Oil Spill Detection Using Deep Learning Techniques

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***Abstract*—Oil spills are one of the most dangerous environmental threats to marine ecosystems and coastal regions. The increasing volume of oil transported by ships amplifies the risk of spills due to accidents, leaks, or other operational failures. Rapid detection of these spills is crucial to minimizing their environmental impact and enabling timely cleanup. This research presents the automated detection of oil spills in ocean waters, utilizing deep learning techniques. Specifically, the study applies both the Inception V3 model and ResNet algorithm to analyze aerial and satellite images of the sea surface. A carefully curated dataset, containing both oil spill and non-oil spill images, is preprocessed and augmented to ensure robust model performance under various environmental conditions, such as changes in weather, lighting, and sea surface features. The primary goal of this study is to develop an efficient and accurate system for early oil spill detection, which can assist maritime agencies and environmental organizations in monitoring large oceanic areas. This system aims to improve response times, enabling faster intervention and reducing the overall environmental impact of oil spills.**

***Index Terms*—Oil spill Detection, Deep Learning, Inception v3, Satellite Imagery, Machine Learning, Image classification, Environmental monitoring, Marine pollution**

I. INTRODUCTION

Oil pollution in marine environments presents a persistent and serious ecological threat. Accidental discharges from oil tankers, offshore drilling operations, or ruptured pipelines result in long-lasting damage to aquatic ecosystems, threatening marine biodiversity and affecting coastal communities economically. As global demand for petroleum continues to grow, the frequency and scale of oil transportation increase, raising the likelihood of future spills.

Traditional methods for monitoring oil contamination, including manual observation, ship-based patrols, and radar analysis, often suffer from limitations such as high operational costs, limited spatial coverage, and delayed response times. Human-based interpretation of large-scale image data remains inefficient and susceptible to errors, especially under poor weather conditions or low visibility. Manual analysis of sea surface imagery is both time-consuming and prone to inaccuracies, highlighting the need for a faster and more reliable detection approach.

Deep learning techniques, particularly convolutional neural networks (CNNs), have emerged as powerful tools in the field of image recognition. Their ability to automatically extract and learn complex visual features makes them ideal for identifying anomalies in ocean surface imagery, such as oil slicks. Employing such models enhances the precision and speed of identifying oil-contaminated regions compared to traditional image processing techniques.

In this research, a deep learning-based framework is adopted to distinguish between clean ocean surfaces and oil-affected areas using two powerful CNN architectures: Inception V3 and ResNet-50. Inception V3 is a well-established deep learning model known for its efficient use of computational resources and high classification accuracy. Its unique architecture, which combines multiple convolutional filter sizes within each module, enables the model to capture intricate patterns across different spatial scales. Complementing this, ResNet-50, a deep residual learning network, is utilized for its ability to effectively train deeper models by addressing the vanishing gradient problem through residual connections. This allows the network to maintain high performance and accuracy even with increased depth, making it suitable for capturing complex patterns in marine images.

Training is conducted on a curated dataset containing diverse marine scenes, accounting for varying weather conditions, light levels, and ocean textures to ensure robust performance. High-resolution images collected from aerial and satellite platforms serve as the input source for both models, offering the potential to monitor vast maritime zones efficiently. Through automation, surveillance coverage is significantly expanded while minimizing dependence on manual intervention. This enables quicker identification of hazardous oil discharges, supporting timely environmental management responses.

Designed for scalability and real-world applicability, the proposed approach can be deployed across different marine regions and integrated with modern surveillance infrastructure such as drone fleets or satellite networks. By combining the strengths of both Inception V3 and ResNet-50, the system achieves enhanced accuracy, resilience, and adaptability in detecting oil spills under diverse environmental conditions. Beyond detection, future enhancements may include predictive modeling to track the potential spread of oil contamination, aiding in emergency planning and mitigation strategies.

Efficient and accurate detection of oil pollution plays a vital role in environmental conservation. By leveraging advanced machine learning techniques, early warnings can be generated to reduce ecological damage and assist response teams in deploying resources where they are needed most. Such innovation promotes sustainable marine management and contributes meaningfully to reducing the global impact of oil-related disasters.

II. METHOD

2.1. Database description

The dataset employed in this research consists of a comprehensive collection of sea surface images, acquired through satellite sensors and unmanned aerial vehicles (UAVs). These images represent a wide range of marine conditions, encompassing both oil-contaminated and uncontaminated waters. Captured under diverse environmental settings—including varying light, weather, and sea states—the dataset exhibits considerable variation in image resolution, dimensions, and color characteristics.

All images are systematically annotated into two distinct categories: oil spill and non-oil spill. The classification is based on the visual presence or absence of oil traces on the water surface, enabling the application of supervised learning algorithms. Special attention has been given to the accuracy of labeling to ensure high-quality ground truth for model development.

To mitigate the risk of training bias, the dataset is constructed with an equal number of samples from both categories. This class balance is essential for improving the model's ability to generalize and preventing skewed predictions. The dataset also integrates images from a variety of geographic locations and sea environments, contributing to its diversity and real-world relevance.

Key Features of the Database are:

1) Acquisition Sources: Satellite imagery and drone-based aerial photography.
2) Label Categories: Binary classification – Oil Spill and Non-Oil Spill.
3) Balanced Distribution: Equal number of images in each class to ensure fair training.
4) Environmental Variation: Captures different sea conditions, lighting, and weather scenarios.
5) Geographical Diversity: Includes data from multiple marine regions.
6) Image Characteristics: Diverse in size, resolution, and color profiles.
7) Research Utility: Suitable for training, validating, and evaluating deep learning models for environmental and marine pollution detection tasks.

Overall, this dataset serves as a valuable asset for developing robust and scalable models aimed at detecting oil spills in maritime settings. Its diversity and balanced structure make it particularly effective for research focused on environmental surveillance and automated pollution monitoring systems.

2.2. Data Preprocessing and Augmentation

Following the compilation and labeling of the dataset, a comprehensive data preparation process was carried out to enhance the quality and usability of the images for deep learning applications. Due to the diverse sources of the data—ranging from satellite sensors to aerial drones—the raw images varied significantly in terms of resolution, aspect ratio, illumination, and noise levels. Such inconsistencies can negatively impact the learning ability of convolutional neural networks (CNNs), necessitating a structured preprocessing pipeline.

To begin with, all images were uniformly resized to match the input requirements of both the Inception V3 and ResNet-50 models. While Inception V3 requires an input size of 299×299 pixels, ResNet-50 typically expects 224×224 pixels. To accommodate both architectures, datasets were prepared in parallel or dynamically resized depending on the model used during training. This resizing ensures consistency in data shape and helps avoid computational issues during model training and evaluation.

Next, pixel normalization was applied, scaling the image intensity values to a standard range between 0 and 1. This normalization is critical for accelerating the convergence of the optimization algorithm and achieving more stable training behavior in both Inception V3 and ResNet-50. These models benefit from normalized data, as it ensures uniform input distribution and reduces the impact of outlier pixel values.

In addition to resizing and normalization, image denoising techniques were implemented to remove unwanted visual noise and distortions that could obscure relevant features. Filters such as Gaussian smoothing were utilized to enhance image clarity while preserving important structural details. Clean and noise-reduced images are particularly important for models like ResNet-50, which rely on deep hierarchies of feature extraction where low-level distortions could propagate through the network and affect higher-level representations.

Once the images were preprocessed, data augmentation was applied to artificially expand the dataset and improve model generalization. Augmentation techniques included random rotations, horizontal and vertical flipping, zooming, brightness and contrast adjustments, and minor translations. These transformations simulate real-world variations in sea conditions, camera angles, and lighting, which a model is likely to encounter during deployment. By introducing such variability, both Inception V3 and ResNet-50 learn to become invariant to positional and environmental changes, making them more robust and reliable in diverse maritime monitoring scenarios. Moreover, data augmentation helps mitigate the limitations of relatively small datasets, particularly in cases where acquiring labeled oil spill images is challenging and expensive. Augmentation also reduces overfitting by exposing the model to a broader range of data instances, even when the core dataset remains limited in size. This is especially beneficial for deep networks like ResNet-50, where overfitting can become a significant concern due to the model's depth and complexity.

Throughout the preprocessing and augmentation process, care was taken to preserve the class balance between oil spill and non-oil spill images. This balance is essential for unbiased training and ensures that the models do not become skewed toward the majority class. Maintaining equal representation also supports fair evaluation and improves the interpretability of performance metrics.

The data preparation phase was crucial in transforming raw image data into a clean, balanced, and diverse dataset suitable for deep learning. These steps significantly contributed to enhancing the ability of both Inception V3 and ResNet-50 to detect oil spills with high accuracy across a variety of environmental and operational scenarios.

2.3. Model Building

In developing an effective oil spill detection system, the model-building phase plays a central role in transforming preprocessed image data into actionable predictions. This research employs two state-of-the-art convolutional neural network (CNN) architectures—Inception V3 and ResNet-50—both recognized for their superior performance in image classification and object recognition tasks. The decision to use both models stems from their complementary capabilities: Inception V3 is optimized for capturing multi-scale spatial features, while ResNet-50 is known for its ability to train very deep networks through the use of residual connections.

The implementation began by initializing the pre-trained versions of both Inception V3 and ResNet-50, each originally trained on the ImageNet dataset. Transfer learning was applied to adapt these models to the specific task of oil spill detection. By retaining the learned convolutional base and replacing the top classification layers, the models were fine-tuned on the custom dataset. This approach significantly reduced training time and improved performance, particularly given the limited availability of labeled oil spill imagery.

For both models, the architecture was modified to accommodate binary classification. The top layers were removed and replaced with a global average pooling layer followed by fully connected layers. A dropout layer was incorporated to mitigate overfitting by randomly disabling a fraction of neurons during training. The final output layer consisted of a single neuron with a sigmoid activation function, yielding a probability score between 0 and 1, where a higher value indicates a greater likelihood of oil contamination.

During model compilation, the binary cross-entropy loss function was selected due to its suitability for two-class problems. The Adam optimizer was employed for its adaptive learning rate capabilities, ensuring faster convergence and better handling of sparse gradients. To further enhance generalization, early stopping and learning rate reduction on plateau were implemented as callbacks during training. These techniques monitor validation performance and dynamically adjust the learning process to prevent overfitting and stagnation.

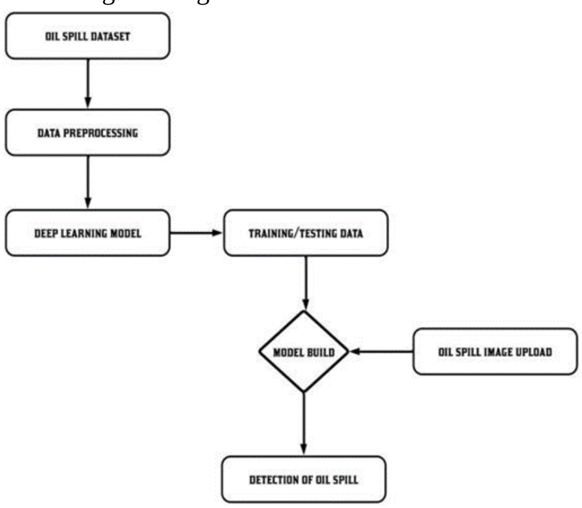


Fig 1: System Architecture

To support a fair comparison, both models were trained on the same preprocessed and augmented dataset, ensuring uniform input conditions. Batch size, learning rate, and number of epochs were carefully tuned through iterative experimentation. Performance metrics such as accuracy, precision, recall, and F1-score were used to evaluate and compare the effectiveness of both models in detecting oil spills across diverse sea conditions.

In summary, the model building process involved leveraging transfer learning, architectural customization, and rigorous training strategies to adapt Inception V3 and ResNet-50 for the task of oil spill detection. Their combined use not only improves the reliability of classification outcomes but also ensures robustness against real-world challenges such as varying image quality, lighting conditions, and ocean textures. These models form the backbone of the proposed automated detection system, which aims to provide timely and accurate environmental monitoring over large maritime areas.

Inception v3 Architecture:

The Inception network introduced a significant shift in convolutional neural network (CNN) design by addressing the limitations of earlier deep learning models that relied heavily on increasing depth to improve accuracy. While models like VGGNet demonstrated high performance, they often required vast computational resources and suffered from overfitting and vanishing gradient problems as their depth increased. The Inception architecture, in contrast, was developed to offer a balance between computational efficiency and model accuracy.

One of the defining features of the Inception network is the incorporation of 1x1 convolutions, which serve to reduce the dimensionality of input feature maps before applying larger filters such as 3x3 and 5x5. This not only minimizes computational cost but also preserves important spatial information. For instance, using a 1x1 convolution prior to a 5x5 operation significantly cuts down the number of operations required, optimizing both memory usage and processing speed without compromising the quality of feature extraction.

The first widely recognized implementation of this architecture, GoogLeNet (Inception v1), is composed of multiple Inception modules, each containing parallel paths with different filter sizes. These modules enable the network to capture features at various scales, enhancing its ability to recognize complex and varied patterns, such as the irregular shapes and textures of oil spills in marine images.

Another innovation in the Inception design is the replacement of fully connected layers with global average pooling, which averages the spatial dimensions of feature maps instead of flattening them. This reduces the number of trainable parameters and helps prevent overfitting, while also maintaining predictive accuracy. The model becomes lighter and more adaptable for real-time applications, especially when working with large image datasets.

To improve training stability, auxiliary classifiers are sometimes included at intermediate layers to help gradients flow more effectively through the deep architecture. Although the original Inception versions didn’t utilize residual connections, later versions such as Inception-ResNet incorporated them, enabling even deeper training while mitigating vanishing gradient issues.

The architecture's design is especially beneficial for remote sensing applications. In the context of oil spill detection, the multi-branch convolutional layers allow the model to analyze varying sizes of oil slicks under diverse lighting and weather conditions. This ensures reliable detection across different environmental scenarios. Additionally, the efficiency of the network makes it suitable for deployment on platforms like drones and satellites, where computational resources may be limited.

In conclusion, the Inception network's focus on efficiency, multi-scale feature extraction, and model regularization has made it a strong candidate for high-performance visual recognition tasks. Its ability to accurately detect complex patterns, combined with lower computational requirements, makes it highly effective for applications such as real-time oil spill monitoring and environmental surveillance.

ResNet Algorithm:

ResNet-50, a deep convolutional neural network comprising 50 layers, is widely recognized for its capability to handle complex image classification tasks, making it a strong candidate for oil spill detection. The architecture consists of an initial convolution and max-pooling layer, followed by four stages of residual blocks—each containing a series of convolutional layers organized into bottleneck structures. These bottleneck blocks use a 1x1 convolution to reduce dimensionality, a 3x3 convolution to process spatial features, and another 1x1 convolution to restore the original dimensions. The identity shortcut connections in these blocks allow feature maps to bypass layers, which facilitates efficient gradient flow and preserves important feature information across layers. This design helps the network learn both low-level details and high-level representations critical for identifying oil spills in remote sensing images.

The 50-layer deep architecture of ResNet-50 enables it to learn intricate and hierarchical features necessary for distinguishing oil spills from other marine patterns such as algae, ship wakes, or sunlight reflections. Its early layers focus on extracting basic textures and edges, while deeper layers interpret complex patterns, including the shape, spread, and contrast of oil slicks. The network incorporates batch normalization and ReLU activations throughout its layers, which stabilize training and improve learning efficiency. A global average pooling layer near the end of the network aggregates features before passing them to a fully connected layer, which performs the final classification—predicting whether an image contains an oil spill or not.

When applied to oil spill detection tasks, ResNet-50 can be fine-tuned using transfer learning, where a pre-trained model is adapted to a specific dataset of satellite or aerial images. This approach is particularly useful for dealing with limited labeled data, allowing the model to generalize well across diverse maritime conditions. Thanks to its deep and structured layer design, ResNet-50 delivers high accuracy, precision, and recall, making it effective in minimizing both false positives and false negatives. Its ability to capture detailed spatial features, combined with its stable and efficient training process, makes ResNet-50 a reliable and scalable architecture for environmental monitoring and oil spill surveillance systems.

2.4. Model Training and Validation

Following the construction of the Inception V3 and ResNet-50 models, they were subjected to a thorough training and validation process using the oil spill dataset. The data was partitioned into training, validation, and testing sets in an 80:10:10 ratio, ensuring a balanced approach for both learning and evaluation.

Both models utilized optimization techniques such as Adam and Stochastic Gradient Descent (SGD) to iteratively adjust model parameters. The primary goal was to reduce the categorical cross-entropy loss, which quantifies the error in classification. By doing so, the models fine-tuned their predictions to minimize the gap between the predicted and true class labels. The validation set was periodically used during training to monitor model performance and to detect any early signs of overfitting, prompting adjustments to the training strategy as needed.

To evaluate the effectiveness of the models, several key metrics were tracked, including accuracy, precision, recall, and F1-score. These metrics provided a comprehensive understanding of model performance, particularly in distinguishing between oil spill and non-oil spill cases. Confusion matrices and ROC curves were also analyzed to provide insights into both true positive and false positive rates, offering a detailed view of the models' ability to classify correctly.

Incorporating strategies like early stopping and model checkpointing allowed the training process to halt once model performance plateaued, ensuring the best version of the model was retained. Additionally, hyperparameters such as batch size, learning rate, and the number of training epochs were adjusted iteratively to accelerate convergence and improve final model accuracy.

ResNet-50's architecture, which employs residual connections, proved valuable in extracting deep hierarchical features. These skip connections facilitated better gradient flow, enabling the model to capture complex patterns within the data. The complementary capabilities of Inception V3, which focuses on multi-scale feature extraction, combined with ResNet-50's deep learning ability, enhanced the overall performance of the system for oil spill detection.

Together, these models offered an effective solution, leveraging the strengths of both architectures for accurate and efficient classification of oil spills in satellite and aerial imagery.

III. RESULTS

In this project, the Inception V3 architecture was used as the core deep learning model for image classification. By leveraging transfer learning and fine-tuning the network on the target dataset, the model was able to achieve a remarkable 97% accuracy with only 3% loss, validating its suitability for advanced image classification tasks. Although ResNet-50 is a powerful and proven architecture, in this project it achieved a modest accuracy of 62% and a relatively high loss of 38%. The results suggest that while the model was able to learn some features from the data, it did not generalize as effectively as Inception V3 under the same conditions.

(a). Classification Report – Inception V3

Classification Report:

	precision	recall	f1-score	support
Non Oil Spill	0.96	1.00	0.98	300
Oil Spill	1.00	0.96	0.98	300
accuracy			0.98	600
macro avg	0.98	0.98	0.98	600
weighted avg	0.98	0.98	0.98	600

(b). Classification Report – ResNet 50

Classification Report:

	precision	recall	f1-score	support
Non Oil Spill	0.58	0.77	0.66	300
Oil Spill	0.65	0.44	0.52	300
accuracy			0.60	600
macro avg	0.61	0.60	0.59	600
weighted avg	0.61	0.60	0.59	600

Fig 2: Classification Report

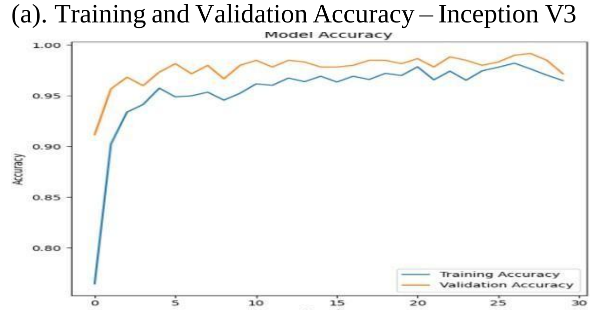
3.1. Training and validation Accuracy and Loss

To evaluate model performance during training, accuracy and loss curves were plotted over the course of epochs. These plots provide a visual representation of how well the model learned the training data and how well it generalized to the validation data.

3.1.1.Accuracy Graph

In the case of inception v3 model, the training and validation accuracy curves show a consistent upward trend, eventually reaching a peak accuracy of 97%. The curves remained close to each other, indicating good generalization and no significant overfitting. For ResNet 50, the accuracy curve rose more slowly and plateaued around 62%, suggesting that the model struggled to learn deeper features effectively on this dataset.

(a). Training and Validation Accuracy – Inception V3



(b). Training and Validation Accuracy – ResNet 50

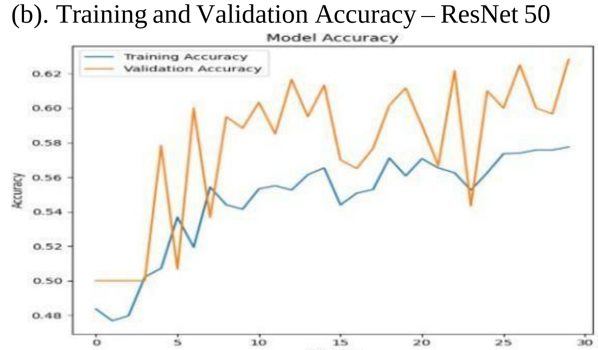
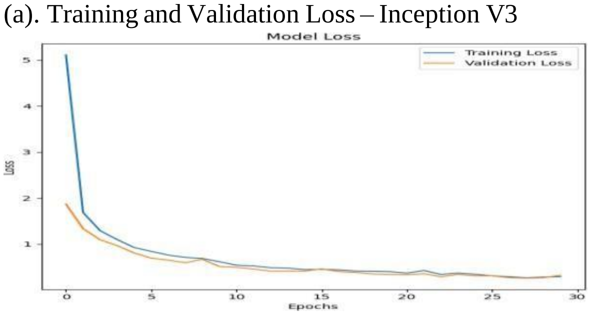


Fig 3: Training and Validation Accuracy Graph

3.1.2.Loss Graph

Inception v3 demonstrated a steady decrease in both training and validation loss, converging to a low value of 3%. This indicates stable learning and minimal error. ResNet 50 exhibited higher validation loss, leveling off at 38%, suggesting that the model faced challenges in minimizing prediction error, possibly due to overfitting or underfitting.

(a). Training and Validation Loss – Inception V3



(b). Training and Validation Loss – ResNet 50

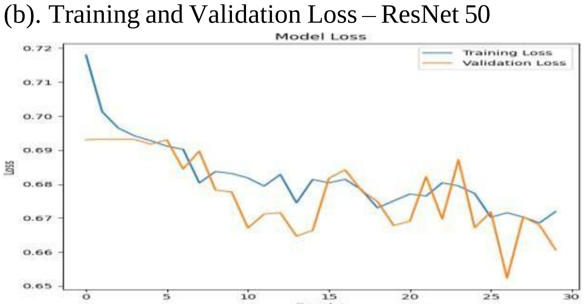
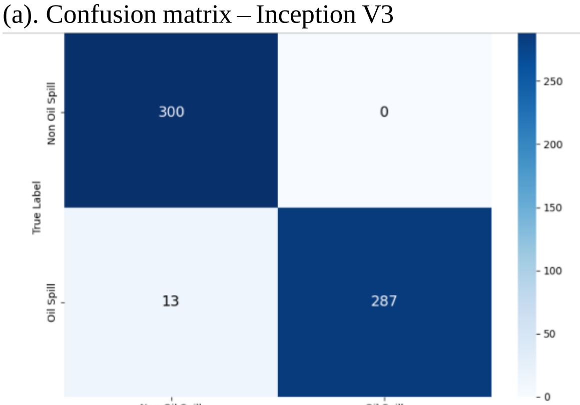


Fig 4: Training and Validation Loss Graph

3.2. Confusion Matrix

A confusion matrix, sometimes called an error matrix, is a particular table arrangement that makes it possible to see how well an algorithm usually one for supervised learning performs.

(a). Confusion matrix – Inception V3



(b). Confusion matrix – ResNet 50

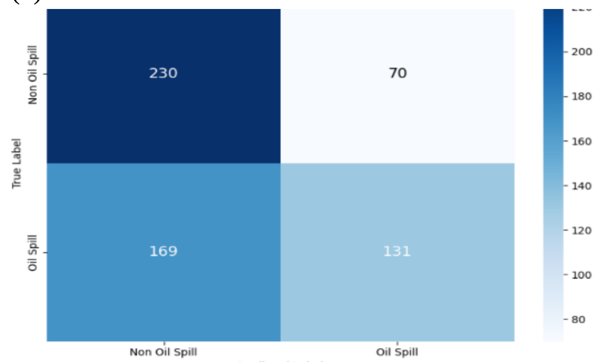


Fig 5: Confusion matrix

3.3. User Interface Development

To make the oil spill detection system user-friendly and accessible, a simple yet effective graphical user interface (GUI) was developed using front-end web technologies, including HTML and CSS. Upon launching the application, users are welcomed with a clean and minimal Home Page. This page serves as the entry point of the application, offering a brief description of the project and guiding the user through the next steps. It has a clear layout and is responsive, ensuring compatibility across various devices such as desktops, laptops, and tablets.

3.3.1.Image Upload Functionality

At the core of the interface is the Image Upload feature. This is implemented through a prominently placed Upload Button that allows users to select and upload an image file— typically a satellite or aerial image containing water bodies. This functionality is essential for the prediction process, as the uploaded image serves as the input to the machine learning model. Once a user selects an image, the file is sent to the backend server, where it is preprocessed and passed through the trained classification model (e.g., Inception V3 or ResNet-50). The backend handles all the computation and returns the result to the front end.

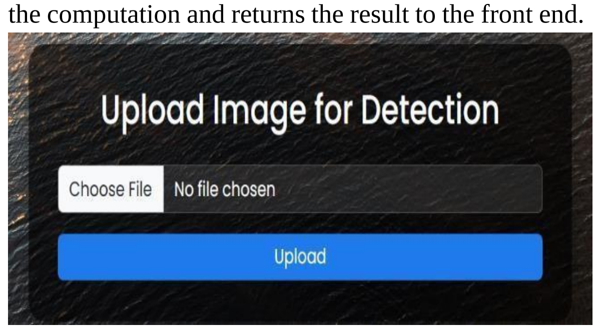


Fig 6: Upload Image for Detection

3.3.2.Prediction Display

After the model analyzes the image, the predicted result is displayed on the same interface. The output is shown as a label—either "Oil Spill" or "Non-Oil Spill"— depending on the classification outcome. This real-time feedback makes the system practical for immediate assessment and decision-making.

(a). Detection Result – Oil spill

(b). Detection Result -Non oil spill

Fig 6: Detection Results

The visual appearance of the interface is handled using CSS, which defines the color schemes, fonts, layouts, spacing, and responsiveness. The interface is designed to be clean, modern, and intuitive, reducing visual clutter and making the workflow easy to follow. Interactive elements like buttons respond to user actions (e.g., hover effects), improving the overall user experience. This UI was developed to make oil spill detection more accessible to non-technical users such as marine biologists, environmental monitoring agencies, and disaster response teams. By removing the complexity of code and placing a simple upload-and-predict interface in front of the deep learning model, the system becomes practical and ready for real-world deployment.

IV. CONCLUSION

This project successfully demonstrates the application of deep learning techniques for the automated detection of oil spills in satellite or aerial imagery. The primary objective was to develop a reliable, efficient, and accessible system that can aid in the early identification of oil spill incidents—thereby supporting timely environmental response and remediation efforts.

To achieve this, state-of-the-art convolutional neural network (CNN) models were employed, namely Inception V3 and ResNet-50. These models were trained and evaluated on a well-curated dataset comprising labeled images of oil spill and non-oil spill scenarios. Through extensive experimentation, it was found that Inception V3 significantly outperformed ResNet-50, achieving an impressive accuracy of 97% with a minimal training loss of 3%. The model demonstrated robust generalization capability and a high degree of classification reliability, making it well-suited for practical deployment in environmental monitoring systems.

On the other hand, ResNet-50, despite its architectural depth, achieved a comparatively modest accuracy of 62%, with a higher loss value. The classification report for ResNet-50 indicated weaker performance in distinguishing oil spills, particularly in terms of recall, which is critical in minimizing false negatives. These results highlight the importance of selecting the appropriate model architecture based on the specific characteristics of the dataset and application domain.

In addition to model development, a user-friendly graphical interface was built using HTML and CSS. This front-end interface enables users to upload satellite images and receive real-time predictions regarding the presence or absence of oil spills. The integration of a clean, responsive UI ensures that users without any technical background can still interact with the system effectively, which significantly broadens the usability of the solution.

Furthermore, various evaluation metrics such as precision, recall, F1-score, and overall accuracy were computed to provide a comprehensive assessment of the model's performance. The classification reports and graphical analysis (accuracy and loss plots) further validate the robustness of the Inception V3 model in handling complex visual patterns related to oil spills.

In summary, this project demonstrates that deep learning, when paired with a carefully designed interface, can serve as a powerful tool for environmental hazard detection. The proposed system offers a scalable, automated solution that can be used by researchers, government agencies, and environmental organizations to monitor water bodies efficiently and take timely action when oil spills are detected.

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