

# Generatively Augmented Neural Network Watchdog for Image Classification Networks

Justin M. Bui

*Department of Electrical and Computer Engineering  
Baylor University  
Waco, TX  
Justin\_Bui@baylor.edu*

Glauco A. Amigo

*Department of Electrical and Computer Engineering  
Baylor University  
Waco, TX  
Glauco\_Amigo1@baylor.edu*

Robert J. Marks II, PhD

*Department of Electrical and Computer Engineering  
Baylor University  
Waco, TX  
Robert\_Marks@baylor.edu*

**Abstract**—The identification of out-of-distribution data is vital to the deployment of classification networks. For example, a generic neural network that has been trained to differentiate between images of dogs and cats can only classify an input as either a dog or a cat. If a picture of a car or a kumquat were to be supplied to this classifier, the result would still be either a dog or a cat. In order to mitigate this, techniques such as the neural network watchdog have been developed. The compression of the image input into the latent layer of the autoencoder defines the region of in-distribution in the image space. This in-distribution set of input data has a corresponding boundary in the image space. The watchdog assesses whether inputs are in inside or outside this boundary. This paper demonstrates how to sharpen this boundary using generative network training data augmentation thereby bettering the discrimination and overall performance of the watchdog.

## I. INTRODUCTION

Neural networks and the techniques associated with machine learning are readily being used in a variety of applications. In fact, machine learning has become ubiquitous throughout many industries, including the medical, automotive, and energy industries [15], [21], [44], [45], [53], [56]. Furthermore, the development of such techniques has been spurred by the continuous development and expanded capabilities of tools such as PyTorch and TensorFlow [1], [47].

An increasing need for quality training data goes hand in hand with the development of new machine learning techniques. Data augmentation and generation have become a standard practice in the development of deep neural networks [40], [48], [57], [60], [68]. As systems become more complex, and pipelines are transitioned from evaluation to production environments, the need for online out-of-distribution detection increases [22]. One technique to help mitigate the impact of out-of-distribution inputs is the neural network watchdog. This paper describes the design and development process for a multi-tiered neural network watchdog designed to improve the on-line performance of an image classification neural network. This is achieved by a more effective sharpening of

the boundary of the image space, resulting in more accurate discrimination of the in-distribution from out-of-distribution data as dictated by the latent layer of the autoencoder.

## II. BACKGROUND

One of the challenges associated with the development of classification neural networks is the detection and classification of out-of-distribution data. Abbasi et al. [2] provide an excellent introduction to the issues and metrics associated with out-of-distribution data in classification networks. Out-of-distribution detection is often times closely coupled to anomaly detection [16], [23], [42] (a.k.a. novelty filtering [12], [20], [59], [61].) Numerous anomaly detection techniques have been proposed [49], [54], [67] which demonstrate some capabilities of detecting out-of-distribution data. One of the more interesting techniques for anomaly detection is the use of autoencoders [38], [50], [55], [69]. Autoencoders have demonstrated an interesting array of capabilities, such as implicit learning [61], missing sensor restoration, [41], [62], data denoising [17], [36] and image enhancement [34], [35], [46].

The neural network watchdog [5], is a technique for out-of-distribution detection. Initially, an autoencoder is used to learn latent representations of in-distribution data, and then reproduce the original input based on the representation. As the autoencoder is trained on in-distribution data, the representations produced by out-of-distribution data result in larger error during reconstruction. The calculated error is then compared to a threshold based on the desired level of detection. This threshold operation acts as an input filter to the original classification or regression network. The evaluation and selection of an appropriate error function depends on the input data type and target system performance. For example, a time-series dataset may use mean bias error, root mean squared error or unscaled mean bounded relative absolute error [8] as a metric, whereas image based data may use structural similarity techniques [65], [66], univariate image difference, or change

vector analysis [4]. Additional error determination methods have been discussed [7], [31].

Preliminary results have demonstrated successful implementations of neural network watchdogs [5], [6], [14]. The watchdog has been augmented to a multi-tiered watchdog [3]. The multi-tiered watchdog uses several different out-of-distribution detection mechanisms designed in coordination to mitigate some of the performance tradeoffs associated with watchdog development.

While leveraging multiple detection mechanisms, the watchdog concept can be further improved using data augmentation techniques. The watchdog relies on the assessment of the boundary of the latent space in the autoencoder.

Without using an autoencoder, classification boundary points can be found directly from the trained neural network classifier using neural network inversion [9], [11], [26]–[30], [33], [43], [51], [63], [64]. Here, a boundary point location is specified at the output of a trained neural network and the corresponding input is found.

Data augmentation has moved beyond neural network inversion techniques with the development of GANs [18]. Training data can now be generated using a variety of GANs [32], [37], [39]. Papers presented by Creswell et al. [10] and Goodfellow et al. [19] provide excellent reviews of the capabilities of GANs. Work done by Zhu et al. and previous work demonstrates the use of GANs in the development of augmented training data [3], [70].

### III. THE NEURAL NETWORK WATCHDOG

The neural network watchdog has been successfully demonstrated as a method to improve classifier performance with mixed-distribution input data [5], [6], [14]. The watchdog first uses a generative component to reconstruct input data, such as an autoencoder. The reconstruction is then compared to the original input data using an error function. An application-specific criterion is then used to determine input validity, and whether or not the original input will be passed into the classifier. Figure 1 shows an example of how data flows through a watchdog guarded image classification network.

#### A. Network Structures

The neural network watchdog can be implemented in a variety of architectures, including disjointed, symbiotic, and multi-tiered. Examples of these architectures can be seen in Figures 2, 3, and 4. Discussions about the differences and trade offs between disjointed, symbiotic and multi-tiered architectures can be found in previous work [3], [6].

The disjointed watchdog (see Fig. 2) consists of a regenerative autoencoder and a primary classifying neural network, which are trained independently using the same training data [5]. The selection of an error function is based on the desired system performance.

The symbiotic watchdog (see Fig. 3) consists of a single-input multi-output hybrid generator/classifier network [6]. The network is trained on a single dataset, with bias towards classifier or generator as necessary. As seen in Figure 3,

both the generated output and classification are produced simultaneously. In order to determine input validity, the generated reconstruction is provided to an error function, and the classification output is only used when the generated reconstruction meets the determined error criteria.

The multi-tiered watchdog (see Fig. 4) is comprised of multiple layers of outlier detection techniques, such as a combined autoencoder and binary classifier [3]. With multiple watchdog layers, layers can be individually tuned in order to achieve the desired results.

#### B. Watchdog Threshold Functions

Fundamental to the successful implementation of a neural network watchdog is the selection of an appropriate threshold function. Previous work demonstrates the use of a root mean squared error based threshold function [3], [5], [6].

#### C. Generative Augmentation

Data augmentation is a common practice to help improve the accuracy of a neural network. Data augmentation can occur in a variety of ways, such as image manipulation and data generation. Previous work [3] uses a GAN to generate training data to be used with a binary classification layer. The additional training data can be used a number of ways:

- 1) Increased amount of training examples for unbalanced datasets.
- 2) Training a binary classifier for in and out of distribution detection.
- 3) Create a  $(N + 1)$ th class to an existing classifier for unrecognized inputs.

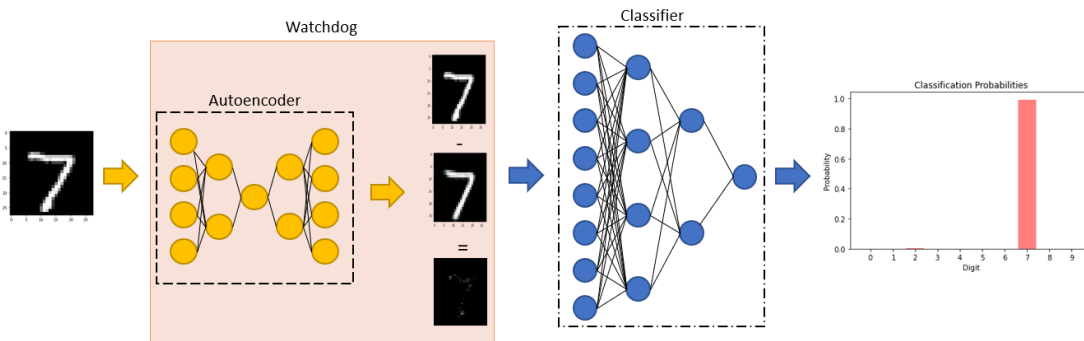


Fig. 1: An example of image data flowing through a watchdog guarded image classifier.

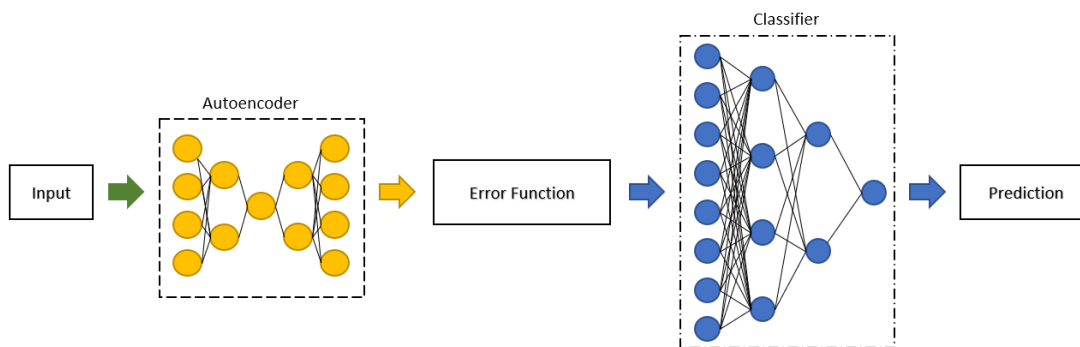


Fig. 2: The general structure of a Disjointed Watchdog.

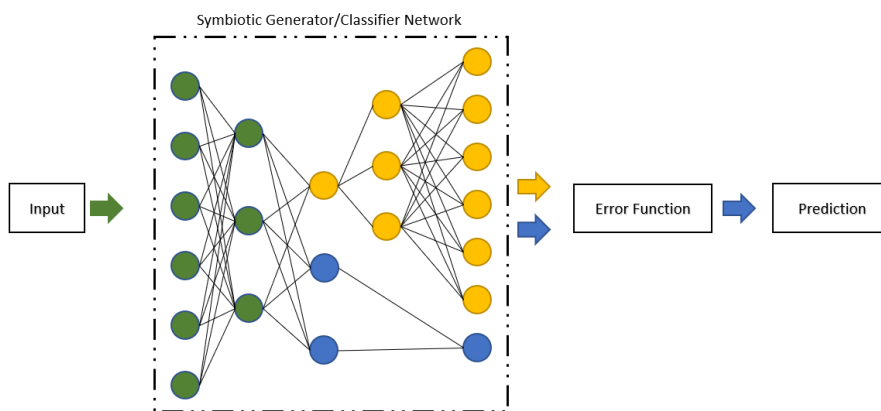


Fig. 3: The general structure of a Symbiotic Watchdog.

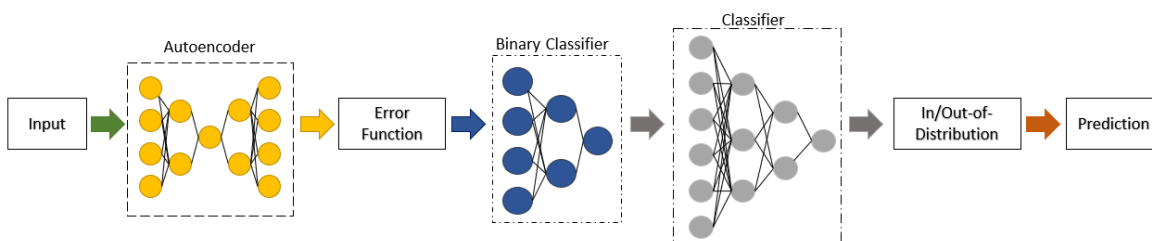


Fig. 4: The general structure of a Multi-tiered Watchdog Structure

## IV. RESULTS

This paper proposes a multi-tiered image classification watchdog for outlier detection and removal. The multi-tiered watchdog is added to the input data pipeline, which in turn feeds into the core classification network. By adding the watchdog to the data pipeline, out-of-distribution images are identified and discarded prior to presentation to the classification network. Doing so decreases computational load and improved mixed-distribution classification accuracy.

### A. Developing a Multi-tiered Watchdog

A multi-tiered watchdog consists of multiple outlier detection techniques that are combined sequentially. The first layer is comprised of an autoencoder and an error function. The second layer is a binary classifier to determine whether input data is in or out of distribution. The multi-tiered watchdog output is then fed in to a traditional multi-class convolutional neural network classifier.

### B. Training and Evaluation Datasets

To evaluate the efficacy of the multi-tiered watchdog, a combination of datasets will be used to train and evaluate the networks. The German Traffic Sign Benchmark (*GTSRB*) dataset [58] is used as the primary dataset, and is considered to be in-distribution. Examples of the *GTSRB* dataset, images of 43 different traffic signs, can be seen in Figure 5. Approximately 39,000 images are used to train the watchdog and core classifier with an additional 12,600 images to be used to independently evaluate all of the networks.

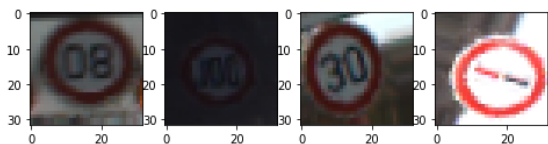


Fig. 5: Examples from the in-distribution German traffic sign dataset.

To augment the evaluation dataset, 10,000 additional images will be used from each the CIFAR-10 and CIFAR-100 datasets to create a 32,600 image mixed distribution dataset. In order to effectively evaluate the networks two series of labels are used for this dataset. The first is the original image label, and the second is a binary label corresponding to either in or out of distribution. These series of labels will allow for an effective evaluation of the core and binary classifiers. Examples of the CIFAR-10 and CIFAR-100 images can be seen in Figure 6.

### C. Training Process

In order to successfully train the multi-tiered watchdog, the training process is divided up into four sub-processes:

- 1) Train the autoencoder.
- 2) Define generative network parameters.
- 3) Train the binary classifier.
- 4) Train the core classifier.

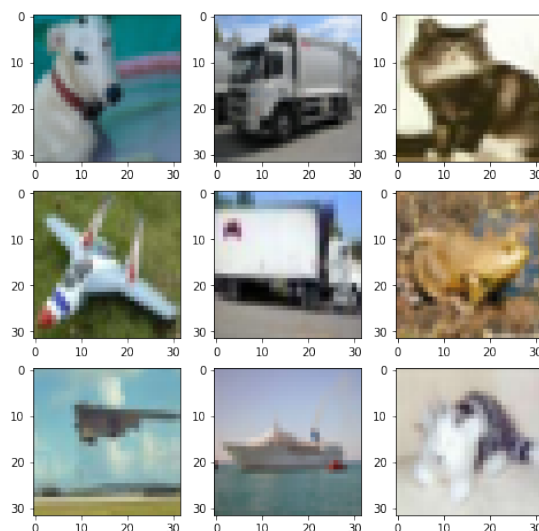


Fig. 6: Example images from the CIFAR-10 and CIFAR-100 datasets, which are added to create a mixed-distribution evaluation dataset.

The core classifier and autoencoder can be trained independently. The generator and binary classifier are dependent on the performance of the autoencoder, and therefore must be trained after. Both the autoencoder and the core classifier will be trained on the in-distribution *GTSRB* images. The binary classifier is then trained on a combination of in-distribution *GTSRB* images, as well as near boundary images created by the generator [3].

1) *Training the Autoencoder*: The autoencoder is trained on in-distribution data, with the intent to regenerate the input with minimal mean squared error. Unlike some datasets, such as the MNIST or CIFAR datasets, the *GTSRB* dataset has relatively low numbers of images per each class. To compensate for this fact, the training data is augmented using tools such as TensorFlow's built in Image or Keras APIs. Such tools allow for traditional image and computer vision processing techniques, including image rotation, cropping, flip, and grayscale conversion. This augmentation allows the autoencoder to produce higher quality results on relatively small training sets.

2) *Training the Binary Classifier*: A key component of training the binary classifier is the generation of new data. A generator is designed to create data which closely resembles near-threshold conditions [3]. The near threshold data is classified as out-of-distribution for training purposes. Once the parameters have been defined and additional training data has been generated, the binary classifier is trained to differentiate between in-distribution and generated out-of-distribution data. One important note is that as adjustments are made to the autoencoder, they must also be made to the generator and binary classifier.

3) *Training the Core Classifier*: The process for training the core classifier is similar to training the autoencoder. Training

data is augmented, as previously mentioned, through the use of the TensorFlow APIs, and the classifier is trained using categorical cross entropy training loss.

Figure 7 shows the training accuracy and losses for the classifier.

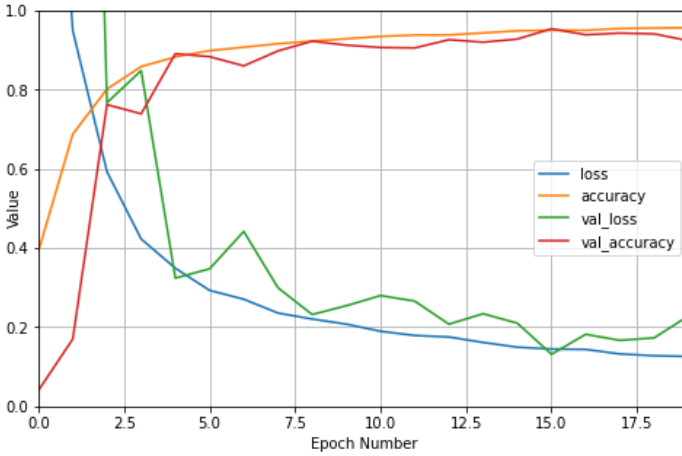


Fig. 7: Classifier training history for validation and training accuracy and losses. The validation dataset is a subset of the training data, and does not overlap with the data that will be used for evaluation.

## V. EVALUATING THE NETWORKS

Once all of the networks have been trained, they are evaluated using the mixed-distribution dataset. The individual performance of the core classifier, autoencoder and binary classifier are first individually evaluated. The autoencoder and binary classifier are then added to the data input pipeline, and the combined system is evaluated.

### A. Unguarded Core Classifier Performance

The performance of the core classifier is evaluated using both the German traffic sign and mixed-distribution datasets. The isolated performance of the classifier, as shown in Figure 8, is determined by evaluation using the in-distribution data, and serves as the performance baseline. The normalized performance of the core classifier can be seen in Figure 9.

In order to understand the impact of out-of-distribution data, the same evaluation is performed using the mixed-distribution dataset. The online performance of the core classifier, as shown in Figures 10 and 11, demonstrates the reduced accuracy due to out-of-distribution data. With a ratio of 1/3 in-distribution to 2/3 out-of-distribution data, our normalized accuracy and precision drops to approximately 33%, as expected.

### B. Autoencoder Performance and Threshold Selection

The performance of the autoencoder is evaluated by measuring the structural similarity score, defined in Equation 1, of the original and regenerated images and comparing it

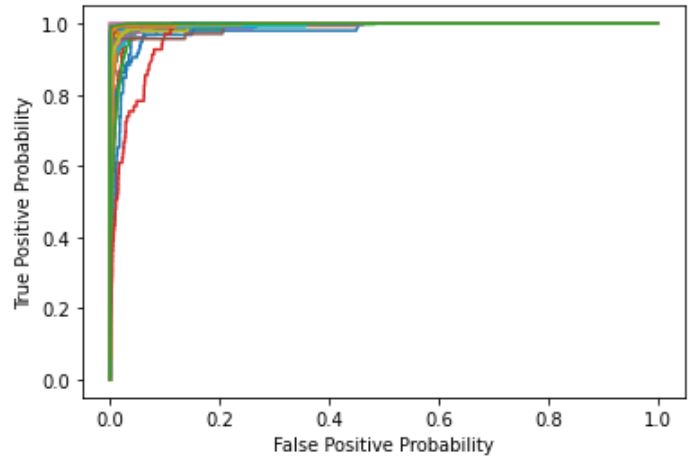


Fig. 8: The ROC curves of the core classifier performance evaluated on the 43 independent classes of the *GTSRB* dataset.

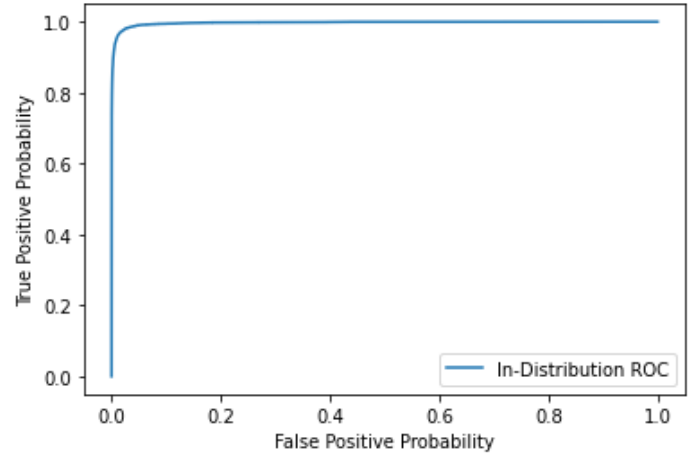


Fig. 9: The normalized ROC curve of the core classifier performance on the *GTSRB* dataset.

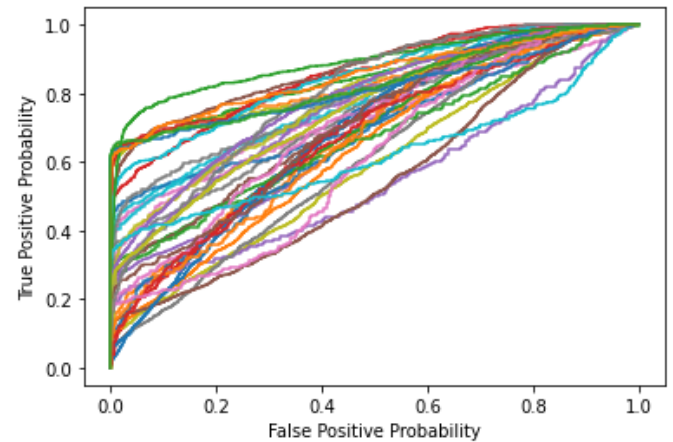


Fig. 10: The ROC curves of the core classifier performance evaluated on the mixed distribution dataset.

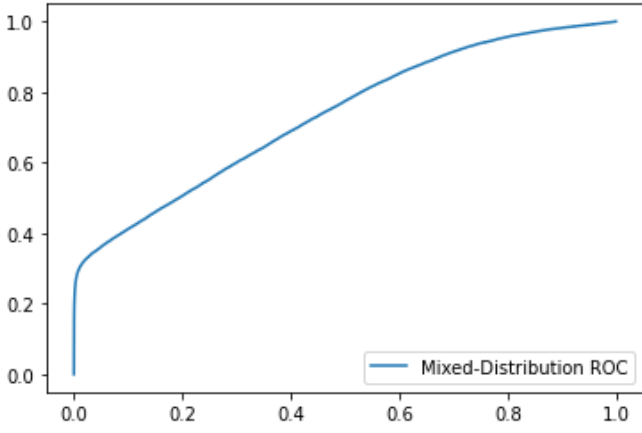


Fig. 11: The normalized ROC curve of core classifier performance evaluated on the mixed distribution dataset.

to the determined structural similarity threshold value. Figure 18 shows the ROC curve for binary classification of in-distribution vs out-of-distributed as across several structural similarity thresholds.

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + C_1) + (2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \quad (1)$$

The constants  $C_1$  and  $C_2$  are defined by Equations 2 and 3, where  $L$  represents the data input range value, and  $K_1$  and  $K_2$  are constants  $\ll 1$  [65].

$$C_1 = (K_1 * L)^2 \quad (2)$$

$$C_2 = (K_2 * L)^2 \quad (3)$$

Examples of the autoencoder image regeneration can be seen in Figure 13, along with their original images in Figure 12 and the structural similarity difference in Figure 14. The structural similarity scores for these images are found in Table I.

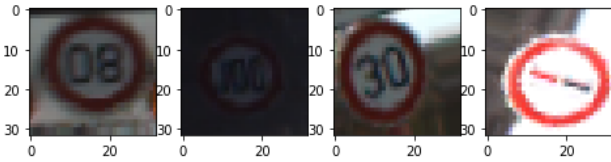


Fig. 12: The original *GTSRB* sign images.

As a reference, the autoencoder regeneration of a sample of CIFAR images is provided in Figure 16, as well as the respective original images in Figure 15 and the difference in Figure 17.

Based on these results, and depending on the desired level of protection, a structural similarity score of between 0.83 and 0.87 is an appropriate selection. For the remainder of this proof of concept, a structural similarity score of 0.85 is used.

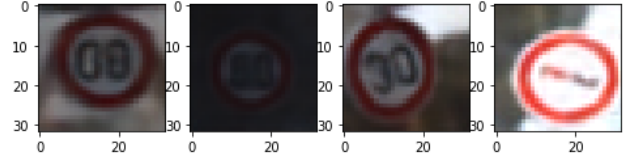


Fig. 13: An example of the autoencoder regenerated *GTSRB* sign images.

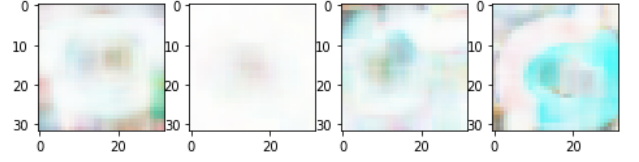


Fig. 14: The structural similarity images of the *GTSRB* examples.

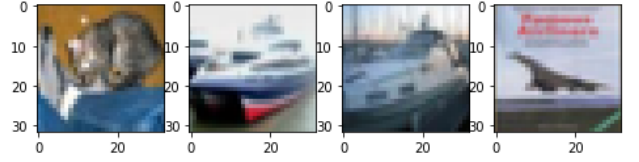


Fig. 15: The original CIFAR images.

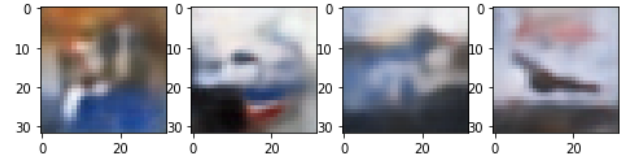


Fig. 16: An example of the autoencoder regenerated CIFAR images.

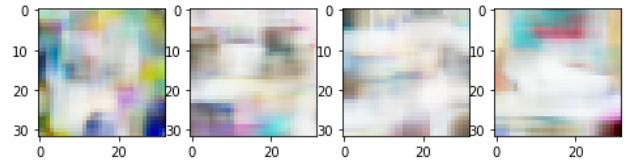


Fig. 17: The structural similarity images of the CIFAR examples.

TABLE I: Structural Similarity Scores

	Image 1	Image 2	Image 3	Image 4
Signs Scores:	0.9303	0.9715	0.9184	0.8903
CIFAR Scores:	0.7488	0.7767	0.8624	0.8318

### C. Binary Classifier Data Generation

With the baseline autoencoder trained and the error function established, a generative network is used to create additional training and evaluation data. The newly generated data is used to train the binary classifier. The generative network is

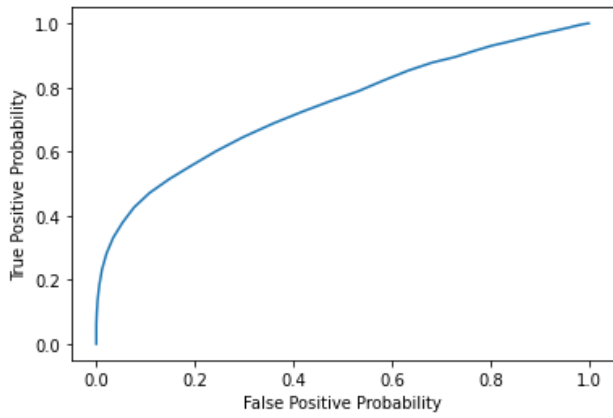


Fig. 18: The ROC curve for the autoencoder’s performance, as a function of structural similarity score.

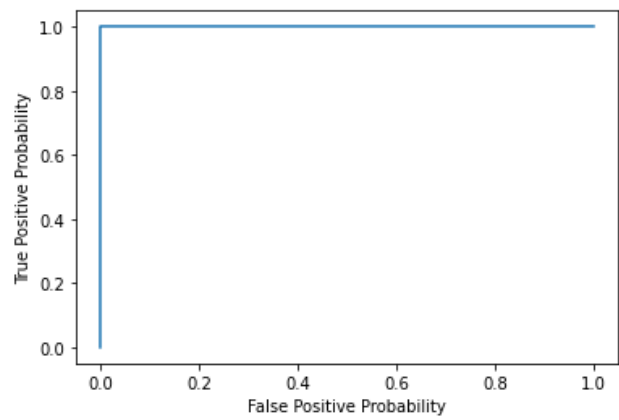


Fig. 20: The ROC curve for the binary classifier, evaluated on the generated test dataset.

designed to generate images with a target structural similarity score. Based on the previously selected 0.85 score, a target score of 0.90 will be used. Example generated images may be seen in Figure 19.

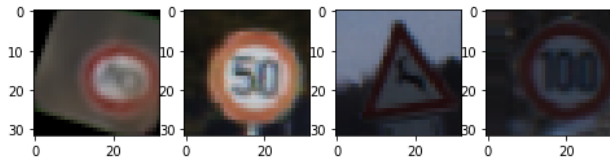


Fig. 19: Generated binary class images with a target structural similarity score of 0.90

#### D. Binary Classifier Performance

The performance of the binary classifier is evaluated on an independent subset of the generated data. The goal of the binary classifier is to differentiate between in- and out-of-distribution images that reside close to the dataset manifold which have been permitted by the autoencoder layer. The ROC curve for the binary classifier can be seen in Figure 20.

#### E. Final performance of the Guarded Classifier

The efficacy of the multi-tiered watchdog is determined by the combined performance of the autoencoder and the binary classifier. With the watchdog fully implemented, the final system performance is evaluated. The ROC curve seen in Figure 21 shows the watchdog guarded performance on the mixed-distribution evaluation dataset.

A final comparison of the ROC curves for the unguarded, guarded, and in-distribution only datasets may be seen in Figure 22. The introduction of the watchdog results in significantly improved performance when compared to the unguarded core classifier alone.

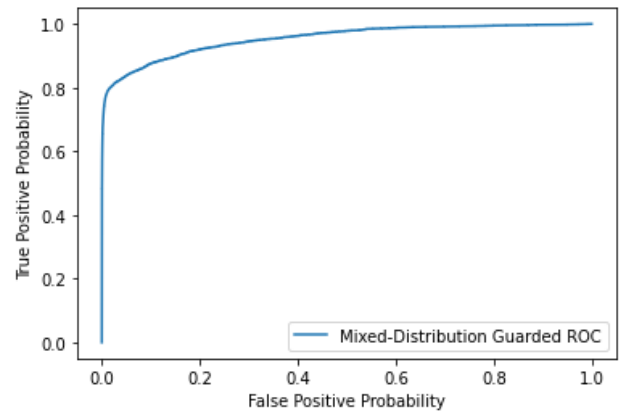


Fig. 21: The normalized ROC curve for the watchdog guarded image classifier.

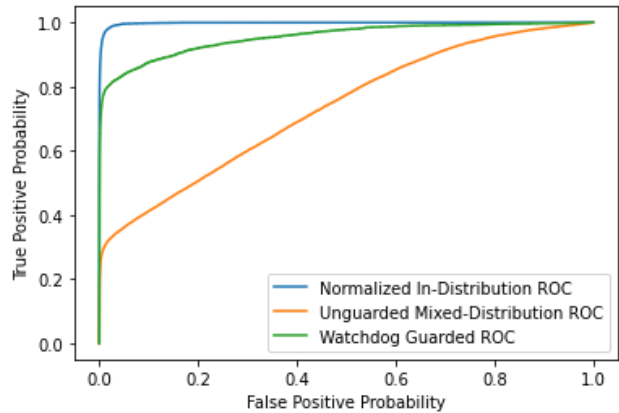


Fig. 22: The normalized ROC curves for the unguarded, watchdog guarded, and ideal core classifier.

## VI. CONCLUSION

A multi-tiered neural network watchdog is developed to improve online classification neural network performance with



respect to out-of-distribution data. A generative network is trained to produce data which resembles out-of-distribution data permitted by the autoencoder. A binary classifier is trained to differentiate between the permitted out-of-distribution data and in-distribution data. The combination of the autoencoder and binary classifier results in reliable out-of-distribution detection and filtering. The final results presented demonstrate classification improvements when evaluated on mixed-distribution input data.

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