TrustGAN: Training safe and trustworthy deep learning models through generative adversarial networks

Hélion du Mas des Bourboux
Thales SIX Theresis
1 av. Augustin Fresnel, 91120 Palaiseau, France
helion.dumasdesbourboux’at’thalesgroup.com

Abstract—Deep learning models have been developed for a variety of tasks and are deployed every day to work in real conditions. Some of these tasks are critical and models need to be trusted and safe, e.g., military communications or cancer diagnosis. These models are given real data, simulated data or combination of both and are trained to be highly predictive on them. However, gathering enough real data or simulating them to be representative of all the real conditions is: costly, sometimes impossible due to confidentiality and most of the time impossible. Indeed, real conditions are constantly changing and sometimes are intractable. A solution is to deploy machine learning models that are able to give predictions when they are confident enough otherwise raise a flag or abstain. One issue is that standard models easily fail at detecting out-of-distribution samples where their predictions are unreliable.

We present here TrustGAN, a generative adversarial network pipeline targeting trustiness. It is a deep learning pipeline which improves a target model estimation of the confidence without impacting its predictive power. The pipeline can accept any given deep learning model which outputs a prediction and a confidence on this prediction. Moreover, the pipeline does not need to modify this target model. It can thus be easily deployed in a MLOps (Machine Learning Operations) setting.

The pipeline is applied here to a target classification model trained on MNIST data to recognise numbers based on images. We compare such a model when trained in the standard way and with TrustGAN. We show that on out-of-distribution samples, here FashionMNIST and CIFAR10, the estimated confidence is largely reduced. We observe similar conclusions for a classification model trained on 1D radio signals from AugMod, tested on RML2016.04C. We also publicly release the code.

Index Terms—Machine Learning, Deep Learning, Trust-AI, Safe-AI, Confidence, Out-of-distribution

I. INTRODUCTION

Deep learning models are being deployed for a large variety of tasks. Even though a lot of these tasks do not primarily require decisions to be confident, e.g., advertisement or content suggestions, regulators around the world are expecting companies to build safer and trustable artificial intelligent (AI) systems (e.g., the European Union proposal for AI regulation [1]). Other AI tasks, especially for critical infrastructures, need to be robust and safe at their core before being deployed in the real world, e.g., secured communication systems, radio surveillance, navigation systems. Building safe deep learning models which can be trusted in the real world is a complex objective. One could think of gathering enough data, but that solution is either too costly, impossible due to confidentiality issues or simply impossible. Indeed a lot of tasks are constantly evolving, e.g., face masks after the covid-19 pandemic and their effect on face recognition systems (c.f. [2]). One could think of modeling the data, but this is not possible in all situations.

One solution is to build a deep learning model which is as successful on a task as possible, but which also is able to raise a flag or abstain if it is not confident enough. Such a deep learning network returns now both a decision and an estimated confidence on the decision. This confidence needs to be robust to rare samples in the training set and more importantly to out-of-distribution (OoD) samples. These samples are data unknown to the network, e.g., if building a classifier to recognise helicopters from planes, a realistic OoD sample could be the image of a bird. Then a robust AI system has to return a low confidence for such an image. Gathering OoD samples or worse OoD data sets is very tedious and most of the time impossible, for similar reasons as the ones discussed above for training data sets.

Standard training pipelines for deep learning models do not focus on the estimation of the confidence on OoD. Instead these pipelines focus on getting the best performances on the training data set. That being said, most machine learning
models still output an estimation of the confidence on their decision, e.g. the maximum class probability (MCP). The estimation is known to be unreliable and overestimated (see for example [3]). We show an example of such a flaw in figure 1 where a number classifier, efficient at its task, robustly classifies the image of a pangolin as the digit 5 (red boxes).

We present here TrustGAN, a generative adversarial network (GAN [4]) pipeline targeting trustness and confidence. The goal of this pipeline is to attack the confidence estimated by a target model in order to improve upon it. We present the effect TrustGAN can have on in-distribution (ID) and OoD samples in figure 1 (green boxes). The idea of the pipeline starts with the understanding that since OoD samples are hard or impossible to gather and train on, then we could leave a GAN learning to produce them. Through these generated adversarial samples, the target network would learn both to be efficient at its target task and to understand what ID samples look like.

TrustGAN is composed of two neural networks:

1) a “target model” we want to be both as good as can be on a given task on a training data set, and be able to produce reliable confidence score on ID and OoD samples;
2) a “confidence-attacker” network, i.e. a GAN, whose goal is to attack the confidence of the target network.

We publicly release the code at github/ThalesGroup/trustGAN

Other works target at improving the estimated confidence a neural network can have on its predictions. TrustGAN can either replace some or work jointly in a confidence improvement pipeline. Among the literature, [5] uses extra layers as confidence estimations. [3] for example trains an extra neural network to output confidence scores by learning to tell when the target neural network fails on the training data set. Other works like [6] uses a GAN to learn a discriminator as a confidence estimator. Their work is similar to ours, but implies that two different networks have to be deployed on the target hardware: the target network for the prediction and the discriminator for the estimated confidence.

To demonstrate how TrustGAN works and its performances, we first present in section II the training pipeline: the specificities of the neural networks, of the different training losses, and of the training process. Then we present in section III the application of TrustGAN to the classification of numbers based on their images and the classification of radio signal modulations based on raw data. Finally we conclude and draw perspectives in section IV

II. ADVERSARIAL NETWORK FOR IMPROVED CONFIDENCE

We present in this section the TrustGAN pipeline, that aims at training a given neural network while improving its estimated confidence on in-distribution and out-of-distribution samples.

https://github.com/ThalesGroup/trustGAN

A. A target model and its confidence-attacker

The TrustGAN pipeline is presented in figure 2. It improves a neural network model, the target, that outputs a decision, e.g. a classification, and a confidence on the given decision. The estimated confidence on the decision can be defined in a variety of ways. We work here in the most popular way, when working on a classification task: the confidence is given by the maximum class probability (MCP [7]). It is defined by:

$$MCP = \max_{0 \leq i < n} \hat{s}_i,$$

where $n$ is the number of classes, $\hat{s}_i$ is the score (or probability) for class $i$ estimated by the target network. With this definition, MCP is between $1/n$, i.e. a random prediction and 1, i.e. 100% confidence. We define then the confidence by a re-normalization of the estimated score $\hat{s}_i$ in order for the confidence to be a number between 0 (not confident) and 1 (very confident):

$$\hat{C}_i = \frac{\hat{s}_i - \frac{1}{n}}{1 - \frac{1}{n}}.$$

It is this confidence we aim at improving, while not hurting the predictive power of the target model.

The target model is presented in blue in figure 2 given an input data, it returns a decision and a confidence. The

![TrustGAN Diagram](https://example.com/trustgan_diagram.png)

Fig. 2. Presentation of the training process for TrustGAN. A target neural network in blue is improved through an adversarial network in yellow targeting its confidence. In this diagram, red lines show inputs used only during training, black lines are both for training and inference.

pipeline does not need to change the target model, however it must be provided with a trainable white box implementation (e.g. Keras [8] or PyTorch [9]) and its training metric (i.e. the training loss). The fact that no changes have to be made on the target model, allows TrustGAN to be agnostic and thus adapt to a large variety of cases. The model parameters will be updated, if the model has been trained beforehand or simply learned from start otherwise.

Beside the target model, a generative adversarial network (GAN: [4]) aims at fooling the target model into being confident on arbitrary inputs. This confident attacker (yellow box on figure 2) generates attacks, i.e. target inputs, from
random data. This attacker must be tailored to the inputs the target model accepts. For example, if the target model is a classifier running on images, the attacker must generate from a vector of random numbers an image. However, if the target model is a classifier running on 1D radio signals, the attacker must then generate 1D data.

In the configuration of figure 2 no extra model is needed. The role of the discriminator which tells if a sample is from the training distribution or not, and which is standard in GANs, is played by the target network itself, through a confidence loss. This simple but special loss is described below (c.f. eqn. 3). Other works, e.g. [6], add a discriminator to estimate the entropy loss. This task is presented on figure 2 by “Loss on decision”.

In order to train both the target and the confidence-attacker model, a training set and a validation set must be provided. Furthermore, as said above, the target model loss must also be provided. We detail below the training process, given in the black and red lines of figure 2.

B. Training the target model

The objective of the target model is two folds:

1) be skilled at the task it has been designed for. This task is defined by the loss provided alongside the target model definition, and is estimated on the training set;
2) refuse to be confident on data where it can not be, for example samples under represented in the training set or on out-of-distribution samples. These samples are represented by the data generated by the confidence-attacker.

These two goals can compete. For example one method to succeed in the second task is to never be confident on any decisions, and thus never provide a decision. This goes against the goal of the first task. The training pipeline has thus to find a balance between these two goals.

For task number 1, the training loss $L_{00}$ is given by the provided loss on the task the target network is aiming at, for example a classification model could be trained with the cross-entropy loss. This simple but special loss is described below (c.f. eqn. 3). Other works, e.g. [6], add a discriminator to estimate the entropy loss. This task is presented on figure 2 by “Loss on decision”.

For task number 2, the training loss aims at setting the confidence to what it would be for a random decision if the decision is:

1) from random numbers generate data to fool the target network into being confident on its decision, whatever the decision is;
2) from different random numbers generate different samples;
3) from different random numbers induce different decisions of the target network.

The first task aims at improving the estimated confidence by attacking it, the other two are diversity tasks, aiming at attacking different aspects of the target model. These different tasks do not compete and can be obtained easily together. However, they do compete with the two objectives of the target network. The training pipeline has thus to find a balance between these different goals.

For task number 1, the training loss is obtained by finding the class where the confidence is maximum:

$$L_{10} = - \frac{1}{\log n} \max_{0 \leq i < n} \log \hat{s}_i$$

$$= \frac{1}{\log n} \times \left( - \max_{0 \leq i < n} (\hat{l}_i) + \log \sum_{i=0}^{n-1} \exp \hat{l}_i \right).$$

This training loss is thus pushing the confidence-attacker at generating samples where the target model confidence is $C_i = 1$ at one of the classes and 0 elsewhere.

For task number 2, the goal is to generate diverse samples, if the random numbers differ. The training loss is thus here defined by:

$$L_{11} = \frac{1}{\sum_{j=0}^{N-1} \sum_{k=0}^{j-1} |r_j - r_k|^m} \times \sum_{j=0}^{N-1} \sum_{k=0}^{j-1} \frac{|a_j - a_k|^m}{1 + |a_j - a_k|^m}.$$ 

In this equation $j$ and $k$ are two different samples of a given set with $N$ samples. This set can be for example a batch or a sub-sample of the batch, for faster computation. For example, one can choose $N = n$. The confidence-attacker model produces the adversarial sample $a_j$ from the random numbers $r_j$ for the sample $j$. The random numbers of the vector $r_j$ are sampled from the uniform distribution $U([0, 1])$. In this equation $m$ gives the order of the $m$-norm, typically $m = 2$. This loss $L_{11}$ goes to 0 if the generated samples are very different.

In a similar way, task number 3, compares the target model outputs:

$$L_{12} = \frac{1}{\sum_{j=0}^{N-1} \sum_{k=0}^{j-1} |r_j - r_k|^m} \times \sum_{j=0}^{N-1} \sum_{k=0}^{j-1} \frac{|s_j - s_k|^m}{1 + \sum_{o=n}^{n-1} s_j o \log \hat{s}_k o}.$$
In this equation, $s^i_{jo}$ is the predicted score by the target model on the adversely generated sample $j$ of data $a_j$ for the class $o$. This loss $L_{12}$ goes to 0 if the generated scores are very different.

These three losses are combined into a single one:

$$L_{13} = \frac{1}{3} (L_{10} + L_{11} + L_{12}), \quad (8)$$

and are presented as "Loss on attack confidence and generated diversity" in figure 2.

D. Training pipeline

In order to obtain a target neural network, efficient at finding a decision and estimating a robust confidence given a sample data, we must apply the TrustGAN training pipeline. This pipeline is composed of three major steps per batch:

1) train the confident-attacker model using random numbers with $L_{13}$;
2) train the target model on adversely generated data with $L_{01}$;
3) train the target model on data from the training set with $L_{00}$.

These three steps are repeated for all epochs and for all batch in an epoch. Different checkpoints are stored to follow the evolution of the different losses during training, on both the training set and the validation set. We store per epoch the state of the best GAN of the epoch and the current state of the training set and the validation set. We store per epoch the evolution of the different losses during training, on both the training set and the validation set. We store per epoch the state of the best GAN of the epoch and the current state of the training set and the validation set. We store per epoch the state of the best GAN of the epoch and the current state of the training set and the validation set. We store per epoch the state of the best GAN of the epoch and the current state of the training set and the validation set. We store per epoch the state of the best GAN of the epoch and the current state of the training set and the validation set. We store per epoch the state of the best GAN of the epoch and the current state of the training set and the validation set. We store per epoch the state of the best GAN of the epoch and the current state of the training set and the validation set. We store per epoch the state of the best GAN of the epoch and the current state of the training set and the validation set. We store per epoch the state of the best GAN of the epoch and the current state of the training set and the validation set.

Different parameters can be set to tune the relative power of the different losses and attacks:

- number of training epochs;
- batch size;
- number of epochs the target model is trained alone, i.e. only step 3, default value is 0;
- number of step 1 for one step 3, default value is 1;
- number of step 2 for one step 3, default value is 1;
- random proportion of times step 1 and 2 are skipped, default value is 0%;
- random proportion of times adversarial samples are generated from a random GAN checkpoints instead of the current GAN state for step 2, default value is 10%.

Finally, we observe that it is best to design a simple GAN, with largely less parameters than the target model. This allows to limit the available attacks the GAN can perform on the target model, and thus do not prevent the target model from learning the target task.

We store at each epoch different metrics: all the training losses. They allow to track the learning process. We also store at each epoch generated adversarial samples: the best attack of the epoch and a random one at the end of the epoch. They allow to visually understand, when possible, what the GAN is learning. The available metrics can help choose the best target model, on the validation set, given a compromise between the performances of the decisions and the estimation of the confidence. We here keep the best model according to the validation loss.

E. Inference

After TrustGAN training, the target model is expected to give both good predictions and robust estimated confidence. This model can thus be deployed as all standard models would be, i.e. during inference we drop all red lines and boxes of figure 2 and drop the confidence-attacker model.

Thanks to the re-normalization of the maximum class probability (eqn. 2), the confidence is provided between 0 (the decision is not confident) and 1 (the decision is confident). This allows a user to now set a threshold $t$ on the confidence, and for a given sample $i$, infer and get $(d_i, C_i)$: the decision and its estimated confidence. We now have:

- if $C_i < t$ then the result is not confident enough, raise a flag or abstain from acting;
- if $C_i \geq t$ then the decision is $d_i$.

The threshold $t$ can be set by a user according to a balance between rejections, i.e. needs a human decision, and automatic decisions by the neural network.

III. APPLICATION TO CLASSIFICATION TASKS

We test the TrustGAN training pipeline and compare it to a standard training pipeline in two different applications: classification of numbers and classification of radio signals. A standard training pipeline can be obtained easily from section II by setting the number of epochs the target model is trained alone to be larger than the actual number of epochs. This allows to guarantee both standard and TrustGAN training are comparable.

A. Classification of numbers

We apply TrustGAN training pipeline to the simple task of the classification of numbers given an image. We use the MNIST (Modified National Institute of Standards and Technology) data set from [11]. The task is thus a classification of 28 pixels by 28 pixels images with only one channel onto 10 classes. The training loss is thus a cross-entropy. The input images are min-max normalized over all channels, then rescaled to $[-1,1]$. If all pixels have the same values, they are all set to 0.

Our target model is a 2D temporal convolutional neural network with residual connections (see [12], [13] and [14]) inspired by the architecture of [15]. Their structure is independent of the image length and width, and depends only on the number of channels. This allows to test the architecture on random images of any sizes, for example from the internet (e.g. figure 1). It allows then to simply test how robust the network is against out-of-distribution samples.

The architecture of the confidence-attacker network is the same as that of the target model. It only differs by few aspects. First, instead of a classification head, the network outputs images. Second, the network is less deep than the target network. This allows the GAN to attack the target model.
without preventing the latter from learning the target task. Third, we use LeakyReLU (see [16]), instead of ReLU (see [17]), which is known to be more adapted for GANs. Finally, for similar reasons we replace weight norm layers (see [18]) by batchnorm layers (see [19]). A tensor of random numbers of the same shape as the training set images is given to the model, which then outputs through a hyperbolic tangent (tanh) activation layer a generated image.

The number of training epochs for the standard pipeline and for the TrustGAN pipeline is set to an arbitrary high number (here 10 000). Both pipelines are stopped when no learning on the target loss is observed, on the validation set. We periodically visually track the generated images to see if the GAN is learning useful attacks.

Both the target loss and the target error rate learning history are shown on figure 3. We observe on both of the panels that with the TrustGAN pipeline the target network takes more time to get similar performances as the same model trained in the standard way. This is expected, since with TrustGAN the target model is learning the task while being attacked, which slows down learning. However after some time, both models have similar performances in term of both loss and error rate. Appendix A presents some randomly sampled GAN generated images.

In order to observe the resulting behavior of the estimated confidence, we use two publicly available data sets as out-of-distribution samples: FashionMNIST from [20] and CIFAR10 (Canadian Institute for Advanced Research) from [21]. FashionMNIST is composed of black and white images of clothes, and thus can be used without transformations. CIFAR10 is composed of colored images of animals and vehicles; we select then only the first color channel of each image.

A random selection of the images in both of the OoD data sets are inferred by our MNIST classifiers. We thus get both
a class and an estimated confidence on this class. Figure 4 presents the distribution of the confidence for a model trained with a standard pipeline (blue) and with the TrustGAN pipeline (orange). The left panel presents the results for FashionMNIST and the right panel for CIFAR10. We observe in both cases that TrustGAN allows to push the confidence of OoD to low values, i.e. both orange distributions are peaked at 0% confidence. At the contrary, the standard model gives relatively high confidences on these OoD samples. This comparison shows how the TrustGAN pipeline helped the target model not to be confident on OoD samples.

B. Classification of radio signals

The same experiment is conducted on 1D radio signals. We benefit from the publicly available data set AugMod of [13] to train a target model to recognise radio signal modulations in raw 1D I/Q signals. The target model of section III-A is modified to accept data with two channels, and 1D data. The latter is simply performed by replacing 2D convolutions with 1D convolutions. We modify in the same way the GAN. After both standard and TrustGAN training we obtain similar performances in term of accuracy (c.f. table I).

As for section III-A we examine the behavior of the estimated confidence with out-of-distribution samples. The publicly available RML2016.04C data set from [22] is trimmed from modulations also present in the AugMod data set. The resulting distribution of the inferred confidence is presented on figure 5. We observe similarly that the target model is able to better estimate its confidence on these out-of-distribution samples.

C. Quantitative results

Table I presents quantitative results for the different tasks defined above:

- MNIST-vs-FashionMNIST, where ID are MNIST and OoD are FashionMNIST;
- MNIST-vs-CIFAR10, where ID are MNIST and OoD are CIFAR10 first color channel;
- AugMod-vs-RML2016.04C, where ID are AugMod and OoD are RML2016.04C without modulations also present in AugMod.

We present results of the estimated MCP (maximum class probability, eqn. 2) for each task and for both a standard training pipeline (“Std., MCP”) and the proposed pipeline (“TrustGAN, MCP”). Along with MCP we present the results of Monte-Carlo Dropout (MCDropout, [5]) evaluated on both the standardly trained model (“Std., MCDropout”) and the TrustGAN model (“TrustGAN, MCDropout”). MCDropout is performed with a mean of the softmax probabilities over 10 realizations, using the dropout layer defined in the target network, applied on the penultimate layer, with a rate of 0.3. The performances of the different techniques are measured on different metrics estimated on the test sets:

- accuracy (recall, true positive rate) of the ID test samples (higher the better);
- mean loss of the ID test samples (lower the better);
- TPR@≥0.xx C, true positive rate at larger than 0.xx confidence (higher the better);
- FPRID@≥0.xx C, false positive rate of in-distribution samples at larger than 0.xx confidence (lower the better);
- FPRID@0.xxTPR, false positive rate of ID samples at 0.xx true positive rate (lower the better);
- mean confidence of the OoD test samples (lower the better);
- FPOoD@≥0.xx C, false positive rate of out-of-distribution samples at larger than 0.xx confidence (lower the better);
- FPOoD@0.xxTPR, false positive rate of OoD samples at 0.xx true positive rate (lower the better).

In the context of a classification task, the true positive rate (recall) is similar to the accuracy, defined as a function of the confidence threshold $C$ on in-distribution samples (ID):

$$TPR(C) = \frac{1}{N_{ID}} \sum_{i \in ID} \mathbb{1}_{y_i = y_i} \times \mathbb{1}_{\hat{C}_i \geq C}. \quad (9)$$

The false positive rate on ID samples is defined as:

$$FPR_{ID}(C) = \frac{1}{N_{ID}} \sum_{i \in ID} \mathbb{1}_{y_i \neq y_i} \times \mathbb{1}_{\hat{C}_i \geq C}. \quad (10)$$

Finally, the false positive rate on out-of-distribution (OoD) samples is defined as:

$$FPR_{OoD}(C) = \frac{1}{N_{OoD}} \sum_{i \in OoD} \mathbb{1}_{\hat{C}_i \geq C}. \quad (11)$$

We can observe from this table I that on the ID testset the estimated metrics are similar between the two training techniques. However, on OoD samples, TrustGAN produces significantly best scores. We observe that MCDropout alone improves the performances for the standard models, however...
TABLE I

|                           | Accuracy ↑ (ID) | Loss ↓ (ID) | TPR@0.90C ↑ (ID) | FPR@0.90C ↓ (ID) | FPR@0.90TPR ↓ (ID) | Confidence ↓ (OoD) | FPR@0.90C ↓ (OoD) | FPR@0.90TPR ↓ (OoD vs. ID) |
|---------------------------|----------------|-------------|------------------|-----------------|-------------------|-------------------|-------------------|-----------------------------|
| MNIST-vs-FashionMNIST     |                |             |                  |                 |                   |                   |                   |                             |
| Std., MCP                 | 0.99           | 0.034       | 0.98             | 0.0042          | 0.00019           | 0.84              | 0.57              | 0.15                        |
| Std., MCDropout           | 0.97           | 0.024       | 0.98             | 0.0032          | 0.000020          | 0.76              | 0.41              | 0.13                        |
| TrustGAN, MCP             | 0.99           | 0.027       | 0.97             | 0.0022          | 0.000020          | 0.030             | 0.00080           | 0.0                          |
| TrustGAN, MCDropout       |               |             |                  |                 |                   |                   |                   |                             |
| MNIST-vs-CIFAR10          |                |             |                  |                 |                   |                   |                   |                             |
| Std., MCP                 | 0.71           | 0.28        | 0.71             | 0.0039          | 0.00057           | 0.93              | 0.81              | 0.60                        |
| Std., MCDropout           | 0.62           | 0.15        | 0.62             | 0.0024          | 0.0018            | 0.82              | 0.50              | 0.46                        |
| TrustGAN, MCP             | 0.031          | 0.0018      | 0.031            | 0.0007          | 0.000020          | 0.00060           | 0.00018           | 0.00020                     |
| TrustGAN, MCDropout       | 0.029          | 0.0014      | 0.029            | 0.0015          | 0.0016            | 0.0057            | 0.0014            | 0.0                          |
| AugMod-vs-RML2016.04C     |                |             |                  |                 |                   |                   |                   |                             |
| Std., MCP                 | 0.98           | 0.042       | 0.96             | 0.0039          | 0.00057           | 0.93              | 0.81              | 0.60                        |
| Std., MCDropout           | 0.92           | 0.0024      | 0.92             | 0.00024         | 0.0018            | 0.82              | 0.50              | 0.46                        |
| TrustGAN, MCP             | 0.95           | 0.0027      | 0.95             | 0.00070         | 0.000070          | 0.0060            | 0.000070          | 0.0                          |
| TrustGAN, MCDropout       | 0.89           | 0.0015      | 0.89             | 0.0016          | 0.0016            | 0.0057            | 0.0015            | 0.0                          |

either TrustGAN alone or TrustGAN combined with MCDropout are systematically better. It is important to remember that all these results are observed even though the network has never seen these specific OODs during training, but has only been presented GAN generated samples instead.

IV. Conclusion

In this study we presented a novel training pipeline, TrustGAN, designed to robustify the estimated confidence a deep learning model returns on a given prediction. This pipeline allows to improve the behavior a given model has with respect to out-of-distribution samples or samples rare enough in the training set.

This TrustGAN pipeline does not need to change the target model in any ways, except by updating its learned weights if the model is provided already trained. The pipeline also requires a trainable white-box implementation of the target model and of its training loss. A generative adversarial network will learn to attack the target model. These special attacks, targeting slowly the model confidence, result in a model as predictive as a standard one, but also able to tell when a given input is unknown or too complicated.

We test TrustGAN on two different tasks: the classification of numbers using 2D images of the MNIST data set, and the classification of the input radio modulation in raw 1D signals of the AugMod data set. On both of these tasks we observe no significant impact on the prediction accuracy, but a large positive impact on the estimated confidence.

In the future we would like to better quantify the performances of the TrustGAN pipeline in terms of the balance between missed prediction and out-of-distribution leakage on more datasets. Furthermore, we would like to compare the resulting confidence to other different confidence estimators and robustifiers, e.g. data augmentation methods and entropy methods. We would then study how TrustGAN could be integrated to these estimators and thus see how all could combine forces to improve the estimated confidence and bring even safer, trustworthy, and deployable deep learning models for critical systems.

APPENDIX

A. GAN generated images

In figure 6 we present some GAN generated images learned while training a classification neural network on the MNIST dataset. These images are randomly sampled after training is complete, furthermore they are produced through randomly picking GANs among all stored on discs and used for experience replays.

Fig. 6. GAN generated images learned while training a classification neural network on the MNIST dataset.

REFERENCES

[1] "Proposal for a regulation of the european parliament and of the council laying down harmonised rules on artificial intelligence (artificial intelligence act) and amending certain union legislative acts," eur-lex, 2021-04-21, [Online]. Available: https://eur-lex.europa.eu/legal-content/EN/ALL/?uri=CELEX:52021PC0206.
