Report on Image Compression System for Autonomous Underwater Vehicles

Problem Statement:
Welcome to our Machine Learning Hackathon focused on creating an Image compression system for Autonomous Underwater Vehicles (AUVs). AUVs explore the ocean's depths, capturing images that need to be transmitted to the surface for real-time analysis. However, due to limited bandwidth and transmission constraints, it is necessary to compress these images efficiently before sending them to the surface. Your task is to use Machine learning to develop an image compression model that can compress a typical underwater image taken by an AUV so that it can be transmitted and then reconstructed accurately at the surface.

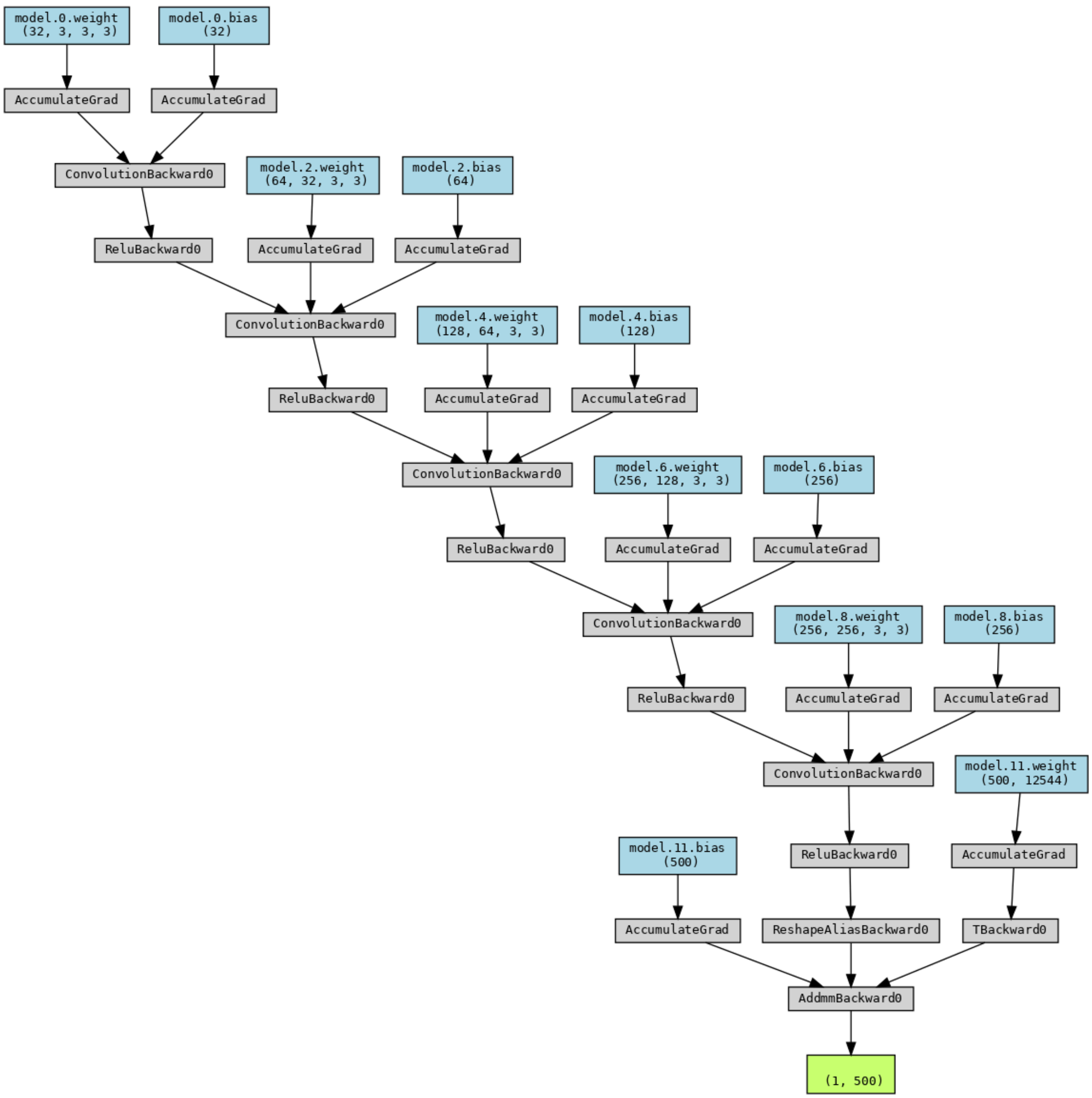
Objective:
Design and implement a system that compresses images captured by AUVs for transmission and accurately reconstructs them at the surface with minimal error. The desired compression ratio should be at least 300 times, translating to a size of about 500-dimensional latent feature space. Mean Squared Error (MSE) loss between actual and reconstructed images will be considered as the metric for the competition.

Context:
To address the image compression challenge for AUVs, we have implemented a system comprising an AutoEncoder and a Generative Adversarial Network (GAN).

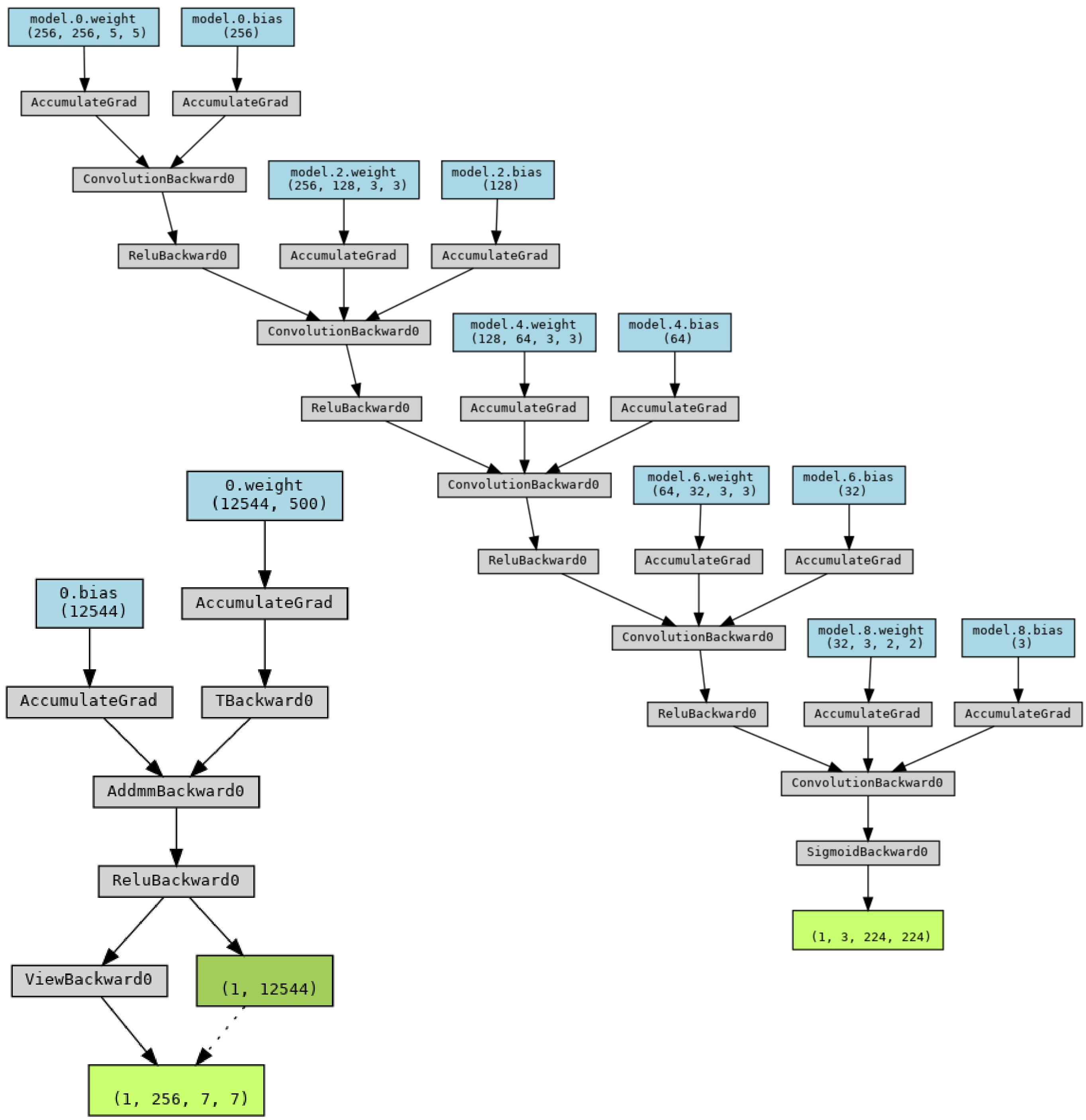
AutoEncoder:
The AutoEncoder serves as the primary component for image compression. It consists of three parts: Encoder, Bottleneck, and Decoder. The Encoder compresses the input image into a 500-dimensional latent space, which reduces computational effort on the GPU, enhancing endurance. The Bottleneck layer holds the encoded representation. The Decoder reconstructs the image from the encoded representation. When an image is encoded, it returns a tensor of shape [500]. The Decoder returns a tensor of the original image shape and additional information from the Decoder as a skip connection with a shape of [256, 7, 7].

The AutoEncoder model is trained using the Adam optimizer with a learning rate 0.001 for 30 epochs. A learning rate step occurs at epoch 15 with a gamma of 0.8. Mean Squared Error (MSE) is utilized as the loss function.

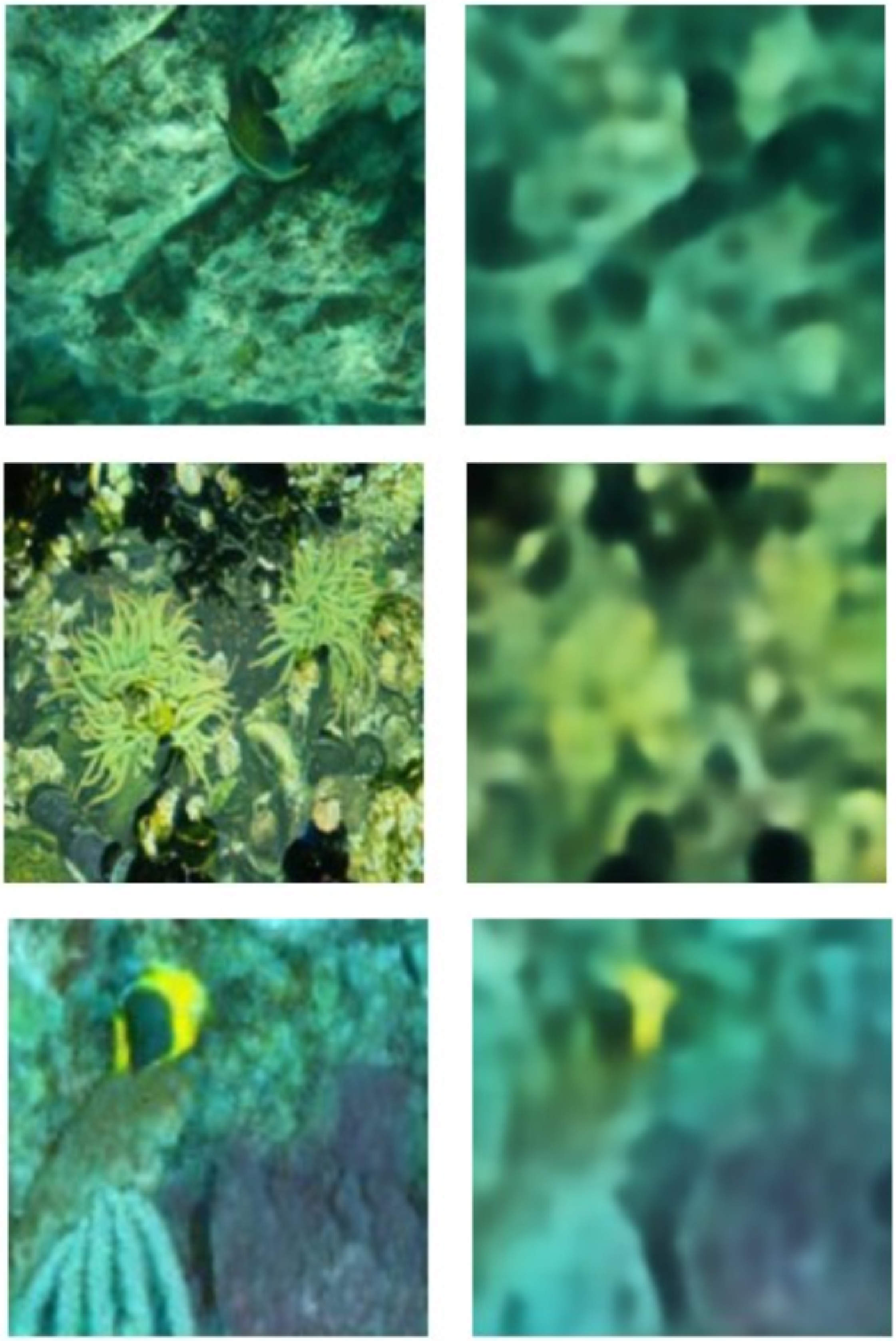
Encoder Architecture:



Decoder Architecture:



AutoEncoder RESULTS:



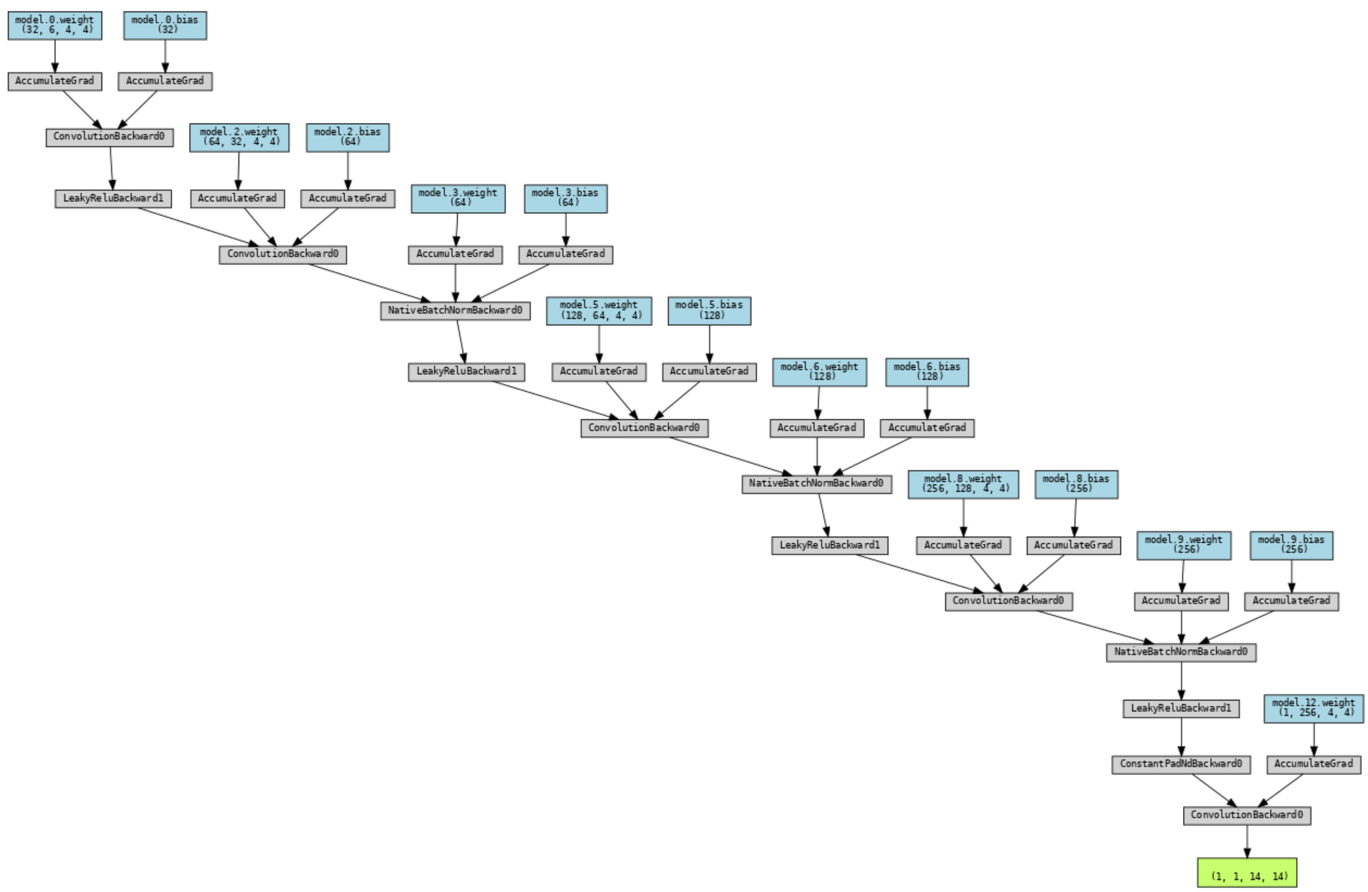
Generative Adversarial Network (GAN):

A GAN-based approach is employed to enhance the quality of reconstructed images. The GAN consists of two components: Generator and Discriminator. The Generator takes tensors of image size skips connections from the Decoder of the AutoEncoder, and returns an enhanced tensor of the image size. The Discriminator, on the other hand, takes clear images and decoded images, returning patches of 14x14.

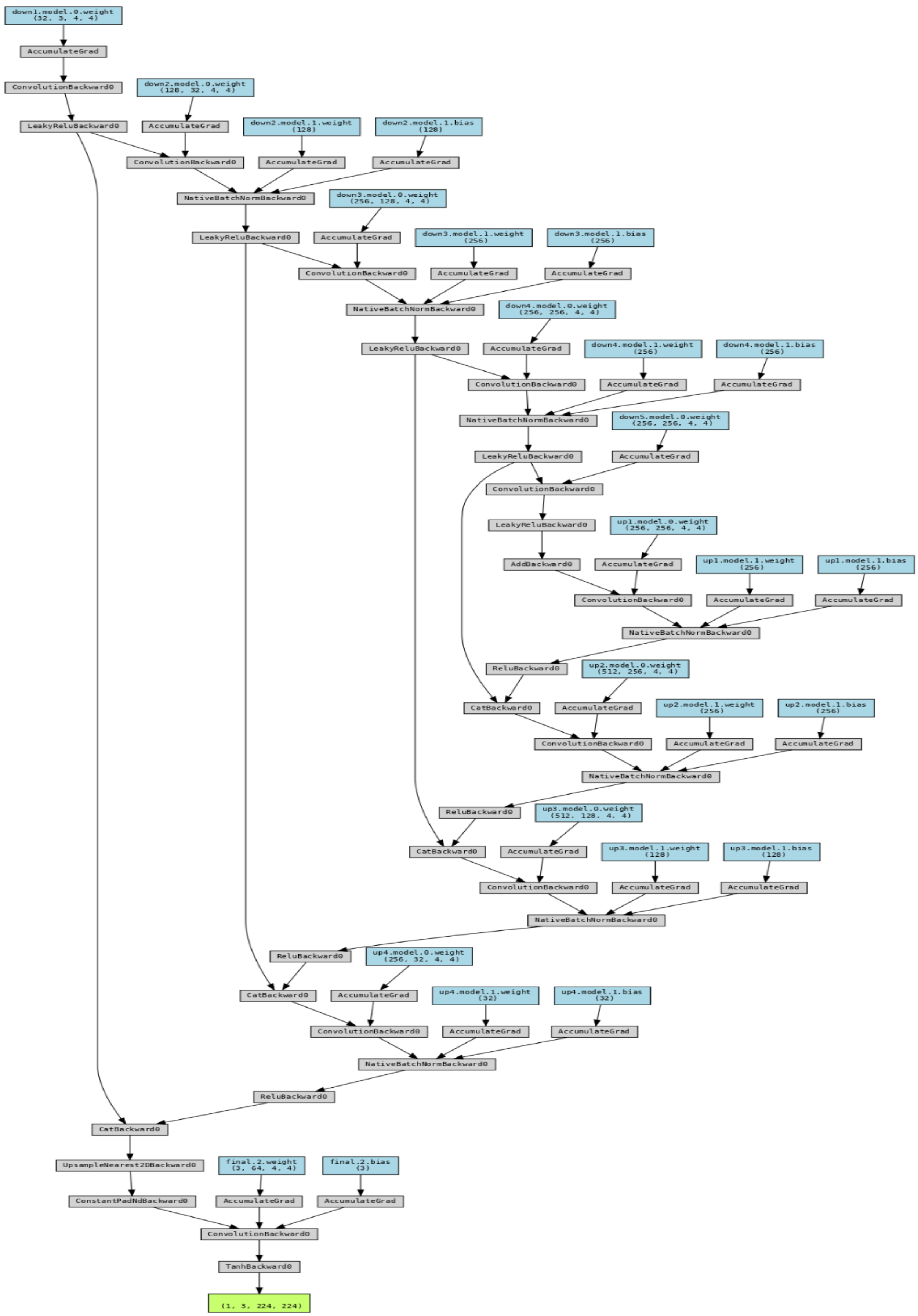
The GAN employs three loss functions:
1. Adversarial Loss: Calculated using MSE loss from the Discriminator.
2. VGG Loss: Utilizes a pre-trained VGG model to compute Perception Loss.
3. L1 Loss: Measures the difference between the image and its decoded counterpart.

The GAN model is trained using the Adam optimizer with a learning rate 0.0001 for 40 epochs. A learning rate step occurs at epoch 10 with a gamma of 0.75.

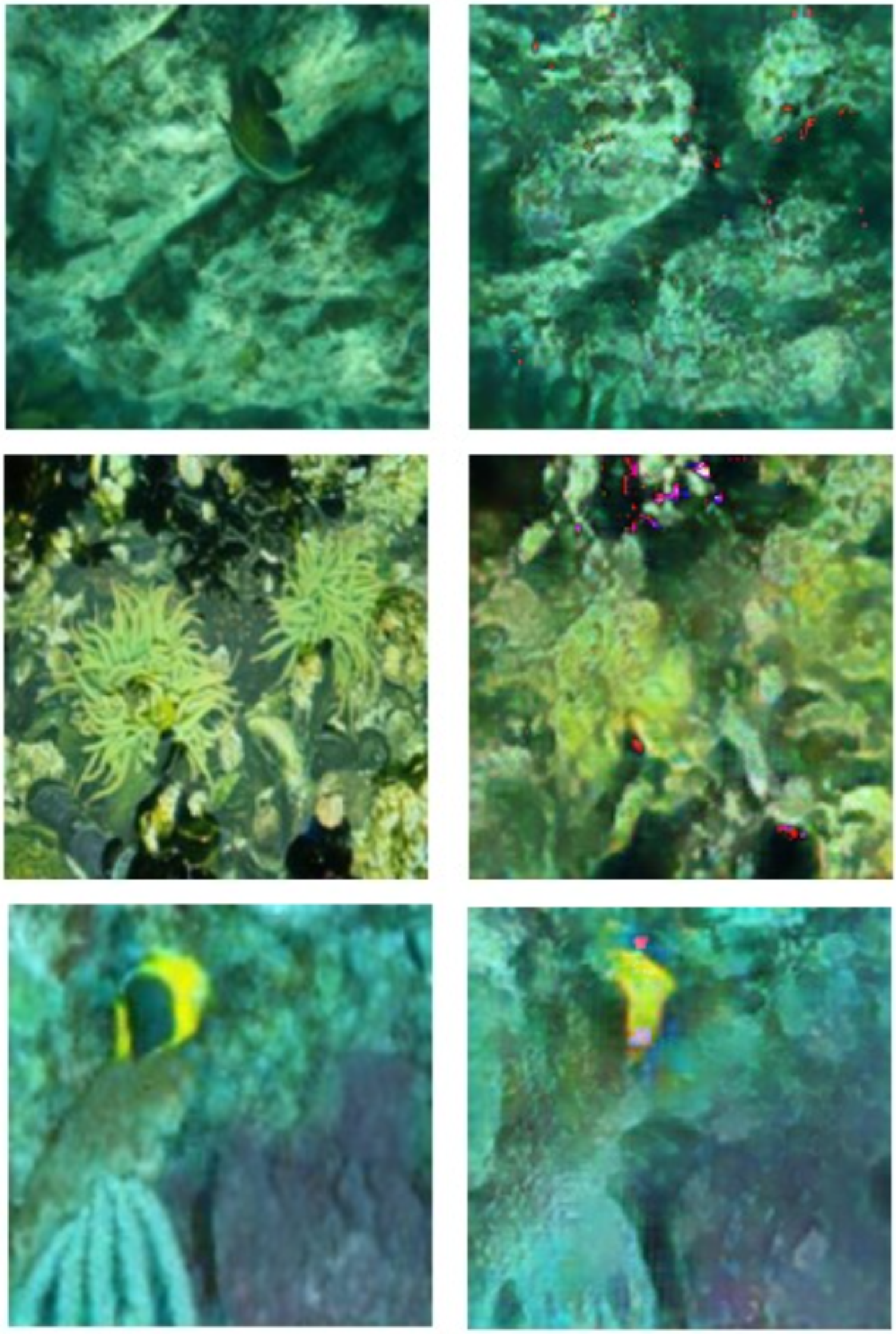
Discriminator Architecture:



Generator Architecture:



GAN Enhanced Image Results:



Conclusion:

Integrating the AutoEncoder and GAN presents a compelling solution for image compression in Autonomous Underwater Vehicles (AUVs). Through machine learning techniques, significant compression ratios are achieved while maintaining reconstruction accuracy, which is crucial for real-time analysis and efficient transmission of underwater images.

The evaluation of the system's performance using Mean Squared Error (MSE) as a metric indicates the reliability of the compression process. However, more than MSE is required to fully capture the quality improvement achieved by the GAN, particularly in enhancing image features and overall visual fidelity. Thus, supplementary evaluation metrics focusing on perceptual quality could provide a more comprehensive assessment of the generated images.

Furthermore, while the computational complexity of the integrated system may seem high, the offloading of a significant portion of computation from the AUV to external processing units mitigates this concern. The AUV only requires the Encoder, reducing onboard computational requirements and enhancing operational efficiency.

In summary, the developed system demonstrates promise in addressing the image compression challenges AUVs face, paving the way for more effective exploration and analysis of underwater environments. Future iterations could explore additional evaluation metrics and optimizations to enhance system performance and efficiency further.