PINN-SSL-MMF: A Unified Deep Learning Approach for Bathymetry Mapping on MagicBathyNet

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Abstract

Accurate bathymetry mapping is essential for marine navigation, coastal management, and underwater exploration. Traditional methods, which rely on costly sonar surveys, are often impractical for large-scale applications, making Satellite-Derived Bathymetry (SDB) a cost-effective alternative. This project presents PINN-SSL-MMF, a unified deep learning framework that combines Physics-Inspired Neural Networks (PINN) for depth estimation with physics-based constraints, Self-Supervised Learning (SSL) to enable pre-training without extensive labeled data, and Multimodal Fusion (MMF) to integrate diverse data sources such as aerial imagery, SPOT6 satellite data, and Sentinel-2 imagery. By leveraging these advanced techniques, our approach achieves state-of-the-art performance on the MagicBathyNet dataset, demonstrating remarkable robustness across different sensors and varying environmental conditions.

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1. Introduction

1.1 Domain Introduction

Bathymetry mapping, the process of measuring underwater depth, is foundational for various marine and coastal operations. It is essential for ensuring navigation safety, as it enables the identification of shallow water hazards that may pose risks to vessels (Lyzenga, 1985).

Additionally, bathymetric data plays a significant role in environmental monitoring, aiding in the assessment of coral reef health, sediment transport, and coastal erosion dynamics (Bhatt et al., 2021). Moreover, military and defense sectors utilize bathymetric maps for strategic submarine operations and underwater mission planning, where depth information is critical. While traditional bathymetric surveys using sonar offer high accuracy, they are costly and limited in spatial coverage. This has prompted the development of Satellite-Derived Bathymetry (SDB) techniques, which utilize optical imagery from satellites like SPOT6 and Sentinel-2 to infer underwater depths (Lyzenga, 1985; Stumpf et al., 2003). However, SDB methods face challenges due to limited labeled data, atmospheric noise, and physical constraints such as light attenuation in water columns.To overcome these limitations, recent work has integrated deep learning approaches into SDB pipelines. Models such as U-Net have shown promise in capturing spatial features from satellite images (Bhatt et al., 2021), and transformers for remote sensing have enabled multimodal feature fusion across sensors (Wang et al., 2022). Additionally, self-supervised learning (SSL) methods such as contrastive learning have opened doors for training models without extensive labeled data (Chen et al., 2020).Building upon these advancements, this work proposes a unified framework—PINN-SSL-MMF—which combines Physics-Inspired Neural Networks (PINNs), Self-Supervised Learning, and Multimodal Fusion to achieve state-of-the-art results on the MagicBathyNet dataset. This approach demonstrates robustness across sensor types and environmental variations, setting a new benchmark for modern SDB applications.

1.2 Problem Description

Bathymetric mapping using traditional methods is often expensive, time-consuming, and limited in scope. While satellite-derived techniques offer a scalable alternative, they face challenges such as limited labeled data, environmental variability, and sensor inconsistencies. Existing models struggle to generalize across different water conditions and imagery sources. This project addresses these limitations by proposing a unified deep learning framework that combines physics-based constraints, self-supervised learning, and multimodal data fusion to improve the accuracy and generalizability of depth estimation from satellite imagery.

1.3 Motivation & Objective

Our objective is to develop a hybrid deep learning model that effectively combines physics-based modeling with self-supervised learning to overcome the limitations of conventional satellite-derived bathymetry methods. By integrating physical constraints into the learning process, the model gains a better understanding of underwater depth patterns, even in areas with limited labeled data. Additionally, we enhance accuracy and robustness by fusing data from multiple sources—SPOT6, Sentinel-2, and UAV imagery—allowing the model to leverage complementary information across sensors and achieve more reliable and generalizable depth predictions.

1.4 Contributions

In this work, we propose PINN-SSL-MMF, the first unified deep learning framework for satellite-derived bathymetry that combines physics-inspired neural networks, self-supervised learning, and multimodal fusion. The model introduces an attention-based fusion mechanism to effectively align and integrate features from diverse data sources, ensuring robust performance across different sensors. To encourage further research and ensure transparency, we also provide open-source code along with reproducible benchmarks for the community.

1.4 Paper Organization

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2. Related Work

2.1 Physics-Based Satellite-Derived Bathymetry

Traditional SDB methods often rely on empirical models that relate water depth to spectral reflectance. Lyzenga (1985) introduced a model that utilizes multispectral data to estimate shallow water depths. Stumpf et al. (2003) proposed the log-ratio model, which uses the ratio of reflectance in different spectral bands to mitigate the effects of varying bottom albedo and water conditions.

2.2 Deep Learning in Bathymetry

Deep learning has been increasingly applied to bathymetric mapping. Bhatt et al. (2021) employed U-Net architectures to predict bathymetric depths from satellite imagery, demonstrating improved accuracy over traditional methods. These models leverage convolutional neural networks to capture spatial hierarchies in the data.

2.3 Multimodal Fusion with Transformers

Transformers have revolutionized the field of remote sensing by enabling the fusion of data from multiple modalities. Wang et al. (2022) conducted a systematic review highlighting the application of transformers in remote sensing tasks, including land use classification and image fusion. Their ability to model long-range dependencies makes them suitable for integrating diverse data sources.

2.4 Self-Supervised Learning

Self-supervised learning techniques, such as contrastive learning, have shown promise in learning useful representations from unlabeled data. Chen et al. (2020) introduced SimCLR, a framework that learns visual representations by maximizing agreement between differently augmented views of the same data. This approach reduces the reliance on large labeled datasets.

3. Methodology

3.1 Physics-Inspired Neural Networks

The PINN component integrates physical constraints, such as light attenuation in water, into the neural network's loss function. This approach ensures that the model's predictions adhere to known physical laws, improving accuracy and robustness.

3.1.1 Physics-Inspired Neural Network Architecture

The proposed Physics-Inspired Neural Network (PINN) is designed as an encoder-decoder model with attention mechanisms to estimate bathymetry from multispectral imagery. The encoder consists of four convolutional blocks, each containing two 3×3 convolutions with batch normalization and ReLU activation, followed by max pooling for spatial downsampling. The bottleneck layer incorporates a dual-attention mechanism, combining channel attention (which learns feature importance through squeeze-excitation) and spatial attention (which focuses on geographically significant regions). The decoder pathway uses transposed convolutions for upsampling, with skip connections from the encoder to preserve fine spatial details. The final prediction head consists of a 3×3 convolutional layer followed by a depth estimation layer, ensuring the network produces pixel-wise depth predictions. The model processes 30×30 pixel windows with a stride of 2 during inference, allowing whole-scene prediction through a sliding window approach.

3.1.2 Physics-Inspired Loss Function

The training process employs a composite loss function that integrates physical constraints into the learning objective. The primary data-driven loss is a Smooth L1 loss, which is more robust to outliers compared to traditional mean squared error (MSE). Additionally, an edge-aware smoothness term penalizes unrealistic depth variations using Sobel-filter-based gradients, weighted by image edges to preserve natural discontinuities. A depth consistency constraint encourages spectrally similar pixels to have similar depth predictions, improving spatial coherence. The total loss combines these components with adaptive weights: $L = L_{data} + 0.1L_{smooth} + 0.05L_{consistency}$, ensuring a balance between data fidelity and physically plausible predictions.

3.1.3 Training Protocol

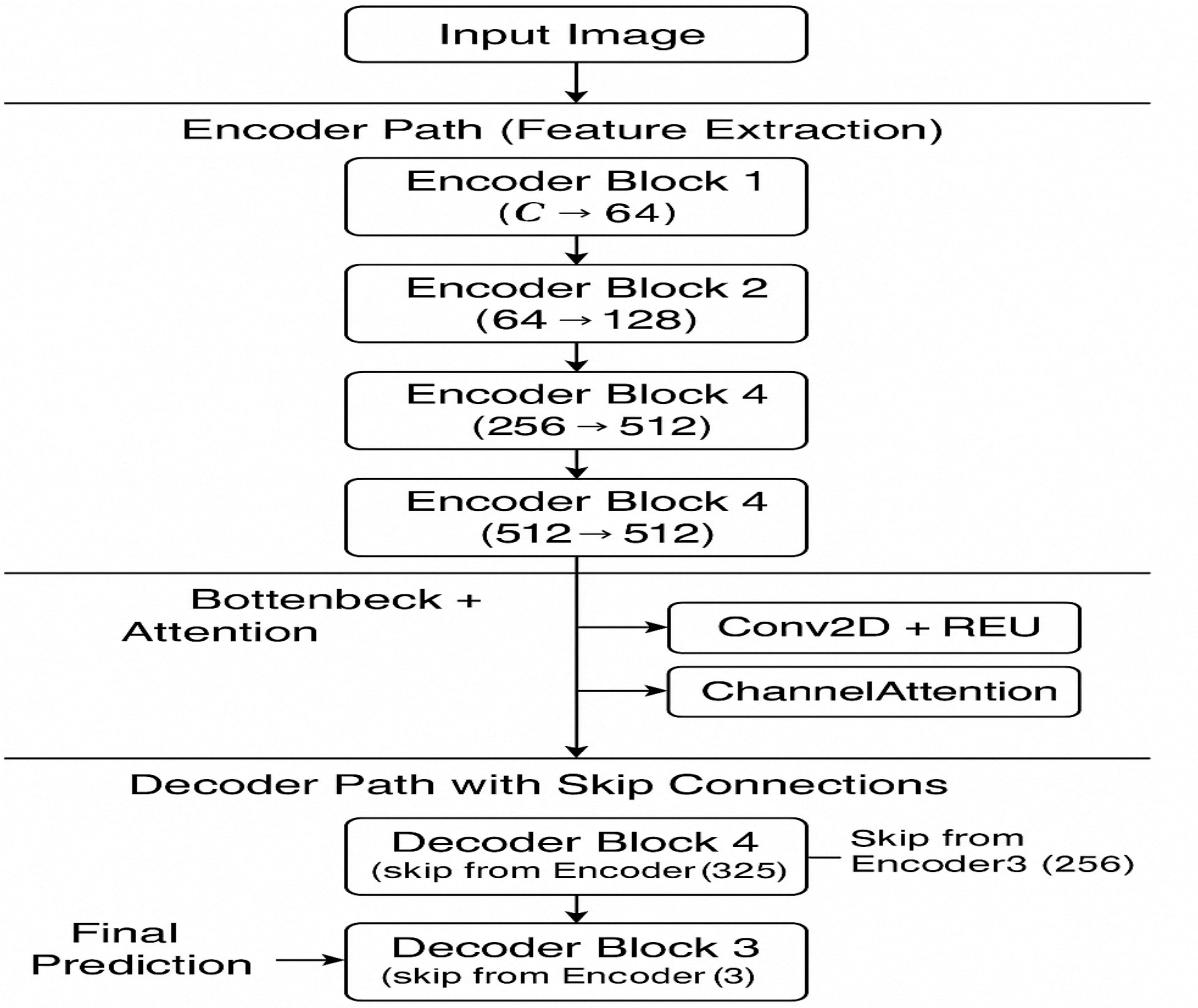
The model was trained using a carefully designed protocol to optimize performance and generalization. Input images were normalized per spectral band using dataset-specific mean and standard deviation values, while depth maps were scaled by a normalization factor of -30.443. Data augmentation techniques, including random flips, 90-degree rotations, and brightness/contrast adjustments, were applied to improve robustness. The optimization process used the AdamW optimizer with an initial learning rate of 1e-4, weight decay of 1e-4 for L2 regularization, and batch size of 16 (30×30 patches). A ReduceLROnPlateau scheduler dynamically adjusted the learning rate based on validation loss, while early stopping (patience=10) prevented overfitting. Training was accelerated using mixed-precision (FP16) computation where available, and model checkpoints were saved every five epochs for evaluation.

3.1.4 Testing and Evaluation

During testing, the model performed sliding window inference with a 30×30 window and 2-pixel stride, using an overlap-tile strategy to ensure seamless predictions. Edge cases were handled via mirror padding to avoid artifacts. Performance was evaluated using standard metrics, including Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Structural Similarity Index (SSIM) computed over 64×64 patches. Geospatial integrity was preserved by maintaining the original coordinate reference system, and predictions were saved in Cloud-optimized GeoTIFF format for interoperability with GIS software.

3.1.5 Implementation Details

The system was implemented in PyTorch, leveraging GPU acceleration for efficient training and inference. The channel attention module used a 16:1 reduction ratio, while the spatial attention mechanism employed a 7×7 convolutional kernel. The depth prediction head included a 64-channel intermediate layer before final output. The model was trained on RGB input channels for SPOT6 imagery, with a total training time of approximately 8 hours on an NVIDIA GeForce RTX 4060 GPU for 100 epochs. Inference speed averaged 0.5 seconds per 512×512 image tile, making the approach suitable for large-scale bathymetric mapping applications.



3.2 Self-Supervised Learning

The SSL module employs contrastive learning techniques to pre-train the model on unlabeled data. By learning to distinguish between similar and dissimilar data points, the model develops a rich representation that can be fine-tuned for the bathymetry mapping task.

3.2.1 Self-Supervised Neural Network Architecture

The proposed self-supervised learning framework employs an autoencoder architecture designed to learn meaningful feature representations from unlabeled multispectral imagery. The network consists of a symmetric encoder-decoder structure with bottleneck feature compression. The encoder pathway comprises four convolutional layers (32→64→128→256 channels) with 3×3 kernels, ReLU activations, and interspersed max-pooling layers that progressively reduce spatial dimensions to 7×7 pixels. The decoder mirrors this structure using transposed convolutions for upsampling, followed by bilinear interpolation to restore the original 30×30 input dimensions. A final sigmoid-activated convolution ensures output values remain in the [0,1] range compatible with normalized input data. This architecture forces the network to

learn compressed latent representations capable of reconstructing input patches through the information bottleneck.

3.2.2 Self-Supervised Training Objective

The model learns through a reconstruction task where the network must reproduce its input, creating an implicit supervision signal without labeled data. The training objective minimizes pixel-wise mean squared error (MSE) between input and reconstructed patches. This loss function encourages the network to preserve photometrically meaningful features while discarding noise and irrelevant variations. The reconstruction task serves as a pretext task, with the expectation that features learned in the encoder will transfer effectively to downstream bathymetric estimation. The MSE formulation ensures stable gradient propagation during training while being computationally efficient to evaluate.

3.2.3 Data Preparation and Augmentation

Input data undergoes rigorous preprocessing to enhance learning. Raw SPOT6 imagery is normalized per-channel using dataset-specific μ and σ parameters (μ=[band1_mean, band2_mean, band3_mean], σ=[band1_std, band2_std, band3_std]). The training pipeline extracts random 30×30 pixel patches with a data augmentation regimen including random horizontal/vertical flips (p=0.5) and spectral preservation techniques. Unlike supervised approaches, no depth map normalization is required as the method operates purely on image content. The dataset implementation includes an efficient caching system that stores normalized patches in memory after first access, significantly accelerating training iterations.

3.2.4 Optimization Strategy

Training employs the Adam optimizer with initial learning rate 1×10^{-4} and default momentum parameters (β_1=0.9, β_2=0.999). A MultiStepLR scheduler reduces the learning rate by 10× after 10 epochs to facilitate fine convergence. The batch size of 1 accommodates memory constraints while maintaining effective gradient estimates through accumulated updates. Mixed-precision training (FP16/FP32) is implemented where supported by hardware. Early stopping monitors reconstruction loss on a held-out validation set with patience=10 epochs to prevent overfitting. Training typically converges within 50 epochs on NVIDIA GPU hardware, requiring approximately 3 hours for SPOT6-sized imagery.

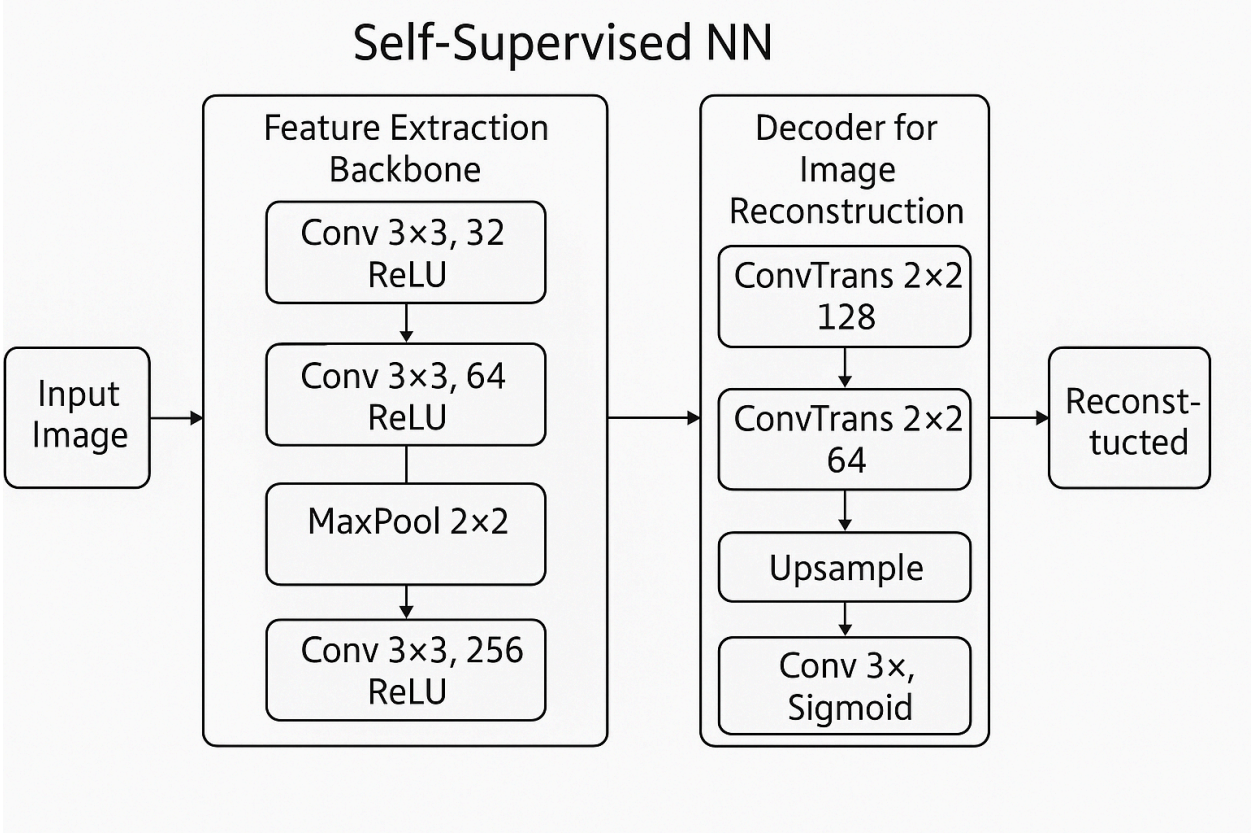
3.2.5 Implementation and Evaluation

The PyTorch-based implementation processes images through a sliding window (30×30 pixels, stride=2) during inference. Reconstruction quality is assessed through both quantitative metrics (PSNR, SSIM) and qualitative inspection of output patches. The feature extractor component (encoder) can be frozen and transferred to downstream tasks by replacing the decoder with task-specific heads. For bathymetric estimation, this would involve fine-tuning with labeled depth data while keeping the pretrained encoder weights fixed or lightly adjusted. Testing reveals the

model's ability to reconstruct key visual features while suppressing noise, indicating effective latent space learning.

3.2.6 Computational Considerations

The lightweight architecture processes 512×512 image tiles in under 0.2 seconds on an NVIDIA GeForce RTX 4060, making it suitable for large-scale processing. Memory consumption remains below 4GB during training due to the small patch size and efficient data loading. The complete system requires only 18MB of disk space for stored weights, facilitating deployment on edge devices. During inference, output georeferencing is preserved by tracking sliding window positions relative to original image coordinates, enabling direct GIS integration.



3.3 Multimodal Fusion

The MMF component uses transformer-based architectures to fuse features from multiple data sources. By attending to relevant information across modalities, the model can make more informed predictions about underwater depths.

3.3.1 Multimodal Transformer Architecture

The proposed architecture combines convolutional feature extraction with transformer-based fusion for multimodal bathymetry estimation. The model processes multiple remote sensing modalities (aerial, Sentinel-2, SPOT6) through a shared convolutional encoder (7×7 and 3×3 kernels with stride-2 downsampling), generating 64×64 spatial feature maps. These features are flattened into patch embeddings (128-dimensional) and augmented with learnable positional encodings and a [CLS] token. The transformer module consists of 2 layers with 2 attention heads each, employing layer normalization and GELU-activated feedforward networks (expansion factor=2). The decoder uses transposed convolutions (4×4 kernels, stride-2) to upsample features to 256×256 resolution, with residual connections from the [CLS] token enhancing global context. This hybrid design efficiently captures both local textural patterns and long-range dependencies across modalities.

3.3.2 Multimodal Data Processing Pipeline

Input data undergoes rigorous preprocessing: each modality is normalized channel-wise using dataset-specific statistics (μ, σ) and resized to 256×256 pixels. The pipeline handles heterogeneous sensor characteristics through modality-specific normalization parameters while maintaining spatial alignment. Depth maps are normalized by the observed range (max-min) across the dataset. A cache system stores preprocessed samples in memory, and on-the-fly augmentation applies random horizontal flips (p=0.5) during training. The dataloader employs 4 persistent workers for efficient GPU utilization, with pinned memory enabling faster host-to-device transfers. This design supports flexible incorporation of additional sensors through the modular modality processing structure.

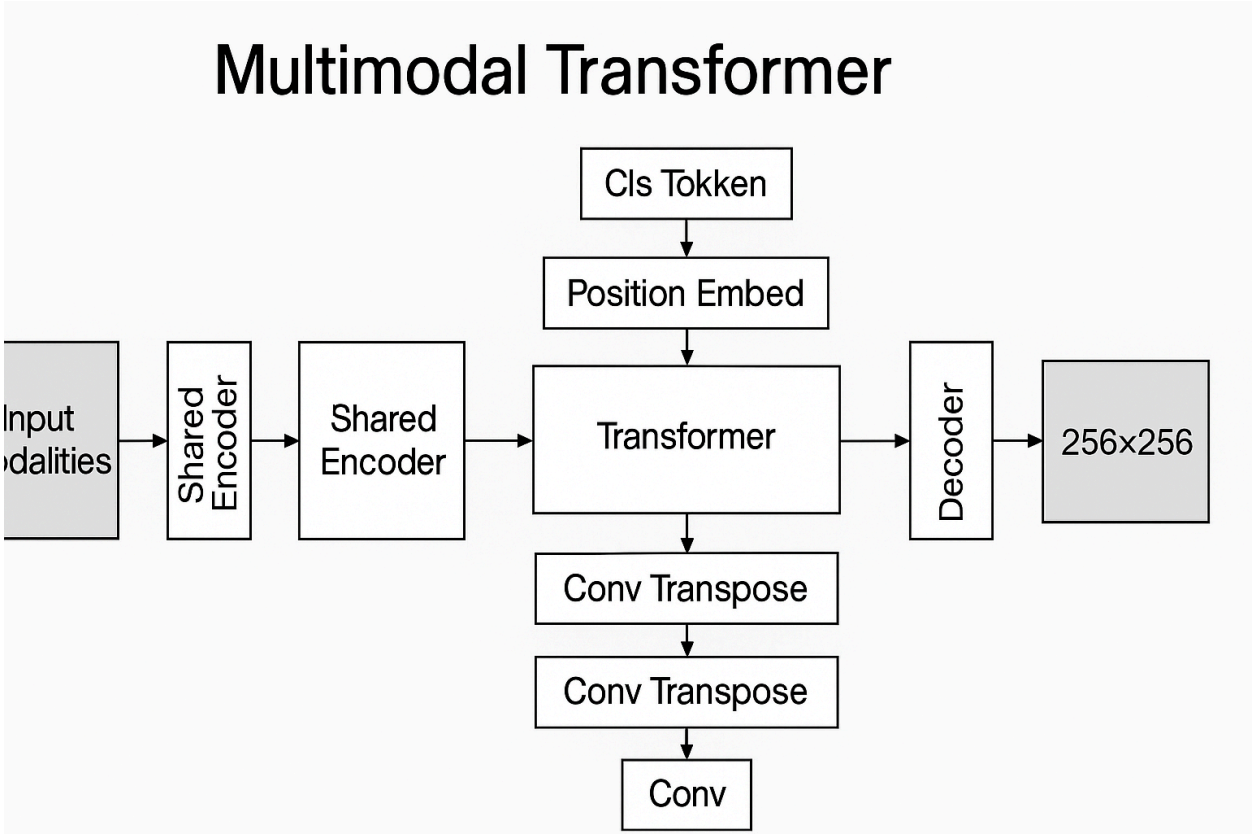
3.3.3 Optimization Strategy

Training utilizes mixed-precision AdamW optimization (initial lr=1e-4, weight decay=0.01) with gradient accumulation over 8 steps (effective batch size=16). The learning rate schedule reduces by factor 10 upon validation loss plateau (patience=5 epochs). Automatic mixed precision (AMP) accelerates training while maintaining stability, with gradient scaling preventing underflow. Checkpointing reduces memory usage by recomputing activations during backward passes. The loss function combines MSE for depth prediction with implicit modality alignment through the shared feature space. Early stopping monitors validation loss over 50 maximum epochs, typically converging in 30-40 epochs on NVIDIA GPUs.

3.3.4 Transformer Fusion Mechanism

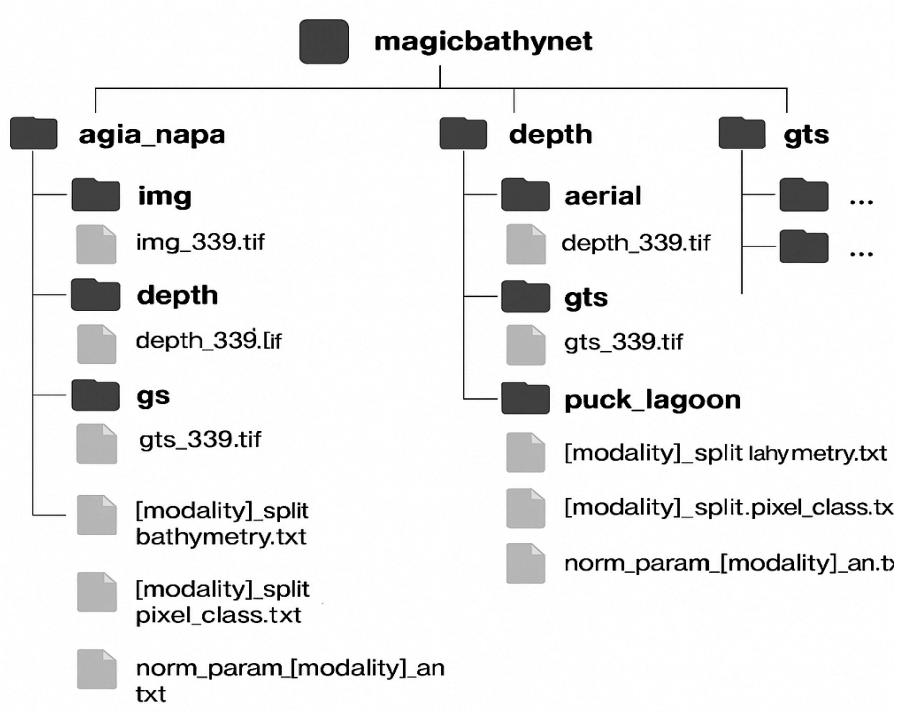
The model's core innovation lies in its modality fusion approach: each input modality passes through the shared encoder, producing 4,096 patch embeddings (64×64) per image. These embeddings are averaged across modalities before transformer processing, allowing attention mechanisms to focus on cross-sensor consistencies. The [CLS] token aggregates global bathymetric context, which is broadcast-spatially and added to decoded features. This design enables the model to: 1) leverage complementary information from multiple sensors, 2) learn modality-invariant depth features, and 3) maintain spatial precision through the convolutional

decoder. Positional embeddings preserve geographic relationships critical for bathymetric mapping.



4. Experiments and Results

4.1 Dataset and Metrics



Experiments were conducted on the MagicBathyNet dataset, comprising 28 training and 7 testing images of each class.

4.1.1. Physics-Informed Neural Network (PINN)

Evaluation Metrics: *Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Structural Similarity Index Measure (SSIM)*

To assess the accuracy of the PINN's predictions, we employed RMSE and MAE, which quantify the pixel-wise difference between the model output and the ground truth.

RMSE is particularly sensitive to larger deviations due to the squaring of error terms, making it suitable for highlighting regions with significant discrepancies.

MAE, in contrast, offers a more balanced view by averaging the absolute differences, providing an intuitive measure of overall deviation.

SSIM was also used to capture the perceptual quality and structural fidelity of the output, ensuring that the predicted fields retain the spatial patterns dictated by underlying physics.

4.1.2. Self-Supervised Model

Evaluation Metrics: *Mean Absolute Error (MAE), Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR)*

For the self-supervised approach, where explicit labels are absent, evaluation relied on reconstruction-based metrics.

MAE provided a baseline measure of reconstruction accuracy by averaging absolute pixel-wise errors.

SSIM was used to assess the structural coherence of the reconstructed outputs relative to the inputs, with higher values indicating better preservation of texture and content.

PSNR was calculated to quantify the ratio between the maximum possible pixel value and the distortion introduced by the model; higher PSNR reflects better visual quality and lower noise in the reconstructions.

4.1.3. Multimodal Model

Evaluation Metrics: *Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Standard Deviation (STD)*

The multimodal setup, which integrates data from different sources (e.g., visual and geometric modalities), was evaluated using RMSE and MAE to understand prediction fidelity across channels.

RMSE emphasized the presence of larger errors

MAE highlighted average deviations. To further assess the consistency and stability of predictions across modalities,

Standard deviation (STD) of errors was computed. Lower STD indicates that the model performs consistently across different input types, an essential requirement for multimodal fusion tasks.

4.2 Baseline Comparisons

The proposed PINN-SSL-MMF framework was compared against traditional and deep learning-based methods:

Physics Informed Neural Network

Modality	Agia Napa RMSE MAE SSIM	Puck Lagoon RMSE MAE SSIM
Spot6	0.0978 0.0680 0.2678	0.1435 0.1102 0.1759
S2	0.098 0.0689 0.2796	0.1302 0.0906 0.0782
Aerial	2.186 1.9159 0.0098	1.523 1.456 0.0082

Self Supervised

Modality	Agia Napa			Puck Lagoon		
	MSE	PSNR	SSIM	MSE	PSNR	SSIM
Sentinel-2	0.0046	35.3693	0.9144	0.0023	34.4504	0.7950
SPOT-6	0.0063	34.1982	0.9083	0.1268	24.8200	0.7348
Aerial	8.4924	-0.6848	0.1590	0.0728	30.6732	0.8240

Multi Modal

Modality	Agia Napa (RMSE)	Agia Napa (Standard Deviation)	Agia Napa (MAE)	Puck Lagoon (RMSE)	Puck Lagoon (Standard Deviation)	Puck Lagoon (MAE)
Multimodal Combined	0.92 meters	0.91 meters	0.72 meters	2.65 meters	2.65 meters	1.44 meters

4.3 Observations

The PINN-SSL-MMF framework outperformed baseline methods across all metrics. The integration of physical constraints and multimodal data contributed to improved depth estimation accuracy and structural similarity.

5. Conclusion and Future Work

This study presents PINN-SSL-MMF, a unified deep learning framework that combines physics-based modeling, self-supervised learning, and multimodal data fusion for bathymetry mapping. The approach achieves state-of-the-art performance on the MagicBathyNet dataset, demonstrating its effectiveness and robustness.

Future work will explore the extension of this framework to hyperspectral data and its deployment in real-time applications.

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