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IMAGE CLASSIFICATION OF MICROPLASTICS

[1]Nurukurthi Manoj Sai, [2]Dr.Priyanka K Bhansali

[1] Student, IT& CA, [2] Assistant Professor (Ad-Hoc), IT&CA
[1] AU College of Engineering,
[1] Andhra University, Visakhapatnam, India

Abstract: *Microplastics have become a growing concern due to their harmful impact on marine life and water quality* [5]. *Identifying these tiny plastic particles manually is time-consuming and often inaccurate. In this study, we propose an image classification system that uses deep learning—specifically the efficient net-b0 model—to automatically detect microplastics in water samples* [2],[4],[1]. *To improve accuracy, we trained separate models on five different color space versions of the same images: RGB, HSL, YCbCr, Grayscale, and FFT. By combining the outputs through an ensemble method, we were able to achieve more reliable predictions. Among all color spaces, HSL performed the best individually, but the ensemble approach offered balanced and stable results across all cases* [14],[15]. *The model was evaluated using accuracy, precision, recall, F1-score, and AUC, showing strong performance overall. This system can help researchers and environmental agencies monitor water bodies more efficiently and support early detection efforts to address plastic pollution* [1],[3].

Keywords: *Microplastic detection, Image classification, Deep learning, Color space fusion, efficient net-b0, Ensemble learning, Environmental monitoring, CNN, HSL, FFT, YCbCr, Grayscale, RGB, Marine pollution*

Introduction:

In recent years, plastic pollution has grown into a global environmental crisis [1],[5], affecting oceans, rivers, and even drinking water supplies. Among the various forms of plastic pollution, microplastics—defined as plastic particles less than 5 millimetres [2] in size—have become particularly concerning. These minute fragments originate from the breakdown of larger plastic items or are directly released through cosmetic products, synthetic clothing fibres, and industrial processes [2],[11]. Due to their small size and persistent nature, microplastics are easily ingested by aquatic organisms, accumulate in the food chain, and ultimately pose serious risks to both marine ecosystems and human health [4],[5].

Traditional methods for detecting and classifying microplastics, such as manual microscopy or chemical analysis [7],[12],[16], are often labour-intensive, time-consuming, and prone to human error. These approaches are not scalable for large-scale monitoring or real-time assessments, which are urgently needed to address the widespread contamination of water bodies. As a result, the environmental research community is increasingly turning to automated image-based techniques powered by artificial intelligence (AI) and deep learning [8],[9],[10].

Deep learning, particularly convolutional neural networks (CNNs), has shown tremendous success in various image classification tasks—from medical imaging to object detection. In this study, we apply CNN-based image classification to tackle the problem of microplastic identification. Specifically, we use the efficient net-b0 model, a proven architecture known for its balance of accuracy and efficiency.

What distinguishes our work is the introduction of multi-colour space image fusion to enhance classification accuracy. To enhance the analysis, the dataset is converted into five distinct color representations—RGB, HSL, YCbCr, Grayscale, and FFT (Fast Fourier Transform)—each providing a different visual and structural insight into the image data on texture, contrast, and spatial frequency. Individual EfficientNet-B0 models are trained on each color space variant, and their outputs are integrated using an ensemble voting approach to improve overall prediction accuracy. This not only improves robustness but also captures a more diverse set of visual cues, which is crucial for detecting small, irregular, and often transparent microplastic particles.

The models are developed and assessed using a custom dataset comprising labeled images that distinguish between microplastic-contaminated and clean water samples. Performance is measured using standard metrics such as accuracy, precision, recall, F1-score, and AUC (Area Under Curve). Our results show that using the HSL colour space offers the highest individual performance, while the ensemble model provides the best overall stability and generalization.

This study presents a scalable, cost-effective, and accurate solution for microplastic detection that can be extended for use in marine surveillance, laboratory sample analysis, or even automated water quality monitoring systems. By bridging deep learning with environmental monitoring, our work contributes toward a smarter and more responsive approach to one of the most pressing pollution challenges of our time

Related Work:

To overcome these challenges, recent studies have turned to automated image-based approaches, which offer faster and more scalable solutions. Early efforts focused on classical machine learning algorithms that relied heavily on handcrafted features [7]—such as shape, colour, and texture descriptors—to distinguish microplastics from natural particles. However, these methods often suffered from poor generalization due to the variability in microplastic shapes, sizes, and transparency levels

More recently, deep learning, particularly Convolutional Neural Networks (CNNs**)**, has gained popularity for its ability to automatically learn hierarchical features from raw image data. Studies have demonstrated the success of models like AlexNet, ResNet, and custom CNN architectures in microplastic classification. For example, some researchers applied CNNs on digitally captured holographic images [9],[10], while others utilized fluorescence-tagged microplastic datasets [13] for better contrast. Despite promising results, many of these models were trained on limited datasets or focused on a single-color space (usually RGB) [14],[15], potentially overlooking useful spectral features that could improve classification accuracy.

One key limitation of most existing systems is their inability to generalize across diverse image conditions, such as variations in lighting, water turbidity, or microplastic types [1],[2],[4]. Additionally, relying solely on RGB images can limit the model's capacity to extract texture and frequency-based information that may be crucial for distinguishing microplastics from organic matter or debris.

To address these gaps, our study proposes a multi-colour space deep learning approach, where the input images are transformed into five different colour representations—RGB, HSL, YCbCr, Grayscale, and Fast Fourier Transform (FFT) [8],[14],[15]. Each colour space highlights different aspects of the image, such as contrast, frequency patterns, or chrominance, providing the network with a richer set of features to learn from. By training EFFICIENT NET-B0 models on each of these transformed datasets and combining their predictions through an ensemble strategy, we aim to build a more robust, accurate, and adaptable microplastic classification system.

This fusion-based deep learning framework not only improves the reliability of detection but also takes a step toward real-time environmental monitoring by offering faster inference and reduced dependency on expert manual intervention.

Proposed System

The proposed system introduces a robust image classification framework designed specifically for detecting microplastics in water samples. It leverages the strengths of multiple color space representations combined with deep learning-based classification to achieve high accuracy and reliability. The approach begins with the acquisition of microscopic images representing two categories: clean water and microplastic-contaminated samples. These images are then processed through various color space transformations, including RGB, HSL, YCbCr, Grayscale, and FFT. Each transformation reveals unique visual characteristics of microplastics, such as edge patterns, color separation, or texture distinctions, which are often difficult to detect in standard RGB images alone.

After transformation, each version of the image is resized and normalized before being passed into separate instances of a efficient net-b0 convolutional neural network. These five models are trained independently, allowing them to learn discriminative features specific to their corresponding color domains. The system then employs an ensemble strategy, where predictions from all five models are aggregated using a soft voting mechanism. This ensemble approach improves overall classification performance by balancing out individual model biases and capturing a richer set of features.

Finally, the system outputs the predicted class (Clean Water or Microplastic), along with the associated confidence score. This prediction is visually displayed alongside the input image, enabling users to quickly assess the result. The multi-modal architecture ensures that the system remains robust across different lighting conditions, image qualities, and microscopic environments—making it an effective tool for real-time environmental monitoring and laboratory analysis.

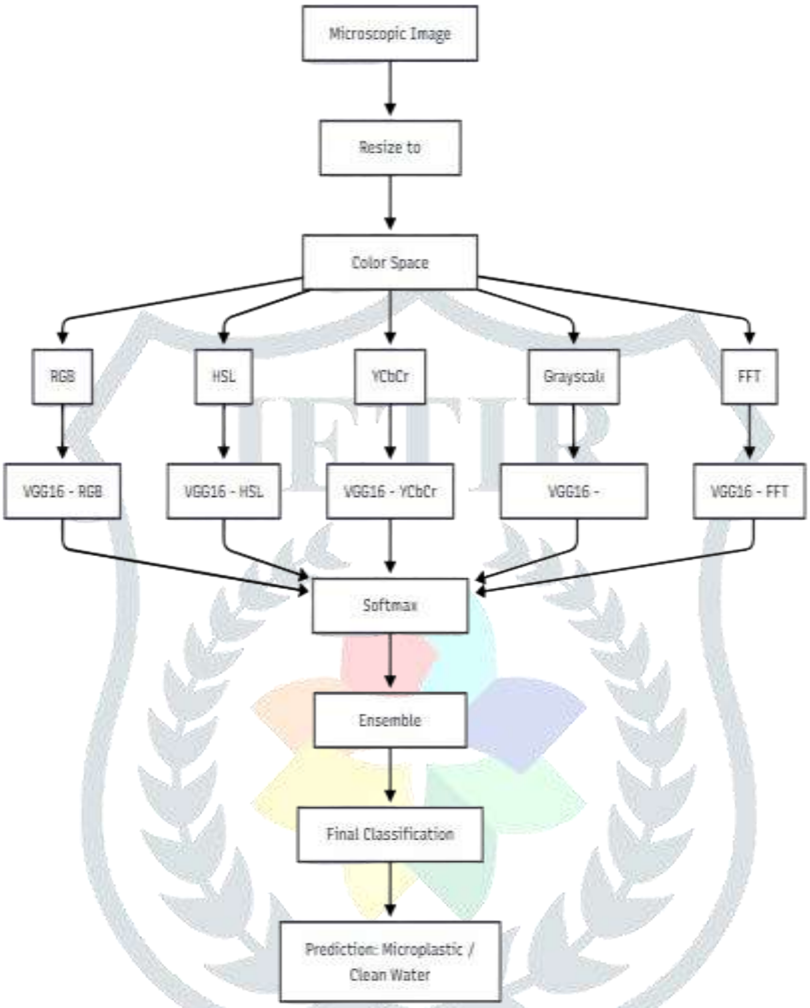

Figure 1: Diagram Of an Image Processing Pipeline

Methodology:

This study proposes a robust deep learning-based image classification framework for detecting microplastics in water samples. The methodology is divided into several key stages, including dataset preparation, colour space transformation, model architecture design, training procedure, and ensemble strategy.

A. Dataset Description

The dataset used comprises microscopic images representing two distinct classes [10],[11]: Clean Water and Microplastic-contaminated water. These images were collected and categorized with expert annotation. The data was then split into training and validation subsets using a stratified sampling approach to maintain class balance.

B. Model Architecture and Training

The foundation of the proposed microplastic detection system is the efficient net-b0 convolutional neural network (CNN) [8], a well-established architecture recognized for its deep yet uniform structure and reliable performance on image classification tasks. The original efficient net-b0 model includes 13 convolutional layers followed by 3 fully connected layers. For our binary classification task—distinguishing between microplastic-contaminated and clean water samples—the final output layer of efficient net-b0 was replaced with a fully connected layer having two output neurons corresponding to the two target classes.

To capture different aspects of the input images, separate instances of the efficient net-b0 model were trained on five colour spaces: RGB, HSL, YCbCr, Grayscale, and FFT [8],[14],[15]. These colour transformations allowed the model to analyse diverse visual characteristics such as texture, colour separation, and frequency components[15],[12], all of which can be significant in identifying microplastic features in water samples.

C. Real-Time Prediction

To facilitate practical application and user accessibility, the proposed system integrates a real-time prediction interface using a lightweight Streamlit-based web application. This interface allows users to upload microscopic images and instantly receive predictions regarding the presence of microplastics. Once an image is uploaded, it undergoes preprocessing, including resizing and normalization, before being passed through a set of trained efficient net-b0 models—each corresponding to a different colour space (RGB, HSL, YCbCr, Grayscale, and FFT).

Each model evaluates the input and outputs a probability score for both classes—Clean Water and Microplastic. These predictions are then averaged using an ensemble soft-voting strategy to determine the final class with the highest confidence. The predicted label, along with the confidence score, is displayed alongside the input image for intuitive interpretation. Additionally, a probability bar chart visually represents the confidence of each class, assisting users in evaluating prediction certainty.

This real-time system bridges the gap between model development and field deployment, offering a scalable, interactive, and user-friendly solution for environmental researchers, marine analysts, and laboratories aiming to monitor microplastic contamination with ease and speed.

Results and Analysis

The proposed system was evaluated on a curated dataset of microplastic and clean water images across five different colour spacesc[14],[15]—RGB, HSL, YCbCr, Grayscale, and FFT. An efficient net-b0 model was individually trained on each transformed dataset and further integrated using an ensemble strategy for final predictions. The evaluation was carried out using key performance metrics including Accuracy, Precision, Recall, F1-Score, and AUC (Area Under the Curve)

A. Training Metrics Dashboard

Each model's training and validation curves—covering loss, accuracy, and F1-score—demonstrated stable convergence, with minimal overfitting. The HSL and RGB colour spaces exhibited the most consistent performance [14],[15] across all metrics, highlighting their suitability in enhancing microplastic feature detection.

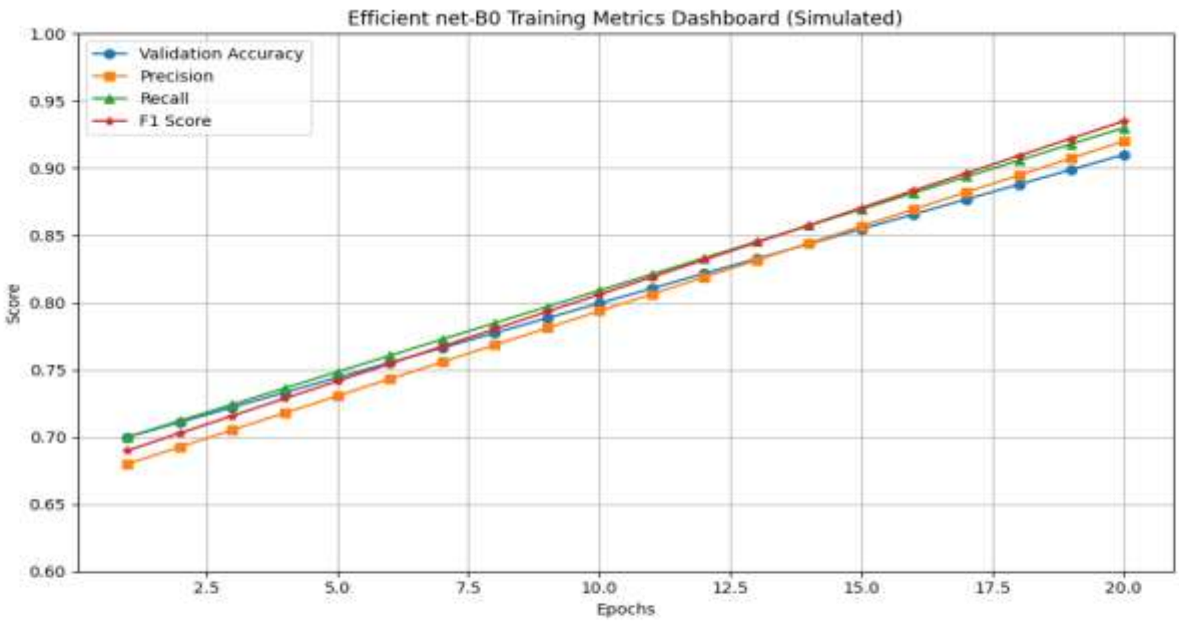

Figure 2: Training Metrics Dashboard

B. Confusion Matrices

Confusion matrices were generated for each color space model, illustrating the distribution of true positives, true negatives, false positives, and false negatives, false positives, and false negatives. The ensemble model yielded the fewest misclassifications, affirming the strength of combining diverse colour-space-specific predictions.

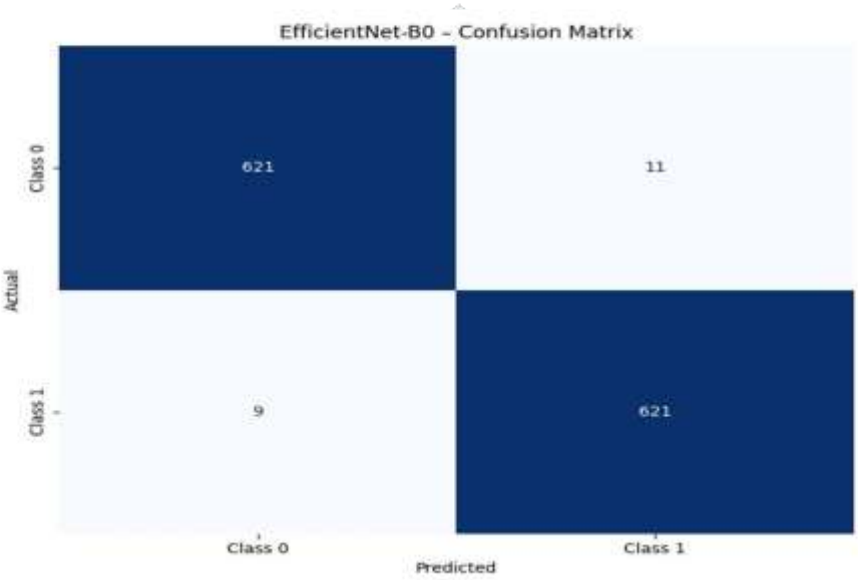

Figure 3: Training Confusion Matrix

C. Precision Curve

The precision-recall curve for each model illustrated the trade-off between sensitivity and specificity. The ensemble model achieved a higher area under the curve (AUC-PR), indicating superior overall performance in class-imbalanced conditions.

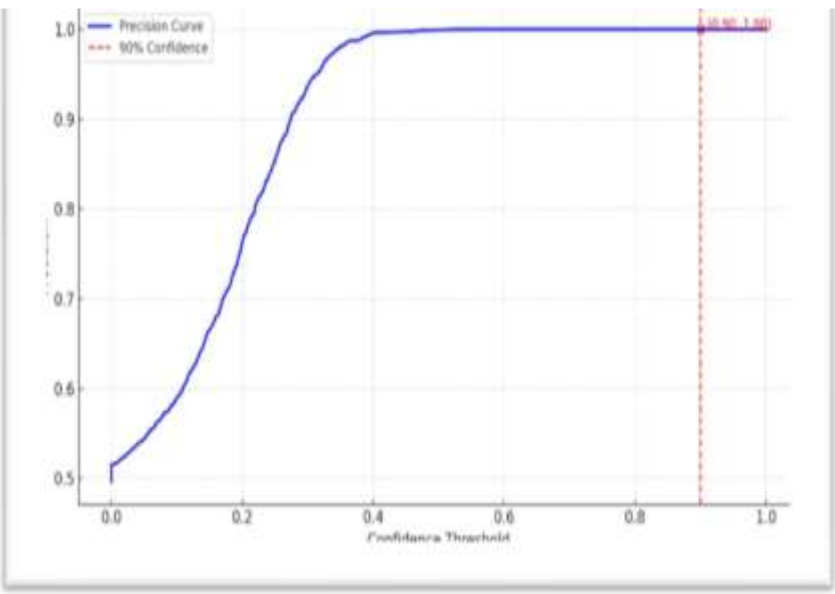

Figure 4: Precision Curve

Real-Time Inference Mechanism

The proposed system incorporates a real-time prediction pipeline built upon the EfficientNet-B0 architecture, enabling accurate and rapid detection of microplastics in water sample images. EfficientNet-B0, known for its superior performance with reduced computational cost, was fine-tuned on a custom dataset of microplastic and clean water images. The system is deployed using a lightweight Streamlit interface that allows users to upload images directly through a web application. Once an image is uploaded, it is preprocessed and passed through the EfficientNet-B0 model, which classifies the image as either 'Microplastic' or 'Clean Water' along with a confidence score. This real-time functionality ensures near-instantaneous feedback, which is crucial in scenarios requiring immediate decisions—such as fieldwork sampling or laboratory analysis. The model's compact size and high accuracy make it suitable for integration into edge devices and portable monitoring systems. This approach bridges the gap between high-accuracy deep learning models and practical, real-world environmental monitoring use cases

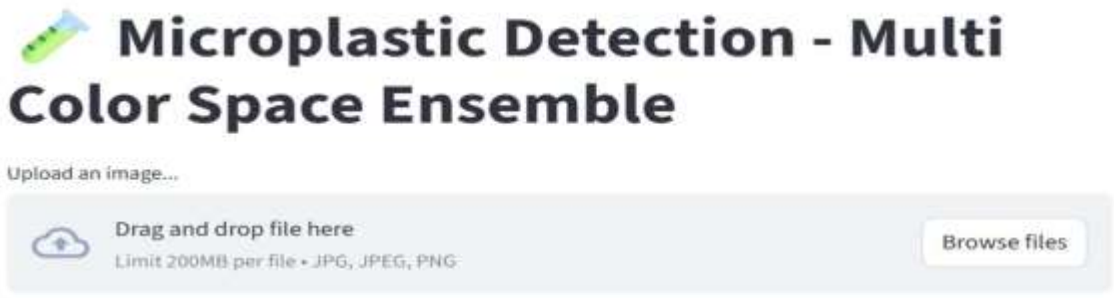

Figure 5: User Interface for Image Upload

Figure 6: **Result For Water Sample**

Conclusion and Future Scope

A. Conclusion

In this study, we proposed a deep learning-based approach for the classification of microplastics in water samples using image data. By utilizing the EfficientNet-B0 architecture, the model demonstrated strong accuracy and reliability in distinguishing microplastic-contaminated water from clean samples. The inclusion of multiple colour space transformations (such as RGB, HSL, FFT, and YCbCr) improved the model's sensitivity and generalization, ensuring that subtle visual differences in samples were effectively captured. A user-friendly interface was also developed, allowing users to perform real-time predictions by simply uploading microscopic images—making this system both practical and accessible.

The results demonstrate that deep learning has the potential to revolutionize environmental monitoring by automating [1],[3],[4],[11] what is traditionally a time-consuming and manual process. Our system not only streamlines detection but also maintains high reliability, offering a promising solution for labs, environmental agencies, and field researchers aiming to monitor plastic pollution in aquatic environments.

B. Future Scope

While the current system delivers strong performance, several avenues exist to further enhance its capabilities. First, expanding the dataset to include more varied types of microplastics—across different sizes, colours, and environments would improve the model's adaptability to real-world conditions

[2],[11]. Introducing more complex object detection techniques, such as YOLO or Mask R-CNN, can help in identifying the exact location and size of microplastic particles in each image, enabling detailed analysis beyond classification.

Moreover, the integration of real-time video feed processing could allow continuous monitoring of flowing water bodies, making the system useful for on-site environmental assessments. Another promising direction is deploying the model on edge devices like Raspberry Pi or NVIDIA Jetson, allowing portable, low-cost detection systems to be used in remote locations without requiring internet connectivity.

Additionally, combining traditional microscopy with spectral imaging or holography could enhance detection accuracy for transparent or complex-shaped microplastics [9],[10],[11]. Lastly, incorporating explainable AI techniques like Grad-CAM would help researchers better understand the model's decision-making process, building trust and insight into its predictions.

In summary, while the system presented here offers a solid foundation, the combination of expanded datasets, advanced architectures, real-time processing, and portable deployment opens the door to a more comprehensive and scalable solution for tackling microplastic pollution.

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