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APPLIED RESEARCH

Illegal Microdumps Detection in Multi-Mission Satellite Images With Deep Neural Network and Transfer Learning Approach

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ABSTRACT This paper presents an innovative approach for detecting illegal microdumps using very high-resolution optical satellite imagery, addressing a significant environmental monitoring challenge in Campania, Italy. Due to the regional vulnerability to illegal dumping, exacerbated by the waste management crisis, there is a pressing need for enhanced surveillance and accurate identification of microdump locations. This paper uses deep learning techniques to introduce an effective technology for detecting microdumps in high-resolution optical satellite images from Pleiades and GeoEye-1 satellites in an end-to-end solution, from images to detection. Its primary aim is to preliminarily assess dumping sites within specific target areas of interest (patrolling cells) for subsequent on-ground confirmation and characterization. The proposed system comprises two neural networks: the first, based on RetinaNet, identifies regions containing microdumps, while the second, utilizing InceptionV3, enhances the detection through pixel-wise classification. A fusion rule is then applied to combine the decisions of these networks. This technology addresses an environmental issue and is part of a progressive monitoring process. Validation was performed through a significant case study focusing on an extensive area between Naples and Caserta in the Campania region in Italy, particularly affected by illegal microdumps. A model was trained and validated using the pansharpened version of Pleiades multispectral images. This model exhibits potential for detecting microdumps in images from other satellite missions, as confirmed by validating it with GeoEye-1 imagery without further fine-tuning or training. The performance of the proposed detection system, evaluated for the reference application, achieves a detection rate of approximately 90% and a false discovery rate of about 40%. Notably, this is attained using a fully automatic processing chain without geospatial integration with additional information sources. In conclusion, despite satellite images having limited ground sampling distance and subsequent lower accuracy of image understanding algorithms, they remain suitable for environmental monitoring applications from an end-user perspective.

INDEX TERMS Microdump detection, remote sensing, RetinaNet for object detection, InceptionV3 for classification, GeoEye-1 and Pleiades satellite imagery.

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I. INTRODUCTION

A. OVERVIEW OF THE ENVIRONMENTAL APPLICATION

From 1994 to 2008, the Campania Region in Italy, specifically the agricultural and industrial areas north of the city of Naples and east of the city of Caserta, experienced a serious crisis in the municipal solid waste cycle. This crisis, compounded by the proliferation of illegal manufacturing activities, made the agricultural areas surrounding urban centers highly vulnerable to illegal microdumps. Extensive territory-wide surveillance remains necessary today to identify high-risk areas and prevent the accumulation of combustible materials prone to causing fires.

Monitoring action is presently coordinated by the Civil Protection, with support from the regional Government's in-house company, SMA Campania, to identify dumping sites and the Regional Environmental Protection Agency (ARPAC) to characterize these sites. SMA Campania utilizes a geographical information system to store and analyze gathered data. SMA Campania conducts ground patrols at various intervals in areas most susceptible to illegal dumping. Given the vast area to be monitored, optimizing available human resources involves collecting preliminary information on areas requiring more frequent patrolling.

For this purpose, the territory has been divided into hexagonal cells. Very High-Resolution (VHR) optical remote sensing images (with decimetric ground sampling distance) have been periodically collected to assess the presence or absence of microdumps in each cell. This information aids in establishing priority criteria for on-ground inspections by human operators based on the environmental risk associated with each cell. On-ground patrols contribute to a more accurate environmental risk assessment, prompting mitigation actions that involve reporting and describing dumping sites to the relevant authorities for removal.

This paper discusses a technique capable of automatically extracting necessary information regarding the presence and location of microdumps in target cells from VHR optical satellite images. Expert photointerpreters can further refine this information or directly employ it in environmental risk assessments for the cells, aiming to reduce response times with slightly less precision.

B. OVERVIEW OF THE REFERENCE PROGRESSIVE MONITORING PROCESS

To comprehend the integration of the proposed detection technology within the application context, the overall technological solution is briefly described below, referencing published works that cover complementary aspects of the reference progressive monitoring process[1] (see Fig. 1).

This project aimed to design a progressive and multi-layer monitoring process and develop a related prototype information system [1]. The system's objective is to provide Environmental Protection Institutions with frequently updated environmental risk maps [2], integrating heterogeneous information from crowd-sourced free text data (such as social media posts) to VHR satellite acquisitions, as previously proposed in [3]. The proposed progressive monitoring process comprises three phases. In the initial phase, probable environmental hazard sites are detected through automatic analyses of frequently updated big data sources [4]. In the second phase, these hazards are confirmed via back-office operations (by photointerpreters and environmental analysts) [5], aerial surveys, or on-the-field operators (on-ground patrols). In the final step, the recognized environmental hazards are confirmed using on-the-field instrumentation, such as drones [6].

Within the C4E project, big data sources are employed during the environmental monitoring process detection phase to determine ground patrol deployment areas [7], where they have to confirm and characterize sites prone to environmental hazards. Microdumps constitute one of the primary targets in this context. The analysis is conducted on cells spanning tens to hundreds of meters in both orthogonal dimensions, aligning with the smallest surface unit inspected during ground patrols.

C. THE PROPOSED MICRODUMP DETECTION SYSTEM

Microdumps are often produced by illegal industrial or agricultural activities that are unable to dispose of waste through normal disposal processes or can be accumulated in temporary moments of crisis in the normal urban waste disposal cycle. Microdumps can typically range from a few square meters to tens of square meters. In the most serious cases, they can reach hundreds of square meters.

Several approaches have been proposed in the scientific literature for the automatic detection of microdumps in satellite images, e.g. [8], [9], and [10]. The main weakness in these methods is that they often lack sufficient numerical results to effectively estimate their capability in identifying dumps. It is also important to highlight that, due to the significant challenge posed by the problem and the resulting limited performance of image processing algorithms, the methods used for dump detection in remote sensing images often involve subsequent analysis by photointerpreters and/or GIS processing [9]. This process also involves considering data fusion with predictive model outcomes and/or additional data sources.

In addition to various proposed techniques for detecting dumping sites, recently, techniques based on Deep Learning have been suggested [11], [12], although these are still in limited numbers. Here, we propose a deep learning technique to detect microdumps in satellite imagery. The proposed system comprises two neural networks: the initial network is based on RetinaNet [13], specialized for detecting regions containing microdumps, while the second network utilizes the InceptionV3 model [14] to enhance the detection through pixel-wise classification. To reach a final decision,

[1] "Progressive monitoring process" refers to a process structured into subsequent monitoring phases, characterized by decreasing spatial scale, increasing spatial resolution, revisit times, and accuracy.

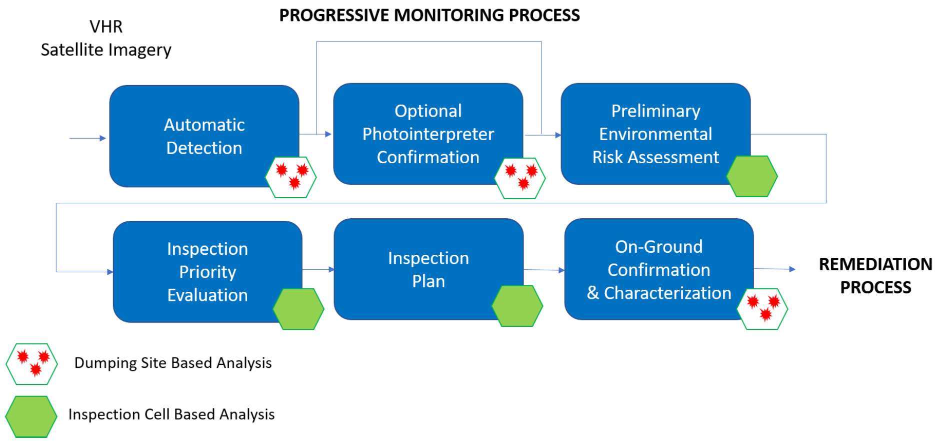


FIGURE 1. Reference progressive monitoring process.

we employ a fusion rule combining both networks' outcomes. As previously said, the case study is concentrated on a geographically extensive area in the Campania region in Italy, where illegal microdumps have been significantly impacted. We constructed a dataset for training the deep learning system, labeling pansharpened versions of multispectral images acquired from the Airbus Pleiades satellite mission. To prove the proposed approach's multi-mission remote sensing capability, we also tested the model on Maxar GeoEye-1 imagery.

This work introduces several novelties, including:

- A dedicated image processing architecture.
- A proven multi-mission remote sensing capability.
- The relation to a wider referenced monitoring process and technological solution.
- Performance assessment by image understanding and end-user perspectives.
- A significant application impact (as discussed below).

D. THE MAIN CHALLENGES AFFORDED AND CONTRIBUTIONS OF THIS PAPER

The microdumps issue not only afflicts Campania but is one of the most widespread environmental hazards worldwide in many urban and rural areas. VHR satellite imagery has the potential for detecting microdumps, but it faces a limitation in spatial resolution (with a ground sampling distance of some decimeters in the panchromatic channel), which is not adequately high for this specific application. Although information regarding individual microdumps is unreliable, the combined data at the inspection cell level provides enough insight to assess environmental risks. This aggregated information enables the formulation of an informed resource optimization strategy for on-ground inspections, a crucial step for facilitating remediation actions. Furthermore, the detection technology needs to be independent of the mission due to the low revisit time of a single VHR optical satellite mission (at most, some acquisitions per month). Finally, the performance of the detection solution should be evaluated not just in terms of image understanding but also about its impact on the on-ground confirmation process.

This paper aims to:

- Describe a multi-mission image understanding technology capable of detecting the presence of microdumps in VHR optical images obtained from different satellites.
- Situate the solution within a broader progressive monitoring process and a wider innovative solution.
- Evaluate the performance of the proposed algorithmic solution from the perspective of image understanding and the effectiveness of the aggregated information for informed ground inspections, confirming and characterizing the detected sites.

E. ORGANIZATION OF THE PAPER

The rest of the paper is structured as follows: Sect. II provides an overview of the literature concerning the utilization of remote sensing data for dumping site detection is provided. Sect. III describes the case study and data preprocessing. Sect. IV explains the proposed Deep Learning architecture. Sect. V reports experiments and their respective results. Finally, a dedicated section presents the discussion and conclusions, closing the paper.

II. RELATED WORK

Detecting microdumps in satellite images presents a diverse challenge, resulting in an equally varied and somewhat unsystematic body of related literature. Methods in the literature focus primarily on utilizing spectral information, while others integrate spatial features into their analysis. The first group concentrates on utilizing hyper and multi-spectral images to recognize waste spectral signatures [9] or analyze spectral characteristics of the vegetation surrounding or covering dumping sites [8]. These techniques often process individual pixels, focusing only on spectral data and neglecting spatial context. Object-Based Image Analysis (OBIA) is based on a higher abstraction level and works on pixel groups, providing higher semantic content. OBIA-based dump detection workflows are explored in [15] and [16]. In [17], although the authors do not explicitly refer to an OBIA framework, a Random Forest is used for classifying segmented objects identifying street litter. However, while considering spatial context, the object-oriented approach does not always rely exclusively on spatial features. Some studies, e.g., [18] or more recently [19], attempt to identify dumping sites, focusing only on spatial characteristics without an OBIA framework. Spatial information can also combine with spectral data in more complex ways. For instance, [10] proposes the Dump Detection Index (DDI), which combines vegetation indexes with vegetation stress spatial patterns caused by dumping.

Features distinguishing dumping sites were pre-decided in all the previously mentioned techniques. However, this approach has been superseded by Deep Learning (DL) techniques, which have proven effective in numerous applications [20]. Despite challenges in labeled data availability, they show promise in Object Detection [21], [22], [23], Segmentation and Classification [24], [25], [26] of Remote Sensing images. Of particular interest for our aims are, for example, the works that propose Convolutional Neural Networks (CNNs) to identify small objects such as vehicles in aerial and satellite images [27], [28], [29].

DL-based approaches, including CNNs, form the core of object detection methods. These methods fall into two main categories: Two-stage detectors like Faster R-CNN [30], and one-stage detectors like YOLO [31] and Single Shot Detectors (SSD) [32]. Two-stage detectors are generally recognized for their superior object localization and recognition accuracy. In contrast, one-stage detectors are known for their exceptional inference speed [33], [34]. In a two-stage approach, the initial stage generates candidate regions likely to contain objects, effectively filtering out the majority of negative proposals. Subsequently, the second stage focuses on classifying these candidates into foreground/background classes and refining the object localization based on the proposals generated in the previous stage.

In [12], the authors tried to identify instances of waste dumped along the banks of the Saint Louis Senegal River using images captured by a drone and a multi-scale object detection technique. They labeled 5, 000 images, each with an average of 5 bounding boxes, and trained an SSD model using 10% of the data for testing purposes. From their qualitative analysis, they noticed variations in the model's predictions depending on the location. The model produced many false positives due to confusion with non-waste objects like trees. In [11], a data set of 3, 000 aerial images at 20 *cm* resolution was used to create a data set used to train and test a multi-scale CNN architecture consisting of the merge of ResNet50 and Feature Pyramid Network.

Nothing of these approaches proposes an end-to-end solution that can work directly on satellite images and generate bounding boxes of microdumps based on a deep learning approach. So, to the best of our knowledge, this is the first solution proposed in the literature in this direction. Furthermore, this is the first case of a system that can work cross-satellites: our system has been trained on images from the Pleiades and successfully tested on GeoEye-1 without retraining.

III. CASE STUDY AND DATA PREPARATION

In this section, the case study is detailed together with a description of how images are collected and prepared for the following steps.

A. VALIDATION AREA AND IMAGERY

The validation area is located in the Campania Region, specifically north of Naples and east of Caserta (see Fig. 2). Like those commonly affected by illegal microdumping, these regions are extensive agricultural areas amidst urbanized zones. The problem of illegal microdumping primarily occurs along roadsides or in empty or vegetated fields within abandoned industrial areas.

The satellite data used in this study comprises the pansharpened version of Pleiades and GeoEye-1 multispectral images, with only the RGB bands considered for both datasets. The images have a ground sampling distance of 0.50 m per pixel for Pleiades and 0.40 m for GeoEye-1. All input data have been orthorectified and radiometrically calibrated. The area has been covered by many satellite acquisitions on different dates. In particular, this paper considers Pleiades of May 2016 and GeoEye-1 of May 2020.

Before processing, the input satellite data have been converted from 16 to 8 bits performing a *histogram stretching* operation to avoid excessively bright or dark images, using as the lower and upper limits, respectively, the 2nd and 98th percentile values (see Fig. 3).

B. INSPECTION CELLS

The overall territory of interest is divided into a grid of hexagonal cells (referred to as "inspection cells"), each with an apothem of 50 m. These cells represent the smallest surface that can be comprehensively inspected by a generic on-ground patrolling team during inspection activities, based on evaluating the inspection plan by the decision support system organizing the patrolling tasks.

For several reasons, hexagonal grid cells are preferred over square grid cells in certain GIS applications. Among the three regular polygons that can tile the plane (triangles, squares, and hexagons), hexagons offer the most compact form, providing the smallest average error in quantizing the plane and allowing for more efficient storage. Unlike square and triangle grids, hexagonal grids offer uniform adjacency; each hexagonal cell has six neighbors, all sharing an edge with it and having centers exactly equidistant from its center, thereby reducing edge effects. Additionally, each hexagonal cell has no neighbors with which it only shares a vertex [35]. These characteristics have contributed to the growing popularity of hexagons as a fundamental tool for

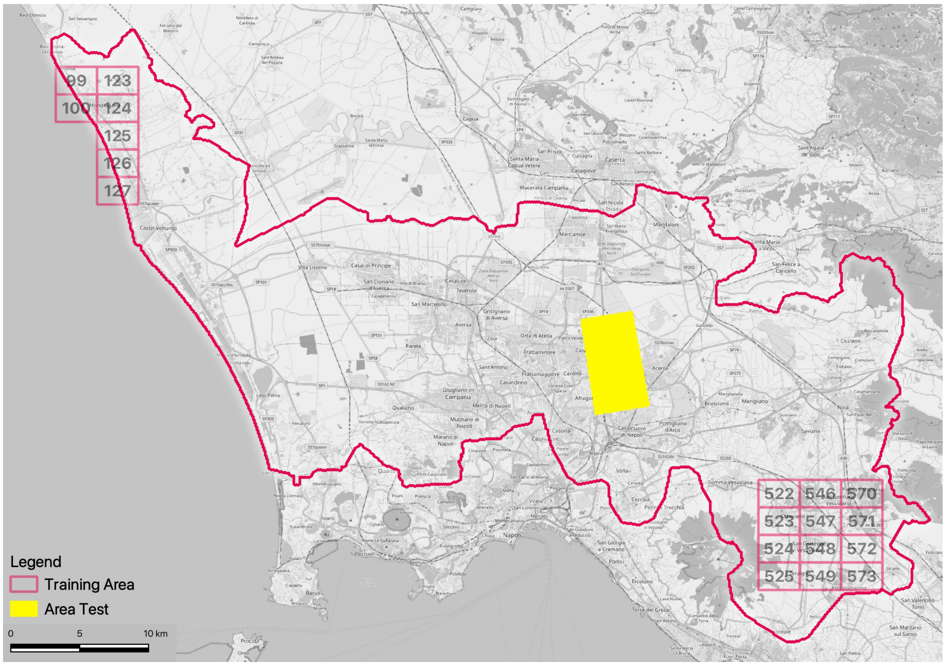
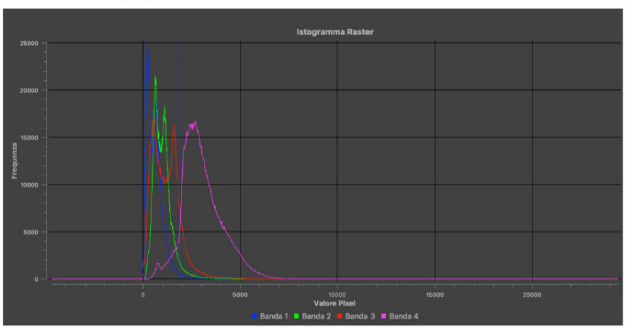


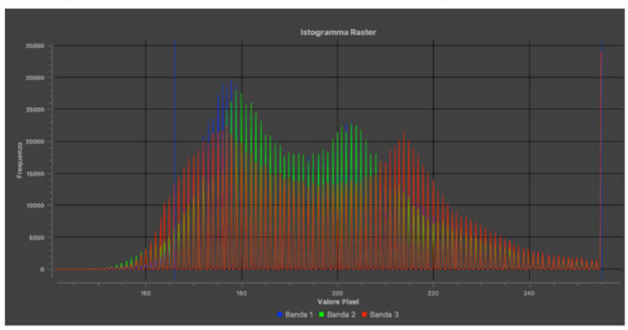
FIGURE 2. Area of interest: the red rectangles represent the images collected for training, and the yellow rectangle represents the area for the final test.

(a) Original 16-bit RGB image

(b) 8-bit histogram stretched (HS) RGB image



(c) Original 16-bit RGB image histogram



(d) 8-bit HS RGB image histogram

FIGURE 3. Images before and after 16-bit to 8-bit downscale and histogram stretching.

spatial analysis, including examining land use patterns and wildlife distribution, owing to their ability to represent spatial relationships between adjacent cells more accurately.

The image understanding technology presented in this work aims to provide information regarding the presence or absence of microdumps in each inspection cell.

C. GROUND TRUTH GENERATION

One of the most critical aspects of any machine learning procedure is the availability of large and consistent labeled datasets for training and testing algorithms. This issue becomes particularly evident in highly specific applications, such as dump detection, where published datasets are often unavailable. The ground truths used in this paper originate from a previous project called MIDA (Integrated Monitoring of Illegal Dumping Sites).

The 2016 MIDA project [5] aimed to locate and map areas covered by waste exclusively using satellite data (specifically, Pleiades and ErosB missions were employed for monitoring illegal landfills and microdumps). The surveyed area covered approximately $1,500$ km^2 (known as the ''Land of Fires'' area). The remote sensing company Mapsat thoroughly assessed and classified the dumping sites. Subsequently, these identified areas were validated using complaints from citizens and on-ground survey reports from SMA Campania.

Based on the results of the MIDA project, a further process was introduced within the C4E project to extract ground truth from the identified areas and utilize it to train the deep learning models proposed in this paper. The ground truth was explicitly constructed by examining Pleiades images acquired in May 2016. The proposed detection workflow is designed for generic urban waste dumping sites (as defined in [5]).

Initially, a preliminary deep learning model was constructed using a ''filtered'' training set. This original version of the training set was relatively raw because the perimeters of the dumping sites did not strictly delineate the waste evidence but inclusively delimited the entire dumping area of interest. Consequently, a team of photointerpreters reclassified the geopolygons, creating boundaries strictly encompassing the evidence (i.e., only pixels representing waste and their immediate neighbors). A preliminary deep-learning model was developed using this refined training set. Despite not performing very well (estimated false discovery rate of 70%), it managed to detect some microdumps that were omitted in the previous photointerpretation work.

Building on the results of this preliminary detection model, additional photointerpretation work helped identify false alarms among the positives provided by the algorithm and newly discovered true positives that were previously omitted. These ''new positives'' were added to the final ground truth, which was then used to train the deep-learning models in this paper.

The processing steps for ground truth generation are illustrated in Fig. 4. Through this described process, 593 bounding boxes with microdumps were obtained in the training areas.

IV. METHODOLOGY

This section details our methodology to detect microdumps in satellite images. The detection is achieved by fusing two methods, Object Detection (OD) and Pixel-Wise Classification (PWC), leveraging CNNs and employing a sliding window approach with specific patch sizes and step sizes.

OD and PWC operate on the same images, generating lists of objects and pixel-wise probability maps, respectively. The final output results from combining these outcomes. Due to the limited datasets in this domain and the time-consuming nature of annotations, we utilize Transfer Learning. This approach employs pre-trained models from large-scale datasets like ImageNet [36] and COCO [37] to mitigate data limitations, reduce training time, and yield effective results.

A. OBJECT DETECTION MODEL

For the OD model, we utilize RetinaNet [13], a detector operating in a one-stage fashion that efficiently detects objects of varying scales. RetinaNet incorporates backbones such as ResNet and Feature Pyramid Network (FPN) to extract multiscale features and two subnetworks for regression and classification to predict and classify bounding boxes. Focal Loss is used to address class imbalance, increasing training efficiency.

In this work, the training is made using the RetinaNet model with a ResNet50 backbone and COCO weights initialization, resulting in improved training efficiency. Regions of Interest (ROIs) are obtained using a sliding window with a horizontal and vertical step of 250 pixels, each patch being 500×500 pixels. Fig. 5 illustrates the OD module.

B. PIXEL-WISE CLASSIFIER

We implement Transfer Learning for PWC by fine-tuning pre-trained models with unfrozen layers. The standard Transfer Learning workflow comprises three main steps: (i) loading the model architecture and pre-trained weights from the large-scale ImageNet database (with $1,000$ classes), (ii) replacing the last fully connected layer with a task-specific classification layer (in our case, distinguishing between 'dump' and 'non-dump'), and (iii) training the compiled model. In our approach, the model is fine-tuned with L2-regularization that penalizes large weight values, shifting them to 0. This helps prevent overfitting by keeping less significant features and enhancing model generalization, thereby improving prediction accuracy.

In this context, we have opted for InceptionV3 as our pre-trained model [14]. To tackle class distribution imbalance in skewed datasets, the weighted cross-entropy loss is used during training to assign higher weights to the minority class. ROIs are determined using a sliding window with a horizontal and vertical step of 2 pixels, with each patch measuring 24×24 pixels. Fig. 6 illustrates the PWC module.

C. FUSION RULE

The OD algorithm generates an XML file containing bounding boxes around positive samples. The grayscale probability map obtained from PWC consists of values rescaled within the [0, 255] range, which is then thresholded at 254, yielding a binary mask.

This binary mask is combined with the OD results to reduce false positives. A bounding box is retained if at least

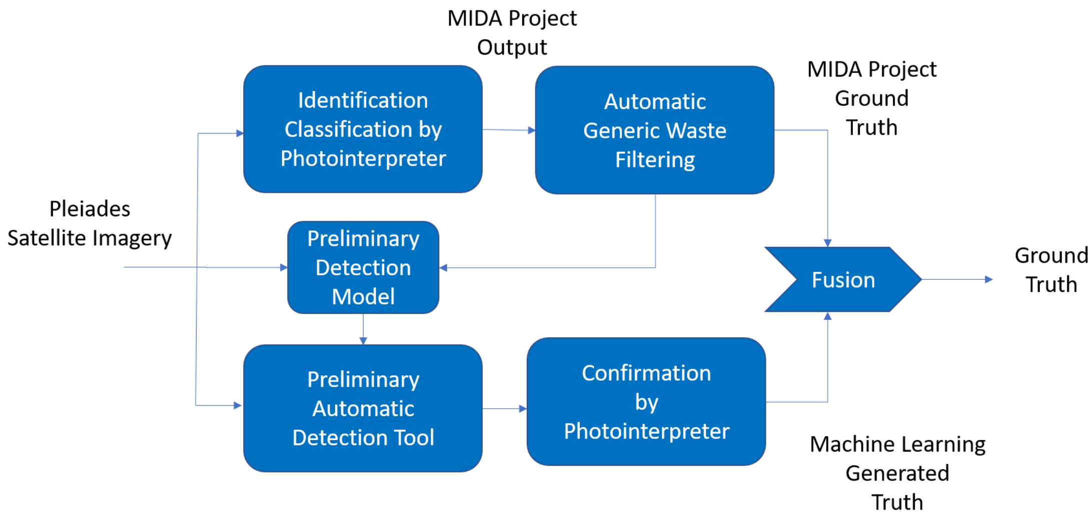


FIGURE 4. Ground truth generation process.

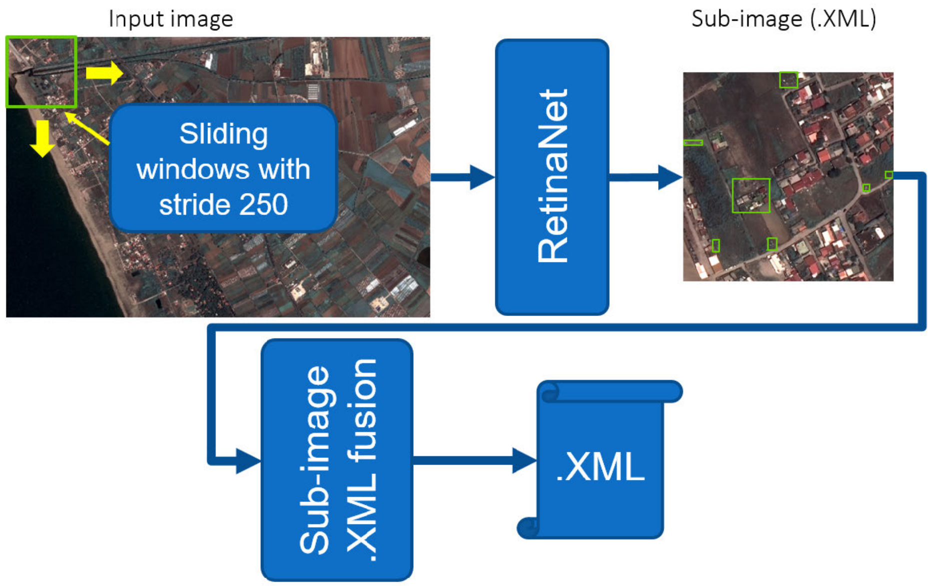


FIGURE 5. The object detection module.

one of its pixels in the binary mask is white. The outcome is a new XML file containing bounding boxes corresponding to areas detected using the fusion rule. An overview of the entire system is presented in Fig. 7.

V. EXPERIMENTS AND RESULTS

In this study, we conducted two experiments. The first experiment aimed to assess the effectiveness of the proposed approach using available data. The second experiment aimed to validate the performance of the approach in a real-world scenario.

A. DATASET FOR TRAINING

To train and validate the model, we used 19 Pleiades image tiles from May 2016, including both urban and suburban areas, with dimensions of $6,000 \times 4,000$ pixels ($3.0\ km \times 2.0\ km$).

For the PWC, patch sizes of 24×24 pixels were extracted from these 19 image tiles. This dimension balances capturing microdump sizes (often identified as white spots of 12×12 pixels, see Fig. 8) and larger patches that might include irrelevant information for dump localization. Positive samples were manually chosen from the ground truths provided with the images. About 200 non-overlapping positive samples per image were extracted. To diversify the dataset and increase robustness, each positive sample underwent a small multi-directional shift of 5 pixels horizontally and vertically, resulting in 8 variations per sample (as shown in Fig. 9). This augmentation technique helped enhance dataset variability, totaling around 16,293 positive samples, and improve the

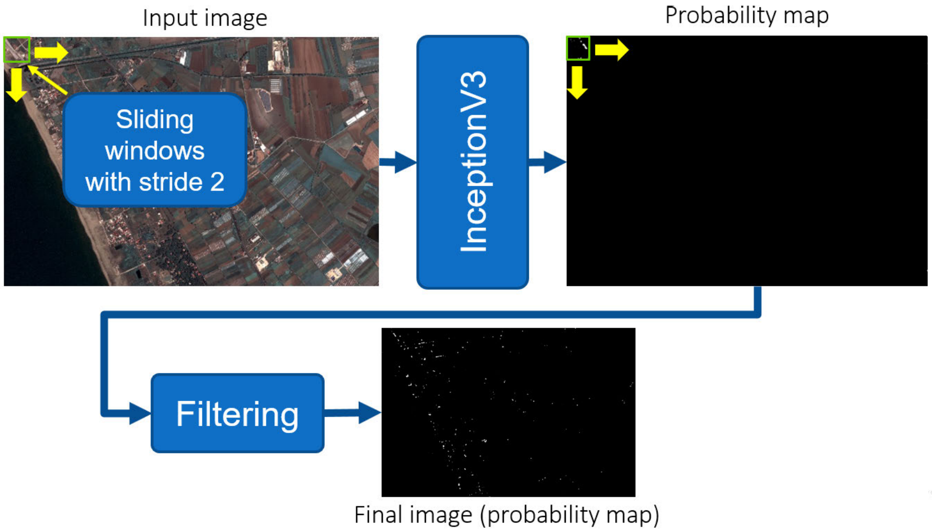


FIGURE 6. The pixel-wise classification module.

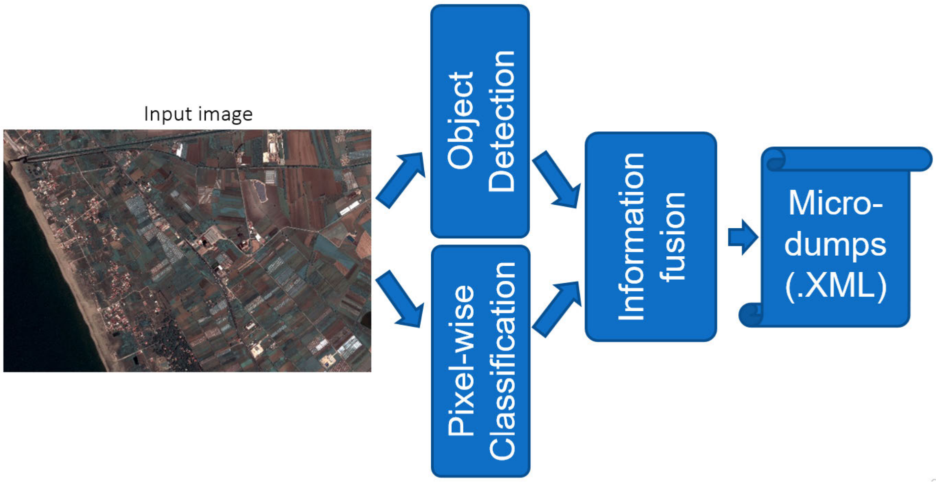


FIGURE 7. The detection system at a glance.

FIGURE 8. An example of microdumps positive patches.

model's ability to generalize. To ensure a balanced dataset, negative samples were strategically selected at a certain distance from each other (refer to Fig. 10), maintaining an imbalance ratio of 1 : 4 between positives and negatives.

Regarding the OD dataset, each image was divided into sub-images of size 500×500 pixels, with a 250-pixel overlap in both horizontal and vertical directions. Bounding boxes were automatically generated based on the provided ground truth to identify microdumps. Any bounding boxes falling on the sub-image borders were not considered. Approximately 250 sub-images per sector were obtained on average, totaling 4,715 sub-images (an example is shown in Fig. 11).

B. MODEL VALIDATION BY IMAGE UNDERSTANDING PERSPECTIVE

To enhance the robustness of the proposed approach, 6-fold cross-validation was utilized to split the images into training and test sets, creating 6 distinct training sets. Consequently, 6 models were generated for both the PWC and OD networks. This process involved employing 16 images for the training phase, with 13 allocated for training and 3 for validation. The remaining 3 images constituted the test set to evaluate the performance of each model.

This experiment's primary aim was to validate each stage within the proposed model thoroughly. Therefore, each trained model was evaluated by employing patches and sub-images extracted from its respective test set for both PWC and OD. The final fusion stage was also tested for each model pair using the corresponding test set. To assess the fusion algorithm, the evaluation was not limited to patches and sub-images extracted from the test set but extended to applying each trained model across the entire images of the corresponding test set via a sliding window technique.

RetinaNet models for OD were trained using transfer learning from the COCO dataset with Stochastic Gradient Descent (SGD). Network weights were updated in batches of 8 patches using the back-propagation algorithm, starting with an initial learning rate of 10^{-4}. The learning process was stopped after 100 epochs, with a patience setting of 10 epochs. Regarding PWC, Inceptionv3 networks were trained using transfer learning from the ImageNet dataset with SGD. Network weights were updated in batches of 32 patches using the back-propagation algorithm, starting with an initial learning rate of 10^{-2}. The training was stopped after 3,000 epochs, with a patience setting of 300. In both cases, patience values were experimentally determined, being the compromise between training precision and duration.

The results regarding precision and recall for patch classification and the final fusion performance were presented. The evaluation also included mean Average Precision (mAP) for the object detection phase. The results obtained from the 6 PWC and OD models are detailed for each fold in Tables 1 and 2 respectively. Table 3 exhibits the results achieved on the entire images across the 6 test sets after the fusion procedure.

Although it would be interesting to understand the significance of such results in the context of dump detection literature, the comparison is not straightforward. As highlighted in the introductory sections, the literature in this field is characterized by extreme variability in terms of data used, dump typologies (size, contents, etc.), datasets,

TABLE 1. Image understanding results on the six test sets for the PWC.

Fold	Precision	Recall
1	0.8954	0.7035
2	0.9029	0.7659
3	0.8343	0.7176
4	0.8150	0.6594
5	0.8980	0.6918
6	0.8269	0.7840
Mean	0.8621	0.7204
SD	0.0407	0.0468

and metrics employed. This makes direct comparisons very challenging, especially because, unlike in other fields, there are currently no standard benchmark datasets for machine learning available. Furthermore, many studies do not report quantitative results but only qualitative ones (e.g. [10], [12]), or they present results only after further analyses, such as that with GIS tools [9]. Some other papers report numerical results, but differences in datasets do not allow for comparative analysis. For example, in [11] an f-measure of nearly 0.88 is reported. At first glance, these performances are much superior to ours, which exhibit an f-measure of barely 0.46 (Table 3). However, it should be considered that the comparison is not fair, as many factors are playing against our experimental approach. First, the data employed in [11] are aerial images with a resolution of 0.20 m, whereas the satellite images used here have a resolution of 0.40 or 0.50 m. Secondly, the purpose of the paper presented in [11] is not to detect all dumps in a given area but to determine if square images of different dimensions (from 120 $m \times 120$ m to 200 $m \times 200$ m) contain or not dumps. Furthermore, in [11], the disproportion between positives and negatives is not representative of real-world scenarios, as 990 positives and only 2,000 negatives are used, for a ratio of approximately 1 to 2. Moreover, since the negative instances are so few, although they are chosen to represent as many different land cover types as possible in a remote sensing image, they cannot adequately represent the typical variability of the scene. In [4], results are also reported. It's worth noting that when the technique is used to distinguish between patches with and without dumps, with a partial imbalance of 1 to 14 and modeling only a subset of the possible land covers present in a generic remote sensing image, in an experimental setup of significance similar to the one proposed in [11], results are quite good, with an f-measure of 0.75. However, when the technique is applied to a more extended validation image of 0.9 $km \times 1.2$ km and performance measures for object detection are employed, as done in the present study, the performance drops to an f-measure of 0.22. Such considerations show how different approaches of validation can quantitatively impact results.

C. MODEL VALIDATION BY END-USER PERSPECTIVE

The performance of the detection technology in locating individual microdumps holds significance as ground patrols

FIGURE 9. Generation of positive samples through multi-directional shift.

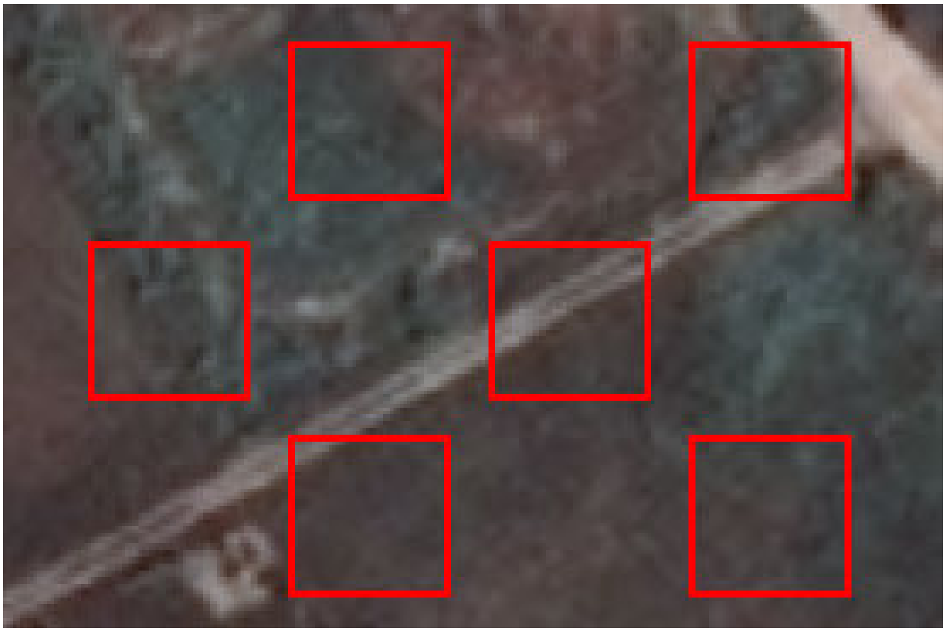


FIGURE 10. Example of negative patches used for image classification.

typically inspect broader areas instead of individual sites. This approach arises from the need to confirm spill sites presence and explore unreported or satellite-undetected locations. Basically, satellite detection has limitations in detection performance since satellite images are infrequently updated due to long revisit times and high acquisition costs. This contributes to evaluating the detection system performance in line with environmental requirements.

The primary goal of this system is to reduce the cost of manual photointerpretation or physical inspection of dumping sites. Assessing results within the hexagonal "inspection cell" framework (as defined in Sect. III-B) proves useful in this context.

End users must associate a *commission cost* (unproductive inspection) with an erroneous inspection by photointerpreters or ground patrols of a cell without dumping sites, and *omission cost* (missed intervention) with uninspected cells. Commission cost varies based on the erroneously inspected site location in case of ground patrolling or the photointerpretation cost in case of confirmation by photointerpreters.

TABLE 2. Image understanding results on the six test sets for the OD.

Fold	Precision	Recall	mAP
1	0.3267	0.5568	0.2615
2	0.3905	0.5775	0.2891
3	0.2926	0.4955	0.1846
4	0.4159	0.2919	0.2163
5	0.4230	0.4939	0.3692
6	0.2835	0.6039	0.3908
Mean	0.3554	0.5033	0.2853
SD	0.0623	0.1125	0.0820

Omission cost is evaluated ex-ante and relies on the environmental risk of a cell. Estimating these costs is highly scenario-dependent and necessitates estimating commission and omission probabilities. Our analysis focuses on precision and recall to address these considerations.

FIGURE 11. Example of sub-images used for Object Detection.

TABLE 3. Image understanding results on the six test sets after the fusion procedure.

Fold	Precision	Recall
1	0.3710	0.5227
2	0.6364	0.4930
3	0.4000	0.4685
4	0.5205	0.2360
5	0.5461	0.4512
6	0.3727	0.5325
Mean	0.4745	0.4506
SD	0.1096	0.1096

We assessed model performance in a test area referred to as "Area 3," covering 25 km^2 north of Naples between the municipalities of Acerra, Caivano, and Afragola (see Figs. 2 and 12). Despite the model being trained on Pleiades data, the test performance is evaluated using GeoEye-1 images from May 2020 for cross-sensor validation.

The area was divided into 3, 111 hexagonal grid cells, each 50 m of apothem and 8, 660 m^2 of area. A photointerpreter analyzed each cell to identify microdumps, establishing the ground truth for validation. The model validation strategy is graphically outlined in Fig. 13.

To evaluate our approach from an application standpoint, all hexagons intersecting with a polygon returned by the algorithm are considered positive, while those without intersections are considered negative. Comparing this outcome with ground truths established by photointerpreters allows the identification of true/false positives/negatives.

As mentioned before, using 6 distinct training sets, 6 classifiers were developed for PWC and OD networks. Each individual classifier produces different results and is separately validated against the same ground truth. Results from the first classifier, overlaid on the test area, are shown in Fig. 14, whereas its validation on inspection cells in Fig. 15.

Precision and recall were evaluated for each classifier and detailed in Table 4. The average false discovery rate is around 25.46%, i.e., approximately one cell in four is falsely indicated as containing microdumps. On the other hand, the detection probability is 47.86%, implying nearly half of the cells affected by microdumps were submitted to photointerpreters by the proposed detection system.

The overall performance is not particularly impressive, especially regarding the recall values. In our ground truth,

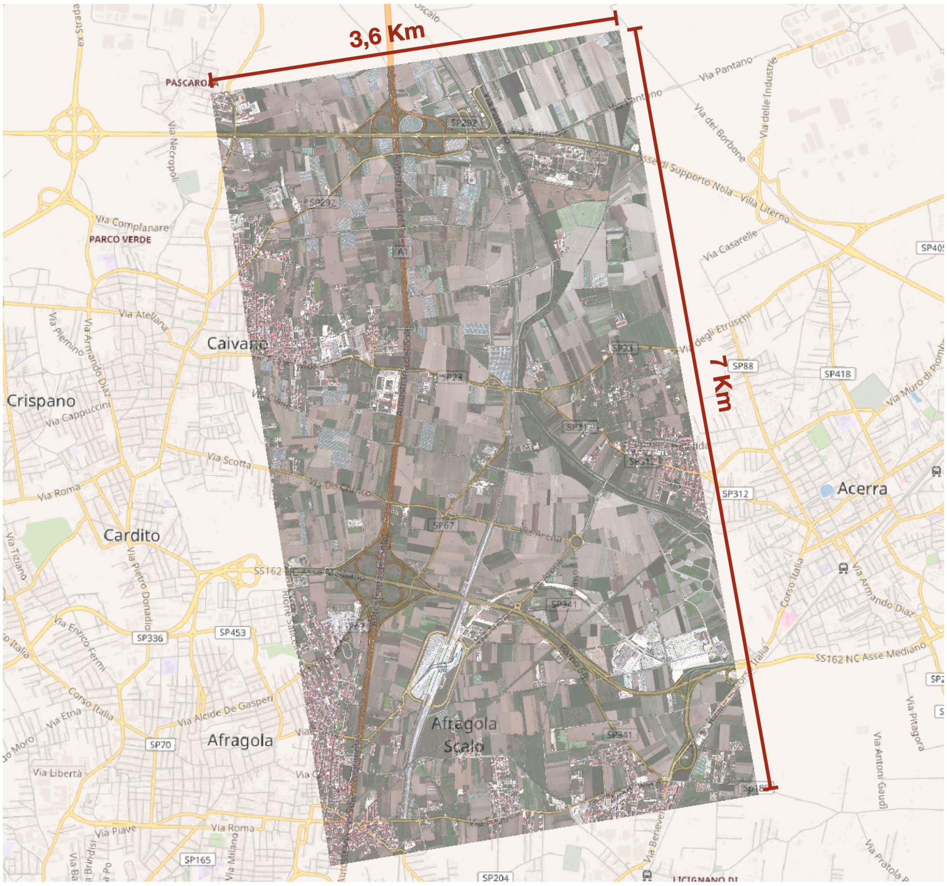


FIGURE 12. Extent of the area used for end-user validation.

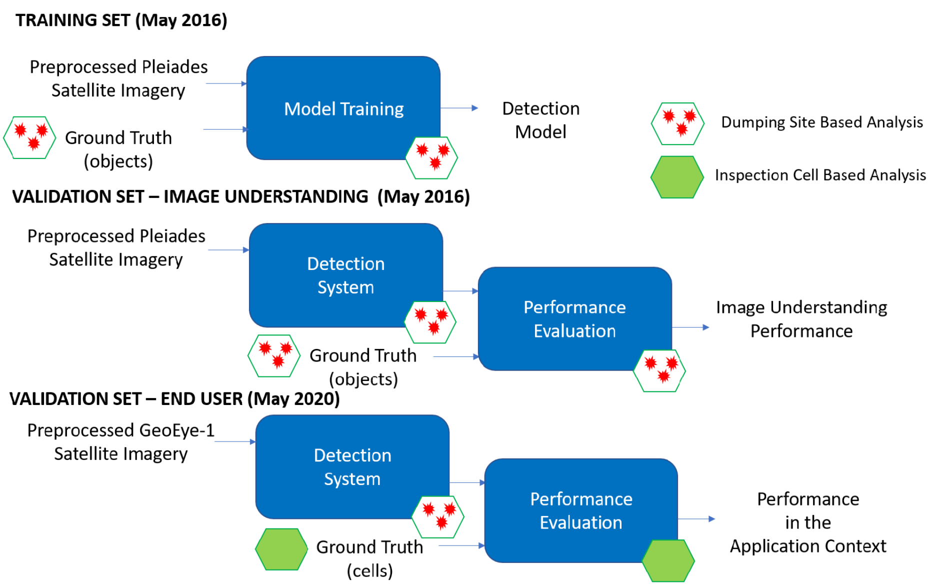


FIGURE 13. Model validation strategy.

out of 3, 111 cells, only 506 were confirmed to contain microdumps (similar statistics were calculated over the extended ROI spanning Naples and Caserta provinces). Due to the considerable variation in recall among individual models, an ensemble approach was employed to improve recall at the expense of precision. This approach considers a

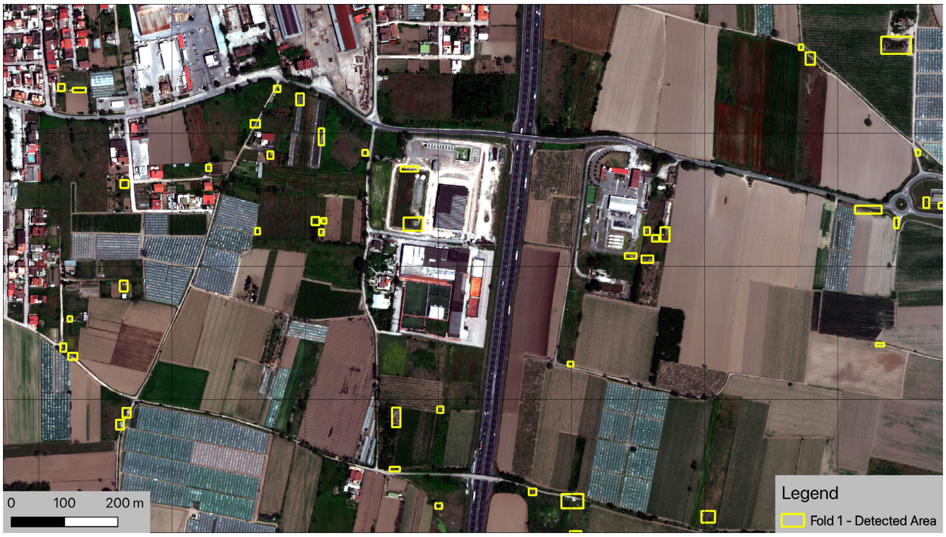


FIGURE 14. Detection results of the classifier trained on the first fold.

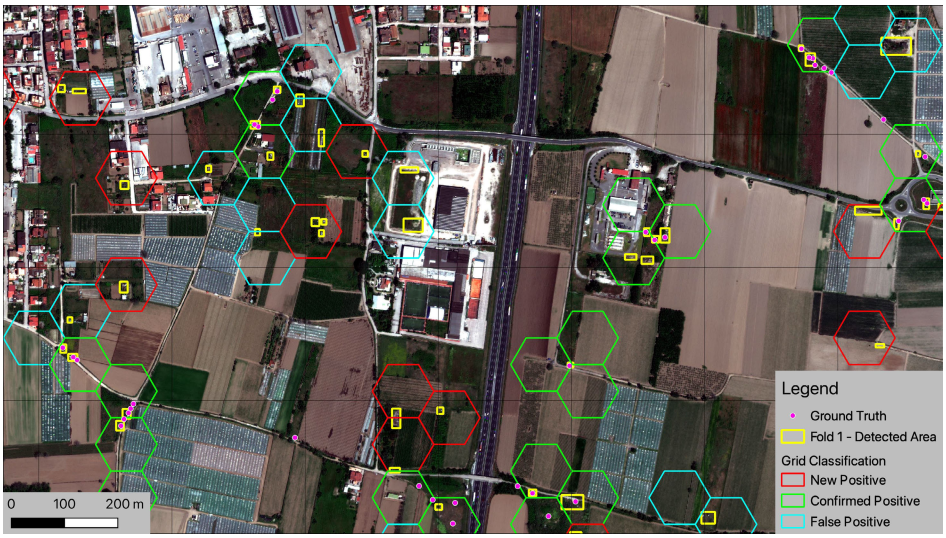


FIGURE 15. End-user validation of the classifier trained on the first fold, performed on inspection cells.

TABLE 4. Precision and recall by the end-user perspective for the 6 classifiers, performed on the inspection cells.

Fold	Precision	Recall
1	0.6938	0.6047
2	0.7150	0.5553
3	0.8202	0.2885
4	0.8325	0.3241
5	0.7119	0.4150
6	0.6990	0.6838
Mean	0.7454	0.4786
SD	0.0633	0.1600

cell positive if at least one of the six models labels it as such. Additionally, using all six classifiers together for ensemble classification is an acceptable solution as the validation set,

TABLE 5. Precision and recall by the end-user perspective for the ensemble classifier, performed on the inspection cells.

Fold	Precision	Recall
Ensemble	0.5876	0.9150

i.e., Area 3 image, was not used to train these classifiers. The proposed ensemble strategy, as depicted in Tables 5 and 6, notably boosts recall to 91.50%, whereas precision decreases to 58.76% (resulting in a false alarm rate of 41.24%). Results from the ensemble classifier, overlaid on the test area, are shown in Fig. 16, whereas its validation on inspection cells in Fig. 17.

These performance values effectively meet the users' requirements. This detection product enables environmental monitoring companies to identify approximately 91.50% of

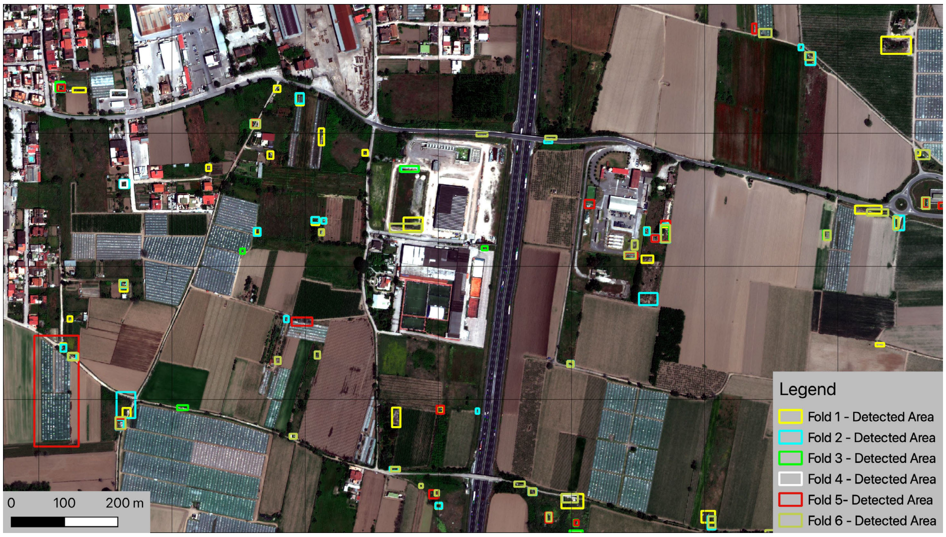


FIGURE 16. Detection results of the ensemble classifier on a GeoEye-1 image.

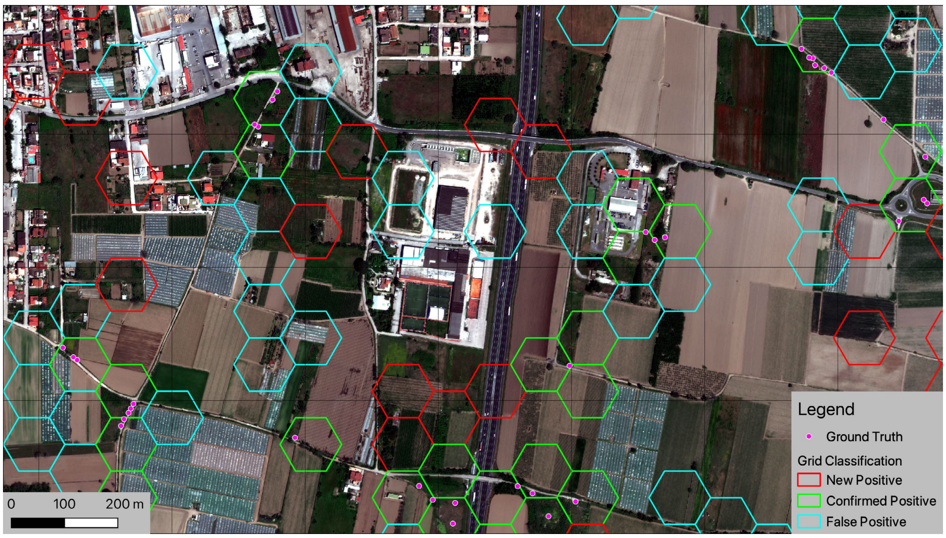


FIGURE 17. End-user validation of the ensemble classifier, performed on inspection cells.

TABLE 6. Confusion matrix for the ensemble classifier over the inspection cells.

	(Tot. Pop.)	Estimated Positives (788)	Estimated Negatives (2323)
True Positives	(506)	463	43
True Negatives	(2605)	325	2280

the inspection cells affected by microdumps, neglecting only one positive cell among tens. This yields a commission error of around 41.34%, meaning roughly that four cells per ten are needlessly inspected, achieved through a fully automated data processing chain. The potential of this information significantly expands when photointerpreters are systematically or occasionally engaged (to reduce false alarms drastically) and data are fused with additional geographic information layers. Both approaches relate to other information sources and observed historical trends on each inspection cell, which is expected to improve precision and recall. Quantifying these aspects goes beyond the scope of this paper. However, these considerations allow readers to reasonably interpret these performance values as a conservative lower bound.

VI. DISCUSSION AND CONCLUSION

The objective of this paper was to present an approach to analyze VHR optical satellite images for microdump detection, applicable in real-world contexts. This application focuses on identifying areas posing high environmental risks, requiring inspection to confirm the presence and precise locations of microdumps for subsequent remediation.

A specific deep learning solution was introduced to address the application requirements, integrating two approaches: pixel-oriented using InceptionV3 and object-oriented based on RetinaNet. The deep learning models were trained using data from the Airbus Pleiades multispectral satellite mission and validated on Maxar GeoEye-1 data, demonstrating the multi-mission remote sensing capability of the proposed solution. This capability is crucial due to the low revisit time of the VHR satellites within the same mission.

Regarding the future development directions of this work, the following considerations can be formulated.

The limitations of VHR optical satellite data, including the restricted ground sampling distance, result in poorly accurate image understanding products, which are nevertheless precious from an application point of view. An improvement in detection accuracy can certainly be achieved by evaluating not only satellite data but also the results of previous surveys and the morphology of the territory (for example, proximity to roads). The main application of satellite data in this field, in a broader analysis context that also integrates additional sources of information, is to support end users in identifying the areas at greatest risk of microdumps, for subsequent confirmation using on-ground patrolling actions. The expectation is that the effectiveness of such on-ground actions can be significantly improved, thanks to the use of information extracted from remote sensing data.

The integration of prediction model outcomes with complementary information sources and quantitative impact estimation on the performance of the overall monitoring process will be the subject of future works.

VII. AUTHOR CONTRIBUTIONS

Conceptualization: Mario Molinara, Alessandro Bria, Claudio Marrocco, Luca Cicala, Sara Parrilli, Francesco Tortorella, Giuseppe Meoli, and Mariano Focareta; Methodology: Mario Molinara, Alessandro Bria, Claudio Marrocco, Luca Cicala, Sara Parrilli, Francesco Tortorella, Giuseppe Meoli, and Mariano Focareta; Software: Mario Molinara and Alessandro Bria; Validation: Mario Molinara, Giuseppe Meoli, and Mariano Focareta; Formal analysis: Mario Molinara, Luca Cicala, Sara Parrilli, Francesco Tortorella, Giuseppe Meoli, and Mariano Focareta; Investigation: Mario Molinara and Francesco Tortorella; Resources: Mario Molinara, Giuseppe Meoli, and Mariano Focareta; Data Curation: Mario Molinara, Luca Cicala, Sara Parrilli, Giuseppe Meoli, and Mariano Focareta; Writing—Original Draft: Mario Molinara, Claudio Marrocco, Luca Cicala, and Sara Parrilli; Writing—Review & Editing: Mario Molinara, Alessandro Bria, Claudio Marrocco, Luca Cicala, Sara Parrilli, Francesco Tortorella, Giuseppe Meoli, and Mariano Focareta; Visualization: Mario Molinara, Alessandro Bria, Claudio Marrocco, Luca Cicala, Sara Parrilli, Francesco Tortorella, Giuseppe Meoli, and Mariano Focareta; Supervision: Mario Molinara; Project administration: Mario Molinara, Luca Cicala, Sara Parrilli, and Francesco Tortorella; Funding acquisition; Luca Cicala and Francesco Tortorella. All authors have read and agreed to the published version of the manuscript.

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