Automatic Detection of Garbage in Rivers Using Deep Learning

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Abstract

Rapid population growth has resulted in a staggering amount of garbage production worldwide. In less developed countries, proper and mechanized garbage collection presents a significant challenge, leading to difficulties in waste disposal and management. Unfortunately, the situation is worsening as the volume of home garbage continues to rise, while the capacity for treatment and management is on the decline. Consequently, the timely and efficient removal of debris is becoming increasingly problematic. To address this issue, we propose a low-cost, accurate, and straightforward approach to successful trash disposal, utilizing Unmanned Aerial Vehicles (UAVs) and Deep Learning technology. By developing a UAV-based intelligent trash detection system that employs deep neural networks (DNN) and image processing technologies, we can swiftly identify and remove debris floating in rivers, thereby delivering clean water to riverside inhabitants. There is a growing interest in constructing DNN-based models, resulting in high-performance capabilities in detecting and removing garbage. The dataset model can also assist higher authorities in monitoring river waste and advising appropriate departments to relocate and remove it, as well as helping towns automatically detect waste spots in outlying areas. The proposed UAV-based intelligent trash detection system, which utilizes two Convolutional Neural Network (CNN) models and image processing technologies, can assist higher authorities in monitoring river waste and help towns automatically detect waste spots in outlying areas. The CNN models were trained on picture datasets with varying learning rates, optimizers, and epochs, achieving an accuracy of 94% for automated solid waste identification. This is crucial as the rapid expansion of large-city populations has resulted in significant volumes of solid waste, posing a threat to public health and the environment. Current waste identification and management systems are essential to prevent blockages in sewer systems, flooding, and other disasters. However, there are currently no public records on waste recovery and disposal methods, highlighting the need for effective detection and categorization of various forms of trash to enhance the quality of life and the environment. The proposed technique employs a fully convolutional neural network model for text identification, which directly predicts the existence of text instances and their accompanying geometries in the full image, removing the need for intermediary stages like candidate sentences in conventional models. Overall, this essay aims to identify the best algorithm from all recently released studies and projects to improve waste management systems.

Keywords –

- DNN.
- UAV.
- CNN.

Introduction

Global pollution is becoming one of the most serious issues confronting citizens, lawmakers, and environmentalists. We are working hard to reduce air and water pollution. Humans are a key contributor to rising levels of many sorts of pollution. As a result, rubbish may be found everywhere on Earth, including in the backwoods, the Himalayas, and the Indian Ocean. There are currently roughly 5.25 trillion garbage objects in the ocean, and the quantity is continuously rising every day. There is significant evidence that these dump sites include a variety of hazardous materials that harm marine ecosystems. Plastics, bottles, chemicals, and various other harmful contaminants from the sea and other bodies of water are among these hazardous wastes. These contaminants cause pollution, which endangers marine ecosystems and has significant environmental repercussions. Marine ecosystem degradation harms the environment and is extremely hazardous to small-scale economic enterprises involving marine species. It is believed that 90% of the world's fisheries are already under threat. The ratio of fish to plastic trash is expected to reach 1:1 by 2050, up from 1:5 in 2014. This indicates we're on a high-risk path and must control deterioration since it's needed. To address the issue of river water garbage detection, deep learning and Keras can be utilized. By employing deep neural networks (DNN) and image processing techniques, debris floating in rivers can be detected and efficiently removed. The proposed approach involves a UAV-based intelligent trash detection system that uses a low-cost, accurate, and straightforward method for successful trash disposal. The system consists of two Convolutional Neural Network (CNN) models that are trained on picture datasets with varying learning rates, optimizers, and epochs. The models can assist higher authorities in detecting river waste and advising appropriate departments to relocate and remove it. Furthermore, the models can automatically detect waste spots in outlying areas, assisting towns with waste identification and management. By employing symmetry for trash image sampling and applying symmetry to extracted features for picture scaling, uniformity is achieved. In addition to addressing river water garbage detection, it is crucial to find a solution to the global pollution problem. Collaborative efforts must be made at the local, national, and international levels to reduce pollution levels. Governments, NGOs, and individuals must work together to reduce, reuse, and recycle waste products. Moreover, reducing the usage of single-use plastics, properly disposing of hazardous waste, and encouraging the use of environmentally friendly alternatives are some steps that can be taken to tackle the issue. Furthermore, education and awareness campaigns can be launched to inform the public about the environmental repercussions of pollution and ways to combat it. By taking a collective approach, we can protect the environment, preserve marine ecosystems, and safeguard the planet's future.

RELATED WORK

Deep learning techniques have become a popular solution for solving real-world problems across various fields, including environmental engineering. These methods are being used to identify and predict the presence of undersea garbage, which is becoming a growing concern for the world's oceans. Researchers are focusing on developing systematic management solutions for undersea garbage, and are using various deep-learning approaches to achieve this goal. For instance, studies have employed machine learning classifiers, such as k-nearest neighbours (kNN), support vector machines (SVM), single-layer neural networks, and deep neural networks (DNNs) to categorize water quality and detect garbage items. Among these classifiers, DNNs have been found to be more efficient and accurate, achieving up to 93% accuracy rates. Additionally, long-term short-term memory (LSTM) networks have been used to predict drinking water quality in the Yangtze River. The TrashNet dataset has also been utilized in several designs, including MobileNet, DenseNet121, DenseNet169, InceptionResNetV2, and Xception to classify and detect garbage items. Optimizers such as Adam and Adadelta have been used, with Adam showing better test accuracy. Data augmentation techniques have been employed to increase classification accuracy due to the limited size of the TrashNet dataset. The VN-Trash dataset has also been used to train deep neural network architectures, with the DNN-TC model achieving high accuracy rates of up to 98%. Marine debris detection and classification using deep learning has gained significant attention in recent years due to its potential for automated and efficient monitoring of the oceans. Various studies have explored the use of deep learning algorithms such as YOLOv3, transfer learning, and convolutional neural networks (CNNs) for this purpose. Zhang et al. (2021) proposed a deep learning-based approach for real-time monitoring and classification of plastic waste in marine environments. They used a Faster R-CNN model with a ResNet-50 backbone to detect and classify plastic waste in images. Similarly, Zhang et al. (2021) used a deep learning approach for floating marine debris detection and classification from images, using a Faster R-CNN with a ResNet-101 backbone. Jiang et al. (2020) and Liu et al. (2021) also proposed deep learning-based approaches for the detection and classification of floating marine debris in remote sensing imagery. Jiang et al. (2021) used a CNN-based approach with transfer learning to detect marine debris in remote sensing imagery, while Liu et al. (2021) used a Mask R-CNN with a ResNet-50 backbone. Al Maadeed et al. (2020) proposed a deep learning-based approach for waste detection in underwater environments, using a CNN with a VGG-16 architecture. Le et al. (2020) also explored the use of deep learning for detecting marine debris, using a Mask R-CNN with a ResNet-101 backbone. In addition, some studies have used advanced deep learning techniques such as high-resolution representation learning (Sun et al., 2019) and multivariate statistical techniques (Gupta et al., 2012) for marine debris detection and classification. It is worth noting that the quality of the input data is crucial for the accuracy of the detection and classification results. Some studies have used high-quality images captured by UAVs (Meneghello et al., 2019), while others have focused on assessing the water quality of rivers such as Yamuna in India (Sood et al., 2008; Kumar et al., 2011; Mittal et al., 2008; Aggarwal and Sharma, 2010) to improve the accuracy of the detection results.

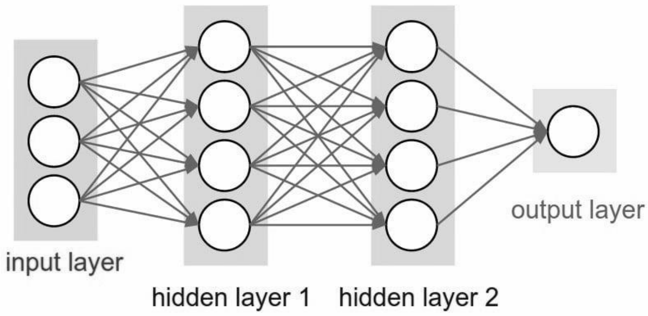

Fig 1: DNN Model

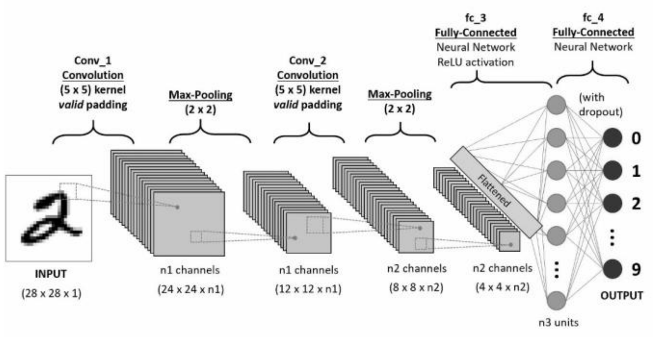

Fig 2: CNN Model

MODULE DESCRIPTION

In recent years, deep neural networks have proven to be a powerful class of machine learning algorithms that have enabled significant progress in a range of applications across various fields, including marine scene categorization. With the ability to stack neural network layers at the depth and breadth of lesser structures, deep networks have shown that they can learn identification and representation in a variety of current applications. Deep learning researchers are broadening their horizons by discovering intriguing applications in other fields, such as identifying floating marine macro debris in aerial photos. For training, deep networks require a huge volume of labelled data. In the case of identifying marine debris in aerial photos, this requires the collection of vast amounts of tagged images, which can be a time-consuming and challenging process. However, deep neural networks can separate millions of tagged pictures using effective training procedures. Furthermore, the trained network may be utilized to create effective picture representations for various benthic data sets. Before delving into the applications of deep learning in coral classification, it's important to understand deep learning and its cutting-edge architecture. Deep learning refers to a set of algorithms that are modeled after the structure of the brain's neural networks. These networks are built using artificial neurons that are connected in layers, and these layers can be deepened to create more complex and accurate models. Convolutional Neural Networks (CNNs) are a type of deep neural network that are particularly effective in image recognition and classification tasks. When implementing DNN training in short-term generation or load forecasting, a set of training samples consisting of an input vector consisting of weather, calendar, or other variables and a target vector consisting of generated power or load power must be collected, and an optimization regression problem will be formulated. As a result, the DNN parameters are determined by minimizing the sum-of-squares error function generated from the DNN outputs. A stochastic gradient descent process is constantly performed to lower the error function until it converges to a given lowest value, beginning with an initialization stage in which the model parameters are initialized to an initial set of values. The DNN training process consists of two passes, the forward pass, and the backward pass, which are based on the error backpropagation algorithm. The affine transformation and nonlinear activation are computed layer by layer from the input to the output layer in the former. In the backward pass, the error is calculated for each output layer neuron and propagated backwards through the network, with each layer updating its weights based on the calculated error. In the case of marine debris identification, researchers have developed a CNN-based system using the Pytorch module for identifying floating marine macro debris in aerial photos. This system utilizes the power of deep neural networks to learn and classify different types of marine debris from aerial images with high accuracy. The CNN architecture is designed to detect and classify different types of debris, such as plastics, fishing gear, and other floating objects, from aerial images. While this is just one application of deep learning in marine science, it highlights the potential for these advanced algorithms to make significant contributions in various areas, from environmental monitoring and conservation to fisheries management and oceanography. As research continues to advance, it's likely that deep learning will become an even more powerful tool in marine science and other fields, allowing us to gain new insights and better understand the complex systems that make up our world. Artificial intelligence has come a long way in bridging the gap between human and machine capabilities. One of the most promising applications of AI is in computer vision, which aims to enable machines to perceive the world in a way that is similar to humans. This field has many applications, such as image and video recognition, image analysis and classification, media recreation, recommendation systems, natural language processing, and more. Over time, many advances have been made in computer vision, with one specific method standing out - the convolutional neural network (ConvNet/CNN). This deep learning method can take an input picture, assign importance to distinct aspects or objects in the image, and distinguish one from the other. Compared to other classification methods, ConvNet requires less pre-processing. Hand-engineered filters in primitive approaches are replaced by ConvNet's ability to learn filters and characteristics through training. ConvNet's design is inspired by the arrangement of the visual cortex and mirrors the wiring of neurons in the human brain. Individual neurons in the visual cortex respond to stimuli only in a narrow region of the visual field known as the receptive field. These overlapping sets of fields cover the entire visual field. ConvNet's architecture mirrors this by having multiple layers that perform feature extraction in a hierarchical manner. The early layers focus on simple features, such as edges and corners, while the later layers combine these features to detect more complex patterns. PyTorch is a popular open-source machine learning package that focuses on tensor computation, automated differentiation, and GPU acceleration. PyTorch, an open-source machine learning package, has made it easier to develop and deploy deep learning models. With further advances in AI, we can expect to see more applications of deep learning in various domains, paving the way for more sophisticated and intelligent machines.

PROPOSED MODEL

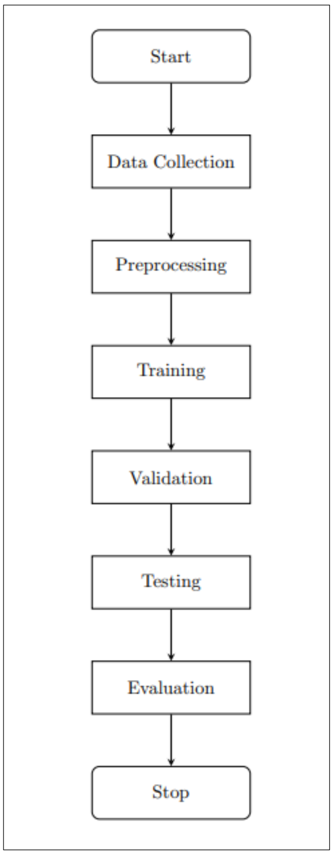

Fig 3: Architecture Diagram

In computer vision, one of the primary tasks is object detection, which involves identifying objects within an image or video and localizing them with bounding boxes. There are various approaches to object detection, and one of the most basic ones is the sliding window approach. In this method, the image is divided into small windows, and the classifier is applied to each window to determine if it contains an object of interest. However, this approach has limitations, such as being useful only for detecting a single object type with a fixed aspect ratio. To overcome the limitations of the sliding window approach, object detection models have been developed that can suggest bounding box positions that enclose the object. One such model is AlexNet, which achieved an accuracy of 91%. However, deeper models such as GoogleNet, Inception, and VGG have shown even better performance. These models are more suitable for detecting waste items, but they can be heavy and require significant processing time, particularly for large categories. GoogleNet, for example, has been trained to detect 1000 objects in 1.2 million photos. The image is divided into regions, and the model predicts the bounding box and probability of each region. This method requires only one forward propagation through the network for prediction, and after non-maximal suppression, the returned items have bounding boxes. While models more suitable for autonomous unmanned vehicles have performed well in real-time, they may not identify objects correctly due to the camera's low ground height. Another approach to object detection is using Support Vector Machines (SVM) with a radial basis function (Gaussian) kernel to emulate AlexNet. Another method is the use of trainable machine learning algorithms to develop object detection models by categorizing items. One such approach is the use of Keras and TensorFlow on the lightweight Mobilenet v2 model. This model is faster and more efficient, making it suitable for deployment on mobile devices or in real-time applications. Overall, object detection is a critical task in computer vision, and various approaches and models have been developed to achieve accurate and efficient results. As technology advances, it is expected that these models will continue to improve and become more widely applicable in various fields, from waste management to autonomous vehicles.

DATA COLLECTION

The detection and removal of marine litter is an important issue, particularly in coastal areas where it can have a significant impact on local ecosystems and tourism. Aerial photography is an effective method for monitoring litter distribution and assessing the effectiveness of cleanup efforts. However, manual detection of litter in aerial photography is time-consuming and requires significant expertise. Therefore, the development of an automated system for detecting marine litter in aerial photography is crucial. To address this issue, the study proposes the creation of a convolutional neural network (CNN) based algorithm for detecting floating marine macro litter in aerial photos. CNN is a type of deep-learning neural network that can be trained to recognize and classify images based on specific features. In this case, the algorithm is trained using a large dataset of aerial photos of coastal areas, including images with and without litter. The CNN algorithm is designed to detect floating marine macro litter, such as plastic bags, bottles, and other large debris that can be seen from above. To facilitate the use of the CNN algorithm, the study also proposes the integration of the algorithm with a web-based application built with the Py-Torch module. PyTorch is a free and open-source machine learning library that provides tools and resources for building and deploying deep learning models. The web-based application allows users to upload aerial photos and automatically detect marine litter in the images. The application provides a user-friendly interface that allows users to easily visualize and analyze the detected litter. The integration of the CNN algorithm with the web-based application provides a powerful tool for monitoring marine litter in coastal areas. The system can be used by researchers, government agencies, and non-profit organizations to assess the impact of marine litter on local ecosystems and develop effective cleanup strategies. Additionally, the system can be used by local residents and tourists to report litter sightings and support cleanup efforts. In conclusion, the creation of a CNN-based algorithm for detecting floating marine macro litter in aerial photos, along with its integration with a web-based application built with the Py-Torch module, is a significant contribution to the field of marine litter monitoring and cleanup. The system provides a powerful tool for identifying and analyzing marine litter in coastal areas and supports efforts to protect local ecosystems and tourism.

FEASIBILITY

Real-time tracking has become an essential component of several applications in various fields. Many studies have been conducted in the past to develop and improve real-time tracking algorithms. In this project, we aim to address a unique problem of detecting floating marine macro litter in aerial photos using a convolutional neural network (CNN)-based algorithm. To develop this algorithm, we have employed a straightforward approach that allows us to efficiently and accurately detect marine macro litter in aerial photos. The algorithm has been implemented using Python as the programming language and is available for public use on GitHub. In terms of cost-effectiveness, this project has been designed to minimize costs for both participants and the development team. Participants are not required to pay any fees to participate in online surveys, and the project has been designed to be cost-effective both before and after its execution. To ensure that the product meets the requirements and expectations of its users, we have incorporated survey findings into our product introduction process. This allows us to identify any potential issues or areas of improvement before the product is launched. The product management process is completely automated, ensuring that our products are created and maintained regularly. Additionally, our backend personnel are available 24/7 to ensure that any issues are addressed promptly. Proper testing and execution of the algorithm take approximately 2-3 months, with surveys and testing being the aspects that take the most time. However, we believe that this investment in time is necessary to ensure that the algorithm is effective and accurate in detecting floating marine macro litter in aerial photos. In summary, this project presents a unique solution to the problem of detecting marine macro litter in aerial photos using a CNN-based algorithm. It has been developed using a cost-effective approach, and the product management process is completely automated. Additionally, proper testing and execution have been incorporated to ensure that the algorithm is effective and accurate.

CONCLUSION AND FUTURE WORK

The problem of marine litter and water pollution is a growing concern worldwide, and Delhi's Yamuna River is no exception. In an effort to tackle this issue, the proposed model for detecting floating marine macro litter in aerial photos using a CNN-based algorithm has the potential to be a valuable tool for identifying and addressing the problem in a timely and efficient manner. The development of this model is just one small step towards the larger goal of cleaning up the Yamuna and other water bodies in the region. The model's accuracy will be critical to its success, and further studies will need to be conducted to refine its capabilities and ensure its effectiveness in identifying all types of floating debris. The use of Python as the programming language for this project provides a flexible and adaptable platform for the development of the algorithm. The availability of the code on GitHub ensures that the project is accessible to a wider audience, encouraging collaboration and further development. Moreover, the cost-effectiveness of this project is an important consideration, particularly in the context of environmental efforts that often require significant resources. By leveraging online surveys and automated product management, the project is able to minimize costs and maximize efficiency, ensuring that resources are focused on the most critical aspects of the project. The potential impact of this project on the clean Yamuna effort cannot be overstated. The development of a reliable and accurate model for identifying floating debris can help to target clean-up efforts and prevent further contamination of the river. With proper testing and execution, this model can be a significant step towards a cleaner and healthier Yamuna for all.

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