Image anomaly detection.

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Abstract

Problem Motivation: Anomaly detection plays a vital role in various fields, including cybersecurity, healthcare, and manufacturing quality control. In cybersecurity, it is essential to identify unusual activities or patterns that may indicate a security breach or cyber attack. Anomaly detection techniques help detect and mitigate potential threats proactively. In healthcare, anomaly detection is employed for diverse purposes, ranging from detecting disease outbreaks to monitoring patients' health journeys. Medical professionals rely on anomaly detection techniques to identify anomalies in medical imaging, enabling accurate diagnoses and effective treatments.
Aims: The aim of this project is to develop an effective image anomaly detection system using unsupervised learning with autoencoders that can accurately identify anomalies or abnormalities in images **Main Findings:** Through comprehensive experimentation and evaluation, we demonstrate the potential of autoencoders as powerful tools for unsupervised anomaly detection tasks. Our models showcase excellent performance in identifying anomalies
Github The README.md file contains dataset link available online).

Contents

1 Introduction

The purpose of this project is to present an image anomaly detection project focused on detecting clouds using satellite photos. the input to our algorithm is an image taken by a satelite of an area .We then use a neural network to output a predicted statement of weather (cloudy or not cloudy)

1.1 Problem

The task at hand entails the creation of an image anomaly detection system that can effectively detect and classify cloud formations in satellite photographs. Cloud detection poses several challenges due to the constantly changing nature of clouds, their varied shapes and sizes, and the potential presence of other objects in satellite images. The primary goal is to develop an algorithm that is both accurate and efficient in distinguishing clouds from other features present in the images. This algorithm will play a crucial role in enabling reliable analysis and interpretation of satellite data related to cloud formations.

1.2 importance of cloud detection

Cloud detection plays a vital role in various domains, offering significant benefits in several areas:

Weather Forecasting: Accurate cloud detection facilitates meteorologists in analyzing cloud patterns and movement, leading to enhanced weather predictions. It assists in forecasting precipitation and identifying severe weather conditions.

Solar Energy Planning: Cloud cover significantly impacts solar energy generation. By detecting clouds in satellite images, precise assessments of sunlight availability can be made, aiding in solar energy planning, site selection, and system optimization.

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1.3 Motivation for Pursuing the Problem:

Cloud detection using satellite photos will contribute to facing real-world challenges in weather forecasting, climate, renewable energy, and environmental monitoring. Solving this problem lead to major advancements in these domains and potentially society at large.
Also, this project contributes to our academic advancement. Image anomaly techniques and deep learning techniques: leveraging these techniques for cloud detection in satellite photos opens new avenues for personal research, innovation, and new technologies to discover. The project aligns with the growing field of computer vision and its application to satellite imagery analysis.

1.4 background

To understand the problem and devise effective solutions, it is crucial to have a background understanding of image anomaly detection,deep learning and autoencoder techniques .This project builds upon existing research in computer vision and deep learning.

2 Related work / Basic concepts

2.1 Machine learning

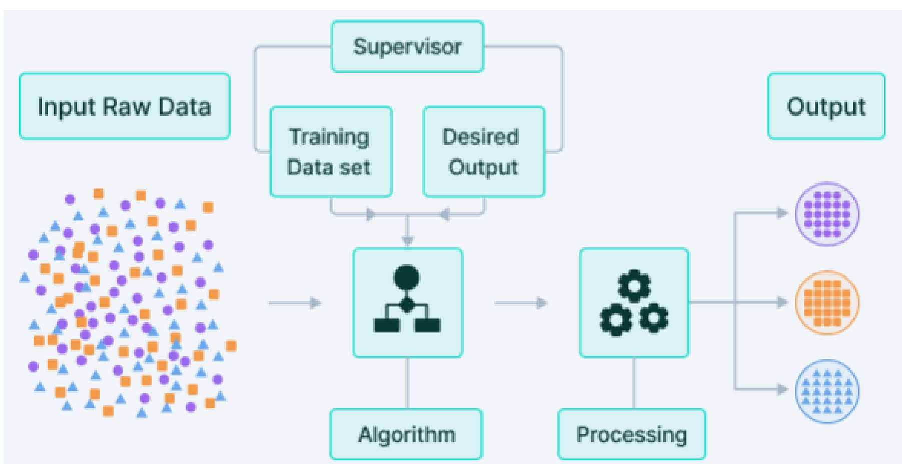
2.1.1 Definition

Machine learning is a field of study and practice that focuses on developing algorithms and models that enable computers to learn from data and make predictions or decisions without being explicitly programmed for every specific task. It uses these algorithms to interpret data in a way that replicates how humans learn. It is a subset of artificial intelligence (AI) and is based on the idea that machines can automatically learn and improve from experience.

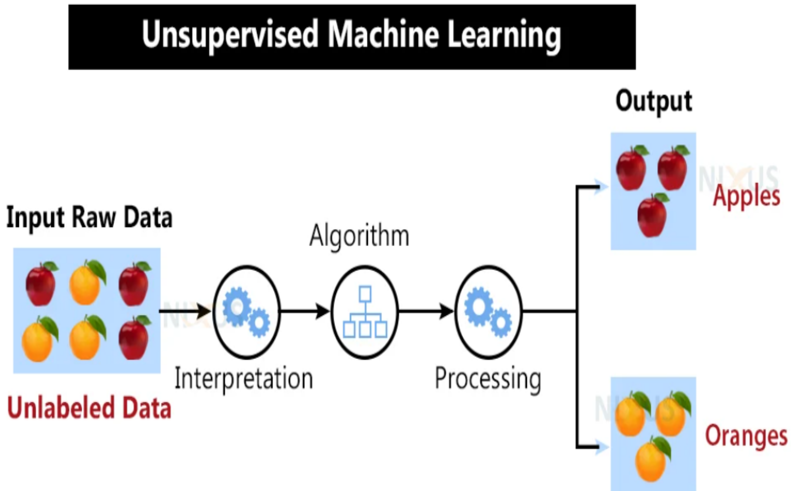
2.1.2 types of ML:

there are 3 types of machine learning :

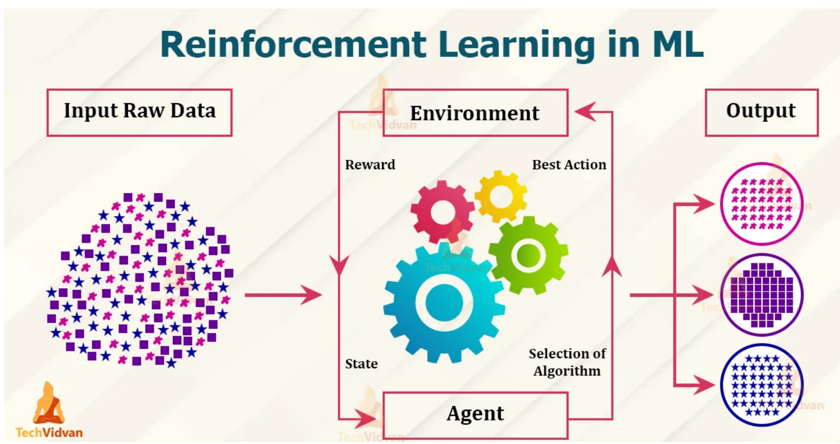
- **Supervised learning:** Supervised learning involves training a model using labeled examples, where the training data comprises input-output pairs. The model learns from these pairs to establish a mapping between inputs and their corresponding outputs. The objective is to generalize the acquired patterns and knowledge so that the model can accurately predict outputs for new, unseen inputs



- **Unsupervised Learning :** Unsupervised Learning deals with unlabeled data.It uses machine learning algorithms to analyze and cluster unlabeled datasets. Unsupervised learning focuses on finding inherent patterns or organizing the data without explicit guidance. It aims to discover hidden patterns or groupings in the data.



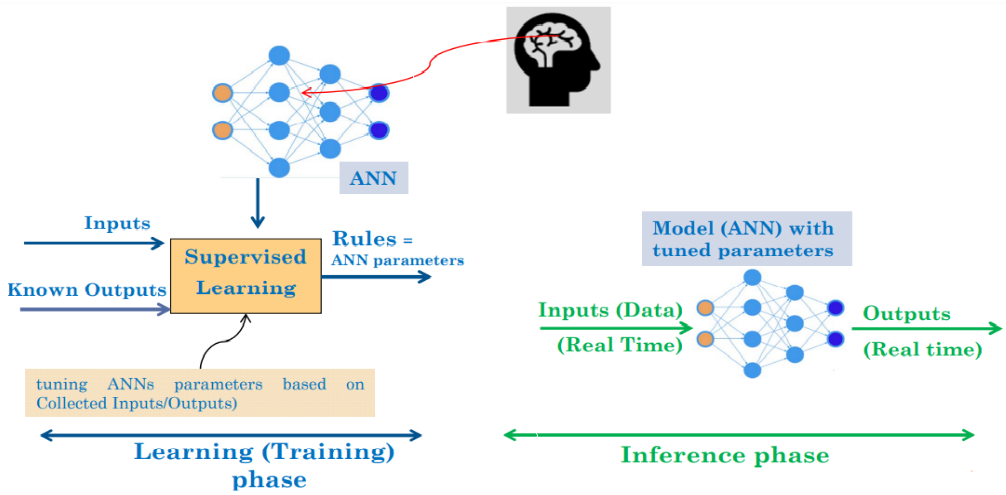
- **Reinforcement learning:**In reinforcement learning, an agent actively engages with an environment and learns to make decisions that maximize a reward signal. Through a process of trial and error, the agent takes actions and receives feedback in the form of rewards or penalties based on its behavior. The goal is to discover an optimal policy that maximizes the cumulative reward the agent receives over time.



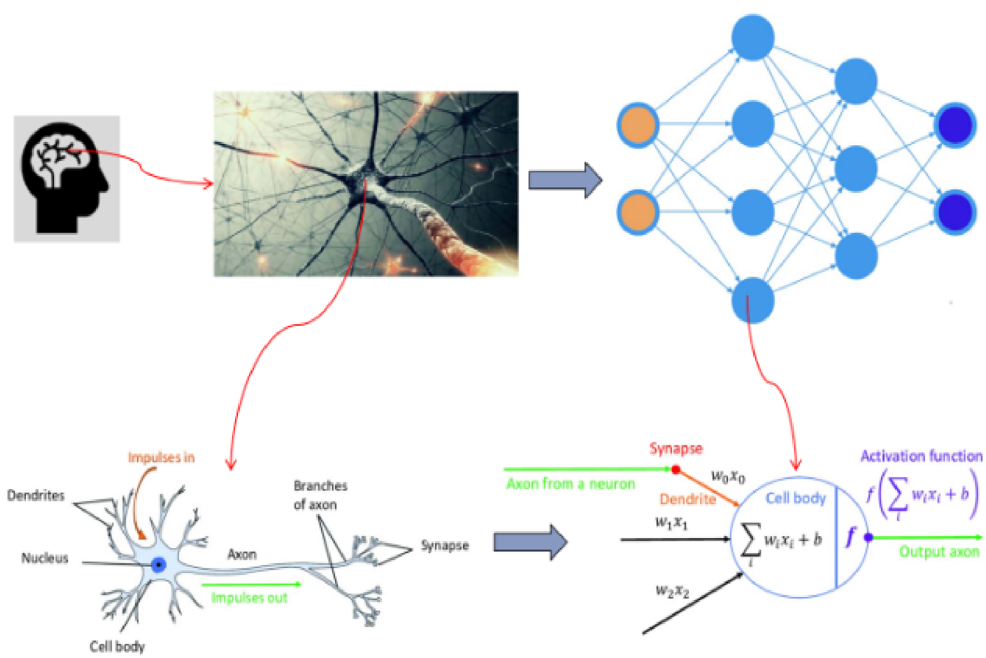
2.2 Deep Learning

2.2.1 Definition

Deep learning is a subset of machine learning that uses Artificial Neural Networks "ANN" (as algorithm) to mimic the learning process of the human brain.

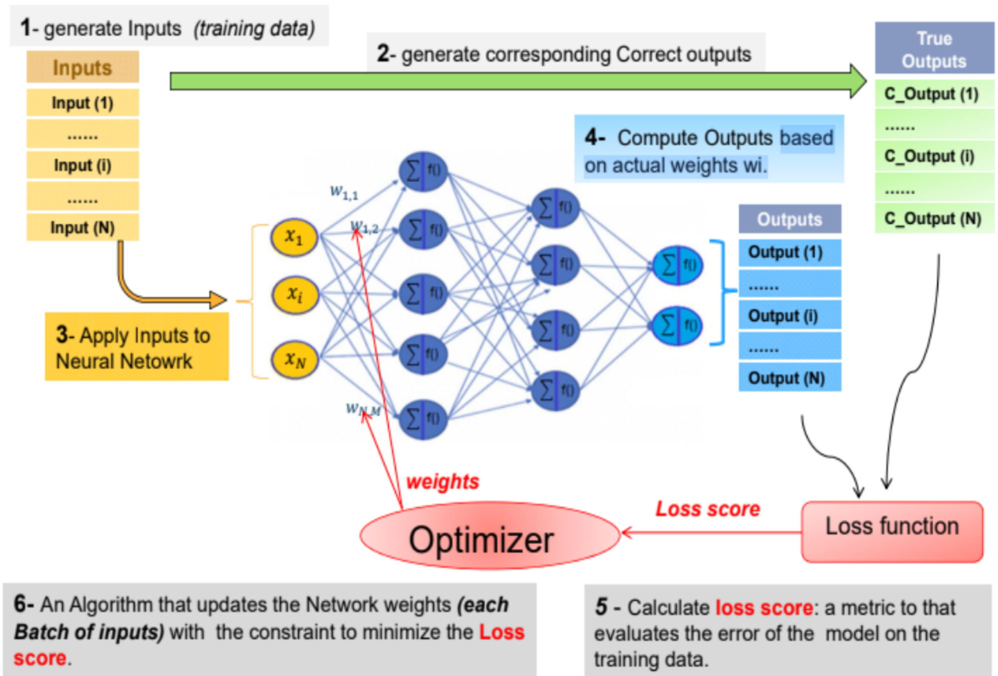


Deep learning algorithms are designed to automatically learn hierarchical representations of data through multiple layers of interconnected nodes, known as artificial neurons or units. These layers form a deep neural network, hence the name "deep learning." Each neuron receives inputs, applies a mathematical function to them, and produces an output that is passed on to the next layer. The network learns to recognize patterns and relationships in the data by adjusting the connection weights between neurons during a training phase



2.2.2 Training phase

For the first phase (training phase)this neural network takes as input: the input of the training data and the correct output .then it applies the inputs to our neural network to generate an estimated output based on actual weights wi. Then it evaluates the error between the correct output and the generated outputs with a loss score that we use to update the weights wi.



2.2.3 types of DL

There are several types of deep learning architectures used in various domains:

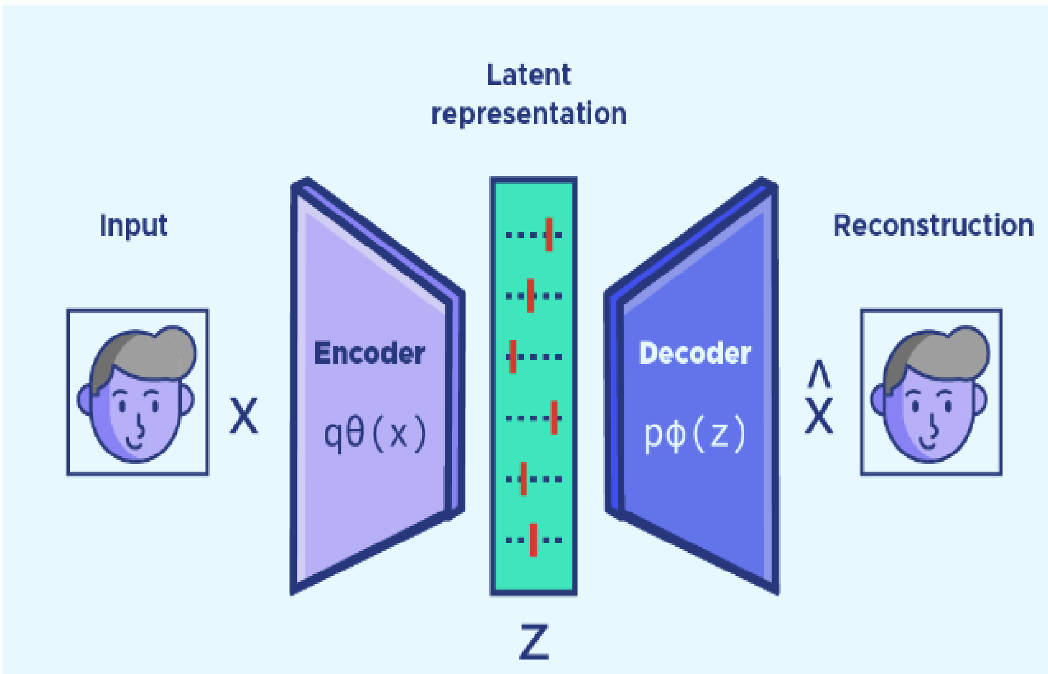
- **Convolutional Neural Networks (CNNs):**is a class of artificial neural network most commonly applied to analyze visual imagery.CNNs use the mathematical operation convolution in at least one of their layers.
- **Recurrent Neural Networks (RNNs):**are suitable for processing successional data, similar as natural language processing, speech recognition, and time series analysis.It is a class of ANN where connections between nodes can create a cycle, allowing output from some nodes to affect subsequent input to the same nodes.
- **Deep Reinforcement Learning :**Deep reinforcement learning combines deep learning with reinforcement learning, where algorithms make sequential decisions based on rewards and punishments from the environment
- **Autoencoders:**Autoencoders are unsupervised learning models that aim to reconstruct the input data by learning a compressed representation (encoding) and a reconstruction (decoding) process.They are generaly used for tasks like dimensionality reduction, feature learning, and anomaly detection.

=> in this project we used the architecture autoencoder .

2.3 Autoencoders

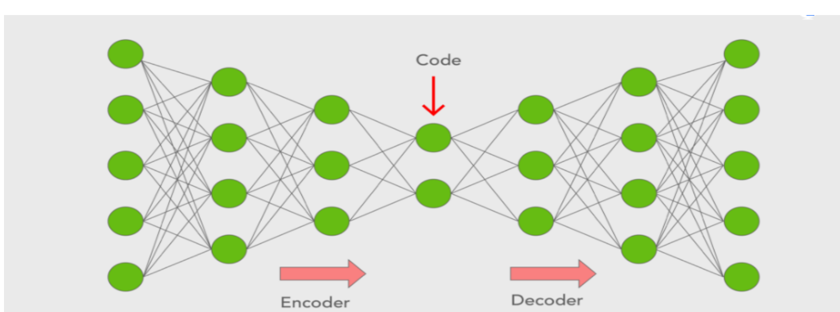
2.3.1 Definition

An autoencoder is a type of artificial neural network applied to learn effective codings of unlabeled data(unsupervised learning).An autoencoder learns two functions an encoding function that transforms the input data, and a decoding function that recreates the input data from the decoded representation. The autoencoder learns an effective representation(encoding) for a set of data, generally for dimensionality reduction.



2.3.2 Architecture of autoencoders:

- **encoder:**An encoder is a completely connected neural network that compresses the input into a smaller space representation and encodes the input image as a compressed representation in a reduced dimension.
- **code :**This part of the network contains the reduced representation of the input that is applied to the decoder.
- **Decoder:** has a similar structure to the encoder. This network is responsible for reconstructing the input back to the original dimensions from the code.



An autoencoder consists of an encoder and a decoder. The encoder compresses the input into a code, and the decoder reconstructs the original input from the code. The goal of the autoencoder is to achieve an output that closely matches the input.

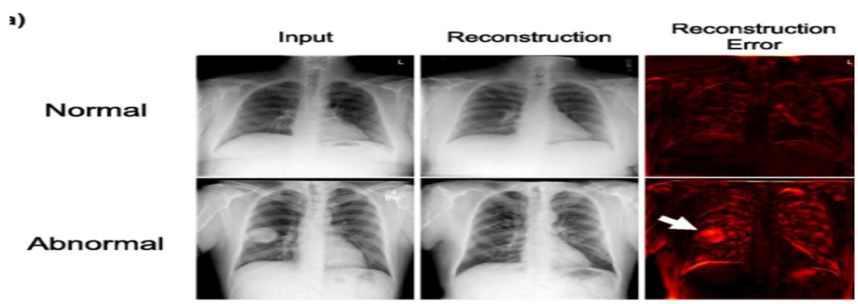
2.3.3 Application of autoencoders

- Data Compression
- Image Denoising
- Dimensionality Reduction
- Feature Extraction
- Image Generation
- Image colourisation
- Image anomaly detection

in this project we used the autoencoder in order to detect the image anomaly .this anomaly present the a non cloudy weather .so if we dectect an anomaly we detect a clear weather .

2.4 Image anomaly detection

Image anomaly detection is a computer vision task that involves identifying and flagging anomalous or abnormal instances within a collection of images. The goal is to automatically detect images that deviate significantly from the expected or normal patterns.



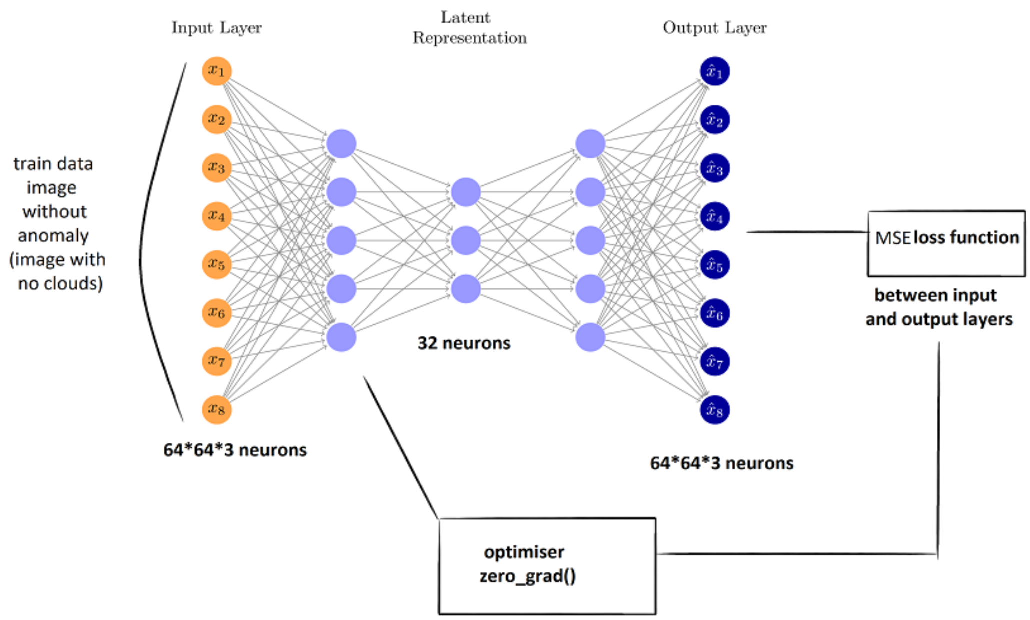
In image anomaly detection, various approaches are utilized:

- Statistical Methods: These methods employ statistical models to learn the distribution of normal images. Anomalies are identified by detecting deviations from this learned distribution. Common techniques include Gaussian Mixture Models (GMMs).
- Reconstruction-Based Methods: These approaches utilize autoencoders.Anomalies are detected by measuring the reconstruction error, where higher errors indicate anomalous instances.
- Deep Learning Approaches: Deep learning models, particularly Convolutional Neural Networks (CNNs) and other deep architectures, are employed for anomaly detection.
- Transfer Learning: Transfer learning leverages pretrained models, such as CNNs trained on large-scale datasets like ImageNet.

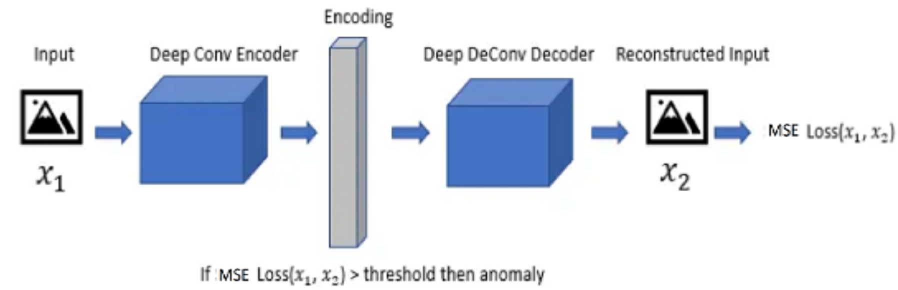
3 Methods

3.1 general overview

The encoder compresses the input data into a latent representation, while the decoder decompresses the encoded latent representation to reconstruct the original input. **The MSE loss function** is used to measure the similarity between the original input and the reconstructed input.



After the training phase, we define a threshold (a limit loss error for normal data).
The reconstruction error, which is the difference between the input and output, tends to be significantly higher for anomaly data compared to normal data. This discrepancy in the reconstruction error is utilized to distinguish between normal and anomalous data.



3.2 MSE (Mean Squared Error)

It measures the average squared difference between the predicted which is the reconstructed version of the input data and actual values.

$$\frac{1}{n}\sum(y_i - \hat{y}_i)^2$$

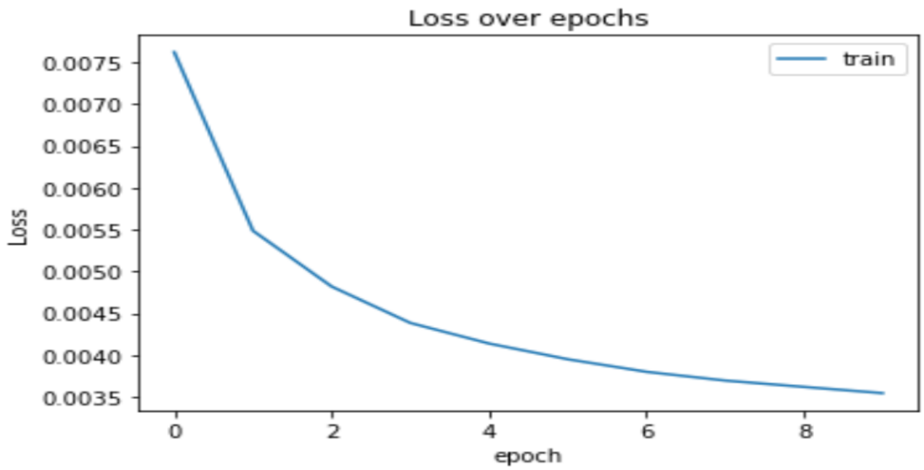
with:

- n nombre of images of our data set (1500)
- yi the input :image matrix (12228,) .
- $\hat{Y}i$ the image after the reconstruction

Throughout the training process, the model gradually improves its ability to reconstruct the image by minimizing the loss.

```
Epoch:1, Loss:0.0024
Epoch:2, Loss:0.0024
Epoch:3, Loss:0.0022
Epoch:4, Loss:0.0028
Epoch:5, Loss:0.0019
Epoch:6, Loss:0.0019
Epoch:7, Loss:0.0019
Epoch:8, Loss:0.0019
Epoch:9, Loss:0.0018
Epoch:10, Loss:0.0019
```

- **Initial High Loss:**
  At the beginning of training, the loss is relatively high because the model's parameters are randomly initialized, and the reconstruction output is highly divergent from the original input data.
- **Rapid Decrease:**
  during the first epochs, the loss rapidly decreases as the model starts to learn and update its parameters to better reconstruct the input data. The loss reduction is notable during the initial epochs .
- **Gradual Decrease:**
  As training continues, the loss reduction becomes slower.
- **Plateau:**
  After a certain number of epochs, the loss may reach a plateau, where it no longer decreases . This indicates that the model has converged to a certain level of reconstruction accuracy.



The goal of the autoencoder is to minimize the difference between the original input and the reconstructed output

3.3 Adam optimizer

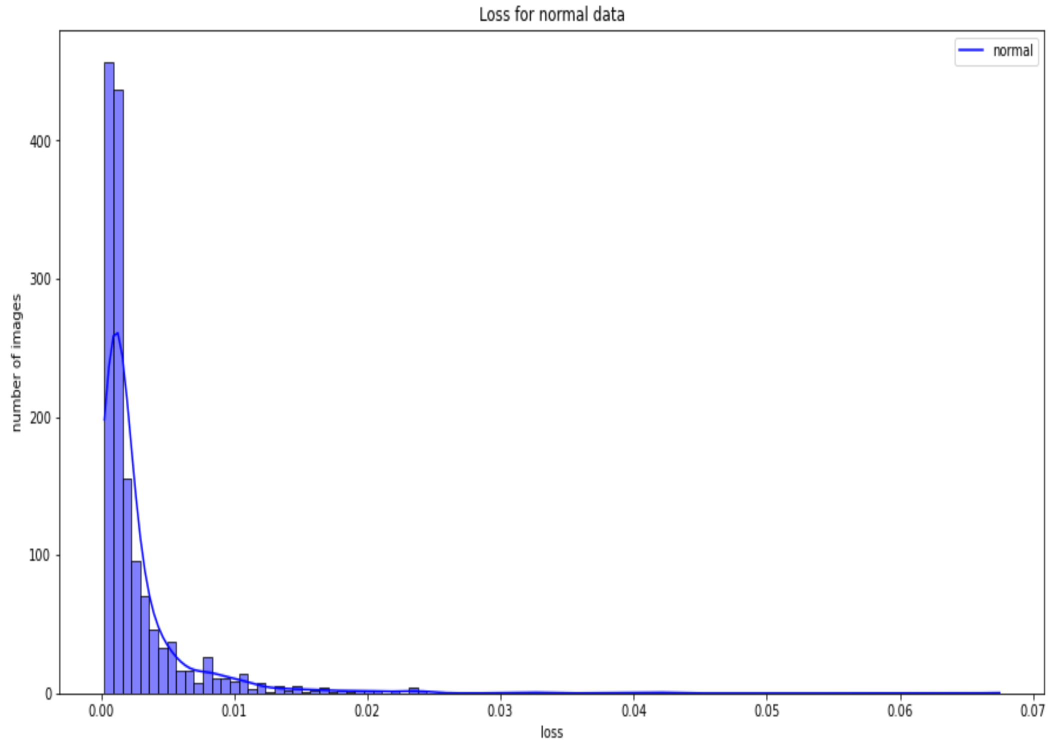
what is an Optimizer? :it is An Algorithm that updates the Network weights (each Batch of inputs) with the constraint to minimize the Loss score.

The Adam optimizer is a popular choice for training deep neural networks because of its efficiency and effectiveness. It automatically adjusts the learning rate for each parameter based on the gradient history, making it adaptable to different data characteristics. Additionally, its adaptive moment estimation helps handle challenges such as sparse gradients and noisy data during the training process.

3.4 Loss for normal data

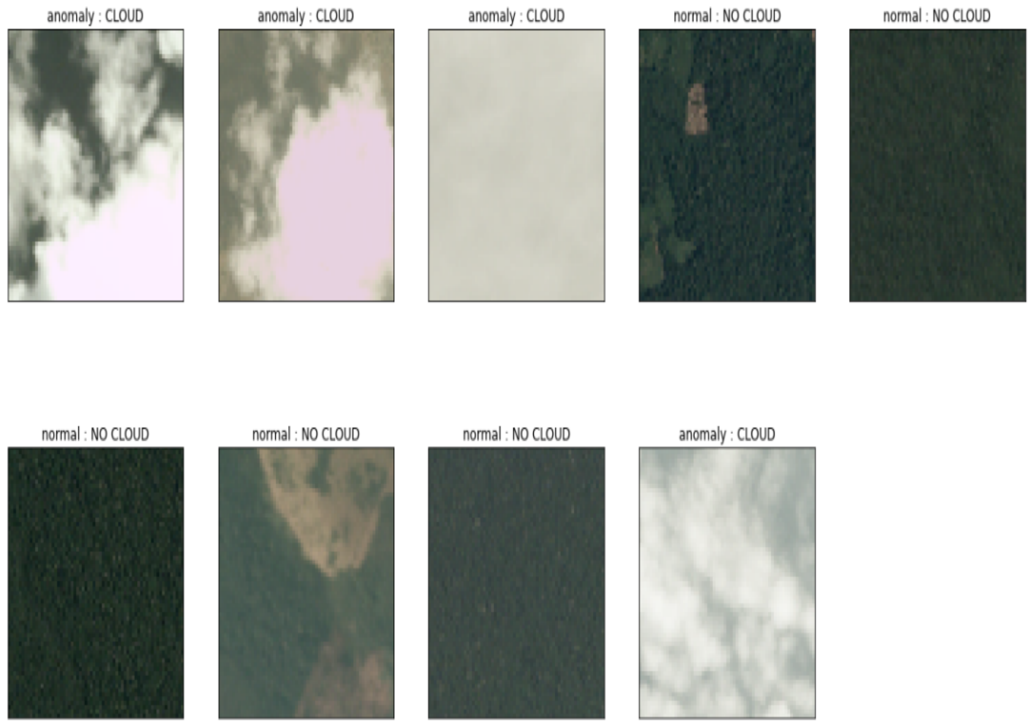
To visualize the distribution of the error between the reconstructed image and the original image for normal data (no cloud images) we should plot a histogram of final loss errors and the number of images corresponding to each loss error
the distribution of errors for normal data is primarily between 0 and 0.02.So,we can define 0.02 as a threshold for classifying anomalies. Any error above this threshold could be considered as an indication of an anomaly or an abnormal data point.

Using a threshold can be a straightforward way to differentiate normal and anomalous data based on the reconstruction error. However, the choice of the threshold depends on the specific characteristics of the dataset



4 Experiments/Results/Discussion

In our study, we curated a small dataset of satellite images specifically focused on detecting clouds. The dataset consisted of diverse satellite images captured from different locations and time periods. We used this dataset to evaluate the performance of our cloud detection model. The results of our experiments were promising, demonstrating the model's ability to accurately identify and differentiate clouds from other image components.
While autoencoders can be effective for anomaly detection, there are alternative approaches that can potentially improve the accuracy of the results
lets take as an example Generative Adversarial Networks (GANs): GANs are composed of two networks: a generator and a discriminator, which engage in a competitive game. GANs excel at learning how to produce remarkably realistic samples that closely resemble normal data. This capability makes them valuable for capturing complex patterns and generating improved reconstructions. Additionally, the discriminator network can be utilized to identify anomalies by detecting differences between real data and the generated samples. By leveraging this adversarial framework, GANs offer a powerful approach for both generating realistic data and detecting anomalies in a given dataset.



5 Conclusion/Future Work

In summary, the project focused on using satellite images for image anomaly detection, specifically targeting the detection of clouds. Autoencoders, a type of neural network architecture, were employed for this task. The autoencoder model was trained using a loss function called Mean Squared Error (MSE), which measures the difference between the original and reconstructed images. The key objective was to accurately identify and isolate cloud regions within the satellite images.

By leveraging autoencoders and MSE loss, the project aimed to achieve accurate cloud detection in satellite images. The results obtained from the implementation of the autoencoder model were analyzed and evaluated for their effectiveness in distinguishing clouds from other image components. The performance of the model in terms of precision, recall, and overall accuracy was assessed to determine its suitability for cloud detection tasks.

Overall, the project focused on utilizing autoencoders with MSE loss as an approach for image anomaly detection specifically tailored for cloud identification in satellite images. The results obtained from this approach provided insights into the model's capability and potential effectiveness in accurately detecting clouds within the satellite imagery.
these are the key points :

- Project objective: Image anomaly detection in satellite images with a focus on cloud detection.
- Methodology: Utilizing autoencoders, a type of neural network architecture, for anomaly detection.

- Loss function: Mean Squared Error (MSE) used to measure the difference between original and reconstructed images.
- optimiser : Adam optimiser
- Target: Accurately identifying and isolating cloud regions within satellite images.

For future work,if we had more time, or more team members,we would use this methodology of image anomaly detection to detect dust ,haze or even smoke : Timely detection of smoke provides critical information to fire management authorities, allowing them to mobilize firefighting resources and coordinate evacuation efforts. This helps in minimizing the impact on human lives, wildlife, and forest ecosystems.

6 Contributions

- **Oussama ziada :**
  - implementing the autoencoder architecture for image (64*64)
  - taking charge of the training phase of autoencoder
  - writing the general conclusion in the report
- **Achraf habib:**
  - creating a video demonstrate our project
  - data preprocessing
  - writing the methodes part and the abstract
- **Ahmed Cherif:**
  - writing the introduction ,related work/basic concepts and Experiments/Results/Discussion
  - take charge of the test phase
  - visualisation of the distribution of the error between the reconstructed image and the original image for data and determination of threshold sections in the project report

References

Dataset : here).
anomaly-detection-using-pytorch-autoencoder-and-mnist
Autoencoder-Anomaly-Detection