# SINVAD: Search-based Image Space Navigation for DNN Image Classifier Test Input Generation

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# ABSTRACT

The testing of Deep Neural Networks (DNNs) has become increasingly important as DNNs are widely adopted by safety critical systems. While many test adequacy criteria have been suggested, automated test input generation for many types of DNNs remains a challenge because the raw input space is too large to randomly sample or to navigate and search for plausible inputs. Consequently, current testing techniques for DNNs depend on small local perturbations to existing inputs, based on the metamorphic testing principle. We propose new ways to search not over the entire image space, but rather over a plausible input space that resembles the true training distribution. This space is constructed using Variational Autoencoders (VAEs), and navigated through their latent vector space. We show that this space helps efficiently produce test inputs that can reveal information about the robustness of DNNs when dealing with realistic tests, opening the field to meaningful exploration through the space of highly structured images.

#### **KEYWORDS**

Test Data Generation, Neural Network, Search-based Software Engineering

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#### **1** INTRODUCTION

The use of convolutional neural networks for image classification [13] has sparked significant growth in the use of such techniques; for example, Deep Neural Networks (DNNs) are widely used in computer vision, natural language processing, and playing games [15]. As DNNs can greatly enhance the accuracy of computerized perception, their use even in safety-critical domains, such as autonomous driving [2, 3] or medical imaging [18], has also seen a rise.

However, despite the increasing adoption of DNNs in these domains, many of their safety properties are difficult to comprehend

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or fix. For example, adversarial examples [1, 6, 14, 23] add a highly targeted noise vector to normal inputs, causing DNNs to deviate from human perception. Such attacks are not only also possible by manipulating real world physical objects that intereact with DNNs [14], but also possible for other domains such as speech recognition [28] and machine comprehension of texts [9].

As the necessity of thorough testing of neural networks has received wide acknowledgement, various methods have been proposed to fix this, particularly through the traditional approach of coverage. Pei et al. [24] track the activation status of each neuron, and argues that tests should aim to activate a diverse set of neurons. Ma et al. [19] posit that test suites should have each neuron emit multiple strata of outputs. Kim et al. [11] quantify how surprising an unseen input is and argues that effective test suites should use inputs with differing levels of surprise.

While the number of approaches to create adversarial and difficult examples has grown, there has been relatively little effort in attempting to search the larger space of valid image representations. It is important to search this space, as images made by tweaking a few pixels without regard to what images are realistic are often not helpful. For example, even if we find that perturbed pixel values within a certain image region cause the neural network to misclassify as presented in DeepXplore [24], it is unclear what one can do to fix this and whether it matters, as such a perturbation is unlikely to appear in practice. Ideally, we would like to identify real-world scenarios in which the classifier fails; this is possible when one searches over the space of valid image representations, not when search is performed over small perturbations of an existing image.

In this work, we present SINVAD (Search-based Input space Navigation using Variational AutoencoDers). SINVAD navigates in the space of plausible images, a subspace of images that semantically resemble those of a specific dataset, by leveraging Variational Autoencoders (VAEs) [12], a class of generative models. It is first shown that, as argued beforehand, optimization over the entire image space yields static-like noise images that are challenging to interpret, while optimization over the latent space of a VAE yields realistic images that may appear as a harmless input, and thus are related with the dataset in question. Equipped with this validation of our initial premise, we subsequently perform a guided search for plausible images that reside close to the decision boundary, enhancing our ability to perform boundary testing using images that lie on the semantic boundary of labels, found though SINVAD.

We further verify that search is not only possible on one DNN, but can be adapted so that multiple DNNs provide guidance to search. Specifically, we employ a GA-based technique to uncover the differences between neural networks within the space of plausible images. By analyzing the characteristics of images that cause

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judgement differences between neural networks, one may uncover plausible faults and differences in neural networks.

Finally, leveraging certain semantic properties (e.g. it is difficult to draw a 3 that looks like a 4), and that our test data generation algorithm closely emulates such characteristics, a test case generation technique that picks up pairs of categories which are at risk of being confused with each other is provided. We show that the results of the tool roughly correlate with the semantic separation between categories, and further verify that when training data labels are mixed, our technique picks up such change faster than the default test data can.

The contribution of the paper is as follows:

- We introduce SINVAD, a novel method to search through the space of plausible images using a neural network based representation of images, which is shown to be a valid way of searching for images that meet desiderata while remaining plausible;
- We evaluate border images, images optimized to be confusing to the neural network, to show that dropout-induced models indeed provide widely different predictions between each other, to a greater extent than standard dataset test images; a qualitative assessment of generated border images confirms that they are semantically 'in between';
- We present a technique using the test generation algorithm that produces tests capable of identifying training problems earlier than the provided test set.

The remainder of this paper is organized as follows. Section 2 introduces the related literature, providing background to this paper. Section 3 presents nomenclature, and defines the problem of searching the space of DNN inputs in a formal way. How SINVAD performs search in the large DNN input space is subsequently explained. Section 4 presents the research questions we aim to answer with experiments that are described in Section 5. Section 6 presents threats to validity, and Section 7 provides discussion and concludes.

# 2 BACKGROUND

This section presents background information relevant to SINVAD.

# 2.1 Testing of DNNs

As the need to test and validate DNN models increases, many recent work focused on testing techniques for DNNs. The early work mostly concerns how to differentiate good and bad inputs, i.e., how to choose inputs that are more likely to reveal suboptimal behavior of a given DNN. Neuron Coverage (NC) was the first test adequacy metric proposed for DNNs: it computes the ratio of neurons in a given DNN that were activated above a predetermined threshold value by a set of test inputs [24]. Many different adequacy criteria based on neuron activation have since been proposed, including k Multisection Neuron Coverage (kMNC), a finer granularity refinement of NC, and Strong Neuron Activation Coverage, a criterion that focuses on out-of-distribution activations (i.e., ones that are beyond the range of activations observed during training) [19]. Surprise Adequacy (SA) subsequently focused on the similarity between neuron activations observed during training (aggregated as probability distributions) and a single input, allowing the tester to measure how surprising a new input is, and consequently how

likely it is to reveal unexpected behavior [11]. We use SA to guide our search for new inputs for DNN based image classifiers in this paper. Zhang et al. [35] use GANs to generate realistic road images for autonomous driving applications.

In addition to dynamic testing, there are work that try to verify DNNs with a correctness guarantee. ReluPlex extends the simplex method, applying SMT solvers to provide safety guarantees for DNNs [10]. Huang et al. proposed a verification technique for image recognition DNNs, checking whether images within a certain distance of each other are classified identically [8]. A general discussion of testing machine learning techniques is provided in Zhang et al. [34].

# 2.2 Difficulties of Input Search for DNNs

One of the biggest challenges in searching for new test input for DNNs is the semantic manifold problem [33]. Only a miniscule fraction of the entire input space of a image classifier constitutes the space of valid inputs that are meaningful images; the vast majority of the space is uninterpretable noise. However, it is not possible to clearly define which regions of the overall input manifold are semantically meaningful to humans, preventing us from navigating the space freely guided by fitness functions. Most of the existing testing techniques for DNNs circumvent this issue by adopting the metamorphic testing principle: given a seed image, a DNN under test should behave the same after we either inject a small amount of noise (e.g., adding noise that humans can safely ignore), or apply semantically irrelevant changes (e.g., synthesizing an image with the same semantic content but under a different weather condition) [11, 24, 32]. SINVAD is an attempt to search in the space of semantically meaningful inputs, by using VAEs as an approximation of the space of meaningful inputs.

# 2.3 Generative Models

As DNNs became more powerful function approximators, generative models that can imitate complex distributions became more plausible to implement. The core theme of generative models is that if one can model a distribution to calculate the odds of a certain input, one can also sample from that distribution to make plausible inputs. The advent of machine learning has brought many powerful generative models that approximate distributions, either explicitly or implicitly. Generative Adversarial Networks [7] employ a generator and discriminator network, in which the generator attempts to match the input distribution while the discriminator tries to find the discrepancies between the generator-approximated distribution and the true distribution. The training process implicitly guides the generator network to resemble the true distribution. PixelCNNs [22] model the dependencies between neighboring pixels, sampling each pixel conditionally on nearby pixels. PixelCNNs are trained explicitly to assign high probability to provided images. Variational AutoEncoders (VAEs) [12] do not explicitly calculate the odds of an image, but maximize the evidence lower bound (ELBO), which acts as a lower bound of the odds of an image. There are many other generative models; one may look to Foster [5] for further examples. For our purpose, any generative model with latent variables (e.g. GANs or VAEs) that can function as a condensed search space may be used.



Figure 1: Diagram of SINVAD. SINVAD uses the VAE encoder (E) to encode images into a *latent space* (bars). Search-based optimization is performed not on raw pixels, but on latent representations. A representation is transformed back to an image using the VAE decoder (D). The use of VAE networks before and after keeps search within the subset of plausible images.

# 3 SINVAD: SEARCH-BASED INPUT SPACE NAVIGATION USING VAES

#### 3.1 Problem Statement

A common application of DNNs is as image classifiers. In such applications, a neural network N acts as a function that maps the space of images  $\mathcal{I} = [0, 1]^{c \times w \times h}$  to a space representing the probability of each class  $\mathcal{P} = \{v \in [0, 1]^n : \sum_{i=1}^n v_i = 1\}$ , where there are ncategories. Formally, the DNN is a mapping  $N_p : \mathcal{I} \to \mathcal{P}$ , and a mapping  $N_c(i)$  =one-hot(arg max  $N_p(i)$ ) is derived.

In practice, the semantic meaning of most images is unclear, so the neural network is trained on a subset of images from the space of plausible images  $\mathcal{D}$  and maps to  $\mathcal{P}$ . In test generation, this becomes a problem as the space of all images of a certain resolution is usually much larger than the space of all such images that are valid  $\mathcal{D}$ . If one looks at the MNIST dataset for example, it is clear that the space of grayscale 28 by 28 images is much larger than the space of digit images, for most random grayscale images look more like static noise than coherent numbers [33]. Then, due to the vast size difference between I and D and the complexity of the neural networks employed to solve classification problems, it is often easy to obtain images that meet a certain criteria that are not particularly interesting or meaningful. For example, it is relatively easy to construct an image that resembles noise, but is classified with high confidence as a cheetah [21]. While this is interesting, our concern is often more closely related to the implications of when neural networks are released in the wild, e.g. in what situations would there be a risk of failure? As such, it would be beneficial if we could search exclusively in the space of plausible inputs.

#### 3.2 SINVAD

We propose to use DNN based generative models, such as VAEs or GANs, to solve this problem. A schema of our approach SINVAD is provided in Figure 1. Generative models estimate the distribution of a provided dataset over the entire space of all images I. In particular, VAEs effectively try to find a mapping between  $\mathbb{R}^d$  and  $\mathcal{D}$ ; the encoder  $(E : \mathcal{D} \to \mathbb{R}^d)$  maps from images to latent representations, and decoders  $(D : \mathbb{R}^d \to \mathcal{D})$  operate vice versa. By executing

traditional search-based optimization algorithms, but within the latent representation space, we can restrict our search space to  $\mathcal{D}$ , instead of the full image space  $\mathcal{I}$ . Hence the result of search will mostly be images that closely resemble true images from  $\mathcal{D}$ . Note that since the VAE itself has only been trained on a small sub-sample of  $\mathcal{D}$ , i.e. the training set, it might not be a very good mapping to/from the actual  $\mathcal{D}$ . We thus have to investigate the practical value of our approach empirically, in the following.

#### **4** RESEARCH QUESTIONS

In this paper, we seek to find the answer to four research questions.

**RQ1.** Plausibility: Can SINVAD generate images closely related to  $\mathcal{D}$ ? Our justification for using complex generative models is the assumption that, if employed to reduce the search space, the resulting images will be more closely aligned with the true data distribution  $\mathcal{D}$ , i.e. more 'realistic' than similar techniques that do not employ generative models. To verify this point, we compare SINVAD with search-based optimization algorithms that do not use VAEs. We qualitatively compare whether an image is realistic or not, as human perception is the only true guide in this case.

**RQ2.** Indecisiveness: Can SINVAD generate images near the decision boundaries of neural networks? Using SINVAD with a certain fitness function, one can make VAE-generated images that are near oracle decision boundaries, i.e. the category identity of generated images is unclear even to humans. We verify whether generated images are also close to neural network decision boundaries by employing dropout. When certain neurons are dropped, neural networks are more likely to make mistakes on confusing inputs rather than straightforward inputs. Using this, we aim to observe that our images are indeed more difficult to classify than default test sets, thus providing additional scrutiny while testing.

**RQ3. Differential Testing:** Can SINVAD perform differential testing for neural network comparison? To further investigate the potential of the image space search that SINVAD enables, we use it for differential testing of neural networks. By traversing the space and comparing the outputs of the networks, we investigate whether we can identify meaningful semantic differences in their behavior. In turn, this may highlight important properties of DNNs under test.

**RQ4.** Application: Can SINVAD be utilized to identify 'weak spots' of neural network classifiers? Using SINVAD, we attempt to find pairs of categories that a given DNN based image classifier frequently confuses. For example, we would like to answer whether a given image classifier is more easily confused between the pair of 0s and 1s, or 4s and 9s. Such information can reveal potentially harmful pairs, indicating where the classifier needs more data and further training. If we ask SINVAD to find an image that looks like class X but is classified as Y, the success rate of this optimization differs by pair. We posit that the success rate is correlated with the risk of the DNN under test making a mistake, and verify this by artificially mixing labels and checking whether the genetic algorithm's success rate increases as the labels become more mixed.

# 5 EMPIRICAL ANALYSIS

# 5.1 Experimental Setup

Two datasets are used throught the paper. MNIST [16] is a grayscale digit image dataset, each  $28 \times 28$  pixels large. There are 50000 training, 10000 validation, and 10000 test images, but in this paper all training and validation images are used for training. SVHN [20] is a dataset containing real-world digits obtained from Google Street View images. There are 73257 training images and 26032 tests. Each image is  $32 \times 32$  pixels large, with RGB colorization.

For MNIST, a VAE that has one hidden layer of size 1600 for both encoder and decoder structures is used. The encoding vector size is 400. For SVHN, we employ a network with 8 hidden layers in the encoder and decoder respectively. The larger VAE for SVHN is needed due to the greater difficulty of modelling images with background variation and color schematics. VAEs for both datasets are trained for 50 epochs, which was sufficient for training to convergence.

Regarding the neural networks to emulate the DNNs under test, a convolutional neural network with 6 hidden layers is used for MNIST. A network of an overall similar architecture with 9 hidden layers is used for SVHN. In Section 5.4, we use a VGG-19 [29] network to perform differential testing with our 9-layer model. The likelihood-based surprise adequacy (LSA) metric is calculated using the activation traces of the penultimate layer, i.e. the input vector to the final neural network layer which produces softmax logits.

# 5.2 Plausibility (RQ1)

Through this experiment, we seek to answer RQ1: whether VAEbased optimizations yield more 'realistic' result images. To verify this point, we perform the following experiment. We attempt to obtain images that have a target Surprise Adequacy [11]. To do this, we perform a variant of random hill climbing in which we add a random value sampled from the standard normal distribution to a single element in the vector representation and compute fitness based on the function  $f(i) = |LSA_N(i) - t|$ , where  $LSA_N$  is LSA calculated using a neural network N, and t is a target SA value. If the fitness is lower, we keep the change and move on to the next element, modifying each element one by one in order. On raw pixels, we modify a precursor representation r which has the same dimension as normal images. The image from representation is obtained by applying the *tanh* function elementwise on *r*. This normalization restrains the values of pixels to be within a certain range, so that the image is within the typical image space. For the VAE representation, we modify a latent vector *z* and obtain the image through D(z). Search starts from a random representation so that comparison is fair. Specifically, *r* is generated by sampling from unif(0, 1) for each element, while *z* is generated by sampling from the standard normal distribution N(0, 1) for each element.

A result is presented in Figure 2; while both images achieve similar performance in terms of the fitness function, the raw pixel-based optimization result appears to lack any global structure, whereas the optimization guided by a VAE yields images with coherent structure that indeed appear like a digit.



(a) Raw Pixel Optimization

(b) VAE Optimization

Figure 2: Images produced by optimization either at the raw, pixel level (a, left) or using SINVAD (b, right). Despite having the same fitness value the VAE based image looks closer to a "real" digit.

We may also look at these results through the prism of activation trace (AT) space [11]. The activation trace of an image is the set of neuron activations that are elicited when it is provided as input. While neural networks are high-dimensional and thus it is difficult to directly observe AT space, we may perform dimension reduction techniques such as PCA to get a glimpse of the structure. In turn, we may observe where each image is positioned in the AT space, providing a visual persepective on 'familiarity' to the neural network. This paper uses PCA as it allows projection of new data. Figure 3 depicts the PCA projection of the AT of training data, each color representing the AT of a certain digit.

Using this projection, we can visualize where both VAE-based images and raw pixel search based images are, to check where they are positioned in the space. Figure 4 shows an example of such a visualization. As one can see, the GA-based images are closer to the true data distribution, while raw pixel based images end up around the outskirts of the real image activation trace distribution.

Using the visualization properties of the PCA projection, we can further illustrate how search can be performed over the VAE latent space, and how this can yield more plausible results than searching over raw pixels. Given two images, we interpolate over both raw pixels and the latent space; specifically, we obtain raw pixel interpolations for a certain pixel [i, j] through  $i_t[i, j] = (1-t)*i_0[i, j] + t * i_1[i, j]$ , while VAE interpolated images for image  $i_0$  and  $i_1$  are obtained with:  $i_t = D((1-t) * E(i_0) + t * E(i_1))$ . We compare

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Figure 3: PCA projection of training data AT space, with each color signifying ATs from different digits.



Figure 4: Placement of images optimized either at the raw, pixel level (green) or at VAE latent vector level (red), in relation to the PCA projection of the training images.

these interpolated images side by side in Figure 5(a), while their PCA trajectory in the AT space is presented in Figure 5(b). Note that in Figure 5 (a), the raw representation has no understanding of semantics, hence it mixes the images unnaturally. On the other hand, the VAE representation tries to naturally interpolate between the images, keeping intermediate images somewhat plausible. This effect also appears in Figure 5 (b); while the raw representation just takes a straight trajectory from the first to last point without regard of semantics, the VAE representation spends little time in the implausible regions where there are few previous images and more time where there is a dense distribution of real images. This again testifies that VAEs can generate plausible images more consistently.

By changing the fitness functions used within SINVAD, we can achieve different semantic objectives. For example, we may want to construct images that look like one category, but are classified as another (as in adversarial examples), and yet are still plausible. The setting here is similar to Song et al. [30], but with different



Figure 5: Trajectories of interpolated images projected into the PCA space.

generative models and optimization methods. Using the fitness function in Equation 1,

$$f(i) = \begin{cases} \infty & N_c(i) = N_c(i_0) \\ |E(i) - E(i_0)| & else \end{cases}$$
(1)

we may obtain images that are semantically ambiguous. The upper case denotes the case in which the new image's classification has not changed; we do not want to accept such images. The lower case is when the new image's classification is different from the original image; in such cases we want the image to look as similar to the original image as possible. Specifically, we employ the following genetic algorithm. A random image  $i_0$  is sampled from the test dataset. The latent representation of this image,  $E(i_0)$ , is obtained. The initial population is constructed by sampling new representations  $z_i$ , where  $z_i = E(i_0) + \epsilon_i$ , and  $\epsilon_i \sim N(0, 1)$ . An image can be reconstructed using the decoder, so that  $i_i = D(z_i)$ . Using this image we calculate the fitness of the representation as in Eq. 1. Single-point crossover is used; mutation is performed by adding a small noise vector on each genome. Individuals with smaller fitness are selected for the next generation. An example result of this optimization is shown in Figure 6. Observe that while this image does look somewhat similar to a digit, it is not clear whether this image is a 4 or a 9. On the other hand, raw pixel search does not yield semantically plausible results as in Fig. 2, reducing the utility in terms of analyzing and reasoning about the network.

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Figure 6: An ambiguous image generated through GA optimization using Eq. 1 as a fitness function.

Dataset	GA-generated	Provided
MNIST	0.7456	0.1365
CIFAR-10	0.7853	0.0202

Table 1: A comparison of the variance in prediction between provided test images and GA-generated 'boundary' images. The boundary images vary more in their predictions than the test images, suggesting that they are closer to the decision boundary.

#### 5.3 Indecisiveness (RQ2)

One can suspect that the objective function provided in Eq. 1 will yield images close to the decision boundary of corresponding neural networks. To verify whether this is the case, we utilize dropout [31] and measure the variability of predictions. Dropout is a training technique that drops a certain proportion of neurons during training; it is known to make neural networks more robust in general. While dropout is usually used only when training, we keep dropout on and measure how much predictions vary when different neurons are dropped. It is likely that images that are close to the decision boundary will vary in final prediction results much more than images that are safely within a certain category's boundary. This bears some resemblance to previous methods that use dropout to detect adversarial examples [4, 17], but is simpler than those approaches which incorporate Bayesian optimization. Using the objective function in Eq. 1, we sample 10,000 images and measure the prediction variability using the following metric:

$$V(I) = \sum_{j=1}^{c} \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (p_i[j] - \mu_{ij})^2}$$
(2)

where  $p_i[j]$  is the *j*th class's predicted confidence in image *i*, and  $\mu_{ij} = \frac{1}{n} \sum_{i=1}^{n} p_i[j]$ . Upon inspection, one can note that the expression  $\sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (p_i[j] - \mu_{ij})^2}$ , which appears in Equation 2, is essentially the Bessel corrected standard deviation of each category's predicted likelihood, summed over all categories. We use this metric as it continuously measures how much a DNN's prediction varies. Table 1 shows the comparison results for this experiment.

As the table shows, the boundary images cause the classification results of a given neural network to vary much more than when the same neural network is exposed to the provided test images. These results indicate that slight changes to the composition of neurons will significantly alter the final prediction in the case of boundary images. In turn, this indicates that the boundary images are close to the neural network's decision boundary itself.

### 5.4 Differential Testing (RQ3)

To answer RQ3, we perform differential testing to uncover hidden properties of neural networks. Performing differential testing only requires a minor change from previous experiments: namely, the fitness function would be changed to Equation 3, where N and N' are distinct neural network classifiers and  $i_0$  is an initial image.

$$f(i) = \begin{cases} \infty & N(i) = N'(i_0) \\ m|E(i) - E(i_0)| & else \end{cases}$$
(3)

The genetic algorithm used to find such images is the same one as explained in Section 5.2, except that the fitness function is defined as in Equation 3. The multiplication factor  $m = (2 + N_p(i)[c]) - N'_p(i)[c])$  where  $c = N'(i_0)$  in the fitness function encourages neural networks to diverge as much as possible, where two is added to keep the multiplication factor positive. If we perform this search in the VAE latent space, we are effectively finding plausible images that cause neural networks to diverge in decision. Hopefully, it will be possible to identify the underlying reasons behind different decisions in neural networks. Results of differential testing performed on the SVHN dataset are shown in Figure 7. Here, our custom network for SVHN and a VGG-19 network are compared, with architectures described in Section 5.1.





Given many such results, one may be able to discern distinct semantic properties that different neural networks have, and construct an accurate ensemble of DNNs. For example, if as a result of comparing network A and B, many gray background images as in the lower right image of Figure 7 appear, we may infer that network A is having a hard time with gray background images. While these results are far from conclusive, the images show the potential of SINVAD to compare cases in which neural networks diverge, opening the possibility of further analysis of the decision boundaries in neural networks. SINVAD: Search-based Image Space Navigation for DNN Image Classifier Test Input Generation

### 5.5 Application (RQ4)

Using SINVAD, we attempt to find pairs of categories that a given neural network may be confused by. Specifically, a targeted fitness function is devised, and presented in Equation 4, where t is a target class.

$$f(i) = \begin{cases} \infty & \nu(i) \neq t \\ |E(i) - E(i_0)| & else \end{cases}$$
(4)

In fact, this optimization quite often fails, i.e. the search does not find an image that has the target class *t* starting from the image  $i_0$ . What is of interest is not that it fails, but how often, i.e. the proportion of failures. It turns out that image pairs that are confused between each other have a higher success rate, while image pairs that are clearly distinguished have a lower success rate. Concretely, we define a *GA class escape rate* as the number of times an attack successfully finds a solution that causes the DNN to classify an image as the target class divided by the number of all attempts. We can compare this to the targeted error rate which is the number of times an image in the dataset test set with the source class is classified as the target class. The change in GA class escape rate is more pronounced than the targeted error rate of the test cases, as is showcased in Figure 8, by juxtaposing the confusion matrix using provided test cases and the GA class escape rate for a simple neural network classifier.



Figure 8: Comparison between (a) the error matrix of the provided MNIST test set and (b) the number of successful optimizations of the GA algorithm out of 1000 attempts. Note that the differences are more pronounced in the GA algorithm's matrix.

To show the effectiveness of the GA class escape rate, target labels are artificially mixed during the training phase according to a proportion  $\alpha$ . For each  $\alpha$ , a corresponding neural network is trained. For each such neural network, we measure the error rate between the mixed pair and the GA class escape rate. Results where 0 and 1 are mixed with varying  $\alpha$ s are presented in Figure 9. As evident from the figure, GA class escape rate has a much tighter correlation relationship with the gradual mixing of labels; default test cases only pick up this change when labels have been mixed quite a lot. This shows the effectiveness of SINVAD-generated test cases in finding potential flaws in neural networks.



Figure 9: Performance change when labels are mixed. GA class escape rate increases more rapidly than error rate when labels are mixed.

#### 6 THREATS TO VALIDITY

Internal Validity. Internal validity regards whether there are experimental factors that may influence the conclusions reached in the paper. The results in Section 5.3 and 5.5 are somewhat stochastic and values may change in a reproduction experiment. To mitigate this issue, we ran these experiments over a large number of images  $(n \ge 1000)$  so that we could be fairly confident that the overall trend of these results would be stable despite their randomness.

*External Validity.* External validity is threatened when the study's results may not generalize. In this work, we used a small number of neural network architectures for convenience. As such, it has not been verified whether the results of this study will generalize to other architectures. Small and simple image datasets such as MNIST or SVHN are employed instead of larger and more complex datasets such as CIFAR-100 or the ImageNet dataset; this was a decision made mostly out of convenience. Additional experiments are required to verify our results on other datasets.

#### 7 DISCUSSION AND CONCLUSION

In this paper, we introduce SINVAD, a technique that uses generative models to focus the search for images so that more plausible/ realistic ones can be generated. Through experiments, we demonstrate that SINVAD can provide potentially more useful inputs when assessing a neural network, both quantitatively for various testing scenarios, and qualitatively via visualization and human input. We also show that, coupled with search, we can find images that are close to decision boundaries, which can be used for boundary value testing and for diagnosing whether the boundary is actually where it is expected to be. Finally, we show how SINVAD can provide unique insights into the behavior of neural networks through differential testing and targeted class escape rate analysis.

While the paper focuses on image classifier neural networks, future work should also target other data modalities, generative models, and types of machine learning models. The specific generative model used, Variational Autoencoders, have been applied to non-image data such as text [26]. Moreover, techniques to use them for multi-modal datasets [27] or test suites [25] have been proposed. Thus, future work should investigate if generative models coupled with search are a general method for generating semantically meaningful software inputs and data. As other and more powerful generative models are introduced they can also be used. Similarly, we aim to investigate how our approach can be used to test machine learning models other than neural networks. As long as the fitness function we use in our search is agnostic to the model under test, i.e. it does not rely on internal computations of the model, our method should generalize basically unchanged.

In summary, we believe that the shifting of focus from low-level, "syntactic", here pixel-level, perturbations to semantically meaningful changes that search coupled with SINVAD allows can benefit many interesting software engineering and testing applications.

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