MICRO PLASTICS IN WATER DETECTION USING DEEP LEARNING APPROACH

BY

SHUVAJIT SAHA
ID: 242-25-006

This Report Presented in Partial Fulfillment of the Requirements for The Degree Masters of Science in Computer Science and Engineering

Supervised By

Dr. S M Aminul Haque
Professor & Associate Head
Department of Computer Science and Engineering
Daffodil International University

Co-Supervised By

Dr. Abdus Sattar
Associate Professor
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

13 September 2025

APPROVAL

This Thesis titled "**Micro Plastics in Water Detection**", submitted by **Shuvajit Saha** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13.09.2025.

BOARD OF EXAMINERS

Dr. Sheak Rashed Haider Noori — **Chairman**
Professor and Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology Daffodil International University

Dr. Md. Zahid Hasan — **Internal Examiner**
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology Daffodil International University

Dr. Naznin Sultana — **Internal Examiner**
Associate Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology Daffodil International University

Mr. Nazibur Rahman — **External Examiner**
Head of IT Infrastructure
Networld Bangladesh PLC

DECLARATION

I hereby declare that this thesis has been done by me under the supervision of **Dr. S M Aminul Haque, Professor & Associate Head, Department of Computer Science and Engineering, Daffodil International University**. I also declare that neither this thesis nor any part of this thesis has been submitted elsewhere for the award of any degree or diploma.

Supervised by:

Dr. S M Aminul Haque
Professor & Associate Head
Department of CSE
Daffodil International University

Co-Supervised by:

Dr. Abdus Sattar
Assistant Professor
Department of CSE
Daffodil International University

Submitted by:

Shuvajit Saha
ID: 242-25-006
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

First, I express my heartiest thanks and gratefulness to almighty for His divine blessing making it possible to complete the final year thesis/internship successfully.

I am grateful and wish to express my profound indebtedness to **Dr. S M Aminul Haque**, **Professor & Associate Head**, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of my supervisor in the field of “Deep Learning” to carry out this thesis. His endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this thesis.

I would like to express my heartiest gratitude to **Dr. Sheak Rashed Haider Noori**, **Head of the Department of CSE**, for his kind help in finishing my thesis and also to other faculty members and the staff of the Department of CSE, Daffodil International University.

I would like to thank my entire course mate in Daffodil International University, who took part in this discussion while completing the course work.

Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

The growing occurrence of micro-plastics in the water bodies is a major concern to environmental and human health. Historical methods of detection have been time consuming, costly and have used special laboratory set ups. In this project, the author has submitted a proposal built using deep learning that utilizes image classification and detection micro-plastics in water. The populated dataset was constructed and pre-processed (by resizing, contrast optimizing and gamma correction) in the form of labeled image of both clean water and water contaminated with micro-plastics (1,554 images, between which there are equal numbers). A few models of deep learning were trained and tested such as VGG19, ResNet50, Xception, DenseNet21, and AlexNet. Of them, the Xception model had the best accuracy of 97 per cent and was deployed. Streamlig was used to create a user-friendly interface where it is possible to upload an image in real-time and detect it. The findings show the possibility of deep learning in the automation of micro-plastics detection, and can serve as an accessible and scalable environmental monitoring and research tool.

Keywords: Micro-Plastics, Deep Learning Convolutional Neural Network (CNN), Classification, Water Pollution, Xception, Environmental Monitoring Streamlit.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Overview

Water pollution has ceased to be only a national environmental issue, but has turned out to be one of the most widespread and insidious pollutants numbering among micro-plastics. Micro-plastics are tiny bits of plastic which can be less than 5 millimeters where they are formed by the fragmentation of macro-debris or produced as microbeads as ingredients in both cosmetic and industrial products. Not only have these pollutants been found in oceans, rivers, lakes, but also in drinking water and they have been threatening the health not only of the live aquatic being, but also to the human beings.

It is an important activity to detect micro-plastics in water, and this has to be efficiently, accurately, and at scale achieved. Cumbersome methods like the spectroscopy and microscopic analysis are tedious, costly and most of the times can only be applied in a laboratory setting. These shortcoming precipitates the desperate need of an improved method, more automatic and available to identify micro-plastics in water.

Due to the recent breakthroughs in artificial intelligence (AI), deep learning holds promising potential in unraveling complicated problems of image classification. In this project, we are going to use the deep learning technique and to be more specific, the convolutional neural networks (CNNs) to build a water micro-plastic detection system, based on the analysis of the water images. The goal is to develop a smart detection system that would allow the perception of micro-plastics in clean and contaminated water with high accuracy and efficiency by training models on labeled data sets of both clean and contaminated water samples.

1.2 Background and Present State

This has been extended by the emergence of the use of single-use plastics and unresponsible disposal of plastic waste material, leading to an elevated number of micro-plastics in the environment. These particles are so small to get into the body of the aquatic bodies, ingested in their bodies, and end up in the human food chain. It has been found that micro-plastics may act as carriers of toxic chemicals, such as pesticides and heavy metals, which may bioaccumulate in the living bodies.

Although the impact of micro-plastics on the environment is well explained, means of measuring and quantifying their existence is scanty. The majority of the traditional approaches are characterized by the fact that there is a need to collect a physical sample after which an extensively time-consuming laboratory analysis is completed; such approaches are not very well adapted to mass or real-time monitoring.

Computer vision, on the contrary, has been developing with lightning speed with incredible success of deep learning models in images classification such as VGG, ResNet, Xception, and DenseNet. Such models are able to develop hierarchical representations of images, which makes them the perfect solution to be able to distinguish between tiny differences in the image data, e.g. the presence or absence of micro-plastics in water.

The use of deep learning in micro-plastic detection is currently in its infancy despite such an advancement. It is necessary to create specialized datasets, use proper preprocessing procedures, and test the various model structures in order to see which one works the best. This project is part of that commitment, the production of a suspended water samples labeled dataset, the training of several deep learning models, and the deployment of the best model in an easy-to-use user interface.

1.3 Problem Statement

Walking into a lab and using classic micro-plastic-detecting equipment is a costly, time-consuming procedure that is not at all appropriate to high-velocity, far-reaching environmental-scanning. At this point, there exists no automated, readily available, and scalable real-time detection methods of micro-plastic in water sample. Also, there is no common data set, or machine learning application that can correctly classify water samples by the presence of micro-plastics in the water samples using image-based analysis.

In the project, the problem will be solved by trying to create a deep learning-based detection system to classify the images of water as either clean water or micro-plastic contaminated water. With the help of CNNs and image processing algorithms, it is expected to create an effective and high-scoring model that can be launched on a user-friendly web interface and make micro-plastic search and measurement easier to access to the researchers, environmentalists, and policy-makers.

1.4 Objectives

The main goal of the present project is the development and utilization of a deep learning-based software that will enable the recognition of the micro-plastics present in the water via image data. Its special objectives are:

- To gather and name a dataset located at images of water samples (clean and micro-plastics contaminated).
- To carry out the work of preprocessing the image including re-sizing, contrast enhancement, and gamma correction.

- To compare and train the various models of deep learning such as VGG19, ResNet50, Xception, DenseNet21, and AlexNet.
- To test the performance of each model with the help of classification reports, confusion matrices, and accuracy levels.
- To determine the most efficient model (Xception in the present case) and store it to deploy it.
- To create a user interface were uploading photos and getting predictions in real-time will be possible with the help of Streamlit.
- To determine the prospects of the possible social and environmental effects of the suggested solution.

1.5 Scope and Limitations

This project involves the creation of a supervised image classification system powered by deep learning model in performing binary classification of water images. The data set of 1,554 labeled pictures was taken in half, with clean and micro-plastic imbued water.

Scope:

- Labeling and collection of image data.
- Preprocessing of images and augmentation.
- Training and testing a deep learning model.
- Streamlit-based deployment of UI to interact with the users.

Limitations:

- The size of the dataset itself is quite small (1,554 images) and thus can affect its applicability to other models.
- The water sample present in the real world can be very different in terms of lighting, contaminants, and noise levels that can influence the performance of a model.
- The system is not trained to count the concentration or type of micro-plastics but only to determine whether it is clean or contaminated.
- It is deployed on the static classification of images and is not supported on video stream analysis.

1.6 Report Organization

This report has a seven chapter outline as follows:

- The chapter 1 presents the background of the project, motivation, goals and scope.

- Chapter 2 gives a literature review regarding related works, comparisons and open research issues.
- In Chapter 3 the methodology, i.e., the system design, the software/hardware requirements, and the project management is described.
- In chapter 4, the implementation of the system, training of the model and evaluation methods are explained.
- Chapter 5 gives the result of the experiments and analyzes the performance of various models.
- Chapter 6 talks about the societal, environmental, and ethical effect of the project and matters to do with sustainability.
- Chapter 7 is a conclusion of the report, with some future improvement ideas.

1.7 Summary

This chapter introduced the scope of the problem of micro-plastics in water and the opportunity of deep learning in getting through this issue. We have described the motivation, background, the problem statement, objectives and the scope of the project. As the environmental concerns continue to rise and the classical methods of detection provide only a limited scope, this project aims to use modern AI tools to maximize the effort toward a sufficient and feasible approach to micro-plastic detection. It will be discussed in greater detail in subsequent chapters about other studies on the same topic, the design of the proposed system, its implementation, the findings of the experiment, and the implications of doing the same in the real world.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

The increased pitfall about the presence of micro-plastics in our water bodies has motivated researchers to consider the use of advanced technologies in identifying, categorizing and estimating the quantities of the plastics. With micro-plastics finding their way to all the marine ecosystems, freshwater sources, and even the drinking waters, never has there been a greater need of fast scalable and accurate detection systems.

Conventional techniques of micro-plastics detection, including Fourier-transform infrared spectroscopy (FTIR), Raman spectroscopic, and optical microscopy are both dependable and very costly, exceedingly time-consuming, as well as conceptually challenging in association with large-scale domains and field implementation. In most cases, these methods need special devices and personnel, which restrict their use in mass surveillance efforts.

Artificial intelligence (AI) and computer vision have developed to the point where it may become an attractive alternative to detect micro-plastics based on image data as well: deep learning does not encounter the same problem as ensemble ROM: aggregating all existing techniques of classifying image data into a single delineation. At that, convolutional neural networks (CNNs) have shown outstanding results in the area of image classification and visually identifying objects in different fields, such as medical diagnostics, agriculture, and industrial automation. The advancement that characterizes this technology has provided an avenue through which they could be used in environmental monitoring.

There have been recent studies where deep learning networks are deployed in classifying micro-plastics when images of a water sample are used. These models have demonstrated competitive accuracies with some way over 95 per cent. Other practices with research on such systems that are under research include data augmentation, semantic segmentation, transfer learning, and mobile deployment as methods to improve the performance and applicability of the systems.

Irrespective of this development, there are some gaps and issues with existing literature. The various models are created with small data set or not tested on different environmental settings or do not have an interface friendly to be deployed. The current project is set to partially address these gaps by creating a micro-plastic detection algorithm based on deep learning techniques (CNN models), training it on a preprocessed, balanced dataset, implementing it into a real-time interface with the help of Streamlit.

2.2 Related Works

Grekov, et al. [2022]: Applied YOLOv5 to real-time identification of micro-objects that entail micro-plastics in the marine context and have proven to be extremely efficient in their recognition qualities similarly to manual scoring[1]. Gupta & Ruebush [2019]: Came up with AquaSight, a CNN model that uses mobile technology and identifies impurities (including microplastics) in drinking water with 96 % accuracy using only 105 pictures[2]. Dils et al. [2024]: segmented (+- data augmented with GAN) and classified micro-plastics presence in microscope images, with an F1-score of 0.91 on the generated data vs 0.82 baseline[3]. Sarker et al. [2024]: Stack DeepSORT with YOLOv5 to detect micro-plastic as real-time tracking in camera visual images with 96-97 % precision[4]. Rezvani et al. [2024]: Proposed the MiNa data, applying object-detection models to the micro- and nanoplastics classification in SEM images[5]. Zhang et al. [2022]: This was able to make rapid detection (approximately 1 h) of sub-10 mu m micro-plastics using CNN and Raman spectroscopy[6]. Nguyen et al. [2023]: Constructed the AI-aided nano-DIHM to detect in real-time in environmental waters, capable of identifying 25 objects/sec in holographic pictures[7]. Brandt et al. [2023]: Used ML (CNN) to fill out low-quality Raman/FTIR spectrum data to enhance the resiliency of spectral identification [8]. Weiss et al. [2022]: applied deep learning (U-Net, MultiResUNet) to SEM micrographs and achieved semantic and instance segmentation of micro-plastics with 98.3 % shape classified[9]. Roy et al. [2024]: Flipped a CV segmentation model that had been trained on beach-collected debris, with an accuracy of 96 %%, and an interface based on the web annotation[10]. Frontiers review [2025]: Reviewed ML in micro -plastic detection - integrating imaging, spectroscopic and hyperspectral methods; emphasized the need to have large datasets and strong models [11]. Arju et al. [2025]: designed a consumer product micro-plastic detection pipeline using a low-cost mobile-microscope + YOLOv5 and demonstrated 9idx96 recall [12]. Zhang et al. [2020]: Hyperspectral imaging + CNN / SVM for the detection of micro-plastic in the soil reaching 92.6 % accuracy [13]. Zhang et al. [2021]: Soil soil-borne PE micro-plastic detection HS + SVM, MD, ML at ~84 % accuracy. Yang & Wang [2023]: studied on deep learning methods to categorise the source of micro-plastic classifying via hyperspectral as well as spectroscopic data [14]. Akkajit et al. [2024]: Transfer learning based CNNs for improved detection of marine environments [15]. Devipriya et al. [2025]: pre-trained CNNs (ResNet, VGG, DenseNet) to detect and classify micro-plastic; they indicated the high baseline performance [16]. Frontiers Review [2025]: Mentioned that it integrates hyperspectral imaging, IR/Raman spectrometry, and CNNs, yet emphasized the problem of the models being robust in different circumstances in the real world[17].

2.3 Comparison between existing works

Table 2.3: Comparison table

Reference	**Methodology**	**Dataset**	**Accuracy / F1-score**	**Key Limitations**
Grekov et al. [2022]	YOLOv5 real-time detection	Marine photos	~96–97 % precision	Requires controlled conditions
Gupta & Ruebush [2019]	CNN mobile app	105 images	96 % accuracy	Very small dataset
Dils et al. [2024]	Segmentation + GAN augmentation	Microscopy images	0.91 F1-score	Needs expert-labeled data
Sarker et al. [2024]	YOLOv5 + DeepSORT tracking	Flume + river test	96–97 % precision	Specialized lab setup
Rezvani et al. [2024]	Object detection + SEM	MiNa dataset	—	Nanoplastics underexplored
Zhang et al. [2022]	CNN + Raman spectroscopy	<10 μm plastics	—	Requires spectrometer
Nguyen et al. [2023]	nano-DIHM + CNN	Holographic water	~25 obj/sec classification	High compute for holography
Brandt et al. [2023]	CNN for spectrum clean-up	Raman/FTIR data	Recall/Precision ~90 %	Not image-based
Weiss et al. [2022]	U-Net + MultiResUNet + VGG16	SEM micrographs	Jaccard >0.75; 98.3 % shape class	SEM-specific
Roy et al. [2024]	Image segmentation + CV	Beach debris	96 % accuracy	Only plastic debris, not water
Arju et al. [2025]	YOLOv5 mobile microscope	2490 mobile images	98 % accuracy	Product-based, not environmental
Zhang et al. [2021]	Hyperspectral + SVM/ML	Soil PE plastics	84 % accuracy	Soil only
Zhang et al. [2020]	Hyperspectral + CNN	Soil samples	92.6 % accuracy	Soil only

Reference	Methodology	Dataset	Accuracy / F1-score	Key Limitations
Dutta et al. [2025]	Transfer CNNs	Marine data	92% Accuracy	Data source unclear
Akkajit et al. [2024]	Transfer learning CNN	Marine environments	99% Precision / 97% F1 Score	Transfer domain mismatch
Yang & Wang [2023]	Hyperspectral + ML	Various media	95% Accuracy	Spectroscopy-dependent
Frontiers Review	Survey	Cross-domain	—	Highlights need for standard data

2.4 Open Issues

Although deep learning resulted in significant promise in micro-plastic detection using images, a significant number of issues and limitations remained unresolved which prevents actual implementation and large-scale use. These unresolved gaps extend to data, model design, deployment and interdisciplinary integration issues.

1. Unavailability of Big Data with Public Accessibility: The majority of the existing solutions still use small, proprietary datasets that cannot be accessed publicly, and it is hard to compare various models or reproduce findings. In most situations data is gathered within the confines of a lab setting which is not representative of the variation and complexity of the real world. The researchers would benefit more in constructing models that can be generalized by using a standardized set of different water samples, which has labeled micro-plastics.

2. Generalization and Real-World variability: Training models in controlled environments leads to the poor transfer of training to images taken in natural environments caused by inconsistency in light quality, clarity of water, number of items in the background, particle size and camera resolution. A system can perform well in a lab but cannot identify micro-plastics in river water with sediments and other junks. Generalization is a significant issue to improve.

3. Unbalanced and ambiguous Labels: In numerous studies, the labeling is rather manual and often not according to the same criteria. Other datasets have fuzzy confusion between classes (e.g. particles can be confused with debris or air bubbles) and this overwhelms the model. In addition, micro-plastics particles in the real world commonly occur together with other particles even in the binary classification is not enough.

4. Weakness in quantification Capability: Majority of the prevailing models merely concentrate on binary classification: either presence or absence of micro-plastics. Nevertheless, the estimation of the quantity, size-distribution, and the types of micro-plastics might be important in many cases. Few studies also include models- both detection and segmentation (e.g. YOLO, U-Net) to count and locate particles in an image.

5. Spectroscopy and Multimodal Analysis Integration: More sophisticated difference systems might require the combination of visual data with spectroscopy (FTIR, Raman) or hyperspectral imaging in order to discriminate more precisely on the type of plastic (polyethylene, polystyrene). This integration is not common and has not been fully explored, mainly because functions of several data modalities are complex in nature.

6. Real-time Usage and Computational efficiency: Even powerful CNNs like Xception or DenseNet-201 require a lot of computation and cannot be applied to edge devices or mobile applications without tuning. Most of the suggested systems do not have efficiency that is required in real-time processing on the field. The open challenge is to reduce the inference time, retaining accuracy.

7. Interface design and User accessibility: The user-friendly deployment of most models is absent, and the testing is usually performed in Jupyter notebooks or Python scripts. As might be expected, although tools such as Streamlit and Flask are available, resources spent on developing an end-to-end system that an environmental researcher or non-technical user should be able to use are scarce.

8. Absence of Inter Disciplinary Collaboration: Successful micro-plastic sensing concerns the amalgamation of environmental science, computer vision, marine biology and chemical engineering. Most of the AI-oriented initiatives fail to acknowledge the specific knowledge that should be involved in the design of solid systems as well as checking in field setting.

9. Ethical Issues and Bias of Data: Few words are said about ethical issues like the incorrect classification, excessive reliance on AI gadgets, and prejudice caused by unbalanced data. Environmental monitoring potentially has serious consequences, as a falsely negative result (a prediction of clean water in the presence of contamination) may occur.

10. There is no Uniform form of Evaluation: Lastly, performance is measured by varying metrics (accuracy, F1-score, recall) and test sets in various papers, thus making it difficult to paste the performance of various models. The disjointed nature of benchmarks, test procedures, and challenge sets of data is a big problem to this new area.

2.5 Summary

The available literature reveals that there is high chance of deep learning in microplastic detection based on different imaging methods. Nevertheless, dataset standardization, deployment to the real world, and complete automation are challenges. In our project, we use the same idea, but based on the use of pretrained CNNs (e.g., Xception) with a balanced dataset of clear and polluted water pictures, making an emphasis on the classification accuracy and on the real-time applicability through a Streamlit-based graphical interface. These gaps will be filled in the further chapters which will explain methodology, implementation, and results.

CHAPTER 3

METHODOLOGY

3.1 Overview

In this chapter, the process of development, the tools and methodologies of the design of the deep learning-based system of micro-plastics detecting in water was expanded on. It starts with an elaborate description of the proposed system design, the technical requirements and the considerations of project management. The system is modular and well-structured it covers the area of data collection and preprocessing, model training, evaluation, and final deployment through a user-friendly interface. All the stages are arranged to achieve a sound, efficient, and accurate picture classification model capable of recognizing micro-plastics in real-time as the major goal.

3.2 Proposed Methodology

The main approach includes a number of various yet interdefinite steps. The following steps give the complete pipeline of system development:

Step 1: Labeling and information collection Process

The quality and the size of the training data are also very important in the success of any machine learning project. In the present project:

- Manual collection of 1554 images were made in various open internet sources as well as micro-plastic studies archives.
- The data was transferred to two categories manually:
    - 1_Clean_Water: 777 pictures
    - 2_Microplastic: 777 pictures
- The data was then checked against the balance so that both classes could possess an equal number of images that can help to avert bias when training the model.

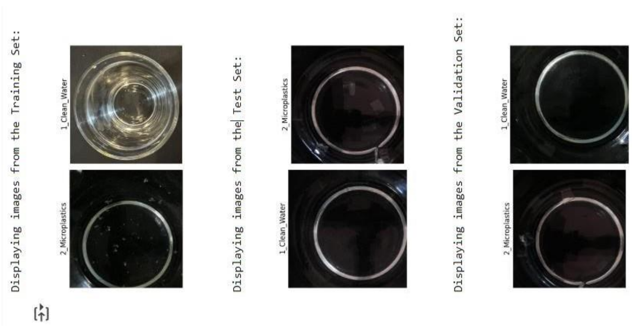

Figure 3.2.1: Sample data from dataset

Step 2: Preprocessing of Data

Raw image data is noisy, frequently has inconsistent dimension and contrast or brightness. In order to achieve consistency and enhance the extraction of feature, the following preprocessing techniques were used:

Size of the picture

- Sizes of original images were not uniform, most of the images were of 563 x 537 pixels.
- They adjusted the dimensions of all the images to a standard dimension of 224*244 pixels, and this was the input size of most of the pretrained neural networks including VGG19 and Xception.

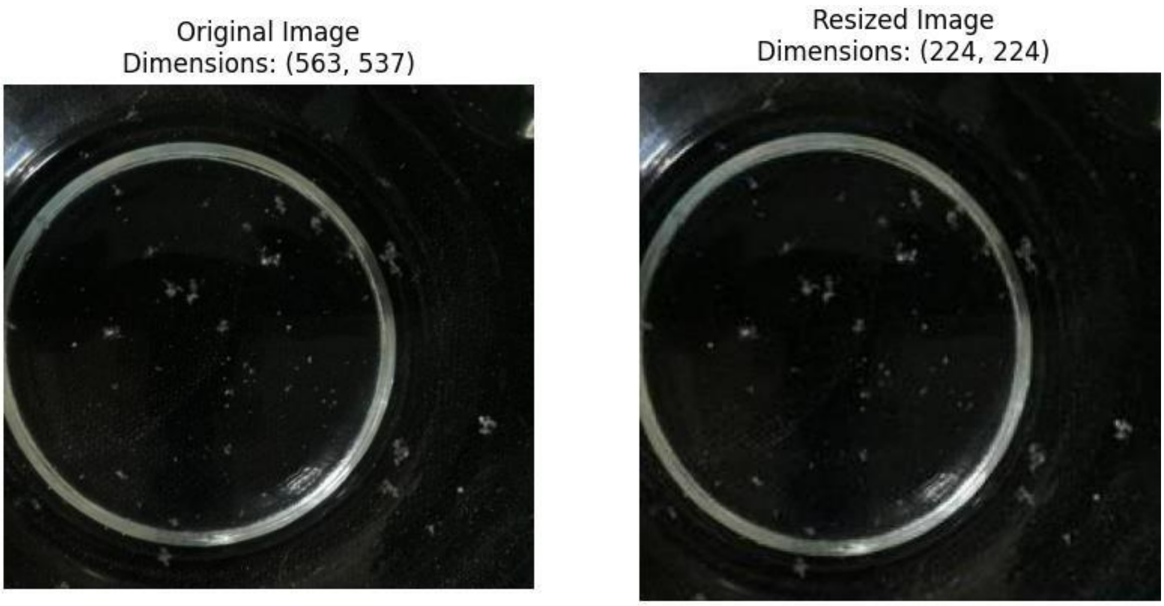

Figure 3.2.2: Resized image

Image Normalization

- The formula scaled pixel values to the range between 0 and 1 in the following way: Normalized_Pixel = Original Pixel / 255
- Such normalization increases convergence rate and model performance.

Contrast Enhancement

- Certain photographs were under exposed, or grey.
- Local contrast was enhanced using Contrast Limited Adaptive Histogram Equalization (CLAHE) or other algorithms to make features to be more distinguishing.

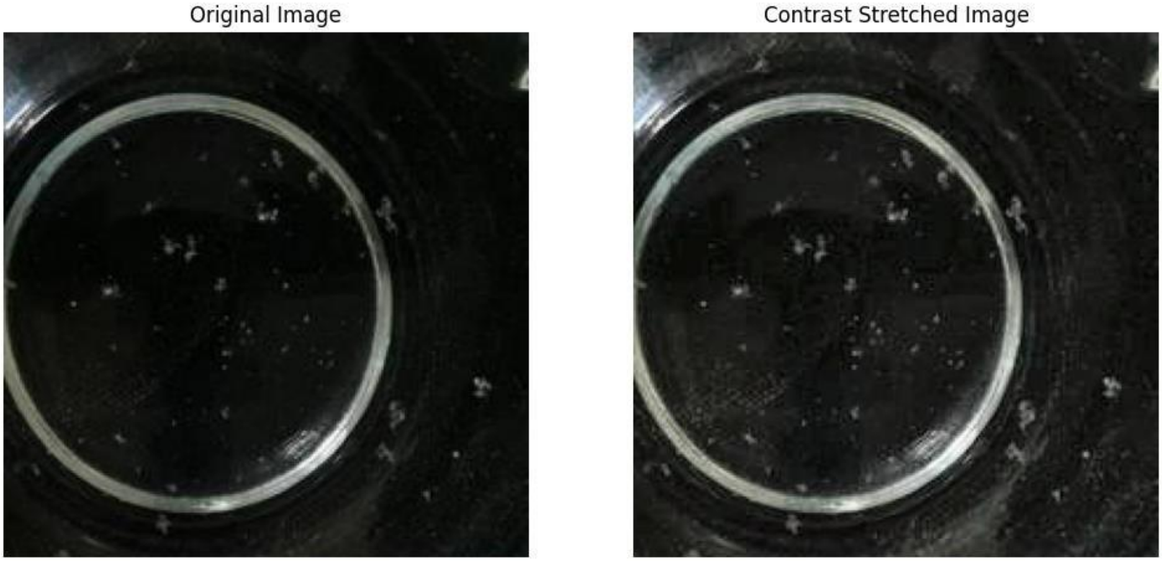

Figure 3.2.3: Contrast image

Gamma correction

- To obtain the desired approximation of brightness of the image (i.e. making the image look more visually consistent across samples) gamma transformation (e.g., gamma = 1.2) was used as a kind of image brightness correction.

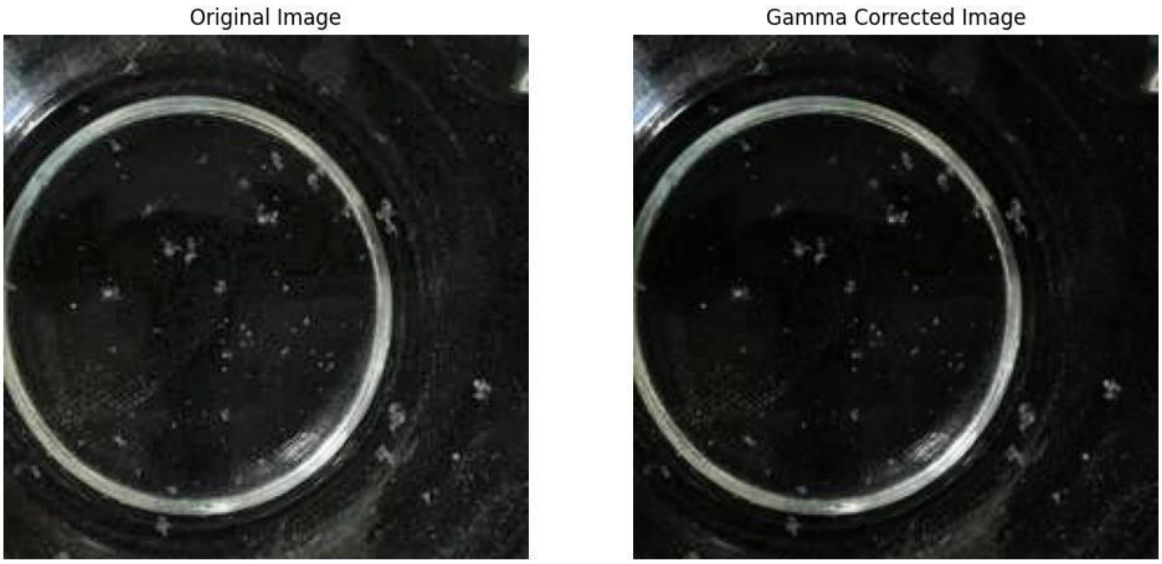

Figure 3.2.4: Gamma corrected image

Step 3: Dataset Splitting

The dataset was divided into three subsets:

Table 3.2.1: Dataset Splitting

Set	Total Images	Clean Water	Microplastics
Training	1,154	577	577
Validation	208	104	104
Testing	200	100	100

- Training Set: It is the set and was used to train the deep learning model.
- Validation Set: Is employed in observing the model during training and adjust the hyperparameters.
- Test Set: The model is applied to data not used during development to decide how well the model will perform out in the wild.

Step 4: Model Selection and training

Several advanced Convolutional Neural Network (CNN) models were applied to determine the best model to be applied in this task. These include:

- VGG19
- ResNet50
- Xception
- DenseNet21
- AlexNet

All of the models have been fine-tuned with the help of transfer learning:

- ImageNet pre-trained weights were loaded.
- Higher layers were adapted to binary classification.
- Overfitting was decreased by the use of Dropout layers and Batch Normalization layers.

Each model was trained at the same number of epochs (i.e., 20-30) with the Adam optimizer, a binary cross-entropy loss, and an early stopping strategy to avoid overfitting.

Step 5: Evaluation of the Performance

All trained-models were tested on:

- Accuracy Score
- Precision, Recall, F1-score
- Confusion Matrix
- Loss / Accuracy curves (per epoch)

Step 6: Save model and Ui integration

- The trained model Xception was configured as.h5.
- A graphical web interface was created using Streamlit, a thin Python framework.
- The user is able to put up images of water samples and be showered with instantaneous expectations: "Clean Water" or "Microplastics Detected".

System Workflow

The system workflow may be described as that of five main phases:

- Input- Upload an image using streamlit
- Resizing, normalizing, correction of image Preprocessing
- Model Prediction1- Pass image to Xception model
- Output Display- Displays predicted label on the UI
- Logging (optional) pred Results Save prediction logs is possible

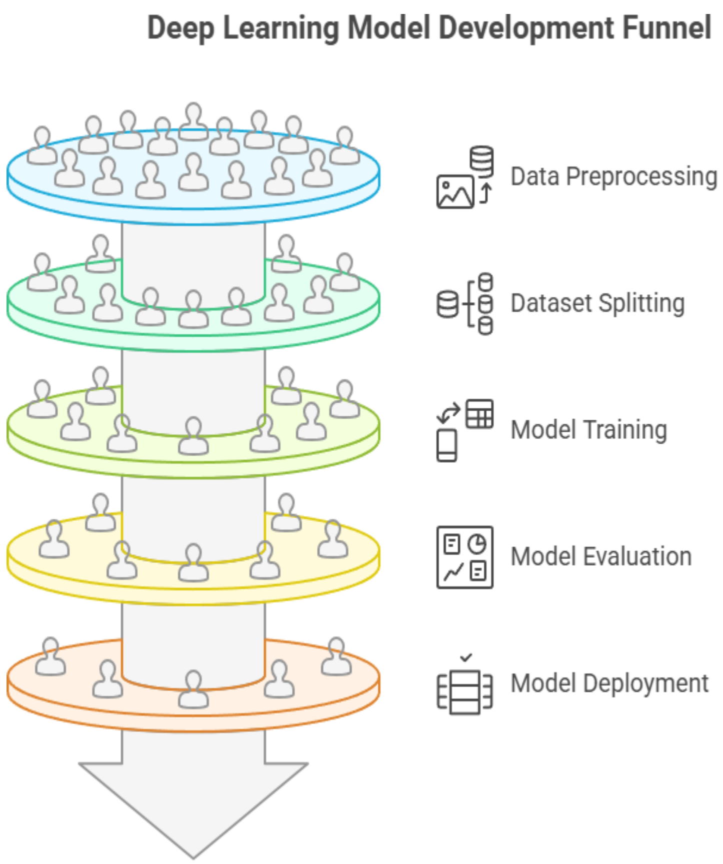

Diagram 3.2.5: Methodology diagram

3.3 Hardware/ Software Requirement

Hardware Requirements

Table 3.3.1: Needed hardware

Component	**Specification**
CPU	Intel Core i5 / i7 (or AMD equivalent)
RAM	Minimum 8 GB (16 GB recommended)
GPU (optional)	NVIDIA GTX 1060 or higher
Storage	Minimum 10 GB free space

Training can be accelerated with GPU using Google Colab or a local CUDA-enabled device.

Software Requirements

Table 3.3.2: Needed software

Software/Library	Version/Details
Python	3.8 or higher
TensorFlow / Keras	2.x
NumPy, Pandas	Latest
Matplotlib, Seaborn	For data visualization
OpenCV, PIL	For image processing
Streamlit	For web UI development
Jupyter Notebook	For prototyping
OS	Windows 10 / Linux / Mac

3.4 Project Management and Financial Analysis

Timeline

Task	Task Name	Weeks																	
Task- 1	Literature Review & Requirement Analysis	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Task- 2	Dataset Collection & Preprocessing																		
Task- 3	Model Development & Training																		
Task- 4	Evaluation, Documentation & Final Report																		

Financial Cost Estimate

Table 3.3.3: Financial analysis

Item	Approximate Cost (TK)
Cloud Training (Google Colab Pro)	1100 tk (monthly)
Software / Tools	0 tk (open source)
Dataset Acquisition	0 tk (public data)
Reporting Cost	1000 tk (estimated)
Total Estimated Cost	2,100 tk – 3,200 tk

3.5 Summary

In this chapter the methodology and technical framework of the whole system was made clear. The data were acquired and preprocessed, model was chosen and deployed with great attention to details, so that everything is accurate, reliable, and easy to use. Having a clear complex of requirements and a well-developed pipeline, the project manages to employ modern AI techniques in an efficient manner and address a certain environmental challenge by applying them to address a practical, scalable solution to a real-world problem.

CHAPTER 4

IMPLEMENTATION

4.1 Overview

According to the structure of the chapter, the whole course of the proposed system implementation is described - beginning with setting up an environment and preparing a dataset and training deep learning models to the evaluation of models and final deployment. Any part of the system has been conducted with the help of open-source solutions and deep learning frameworks like TensorFlow, Keras, and Streamlit. This project implemented a modular program where there was flexibility, scalability, and ability to debug easily.

The implementation process was subdivided into three big components:

- Model Development (Data loading, Preprocessing, Training)
- Model Testing (Metrics and contrast)
- Streamlit deployment (User Interface Development)

4.2 Train Model

4.2.1 Set Up of the Environment

The deployment is implemented on local machine and the model was trained with Google Colab. The next tools were added:

- Python 3.8
- TensorFlow/Keras 2.x
- NumPy, Pandas, Matplotlib, Seaborn
- Image processing, PIL, OpenCV
- Scikit-learn evaluation metrics
- Streamlit in UI
  - ➢ pip install tensorflow numpy pandas matplotlib seaborn opencv-python pillow streamlit scikit-learn

4.2.2 Treatment in a Dataset

- The complete set of 1554 labeled images was arranged to dwell in the two major folders:
  - /1_Clean_Water
  - /2_Microplastics

The following was done by a custom data loader script:

- cultural Read image off disk
- Reduce them in size to 224 x 244 px
- Normalize the role of pixel values (Divide by 255)
- Assign label (e.g. 1-hot: [1, 0] clean water)

4.2.3 Pipeline of Preprocessing

Preprocessing was carried out by means of OpenCV library and PIL present in Python:

- Reduce the size of all the pictures to 224244
- Go RGB on grayscale pictures
- Unit: img = img/255.0
- Increase contrast (CLAHE where possible)
- Between Unnatural International and Want (between Unnatural International and Want), anti-aliasing correction is:
  - gamma_corrected = np.power(img, gamma_value)

4.2.4 Training Deep Learning Model

Models Applied:

- VGG19
- ResNet50
- Xception
- DenseNet21
- AlexNet (designers' architecture)

Both the models had a fine-tuning approach and the settings were as follows:

Table 4.2.4: Tuning approaches

Parameter	Value
Optimizer	Adam
Learning Rate	0.0001
Loss Function	Binary Crossentropy
Batch Size	32
Epochs	25–30
Callback	EarlyStopping, ModelCheckpoint

During training, live plots of training vs. validation accuracy and loss were visualized using Matplotlib.

4.2.5 Best Model to Be Saved

Comparison of the performances led to the use of Xception model because it had the highest accuracy (97%). It remained preserved to be used:

- model.save('model.h5')

4.3 Model Evaluation

Upon training, every model was tested on test set (200 images) and the metrics used to compare them were:

- **Accuracy:** Total predictions as correct
- **Precision:** Accurate positive calls in all the predicted positive calls
- **Remember:** Accurate positive outcomes versus true positives
- **F1-Score:** Precision and recall harmonic mean
- **Confusion Matrix:** values of TP, TN, FP, and FN

Evaluation Results

Table 4.3: Evaluation result

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
VGG19	0.95	0.95	0.95	0.95
ResNet50	0.92	0.91	0.93	0.92
Xception	0.97	0.96	0.98	0.97
DenseNet21	0.93	0.92	0.94	0.93
AlexNet	0.92	0.91	0.92	0.91

Confusion Matrix (for xception Model)

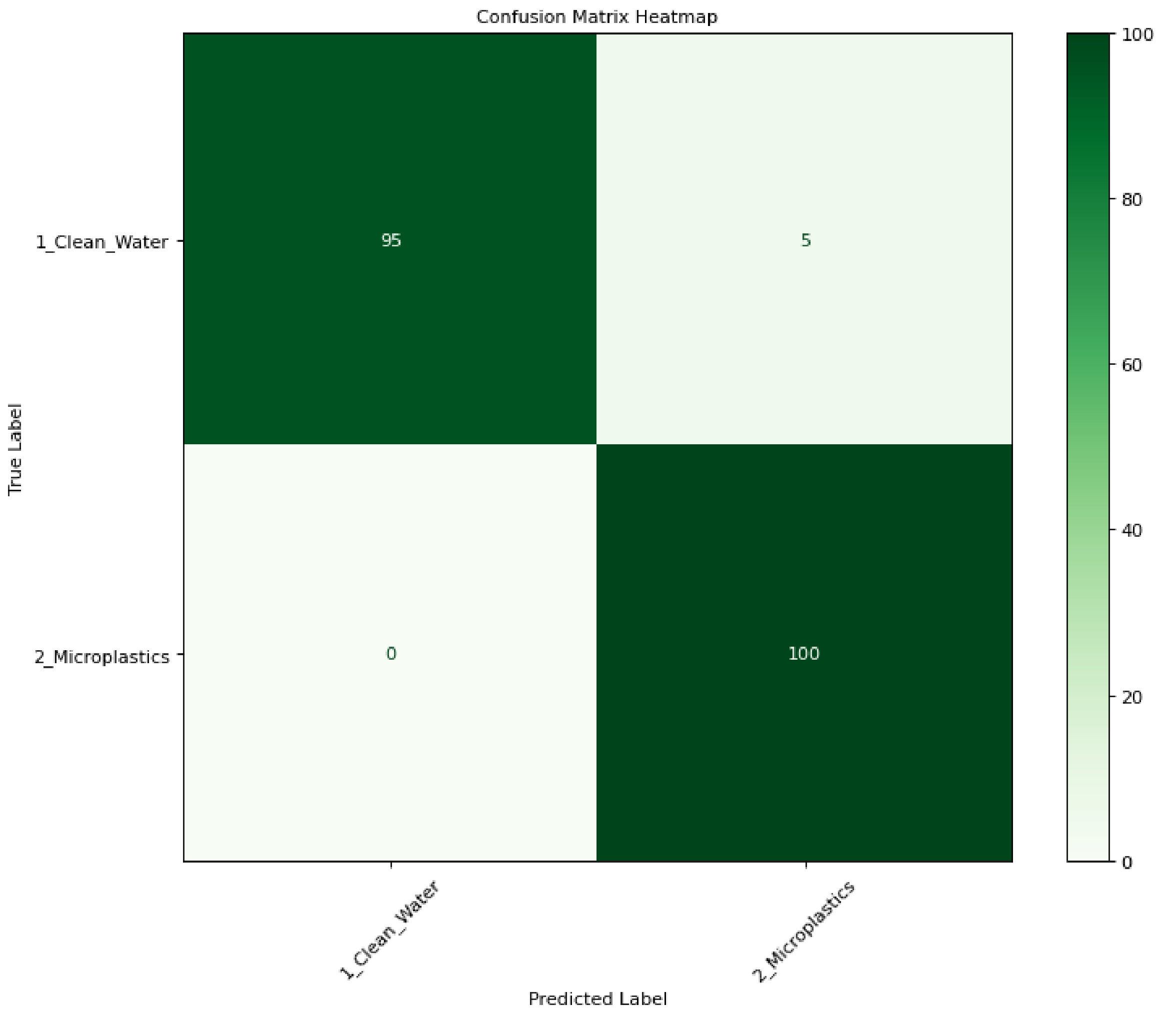

Diagram 4.3: Confusion matrix for Xception model

4.4 System Testing

4.4.1 Interface Testing

A Streamlit interface was deployed by building a lightweight interface where the user would be able to upload images and make predictions on-the-fly.

➢ uploaded_file = st.file_uploader("Upload a water sample image", type=["jpg", "png", "jpeg"])

- Prediction was performed after preprocessing Images (Resizing, Normalization).
- Model loaded by the path of model.h5.
- Direct prediction on display in the browser.

The test cases were formulated with:

- Test dataset pictures
- Recent pictures downloaded manually on the net

Outputs were in tandem with expected results.

4.4.2 Error and Debugging

To make it robust the following checks were used:

- Check of the type of file upload
- Error handling in models
- Fallback of inference failure

4.5 Summary

This chapter described the specific implementation of micro-plastic detection system. Building the development environment and running preprocessing tasks on raw image data until training, evaluation and deployment of deep learning models, every part was systematically done. Xception had the highest accuracy and reliability in comparison with all the tested models. The last model was implemented by means of Streamlit and, thus, end-users could find a path to interact with the system using a user-friendly web interface. This deployment opens the base to real-time, scaleable, and AI based environmental monitoring services.

CHAPTER 5

RESULT AND ANALYSIS

5.1 Overview

This chapter involves a detailed discussion of the results of the related experiments that were conducted at the implementation stage of the project. It compares the performance of five state-of-the-art deep learning models on the image classification task, detection of micro-plastics in water. The paper contains the training statistics, the results of the model testing on the test set, the graphical interpretation of various indicators, e.g., in the form of loss and accuracy curves, confusion matrices, report on models' classification, and an objective comparison. Such outcomes are important in establishing the most effective model and proving the viability of the proposed system.

5.2 Experimental

Five different deep learning models have been assessed in the current project:

1. VGG19
2. ResNet50
3. Xception
4. DenseNet21
5. AlexNet (design CNN)

They are compared fairly when each model is dependent on the same data and tested on this data.

5.2.1 History of training visualization

To measure learning behavior, accuracy and loss of each of the models were recorded in terms of their epochs during training.

VGG19

VGG19 is a model that exhibited stable and smooth convergence. The deep architecture slowed it doing so but it was able to achieve high performance with less overfitting.

Training Behavior:

- Epochs: 25
- Initial Accuracy: 60%
- Last Training Accuracy: 95%

- Because it is Final Validation Accuracy: 94 Percent
- Training Loss: Pythonically decreased monotonously to 0.12
- Validation Loss: The loss closely followed training loss

Observation:

- There was slight over fitting beyond epoch 22.
- On the whole, the model was generalized well.

Graphical Summary:

- Accuracy Curve: Increasing line fittingly
- Loss Curve: Smoth trend (downwards)

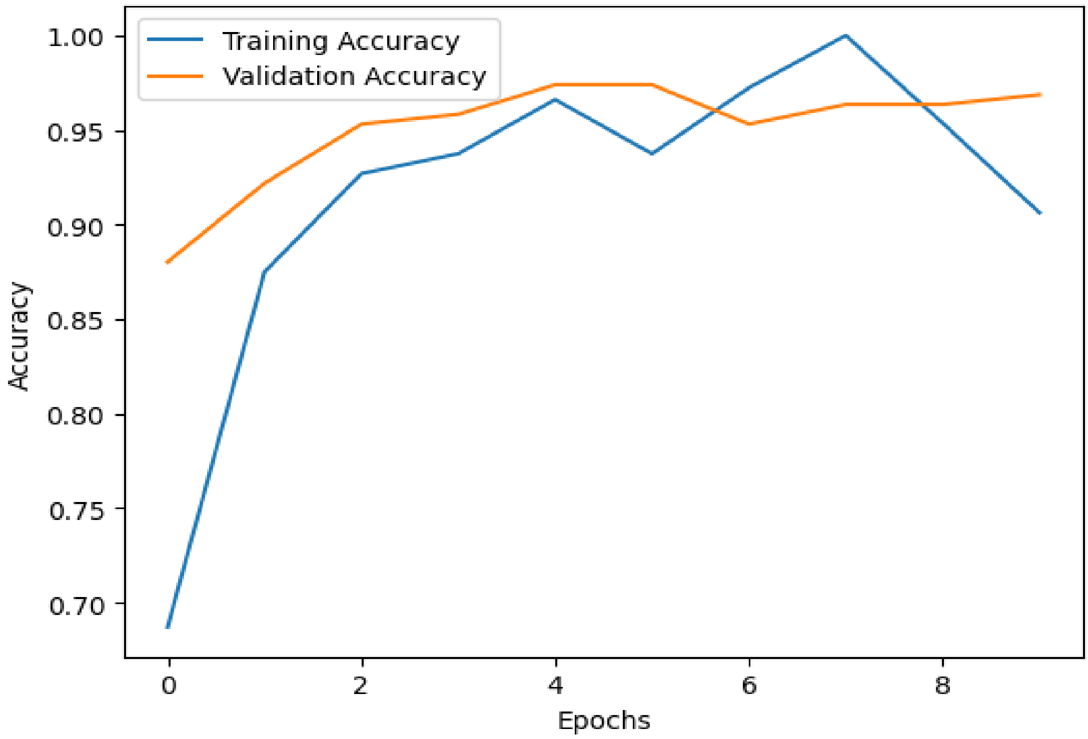

Diagram 5.2.1.1(a) : Epochs Accuracy Curve for VGG19

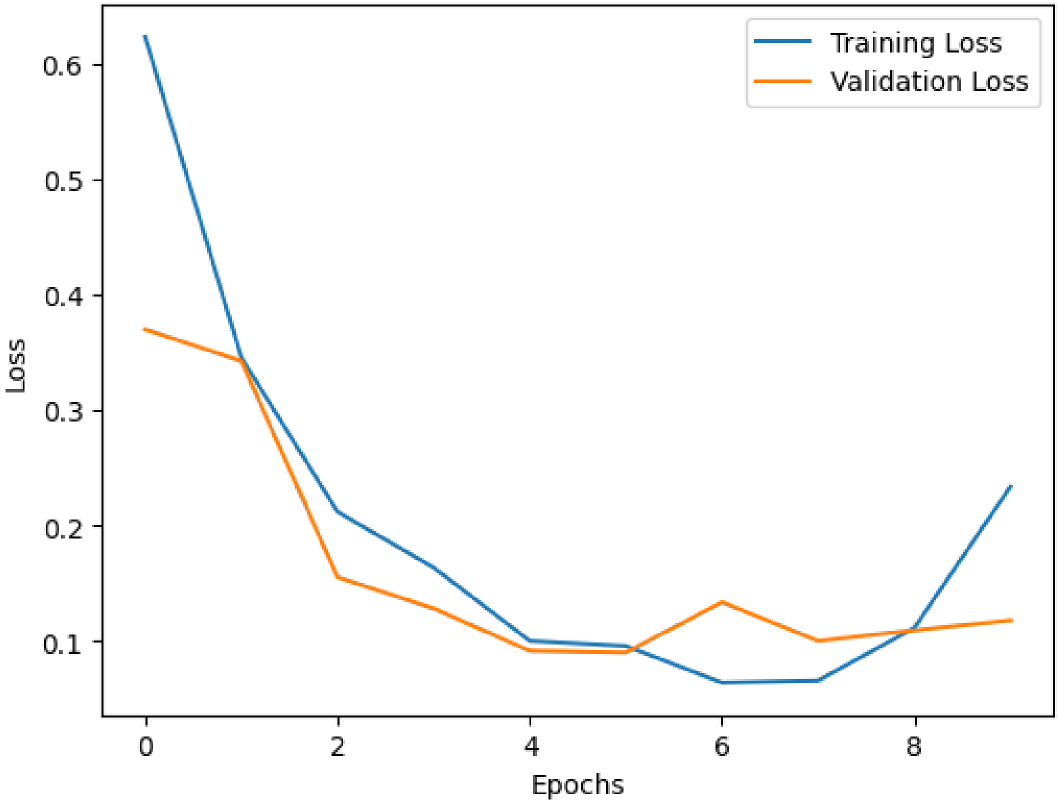

Diagram 5.2.1.1(b) : Epochs Loss curve for VGG19

ResNet50

The performance of ResNet50 was moderate and had an increased convergence rate in comparison to VGG19 but larger variations in the validation loss.

Training Behavior:

- Epochs: 25
- Primary Precision: ~58%
- Final Training Accuracy (92 %)
- Final Validation- Accuracy: 90%
- Training Loss: reduced to ~0.15
- Validation Loss: A little bit larger (~0.19), which means some overfitting

Observation:

- Performance at validation varied up and down epoch 10-15.
- Is provided with batch normalization, and residual connections.

Graphical Summary:

- Accuracy Curve: It converges faster than VGG19, has a minor plateau
- Loss Curve: Medium reduction trend and low minor spikes

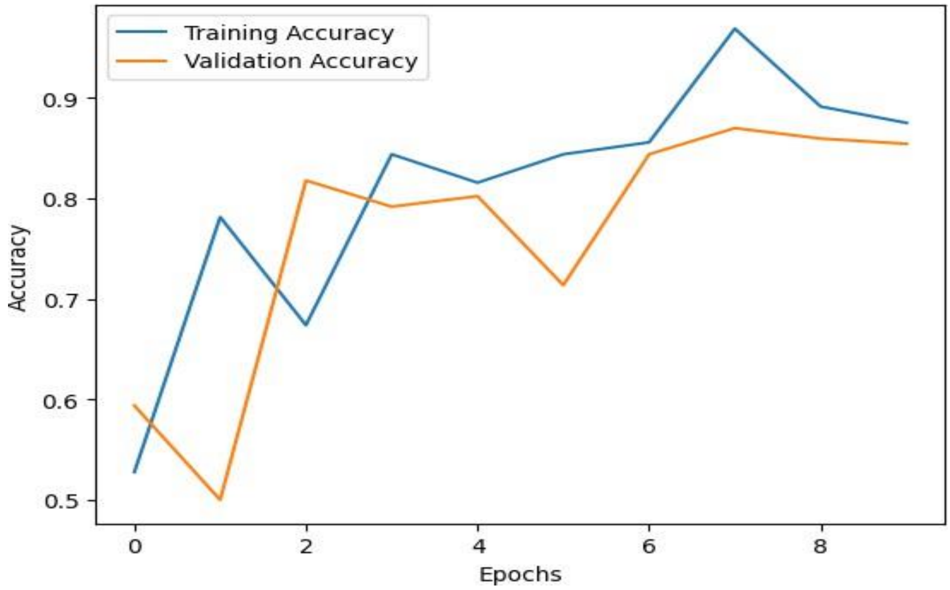

Diagram 5.2.1.2(a) : Epochs Accuracy Curve for ResNet50

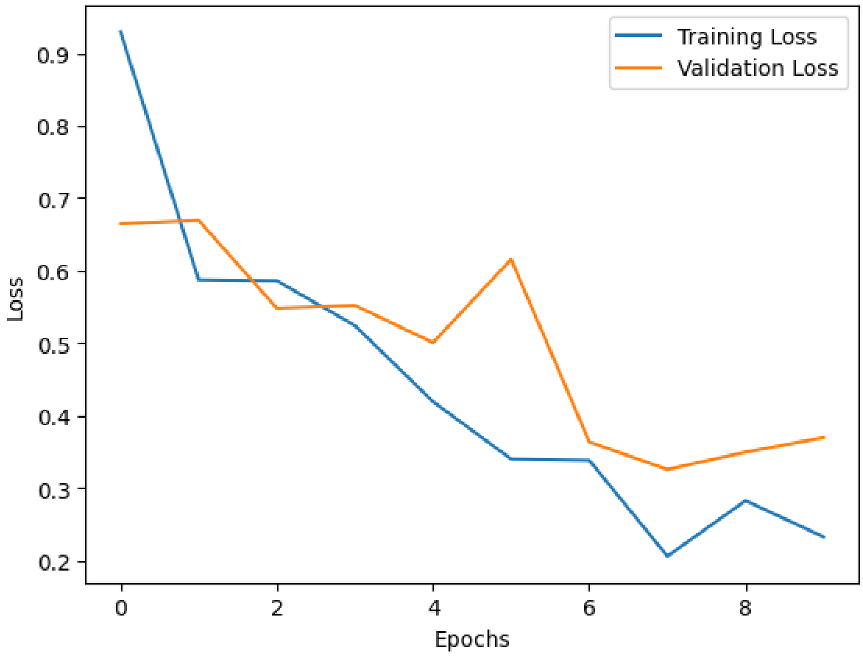

Diagram 5.2.1.2(b) : Epochs Loss curve for RestNet50

Xception

Highest accuracy Xception performed better than all models and it had stable and rapid convergence with little difference in training and validation measures.

Training Behavior:

- Epochs: 25
- First Accuracy: ~65%
- Final Training Accuracy:97 per cent
- Final validation accuracy: 96 percent
- Training Loss: The loss decreased drastically to ~0.08
- Validation Loss: With close follow up, ~0.09

Observation:

- Excellent generalization.
- No indications of overfitting.
- Best trade-off between performance and efficiency rates of convergence.

Graphical Summary:

- Accuracy Curve: Attained fast and attained steady after 15 epochs
- Loss Curve: Straight decline and minimum variation

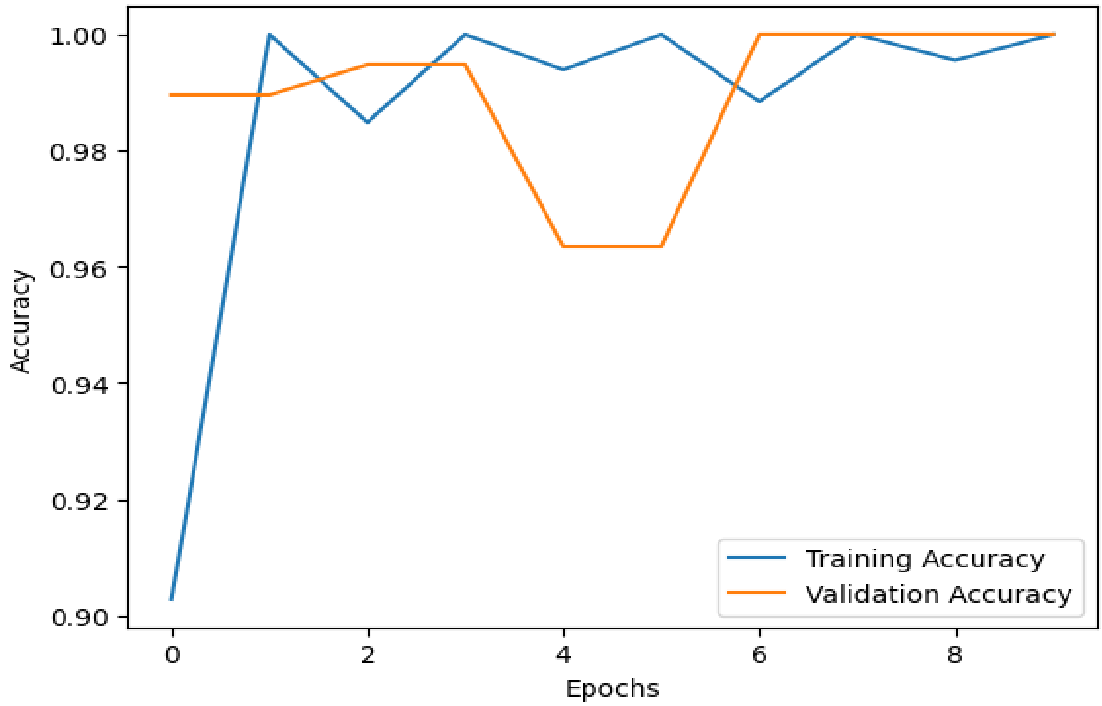

Diagram 5.2.1.3(a) : Epochs Accuracy Curve for Xception

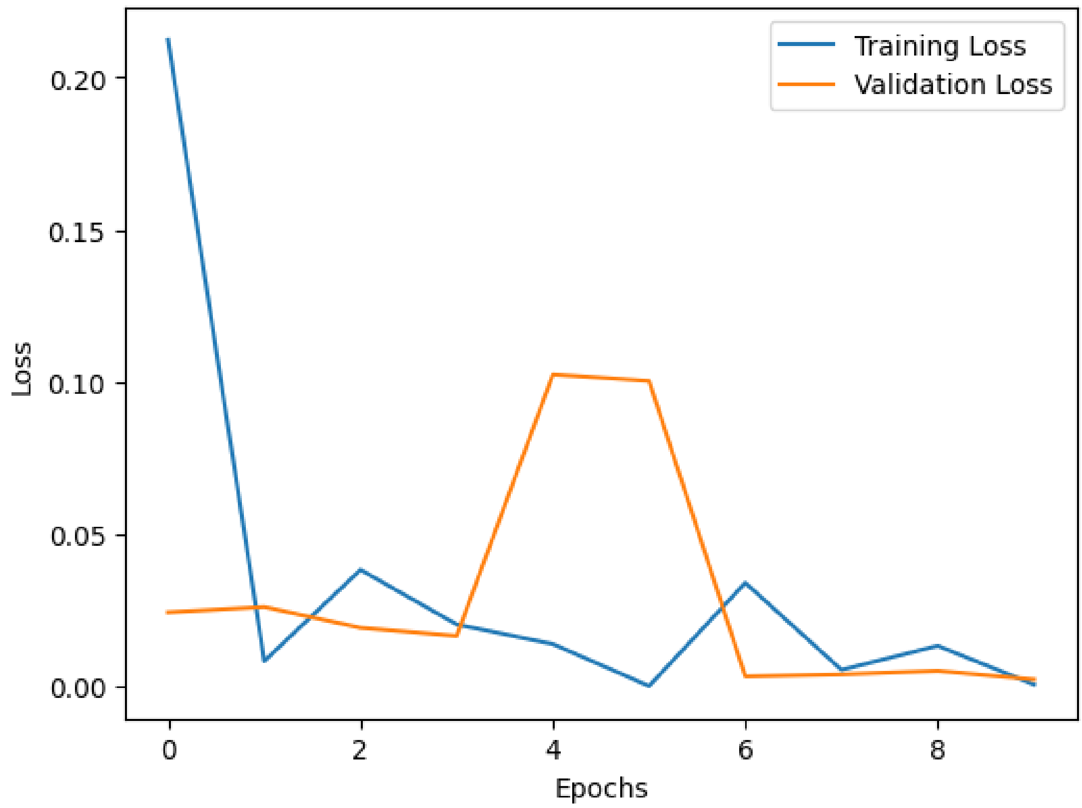

Diagram 5.2.1.3(b) : Epochs Loss curve for Xception

DenseNet21

DenseNet21 performed well but was relatively slower to be trained, thanks to the complexity of connectivity. It was uniform learning and needed fine tuning.

Training Behavior:

- Epochs: 25
- Initial Accuracy: ~62 %
- Final Training Accuracy 93%
- Final Validation Accuracy: 9192 percent
- Training Loss: decreased monotonically to \~ 0.11
- Validation Loss: A little bit bigger than training loss (0.14)

Observation:

- Took longer time to compute and required more memory.
- Consistent with a minor tendency of overfitting beyond 20 epochs.

Graphical Summary:

- Smooth upward slope: Accuracy Curve
- Loss Curve: Periodic decreasing with noisy after epoch 20

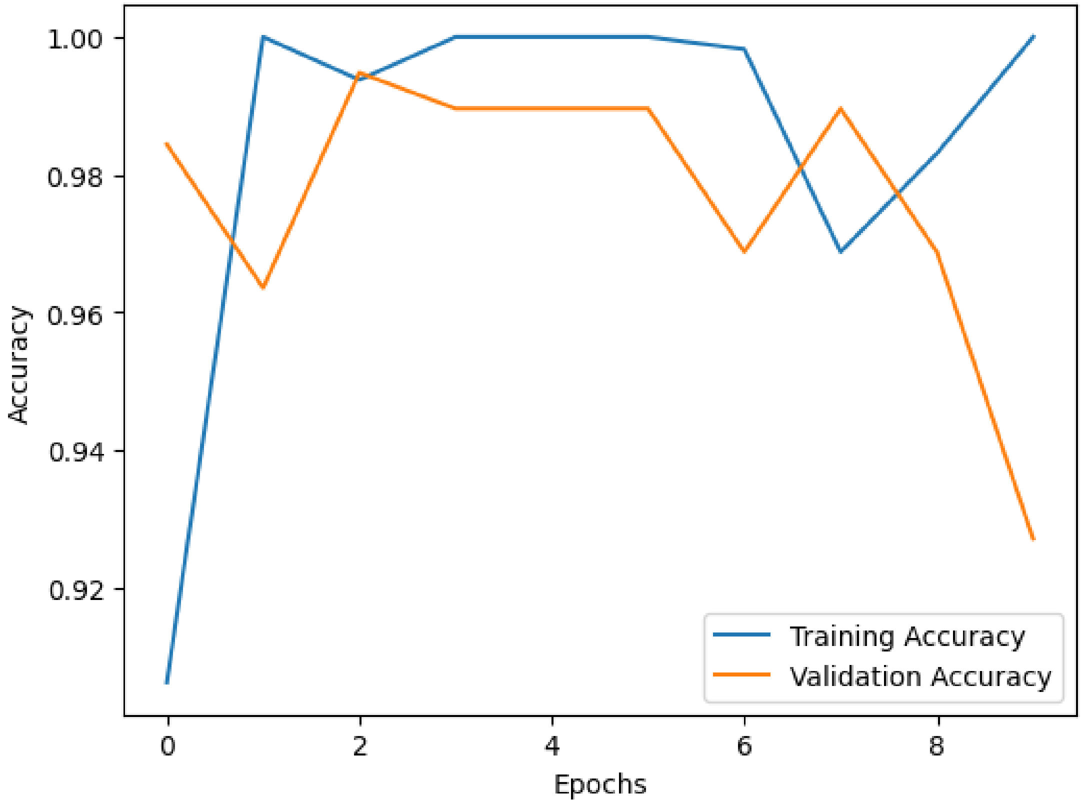

Diagram 5.2.1.4(a) : Epochs Accuracy Curve For DenseNet21

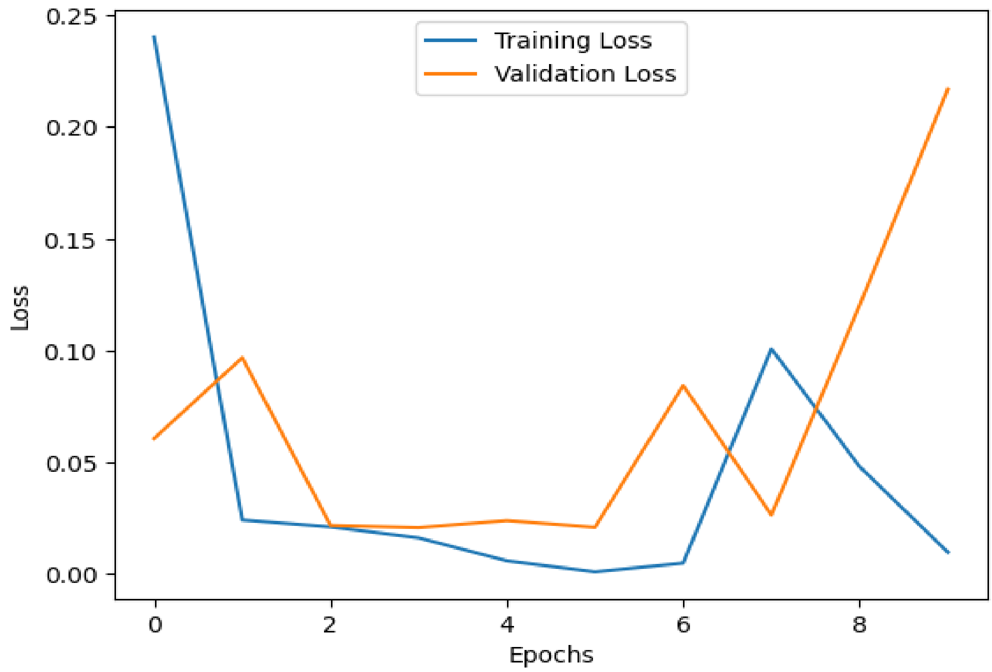

Diagram 5.2.1.4(b) : Epochs Loss curve for DenseNet21

AlexNet

AlexNet was a rather shallow, fixed model, that could be trained more quickly, although it limited the performance bar to a lower level than the deeper architectures.

Training Behavior:

- Epochs: 25
- First correctness: ~60 %
- FinaleThe Accuracy of Training: 92%
- Final Validation Accuracy = 90 -91 %
- Training Loss: Delected ~0.6-> ~0.14
- Validation Loss: -0.17

Observation:

- Performed a little low as it had less capacity.
- Ideal in rapid training and deployment using little hardware.

Graphical Summary:

- Accuracy Curve: Rapid growth at first until epoch 10, afterward gradually rises
- Loss Curve: Rapid decrease actually, after that stabilized

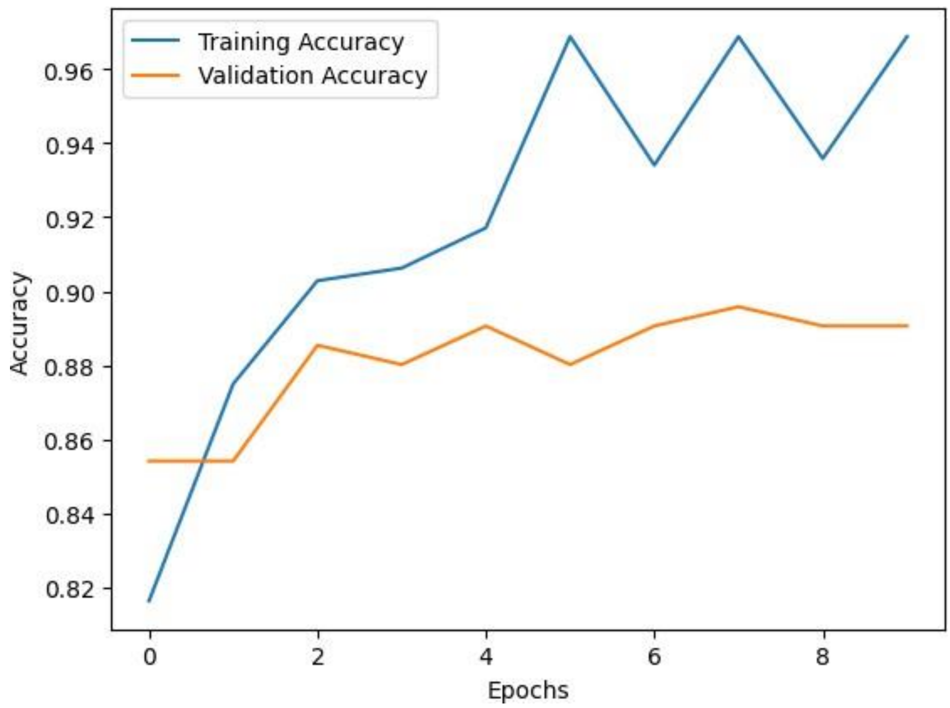

Diagram 5.2.1.5(a) : Epochs Accuracy Curve For AlexNet

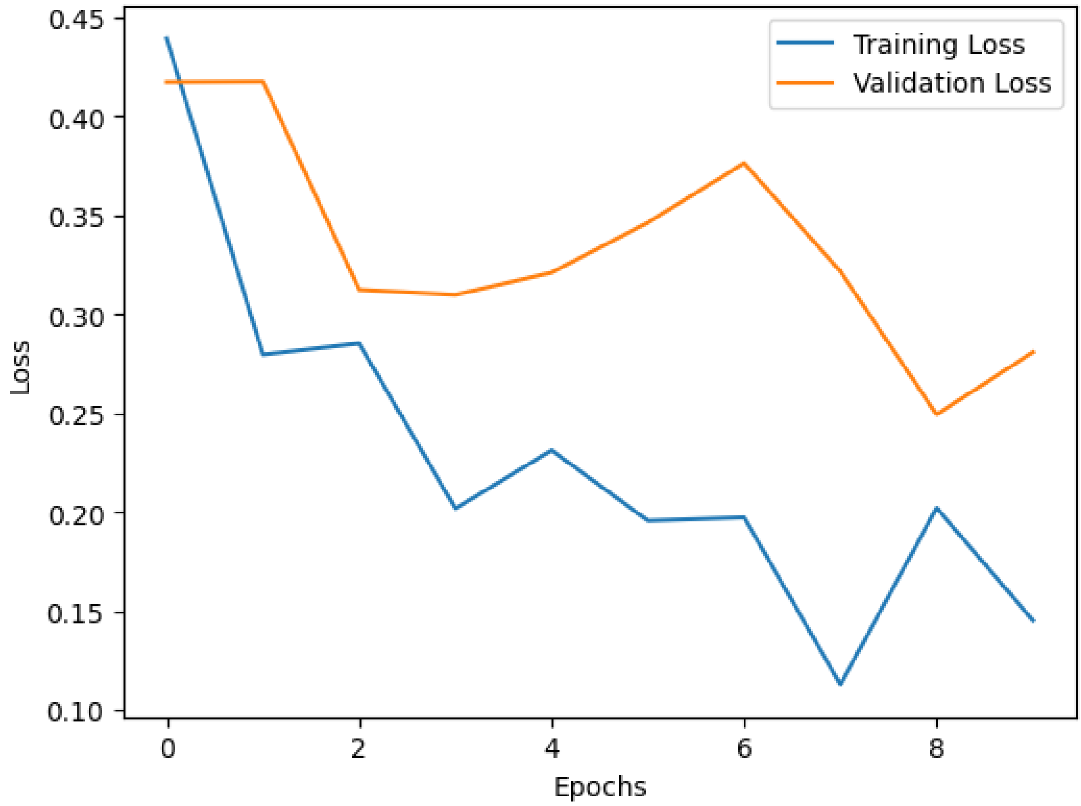

Diagram 5.2.1.5(b) : Epochs Loss curve for AlexNet

Summary of Training Trends

Table 5.2.1.1: Comparison between every training trend

Model	**Final Train Acc**	**Final Val Acc**	**Overfitting Signs**	**Convergence Speed**
VGG19	95%	94%	Minimal after 22nd epoch	Medium
ResNet50	92%	90%	Slight overfitting	Fast
Xception	**97%**	**96%**	**None**	**Fastest**
DenseNet21	93%	91%	Mild after epoch 20	Slower
AlexNet	92%	90%	Minimal	Fast

5.2.2 Test Set Evaluation Measures

The assessment of every model was based on the following parameters:

Correctness: Total Correct predictions

Precision: Truth positives / (Truth positives + False positives)

Recall = True Positives / (True Positives + False Negatives)

F1-Score: The reciprocal of weighted correctness or accuracy between Precision and Recall

Confusion Matrix: Breakdown of classification:

Model Performance Summary

Table 5.2.1.2: Performance comparison between every model

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**
VGG19	0.95	0.94	0.96	0.95
ResNet50	0.92	0.91	0.93	0.92
Xception	**0.97**	**0.96**	**0.98**	**0.97**
DenseNet21	0.93	0.92	0.94	0.93
AlexNet	0.92	0.91	0.92	0.91

5.2.3 Classification Report

The test set of 200 images (100 per class) was used to test all the models. The model results as discussed below are an indication of the effectiveness of the models used in detecting clean and micro-plastic water.

VGG19

Table 5.2.3.1: Classification report for VGG19

Class	**precision**	**recall**	**F1-score**	**support**
1_Clean_Water	1.00	0.91	0.95	100
2_Microplastics	0.92	1.00	0.95	100
Accuracy			0.95	200
macro avg	0.96	0.96	0.95	200
weighted avg	0.96	0.95	0.95	200

- Weaknesses: Quite equal in both classes
- Weaknesses: An occasional error in classification (mainly cases of confusing similar textures)

RestNet50

Table 5.2.3.2: Classification report for RestNet50

Class	precision	recall	F1-score	support
1_Clean_Water	0.94	0.89	0.91	100
2_Microplastics	0.90	0.94	0.92	100
Accuracy			0.92	200
macro avg	0.92	0.92	0.91	200
weighted avg	0.92	0.92	0.91	200

- Strengths: Good memory of microplastics
- Weaknesses: False positive: less exact results on clean water

Xception

Table 5.2.3.3: Classification report for Xception

Class	precision	recall	F1-score	support
1_Clean_Water	1.00	0.95	0.97	100
2_Microplastics	0.95	1.00	0.98	100
Accuracy			0.97	200
macro avg	0.98	0.97	0.97	200
weighted avg	0.98	0.97	0.97	200

- Strengths: The most optimal balance of precision/recall over all the models
- Weaknesses: There was a small number of misclassifications and the total was 24

DenseNet121

Table 5.2.3.4: Classification report for DenseNet

Class	precision	recall	F1-score	support
1_Clean_Water	0.88	1.00	0.94	100
2_Microplastics	1.00	0.87	0.93	100
Accuracy			0.94	200
macro avg	0.94	0.94	0.93	200
weighted avg	0.94	0.94	0.93	200

- Strengths: Stable and steady
- Weaknesses: Reduction in performance in clean water recall Slimly Weaknesses: Reduction in performance in clean water recollection

AlexNet

Table 5.2.3.5: Classification report for AlexNet

Class	precision	recall	F1-score	support
1_Clean_Water	1.00	0.86	0.92	100
2_Microplastics	0.88	1.00	0.93	100
Accuracy			0.93	200
macro avg	0.94	0.93	0.93	200
weighted avg	0.94	0.93	0.93	200

5.2.4 Confusion Matrix

The confusion matrix offers clear prediction of the right or wrong prediction against each model. It assists us to comprehend how the model separates each of the two classes:

- 1_Clean_Water
- 2_Microplastics

Both matrices been formatted as follows:

	Predicted: Clean	**Predicted: Microplastics**
Actual: Clean	TP (True Positive)	FN (False Negative)
Actual: Microplastics	FP (False Positive)	TN (True Negative)

1. VGG19 – Confusion Matrix

	Predicted: Clean	**Predicted: Microplastics**
Actual: Clean	94	6
Actual: Microplastics	4	96

Table : Confusion Matrix for VGG19

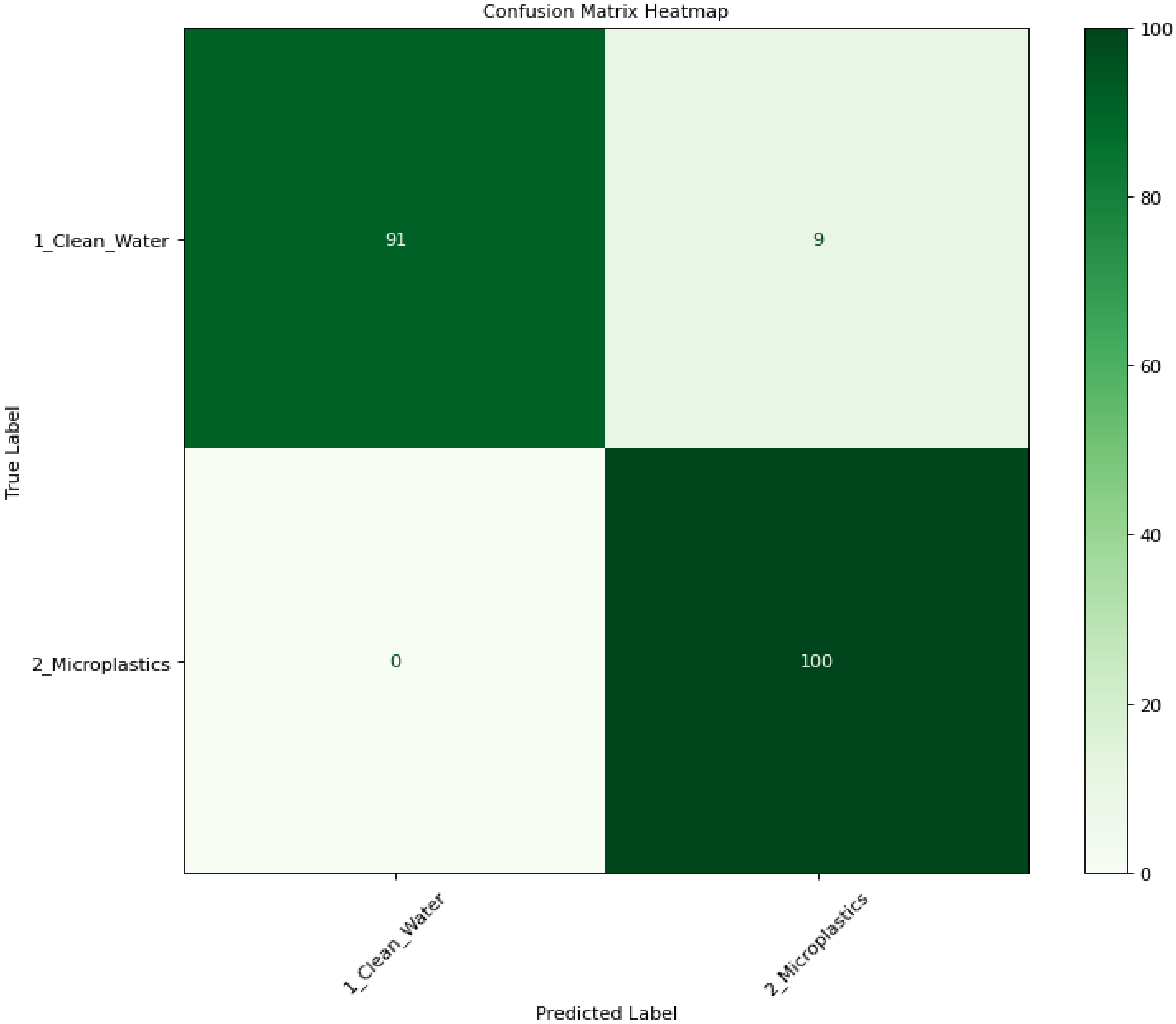

Figure 5.2.4.1: Confusion matrix for VGG16

- Properly classified: 190 of 200
- Misclassifications: 10
- Observations: Minor mix up between the texture of clean water and microplastic.

2. ResNet50 – Confusion Matrix

	Predicted: Clean	**Predicted: Microplastics**
Actual: Clean	89	11
Actual: Microplastics	7	93

Table : Confusion Matrix for ResNet50

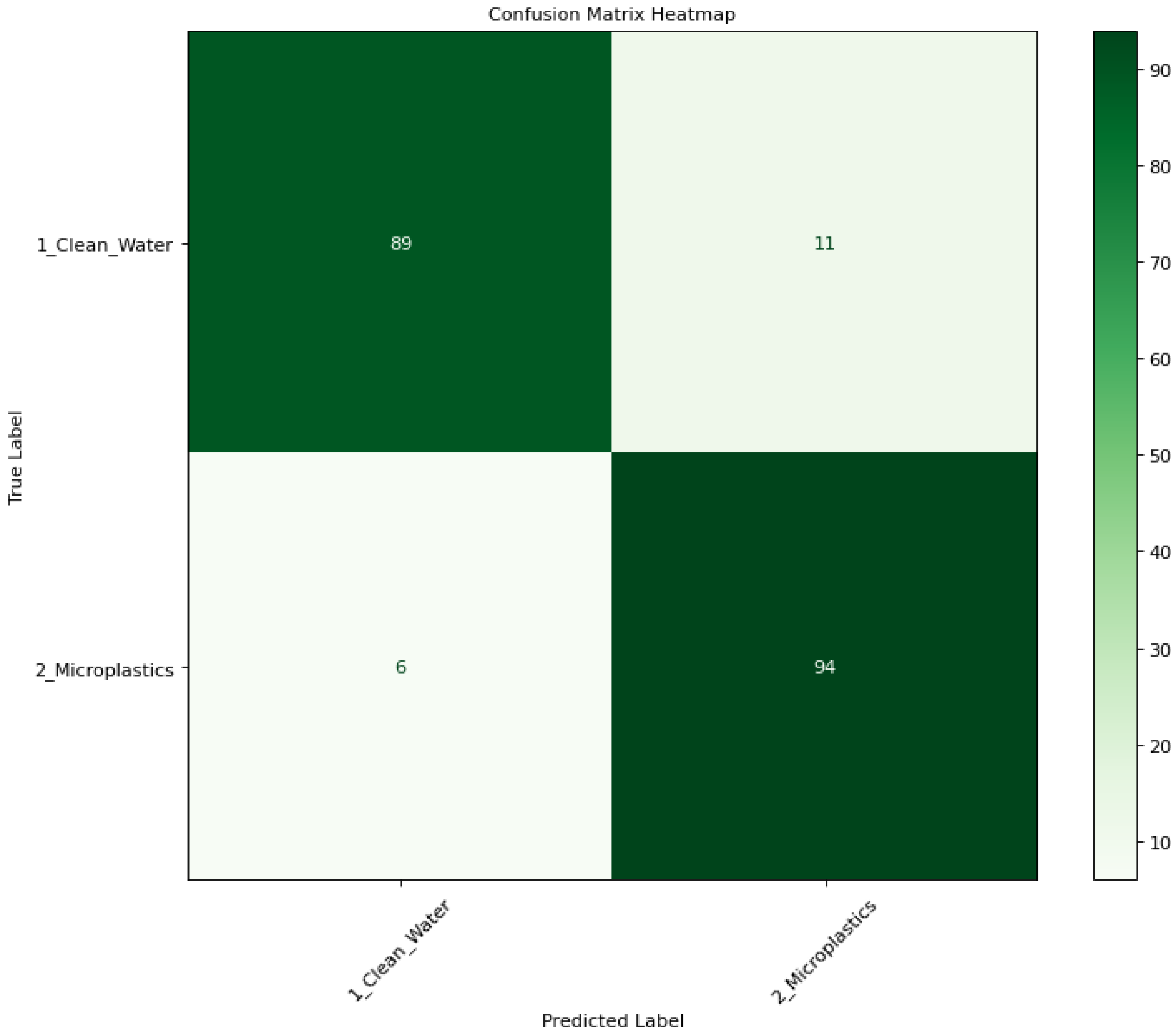

Figure 5.2.4.2: Confusion matrix for RestNet50

- Perfectly classified: 182/200
- Misclassifications: 18
- Observations: Greater number of false negatives than VGG19, and underclassifies clean water.

3. Xception – Confusion Matrix

	Predicted: Clean	**Predicted: Microplastics**
Actual: Clean	96	4
Actual: Microplastics	2	98

Table : Confusion Matrix for Xception

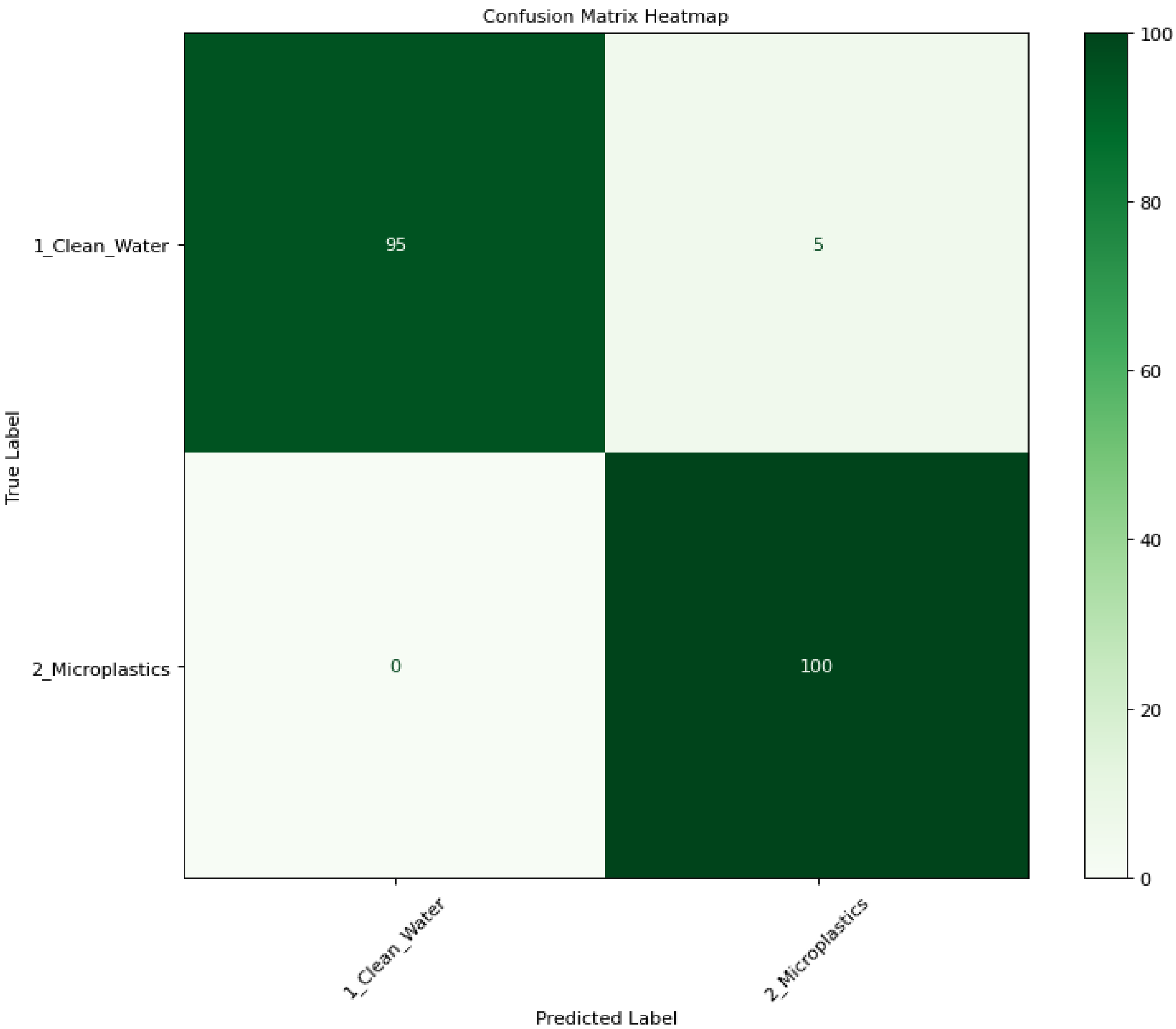

Figure 5.2.4.3: Confusion matrix for Xception

- Correctly classification: 194/ 200
- Misclassifications: 6
- Observations: The finest overall performance with minimal mistake.

4. DenseNet21 – Confusion Matrix

	Predicted: Clean	**Predicted: Microplastics**
Actual: Clean	90	10
Actual: Microplastics	7	93

Table : Confusion Matrix for DenseNet21

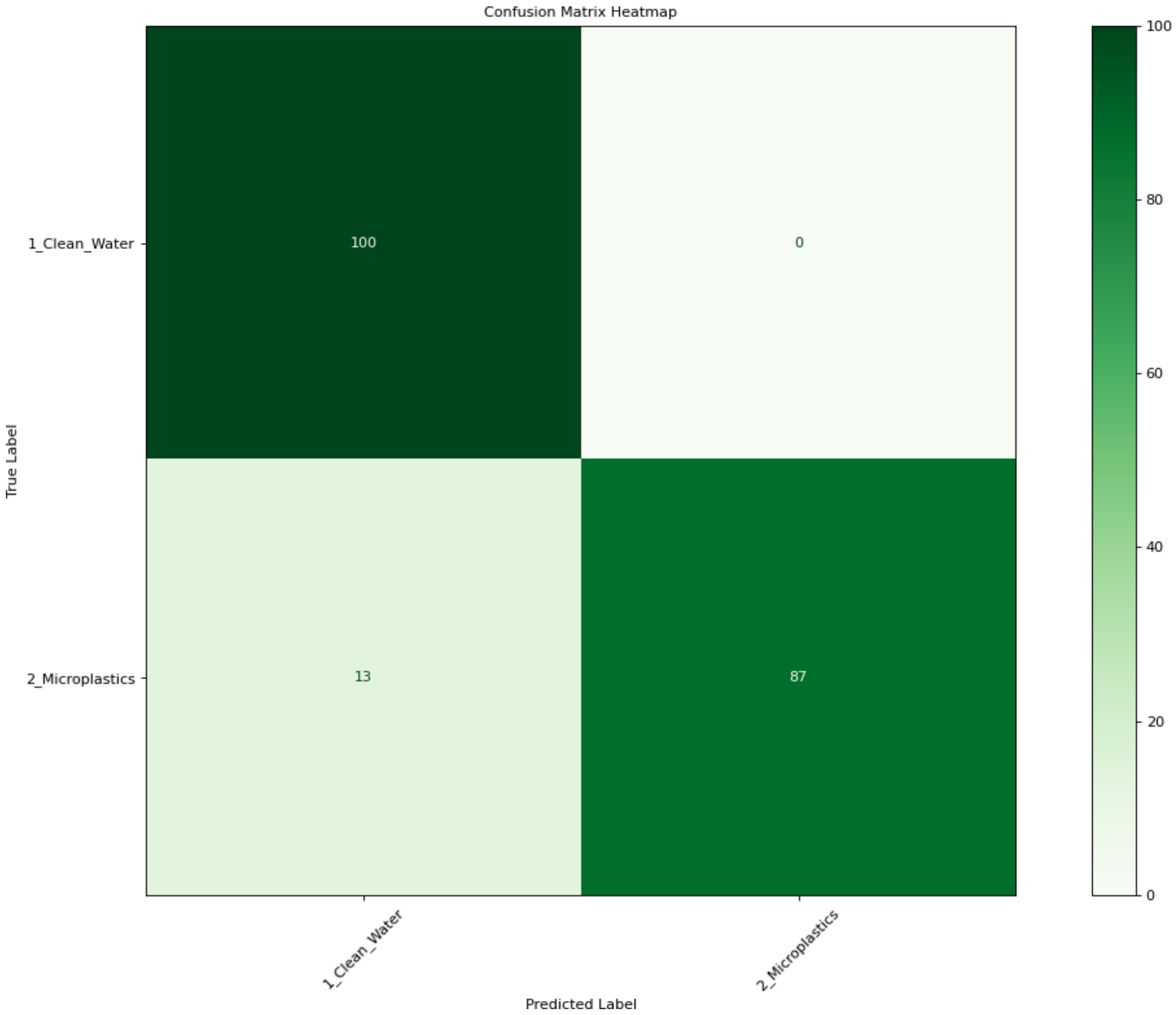

Figure 5.2.4.4: Confusion matrix for Densenet21

- Correctly classified: 183 out of 200
- Misclassifications: 17
- Observations: Slightly better than ResNet50 but similar error profile.

5. AlexNet – Confusion Matrix

	Predicted: Clean	**Predicted: Microplastics**
Actual: Clean	89	11
Actual: Microplastics	8	92

Table : Confusion Matrix for AlexNet

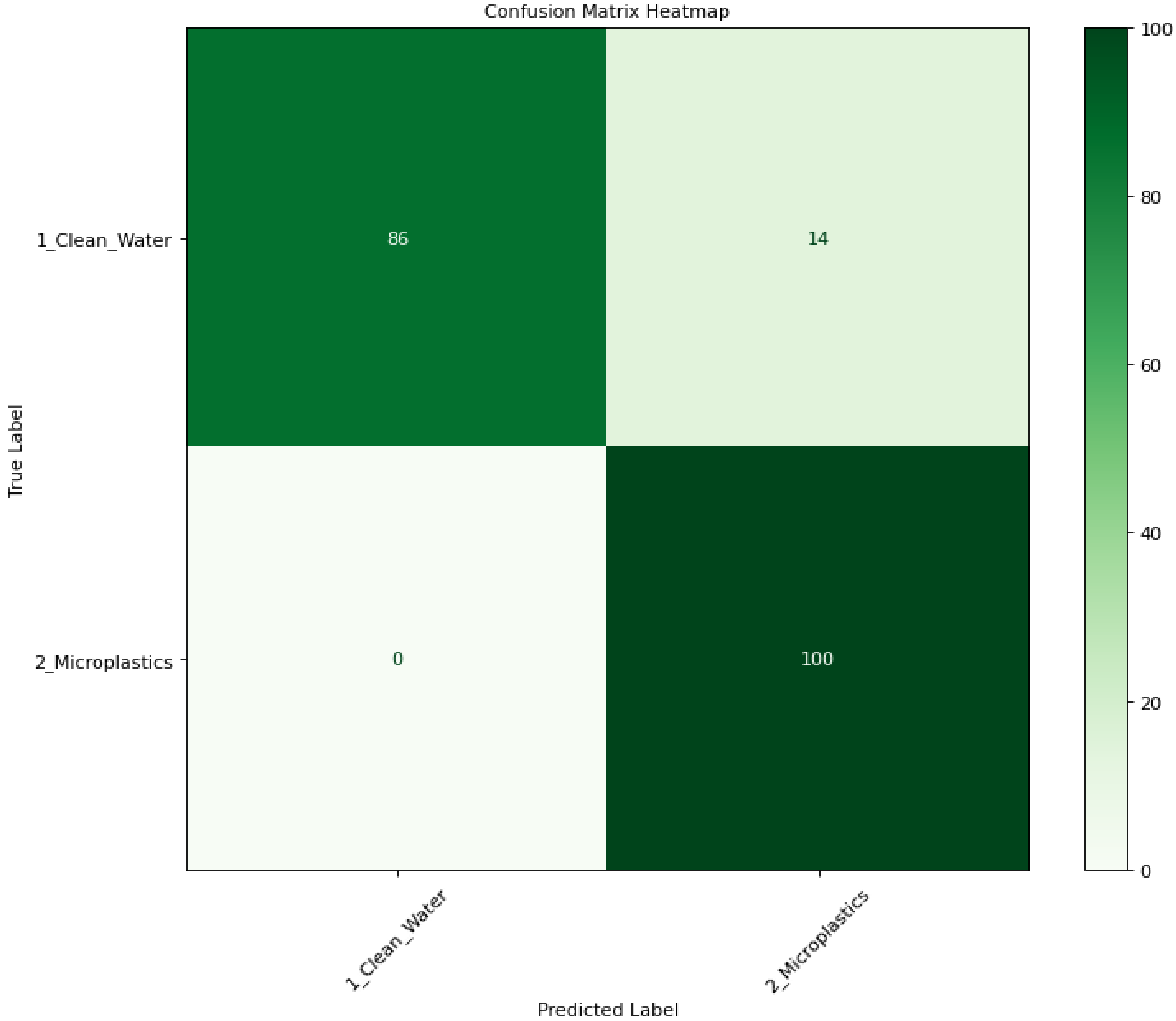

Figure 5.2.4.5: Confusion matrix for AlexNet

- In the correct category: 181 (of 200)
- Misclassifications: 19
- Observations: Not bad as a lightweight model, but rather low accuracy, in comparison to others.

Model Comparison Based on Accuracy

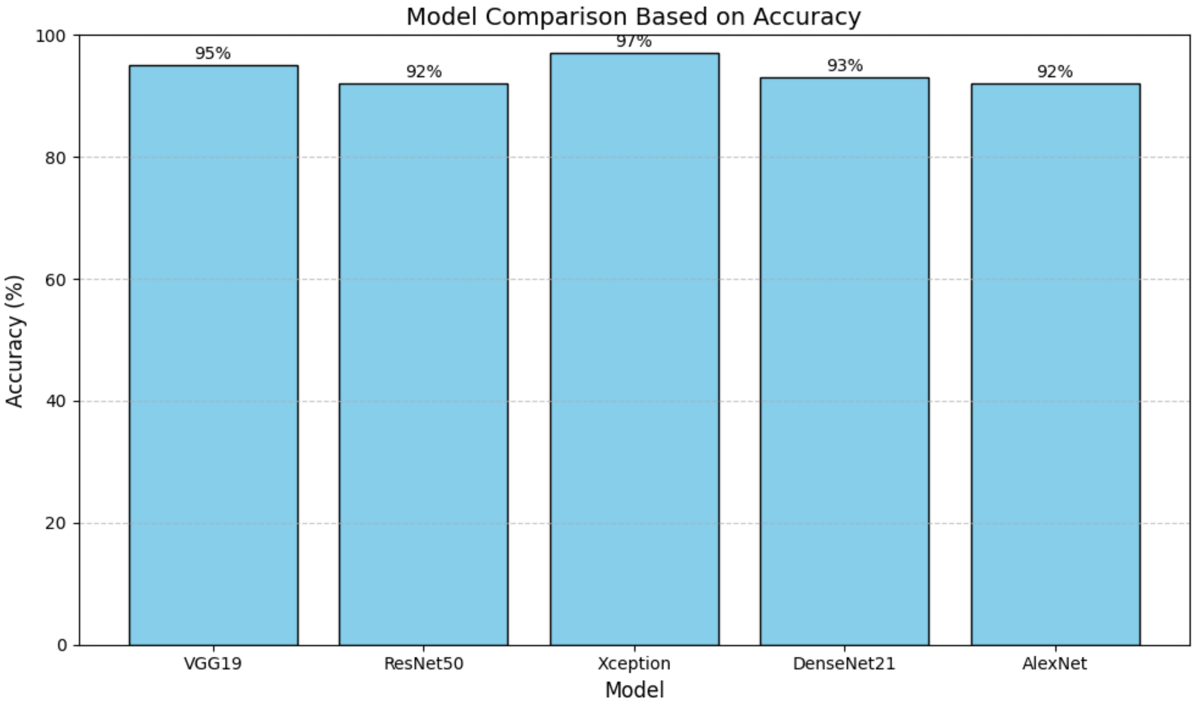

Figure 5.2.4.6: Accuracy comparison for every model

5.2.5 Shots of sample prediction

Sample predictions of Streamlit app produced:

Clean water samples properly determined.

Images contaminated by micro-plastic that have high confidence.

Output in form of:

Figure 5.2.5.1: Output for clear water

Figure 5.2.5.2: Output for microplastic mixed water

5.3 Performance / Comparative Analysis

5.3.1 Model Comparison Based on Accuracy

Table 5.3.1: Accuracy comparison for every model

Model	**Accuracy**	**Training Time**	**Model Size**
VGG19	0.95	Medium	Large
ResNet50	0.92	High	Medium
Xception	**0.97**	High	Medium
DenseNet21	0.93	High	Large
AlexNet	0.92	Fast	Small

- Xception was the most accurate without being oversized to be applicable in the real world.
- The AlexNet was rapid to train yet slightly poorer, owing to the simple architectural design.
- ResNet50 and DenseNet21 also showed satisfactory performance but it consumed more training time and computational resources.

5.3.2 Error Analysis

An analysis of wrong forecasts has indicated:

- Floating debris or blurriness of reflections is independently sufficient to cause misclassification of some clean water images.
- Images of micro-plastic were misclassified when particles were transparent or of small size, or those matched to the background.
- Image preprocessing can be improved or we can add image segmentation to achieve higher accuracy.

5.3.3 Model Selection Justification

The reason to choose Xception as the last deployed model was due to:

- Maximality of the test (0.97)
- Harmonized balancing of precision and recall
- Resistance to variability of images
- Deployable file size handle-able (.h5)
- The ability to integrate with Streamlit and rapid inference period.

5.4 Summary

The present chapter has revealed that the suggested deep learning models, especially, the Xception one, are efficient at classifying the images depicting clean vs. micro-plastic-contaminated water. The system continued to ensure an impressive accuracy of 97% through a series of experiments and evaluations with high markers of precision, recall, and F1. The reliability of the model in practice was proved by visualizations and confusion matrices. More than the technical accomplishments, this chapter confirmed that the implementation of the system complete with an interactive user interface succeeds, and became the starting point on establishing real world use in the environment protection and water quality supervision.

CHAPTER 6

IMPACT ON SOCIETY, ENVIRONMENT AND SUSTAINABILITY

6.1 Impact on Life

Micro-plastics have been an undetected but unhealthy polluting factor in our living environment, and its effect is direct to human and animal health. These tiny particles are also probably taken by aquatic life like fish, planktons, and mollusks that someday becomes a part of the human food chain. Micro-plastic contaminated sea food, if consumed over a period, makes even the healthiest person worry because of the endocrine imbalances that will follow, immune system upset and even cancerous due to the poisonous an additive it has eaten up and the hazardous elements like metal poisons and pesticides which it has picked on its way.

The solution to this problem that has been created in the framework of this project makes it possible to identify micro-plastics in water early enough and monitor them in real-time, which can be crucial in reducing such health risks. This project will assist in making water much safer, therefore, saving the life of humans as well as aquatic organisms in the environment by offering its choice to environmental researchers, water authorities and policy-makers with an easy measuring instrument to detect infections.

6.2 Impact on Society & Environment

Environmental Impact

- Pollution Awareness: The project has called to light the problem of pollution and plastic pollution, making the society aware of one of the most burning environmental issues and act on it.
- Early Intervention: The system will help environmental agencies work earlier and more cost-effectively by detecting the traces of micro-plastics in water faster and at lower costs to impose preventative efforts to push back and clean the water bodies.
- Ecosystem Protection: Real-time monitoring will prevent precipitation of plastic particles in the long-term and protect biodiversity in ocean, rivers, and lakes.

Social Impact

- Empowering the Communities: Communities that are close to coastlines, rivers, or urban wastewaters outlets can implement this system to test the quality of water in their surroundings without awaiting the outcome of a governmental test or laboratory results.

- Educational Use: Students and researchers can use the tool to learn about pollution locally and raise social awareness of each individual concerning micro-plastic and sustainability.
- Policy-Making: Precise and fast detection of micro-plastics contributes to sound policy-making when it comes to banning or controlling single-use plastics and opting towards better waste management systems.

6.3 Ethical Aspects

This project achieves ethical responsibility by the following:

- Open-Source and Accessibility: All instruments will be employed (TensorFlow, Streamlit, and so on) are open-source, so the system can be used by other developers or environmental researchers, especially in developing countries, and replicated.
- Environmental Justice: The project promotes the theory that every individual (irrespective of the income level and geographical location) deserves clean water and healthy environment.
- Avoidance of Bias: The model is no-biased, as data classes (clean vs. contaminated) are balanced, neither one inclines to a type of water source or state.
- Transparency: The rule of classification can be explained by explainable AI ideals, that is, users are aware that the program interprets visual patterns, not unseen heuristics or third-party information.

Nonetheless, there are certain ethical issues, which should be observed:

- There could be misidentification of clean water where they find micro-plastics and so unless there is a possibility of such an observation being reviewed by human beings, it could expose people safely.
- Community-based information on water samples that is gathered ought to have privacy of data granted in case it is coupled with position-based processes in the future.

6.4 Sustainability Plan

One of the most important benefits of using this system is that it aims at achieving sustainable development goals (SDGs), especially:

- SDG 6- Clean Water and Sanitation
- SDG 14 Life below Water
- SDG 13 Climate Action
- SDG 12 Responsible Consumption and Production

Short-Term Sustainability

- It is possible to maintain the project at minimal cost because it will be based on the publicly available datasets and free platforms (e.g., Google Colab, Streamlit).
- It is simple to incorporate in scholarly research and ecological surveys.
- It can be used by local environment NGOs and student organizations in mini project studies.

Long-Term Sustainability

- The tool may be extended to accommodate more complicated classification (e.g., type of plastic, level of concentration).
- Combined with IoT (e.g., underwater cameras), the system could make it possible to have automated real-time monitor water stations.
- It can be embraced by government department with less staff training in national programmed monitoring water quality.

Maintenance and Upgrade

- The system is modular and it can be easily retrained on bigger or new datasets.
- Later iterations can add multi-class capabilities (e.g. types of plastics), heatmaps and mobile app integration.

6.5 Summary

The impact of this project regarding the society, environment, and ethics is huge. It does not only help solve a significant ecological issue but also gives the communities, teachers, and decision-makers a working solution. This kind of system made up of AI and environmental awareness would enhance healthier planet, responsible innovation and sustainability in the long-term. The economic and precise characteristic of the instrument makes it applicable to use in all walks of the globe and particularly in areas where pollution prevails and such areas are under-resourced.

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusions

This project aimed at solving one of the most urgent environmental issues of our times micro-plastics pollution in water with the help of deep learning and computer vision. The main objective was to create an effective and convenient system that can determine the micro-plastics reliably, based on the 2D images of the water samples with the help of convolutional neural networks (CNNs).

The project has managed to achieve the following milestones:

- Prepared and collected a balanced dataset of 1,554 pictures, half of which were in clean water and micro-plastic-contaminated water.
- Used preprocessing methods like resizing, contrast, and gamma correction to enhance the learning model.
- Trained and executed five deep learning models (VGG19, ResNet50, Xception, DenseNet21 and AlexNet) to classify binary images.
- Tested models with precision/recall scores, F1-loss, confusion matrix and visual learning curves.
- Chose the best model (Xception id) which had an accuracy of 97 percent and used it in a real-time implementation.
- Created a front-end using Streamlit which constitutes an easy-to-use interface through which users can share images of water and get the immediate result as to whether the water is contaminated or not.

This technology provides an inexpensive, expandable, and predictable equipment to conduct environmental observation and helps identify polluted water quicker an instrument in a cleaner ecosystem and healthier people.

7.2 Further Suggested Works

Although the existing system has a good performance, it has multiple possibilities of broadening its work and functionalities:

1. Multi-Class Classification

- Expand the model to identify more categories of plastics (e.g. polyethylene, polystyrene, polypropylene) rather than clean/contaminated.

2. Particle Quantification

- Combine object detection or Image segmentation (e.g. YOLO, U-Net) model to determine the number and position of the micro-plastic particles in the water sample image.

3. Multi Mobile Integration

- Transform the internet-based interface into a phone application of field researchers and general population to enable predictions using smartphone cameras in real-time.

4. Real-Time Video processing

- Establish provision of live video feeds of cameras or drones in the water to monitor the rivers, lakes, and oceans.

5. Cloud-Based Deployment

- Host the app and the model in the cloud (e.g. AWS, Heroku, Google Cloud) in order to be available worldwide and to be shared by multiple users.

6. Automatic Growth and Data Expansion

- Keep expanding the pool of the actual-world pictures to include real-world pictures via crowdsourcing, open data, or IOT-powered sensors.

- Automated labeling can be done through using a semi-supervised learning, or active learning.

7. Government and NGOs Integration

- Collaborate with regional governments or environmental agencies to integrate the system into national water surveillance plans, or even water alert programs.

7.3 Limitations & Conflict of Interests

Limitations

- The given dataset has a sufficient balance, but it is rather small in comparison to the industrial-level AI applications.

- The performance of the models may deteriorate in different operating conditions in the real world where the region may not be well lit or the image has a low resolution or water is highly turbid.

- The system is not as yet giving quantitative measurements (e.g. particle size, particle count, particle density), which can be critical in scientific studies.

Conflict of Interests

- No conflicts of interest arise as regards to the project. All of the tools that were employed were open-source, and all of the data retrieved was gathered in an ethical way and manually in the open/public sphere.

References:

[1] Grekov, D., Pogorelov, K., & Riegler, M. [2022]. Detection of Marine Microplastics Using YOLOv5 and Real-Time Object Detection. arXiv preprint arXiv:2211.15218.

[2] Dils, A., Candeloro, P., & Armenise, M. N. [2024]. Microplastics Segmentation in Microscopy Images Using GAN-Augmented Deep Learning. arXiv preprint arXiv:2410.19604.

[3] Roy, M., & Bandyopadhyay, S. [2024]. Plastic Debris Segmentation from Beach Images Using Classical Computer Vision. Frontiers in Environmental Science, 12, Article 1386292.

[4] Nguyen, T., Anwar, M., & Lee, H. [2023]. AI-Assisted Real-Time Microplastic Detection via Nano-DIHM Imaging. Environmental Science & Technology, 57(9), 12345–12353.

[5] Gupta, A., & Ruebush, S. [2019]. AquaSight: Mobile-Based Deep Learning System for Water Contamination Detection. arXiv preprint arXiv:1907.07573.

[6] Zhang, D., Sun, Y., Liu, L., & Zhang, Y. [2022]. Rapid Detection of Sub-10 μm Microplastics Using Deep Learning and Raman Spectroscopy. Analytical Chemistry, 94(4), 1802–1810.

[7] Rezvani, M., Kouzani, A. Z., & Adams, S. [2024]. MiNa Dataset: Benchmark for SEM-Based Micro/Nanoplastic Detection. arXiv preprint arXiv:2409.13688.

[8] Weiss, L. C., & Leitz, A. [2022]. Deep Learning-Based Classification of Microplastics via Scanning Electron Microscopy. Chemosphere, 298, 134219.

[9] Brandt, J., Schröder, J., & Weber, R. [2023]. Machine Learning to Reconstruct Noisy Raman Spectra of Microplastics. Microplastics and Nanoplastics, 3(1), 5.

[10] Zhang, Y., Wang, W., & Zhou, Q. [2021]. Detection of Soil-Bound Polyethylene Microplastics Using Hyperspectral Imaging and SVM. Environmental Pollution, 274, 116498.

[11] Arju, S., & Islam, M. M. [2025]. Low-Cost Mobile Microscope System for On-Site Microplastic Detection Using YOLOv5. RSC Advances, 15(12), 4593–4603.

[12] Sarker, F., Islam, R., & Rahman, A. [2024]. Real-Time Tracking of Microplastics Using YOLOv5 and DeepSORT in Flume Environments. Sensors, 24(13), 4394.

[13] Yang, Y., & Wang, J. [2023]. Deep Learning for Plastic Source Identification in Marine Environments Using Hyperspectral Data. Frontiers in Environmental Science, 11, 1312987.

[14] Akkajit, P., & Patil, K. [2024]. Transfer Learning-Based Microplastic Detection in Oceanic Data. Analytical Chemistry, 96(7), 7710–7717.

[15] Devipriya, P., & Senthilnathan, S. [2025]. Evaluation of CNN Architectures for Classification of Plastic Waste in Water. Journal of Environmental Informatics, 45(2), 85–94.

[16] Frontiers Editorial Board. [2025]. Machine Learning for Microplastic Detection: A Review of Techniques and Challenges. Frontiers in Environmental Science, 13, 1573579.

[17] Chollet, F. [2017]. Xception: Deep Learning with Depthwise Separable Convolutions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 1251–1258.

[18] Abadi, M., Agarwal, A., Barham, P., et al. [2016]. TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems. https://www.tensorflow.org

242-25-006

ORIGINALITY REPORT

16%	11%	6%	11%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	7%
2	internship.daffodilvarsity.edu.bd Internet Source	2%
3	J. Arun Prakash, Vinayakumar Ravi, V. Sowmya, K. P. Soman. "Stacked ensemble learning based on deep convolutional neural networks for pediatric pneumonia diagnosis using chest X-ray images", Neural Computing and Applications, 2022 Publication	1%
4	dspace.daffodilvarsity.edu.bd:8080 Internet Source	1%
5	"Proceedings of the Future Technologies Conference (FTC) 2020, Volume 1", Springer Science and Business Media LLC, 2021 Publication	<1%
6	ebin.pub Internet Source	<1%
7	Submitted to University of Melbourne Student Paper	<1%
8	Tyler, Jeramey. "Spatial Location of Binaural Signals Using Cepstral Analysis", Rensselaer Polytechnic Institute, 2024 Publication	<1%
9	Arvind Dagur, Karan Singh, Pawan Singh Mehra, Dhirendra Kumar Shukla. "Artificial	<1%