AE-FLOW: AUTOENCODERS WITH NORMALIZING FLOWS FOR MEDICAL IMAGES ANOMALY DETECTION

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Abstract

Anomaly detection is a critical task in various fields, including medical imaging, cybersecurity, and fraud detection. Deep learning models can learn complex representations of data and detect anomalies based on deviations from these learned representations. We will focus on a recent approach called AE-FLOW, which combines the benefits of normalizing flow methods with autoencoders for efficient and effective anomaly detection in medical images. We will discuss the proposed model and its implementation details by firstly reproducing the original AE-FLOW model, studing its architecture, and finally made novel changes to its structure to improve the performance. The method provides not only image-level computability for normal data, but also pixel-level interpretability for anomalous data. Experiments conducted on different medical image datasets show the effectiveness and robustness of AE-FLOW, which has a large room for improvement in terms of anomaly detection compared with other relevant and representative methods.

Introduction

The following are the key components of AE-Flow:

Encoder:

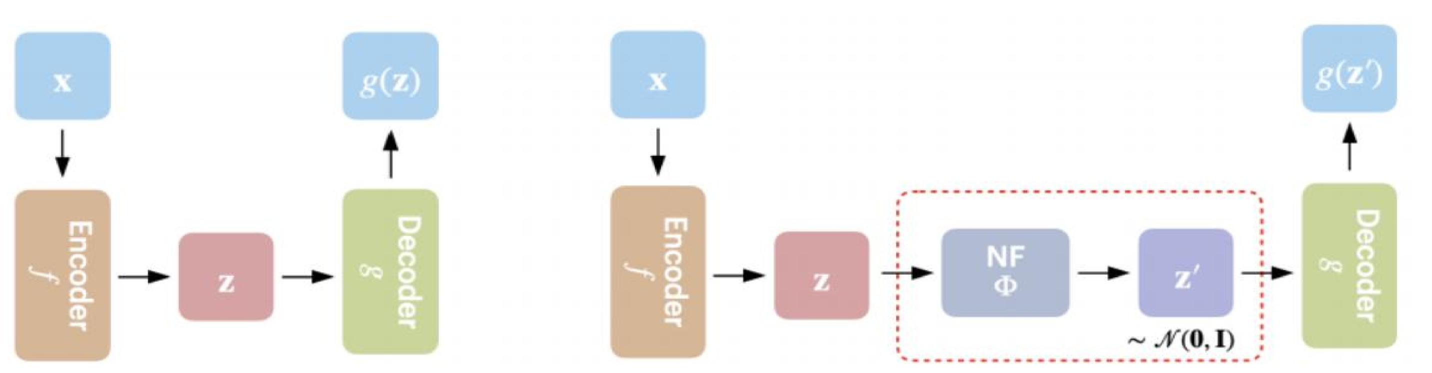
The encoder block in the AE-FLOW model takes an input image x and extracts low-dimensional features z using a function f : X → Z. The encoder is typically implemented as a convolutional neural network (CNN) that applies a series of convolutional and pooling layers to the input image x to extract features at different scales.

Normalizing flows:

Normalizing flow is a technique used in deep learning to transform a probability distribution into another distribution that is easier to work with. The idea behind normalizing flow is to apply a series of invertible transformations to the input distribution that preserve its dimensionality and allow for efficient computation of likelihoods.

Decoder:

The decoder block in the AE-FLOW model takes as input a normalized feature vector z' and reconstructs an output image x' using a function g : Z → X'. The decoder is typically implemented as a CNN that applies a series of deconvolutional and upsampling layers to transform the normalized feature vector z' back into an image.



Anomaly Score

$$\mathcal{S} = \beta * \mathcal{S}_{\text{flow}} + (1-\beta) * \mathcal{S}_{\text{recon}},$$

$$\mathcal{S}_{\text{flow}} = -p_{\mathbb{Z}'}(\mathbf{z}'),$$
$$\mathcal{S}_{\text{recon}} = -\text{SSIM}(\mathbf{x}, \mathbf{x}').$$

Novel Contribution

1. Extend ways fror the evalution of AE-FLOW

In our study, we went beyond the development of the AE-FLOW model and sought to enhance the evaluation process by incorporating various metrics. By considering metrics such as Area Under the Curve (AUC), F1 score, accuracy, sensitivity, and specificity, we aimed to provide a comprehensive assessment of our model's performance in detecting anomalies within medical images. This multi-faceted evaluation approach allowed us to gain deeper insights into the capabilities and limitations of the AE-FLOW model.

2. Conduct semi-supervised techniques with the help of abnormal data

Our proposed method combines the benefits of normalizing flow models with semi-supervised learning to improve anomaly detection performance on unlabeled data. Specifically, we consider to use Flow Gaussian Mixture Model (FlowGMM) introduced in the paper Semi-Supervised Learning with Normalizing Flows as the generative model component of AE-FLOW.

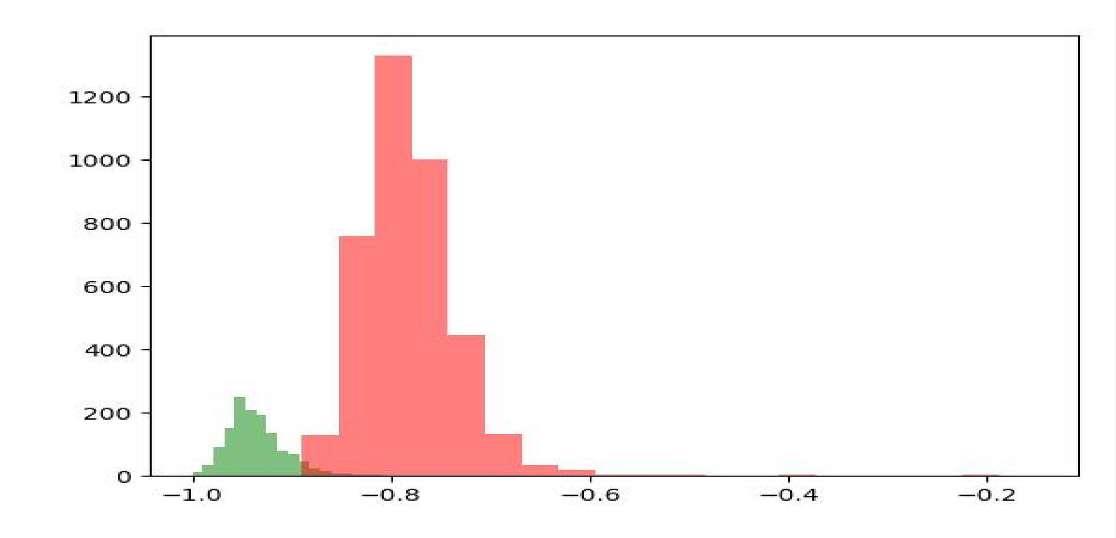
In FlowGMM, the density in the latent space is modeled as a Gaussian mixture, with each mixture component corresponding to a class represented in the labeled data. This allows for sharing structure over labeled and unlabeled data, which can improve predictions on unseen data. The resulting FlowGMM provides an exact joint likelihood over both labeled and unlabeled data for end-to-end training.

FlowGMM has several advantages over other semi-supervised learning approaches. First, it provides an exact likelihood over both labeled and unlabeled data, which allows for more accurate modeling of complex probability distributions. Second, it is interpretable, meaning that it can provide insights into how the model is making predictions. Third, it has broad applicability beyond image data and can be used on tabular or text data as well.

Results

The distribution curves:

Representing the computed anomaly scores for both categories, namely normal and anomaly, are depicted in the provided Figure, which is one of the figures we got during training. The color red represents anomaly data, while green signifies normal data.



Anomaly Detection Performance

To evaluate the anomaly detection performance of the AE-FLOW model, we employed a comprehensive set of evaluation metrics. These metrics included the Area Under the Receiver Operating Characteristic Curve (AUC), F1 score, accuracy, sensitivity, and specificity.

	AUC	F1	ACC	SEN
Original	92.00	88.92	85.58	91.28
Ours	73.04	81.12	71.71	95.05

Difficulties

1) Limited availability of labeled anomaly data

2) Hyperparameter tuning:

3) Computational resource requirements:

4) Interpretability and analysis of results:

5) Possibility of successfully incorporating semi-supervised approach is low:

In a semi-supervised setting, the model requires both labeled and unlabeled data to learn from. Acquiring labeled data can be costly, time-consuming, and sometimes challenging in domains such as medical imaging, where expert annotations are required. Limited resources, including time and personnel, restricted our ability to gather a significant amount of labeled data for training. Implementing a semi-supervised approach often involves developing additional techniques, such as designing appropriate loss functions, creating strategies for combining labeled and unlabeled data during training, and optimizing the model's performance with limited labeled samples.

Additionally, the AE-FLOW model's original paper did not provide sufficient details and guidance on the specific techniques used for the semi-supervised setting.

6) Limited time and resources:

Conclusion

The AE-FLOW model, coupled with our proposed improvements, represents a significant advancement in anomaly detection in medical images. While further research and experimentation are needed, these advancements provide a foundation for continued development and application of the AE-FLOW model in real-world scenarios, ultimately benefiting various industries and improving anomaly detection in critical fields.