

INTEGRATION OF AI IN GIS FOR IDENTIFYING AND LOCATING ILLEGAL WASTE DEPOSITS IN ALGERIAN MUNICIPALITIES

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ABSTRACT. Like many municipalities around the world, Algerian municipalities are faced with the challenge of managing the collection of illegal waste deposits located across their territories. These deposits may occur both at authorized household waste collection points and at unauthorized locations. The management of these deposits presents a challenge, as their handling is incompatible with refuse trucks typically used for household waste collection or because they must be covered by collection services other than those provided by the municipality. It is therefore essential to identify and locate these deposits to ensure appropriate handling.

This article aims to address this issue through an innovative solution that integrates artificial intelligence (AI) into geographic information systems (GIS). The method is based on transfer learning combined with MobileNetV2 to generate a classification model for images of illegal waste deposits at authorized and unauthorized points. This model is integrated into a plugin created with QGIS software to perform image classification, enabling the location and identification of these deposits. The model achieved an accuracy of 98% during training, and its application to images from Biskra municipality illustrates its potential effectiveness. Beyond this case study, the approach offers a scalable and adaptable solution for improving illegal waste deposit management practices in diverse municipal contexts.

KEYWORDS: Illegal waste deposits., AI, GIS, Transfer Learning, MobileNetV2, Image classification Model

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INTRODUCTION

Municipalities in Algeria are facing an increasing problem of illegal waste deposits within their territory. These deposits, abandoned by residents, can be found in both unauthorized locations and at authorized waste collection points, where they disrupt regular collection processes. As in many municipalities around the world, particularly in developing countries, managing these deposits represents a major challenge for local authorities (Adipah and Kwame 2019; AND 2021; United Nations 2023; Del Carmen-Niño et al. 2023; Marange et al. 2023). The difficulties encountered may lie in the organizational shortcomings of local waste management systems, as noted by Dregulo and Khodachek (2022). In Algerian municipalities, this organizational deficiency may be attributed to the services in charge of collecting these deposits or the inadequacy of collection equipment, such as refuse trucks, when illegal waste deposits are dumped at household waste collection points. This leads to slowness in collecting illegal deposits, which in turn causes

environmental problems and public health risks (Jakeni et al. 2024; Pathak et al. 2024). Moreover, identification, and geolocation of illegal waste deposits remain critical issues in municipal waste management (Devesa and Brust 2021), which requires effective detection methods to remedy the problem as noted by Yu et al. (2024).

Several studies have emphasized the usefulness of geographic information systems (GIS) in managing illegal waste deposits at the municipal level (Paunović and Krstić 2014; Fatunmibi and Gbopa 2021; Jimoh et al. 2019; Karimi and Ng 2022; Syafrudin et al. 2023; Bošković et al. 2024). GIS facilitate spatial mapping and analysis of such data (Abdulai et al. 2015; Zainun et al. 2016; Krsmanović et al. 2022; Jakeni et al. 2024), helping local authorities identify areas vulnerable to illegal dumping (Thompson et al. 2013; Bodea et al. 2014). Moreover, GIS supports municipal decision-makers in planning and managing waste collection operations (Caputo and Pelagagge 2000; Iacoboaia and Aldea 2011; Awasare and Sutar 2015; Brus et al. 2016; Hua et al. 2016; Rao et al. 2020; Asefa et al. 2022; Sakshi et al. 2023).

However, traditional GIS approaches face limitations in processing the growing volume and complexity of spatial data (Ahmad 2023; Choi 2023; Yang et al. 2024). This is also true for data related to illegal waste deposits, which present similar challenges due to their exponentially increasing volume. Consequently, there is interest in integrating other technologies with GIS technology, such as artificial intelligence (AI). This integration involves the application of AI techniques to enhance the capabilities of GIS software (Ahmed 2024). With AI's computational power, this combination improves the ability of GIS to process complex spatial data. (Cai and Ge 2023) AI, which aims to replicate human cognitive functions (Vozenilek 2009; Panesar 2020; Ghosh and Thirugnanam 2021; Raj 2024), enables the emulation of human intelligence and problem-solving abilities by computers and machines (Saxena et al. 2023; Shrivastava et al 2024). Its effectiveness in managing illegal waste deposits has been demonstrated in numerous studies (Torres and Fraternali 2021; Shahab and Anjum 2022; Kim and Cho 2022; Inamdar et al. 2023; Ulloa-Torrealba et al. 2023), particularly through the application of Transfer Learning (Padubidri et al. 2022; Yu et al. 2024). The latter is based on Deep Learning, which uses neural networks to process large and complex datasets (Shafik 2024; Narayanan and Arjun 2024), and it requires significant computing and memory resources, as noted by Talaei Khoei et al. (2023). DL models are generally based on multilayer neural architectures such as convolutional neural networks (CNNs) (Nandi 2023; Mohanta et al. 2024).

TL uses pre-trained deep learning models (Talaei Khoei et al. 2023; Narayanan and Arjun 2024), allowing for reduced computational demands in terms of CPU and RAM (Puigcerver 2020; Khan et al. 2024; Zorić et al. 2024). MobileNetV2, a lightweight convolutional neural network (CNN) architecture trained on the ImageNet dataset, exemplifies this efficiency by significantly reducing computational load while maintaining high performance in image classification tasks (Howard et al. 2018; Sandler et al. 2018; Gondhalekar et al. 2024). These features make it particularly suitable for use in municipalities of developing countries where technical infrastructure is limited. In this context, combining TL with MobileNetV2 has proven effective in detecting illegal waste deposits (Shahab and Anjum 2022; Inamdar et al. 2023).

This article aims to address the issue of identifying

and locating illegal waste deposits at the municipal level through an innovative solution that integrates artificial intelligence (AI) into geographic information systems (GIS). The proposed method relies on transfer learning combined with the MobileNetV2 architecture to develop an image classification model that distinguishes between two categories of illegal waste deposit locations: authorized and unauthorized points. The model is then integrated into a plugin developed within the QGIS software environment, enabling the automatic classification and localization of these points. This integration is intended to assist municipal authorities in managing such deposits by helping them deploy adequate resources and transmit the relevant information to the responsible collection services. It is important to note that the generated model has been tested on real data from the municipality of Biskra in Algeria, allowing us to assess its operational robustness in a concrete territorial context.

MATERIALS AND METHODS

Study area

The municipality of Biskra, chosen as the study area, is the capital of Biskra Province, located in the southeastern region of Algeria. It covers an area of 127.7 km² (Monographie de Biskra, 2024). According to the most recent official census (2008), the population of Biskra was approximately 205,608 inhabitants. Geographically, the municipality is situated between longitudes 5°39'22'' and 5°46'44'' East and latitudes 34°54'58'' and 34°47'05'' North as shown in Fig. 1.

Data

To enhance the diversity of the dataset and improve the model's generalization capabilities, images were collected from three sources: Algerian municipalities (58.6%), Turkish municipalities (27.3%), and publicly accessible online platforms (14.1%). The Turkish images were gathered during field visits, and selected for their relevance and visual similarity to illegal waste deposits commonly observed in Algeria. Likewise, online images were selected based on these same criteria to ensure visual and contextual consistency throughout the dataset.

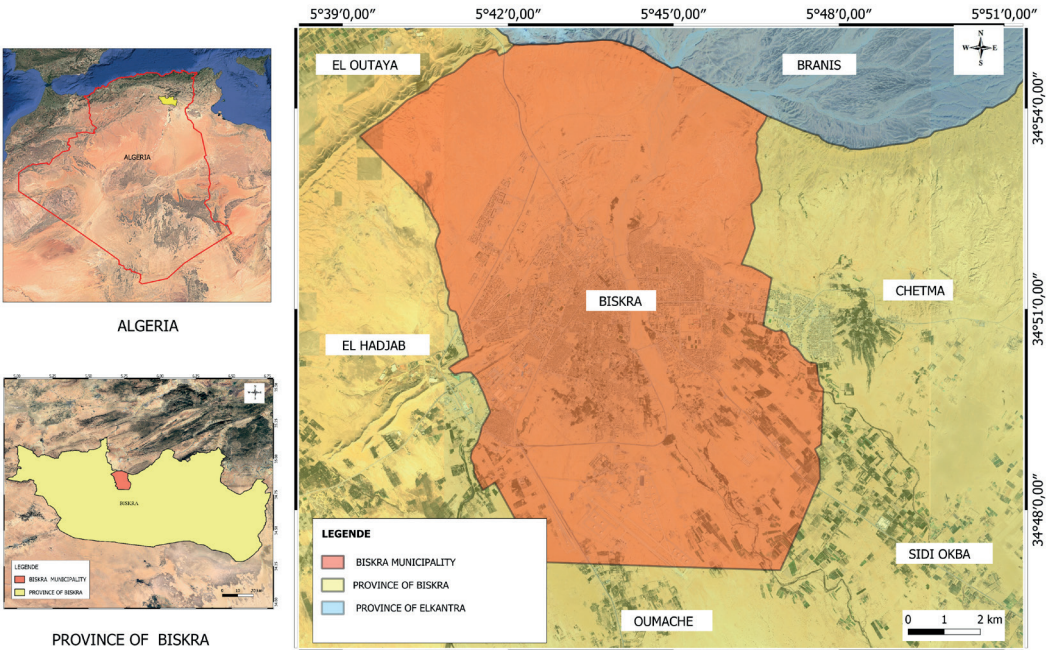


Fig. 1. Location of Biskra municipality

This multi-source approach enabled the construction of a robust image database depicting various instances of illegal waste deposits, whether occurring at authorized or unauthorized locations. Authorized points refer to formally designated areas for household waste collection, recognized in this study by the visible presence of dedicated waste bins, whereas unauthorized points correspond to locations where dumping is strictly prohibited, such as sidewalks, roads, and public spaces. There are two different types of images in the database: authorized and unauthorized points. Each class contains 800 images, for a total dataset of 1,600 images from various sources.

For the first class (authorized points): the waste stored in these collection points is not limited to household waste; however, it has been observed that illegal waste is frequently dumped there. These deposits may come from demolition, construction or renovation work. According to Algerian regulations, this category of waste is classified as inert waste. As stated in Article 37 of Law No. 01-19 of 2001 on the management, control, and elimination of waste, the deposit, dumping, or abandonment of such waste on unauthorized sites is considered an illegal practice and is strictly prohibited. Consequently, failure to comply with this law is punishable by a fine, in accordance with Article 57 of the aforementioned law. The imposition of strict measures to combat these illegal practices is, therefore, aimed at eradicating this phenomenon.

Other types of illegal waste deposits are also abandoned at authorized points, namely bulky waste and special waste. Article 3 of Law No. 01-19 (2001) stipulates that bulky waste is classified as a type of household waste. However, due to its substantial volume, it cannot be collected in the same conditions as household waste. It must be collected, transported and treated separately from household waste. Special waste includes waste generated by industrial, agricultural and service activities. Due to their composition and distinctive nature, these types of waste necessitate specific collection, transportation and treatment methods, which differ from those employed for household, bulky or inert waste. Their management, therefore, requires specific measures to guarantee environmental and health safety.

The management of special waste is governed by a strict regulatory framework that imposes responsibility

on the generators and holders of such waste, with the aim of preventing any illegal practices likely to harm the environment and public health. Article 16 of the law specifies that "the generators and/or holders of special waste are required to ensure, or have ensured, at their expense, the management of their waste". When a holder of special waste fails to comply with the established standards, in particular by abandoning or depositing such waste outside the regulatory procedures, the competent court has the power to intervene and impose the elimination of the waste at the expense of the offender. In this sense, the law ensures that producers and holders of such waste are held accountable, while simultaneously time guaranteeing rigorous application of the law.

For the second class (unauthorized points), these refer to locations not intended or equipped for waste disposal, where dumping is prohibited by municipal regulations. These areas often lack infrastructure for waste management and include spaces where the presence of waste can cause health, environmental, and safety problems. The anarchic accumulation of such waste deteriorates living spaces, obstructs traffic routes, and compromises public health.

In these areas, a variety of illegally dumped waste was identified, including inert waste such as rubble and construction residues, special waste, and household waste discharged by the population outside regulated collection systems.

To combat such practices, Algerian regulations impose financial penalties as a dissuasive deterrent. For example, persons who abandon household waste or refuse to use the facilities set up by local authorities, as well as industrial, commercial and craft operators who fail to comply with waste management systems, are subject to penalties defined by current legislation, Law No. 01-19 (2001). These legal measures serve to reinforce the efforts to combat illegal dumping by making citizens more conscious of their responsibilities, ensuring better waste management and contributing to environmental protection.

The images presented in Fig. 2 illustrate various categories of illegal waste deposits at authorized and unauthorized points in Algeria.



Fig. 2. Different types of illegal waste deposits in Algeria
(a) and (b) at authorized points (c) at unauthorized points

Development environment and system configuration

The development of the classification model and its integration into the GIS environment relied on a combination of Python-based tools and geospatial software. The programming language used was Python 3.10, selected for its compatibility with both deep learning libraries and QGIS scripting interfaces.

Several libraries were employed throughout the pipeline, each serving a specific purpose:

- TensorFlow 2.13 and Keras were used to build, train, and optimize the MobileNetV2-based classification model.
- NumPy supported array manipulation and numerical operations during preprocessing and model structuring.
- OpenCV (cv2) was used for image resizing, applying bilinear interpolation by default via the cv2.resize() function.
- Pillow (PIL) was used for image augmentation tasks such as rotation, zoom, shear, and horizontal flipping, simulating real-world variability in illegal waste deposit imagery.
- PyQGIS enabled seamless integration of the trained model into the QGIS environment, allowing spatial classification and geolocation.
- Qt Designer (v5.11.12) was used to design and customize the plugin's graphical interface for municipal use.

Development was carried out in PyCharm Community 2020.3, while QGIS v3.34.12-Prizren served as the GIS platform for plugin deployment and model execution via its Python console.

The system used for development and testing was a standard laptop equipped with an Intel(R) Core (TM) i3-3217U CPU operating at 1.80GHz, 6 GB of RAM, and a 64-bit operating system based on x64 architecture. This modest configuration reflects the practical constraints commonly encountered within municipal infrastructures and demonstrates the operational viability of the proposed solution in low-resource environments.

Methodology

The originality of this work does not lie in the architecture of the classification model itself, which is based on MobileNetV2 and transfer learning, both of which are well-established in the literature, but rather in its integration

into a Geographic Information System (GIS). Specifically, the model is embedded within a QGIS plugin designed to automate the classification and geolocation of illegal waste deposits. In addition to this integration, a key novelty of the approach lies in training and deploying the model directly within the QGIS environment, without relying on external platforms or cloud-based services. This training workflow enhances the operational autonomy of municipal users in a spatial context. Together, these elements constitute a novel contribution to the management of illegal waste deposits in municipalities.

Despite the absence of documentation of this particular integration in prior studies, MobileNetV2 was selected due to its demonstrated efficacy in image classification tasks. Its lightweight architecture makes it well-suited for deployment within GIS platforms where computational resources may be limited.

For research on AI into GIS, PyCharm and QGIS were used complementarily. PyCharm constituted the principal environment for developing Python scripts for image splitting, resizing and augmentation, as well as coding the classification plugin. The execution of these scripts was conducted in PyCharm, except for of the plugin.

The QGIS software was used on two levels: firstly, to create the plugin for running the classification within a GIS environment, and secondly, to train and evaluate the model via its Python console. Qt Designer was used to design and customize the plugin's interface. These stages are illustrated in the diagram shown in Fig. 3.

It is important to note that the decision to train the model directly in the QGIS environment stems from the difficulties encountered during tests carried out in PyCharm. Running the classification plugin faced incompatibilities between the versions of TensorFlow used by PyCharm and QGIS, resulting in blocking errors when integrating the model into QGIS.

Data augmentation

Data augmentation, a technique widely adopted in neural network training, enhances the robustness of models and improves their generalization power. As indicated by Hernandez-Garcia (2020) and Zeng (2024), this methodological approach relies on applying image transformations to artificially expand the datasets,

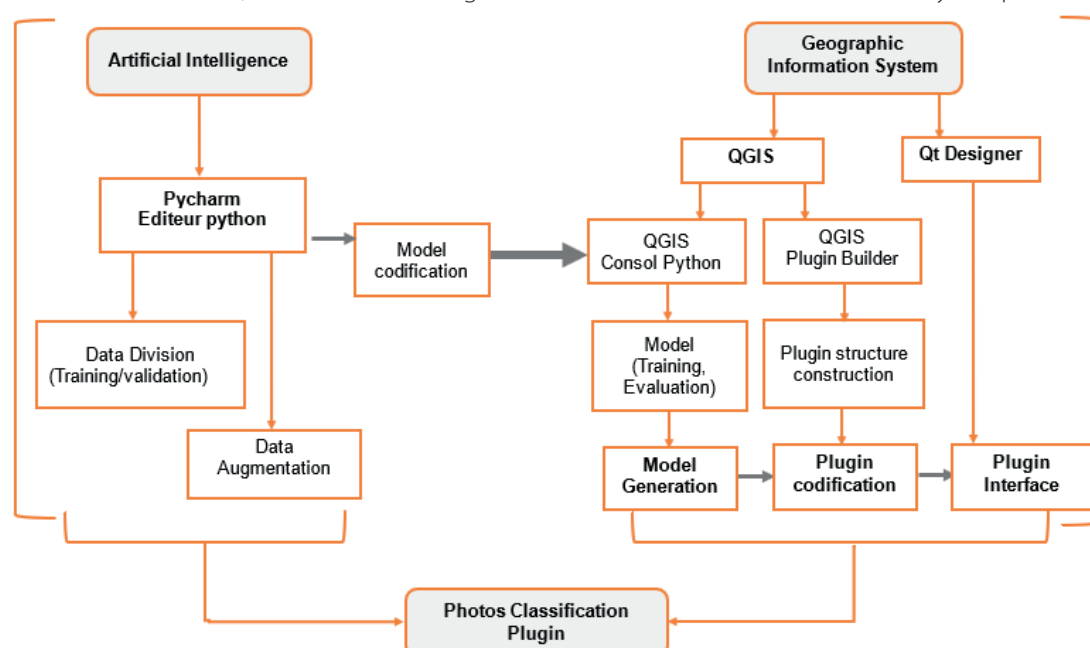


Fig. 3. Diagram illustrating the various stages of the methodology

particularly when datasets are limited. This approach proves effective in improving model performance and reducing the risk of over-fitting.

In the context of this study, prior to any augmentation operation, the initial dataset of 1,600 images was randomly divided into two subsets using an 80/20 ratio: 1,280 images (80%) were allocated to training, while 320 images (20%) were used for validation. This separation was performed programmatically using Python's `random.shuffle` function to ensure randomized distribution across both predefined classes: one designated for images of authorized points (Authorized_pt), and the other for images of unauthorized points (Unauthorized_pt). The dataset was then organized into a directory structure with two main folders (train and validation), each containing subfolders for the respective classes. This organization was designed to facilitate data access during the model training phase.

The limited size of the training dataset (640 images per class) limits the model's capacity to learn. The latter generally requires a larger volume of data to guarantee satisfactory generalization capability. For this reason, the dataset was augmented, with the objective of enhancing model performance. By augmenting the training data set, each class was expanded to comprise 1,250 images, resulting in a balanced dataset totaling 2,500 images; thus, the final dataset comprises 2,820 images.

Furthermore, a range of data augmentation techniques were employed to augment the size of the training dataset while preserving the essential characteristics of the images. These transformations were selected to simulate the spatial and morphological variability of illegal waste deposits observed across municipalities. As such, each original image was transformed using the following techniques: rotational augmentation, translation augmentation, shear transformation, scale transformation, and horizontal flip.:

As discussed by Muñoz-Aseguinolaza et al. (2023) and Qi et al. (2021), rotational augmentation involves applying angular displacement to the original image around its central axis. This transformation is mathematically represented as Eq. (1):

$$I'(x, y) = I(x \cos \theta - y \sin \theta, x \sin \theta + y \cos \theta) \quad (1)$$

where I' and I represent the original and transformed images respectively, and θ denotes the rotation angle. The implementation constrains θ within a predefined range (e.g., $\pm 30^\circ$) to preserve semantic validity. This transformation induces rotational invariance, a critical property for object recognition systems operating in unconstrained environments.

Translational augmentation implements pixel-wise displacement along horizontal and vertical axes (Kumar et al. 2025; Nanni et al. 2021). This transformation is formally defined as Eq. (2):

$$I'(x, y) = I(x + \Delta x, y + \Delta y) \quad (2)$$

where Δx and Δy represent the magnitude of horizontal and vertical translations, typically parameterized as proportions of image dimensions (e.g., $\Delta x \leq 0.2W$, $\Delta y \leq 0.2H$, where W and H denote image width and height respectively). This augmentation facilitates translational invariance, enabling recognition systems to identify objects regardless of their spatial position within the image frame.

Shear transformation, as described by Awaluddin et al. (2023) and Kumar et al. (2025), applies non-uniform scaling, creating a parallelogram-like distortion characterized by Eqs. (3)-(4):

$$I'(x, y) = I(x + y \tan(\alpha), y) \quad (3)$$

For horizontal shear with angle α

$$I'(x, y) = I(x, y + x \tan(\beta)) \quad (4)$$

For vertical shear with angle β

The shear range parameter (e.g., 0.2 radians) controls the maximum permissible distortion. This transformation simulates perspective variations and viewpoint alterations, enhancing model robustness to affine distortions.

Scale transformation (zoom), according Wang et al. (2025) and Khalil et al. (2023), modifies the apparent size of objects within the image through uniform scaling (Eq.5):

$$I'(x, y) = I(sx, sy) \quad (5)$$

where s represents the scaling factor, typically implemented as a random variable within a predetermined range (e.g., $0.8 \leq s \leq 1.2$ for zoom range=0.2). This augmentation induces scale invariance, enabling recognition systems to identify objects across variable distances and sizes.

Horizontal flipping is the process of creating a mirror image of the original along the vertical axis (Awaluddin et al. 2023; Kumar et al. 2025) (Eq.6):

$$I'(x, y) = I(W - x, y) \quad (6)$$

where W denotes the image width. This transformation exploits bilateral symmetry, a prevalent feature in numerous natural and artificial objects, effectively doubling the representation of symmetrical features within the training distribution.

Model creation, training and evaluation

This stage of the methodology involves the creation, training, and evaluation of an image classification model using TensorFlow from the QGIS Python console. The model is based on the MobileNetV2 architecture, incorporating pre-trained weights adapted to the specific classification task. As schematically illustrated in Figure 4, the process includes several key steps: data loading and augmentation, image pre-processing, and the definition and training of the model architecture. The figure provides a visual representation of the model pipeline, from the initial input images to the final classification output.

Data loading and pre-processing was performed using TensorFlow ImageDataGenerator, which enables data normalization and the automated generation of image batches for training. As described in the data augmentation section, the dataset was augmented and split into training and validation subsets (80/20). No cross-validation was applied; instead, a fixed split was chosen to ensure reproducibility and to accommodate hardware constraints typical of municipal deployments.

All images were resized to 224×224 pixels: Validation images were resized prior to training, while training images were automatically resized during the augmentation step, ensuring uniformity across the dataset. Subsequently, all images were rescaled to normalize pixel values between 0 and 1. A batch of 15 images was used during the training process. This configuration enables efficient data processing while ensuring compatibility with MobileNetV2 model requirements.

The adopted model architecture is based on transfer learning from MobileNetV2, a pre-trained convolutional neural network on the ImageNet database. This model was chosen for its computational efficiency and high performance, making it ideal for integration into environments with limited resources.

To adapt MobileNetV2 for binary classification (authorized versus unauthorized points), the following steps were taken to customize its architecture (Figure 5)

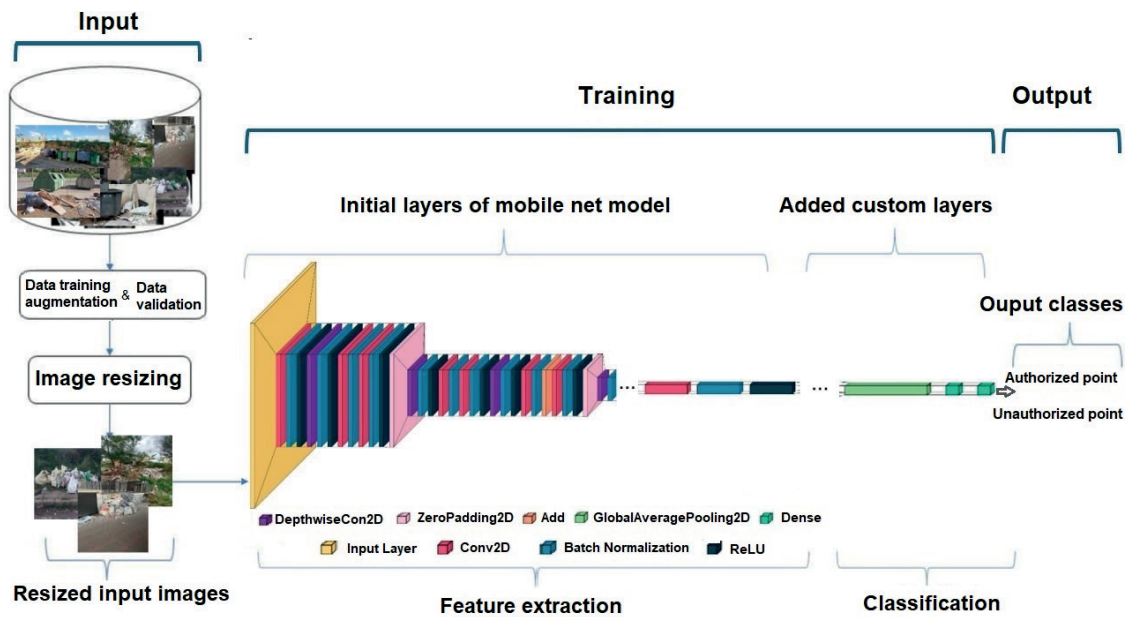


Fig. 4. Image classification pipeline using MobileNetV2 with pre-trained weights: from data input to final classification output

First, MobileNetV2 with pre-trained weights on ImageNet was used as the foundation. Only the last 30 layers were made trainable to enable fine-tuning, and the rest were frozen. This process involves retraining only the final layers of the model so that it can adapt to the specificities of the dataset studied while retaining the general knowledge acquired during the initial training.

Then, feature extraction was achieved using a GlobalAveragePooling2D layer to reduce the spatial dimensions of the feature maps derived from the convolutional network while preserving the essential visual information for classification. These “maps” are internal representations of the image that are automatically generated by the model from patterns detected in previous layers. The pooling layer extracts a compact synthesis, which facilitates learning while limiting the number of parameters to be trained.

Finally, the classification head consists of a dense layer with 128 neurons using ReLU activation, followed by an output layer with 2 neurons using Softmax activation.

The convolutional layers compute features according to Eq. (7):

$$f_l = \sigma(w_l \times f_{l-1} + b_l) \quad (7)$$

where f_l represents the feature maps at layer l , w_l and b_l are the trainable weights and biases, and σ is the ReLU activation function (Eq.8):

$$p(y_i | x) = \frac{e^{z_i}}{\sum_j e^{z_j}} \quad (8)$$

The final classification probabilities are computed using the softmax function:

where z_i is the logit corresponding to class i .

the training strategy involved compiling the model with Adam optimizer at a learning rate of 0.0001 and categorical cross-entropy as the loss function, defined by Eq. (9):

$$L = - \sum_i y_i \log(\hat{y}_i) \quad (9)$$

Where y_i is the true label and $\hat{y}_i$ is the predicted probability.

The model was trained over 20 epochs with the specified hyperparameters. As Toennies (2024) have previously indicated, the number of such epochs is a crucial factor in network training, as it allows network weights to be optimized. Once the training process had been completed, the model was saved in the Keras framework as an h5 - file.

The justification of hyperparameters was guided by both empirical validation and established practices in transfer learning with lightweight convolutional networks. The batch size of 15 was selected to ensure compatibility with limited hardware resources while maintaining stable gradient updates. The learning rate of 0.0001 was chosen to allow gradual fine-tuning of the last 30 layers of MobileNetV2 without disrupting pre-trained weights. The number of epochs (20) reflects a balance between convergence and overfitting risk, as supported by Toennies (2024). The use of categorical cross-entropy as the loss function is standard for multi-class classification tasks, and the Adam optimizer was selected for its adaptive learning capabilities and proven robustness in image classification workflows. The image size of 224×224 pixels aligns with MobileNetV2 input requirements, and the 80/20 train-validation split ensures sufficient data for both learning and generalization assessment. These choices collectively support reproducibility, computational efficiency, and model robustness.

Creation of the plugin in QGIS

Prior to elaborating on the technical steps involved in developing the plugin, it is imperative to clarify that its objective extends beyond the simple visualization of spatial data. The plugin developed in this study performs two key functions: it automatically classifies input images as either authorized or unauthorized waste deposit locations, and it determines and displays the geographic location of each classified point directly within the QGIS interface. The integration of the classification model into a GIS environment provides municipal users with an operational tool that combines image analysis and geospatial visualization for the management of illegal waste deposits.

The development process of the plugin is presented in

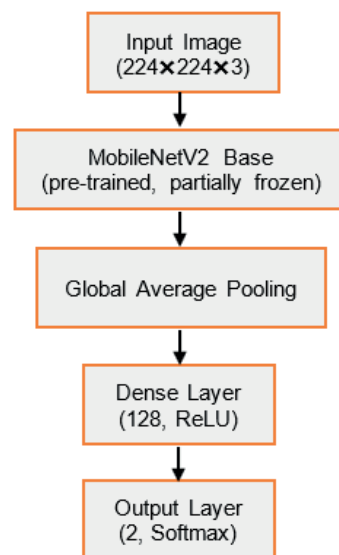


Fig. 5. Architecture of the proposed MobileNetV2-based classification model

three main stages: generating the plugin structure using the Plugin Builder tool, designing the graphical interface with Qt Designer, and integrating the trained classification model into the plugin.

In the first stage, the creation of a QGIS plugin begins with the generation of a standardized and extensible software base, in compliance with the development standards of this open source GIS software. The Plugin Builder tool, developed by the QGIS community automates this process by producing the required file structure for the plugin (Python scripts, metadata, graphic resources, functional directories, etc.). During this phase, various essential metadata elements are entered, including the name, version, author, and description of the project. This ensures effective integration into the QGIS environment and facilitates efficient referencing within the extension manager. This process establishes the technical and documentary foundations for the plugin's maintainability and eventual distribution.

In the second stage, the graphical interface of the image classification plugin was designed using Qt Designer. The interface, defined visually in .ui format, is converted into a Python script using the pyuic5 utility, generating an intermediate file (interface_ui.py) that is compatible with the QGIS PyQt framework. Thereafter, the script is integrated into a class derived from QDialog. The connection between the graphic components and the plugin's internal functions is based on event connectors (self.ui.object.clicked.connect(...)), that link each interactive element to a specific function. In the case of our plugin, these elements activate image classification processes relating to illegal waste deposits points.

In the last stage of the process, the classification model, which had been trained using the TensorFlow library and, exported in .h5 format, was integrated within the QGIS plugin. The aim of this integration is to automatically categorize images into two classes: "authorized_pt" and "unauthorized_pt". The model is then loaded into the plugin upon initialization. The images to be classified are then passed to the prediction model. Thereafter, a binary labeling system is assigned to each image according to the obtained result.

The logic associated with operating the classification model is encapsulated within a modular structure, represented here by the Photoclassification class. This organization guarantees a coherent plugin architecture, facilitating code readability and reusability.

RESULTS AND DISCUSSION

Quantitative Evaluation Results

The proposed approach for classifying illegal waste deposits, distinguishing between authorized and unauthorized categories, has demonstrated a remarkable degree of accuracy, with an overall rate of 98%. This high degree of accuracy highlights the effectiveness of transfer learning, particularly when combined with the MobileNetV2 architecture, in dealing with the challenge of classifying illegal waste deposits. The classification results are summarized in Table 1, and the following key information is highlighted.

Dataset augmentation

The augmentation of the dataset was applied exclusively to the training set, with the objective of enriching the diversity of examples without introducing bias into the validation phase. This strategy proved effective in enhancing the generalizability of the model, particularly in our context where the initial volume of data was limited.

High Precision and Recall for Both Classes:

The model achieves precision values of 0.987 for authorized points and 0.975 for unauthorized points, indicating a low false positive rate. This is essential to ensure that authorized points are not mistakenly marked as unauthorized.

The recall values of 0.975 for authorized points and 0.987 for unauthorized points demonstrate the model's ability to identify most items in both classes effectively.

Balanced F1-Scores

The F1-scores of 0.981 for authorized and unauthorized points reflect a strong balance between precision and recall. This indicates that the model performs consistently well across both classes, without significant bias in favor of one category.

Computational efficiency

The use of MobileNetV2, a lightweight convolutional neural network, guarantees the model's computational efficiency. Consequently, it can be deployed in environments

where resources are limited. This deployment can be implemented at the level of deprived municipalities. The efficacy of this measure is especially significant in developing countries, where it facilitates more effective management of illegal waste deposits.

Scalability and practical implications

The high accuracy and efficiency of the MobileNetV2 model, and its seamless integration into a GIS environment, enables automated management of illegal waste deposits. This scalability is of crucial importance to municipal authorities and environmental agencies, as it facilitates large-scale deployment across multiple regions without the need for substantial computational overheads, provided that basic geospatial data are available to ensure the system's operational viability.

Comparative perspective with existing literature

While the integration of AI into GIS has been explored in various contexts (Ahmed, 2024; Cai and Ge, 2023), most existing approaches rely on external platforms or cloud-based services for model training and deployment. Tools such as Mapflow and dzetsaka offer classification capabilities within QGIS, but they do not support in-plugin training workflows tailored to illegal waste detection. Our method addresses this gap by embedding both training and inference directly within QGIS, enabling autonomous and localized decision-making for municipal users. This distinction reinforces the operational relevance of our contribution, particularly in resource-constrained environments.

Environmental and public health impact

By enabling the classification of illegal waste deposits points, this model strengthens improve environmental protection and public health. It offers a proactive instrument for identifying these illegal deposits, linked to environmental degradation and related risks. Once detected, municipal authorities can initiate targeted clean-up operations and implement preventive monitoring protocols. These interventions not only reduce immediate exposure risks for nearby residents but also contribute to long-term environmental recovery. The system supports informed decisionmaking and timely responses to unmanaged illegal waste accumulation, reinforcing its value as a management tool aligning with municipal policy frameworks, including the Waste Management Plan and public health programs on hygiene that emphasize reducing risks for the population.

Confusion matrix an analysis

A confusion matrix analysis reveals the model's high accuracy, thus demonstrating its robustness in classifying

illegal waste deposits points. As shown in Figure 6, the results obtained indicate a marginal error rate, resulting in only four (4) cases of confusion where authorized points were incorrectly predicted as unauthorized, and two (2) inverse cases where unauthorized points were wrongly classified as authorized.

The low number of errors observed in this study serves as a reliable indication of the predictive model's efficacy, underscoring its ability to accurately distinguish between the two target categories.

For clarity, Table 2 summarizes the confusion matrix values (TP, FP, FN, TN) corresponding to these results.

Training and validation dynamics

The analysis of the learning dynamics revealed a rapid and stable convergence of the model. As shown in Fig. 7, this is illustrated by the training and validation accuracy curves reaching an asymptote as early as the tenth (10th) epoch. By the end of this phase, the model achieved a training accuracy of 99.97% and a validation accuracy of 98.12%, demonstrating its ability to efficiently generalize to novel data. Additionally, the model's resistance to overfitting is confirmed by the low loss function values, with training and validation losses of 0.0107 and 0.0463, respectively, indicating stability and a balance between performance and generalization. This convergence behavior empirically confirms the appropriateness of the 20 epoch training limit, as previously justified in the methodology section. Extending the training beyond this point would have yielded negligible performance gains while increasing the risk of overfitting and computational cost.

Training and inference time

Leveraging the lightweight architecture of MobileNetV2, the model demonstrated significant computational efficiency with an average inference time of 62ms per image. The complete training process required approximately 38 minutes, which demonstrates the feasibility of training the model in low-resource environments, without reliance on high-performance computing infrastructure, and confirms its suitability for municipal-scale experimentation.

GIS Integration and plugin validation validation of the developed plugin

The evaluation of the developed plugin was carried out using an image dataset collected in the municipality of Biskra in Algeria. The objective of this experiment was to assess the efficacy of the classification model integrated into the plugin within a concrete territorial context. The results obtained demonstrate the effectiveness of the classification model on these test images. The geolocalized images are displayed in QGIS as vector points (shapefile), each point corresponding to the location of an illegal waste deposit identified in the field.

Table 1. Results of the classification model of the waste disposal points

Class	Precision	Recall	F1-Score	Support
Authorized_point	0.987	0.975	0.981	160
Unauthorized_point	0.975	0.987	0.981	160
Accuracy	0.980			
Macro Avg	0.980	0.980	0.980	320
Weighted Avg	0.980	0.980	0.980	320

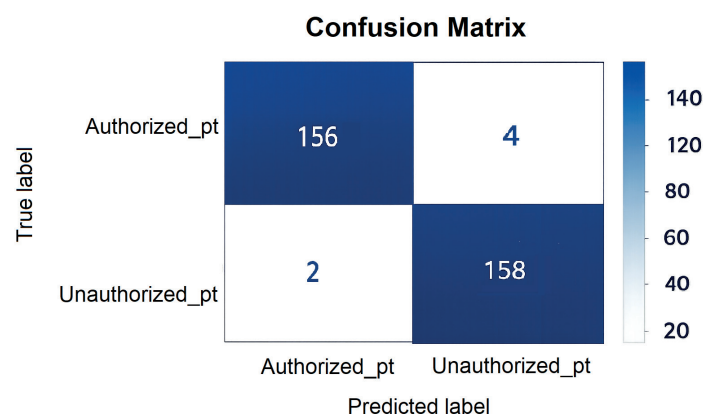


Fig. 6. Confusion matrix of the classification model

Table 2. Confusion matrix summary (TP, FP, FN, TN)

Class	TP	FP	FN	TN
Authorized points	156		4	
Unauthorized points		2		158

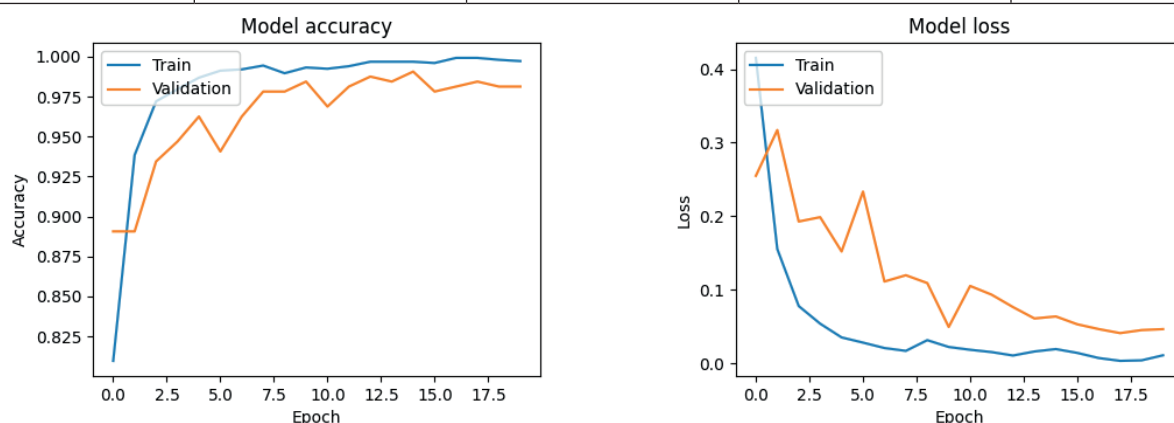


Fig. 7. Training and validation accuracy curves

Potential users are thus able to visualize all the deposits in question as points superimposed on a base map.

As illustrated in Figure 8, when a point is selected, a window opens and displays the corresponding image and the results of the prediction generated by the model. The information displayed includes the predicted class (authorized or unauthorized deposit), the confidence score of the model associated with this prediction, the address of the point, and the date and time the image was taken. It is noteworthy that all geolocated test images, collected independently in the municipality of Biskra and processed through the plugin, were correctly classified into their respective categories, thereby confirming the consistency between the training results and the functional validation in the municipal context.

Operational outputs and GIS visualization

Furthermore, all this information is automatically recorded in the attribute table associated with the shapefile (Figure 9), allowing for immediate exploitation of the data. This structured output supports intervention planning and enhances decision-making processes by providing municipal authorities with precise, contextualized information.

For instance, this data can be directly used to generate a distribution map of illegal waste deposits in Biskra municipality (Figure 10), thus facilitating municipal operations through effective visualization and analysis within a Geographic Information System (GIS) environment.

It should be noted that the municipality of Biskra does not possess geospatial data identifying the locations of legally

designated waste deposit sites. The outputs generated by the plugin, including classified images, geographic coordinates, and contextual metadata, contribute to the development of such geospatial information for municipal use. This structured dataset can support future planning, monitoring, and management of illegal waste deposits within a GIS framework.

The functional evaluation of the plugin confirms both the technical feasibility and the operational relevance of the proposed approach, which enables automated, geolocated, intelligible, and visually interpretable classification of illegal waste deposits based on geolocated photos collected directly in the field.

CONCLUSION

This study demonstrates the relevance of an innovative approach based on the integration of Artificial Intelligence (AI) into Geographic Information Systems (GIS) for managing illegal waste deposits at the municipal level.

The proposed methodology combines transfer learning with the MobileNetV2 architecture, trained directly within a plugin developed in QGIS, ensuring seamless operation inside the GIS environment. This integration enables automatic identification and precise localization of illegal deposits from georeferenced photos, with visual rendering in an interactive cartographic interface, facilitating operational planning and informed decisionmaking. Tests conducted in Biskra municipality confirm the efficiency of the model in distinguishing between authorized and unauthorized points, highlighting its potential as a scalable tool to support territorial

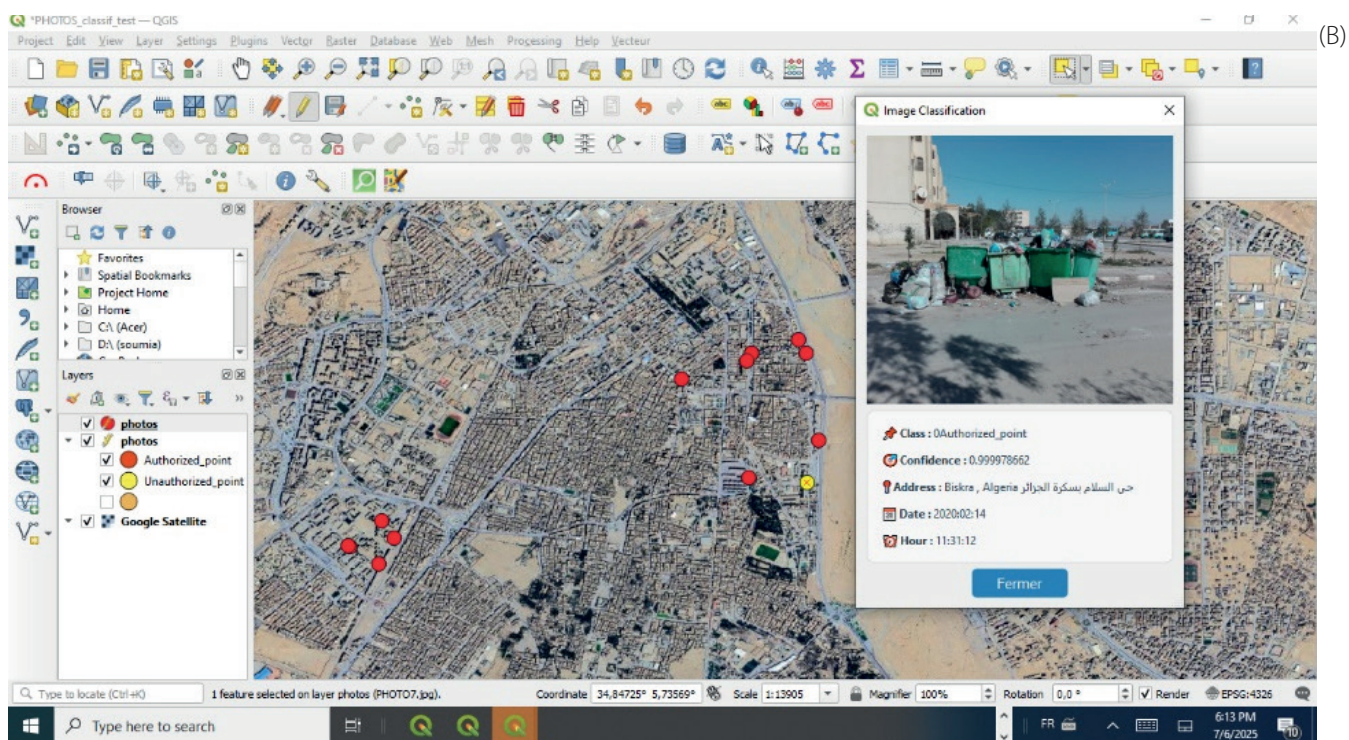
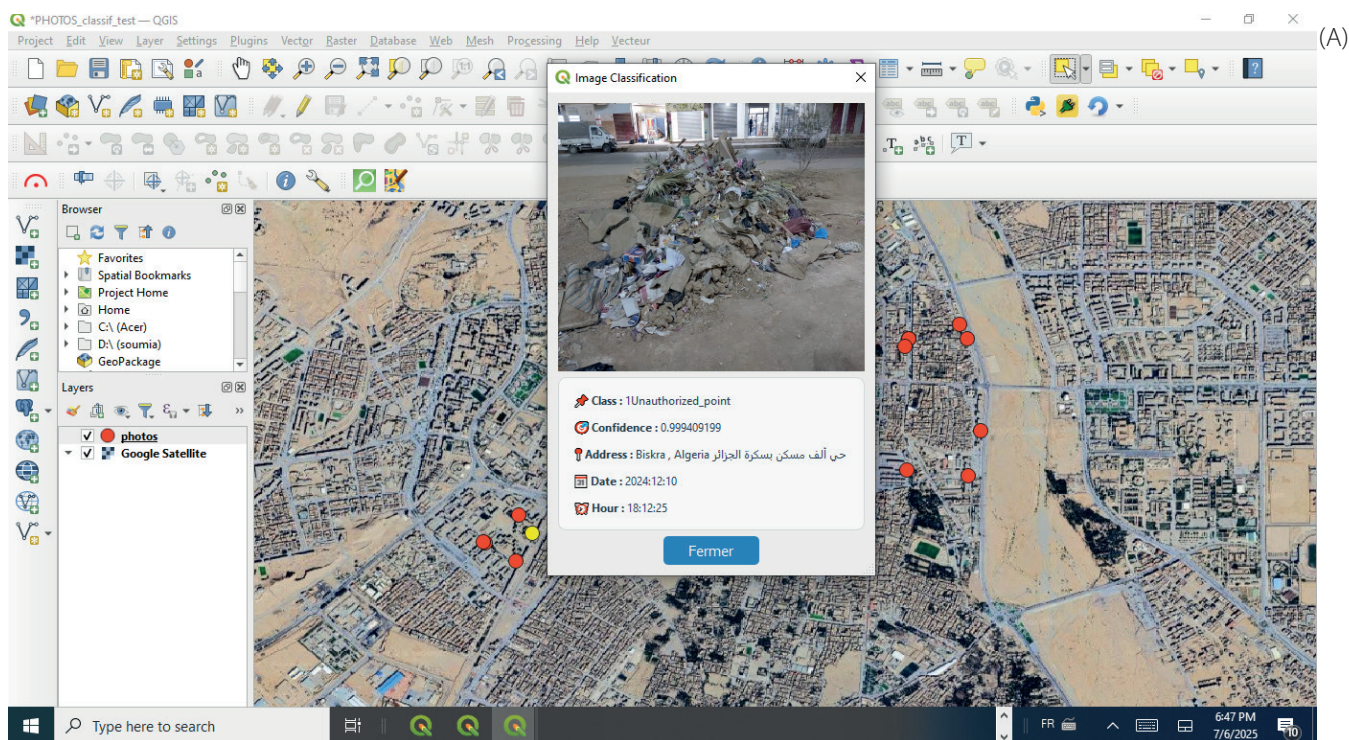


Fig. 8. Plugin image classification results with predictions
(a) illegal waste deposit in authorized point (b) illegal waste deposit in unauthorized point

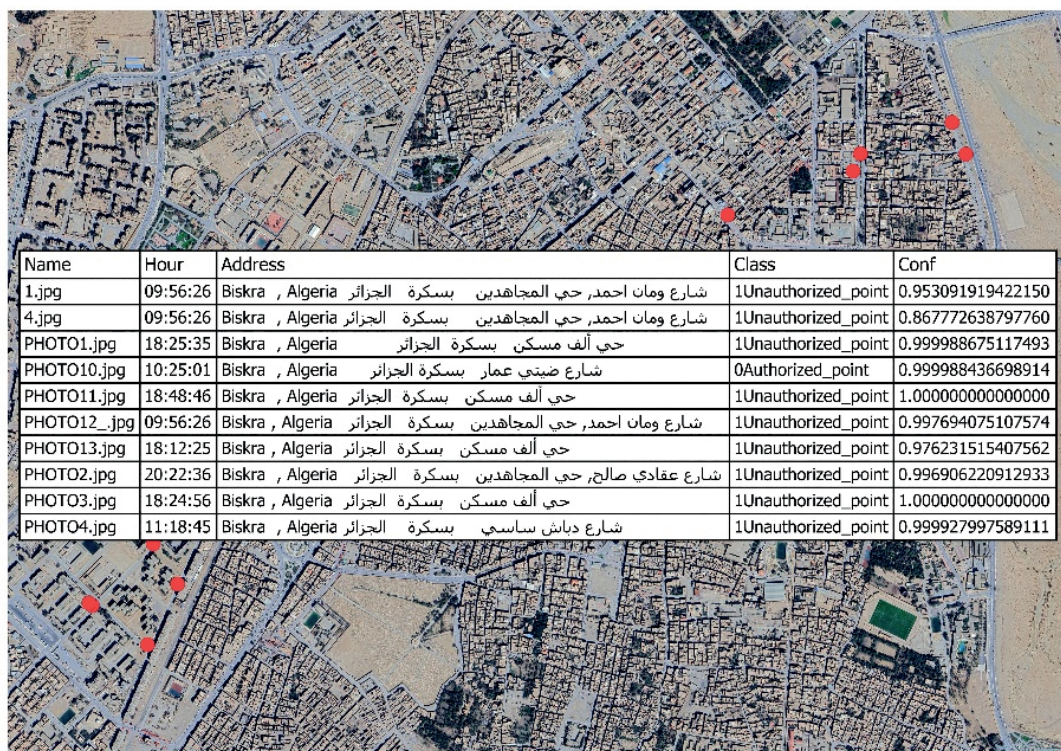


Fig. 9. Plugin output recorded in shapefile attribute table

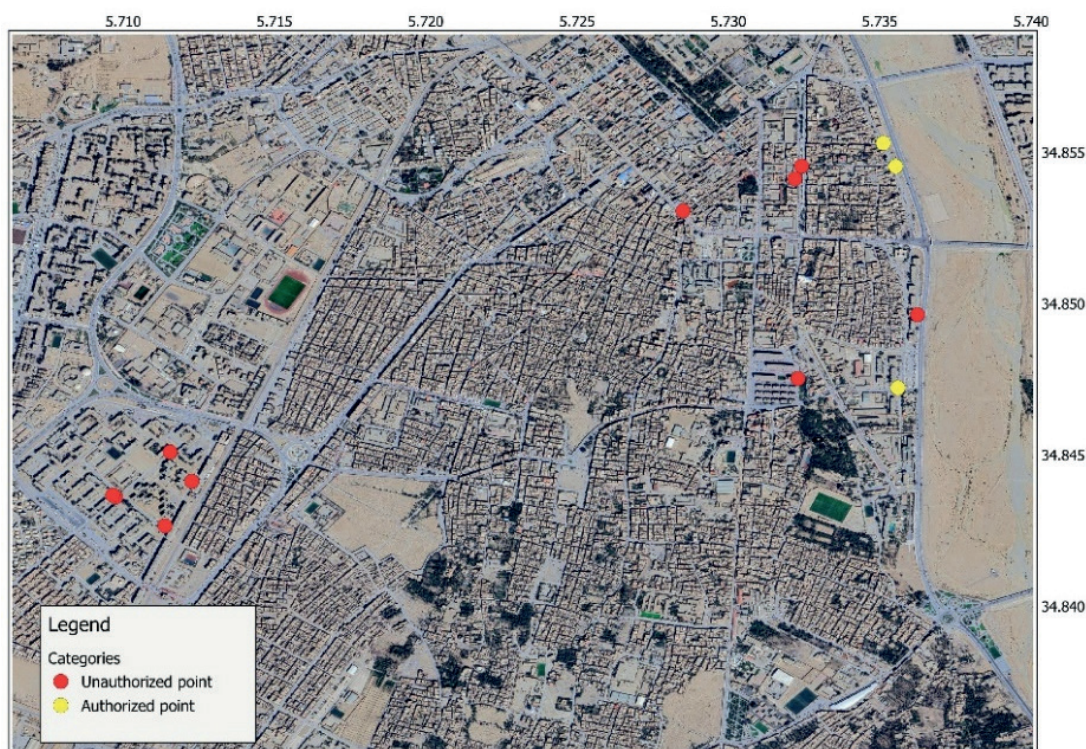


Fig. 10. Distribution of illegal waste deposits by categories in Biskra municipality, based on classified photos

management in municipalities facing illegal dumping challenges.

The main contributions of this work lie in the development of a lightweight and effective classification model that has strong transferability potential and can be implemented in other municipalities worldwide, regardless of their territorial specificities. However, its applicability depends on the

availability of georeferenced images, as the model does not support non-geolocated data. This limitation should be considered when planning deployment in municipalities where such data are inconsistently collected. It would be interesting for future research to expand the dataset to further municipalities across the world. ■

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