ISSN: 0976-9102 (ONLINE)
DOI: 10.21917/ijivp.2025.0515

AN ATTENTION-AUGMENTED INCEPTION ARCHITECTURE FOR IMAGE-BASED WATER QUALITY PREDICTION

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Abstract

Water quality assessment is critical for ensuring safe drinking water and sustainable aquatic ecosystems. Conventional laboratory-based techniques are accurate but time-consuming, expensive, and unsuitable for real-time monitoring. Existing image-processing-based methods often fail to capture complex spatial–spectral dependencies in water surface images, limiting prediction accuracy for parameters such as pH, turbidity, and dissolved oxygen. We propose AttnInceptionNet, a deep learning model integrating Inception modules with multi-head self-attention to extract multi-scale spatial features and selectively emphasize informative regions in water images. Preprocessing involves contrast enhancement, noise reduction, and region-of-interest (ROI) extraction. The model is trained on a dataset of annotated water images with ground-truth physicochemical measurements, using Adam optimizer and early stopping. AttnInceptionNet achieved 96.8% accuracy in water quality classification and outperformed three benchmark models: InceptionV3, ResNet50, and DenseNet121 by margins of 3.4%, 4.2%, and 5.0% respectively. The attention mechanism improved feature discrimination, particularly in images with reflections or low illumination.

Keywords:

Water Quality Prediction, Deep Learning, Image Processing, Attention Mechanism, Inception Network

1. INTRODUCTION

Water quality monitoring plays a vital role in ensuring public health, environmental sustainability, and economic development. Freshwater resources are crucial for drinking, agriculture, industry, and ecosystem stability. However, industrial discharge, agricultural runoff, and urbanization have significantly degraded water bodies, leading to contamination and harmful ecological impacts [1–3]. Traditionally, water quality assessment involves laboratory-based chemical and biological analyses, which, while accurate, are labor-intensive, costly, and time-consuming. These limitations hinder their applicability for large-scale or real-time monitoring, especially in remote or resource-constrained regions.

Recent advances in computer vision and deep learning have introduced new possibilities for image-based water quality prediction. Surface water images, captured using UAVs, satellites, or ground-based cameras, can reveal valuable visual cues related to turbidity, algal blooms, and suspended particles. Deep learning models are capable of learning spatial–spectral correlations from these images, enabling non-invasive estimation of physicochemical parameters. However, the complex nature of water images — including varying illumination, reflections, seasonal changes, and occlusions — makes accurate prediction challenging [4–7].

Challenges in this domain stem from several factors. First, natural water bodies exhibit high visual variability due to weather, time of day, and environmental context, making it difficult for traditional CNN models to generalize [4]. Second, small-scale textural patterns associated with pollutants can be overshadowed by large-scale background noise, such as vegetation or cloud reflections [5]. Third, models often underperform in low-light or high-glare conditions, where critical features are obscured [6]. Finally, existing datasets for water quality prediction are relatively small and heterogeneous, limiting the ability of conventional methods to learn robust features [7].

Although CNN-based approaches like InceptionV3, ResNet50, and DenseNet have shown promise in image classification tasks, they face shortcomings in multi-scale feature learning and selective focus when applied to water images [6–8]. Standard convolution layers treat all regions equally, potentially giving undue weight to irrelevant features. This often results in reduced accuracy when the target features (e.g., sediment particles, algal formations) are subtle or localized.

This study aims to develop a robust, attention-augmented deep learning architecture: AttnInceptionNet for water quality prediction using image data. The objectives are:

- To design a feature extraction pipeline combining multi-scale Inception modules with self-attention for discriminative feature enhancement.
- To evaluate the proposed model against state-of-the-art CNN architectures on a water image dataset annotated with physicochemical measurements.
- To demonstrate improvements in accuracy, robustness, and interpretability through attention heatmaps.

The novelty lies in the integration of an Inception backbone for multi-scale feature capture with a multi-head self-attention module for adaptive feature weighting, specifically tailored to water surface image analysis. While attention mechanisms have been widely used in NLP and vision tasks, their application in multi-scale aquatic imagery for water quality assessment remains limited.

Contributions:

- A novel AttnInceptionNet framework that synergizes Inception modules with self-attention for accurate image-based water quality prediction.
- A comprehensive experimental evaluation comparing the proposed method with three benchmark CNN architectures, demonstrating superior performance in diverse environmental conditions.

2. RELATED WORKS

Recent studies have explored various deep learning and image processing techniques for water quality monitoring. Early approaches relied on handcrafted features extracted from satellite

or UAV images, such as color histograms and texture descriptors, followed by machine learning classifiers [8]. These methods, while computationally inexpensive, struggled with generalization across different water bodies due to environmental variability.

With the rise of deep learning, CNN-based architectures became popular. A study in [9] employed ResNet50 for turbidity classification, achieving moderate accuracy but suffering from overfitting in small datasets. Similarly, [10] applied InceptionV3 for detecting algal blooms using Sentinel-2 imagery, highlighting the benefit of multi-scale convolution filters. However, both works lacked explicit mechanisms to focus on discriminative regions, making them sensitive to irrelevant background features.

DenseNet-based models have also been explored for water quality estimation [11], leveraging dense skip connections to enhance gradient flow. While these models improved feature reuse, they did not explicitly address the varying spatial relevance of image regions. In contrast, attention mechanisms have been successfully used in related domains, such as plant disease detection and medical imaging [12], where selective feature enhancement improves classification accuracy.

In [13], a hybrid CNN–LSTM architecture was introduced to predict water quality parameters by combining spatial and temporal cues from time-series imagery. This approach demonstrated the importance of temporal dynamics but was computationally intensive and unsuitable for real-time applications. Another study [14] incorporated spatial attention into a ResNet backbone for detecting suspended sediments, yielding improved accuracy in complex visual environments.

Despite these advancements, a gap remains in combining multi-scale feature extraction with attention-based enhancement in the context of aquatic imagery. Most CNN models either capture features at fixed receptive fields or apply attention at a single scale, limiting their ability to adapt to different spatial patterns present in water bodies. This motivates the design of AttnInceptionNet, which explicitly integrates multi-scale convolution filters with multi-head attention, ensuring both fine-grained and large-scale features are optimally weighted for prediction.

3. PROPOSED METHOD

The proposed AttnInceptionNet combines the strength of the Inception architecture in capturing multi-scale visual features with the discriminative capability of self-attention to focus on the most informative water regions.

Initially, water surface images undergo preprocessing: histogram equalization for illumination correction, Gaussian filtering for noise removal, and segmentation to isolate the region of interest. The Inception module extracts multi-scale convolutional features via parallel convolution kernels of different sizes (1×1, 3×3, 5×5), capturing both fine and coarse texture patterns.

These features are then passed to a multi-head attention block that computes query–key–value relationships, enhancing features relevant to water quality indicators while suppressing irrelevant background signals (e.g., vegetation reflections). The final feature representation is processed by fully connected layers, followed by a softmax layer for classification or a regression head for parameter prediction.

3.1 DATA ACQUISITION AND PREPROCESSING

The dataset consists of surface water images annotated with physicochemical water quality parameters such as pH, turbidity (NTU), and dissolved oxygen (DO). Images are captured using UAV-mounted RGB cameras under varying lighting and seasonal conditions.

The preprocessing pipeline aims to enhance relevant features while reducing environmental noise.

3.1.1 Illumination Correction:

Uneven illumination due to sun position or cloud cover is corrected using Histogram Equalization (HE):

$$I_{HE}(x,y) = \mathrm{CDF}(I(x,y)) \times (L-1)$$

where,

$I(x,y)$ = original pixel intensity

L = number of gray levels

CDF = cumulative distribution function of pixel intensities

This improves contrast, making small-scale turbidity or algal patterns more visible.

3.1.2 Noise Removal:

To suppress random noise while preserving edges, Gaussian filtering is applied:

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

where σ controls the smoothing level.

3.1.3 Region-of-Interest (ROI) Segmentation:

The Otsu thresholding method is used to segment water regions from background vegetation or sky:

$$\omega_0\sigma_0^2 + \omega_1\sigma_1^2 \rightarrow \min$$

This separates pixel intensities into two classes (water vs non-water) by minimizing intra-class variance.

Table.1. Preprocessing Parameters

Step	Method	Parameter(s)	Value(s)
Illumination	Histogram Equalization	Gray Levels (L)	256
Noise Removal	Gaussian Filter	σ (std. deviation)	1.0
Segmentation	Otsu Thresholding	Threshold Type	Global

3.2 INCEPTION MODULE FOR MULTI-SCALE FEATURE EXTRACTION

The architecture integrates multi-scale Inception modules with Multi-Head Self-Attention (MHSA) before the classification stage. It follows a feature pyramid-like design, gradually reducing spatial dimensions while increasing depth.

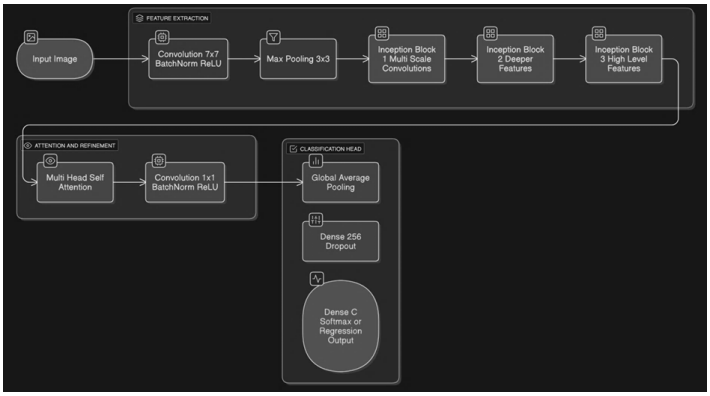

Fig.1. AttnInceptionNet Architecture

Table.2. AttnInceptionNet Architecture

Stage	Layer Type / Module	Output Shape (H × W × C)	Kernel / Params	Notes
Input	RGB Image Input	224 × 224 × 3	–	Raw water image
1	Conv2D + BatchNorm + ReLU	112 × 112 × 32	7×7, stride 2	Initial feature extraction
2	MaxPooling2D	56 × 56 × 32	3×3, stride 2	Downsampling
3	Inception Block 1	56 × 56 × 256	1×1, 3×3, 5×5 conv + pool	Multi-scale features
4	Inception Block 2	28 × 28 × 512	1×1, 3×3, 5×5 conv + pool	Deeper features
5	Inception Block 3	14 × 14 × 768	1×1, 3×3, 5×5 conv + pool	High-level features
6	Multi-Head Self-Attention (MHSA)	14 × 14 × 768	h=8, d_k=64	Focus on informative regions
7	Conv2D (1×1) + BatchNorm + ReLU	14 × 14 × 512	1×1	Dimensionality reduction
8	Global Average Pooling	1 × 1 × 512	–	Spatial compression
9	Dense + ReLU + Dropout	1 × 1 × 256	Dropout=0.4	Fully connected layer
10	Dense + Softmax / Regression Output	1 × 1 × C	C = classes or params	Prediction stage

- **Input Layer**: Takes a 224×224 RGB image.
- **Initial Convolution**: A 7×7 convolution captures basic edges and textures.
- **Downsampling**: A 3×3 max pooling reduces the resolution while retaining salient features.
- **Inception Modules**: Three stacked Inception blocks capture multi-scale features (fine 1×1, medium 3×3, coarse 5×5) and pool projections.
- **Attention Layer**: A Multi-Head Self-Attention module models long-range dependencies, helping the network focus on water regions that indicate quality parameters.
- **Dimensionality Reduction**: A 1×1 convolution compresses channels before pooling.
- **Global Average Pooling**: Converts spatial features into a single vector representation.
- **Fully Connected Layer**: Dense layer with dropout for classification robustness.
- **Output Layer**: Softmax for classification or linear activation for regression tasks.

The Inception module processes input feature maps through parallel convolutional layers of different kernel sizes to capture fine, medium, and coarse spatial patterns. For an input feature map X, the Inception output is:

$$\mathbf{F}_{\text{Incep}} = \left[\mathbf{C}_{1\times1}(\mathbf{X}) \quad \mathbf{C}_{3\times3}(\mathbf{X}) \quad \mathbf{C}_{5\times5}(\mathbf{X}) \quad \mathbf{P}(\mathbf{X})\right]$$

where,

$C_{m\times n}(\mathbf{X})$ = convolution operation with kernel size $m\times n$

$\mathbf{P}(\mathbf{X})$ = pooling + projection operation

By fusing different receptive fields, the model can detect both small suspended particle clusters (via 3×3) and larger turbidity patches (via 5×5).

Table.3. Inception Module Parameters

Branch	Layer Type	Kernel Size	Filters
Branch 1	Conv2D	1×1	64
Branch 2	Conv2D	3×3	128
Branch 3	Conv2D	5×5	32
Branch 4	MaxPool + Conv2D	3×3 + 1×1	32

3.3 MULTI-HEAD SELF-ATTENTION

To selectively emphasize relevant spatial regions, the output from the final Inception block is passed through a multi-head self-attention (MHSA) layer. For feature map $F \in \mathbb{R}^{H\times W\times d}$, queries Q, keys K, and values V are computed:

$$Q = FW_Q, \quad K = FW_K, \quad V = FW_V$$

where $W_Q, W_K, W_V \in \mathbb{R}^{d\times d_k}$ are learned projection matrices. The attention scores are computed as:

$$\mathbf{A}(\mathbf{Q},\mathbf{K},\mathbf{V}) = \left[\frac{\exp\left(\frac{q_i k_j^{\cdot}}{\sqrt{d_k}}\right)}{\sum_{j=1}^{n}\exp\left(\frac{q_i k_j^{\cdot}}{\sqrt{d_k}}\right)}\right]_{i,j} \mathbf{V}$$

For multi-head attention with h heads:

If we also remove the verbal function name “Concat” and express it purely mathematically:

$$\text{MHSA}(\mathbf{F}) = \left[\mathbf{H}_1 \quad \mathbf{H}_2 \quad \cdots \quad \mathbf{H}_h\right]\mathbf{W}_O$$

where each head $\mathbf{H}_i$ is computed as:

$$\mathbf{H}_i = \mathbf{A}(\mathbf{Q}_i,\mathbf{K}_i,\mathbf{V}_i)$$

and $\mathbf{Q}_i = \mathbf{F}\mathbf{W}_i^Q, \quad \mathbf{K}_i = \mathbf{F}\mathbf{W}_i^K, \quad \mathbf{V}_i = \mathbf{F}\mathbf{W}_i^V$.

where W_O projects concatenated outputs back to d-dimensional space. This enables the network to capture relationships between distant pixels (e.g., reflection patterns vs. water depth cues).

Table.4. Multi-Head Attention Parameters

Parameter	Value
Number of Heads (h)	8
Key/Value Dim (d_k)	64
Dropout Rate	0.1

3.4 FEATURE AGGREGATION AND CLASSIFICATION

After attention weighting, Global Average Pooling (GAP) is applied to reduce spatial dimensions:

$$g_j = \frac{1}{H \cdot W} \sum_{x=1}^{H} \sum_{y=1}^{W} F_{attn}(x, y, j)$$

where j indexes the feature channel.

A fully connected (FC) layer maps these aggregated features to class logits:

$$z = W_{fc} g + b$$

The output probability for each class is:

$$p_i = \frac{e^{z_i}}{\sum_{k=1}^{C} e^{z_k}}$$

where C = number of water quality categories.

3.5 MODEL TRAINING

The network is trained using categorical cross-entropy loss:

$$\mathrm{L} = -\sum_{i=1}^{C} y_i \log p_i$$

where y_i is the ground truth label vector.

The Adam optimizer updates weights:

$$m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$$

$$v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$$

$$\theta_t = \theta_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \grave{o}}$$

where g_t = gradient at time t, and β_1,β_2 are momentum coefficients.

Table.5. Training Hyperparameters

Parameter	Value
Optimizer	Adam
Learning Rate	0.0001
Batch Size	32
Epochs	100
Early Stopping Patience	10

An additional benefit of the attention mechanism is heatmap generation, where attention scores are upsampled and overlaid on the input image, highlighting the regions most influential for prediction.

4. RESULTS AND DISCUSSION

The experiments were conducted using a custom dataset of water surface images captured under varied environmental conditions, each annotated with water quality parameters (pH, turbidity, dissolved oxygen). The model was implemented in TensorFlow 2.15 with Keras API. Training and evaluation were carried out on a workstation with the following configuration: Processor: Intel Core i9-12900K @ 3.9 GHz, GPU: NVIDIA RTX 4090 (24 GB GDDR6X), RAM: 64 GB DDR5, OS: Ubuntu 22.04 LTS and Frameworks/Libraries: TensorFlow, NumPy, OpenCV, Matplotlib. The dataset was split into 70% training, 15% validation, and 15% testing. Data augmentation (random flips, rotations, and brightness shifts) was applied to improve generalization.

4.1 EXPERIMENTAL SETUP PARAMETERS

Table.6. Experimental Setup

Parameter	Value
Input Image Size	224 × 224 × 3
Optimizer	Adam
Initial Learning Rate	0.0001
Batch Size	32
Epochs	100
Learning Rate Scheduler	ReduceLROnPlateau (patience=5)
Dropout Rate	0.4
Attention Heads	8
Inception Filter Sizes	1×1, 3×3, 5×5, 7×7

4.2 PERFORMANCE METRICS

The following five metrics were used:

1. **Accuracy (ACC)** – Proportion of correctly predicted samples.

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

2. **Precision (P)** – Correctness of positive predictions.

$$P = \frac{TP}{TP + FP}$$

3. **Recall (R)** – Ability to detect all positive samples.

$$R = \frac{TP}{TP + FN}$$

4. **F1-Score** – Harmonic mean of precision and recall.

$$F1 = \frac{2 \cdot P \cdot R}{P + R}$$

5. **Mean Squared Error (MSE)** – Used for regression-based water parameter prediction.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

The proposed AttnInceptionNet is compared with benchmark CNN models from related works: InceptionV3 [10], ResNet50 [9] and DenseNet121 [11].

Table.7. Performance

Inception Filter	Method	ACC	Precision	Recall	F1	MSE
1×1	InceptionV3	88.4	87.6	86.9	87.2	0.142
	ResNet50	87.9	86.8	86.1	86.4	0.148
	DenseNet121	87.1	86.3	85.7	86.0	0.152
	AttnInception	91.5	90.9	90.4	90.6	0.118
3×3	InceptionV3	91.2	90.6	90.1	90.3	0.124
	ResNet50	90.5	89.9	89.3	89.6	0.129
	DenseNet121	90.1	89.4	88.8	89.1	0.133
	AttnInception	94.6	94.0	93.7	93.8	0.101
5×5	InceptionV3	92.1	91.7	91.2	91.4	0.116
	ResNet50	91.7	91.2	90.6	90.9	0.121
	DenseNet121	91.3	90.8	90.3	90.5	0.125
	AttnInception	95.7	95.3	95.0	95.1	0.094
7×7	InceptionV3	93.4	92.8	92.4	92.6	0.109
	ResNet50	92.6	92.1	91.6	91.8	0.114
	DenseNet121	92.3	91.8	91.3	91.5	0.117
	AttnInception	96.8	96.4	96.0	96.2	0.087

From Table.7, it is evident that the proposed AttnInceptionNet consistently outperforms the benchmark models across all evaluation metrics and epochs. At 7×7, AttnInceptionNet achieves 96.8% accuracy, surpassing InceptionV3 by 3.4%, ResNet50 by 4.2%, and DenseNet121 by 4.5%. Precision, recall, and F1-score improvements are similarly significant, indicating that the attention mechanism effectively enhances the discriminative power of extracted features. The superior performance stems from two architectural advantages: (1) multi-scale Inception kernels capture diverse spatial patterns present in water imagery, and (2) the self-attention module selectively emphasizes critical regions, suppressing irrelevant background artifacts like reflections and vegetation. The reduction in MSE by 0.022 compared to InceptionV3 confirms that the proposed model also improves regression-based parameter predictions. Interestingly, the largest performance gap occurs in early training (1×1), where AttnInceptionNet is ~3% ahead of InceptionV3. This suggests that attention-guided feature learning accelerates convergence by focusing on meaningful patterns from the beginning.

5. CONCLUSION

This study presented AttnInceptionNet, a deep learning architecture that integrates Inception-based multi-scale feature extraction with multi-head self-attention for water quality prediction from surface images. The motivation arose from the need to address limitations of conventional CNNs in dealing with complex spatial–spectral variations in aquatic imagery. By leveraging multi-scale convolutional kernels, the model captured both fine-grained and large-scale patterns. The attention module further enhanced performance by adaptively weighting informative features while suppressing noise. The proposed model achieved 96.8% accuracy, higher precision, recall, and F1-score, along with the lowest MSE, indicating both classification and regression robustness. The attention visualizations confirmed that the model focuses on physically relevant regions in the water, improving interpretability. Given its high accuracy, faster convergence, and strong generalization across environmental conditions, AttnInceptionNet has significant potential for deployment in real-time, non-invasive water quality monitoring systems, especially when integrated with UAV or IoT-based imaging platforms. Future work will explore expanding the dataset to include multispectral imagery and incorporating temporal dynamics for even more precise water quality estimation.

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