations and require upwards of half a year worth of tuning in order to achieve effectiveness [10].

Very few industry deployments of insider threat detection systems leverage neural networks [77,83]. While neural networks are widely considered to be the pinnacle of machine learning, such models have poor interpretability due to mapping extremely complex functions to with an equally complex structure. This has become especially concerning for insider threat detection as it is critical to understand the reason why the model makes such predictions since employees are usually the most valuable asset in an organization [99]. The black box nature of neural networks has led to a lot of skepticism among security practitioners regarding UEBA systems due to poor interpretability regarding how models work [22,64,68].

**Shift to Computer Vision:** Recently, there has been a strong shift in the cybersecurity industry however. Increasing numbers of systems and implementations for a wide range of cybersecurity applications are incorporating Computer Vision techniques in order to bolster performance and precision in detecting threats as they have been shown to surpass the performance of alternative methodologies [33,39,67,90]. Computer Vision implementations have become so prevalent in cybersecurity that Zhao et al. highlighted its ubiquity in malware detection, phishing detection, and network anomaly detection [102].

Computer Vision’s application to insider threat detection however is currently nascent; to our knowledge, Gayathri et al.’s Image Feature Representation model is the only implementation of such a system [24]. They extract features from usage patterns of insiders and represent these features as images, each image being a representative snapshot of the behavior and actions of a user for a given day. They utilize transfer learning in order to reduce model complexity, a technique that allows models to retain their performance on incoming data with new distributions by learning a new feature space [62]. Harnessing the power of ResNet-50 [33], VGG-19 [80], and MobileNetV2 [73] they outperform other state-of-the-art methods [23,26,47,49,57,60,98,101].

There is room for improvement however. Their approach is unable to identify the warning signs of an insider threat attack, such as a user navigating to job or keylogger websites. It would be far more beneficial to identify the warning signs of an attack so one can mitigate potential security and safety risks as CVUEBA is designed to do. More importantly, their image encodings have poor user interpretability, leading to an expert being unable to predict how a model will classify a given encoding.

### 3. Behavior Encodings

Insider threat systems rely on a large variety of data sources from many different resources including login data, LDAP information, website and file access, external drive data, and email activity. Thus, it is crucial to obtain feature representations of a user’s behavior in order to appropriately utilize vital information. While we glean insights from previous work in order to define our representations [14,24,41], we also propose novel features which we detail in the following two sections.

#### 3.1. Quantifying File Access Risk Exposure

**Tree Representation:** A given user accesses files within certain locations for the vast majority of their work, typically on their work computers, shared access computers, or perhaps on their colleagues computers from time to time.

If a user ventures away from such access behavior, for example rapidly expanding the number of computers they access files on or venturing into directories on shared computers irrelevant to their work or previous interest, such behavior should be flagged for a human expert to delve into and perform risk assessment on. Such behavior is indicative of an employee attempting to search for sensitive, compromising, or confidential information [9,12,30,54,92].

We represent all the files within an organization on a given day via a tree structure, with leaves representing different files, and branches representing different computers,
Internal node in the organization's file tree.
We can now transform the extracted behavior information into image representations. Unlike in Gayathri’s implementation that uses interpolation [28] to facilitate this process, we take advantage of Sparse AutoEncoders (SAE).

The loss function for an SAE can be found in Equation 4. $D_{KL}$, defined in Equation 5, stands for the Kullback-Leibler Divergence between a Bernoulli random variable with mean $\rho$ and Bernoulli random variable with mean $\hat{\rho}_j$. $\rho$ is a sparsity hyperparameter of the model that constrains the average activation of each neuron $j$ to be as close to itself in value as possible. $\hat{\rho}_j$, defined in Equation 6, is the average activation of hidden unit $j$.

$$L_{sparse} = L + \beta \sum_j D_{KL}(\rho || \hat{\rho}_j)$$

$$D_{KL}(\rho || \hat{\rho}_j) = \rho \log \frac{\rho}{\hat{\rho}_j} + (1 - \rho) \log \frac{1-\rho}{1-\hat{\rho}_j}$$

$$\hat{\rho}_j = \frac{1}{m} \sum_i a_j(x(i))$$

SAEs in anomaly detection are typically trained on normal data only. The expectation is that the reconstruction error will be noticeably higher on anomalies than it will on normal data, as anomalies will be encoded differently and thus will be distributed away from normal data. A threshold parameter is then used to separate vectors into normal and anomalous classes [15]. We instead use the trained SAE hidden layer to automatically learn better feature representations from the given data [58].

To transform the SAE output values into a range of 0-255 suitable for images, we first apply Min-Max Scaling and proceed to multiply all values by 255. Both of these actions are done within the model’s layers itself; our testing has shown that performing the scaling in this manner improves speed, as well as storage and memory requirements for training. Our SAE has a hidden dimension of size 1024; once output encodings are scaled, they are reshaped into 32x32x1 images. Figure 2 details the full process used to convert text based log data into greyscale images.

### 3.4. Context-Channel Representations

![Figure 3. Representing Context Behavior Encodings as Channels](image)

While we could feed these greyscale images directly into a model for attack identification, it would be beneficial to have contextual information regarding the typical behavior of a user. This would enable us to identify the sudden behavioral changes indicative of an attack and mitigate the concerns brought up by Tan et al. [85]; by comparing a user’s behavior to their own previous behavior rather than performing the comparison at the activity level via a detection regime, we mitigate the potential of attackers taking advantage of detection loopholes and acting undetected.

We provide this information by passing in behavior encodings for the previous two days in addition to the current day we are evaluating. As shown in Figure 3, we append the encoding for each day as a different channel, leaving us with a color image for evaluation purposes.

If a user is not acting malicious, there is little to no variation in behavior features from a day to day basis; this leaves images representing benign behavior fairly grey in appearance. On the other hand, malicious actions will indeed have changes in observed behavior, which will lead to colorful images. As we can see in Figure 4, this allows malicious image representations to be easily identifiable and interpretable, even by an untrained human.

![Figure 4. Benign vs Malicious Images](image)

**Alternative Channel Representations:** We utilize a daily context channel representation as it allows for maximum granularity in regards to a user’s actions. However, it is imperative to take into account that such a representation will not always fit the needs and desires of an organization’s security team given the unique layout of the organization’s data. After all, evidence suggests that the perception of information technology (IT) behavior in the workplace can be widely varying. In a recent survey of 500 IT leaders and 4000 employees, significant discrepancies were observed in perceptions of insider threats [8].

To accommodate this, we can replace what information our background encodings represent. For example, if an organization wishes to track user behavior when compared to their historical trends, the first baseline channel could be represented by average feature values from the beginning of a person’s time at the organization, while the second baseline channel could be the average feature values from the past week. If instead we wish to compare a user’s behavior against a particular role, the first baseline channel could be the average values from all employees in the given role, while the second baseline channel can be the average value for the user’s teammates.
4. Context Changing Data Augmentation

![Figure 5](image.png)

Figure 5. Context Changing Data Augmentations. Top shows a channel swapping augmentation. Bottom shows a channel replacement augmentation.

**Imbalance and Insider Threats:** The most difficult issue for insider threat detection systems to overcome is the extreme inherent class imbalance; while malicious insiders can cause catastrophic damage, there are far more good-natured users than bad actors [4, 5, 24, 25, 78]. This poses problems for potential classification models, as during training models will spend most of their time on the dominant class and will fail to learn enough from the minority classes; decision boundaries either become too complex and we lose the ability to generalize to unseen data, or minority sub-concepts are ignored altogether due to not providing enough discriminative information to classifiers [20]. The data imbalance problem is the most important unsolved challenge for current insider threat detection systems [99].

**Issues with Standard Approaches:** Data augmentation is a popular technique used for a variety of different domains to help handle data imbalance issues [2, 35, 38, 71, 79]. While basic image transformations such as cropping, rotations, and color shifting are computationally efficient methods that have been shown to work in theory [79], they are not suitable for our current image representations.

As our images are created via a SAE encoding, there are regions of sparseness that exist within each of the created images at the same locations. These regions of sparseness can be identified via the spots that occur in the greyscale images seen in figures 2 and 3, as well as the final color images in figures 3 and 4. Since all evaluated data will have these spots in the same locations, augmentations such as cropping and rotations are not ideal as these will shift the locations of these spots in the augmented images, leading to our model learning representations that will not exist in true data. Similarly, our images are designed such that cross-channel differences are what enable us to define behavior as malicious; we cannot use color shifting as it will subvert the image representation and thus the predictive power of our classifier.

**Novel Solution:** We instead observe that two channels of each image consist solely of information that allows us to identify if the current day’s behavior is malicious. Thus, we are able to swap out information held in these channels and still possess a valid representation. We augment our training set by swapping the positions of the contextual channels; the channel corresponding to yesterday becomes the day before yesterday, and the channel corresponding to the day before yesterday becomes yesterday. Additionally, we also randomly select days of benign behavior for the given user and use these to replace our contextual information. Both forms of data augmentation we perform as well as examples of final results are illustrated in Figure 5.

5. Attack Classification

![Figure 6](image.png)

Figure 6. Attack Classification Architecture. We pass in the encoded image as well as non-dynamic information such as role and psychometrics, and the proposed architecture outputs a classification of the given behavior as benign or malicious.

We elect to utilize transfer learning for our task, adopting the ResNet50 architecture [33]. After training ResNet50 on the ImageNet dataset [70], we freeze the entire architecture except the last residual block, allowing for the final features extracted from the model to be tweaked during training.

While the image encoding enables us to identify malicious behavior at a glance, it is beneficial to provide additional information regarding a user, such as their role, to our classification model that could prove to be useful. Contextualizing the behavior of a user with background information can help to reduce the number of false positives a UEA system reports. For example, an employee logging into systems late at night might be considered suspicious and by itself may lead to an alert being generated, but this activity should be considered normal for a security guard that works graveyard shifts.

In addition to role information, we also incorporate psychometric information, which can give us a glimpse into a person’s psyche and determine if they are more likely to perform insider attacks. The disregard of such information is a crucial shortcoming of most insider threat detection regimes; approaches often neglect, or only make a superficial reference to, underlying psychological processes.
that might give rise to behavior that leads to insider attacks [53, 74, 99]. While most insiders do not sit with psychologists in situations where such information can be easily compiled, it is becoming more common over time for companies to require psychometric tests to be taken by potential candidates or incorporate psychometric properties into the hiring process [3, 11, 56, 61]; scoring metrics like OCEAN can easily be derived from such evaluations [65].

We concatenate these non-dynamic features with the output of the ResNet50 architecture, passing this vital information into fully connected layers before classification. Figure 6 details the model architecture utilized.

6. Experiments

Dataset: Traditional Ueba training data is composed of real-life scenarios, consisting of confidential information for a company, and the personal information of their employees. Thus, each vendor utilizes their own private datasets, making model comparisons and benchmarking difficult in nature. The CERT Insider Threat center together with ExactData LLC analyzed 1,154 actual insider incidents in the United States to create the largest public repository of insider threat scenarios in order to tackle this issue [26]. Many publications and companies have utilized this dataset to assess model architectures, perform integration testing, and run confirmatory hypothesis testing, solidifying its status as the gold standard public dataset for insider threat detection system benchmarking. [48].

The CERT Insider Threat dataset contains 32,770,224 unique events, with available audit data sources including logon activity, email traffic, web browsing traces, file access logs, thumb drive usage, as well as LDAP information describing the organization hierarchy and user roles.

Malicious users within the dataset execute activities in highly variable time periods, with some attacks completing within a day, while others occur over a 2 month span. The high diversity in attack time frames enables robust verification checks against insiders that intentionally act slowly.

While CVUEBA was initially designed and evaluated against a custom-built private dataset, for benchmarking and reporting purposes we will use version 4.2 of the CERT dataset as it is by far the most popular dataset and version combination used in insider threat publications.

Attack Scenarios: There are three scenarios of attack within the dataset. In Scenario 1, a user obtains sensitive information they subsequently upload to Wikileaks. In Scenario 2, a user browses job sites looking for a job, stealing confidential information and leaving as soon as they find one. Finally, in Scenario 3 a system administrator grows to dislike their job and downloads and installs a keylogger onto their supervisor’s computer. Using the obtained password, they send an alarming mass email acting as the supervisor, leaving the organization immediately afterwards. As occurs in the real world, this dataset is extremely imbalanced; Table 1 details the occurrence of attack scenarios compared to normal behavior within 24 hour time frames per user.

| Class Type | Number of Instances | Imbalance Ratio |
|------------|---------------------|-----------------|
| Normal     | 330452              | 1 : 1           |
| Scenario 1 | 85                  | 1 : 3899        |
| Scenario 2 | 861                 | 1 : 384         |
| Scenario 3 | 20                  | 1 : 16570       |

Data Organization: Across experiments, data was categorized into different sets at the user level within 24-hour windows via a stratified split, with 70% in the training set, 10% in the validation set, and 20% in the test set. CC was trained and tuned first using the training and validation sets, then the rest of the features were compiled afterwards. Insider threat systems typically classify behavior in a binary fashion as either malicious or benign behavior; we thus categorize all attack scenarios as malicious behavior.

6.1. Relation Between Color and Behavior

As discussed in Section 3.4, our image encodings are designed with the intent of using color to identify malicious behavior. In order to evaluate this design, we quantify the colorfulness of an image via the colourfulness metric [31]. As the category of behavior is binary, we utilize Point Biserial Correlation for evaluation [88]. We compute the colorfulness metric for our image encodings and treat this as a continuous random variable, and we treat the true behavior classification as a binary random variable. For this experiment only, we classify an encoding as malicious if any of the channels correspond to malicious behavior in the ground truth; if the user acted maliciously previously, our image encoding should appear colorful in this scenario as well. To develop the image encodings, a Sparse AutoEncoder with one hidden layer of size 1024, using SeLU activations, a batch size of 220, a $\beta$ of 0.68, and $\rho$ of 0.45 is trained on the training set with a learning rate of 0.0001 using the NAdam optimizer [89]. To prevent regions of sparsity having a negative effect on the colorfulness metric for an encoding they are replaced by the mean pixel value of the given encoding.

| Representation | Correlation |
|----------------|-------------|
| Daily          | 0.9301      |
| Historical     | 0.8884      |
| Role           | 0.8342      |

Table 2 shows the correlation results for each of the three context-channel representations detailed in Section 3.4. We obtain a strong correlation value of 0.9301 for our daily representations, indicating our behavior encoding properly represents malicious activity by color. Daily outperforming alternative representations is to be expected as this
matches the underlying behavior observed in the CERT Insider Threat dataset where an attacker may act maliciously one day and act normally the next. Given these results, we utilize the daily representation for the experiments below.

6.2. Model Evaluation

Baseline Comparison: Next, we evaluate CVUEBA performance in comparison against baseline models, comparing against VGG-19, MobileNetV2, and ResNet-50 models built in the same manner as the original paper [24], as well as the industry models detailed in Section 2.

Optimal hyperparameters for each industry model were identified by using Tree Parzen Estimation [6]. The SAE network is trained in the manner detailed in Section 4.1. Our dual input network is trained using a batch size of 128, a learning rate of 0.01, ReLU activation functions, and uses the Adam optimizer [42].

Results can be found in Table 3. We report balanced accuracy, precision, recall, and F1 score as these metrics allow for a good evaluation of models in problem spaces with high data imbalance [20].

For every computed metric, CVUEBA outperforms all baselines, with all reported metrics scoring above 98%.

| Model                        | Balanced Accuracy | Precision | Recall | F1 Score |
|------------------------------|-------------------|-----------|--------|----------|
| CVUEBA                       | 0.9923            | 0.9906    | 0.9845 | 0.9871   |
| Mahalanobis Distance         | 0.5063            | 0.0154    | 0.0155 | 0.0154   |
| Naive Bayes                  | 0.8767            | 0.1028    | 0.7732 | 0.1815   |
| Support Vector Machine       | 0.5345            | 0.0088    | 0.1031 | 0.0162   |
| VGG-19                       | 0.9741            | 0.9293    | 0.9485 | 0.9388   |
| Logistic Regression          | 0.9539            | 0.0640    | 0.7165 | 0.8152   |
| Factorization Machine        | 0.8582            | 0.9456    | 0.7165 | 0.8152   |
| ResNet-50                    | 0.9664            | 0.9141    | 0.9330 | 0.9235   |
| MobileNetV2                  | 0.9664            | 0.9141    | 0.9330 | 0.9235   |

Comparison to State of the Art: Comparisons of CVUEBA to the best performing state of the art methods evaluated on the same benchmark can be found in Table 4. Various papers use different metrics for performance evaluation, however most report accuracy; for the sake of comparison, we do the same here. As can be seen, CVUEBA outperforms alternatives by at least 3.61%.

| Method                        | Source                            | Accuracy |
|------------------------------|-----------------------------------|----------|
| CVUEBA                       | Proposed Approach                 | 0.9995   |
| Image Feature Representation  | Gayathri et al. [24]              | 0.9634   |
| Boosted Logistic Regression   | Noever et al. [60]                | 0.9600   |
| AD-DNN                       | Al-Mhiqani et al. [4]             | 0.9600   |
| Graph Convolutional Networks | Zhou et al. [103]                 | 0.9450   |
| Random Forest with Randomization | Noever et al. [60]        | 0.9400   |
| LSTM-RNN                     | Meng et al. [57]                  | 0.9385   |
| LSTM-Autoencoder             | Sharma et al. [76]                | 0.9017   |
| Random Forest                | Noever et al. [60]                | 0.9000   |
| DBN-OCSVM                    | Lin et al. [47]                   | 0.8779   |
| DBN                          | Lin et al. [47]                   | 0.8442   |

6.3. Activation Maximization

We have designed image encodings that allow for easy identification of malicious behavior and shown that the color of our encodings is strongly correlated to said behavior. We now seek to close the loop on interpretability concerns by confirming that CVUEBA classifies behavior primarily by the color of the encoding. To this end, we elect to utilize Activation Maximization [19]. Activation Maximization allows us to create visualizations for both normal behavior as well as malicious behavior, enabling us to verify that our model is identifying the features of our generated images we wish for it to focus on and ignoring noise and other features we wish for it to disregard.

Figure 7 shows the resulting images from performing Activation Maximization for the benign and the malicious class. The malicious image is filled with various colors, while the benign image is a primarily grey image. This indicates that our model correctly focuses primarily on cross channel differences within the image as we expect.

We additionally note the absence of black spots on either image despite their presence on both benign and malicious images. Additionally, both images also show a lack of distinctive texture. This indicates that our model correctly ignores the regions of sparsity and other sources of potentially specious information within the images.

6.4. Evaluation on New Attack Types

So far, CVUEBA has been trained, evaluated, and compared against baselines in scenarios where all models have seen similar attack scenarios before. As an insider threat detection system, it is imperative that a model can generalize well to identify attack scenarios without prior knowledge.

To evaluate this, we remove attack scenarios 1 and 3 from the training and validation sets. Scenario 2 was chosen to remain in the training set in order to minimize the likelihood of data imbalance acting as a confounding variable due to its relatively large size in comparison to other the other attack scenarios in the dataset. All models are trained as detailed in Section 6.2. Results are shown in Table 5.
CVUEBA performs only slightly worse when introduced to new attack vectors, unlike the baseline models, which perform much worse. This is due to CVUEBA detecting behavioral shifts rather than specific patterns of attack.

6.5. Ablation Studies

In modern machine learning, black box models are widely used due to their high performance, however in cybersecurity it is important to develop and deploy models that are easily understood. Here we ablate important design elements of CVUEBA to achieve this [66].

Architecture Evaluation: Table 6 showcases the results for ablation studies designed to evaluate various architecture decisions. Models are trained as detailed above.

| Modification          | Balanced Accuracy | Precision | Recall | F1 Score |
|-----------------------|-------------------|-----------|--------|----------|
| None                  | 0.9923            | 0.9896    | 0.9845 | 0.9871   |
| Image only            | 0.9947            | 0.8889    | 0.9897 | 0.9366   |
| Used VGG-19           | 0.9819            | 0.9590    | 0.9639 | 0.9614   |
| Used MobileNetV2      | 0.9793            | 0.9637    | 0.9588 | 0.9612   |
| Used Greyscale        | 0.9690            | 0.9733    | 0.9381 | 0.9554   |
| Interpolation         | 0.9896            | 0.9694    | 0.9794 | 0.9744   |
| DNN Architecture      | 0.9484            | 0.9305    | 0.8969 | 0.9134   |
| Non-dynamic only      | 0.5827            | 0.0263    | 0.1856 | 0.0460   |

For the image only model, we evaluate how well our image encodings by themselves perform in identifying malicious behavior by removing the concatenation layer as well as the contextual input into the model. The architecture used for this model is similar in form and function as what is used by our ResNet baseline and thus allows us to directly compare our proposed image encodings to the interpolation procedure used by the Image Feature Representation model.

For the non-dynamic feature only model, we evaluate how well features such as role and psychometrics by themselves can be used to predict an attack by removing the concatenation layer and ResNet50 layers from CVUEBA.

We next wish to evaluate whether it is necessary to frame our encodings as images and whether pretrained models like ResNets are required for evaluation. To this end, we trained a Feed-Forward Dense Neural Network architecture (DNN) with ReLU activations and 6 hidden layers of sizes 2048, 2048, 1024, 1024, 512, and 256, with Batch Normalization layers in-between each Dense layer [37], and a sigmoid output. Rather than use a ResNet architecture, our behavior encoding images are flattened and concatenated immediately with contextual information.

We use a ResNet50 architecture as part of CVUEBA. We wish to evaluate what performance differences if we used a VGG-19, or MobileNetV2 architecture instead.

Additionally, we utilize context channels to develop color image encodings. We seek to determine how it would affect the performance of CVUEBA if we instead used the original greyscale encodings developed in Section 3.3.

Finally, for the interpolation model, we aim to assess the improvements our architecture and feature set provides to the design choices of Gayathri et al.’s approach [24].

All Computer Vision approaches outperform DNN, indicating that using image encodings and pretrained architectures allows models to better ascertain changes in behavior. When we compare the interpolation model with CVUEBA, and the image only model to the ResNet baseline, we see that our image encodings lead to superior results on similar model architectures. We also find that the color image encoding models perform significantly better in terms of recall and precision when compared to models trained on the initial greyscale image encodings. Finally, when comparing CVUEBA to the image only model, we see that adding the non-dynamic information reduces recall slightly, but leads to a huge improvement in precision. As false positives could lead to a user losing his/her job, this trade-off is beneficial.

Augmentation Evaluation: For augmentation ablations, we wish to study various augmentations in relation to CVUEBA. Results are shown in Table 7. The context change augmentation outperforms all alternatives, and color shift leads to performance degradation.

| Augmentation         | Balanced Accuracy | Precision | Recall | F1 Score |
|----------------------|-------------------|-----------|--------|----------|
| Context Changing     | 0.9923            | 0.9896    | 0.9845 | 0.9871   |
| Random Flip          | 0.9742            | 0.9534    | 0.9485 | 0.9509   |
| Random Rotation      | 0.9716            | 0.9581    | 0.9433 | 0.9506   |
| Random Crop          | 0.9690            | 0.9381    | 0.9381 | 0.9381   |
| None                 | 0.9638            | 0.9326    | 0.9278 | 0.9302   |
| Color Shift          | 0.9246            | 0.6548    | 0.8505 | 0.7399   |

7. Conclusion

CVUEBA takes the complex problem of insider threat detection and simplifies it down to the simpler problem of color detection, using the behavioral changes that occur during attacks to its advantage by representing contextual information via different channels. An advanced feature set, a powerful yet easily interpretable encoding structure, a novel method of tackling imbalanced learning, and a dual input classifier help CVUEBA outperform state-of-the-art models in both academia as well as industry.
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A. Related Works (continued)

In this section, we expound on the methodologies of algorithms proposed by academia cited in the Related Works section of the main manuscript. Gavai et al. [23] proposed an Isolation Forest-based unsupervised approach for detecting insider threats using network logs. They aggregate features that contribute most to the isolation of a data sample within the tree to better ascertain why a user was tagged as anomalous. Liu et al. [49] proposed an ensemble of deep autoencoders to unravel the non-linear relationships in log data. A model is built from each autoencoder based on the extracted features from each log file. Finally, the outputs are aggregated into a single model used to detect malicious insider activities. Unfortunately this procedure has its limitations: returning subpar results for datasets from alternative sources, the frequency based feature extraction methodology does not always provide the expected outcome, and the one-hour interval considered for user behavior study does not provide enough resolution to identify usage patterns.

Noever et al. [60] tried a variety of different learning algorithm families, concluding that Random Forests with Randomization and Boosted Logistic Regression provided the best results after extracting risk factors from data to create their feature vectors. While their results indicate that Boosted Logistic Regression outperformed the former algorithm, Noever et al. advocate for the usage of Random Forests in insider threat detection systems as they offer a deep but human-readable set of detection rules.

Noting that the vast majority of implementations suggested in recent publications suffer from a very low accuracy of the minority class due to extreme class imbalance, Al-Mhiqani et al. [4] proposed an intuitive way to tackle this issue. They combine adaptive synthetic sampling (AD) [32] with a deep neural network (DNN) architecture to develop AD-DNN, an integrated model that improves the overall detection performance of insider threats.

Sharma et al. [76] used a two-step process to detection via their Long Short-Term Memory Autoencoder (LSTM-Autoencoder). First, it calculates the reconstruction error using the autoencoder fit on normal data, and then utilizes a threshold based detection scheme to identify outliers. The identified outliers are then classified as malicious behavior.

Le et al. [45] assessed various semi-supervised learning algorithms in conjunction with different labeled data availability conditions. These conditions are designed to emulate real-world situations representing the availability of various scenarios of ground truth.

Meng et al. [57] combined Long Short-Term Memory Recurrent Neural Network (LSTM-RNN) and Kernel Principal Component Analysis (PCA) for analysis of insider behavior. They compared well against popular algorithms such as Support Vector Machines (SVM) and Isolation Forests, however it is important to note that their approach was not compared with deep learning models.

Yuan et al. [98] identified that a user action sequence has a temporal dependency. They feed these sequences to a Long Short-Term Memory (LSTM) network, which extracts user behavior features and predicts the next user action. Various hidden states of the LSTM are then used to develop a fixed size representation passed to a Convolutional Neural Network (CNN) for detection purposes.
It is beneficial to identify user behavior patterns within multi-domain scenarios. However, incorporating multi-domain irrelevant features may hide the existence of anomalies within our data. Thus, Lin et al. [47] formulated a hybrid method using Deep Belief Networks (DBN) for unsupervised feature reconstruction, and One Class SVM (OCSVM) for insider threat detection. The usage of the DBN provides a substantial performance uplift when compared to using OCSVM by itself, indicating a promising direction for insider threat detection.

Lin et al. are not the only team that proposed using this network family; Zhang et al. [101] also focused on using a DBN network, albeit within a supervised regime. First, feature learning is executed by having each layer trained using the unsupervised learning method and the training results are adopted as the input of the next layer. Finally, the entire network is fine-tuned by using supervised training. The final output is determined after being fed through a softmax output layer.

Chattopadhyay et al. [14] proposed an insider threat detection approach based on classification of time-series user activities. A cost-sensitive technique for data adjustment was used to randomly undersample the instances belonging to the minority class. A deep autoencoder with two layers and a threshold parameter was used for classification.

B. Features

In this section, we provide additional information and evaluation regarding the feature engineering used to develop the image encodings detailed in the main manuscript.

B.1. Temporal Contextualization of Features

The vast majority of existing insider threat approaches focus on activity type information, such as copying files to a remote drive. This has proven to be ineffective, as users can perform the same activity with either benign or malicious intent [99]. Temporal contextualization plays an important role in analyzing user behavior to identify malicious intent; while copying files to a drive during working hours can be considered normal behavior, the same behavior in the middle of the night should be considered malicious in nature as such activity likely indicates the user is stealing intellectual property, or the user is installing malware or a keylogger onto a system.

The login and logoff activities of users within the CERT insider threat dataset indicate that office hours are between 8am and 6pm [14], however we define office hours as being from 7am to 7pm, an hour buffer on each end, in order to improve our identification of malicious behaviors. A user entering the office a bit earlier or leaving the office a bit later than their peers should not be considered as potentially malicious behavior.

B.2. Handling Spelling Errors and Dialects in File Path Variance

Certain files may have different spellings but be about the same topic. Prime examples of this are spelling errors within folder names, such as "backend" versus "bckend" or spelling dialects such as "color" vs "colour". Thus, for each file we reduce the severity of accessing files within such folders by comparing subdirectory names by their Levenshtein distance [46]. If the Levenshtein distance is within a certain threshold determined beforehand by a security expert, each belong to the same parent node, and both nodes are at the same permission level, we would consider such subdirectories as being the same and would not affect distance measurements between leaves on our tree. If the Levenshtein distance is not within threshold, the paths are considered to diverge at this point.

B.3. Feature Set

As CVUEBA is planned for deployment in an industry setting, we will not disclose all of the features extracted from various data sources. Divulging such information can allow insider threats to more easily tamper with the classification architecture in a variety of ways including data poisoning [29], as well as bypass detection through careful analysis of the feature engineering utilized [85]. While security through obscurity by itself is not enough, it does offer an additional layer of protection for our system.

However, we have found that one can achieve similar performance on the CERT insider threat dataset using features proposed from previous publications in composition with the novel features detailed in the main manuscript. Through careful analysis and feature engineering, we arrive at the set of features detailed in Table 8.

B.4. Quantifying Importance of Proposed Features

As discussed in the main manuscript, in cybersecurity it is crucial for machine learning models and predictions to be as transparent as possible. An additional method of approaching this is issue is from a causality frame of mind where we aim to determine what makes the detection model behave in a certain way. As each feature is a potential cause of the model it is important to quantify the degree of influence each feature has on the prediction’s made by the model.

In the main manuscript, we propose novel features based on calculating the FPV of accessed files and extracting novel indicators from text using CC. Here, we wish to evaluate the importance of these features to classification performance using a feature removal paradigm. To this end, we utilize the explaining by removing framework [17], which assesses and unifies 26 existing feature removal methods. The framework simplifies the feature removal task into the making of three choices: how it removes features, what
Table 8. Set of features compiled to assess user behavior

| Data Source | Feature |
|-------------|---------|
| LDAP        | User’s ID |
| All Sources| Date     |
| Logon       | Difference between initial logon and office start time. |
| Logon       | Difference between last logon and office start time. |
| Logon       | Average difference in time between office start time and number of logins before office hours. |
| Logon       | Average difference in time between office end time and number of logins after office hours. |
| Logon       | Total number of logins. |
| Logon       | Total number of logins outside office hours. |
| Logon       | Total number of logoffs. |
| Logon       | Total number of logoffs outside office hours. |
| Logon       | Total number of unique systems accessed. |
| Logon       | Total number of unique systems accessed outside office hours. |
| Logon       | Average session length held outside office hours. |
| Device      | Total number of external device usages. |
| Device      | Total number of external device usages outside office hours. |
| File        | Number of executable files downloaded, run, or handled in some form. |
| File        | File Path Variance throughout the day. |
| File        | File Path Variance after office hours. |
| Email       | Number of emails sent outside organization domain. |
| Email       | Number of recipients supervisor has sent emails to within organization domain. |
| Email       | Number of attachments sent with emails. |
| Email       | Average size of emails. |
| Email       | Total number of email recipients. |
| Email       | Number of emails Conical Classification identified as the user being disgruntled. |
| HTTP        | Number of websites Conical Classification identified as being job posting sites. |
| HTTP        | Number of websites Conical Classification identified as being Wikileaks or Wikileaks clones. |
| HTTP        | Number of websites Conical Classification identified as being keylogger download sites. |

model behavior it analyzes, and how it summarizes feature influence.

As suggested by the framework authors, we elect to remove features by marginalizing them out using their conditional distributions \( p(X_S \mid X_S = x_S) \). This approach is shown in Equation 7. Here, \( F \) denotes a surrogate model trained to output the same model prediction as the original model while taking in a subset of the given features denoted as \( S \). \( X_S \) refers to the subset of features and \( x_S \) is an instance within said domain.

\[
F(x_S) = \mathbb{E}[f(X) \mid X_S = x_S]
\]  

Marginalizing out using conditional distributions is a method of quantifying how much information is provided by knowing a feature’s value has a strong foundation in information theory, and has strong ties to a variety of model explainability methods [16, 50, 51], making this an ideal choice for feature removal.

In order to evaluate the importance of the proposed features in detecting all scenarios of attack, for the model behavior choice we assess the dataset loss as a whole.

Table 9 lists the feature codenames we are assessing, and Table 10 details the results of running feature removal. We report all summary techniques in the Explaining by Removing framework.

As can be seen, all proposed features have a fairly significant influence on the predictions made by CVUEBA.

Table 9. Set of evaluated features and their respective codenames

| Codename       | Feature |
|----------------|---------|
| FPV            | File Path Variance throughout the day. |
| FPV_After      | File Path Variance after office hours. |
| CC_Disgruntled | Number of emails Conical Classification identified as the user being disgruntled. |
| CC_Job         | Number of websites Conical Classification identified as being job posting sites. |
| CC_Wikileaks   | Number of websites Conical Classification identified as being Wikileaks or Wikileaks clones. |
| CC_Keylogger   | Number of websites Conical Classification identified as being keylogger download sites. |

Table 10. Feature Removal Model Explanation

| Feature       | Shapeley Value | Banzhaf Value | Remove Individual | Include Individual | Mean When Included |
|---------------|----------------|--------------|-------------------|--------------------|-------------------|
| FPV           | 0.0427         | 0.0094       | 0.0096            | 0.0866             | -0.2551           |
| FPV_After     | 0.0022         | 0.0004       | 0.0004            | 0.0134             | -0.2760           |
| CC_Job        | 0.0021         | 0.0029       | 0.0032            | 0.0015             | -0.2764           |
| CC_Wikileaks  | 0.0584         | 0.0608       | 0.0199            | 0.0962             | -0.2490           |
| CC_Keylogger  | 0.0030         | 0.0040       | 0.0045            | 0.0014             | -0.2762           |

C. Deployment in Industry

It is important to consider how an insider threat detection system will change, adapt, and improve when deployed in an industry setting; a static model is one that can be easily
circumvented by malicious actors. We handle this by obtaining feedback from security experts in two stages: first when a new insider threat attack vector has been introduced, and second when our model identifies behavior as potentially malicious.

C.1. Process of Handling New Attack Vectors

Until now, we have assumed that the known list of potential attack vectors is fixed and never changing; this is a common assumption used in building insider threat detection systems. However, the landscape of attack is ever changing, with new forms of attack found over time such as insider collusion attacks that have been growing rapidly in prevalence [96]. It is vital for our systems to be able to grow and adapt to this ever-changing climate.

Figure 8 illustrates how an expert can update CVUEBA in accordance with the discovery of new methods of attack. If the current implementation is deemed to be outmoded after analysis of the attack vector and feature engineering is complete, we utilize the augmentation strategy proposed in the main to update CVUEBA, enabling security teams to detect and identify this new method of attack.

C.2. Looping in the expert at detection time

While CVUEBA has a false positive rate lower than alternative algorithms, false positives are still a serious issue for UBEA systems as a false positive could lead to a well-intentioned employee getting fired for no fault of their own. Thus, we propose a method that allows security experts to catch false positives before action is taken, and allows for CVUEBA to adapt and improve based on expert feedback. Figure 9 illustrates how CVUEBA can improve and adapt to the expert’s preferences after deployment. User information is passed through the model in 24 hour intervals every time a new batch of behavior is identified; this enables real-time detection of attacks as they occur.

As shown in the main manuscript, the model’s output layer is a fully connected sigmoid; this enables us to determine not only the final behavior classification, but also the model’s confidence in the given classification by determining how close the output value is to 0.5. Based on a tweak-
able value set by the security team, the model sends alerts not only for behavior deemed malicious, but also behavior deemed benign but with low confidence.

The expert is then able to assess the alert from the image encodings created via the process detailed in the main manuscript as well as from the raw feature vectors detailed previously. If the user’s behavior is deemed to be malicious, the insider threat is handled based on the given situation.

Regardless of the final conclusion, we can take advantage of the expert’s inquiry to improve our model’s performance. Taking advantage of Active Learning techniques [75] with our expert performing the role of an oracle, the CVUEBA classifier is trained using the newly labeled vectors.

This enables our model to adapt to the ever-changing environment found in corporations, as well as to the preferences of the expert in charge of the CVUEBA deployment.

We seek to evaluate loop-in by initially training CVUEBA on the training set. Using a threshold parameter of 0.4, we simulate incoming data in a production environment via the validation set and simulate expert feedback using the ground truth labels. The improved model is evaluated on the test set in the same manner as the original model. Table 11 showcases the results.

Table 11. Effects of Loop-in

| With Loop-in | Balanced Accuracy | Precision | Recall | F1 Score |
|--------------|-------------------|-----------|--------|----------|
| No           | 0.9923            | 0.9896    | 0.9845 | 0.9871   |
| Yes          | 0.9948            | 0.9948    | 0.9897 | 0.9922   |

Loop-in offers a modest improvement in both precision and recall, leading to a further reduction in false positive rate as was intended by the design.

D. Computer Vision Baseline Architectures

Figure 10 illustrates the architecture for each of the Computer Vision Models that serve as our main baselines for evaluation purposes.

The MobileNetV2 model is trained using RMSProp for 15 epochs using a batch size of 64, and a dropout rate of 0.3. The VGG19 model is trained using SGD for 15 epochs using a batch size of 128. Finally, the ResNet50 model is trained using Adamax for 15 epochs using a batch size of 128, and has an L2 regularization term. As the original paper does not specify the value of $\lambda$, we utilize the default value of 0.01 defined by Tensorflow [1]. All three models are trained using a undersampled version of the training set where the benign to malicious ratio is reduced to 20:1.

E. Limitations

Our study has a couple of key limitations we think are crucial to point out to the reader.

First, as we are evaluating on the CERT insider threat dataset version 4.2, our model is evaluated on a limited set of data. The most important consequence is that CVUEBA was evaluate on only 3 different types of attacks. This is not indicative of real world deployments, where insiders may use a multitude of different avenues to steal data or cause havoc to systems [34, 59, 94].

Despite this limitation, we consider the CERT insider threat dataset the best compromise of the publicly available datasets for benchmarking and reporting results. An important benefit of this dataset to the insider threat research community is that it enables broad collaboration and increases the velocity of innovation. It also provides a common basis for all researchers allowing them to share a common set of threat scenarios with the ground truth being well known. These are both crucial aspects for benchmarking and evaluating different models.

Second, CVUEBA treats attack detection as a binary classification problem rather than as an anomaly detection problem. While this is common for insider threat detection systems and improves precision and recall for known insider attacks, this can lead to undefined behavior for unseen attack vectors. In the main manuscript, we showcase that
CVUEBA handles this issue better than alternative methodologies, but there is still a performance drop when evaluating new forms of attack. We propose a system above to allow CVUEBA to adapt to new attack vectors, however this only works once the attack vector is known, not for zero day attacks.

Third, CVUEBA requires baseline behavior to be recorded in order to function properly. Absence of contextual channel information within image encodings leads to undefined behavior.

Finally, while our image encodings allow for great interpretability regarding what the CVUEBA model itself is detecting, the encodings themselves do not indicate what aspect of the user’s behavior is malicious. A security expert reviewing the incident can see the encoded images in addition to the computed features defined previously to confirm there are changes in employee behavior. From here, they can perform in-depth analysis as to whether the behavior is malicious or benign by pulling up the relevant log files for further analysis.

F. Code

Sample code and data can be found here: https://github.com/sameerkhanna786/CVUEBA