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A Machine Learning Approach for River Pollution Assessment from Camera Images

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ABSTRACT

This study focuses on developing a machine learning system for camera-based river pollution assessment using image analysis and Convolutional Neural Network (CNN) architectures. The objective was to design a predictive model, evaluate different CNN architectures, and utilize camera-captured images to predict river pollution. By integrating colour analysis, reflection analysis, turbidity analysis, and object recognition with CNN-based image analysis, a comprehensive and automated method for evaluating river pollution was developed. The study also evaluated several CNN architectures, including MobileNet, CNN Sequential, and VGG16, to identify the most effective model for river health assessment. The results showed that the VGG16 architecture consistently achieved the highest accuracy, thanks to its deep layers and intricate structure that allowed for precise pattern recognition and analysis. The developed machine learning system, integrated with VGG16 and incorporating multiple image analysis techniques, provides a robust and accurate solution for predicting and assessing the pollution of rivers based on camera images. This comprehensive approach enables proactive measures and timely interventions to protect and improve overall river health.

Keywords-Machine learning, Convolutional Neural Network, river pollution assessment, image analysis, VGG16

1. Introduction

River pollution poses significant environmental and public health challenges in Malaysia, where several incidents have underscored the need for efficient monitoring systems. A notable example is the Sungai Kim Kim pollution case in 2019, where improper industrial waste disposal led to severe health impacts on thousands of residents. Conventional river monitoring methods, which primarily rely on manual sampling and visual inspection, are often time-consuming, subjective, and resource-intensive. These limitations highlight the necessity for intelligent, automated systems capable of continuous and objective river quality assessment.

Machine learning presents a promising approach to address these challenges through data-driven analysis and predictive modeling. It involves the study of algorithms and statistical models that enable computer systems to perform tasks without explicit programming. Within this context, machine learning can be applied to river pollution assessment using camera-based image data to detect and classify water quality conditions. The development of such systems encompasses three essential components: defining the task (e.g., pollution detection), leveraging experience through the analysis of extensive datasets comprising clean and polluted river images, and evaluating the performance of the model to ensure reliable prediction accuracy. By employing supervised learning techniques, machine learning can enhance the efficiency and accuracy of river pollution monitoring, thereby supporting sustainable environmental management and safeguarding public health.

2. Problem Statement

River pollution has become an increasingly critical environmental issue, threatening aquatic ecosystems and human health. In Malaysia and many other regions, pollution incidents often result from industrial waste discharge, agricultural runoff, and improper waste management. Conventional river monitoring approaches, which rely on manual sampling and laboratory analyses, are not only labor-intensive but also lack the promptness required for early detection and effective mitigation. These limitations underscore the need for an automated and data-driven monitoring system capable of providing timely and accurate pollution assessment.

This study aims to address these challenges by developing an automated river pollution detection system using deep learning techniques. Specifically, the research focuses on investigating the potential of image-based analysis to identify polluted river conditions from captured images. Through this approach, the system is designed to recognize visual indicators of pollution such as colour variations, surface debris, and turbidity levels that distinguish polluted from clean river environments.

To achieve this, the study proposes the development of a machine learning model based on Convolutional Neural Networks (CNNs). Several CNN architectures are explored and compared to determine the most effective model for classifying river pollution levels. The implementation of multiple CNN variants allows for the optimization of model performance in terms of accuracy, precision, and computational efficiency.

Furthermore, this research seeks to evaluate the performance of the developed models using suitable metrics and validation datasets. The findings are expected to contribute to the advancement of automated environmental monitoring systems and provide valuable insights for environmental authorities in improving river pollution management and sustainable water resource protection.

3. Literature Review

Machine learning is effective data analysis that identifies patterns in big datasets to forecast future data. Machine learning requires experience, data collecting, determination of the appropriate algorithms to categorise the dataset, and training and validation of the algorithms to improve the model's accuracy [1].

A polluted river is often caused by human activities, as water is highly susceptible to pollution due to its ability to dissolve a wide range of substances. Toxins from various sources such as farms, towns, and factories come into contact with water and quickly dissolve, resulting in polluted river. Additionally, sewage is frequently discharged into rivers, contributing to the pollution. Other causes of polluted river is include agricultural runoff, flooding, littering and oil spills [2].

Machine learning begins with the collection of information or data, such as examples, personal experience, or directions. The process involves identifying patterns within the data, which allows the computer to make predictions or conclusions based on the provided examples. The ultimate goal of machine learning is to enable computers to learn independently without human assistance and to adjust their actions accordingly [3] meanwhile deep learning is a type of machine learning that uses neural networks with multiple layers, known as hidden layers, to analyse and process data. The goal of these neural networks is to simulate the behaviour of the human brain, by allowing the model to learn from large amounts of data. The more layers a neural network has, the more accurate the predictions it can make. This is because additional hidden layers can help optimize and refine the model. While a neural network with a single layer can still make approximate predictions, deep learning neural networks with multiple layers are typically more accurate and efficient [4].

Supervised learning is the training data consists of inputs that are paired with their corresponding outputs. The algorithm examines the training data for patterns that match the desired outputs. Once the training is complete, the algorithm can then take in new inputs that it has not seen before and determine the appropriate label to assign to them based on the training data. The goal of a supervised learning model is to correctly predict the label for new input data [5].

Unsupervised learning is a technique of machine learning that utilizes algorithms to analyse and group unlabelled data without human supervision. It discovers underlying patterns in data sets without any prior knowledge of the expected outcome. This method is useful for various applications such as finding similar or dissimilar information, customer segmentation, image recognition, and identifying patterns in data for exploratory analysis. Unsupervised learning is also known as unsupervised machine learning [6].

Semi-supervised machine learning is a technique that combines elements of both supervised and unsupervised learning by using a limited amount of labelled data in combination with a significant amount of unlabelled data. This approach allows for the benefits of both types of learning to be utilized while avoiding the issue of obtaining a large amount of labelled data. This allows a model to learn to label data with relatively less amount of labelled training data [7].

Reinforcement learning is a branch of Machine Learning that focuses on the selection of appropriate actions to achieve the maximum reward in a specific scenario. This technique is used by software and machines to determine the most optimal behaviour or path to take in each situation. Unlike supervised learning, where the training data includes the correct answers, reinforcement learning does not have a set of answers. Instead, the agent must learn from its own experiences and make decisions on its own to accomplish a task. With no pre-existing training data, it relies on its experiences to learn and improve its performance [8].

The automatic monitoring of rivers is based on picture data taken by a commercially available digital video camera and processed using deep learning technology. The photographs of floating plastics in waterways serve as training examples for the algorithm. CNN has recently presented an algorithm for the classification of floating marine plastic trash. CNN categorised things as bottles, buckets, or straws, but required centred, cropped photos. This monitoring method is directly relevant to real-world data by recognising random plastic garbage from video camera photos of a broad river segment [9].

The paper describes a method for estimating the turbidity of water using convolutional neural networks (CNN). CNNs are a type of deep learning algorithm that can be employed to extract image features. CNN has been trained to extract features from images of water that correspond to turbidity levels in this particular instance. As one of its features, CNN isolates the pixel intensity, or the luminosity or darkness of each image pixel. According to the research, greater pixel intensity values indicate greater turbidity levels [10].

The research demonstrated the effectiveness of using deep learning techniques to identify and recognise occurrences of algal blooms in Chaohu Lake. This strategy yielded valuable information for managing and mitigating the effects of algal outbreaks. Reflection analysis plays an important role in the identification of algal outbreaks via remote sensing. It involves analysing how the water's surface reflects light, allowing for the detection of changes resulting from the presence of algal blooms. By measuring the absorption and scattering of light across various wavelengths, the concentration of chlorophyll-a, a pigment found in phytoplankton and a key indicator of algal blooms, can be estimated [11].

This paper research about effectiveness of deep learning for river segmentation. U-Net is one of the most popular deep learning architectures for segmenting rivers. U-Net is a fully convolutional network that was initially designed for the segmentation of biomedical images. It includes an encoder and a decoder. The encoder extracts features from the input image, while the decoder reconstructs the image using those features. It has been demonstrated that the U-Net architecture is effective for river segmentation because it can learn both local and global river features [12].

Convolutional Neural Network (CNN) have demonstrated exceptional results in object detection and image classification. To handle the vast array of objects commonly found in different scenarios, recognition systems make use of machine learning techniques based on pre-trained models. One example of a deep fully convolutional neural network design for semantic pixel-wise segmentation is Segnet. Its applications in scene understanding can take advantage of its segmentation engine, which utilizes an encoding-decoding approach [13].

A method is proposed for detecting oil on water surfaces using only thermal infrared images with the help of a Convolutional Neural Network (CNN). A dual setup is employed to create a large dataset, consisting of both visible spectrum images captured by a RGB camera and thermal infrared spectrum images (7 μm–14 μm) captured by an infrared camera. The RGB images are then labelled using thresholding algorithms and serve as a reference for the CNN, along with the infrared images. Once trained, this network can be used for cost-effective and frequent inspections. This approach combines advanced CNN segmentation techniques and the use of thermal infrared imaging to improve the accuracy of detecting oil spills. In a test setup, the method was able to detect oil with an accuracy of 89% and can also detect oil during night-time [14].

The researcher investigates the image of water's colour to develop a method for the rapid and straightforward identification of water quality. Based on the collection of many types of water samples, image colour features were extracted, the SVM classifier was used to categorise the samples, and a strategy for the rapid assessment of water quality based on water colour was established [15].

The water we encounter on a daily basis contains dissolved minerals and suspended particulate. However, when we fill a container with water from the faucet, it appears colourless to us. On the other hand, unadulterated water is not truly colourless; it possesses a slight blue colour, which is most apparent when observing a large volume of water. The blue colour of water originates from the absorption of red wavelengths in the visible light spectrum by water molecules, unlike the blueness of the sky, which results from light scattering. This absorption occurs because of the vibrational properties of water molecules, which allow them to selectively absorb specific light wavelengths. In essence, the presence of minerals and the behaviour of water molecules contribute to water's minor blue hue, even in its purest form [16].

The study investigates the performance of popular CNN architectures, including AlexNet, VGGNet, and MobileNet, for image recognition on mobile and embedded devices. Comparisons show that while AlexNet and VGGNet achieved high accuracy, MobileNet emerged as a promising choice due to its efficiency, striking a balance between accuracy and resource consumption. These findings provide insights into selecting the appropriate CNN architecture based on performance needs and resource constraints in image recognition tasks on mobile and embedded devices [17].

The use of Python in machine learning and AI projects is preferred by developers due to its ease of use, consistency, and a wide range of available libraries and frameworks for AI and machine learning. The flexibility, platform independence and large community also contribute to the language's overall popularity and the developers' productivity and confidence in the software they create [18].

TensorFlow is a system for experimenting with new machine learning models, training them on large datasets, and deploying them in production. It is based on the experience of a previous system and is designed to make it easier for researchers to explore a wide range of ideas. TensorFlow can handle both large-scale training and inference, using hundreds of powerful servers for fast training and running trained models on various platforms, from large distributed clusters to mobile devices. It is also flexible and general enough to support experimentation and research into new models and optimization [19].

Keras is a deep learning API developed by Google that is written in Python. It is designed to make it easy to implement neural networks, by providing a high-level, user-friendly interface. Additionally, it supports multiple backends for computation, which allows for flexibility in terms of the resources used for computation [20].

OpenCV is an open-source library that provides a comprehensive set of tools for computer vision and machine learning. It is designed to be used in commercial products, with an Apache 2 license that allows for easy modification and use of the code. The library includes over 2500 optimized algorithms for tasks such as face detection and recognition, object identification, tracking camera movements, and creating 3D models. It also includes advanced features like image stitching, image database search, and augmented reality marker recognition [21].

4. Methodology

Machine learning based on river pollution assessment by camera images need large dataset of clean and polluted river to train and test the machine. In this preliminary research, since the water color might be mistakenly attributed to the river's natural soil or substrate, the focus will be on selected images from the existing database that have been previously studied, while omitting others. The quality and quantity of dataset needed to improve the machine learning performance and accuracy to make river pollution assessment. This River dataset can be found at Kaggle and Shutterstock website which contain a lot of river image with different condition, different lighting and different weather that can help to identify the river image in different view.

After collecting the dataset, the river image will be separate into two label class that is clean and polluted river. This will make model know there are 2 categories that it must learn the characteristics of all the image in the class and look for the similarity to predict the outcome of the image based on that class. This method called data pre-processing and data annotation in supervised learning.

After classifying the dataset, the data will be analysed using colour analysis to differentiate between clean and polluted rivers. The machine learning algorithm will learn the colour of clean water and polluted colour by identifying the colour model based on the dataset. This information will be used to make predictions about the colour of water in new images.

The model will utilize image processing techniques to examine the colour attributes of both clean and polluted rivers within the dataset. It will specifically focus on identifying distinct colours associated with pollution, such as those found in oil, industrial waste, and algae blooms. This analysis aims to enable the detection of these characteristic colours in new images. In addition to colour analysis, the machine will also use image processing techniques such as reflection analysis, turbidity analysis, and object recognition to analyse the images of the rivers. Moreover, convolutional neural networks (CNNs) will be employed for image recognition, allowing the identification and classification of contaminants present in the river. These techniques will help the algorithm to identify specific objects or patterns in the images that are indicative of clean and polluted river.

Model testing is a crucial step in the machine learning process as it allows developers to determine the accuracy of the model have created. By using test data, we can evaluate the model's ability to make predictions. If the model has a high level of accuracy, such as 90% or higher, it is a reliable model that can be used for real application to determine the river pollution.

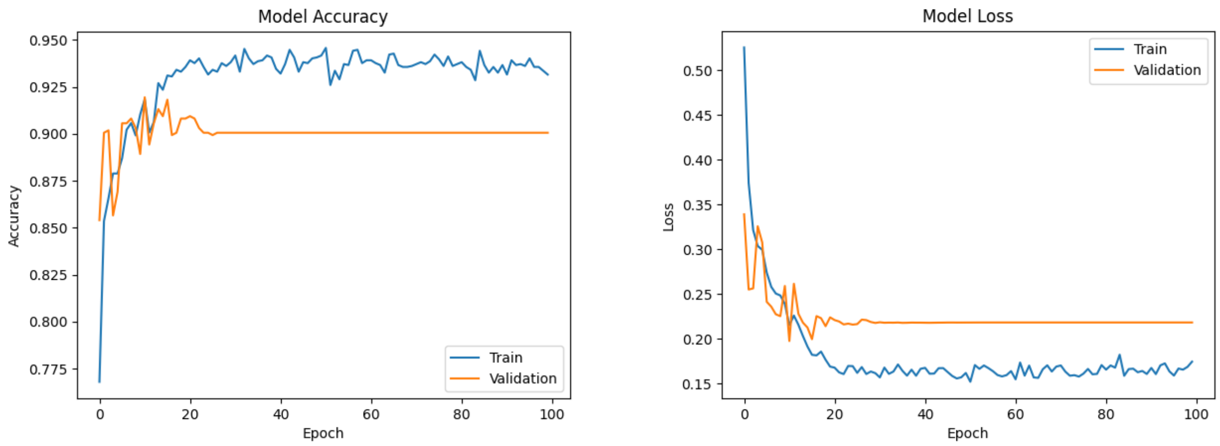
The trained model can be used to make predictions using camera images. However, if the model does not perform well, it may be necessary to readjust the model's hyperparameters or try different algorithms or adding more images to dataset of river image to improve its accuracy. This process is known as model optimization and it is an iterative process that involves testing, analysing, and readjusting the model until it reaches an acceptable level of accuracy.

5. Results

This section presents the findings of the training experiments conducted using different CNN architectures for river pollution detection. The results offer insights into the performance and efficacy of each model in distinguishing between polluted and unpolluted river environments. These experiments provide valuable information regarding the suitability of various CNN designs for the automation of pollution detection in river systems, contributing to the advancement of this research field.

5.1 MobileNet Training and Validation Result

Figure 1 and Table 1 display the training results for the machine learning model used in river pollution assessment, employing the MobileNet architecture. From Figure 1, it is evident that the model exhibits higher accuracy on the training set compared to the validation set, indicating potential overfitting. Additionally, the consistently lower training loss compared to the validation loss further supports this observation. These findings suggest that while the model performs well on the training data, it struggles to generalize and make accurate predictions on unseen data, which is a crucial requirement for robust river pollution assessment models.



(a) Accuracy (b) Model Loss

Figure 1. MobileNet Performance

Table 1 provides a closer look at the model's performance at different epochs. At the 1st epoch, the model achieved an accuracy of 0.7680 and a loss of 0.5256 on the training set, with a validation accuracy of 0.8541 and a validation loss of 0.3391. As the training progressed to the 100th epoch, significant improvements were observed. The model attained an accuracy of 0.9316 and a loss of 0.1744, accompanied by a validation accuracy of 0.9006 and a validation loss of 0.2182.

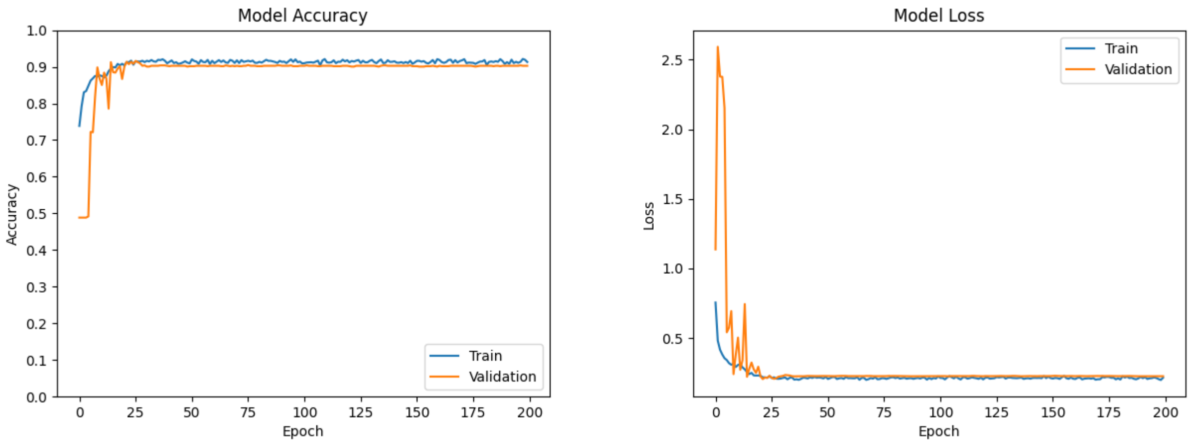
Table 1. MobileNet Accuracy and Loss Table

Epoch	Accuracy	Loss	Val Accuracy	Val Loss
1	0.7680	0.5256	0.8541	0.3391
100	0.9316	0.1744	0.9006	0.2182

Despite these improvements over epochs, the persisting gap between training accuracy and validation accuracy, as well as the consistently lower training loss, indicate ongoing overfitting issues. These limitations suggest that the MobileNet CNN architecture, as implemented in this study, is not suitable for developing a robust machine learning model for river pollution assessment.

5.2 Sequential CNN Training and Validation Result

Figure 2 illustrates the Sequential CNN plot for the river pollution assessment model. From the graph, it is evident that the model exhibits a small gap between training and validation loss, indicating a good fit for the data. The model demonstrates high accuracy in both the training and validation sets, suggesting its effectiveness in predicting river pollution levels. This performance implies that the model is capable of accurately assessing river pollution based on the given features. Hence, the model is well-suited for machine learning-based on river pollution assessment.



(a) Accuracy (b) Model Loss

Figure 2. Sequential CNN Performance

In Table 2, the Sequential Model Accuracy and Loss is presented. The model's accuracy and loss were evaluated at the first epoch, where it achieved an accuracy of 0.7386 with a loss of 0.7550. The validation accuracy and loss were 0.4885 and 1.1367, respectively. As the training progressed to the 200th epoch, the model exhibited significant improvement. It achieved an accuracy of 0.9130 with a loss of 0.2152, while the validation accuracy and loss were 0.9027 and 0.2254, respectively. These results demonstrate the model's ability to learn and improve over time, further reinforcing its effectiveness for river pollution assessment tasks.

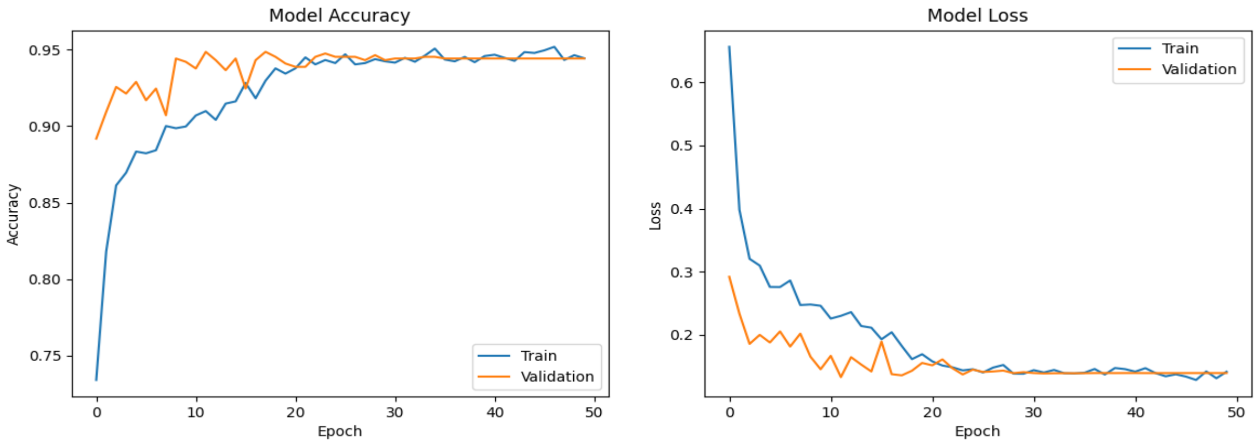
Table 2. Sequential CNN Model Accuracy and Loss Table

Epoch	Accuracy	Loss	Val Accuracy	Val Loss
1	0.7386	0.7550	0.4885	1.1367
200	0.9130	0.2152	0.9027	0.2254

Based on the Sequential CNN plot in Figure 2, the model displays a small gap between training and validation loss, indicating a good fit for the river pollution assessment. Moreover, the model exhibits high accuracy on both the training and validation sets, suggesting its capability to predict river pollution levels accurately. These findings, along with the accuracy and loss values presented in Table 2, demonstrate the model's efficacy and suitability for machine learning-based on river pollution assessment tasks.

5.3 VGG16 Training and Validation Result

Figure 3 presents the VGG16 Accuracy and Loss plot for the river pollution assessment model. After 50 epochs of training, the model consistently achieves higher accuracy in both the training and validation sets, similar to the decrease in model loss over time. This indicates that the model is well-fitted to the data and demonstrates suitability for making accurate predictions in the field of machine learning-based on river pollution assessment.



(a) Accuracy (b) Model Loss

Figure 3. VGG16 Model Performances

In Table 3, the accuracy and loss values are reported for the 1st epoch and the 50th epoch. At the 1st epoch, the model achieves an accuracy of 0.7339 with a loss of 0.6564. Additionally, the validation accuracy and loss are recorded as 0.8918 and 0.2919, respectively. As the training progresses to the 50th epoch, significant improvements are observed, with the model attaining an accuracy of 0.9444 and a loss of 0.1414. Notably, the validation accuracy reaches a remarkably high value of 0.9943, with a corresponding validation loss of 0.1393.

Table 3. VGG16 Accuracy and Loss Table

Epoch	Accuracy	Loss	Val Accuracy	Val Loss
1	0.7339	0.6564	0.8918	0.2919
50	0.9444	0.1414	0.9443	0.1393

These results underscore the model's capability to consistently improve accuracy and reduce loss throughout the training process. The substantial increase in accuracy, accompanied by the minimized loss, further validates the model's efficacy for river pollution assessment.

The VGG16 Accuracy and Loss plot in Figure 3 demonstrates the model's ability to achieve higher accuracy in both the training and validation sets, while decreasing the loss over the course of training. The accuracy and loss values presented in Table 3 provide additional evidence of the model's effectiveness, with notable improvements observed over time. As a result, the model exhibits strong potential for accurate predictions in the domain of machine learning-based on river pollution assessment.

5.3 Confusion Matrix

The confusion matrix for MobileNet [414, 54; 36, 411] reveals the model's classification performance in distinguishing clean and polluted rivers as shown in Figure 4. It correctly classified 414 clean river instances and 411 polluted river instances. However, it misclassified 54 clean river samples as polluted and 36 polluted river samples as clean.

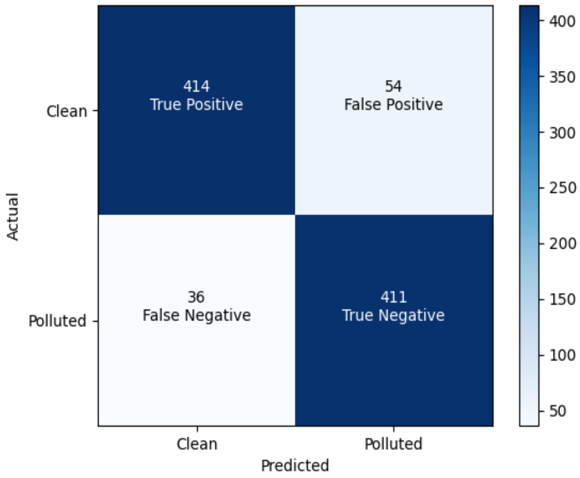


Figure 4. MobileNet Confusion Matrix

Menawhile. the Sequential CNN model's performance in classifying clean and polluted rivers can be inferred from the confusion matrix [429, 39; 50, 397] as shown in Figure 5. It successfully classified 429 instances of clean rivers and 397 instances of polluted rivers. However, it misclassified 39 clean river samples as polluted and 50 polluted river samples as clean.

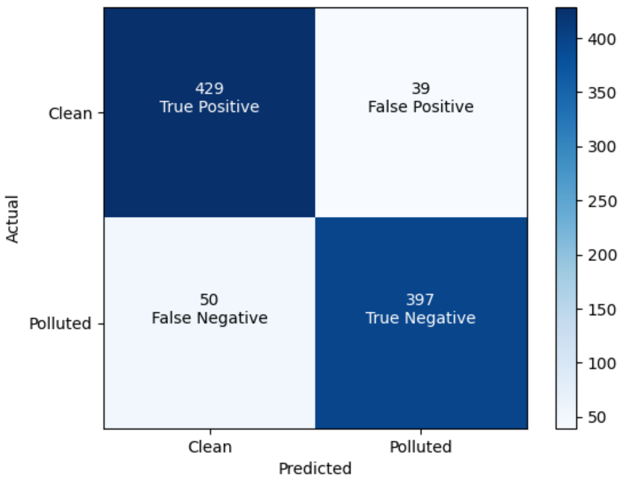


Figure 5. Sequential CNN Confusion Matrix

The Sequential CNN model's performance in classifying clean and polluted rivers can be inferred from the confusion matrix [429, 39; 50, 397]. It successfully classified 429 instances of clean rivers and 397 instances of polluted rivers. However, it misclassified 39 clean river samples as polluted and 50 polluted river samples as clean.

The VGG16 CNN model's classification accuracy in distinguishing between clean and polluted rivers is evident from the provided confusion matrix [436, 32; 19, 428] as shown in Figure 6. It accurately identified 436 instances of clean rivers and 428 instances of polluted rivers. However, there were instances where 32 clean river samples were incorrectly classified as polluted, and 19 polluted river samples were misclassified clean.

Based on the result above, the model that been selected to make river pollution assessment is VGG16 because it give higher accuracy and give low loss compare to the sequential model. MobileNet not suitable to make river pollution assessment because there are gap between model accuracy and loss where indicate the model is overfitting.

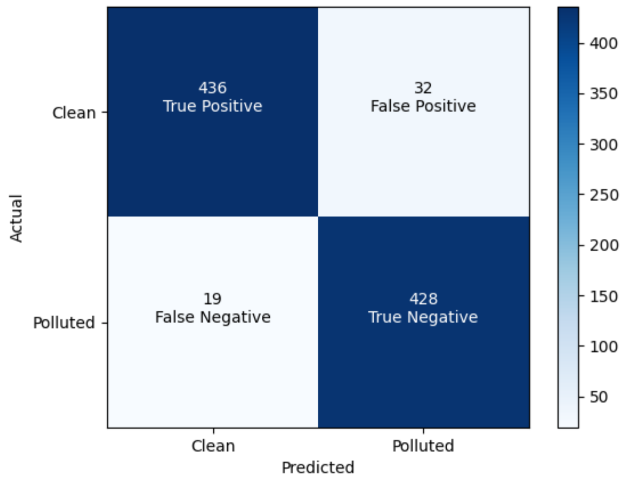


Figure 6. VGG16 Confusion Matrix

5.3 Model Testing

Water colour analysis played a critical role in the pollution assessment process by utilizing machine learning techniques, specifically deep learning. The model examined the features of water colour to identify the presence of pollutants or unusual chemicals. Fluctuations in water colour served as indicators of various pollution issues, including excessive algal bloom, sedimentation, and the presence of toxins. By employing colour analysis, the model could detect and monitor changes in water quality, providing a deeper understanding of pollution levels in the assessed rivers.

Additionally, the model employed deep learning for the evaluation of reflection patterns on the water's surface, enabling the inference of floating trash, oil spills, and other undesirable elements contributing to river pollution. Reflection analysis played a crucial role in identifying physical impurities that posed threats to the river's health and overall pollution levels.

Turbidity measurements, integrated into the pollution assessment process, provided insights into water transparency and purity. Machine learning algorithms assessed high turbidity values, indicative of organic debris, detritus, or suspended particles in the water that could contribute to pollution. Evaluating turbidity levels enabled the model to evaluate overall pollution levels in rivers, identifying anomalies that could potentially harm the river's health and ecological balance. The testing models are shown in the following:

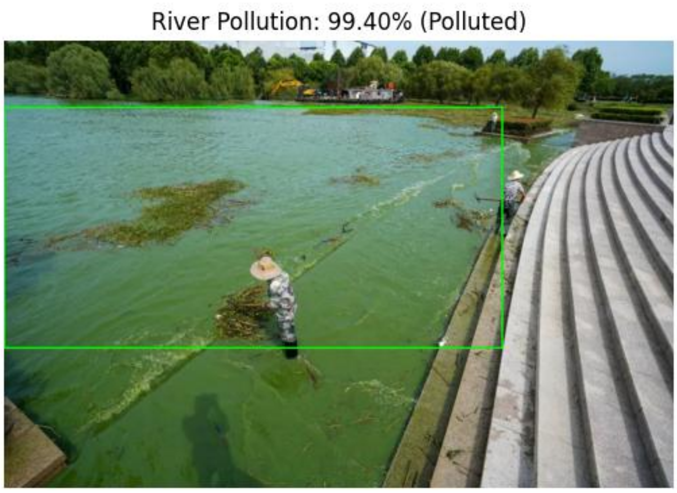


Figure 7. River Pollution in Algal Bloom River

Figure 8. River Pollution in Oil Spill In The River

Figure 9. River Pollution in Murky River

Figure 10. River Pollution with Contaminant

Figure 11. River Pollution Detection in Clean River

The VGG16 architecture, renowned for its efficient feature depiction capabilities, served as the backbone of the deep learning model. The model was trained using annotated river photographs, enabling the identification and categorization of pollution indicators. By combining colour analysis, reflection analysis, turbidity analysis, and object recognition using deep learning techniques, a comprehensive and automated method for river pollution assessment was realized.

This machine learning approach, leveraging deep learning techniques, facilitated a thorough assessment of river pollution, enabling early detection of potential issues and timely intervention measures. By combining various pollution indicators, the developed model offered an accurate and effective method for monitoring and evaluating river pollution. This approach holds significant promise in addressing pollution control and management challenges, ensuring the sustainability of our valuable water resources, and supporting ongoing environmental conservation efforts.

6. Conclusion

This study aimed to design and develop a river pollution assessment system using machine learning techniques based on camera images. The main objectives encompassed investigating the determination of polluted rivers from captured images, developing a machine learning model using deep learning with various CNN architectures, and evaluating the performance of these models.

By combining colour analysis, reflection analysis, turbidity analysis, and object recognition with CNN-based image analysis, a comprehensive and automated method for determining the pollution of a river had been developed. The incorporation of these multiple factors enabled a more precise and comprehensive evaluation of the river's condition, allowing for early detection and prompt intervention to preserve and improve its health.

A machine learning model was successfully developed utilizing deep learning techniques and incorporating diverse CNN architectures. Leveraging the power of deep learning, the model was trained to recognize and categorize specific features and patterns associated with river pollution. This development empowers the system to conduct efficient and accurate assessments of pollution levels, facilitating effective environmental management practices.

Thorough performance evaluation of various CNN models, including MobileNet, VGG16, and Sequential models, was conducted. Rigorous experimentation and analysis allowed for the assessment of accuracy, efficiency, and suitability of these architectures for river pollution assessment. The outcomes of this evaluation process provided valuable insights into selecting the most effective CNN architecture for precise and reliable river pollution assessment, thereby guiding future research and practical implementations.

All the objectives set in this study have been successfully achieved. The design and development of a river pollution assessment system utilizing machine learning techniques based on camera images have been realized. Through the investigation of polluted rivers, the development of a deep learning-based model employing various CNN architectures, and a comprehensive evaluation of model performance, a robust framework for accurate and efficient river pollution assessment has been established. The findings contribute to the advancement of environmental monitoring and management practices, demonstrating the potential of machine learning in addressing the complex challenges of river pollution. All-encompassing strategy enables proactive measures and timely interventions to protect and improve the overall health of rivers.

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