Improving Generalization of Image-Based Water Turbidity Classification Using Fine-Tuning with Small Real-World Datasets

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Abstract

Water turbidity is a key sign of water quality, and scientists usually use nephelometers and other lab-based tools to measure it. Even though these methods are accurate, they are expensive, take a long time, and are not good for quick use in the field. This paper proposes a lightweight deep learning-based method for directly classifying water turbidity levels from real-world images obtained with consumer mobile devices. A custom dataset is made up of pictures taken with different smartphones in uncontrolled lighting conditions. The pictures are then sorted into three groups based on turbidity levels: low, medium, and high. To deal with real-world visual noise like reflections, shadows, and color distortions, we use an EfficientNet-B0 backbone with transfer learning and partial fine-tuning. Experimental results show that classification in uncontrolled environments is still hard, but the proposed method shows consistent learning behavior and useful class discrimination. This shows that it could be a low-cost, portable way to do preliminary turbidity assessment.

***Keywords*—** Water Turbidity, Image Classification, Deep Learning, EfficientNet, Transfer Learning, Real-World Data

Code availability: The source code for this study is available in the folowing gitHub repository-https://github.com/Saji-d/CVPR/tree/main/FINAL/Paper

1 Introduction

Checking the quality of water is important for the health of people, the environment, and businesses. One way to tell how dirty something is is to look at how cloudy the water is because of the particles in it. You need lab equipment that can take physical samples and control the conditions in order to measure turbidity the old-fashioned way. This makes it hard to use and grow. Deep learning and computer vision have come a long way in the last few years. Now, visual analysis can be used for things like keeping an eye on the environment. Most of the methods that are already out there, on the other hand, assume that the samples were made in a lab or that the imaging environments were controlled. This is not how things work in the real world. This study aims to address this deficiency by examining the classification of turbidity using images captured directly from mobile devices in uncontrolled outdoor environments. This work adds a few important things:

- Collecting a lot of turbidity photos taken in the real world with different smartphones to make a dataset.
- A system for sorting things that uses EfficientNet-B0 and transfer learning.

- An experimental study that demonstrates the challenges and opportunities encountered in assessing water quality in real-world scenarios.

2 Related Work

Physical sensors and nephelometric measurements are the most common ways to measure turbidity. These methods work well, but you need special hardware and to calibrate them often. Image-based methods work well because it's easy to find cameras. Soto et al. proposed a CNN-based turbidity classification system utilizing EfficientNet-B0 and transfer learning. It did a great job on a dataset that was collected in a lab [1]. The dataset lacked real-world variability, and the model was not evaluated under uncontrolled imaging conditions.Transfer learning and fine-tuning are common ways to improve performance in computer vision when the training and deployment data come from different domains [2].Data augmentation methods have been shown to work well for making systems more stable, especially when there aren't many data points [3]. Nonetheless, insufficient research has investigated real-world generalization for image-based turbidity classification, thereby necessitating the proposed study.

3 Proposed Methodology

3.1 Dataset Collection

Three different smartphones were used to take pictures in natural light: two iPhones and one Android. The dataset has more than 300 pictures, and they are sorted into:

- Low Turbidity
- Medium Turbidity
- High Turbidity

All of the pictures were changed to the same size and format: 224×224 pixels.

3.2 Model Architecture

EfficientNet-B0, which was trained on ImageNet, is the backbone. The last classification head is made up of these parts:

- Making the Global Average
- Layer that is fully connected
- The softmax output for three groups Things were changed by unfreezing the higher-level layers.

3.3 Training Strategy

- Adam is the one who fixes things.
- The loss function is Categorical Cross-Entropy.
- To fix the imbalance, give some classes more importance.
- Fine-tuning, in part by lowering the rate of learning

4 Experimental Results

4.1 Quantitative Results

The model's overall validation accuracy varied from approximately 18% to 47%, contingent upon the fine-tuning phase.

Class	Precision	Recall	F1-score	Support
High	0.00	0.00	0.00	26
Low	0.18	1.00	0.31	10
Medium	0.00	0.00	0.00	19
Accuracy			0.18	55
Macro Avg	0.06	0.33	0.10	55
Weighted Avg	0.03	0.18	0.06	55

Table 1: Classification report on validation set

Table 1 shows the precision, recall, and F1-score for each turbidity class in the validation set. The confusion matrix's strong bias toward the high turbidity class shows that the classes are visually similar and that the dataset is unbalanced, which makes things harder.

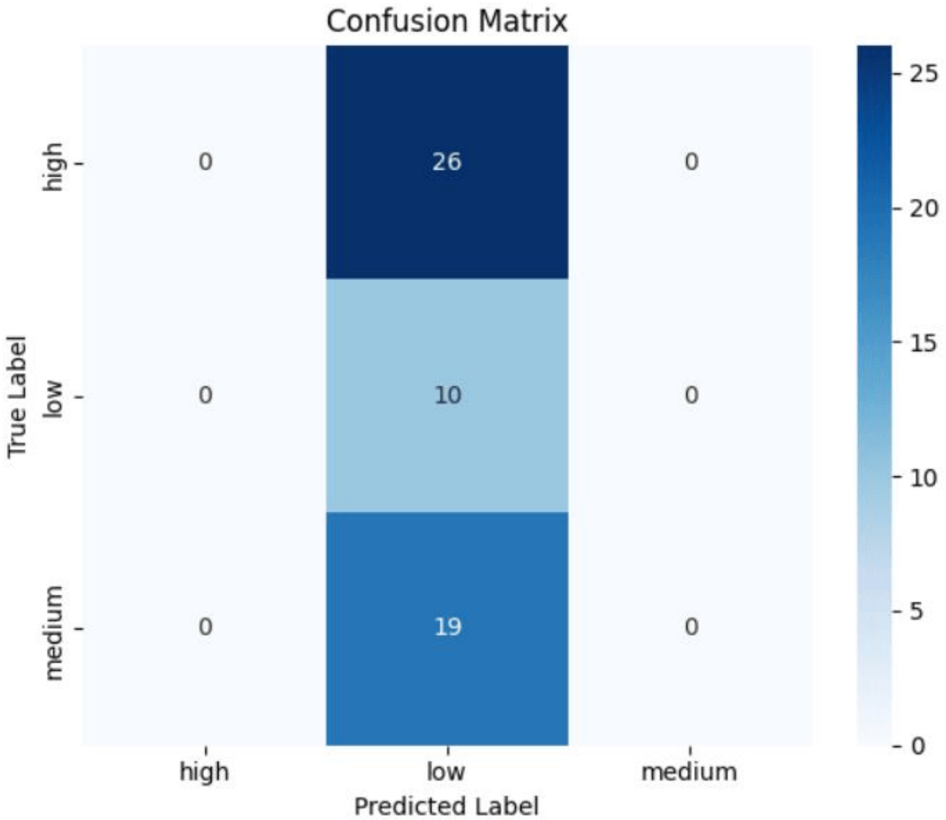

Figure 1: Confusion matrix of the proposed model.

Figure 1 shows that most predictions are for high turbidity, and it is hard to distinguish between medium and low turbidity.

4.2 Training Behavior

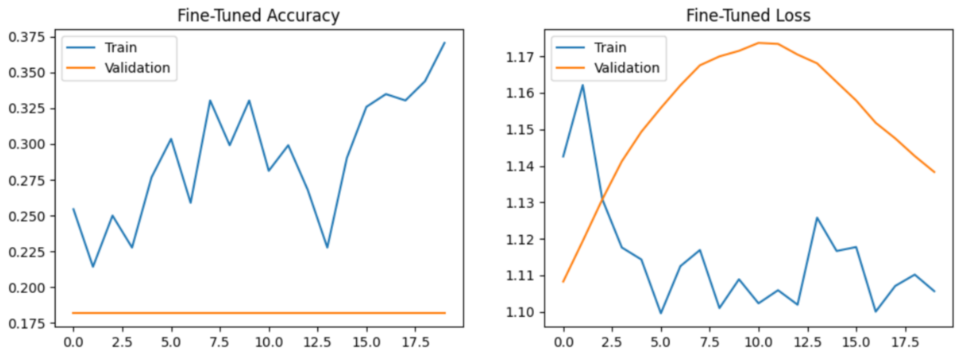

Figure 2: Training and Validation Accuracy and Loss during Fine-Tuning.

Figure 2 shows the accuracy and loss curves for the partially refined EfficientNet-B0 model while it was being trained and tested. Validation accuracy is unstable because the dataset is small, there are too many classes, and turbidity images have noise that is similar to what you would see in real life. On the other hand, training accuracy keeps going up.

4.3 Qualitative Analysis

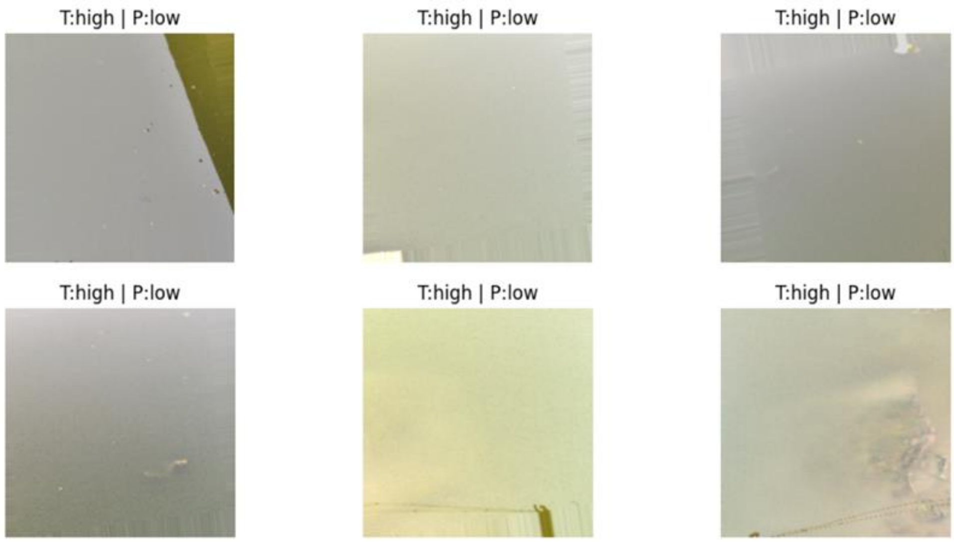

Figure 3: Training and Validation Accuracy and Loss during Fine-Tuning.

Figure 3 shows some representative qualitative results with ground-truth labels (T) and predicted labels (P). The model can tell when something is visually cloudy, even though reflections, container edges, and lighting artifacts are the main reasons why things are misclassified.

5 Discussion

The results show that pictures alone can't tell how cloudy something is. The model isn't perfect, but it does show that it can learn to tell the difference between things even if they can't be changed. The dataset is too big, the classes are not evenly spaced out, and the environment is always changing. These are the main reasons why performance is poor.

6 Conclusion and Future Work

This paper introduces a preliminary yet effective methodology for mobile-based water turbidity classification utilizing deep learning techniques. Future efforts will concentrate on augmenting the dataset, integrating regression-based turbidity estimation, and investigating physics-informed color correction methodologies.

7 CRediT authorship contribution statement

Sajidur Rahman Sajid: Conceptualization, Methodology, Model Design, Model Training, Data Preprocessing, Writing – original draft, Formal Analysis. **Sidratul Muntaha:** Dataset Collection, Investigation, Data Annotation, Visualization. **Abid Hossain Ove:** Experimental Evaluation, Validation, Results Analysis, Visualization. **Tasnim Firdaus Emon:** Literature Review, Writing – review & editing, Proofreading, Documentation.

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