# Impact of Using GAN Generated Synthetic Data for the Classification of Chemical Foam in Low Data Availability Environments

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Abstract: One of the main challenges of using machine learning in the chemical sector is a lack of qualitative labeled data. Data of certain events can be extremely rare, or very costly to generate, e.g. an anomaly during a production process. Even if data is available it often requires highly educated observers to correctly annotate the data. The performance of supervised classification algorithms can be drastically reduced when confronted with limited amounts of training data. Data augmentation is typically used in order to increase the amount of available training data but the risk exists of overfitting or loss of information. In recent years Generative Adversarial Networks have been able to generate realistically looking synthetic data, even on small amounts of training data. In this paper the feasibility of utilizing Generative Adversarial Network generated synthetic data to improve classification results will be demonstrated via a comparison with and without standard augmentation methods such as scaling, rotation,... . In this paper a methodology is proposed on how to combine original data and synthetic data to achieve the best classifier result and to quantitatively verify generalization of the classifier using an explainable AI method. The proposed methodology compares favourably to using no or standard augmentation methods in the case of classification of chemical foam.



## 1 INTRODUCTION

Augmenting available data is already widely used in most deep learning approaches focusing on image classification when presented with limited data. Scaling, translation, rotation,... are some of many standard augmenting techniques to increase the amount of training data artificially. However, this approach has some pitfalls. It is known that these augmentation techniques can lead for example, to overfitting or loss of information (Maharana et al., 2022; Connor and M., 2019). Extending the training dataset with synthetic but realistic images can have a beneficial effect compared to the traditional augmentation techniques.

Synthetic data can refer to manually created data in for example 3D tools such as Blender or it can refer to artificially generated data that is used to train machine learning models. In this paper the focus will lie on artificially generated data. Methods that are often used to generate new data are: variational autoencoders (VAEs) (Kingma and Welling, 2013) and generative adversarial networks (GANs) (Goodfellow et al., 2014). Synthetic data can be generated in a controlled environment, allowing for the creation of data points with specific characteristics and perfect ground truth labels. This enables the use of synthetic data to enhance the performance of classifiers under a wide range of conditions and to ensure that they are robust and generalize well to new data. A risk of using methods to generate synthetic data is when only limited amounts of data are available, is that not all features in the dataset will be equally incorporated in the trained model, and certain details may be left out in the synthetic data (Karras et al., 2020). When using this synthetic data to train a classifier this could lead to models that do not generalize well. One way to validate this, is by using explainable AI (XAI) (Ribeiro et al., 2016). This can help identify the features the classifier is based on and can help understand whether the trained model and the dataset have a problem or not.

This paper will compare the accuracy of a classifier trained on real data, real and augmented data and real data supplemented with synthetic data. The impact of the amount of available training data will also be investigated. All developed classifier models



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will be validated on the same validation dataset and generalization will be checked using explainable AI methods. By combining these steps, a methodology has been obtained that has been applied on a chemical foam dataset.

The dataset used for training and validation contains images of foam in a chemical production context. In the chemical production sector, the usage of cameras to monitor installations is starting to become integrated in the standard way of working. In most cases, these camera feeds are still monitored manually since often AI solutions do not yet exist or are not of high enough quality to be used in a live production process. The main reason few solutions for the chemical sector currently exist is due to the fact that relevant data are only available to a limited extent and collecting additional data is often expensive. Due to this reason, the ability to use data augmentation or synthetic data to increase the accuracy and robustness of machine learning models to automate detection of certain events with limited training data and how to interpret these will be investigated.

The remainder of the paper is organized as followed. Section 2 introduces related work. Section 3 describes the utilized method to generate new data, it describes the different experiments that have been executed as well as give insights in the chemical foaming dataset. Section 4 discusses the experimental results and performance of the different approaches as well as limitations. Section 5 reports final conclusions.

## 2 RELATED WORK

A short overview of related work will be presented in this section. The topics reviewed are augmentation techniques, synthetic data and explainable AI.

*Augmentation techniques* for image classification are commonly used due to their cost-effectiveness and user friendliness to increase the amount of training data with factors of thousands using annotation-preserving operations (Krizhevsky et al., 2012). Usage of augmentation techniques can increase model performance for tasks, such as classification, by overcoming the problem of inadequate or imbalanced datasets by introducing different variations in the input data, which can lead to improved generalization performance. (Kang et al., 2019), for example, combine the lightweight architecture of tiny-YOLOv3 with data augmentation to achieve a better fire detection model compared to other methods. (Agarwal et al., 2020) use data augmentation to increase the amount of data in an unbalanced dataset for classification of tomato leaf diseases. (Taylor and Nitschke, 2018) benchmarked commonly used data augmentation schemes to allow researchers to make informed decisions. However, one known shortcoming of data augmentation is the risk of overfitting or loss of information (Maharana et al., 2022; Connor and M., 2019). These risks appear especially when the augmentation transformations are too aggressive or inappropriate. It could be that, the model, instead of recognizing features of the original data, it starts to focus on the augmented patterns. A possible way to overcome this is by generating realistic looking synthetic data.

*Synthetic data* are artificially created data used to train machine and deep learning models. Synthetic data can be used as a valuable tool to generate realistic looking data. If the simulation-to-reality gap is sufficiently small, the generated data has the potential to be used during the training of classifiers. An often used method to generate synthetic data is through the usage of Generative Adversarial Networks (GANs) (Goodfellow et al., 2014). GANs consist out of two components. The first component is the generator. The generator produces new examples based on the distribution of the training data. The second component is the discriminator. The goal of the discriminator is to distinguish between generated examples and real training data examples. The generator tries to keep improving its generated examples in order to fool the discriminator, while the discriminator tries to correctly classify real and fake generated examples. This adversarial process improves both the generator as the discriminator. GANs have already been used in many fields. (Stuyck et al., 2022) use a GAN architecture to segment clouds using generated aerial images. (Nazki et al., 2019) use cyle-GAN to generate extra data to detect different plant diseases. (Bowles et al., 2018) use GANs to generate synthetic data for brain segmentation tasks. A possible risk of using synthetic data is that if a limited training dataset is available, not all features will be incorporated in the generated synthetic data, and classifier results may be biased towards specific classes (Karras et al., 2020). Explainable AI can be used to make sure the classifier model generalizes well by identifying and visualizing the features that the classifier is based on.

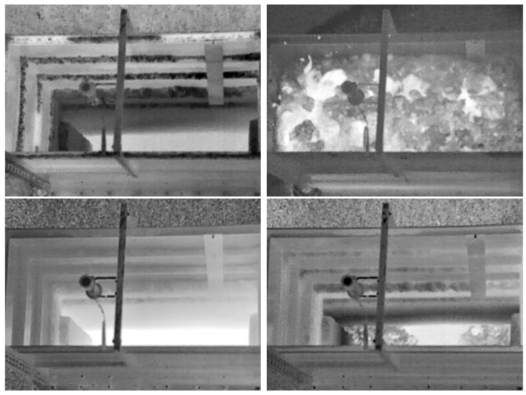
*Explainable AI* has received increasing attention in recent years. For applications in the chemical environment, but also other industrial or medical environments explainability and transparency of AI methods is of extreme importance for end users in correctly understanding the decision making process. An application in the medical world where explainable AI has been used, is in the classification of prostate cancer. (Hassan et al., 2022) compare multiple pre-trained networks for this classification task and use XAI to understand the key features that led the algorithm to make the respective decision and classification. A similar approach has been followed by (Mankodiya et al., 2022), who use XAI models to explain different segmentation models for autonomous vehicles. (Xu et al., 2019) give an overview of the history and current state-of-the-art approaches. (Schorr et al., 2021) use an explanation model named SHAP (Lundberg and Lee, 2017) to explain the categorization of land-use types on aerial images. The explanation model SHAP will also be utilised in the remainder of this work.

## 3 METHOD

In this work we will answer the following questions:

1. What is the impact of the amount of available real data on the accuracy of a classification algorithm on the chemical foam dataset?
2. Does enlarging the dataset using augmentation techniques or GAN generated synthetic data make a difference in the accuracy of a classification algorithm?
3. What is the impact of the amount of synthetic data?
4. Do the results of the classifier generalize well when synthetic data is used in combination with real data and how can we get insights in this generalization?
5. Can the decision regarding generalization of the model on the chemical foam dataset be automated?

In order to answer these questions for our specific dataset, 326 images of a production installation with foam and 424 images of the same production installation without foam were collected over the span of multiple weeks. These images are weakly labeled, meaning that these images were only labeled as either containing foam or labeled as not containing foam. For training, 200 images with foam and 298 images without foam were used. For validation and testing the remaining 126 images with and without foam were used. Figure 1 shows real images of the outdoor scene with foam and without foam. The observed foam can take any possible shape and volume. The images are taken from a production plant where foam can be formed at any moment. The amount of foam is unpredictable so it can be a very limited amount or it could be enough to overflow the buffer tank. It is



(a) No foam (b) Foam

Figure 1: Example images of the scene depicting the two possibles classes of normal (no foam) and foam. The amount of foam can vary from very limited to almost overflowing. For the normal case, the images vary only limited since the camera is static and no changing environment is visible besides possible weather phenomena and residual foam.

important that this foam can be identified before overflowing the buffer tank since the impact of overflowing can be very high due to the impact on safety of operators, a possible impact on the environment as well as the risk of early corrosion of nearby installations. The two right images on figure 1 show both possibilities. In the case no foam is present, there is only a limited amount of variation in the image since the camera and environment are static. The only changes come from weather phenomena such as day/night cycle and rain, mist, snow, ... and possible residue foam that remains on the buffer tank as is shown on the top left image on figure 1.

To be able to answer the above questions the amount of available data for training will be decreased artificially. For training 200 images with foam and 298 without foam are used. This is regarded as the complete dataset. The reduced datasets gradually decrease from the complete dataset to 25% of the original complete dataset in steps of 25% and finally to only 10% of the original complete dataset. This is done by randomly sampling the reduced amount of data from the complete dataset.

A classifier will be trained for all the created datasets. The results of the different classifiers will be used to get insights regarding the first question. Besides training classifiers on these newly created datasets, additional data will be generated using standard augmentation techniques and synthetic generated data from a GAN based on the different reduced datasets. Since there are only a limited amount of images available for training, a light-weight GAN structure proposed by (Liu et al., 2020) is used. The benefit of this light-weight GAN structure is that the model converges from scratch within hours, and has consistent performance even when used with limited amount of training samples as is the case for our application. This paper will not look into the impact of changing the GAN architecture since (Lucic et al., 2018) suggests that different GAN architectures have limited impact, on average, on the final result. Additional datasets will be created by combining the different reduced datasets with the respective augmented and synthetic generated data. For each new dataset the amount of data will be increased with 50% and 100% of the reduced dataset with either augmented or synthetic data. For these datasets a similar classifier as before will be trained to provide insights and answers to question 2 and 3. Table 1 gives an overview of the 25 different datasets that have been created by changing the amount of available and synthetic data as well as changing the augmentation type. In order to answer question 4, all the different classifiers will be subject to the explanation model SHAP in order to identify which features are responsible for the classification. This can give an idea on the generalization of the different classifiers and what the impact might be from decreasing the amount of real data, and increasing the amount of synthetic data as well as the difference between generation methods for the synthetic data. Finally, to provide an answer for question 5, specific subject matter expert knowledge will be used to define a region of interest (ROI) inside the buffer tank. This ROI is typically used by human observers to classify the different images. Using this extra use case specific knowledge, it can be checked quantitatively how many of the responsible features for the classification decision are located inside the ROI and thus, if the model decision is based on similar features as a human observer would use.

# 4 EXPERIMENTAL RESULTS

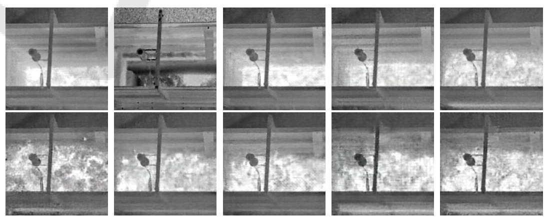
In the following subsections the results of the different experiments that are conducted will be elaborated.

## 4.1 GAN Generated Synthetic Data

From table 1 it is clear that five different GAN models have to be trained for all the experiments conducted where the amount of training data is varied. The experiments are performed using a PC with an Intel i7-10850h at 2.7 GHz and an NVIDIA Quadro RTX 4000 GPU. All the models had a training time of 24 hours. Figure 2 gives some examples of different generated synthetic data using the light-weight GAN approach for the different models where the amount of available data for training was varied. Figure 2 (a) shows generated images when there is a situation with little and heavy foam, for these images 100% of the complete dataset was used. When generating additional synthetic data based on this model, it is possible to generate multiple images with much variation in the amount of foam.

Figures 2 (b) - (d) show generated synthetic images when only 75% till 25% of the original complete dataset is available. These images show that even with reduced amounts of available training data it is still possible to train the light-weight GAN that is able to generate synthetic data with limited amount of variation in the amounts of foam. It can be noticed that as the amount of data is reduced, the amount of noise increases in the generated image. As can be expected, when the amount of available data is extremely low, as is the case in figure 2 (e) where only 10% of the original data if available, the amount of variation present in the generated synthetic data drops. Besides limited amount of variation, the amount of noise also drastically increases.

From a qualitative point of view, it could be judged that the models with lower amounts of available data generate lower quality images, and for a human it would be very easy to determine which one is real and which one is synthetically generated. This leads to an additional question: *Does the quality of the synthetically generated data matter for the accuracy of the classification?* The next subsection will give insights regarding the question of what the effect is of enlarging the dataset with augmented data or generated synthetic images.



(a) 100% (b) 75% (c) 50% (d) 25% (e) 10%

Figure 2: Example images of GAN generated synthetic data for different percentages of available data from the complete dataset. Even with limited amounts of training data the model is still able to generate synthetic data with variation.

## 4.2 Classifier Results

For the classification the most simple convolutional neural network (CNN) is used since the focus of this work is to identify the impact of changes in the training dataset. As is clear from table 1, a different clas-

Table 1: Table showing overview of all 25 datasets that have been created for the different experiments.

| Amount of available data | Amount of extended data | Augmentation technique |
|---|---|---|
| 100%-75%-50%-25%-10% | 0% | None |
| 100%-75%-50%-25%-10% | 100% | Light-weight GAN |
| 100%-75%-50%-25%-10% | 50% | Light-weight GAN |
| 100%-75%-50%-25%-10% | 100% | Standard augmentation |
| 100%-75%-50%-25%-10% | 50% | Standard augmentation |

sification model needs to be trained for each variation in the amount of data and possible augmentation technique, giving a total of 25 trained classifiers. The accuracy of these models are given in table 2 and figure 3. From this table and figure it can be seen that when no augmentation is applied, the accuracy of the classifier drops when the amount of data starts to decrease, which is to be expected according to (Dawson et al., 2023). This is also an answer to the first question from section 3. A maximum accuracy of 87% is achieved when 100% of the total training data is available. A human observer is able to achieve an accuracy of 100% on this dataset. However when the amount of available data is heavily decreased, the classifier has bad performance. When looking at standard augmentation techniques for our dataset it can be observed that when only limited amounts of the original dataset is available, standard augmentation has a positive but limited impact on the accuracy by an increase of around 5%. When all or almost all of the original data is available, standard augmentation does not seem to improve the results by much, but it also does not seem to have a negative impact on the results of the classifier. It seems that standard augmentation techniques have the most impact when datasets are limited. When abundant data is available the impact of these augmentation techniques begins to stagnate, as can be expected. Finally when looking at the classifier results when using GAN generated synthetic data, it immediately becomes clear that this augmentation method provides the best results no matter the amount of available original data. It can be observed that the maximum accuracy can be pushed from 87% to 94% when all of the original dataset can be used as well as being extended by 100% with synthetic generated data. When only 50% of the original dataset is available, synthetic generated data based on this limited dataset can be used to push the accuracy from 52% towards 91%. Even when only 10% of the original dataset is available, extending this dataset with synthetic generated data from the limited dataset can increase the performance of the classifier from only 43% up to 73%. These findings seem to indicate that if it is possible to generate synthetic data the results will be superior compared to the classic augmentation techniques.

## 4.3 Explainable AI Using SHAP

Even though the results of the previous subsection are validated on 126 images of foam and 126 images without foam, it is still unclear how well these models generalize to additional images since the foam can take any size and shape. In order to increase trust in the trained models, an explanation model named SHAP (Lundberg and Lee, 2017) has been utilised on the different trained models to explain the categorization of the images. Each pixel receives a value indicting in what sense it contributed towards the classification. Figure 4 gives two examples of the classification model where 100% of the original data was available and it was extended with synthetic generated data. A red color indicates pixels that contribute to the classification of foam. Blue indicates pixels that contribute to the classification of no foam. From these examples it can be seen that the model correctly indicates the zones of interest for the foam to be in the center of the buffer tank. In case no foam is present in the images, the model correctly understands that information can be found on the inside of the buffer tank as well as in the center of the tank. The additional information gained from the SHAP values indicates that the model uses similar information as a human observer would use in order to classify the images. This information can strengthen the trust in the model. Similar results are achieved for the models where 75% and 50% of the original data was available for the training of the GAN and the classifier. However as was mentioned in subsection 4.1, once the available training data starts to decrease, noise in the generated images starts to increase and variation starts to decrease. Even though the accuracy of these models with low data remain high (table 2), and the images in figure 5 are correctly labeled, the SHAP values indicate that this model does not generalize well since the decision for foam or no foam seems to be distributed randomly (figure 5 (a)) or lies mostly outside the region where foam normally occurs (figure 5 (b)).

The paragraph above describe visual interpretation of the findings, however in order to qualitatively describe the generalization of the models, contextual information regarding the specific dataset has been used. A region of interest is defined based on sub-

Table 2: Table showing an overview of the accuracy of all 25 models for the different amount of used training data when using no (0%), standard or GAN augmentation (50%-100%).

| | Amount of available data from complete dataset | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 10% | | | 25% | | | 50% | | | 75% | | | 100% | | |
| | Amount of extended data | | | | | | | | | | | | | | |
| | 0% | 50% | 100% | 0% | 50% | 100% | 0% | 50% | 100% | 0% | 50% | 100% | 0% | 50% | 100% |
| Standard | 0.43 | 0.43 | 0.45 | 0.52 | 0.57 | 0.57 | 0.57 | 0.56 | 0.6 | 0.8 | 0.7 | 0.79 | 0.87 | 0.87 | 0.87 |
| GAN | 0.43 | 0.72 | 0.73 | 0.52 | 0.75 | 0.77 | 0.57 | 0.88 | 0.91 | 0.8 | 0.91 | 0.9 | 0.87 | 0.92 | 0.94 |

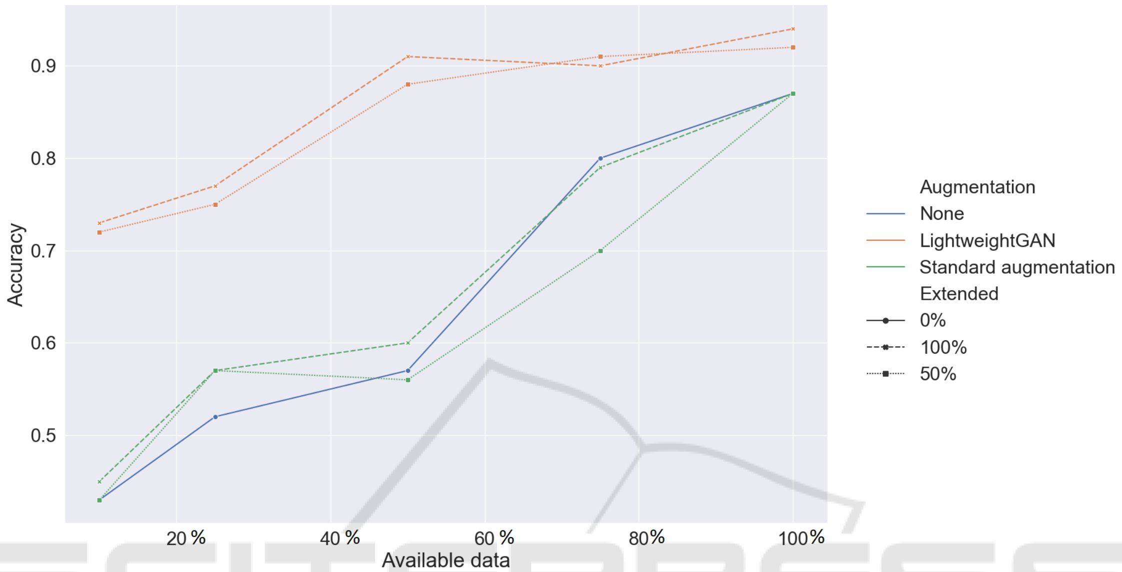



Figure 3: Overview of the results of the accuracy of all 25 models for the different amount of used training data when using no (0%), standard or GAN augmentation (50%-100%). It can be seen that GAN augmentation gives the best results. Extending datasets with synthetic data based on limited percentages of the original dataset is able to push the accuracy from 87% to 94%.



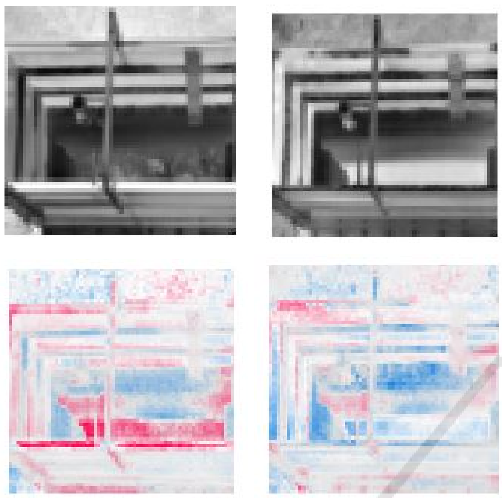
ject matter expert knowledge. This region of interest is normally used by human observers to form their classification decision and can be seen on figure 6. For each SHAP value, that contributes towards a certain decision, it can be checked whether or not this value is located inside the ROI. Using this heuristic a performance indicator can be calculated. This has been done for each validation image and for each trained model. For each model these results are averaged in order to receive one performance indicator value. These results are summarized in table 3. These results clearly confirm the previous visual findings. When the simulation-to-realism gap is small, it can be observed that the ratio of SHAP values lying inside the region of interest versus outside is in the range between 75% and 86%. However when the gap between the simulation-to-realism is larger, this ratio drastically drops and depending on the available data ranges between 40% and 53%. This indicates that for these models only at best around half of the explaining pixels are located their where a subject matter expert would expect them to be and are thus not reliable to use. Using the proposed performance indicator can help automate this procedure and no longer makes it based on subjective visual observations. These results indicate that using GAN generated synthetic data on our dataset is only useful when the simulation-to-realism gap is small. Incorporation of the SHAP values and the performance indicator in the workflow provides the end-user with extra information and insights in the actual performance of the developed models by comparing information used by the model and the information a human observer would use for classifying the images. Besides these extra insights, it also gives an indication on the importance of the quality of the generated data since it can be observed that when the quality of generated data drops, the distribution of SHAP values indicate that the classifier is mostly based on noise.

## 5 CONCLUSION

In this paper, the effect of utilizing GAN derived synthetic data for increasing accuracy of a classifier has been investigated and has been compared to a stan-

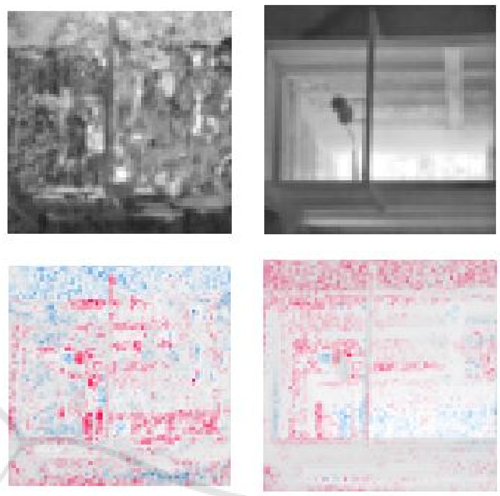
Table 3: Table showing overview of the ratio of shap values that explain classification that lie inside the defined region of interest versus outside for the different amounts of available training data and combination of extended data.

| Amount of available data from complete dataset | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 10% | | 25% | | 50% | | 75% | | 100% | |
| Amount of extended data | | | | | | | | | |
| 50% | 100% | 50% | 100% | 50% | 100% | 50% | 100% | 50% | 100% |
| 0.43 | 0.4 | 0.48 | 0.53 | 0.75 | 0.78 | 0.81 | 0.79 | 0.84 | 0.86 |



(a) Foam (b) No foam

Figure 4: Example images of SHAP values for (a) an image with foam, and (b) an image where no foam is present where the model generalizes well. Red pixels indicate a contribution towards the foam class. Blue pixels indicate a contribution towards the no foam class.



(a) (b)

Figure 5: Example images of SHAP values for (a) an image with foam, and (b) an image where no foam is present where the model does not generalize well. Red pixels indicate a contribution towards the foam class. Blue pixels indicate a contribution towards the no foam class.

dard augmentation method. The GAN based synthetic generated data is proven to yield superior results compared to the utilised standard augmentation techniques on the dataset used in this paper. The proposed methodology employs a generative adversarial network for generation of synthetic data. This extra step for generating extra data before the classification, is low effort and involves only the training of a GAN such as, e.g. the light-weight GAN used in this paper. This work suggest that in order to decide how much data is enough data to create classification models that generalize well, explanation models should be introduced that can help with the interpretation of the classification results. In this paper it was shown that when only 50% of the original data (100 training images) is available, it is possible to increase the final accuracy of the classifier from 57% to 91% by adding GAN based synthetic data in our dataset while still generalizing well. In comparison, standard augmentation methods were only able to increase the accuracy to 60%.

In the future, we would like to validate the proposed method on other datasets as well to see if the approach generalizes to other applications. In addition, we would like to investigate different methods to generate synthetic data and evaluate their impact. Finally, we want to expand our method to quantify the results of the explanation model to work on datasets where region of interests cannot be defined as simply as was the case in the dataset used in this paper.

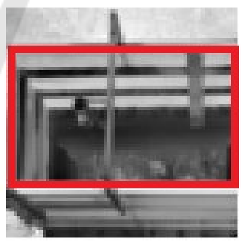


Figure 6: Example image showing the buffer tank with foam inside. The content of the red box indicate the region of interest which human observers use to determine if foam is present or not in the image.

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