Deep Learning Model for Automated Detection of Solid Waste Dumping Sites using Satellite Imagery

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***Abstract*:** *The escalating generation of solid waste has become a severe issue worldwide. With limited landfill capacity, a substantial portion of waste ends up in illegal dumping sites, creating negative economic, social, and environmental impacts. Conventional field surveys to detect these sites demand significant human resources, are time-consuming, and are limited in covering inaccessible areas. To address this challenge, this study proposes using a deep learning model to map solid waste sites in Malaysia using very high-resolution Pleiades Neo satellite imagery with a 0.3-meter spatial resolution. The deep learning model employed is based on the U-Net architecture, leveraging Convolutional Neural Networks (CNN) with ResNet-34 as the backbone. The findings demonstrate the model's exceptional capability in identifying potential waste disposal sites, achieving an impressive 99% performance rate. However, certain limitations were observed in specific areas, particularly within cemeteries. The overall accuracy remained substantial when extended to other regions at 80.62%. This difference in accuracy underscores the importance of ongoing refinement and adaptation to varied environmental contexts and challenges. Nevertheless, this study highlights the potential of deep learning approaches in conjunction with satellite imagery for automatically detecting waste dumping sites, alleviating the burden of routine human visual interpretation. An exposure risk map has also generated using Kernel Density estimation method, to highlight the location of the high-risk regions. The findings reveal the high-risk regions are mostly situated in industrial areas, near rivers and cleared land area, posing potential risks to water quality. In the future, the Malaysian Space Agency (MYSA) plans to disseminate this developed deep learning model through an application system known as Sistem Pemantauan Potensi Lokasi Pelupusan Sisa (e-Sisa), facilitating accessibility for local authorities to bolster enforcement efforts. This proactive initiative aims to enhance waste management practices and mitigate the adverse impacts of illegal waste dumping on Malaysian communities and the environment.*

Keywords: deep learning, neural network, remote sensing, solid waste, u-net

Introduction

According to The World Bank (2022), annual waste generation is expected to increase from 2.24 to 3.88 billion tonnes in 2050, with rapid population growth and urbanization. In addition, more than 33% of the total solid waste generated is not handled in environmentally safer manner (Shahab, Anjum, & Umar, 2022). In Malaysia, almost 38,699 tonnes of solid waste are generated every day, at least 1.17kg per person (TheStar, 2021). However only 60% of the wastes generated are disposed into landfill, meanwhile more than half of the existing landfills has reached its maximum capacity besides the number of landfills are limited (Abd Rahman et al., 2016). Therefore, most waste ends up in illegally dumped on roadsides, abandoned land or rivers, due to weak support and enforcement. Illegal waste disposal poses a significant management issue for the government and can have severe negative impacts on the economy, society and environment. The tragedy on March 2019, has affected more than 5000 people, mainly children with respiratory symptoms such as breathing difficulties, nausea, and vomiting after breath in the poisonous gases after been exposed to different chemicals illegally dumped into the Kim Kim River, located in Pasir Gudang, Johor, Malaysia (Atlas, 2019; Ismail, Abidin, & Rasdi1, 2020). This incident became a national headline and captured the country's attention, including the Malaysian Space Agency (MYSA). Thus, a task force had been form to investigate the capability of satellite images to identify the potential of waste dumping sites to prevent its recurrence in Malaysia. The country also identified the importance of water resource planning and conservation, and the provision of adequate good quality water has been a timely requirement, especially under the United Nations Sustainable Development Goals (SDGs) 2030 Agenda.

This paper aims to utilize the Pleiades Neo satellite images with a spatial resolution of 0.3 meters for solid waste mapping through a deep learning approach. The specific objectives identified for this study are as follows:

1. To develop a deep learning model for the detection of potential locations of solid waste disposal using U-Net architecture; and
2. To map the regions with a high exposure risk to solid waste sites.

Overall, the study seeks to leverage advanced satellite imagery and deep learning techniques to address the challenges associated with solid waste management. By achieving these objectives, the research aims to contribute to more effective waste management practices and mitigate the adverse impacts of solid waste pollution on communities and the environment.

Literature Review

Conventionally, the processes for solid waste detection are costly, time-consuming and often inaccessible especially in private property areas. However, based on the findings from the literature review, solid waste dumping sites can be identify using various risk parameters such as abandoned land, unhealthy/stressed vegetation, road accessibility, soil texture and color, distance from residential areas, proximity to drainage systems, and waste deposits or heterogeneity space.

Characteristics	Justification
Abandon Land	Many abandoned warehouses and industrial sites were reconverted to illegal waste dumps and disposal centers (Andrea Biscontini, 2021) causing aesthetic pollution (Garofalo & Wobber, 2006)
Unhealthy/Stressed Vegetation	Illegal landfills have large areas of stressed vegetation (Shaker, Faisal, El-Ashmawy, & Yan, 2010). The soil contamination reflected through stressed vegetation was used as a reliable indicator for landfill identification (Dutta, Pandey, & Shukla, 2021), as an indirect spatial signature (Glanville & Chang, 2015). NIR band to exploit the presence of stressed vegetation as a clue for buried waste (Torres & Fraternali, 2021). Therefore NDVI is an important indicator near landfill and dump sites and thus for controlling LST, for e.g. LST is lower when NDVI is high and vice versa (Khalil, Mazhar, Shirazi, & Javid, 2018).
Road Accessibility	Landfills should not be located within 300m of main paved roads.(El Maguiri, Kissi, Idrissi, & Souabi, 2016). However, proximity to the roads is one of the factors influencing the geography of illegal waste disposal (Glanville & Chang, 2015).
Soil Texture and Colour	Lead-colored soil around the landfill due to loss of its physical characteristics caused by acid flowing in from the landfill (Ali Algarni & Elsadiq Ali, 1998). High concentrations of heavy metals, organic chemical and hydrocarbons in the soil negatively interfere with the radical absorption of essential nutrients, affecting physiological processes such as respiration and photosynthesis (Mancino et al., 2022); (Slonecker & Fisher, 2014) and cause stressed vegetation (Dutta et al., 2021). Therefore, clay soil is one of the best sites for landfill sites for the prevention of leachate problems (gilvaria, Bajestanib, Kashfic, & Abadd, 2019); (H.T, Tazdari, & M.C, 2013). In terms of texture, bare soils generally appeared as high reflectance and heterogeneous structure. For example when tires are sparsely scattered around property in desert areas with little vegetation, they may blend with the background soil signatures, presenting with much more texture and with much higher digital number (Quinlan & Foschi, 2012).
Isolated from Residential Areas	A good landfill site has to be located away from the residential area, more than 700 meter buffer zone (Jerie, 2017), where the gases produced are not good for the human body (Abd Rahman et al., 2016). However, the location must not be too isolated due to economic factors such as transportation costs must be consider.
Near to Drainage Systems	The location nearby to drainage system is one of the potential disposal locations that have been identified (Mohamad Zulkhaibri Mat Azmi* & Sipit, 2022).
Heterogeneous Areas	Waste appears highly heterogeneous with non-uniform texture by the human vision (Glanville & Chang, 2015; Shahab et al., 2022).

By considering these risk parameters, it becomes possible to identify potential solid waste dumping sites more efficiently and effectively, even in areas that are challenging to access or monitor. This approach can aid in the development of targeted strategies for waste management and enforcement efforts, ultimately contributing to a cleaner and healthier environment.

With increasing availability of Very High Resolution (VHR) satellite imagery captured within shorter revisit times, it has become possible to detect landfills for application include identifying waste quantities, characteristic, and distribution; waste disposal site selection and utilization; waste collection and transportation; and environmental impact on-site and off-site disposal (Garofalo & Wobber, 2006). Remote sensing for mapping illegal waste disposal sites can be based on direct spectral signatures which involve analyzing the spectral characteristics of the landscape to identify anomalies associated with waste disposal sites and indirect spatial signatures that involve identifying spatial features such as stressed vegetation that may indicate the presence of waste such as stressed vegetation associated with waste (Glanville & Chang, 2015). Usually, soil or groundwater contaminants, such as hydrocarbons, heavy metals, and organic chemicals, will have negative effects on the metabolism and growth of typical cover vegetation, such as trees or grasses(Slonecker & Fisher, 2014). Therefore, monitoring changes in vegetation health using remote sensing can provide valuable insights into the presence of waste contamination. Previous studies showed that monitoring and/or mapping illegal domestic waste disposal likely requires the interpretation of very high or extremely high spatial resolution data (Glanville & Chang, 2015). This level of detail is necessary to accurately detect and delineate small-scale waste disposal activities.

Overall, remote sensing techniques offer powerful tools for detecting and monitoring waste disposal sites, providing valuable information for effective waste management and environmental protection efforts.

In more recent years, in the Computer Vision field, Deep Learning methods have been applied to the waste classification and waste dump detection problem (Andrea Biscontini, 2021). Deep learning is a subpart of Artificial Intelligence (AI) which is concerned with emulating the learning approach that humans use to gain knowledge from data patterns (Anadkat, B V Monisha, Patnaik, R, & Syed, 2019). From previous studies, Devesa & Brust (2021) mapped illegal waste dumping sites using Sentinel- 2 satellite images with U-Net architecture based on CNN with a model performance of 0.6304. While Niu et al. (2023) integrates both CNN and Transformer model for solid waste mapping and achieves high accuracy of 90.62% using google earth images.

Indeed, there are several deep learning software options available for satellite image classification, each with its own strengths and considerations. Some of the popular choices include TensorFlow, Pytorch, Keras, Caffe and MATLAB. The selection of software depends on various factors such as specific project requirements, the user's familiarity with the tools and the availability of resources and support. Additionally, for users who prefer an integrated

GIS environment, ArcGIS Pro with the ArcGIS Image Analyst extension can be a valuable option. ArcGIS Pro provides capabilities for the entire deep learning workflow, from data preparation and model training to inference and analysis, all within the GIS environment.
Ultimately, the choice of deep learning software depends on the specific needs and preferences of the user, as well as the requirements of the project at hand. Experimenting with different tools and frameworks can help determine the most suitable option for a particular application.

Methodology

a. Study Area

The study area for this research encompasses Shah Alam, Kuala Lumpur and Gombak in the central region of the West Coast of Peninsular Malaysia as depicted in Figure 1.

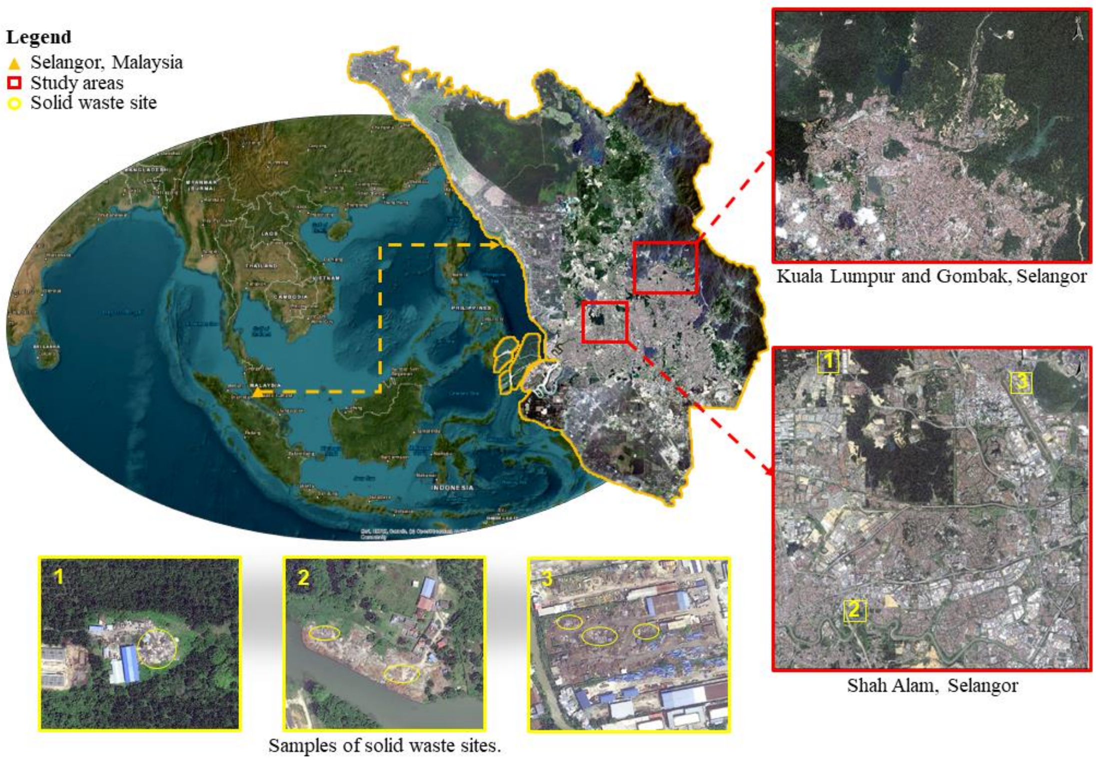


Figure 1: Study areas in Shah Alam, Kuala Lumpur and Gombak.

According to Department of Statistics Malaysia, Selangor is the most developed and progressive state in Malaysia boasting a population of 6.5 million in 2020. As Malaysia's largest economy, Selangor benefits from a well-established infrastructure and serves as a solid investment destination with the support of the state government and an excellent developed commercial ecosystem. Indirectly this would produce more waste as the result of rapid development in Selangor over years. In this study, we select Shah Alam as the training sample area whereas Gombak and Kuala Lumpur were design as a testing area for the model. By focusing on Shah Alam for training, we aim to leverage its representative characteristics to develop a robust model capable of accurately identifying solid waste areas. Subsequently, Gombak and Kuala Lumpur serve as independent testing areas to evaluate the model's performance and generalization capabilities on unseen data from similar urban environments. This approach ensures the reliability and applicability of the developed model across different regions within the study area.

b. Data Collection

For this study, we utilized very high-resolution multispectral imagery from the Pleiades Neo satellite with a resolution of 0.3 meters, covering the areas of Shah Alam, Kuala Lumpur, and Gombak, as detailed in Table 1.

Table 1: Datasets

Study Area	Image Date	Coordinates (Latitude, Longitude)		Image Size	Area (Hectares)
		Upper Left	Lower Right		
Shah Alam, Selangor	7 March 2023	3.159944, 101.448414	3.027351, 101.576735	47516 x 49114	20,985.08
Kuala Lumpur and Gombak, Selangor	7 March 2023	3.319225, 101.623339	3.181793, 101.802595	66456 x 50934	30,453.87

The remote sensing satellite data were receive from The Space Operations Complex (SOC) in Temerloh, Pahang, and were directly transfer to MYSA Headquarters in Kuala Lumpur for further processing. Solid waste including industrial waste, household waste and construction waste are typically distribute near to factories as well as residential areas. According to Niu et al. (2023), the distinctive white appearance of solid waste as well as its irregular shapes and textures , makes it relatively easier to identify them from their surroundings environment.

In this study, the high-resolution multispectral imagery serves as the primary dataset for identifying and mapping solid waste areas within the study area. Leveraging advanced remote sensing technology and image processing techniques, we aim to accurately delineate and analyze solid waste distribution patterns, aiding in effective waste management and environmental monitoring efforts.

c. Data Preparation

i. Image Processing

According to The European Space Agency (ESA), Pleaides Neo is specially designed to cater to a broad range of very-high-resolution (VHR) remote sensing applications across various domains such as for defence, security and crisis management, urban planning (mapping, civil engineering, infrastructure, mobility), maritime activites, agriculture, forestry and environmental monitoring. Pleiades Neo images are available in two primary format which area panchromatic and multispectral images. A panchromatic image with very high spatial resolution of 0.3 meters, which enable detailed observation and analysis of ground features while multispectral image provide high spectral resolution with six bands, in slightly lower spatial resolution of 1.2 meter, offer valuable information for different applications, such as land cover classification and environmental monitoring.

To enhance the visual quality and usability of the Pleiades Neo imagery, we perform the several image processing techniques that are pan-sharpening, conversion of pixel values, band combinations and image enhancement. Pan-sharpening combines the high spatial resolution of the panchromatic image with the spectral information of the multispectral image, resulting in a single image with both high spatial and spectral resolution. Converting of pixel values of the satellite imagery from 16 bit to 8 bit that facilitates easier visualization and allows for more efficient contrast enhancement techniques, thereby enhancing the interpretability of the imagery. Next, we perform band combinations to reduce six bands of the Pleaides Neo multispectral image to red, green and blue bands, creating true-colour imagery. By selecting this appropriate combination of bands, it can highlight specific features of interest while minimizing others. In order to improve the quality and visual interpretability of satellite imagery before selecting samples, we apply image enhancement techniques using Image Analysis Window in ArcMap by enhancing their contrast, brightness and stretch value. By applying these image processing techniques, we aim to optimize the quality and usability of the Pleiades Neo imagery for various applications, including the selection of samples for further analysis or modeling purposes.

ii. Labelling Methodology

For this study, 302 samples were collect through visual inspection to create accurate labels for solid waste areas, as depicted in Figure 2. These samples served as ground truth data, providing precise and reliable labels for training and evaluating the deep learning model. Visual inspection involved direct observation and identification of solid waste areas within the satellite images, ensuring the accuracy of the labelled data. By utilizing these carefully annotated samples, we aim to train a robust and effective deep learning model capable of accurately detecting solid waste areas in satellite imagery.

Figure 2: The collected samples of solid waste

iii. Dataset Specification

To convert labelled vector data into deep learning dataset using satellite images, we employed a process where the training data split into 2775 overlapping patches, each measuring 256 x 256 pixels, and containing information about solid waste areas. The specific parameter used in this process as shown in Table 2.

Table 2: Parameter of export training data for deep learning

Parameter	Value
Tile Size X	256
Tile Size Y	256
Stride X	64
Stride Y	64
Metadata Format	Classified_Tiles

The output of this process consists of two main components that are a folder containing image chips and a folder of metadata files in Classified Tiles format, which is primarily use for pixel classification task. A image chips folder are the segmented patches of satellite images, each corresponding to a portion of the original input image while in metadata files folder, each metadata file corresponds to a classified image chip, providing information about the classification of each pixel within the chip. This process allows for the creation of a deep learning dataset suitable for training models to identify solid waste areas within satellite images. Each classified image chip produced from this process serves as a training sample, facilitating the development of accurate and robust deep learning models for the task, as illustrated in Figure 3.

Figure 3: Chip set images of solid waste

iv. Training Deep Learning Model

The deep learning model proposed in our research is based on the U-Net architecture, which utilizes Convolution Neural Networks (CNN) with ResNet-34 as the backbone model, as illustrated in Figure 4. The U-Net architecture is specially design for image segmentation tasks, wherein the objective is to partitioning the image into smaller parts called segments (Ronneberger et al., 2015). This segmentation process enables the model to identify and delineate distinct regions or objects within the image accurately.

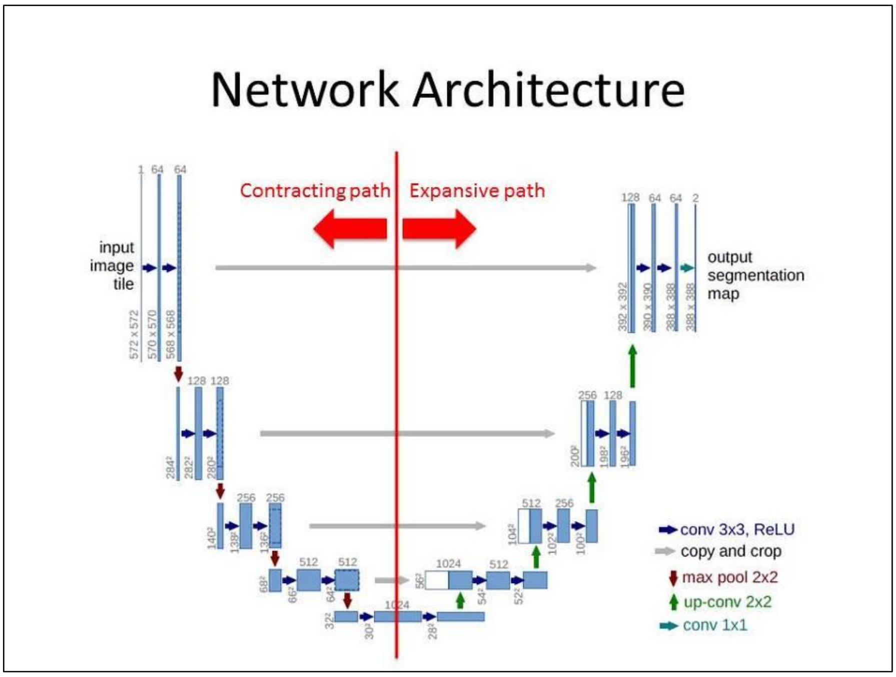


Figure 4: Overview of U-Net architecture based on CNN with ResNet-34 architecture

The training of the deep learning model involves configuring various parameters, as outlined in Table 3. These parameters govern the behaviour of the model during the training process and play a crucial role in determining its performance and convergence. By carefully selecting and tuning these parameters, we aim to optimize the model's ability to learn and generalize patterns from the training data effectively.

Table 3: Training deep learning model parameter

Parameter		**Value**
Max Epochs		40
Model Type		UNET
Batch Size		4
Model Arguments	class balancing	False
	mix-up	False
	focal loss	False
	ignore classes	#
	chip size	224
	monitor	valid_loss
Learning Rate		Optimal
Backbone Model		RESNET34
Validation %		10

In summary, the proposed deep learning model leverages the U-Net architecture with ResNet-34 as the backbone, tailored for image segmentation tasks. Through appropriate parameterization and training, we aim to develop a robust and accurate model capable of effectively partitioning images and identifying solid waste areas within them.

In order to evaluate the performance of a model, we utilize a measure known as loss. Specifically, this loss quantifies the error produced by the model. A high loss value usually means the model is producing erroneous output, whereas a low loss value indicates that there are fewer errors in the model's predictions. In addition, the loss typically calculated using a cost function.

The training loss is a crucial metric used to assess how well a deep learning model fits the training data while validation loss is a metric used to assess the model's performance on the validation set which the model has not seen during training.

In this research, both the training and validation loss exhibit a decreasing trend and stabilize over time as shown in Figure 5. This shows the model has achieved an optimal fit, indicating that the model neither overfit nor underfit. Overall, this observation signifies that the model's performance is satisfactory and it is well suited for the task.

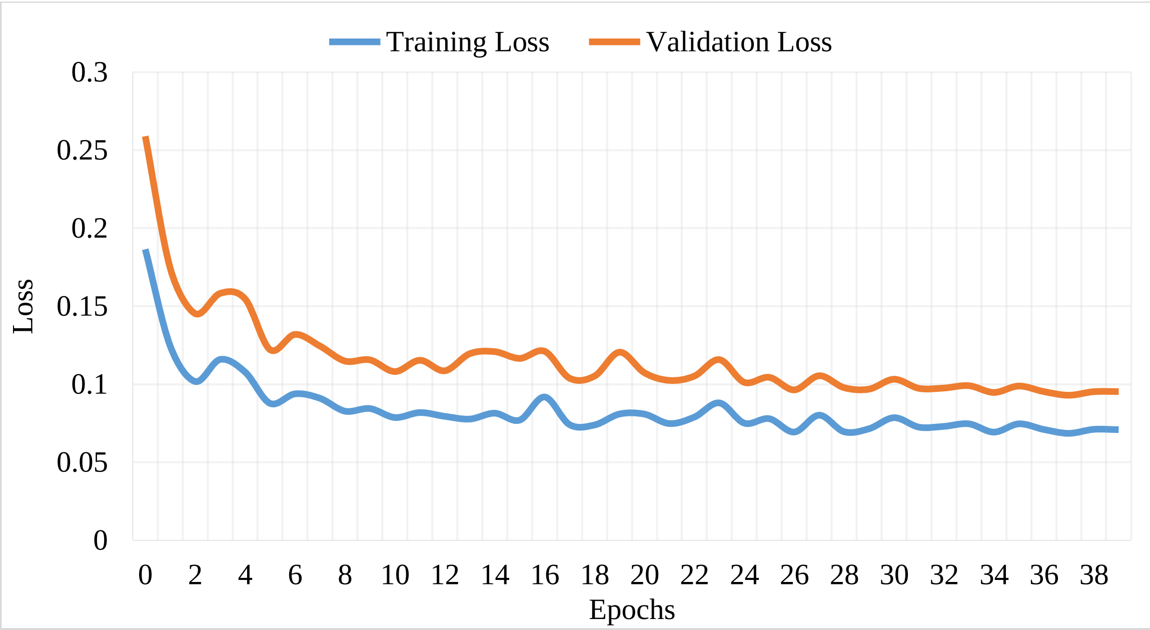


Figure 5: Training and validation loss graph

v. Classify Pixels using Deep Learning Model

The trained deep learning model executed on an input raster covering the Kuala Lumpur and Gombak, Selangor areas to generate a classified raster, with each valid pixel assigned a label corresponding to the solid waste class. The classified pixels tools parameter shown in Table 4. This process allows for the identification and mapping of areas containing solid waste within the specified regions.

Table 4: Classify pixel parameter

<table>
<tr><th colspan="2">Parameter</th><th>Value</th></tr>
<tr><td colspan="2">Model definition</td><td>Train model .dlpk</td></tr>
<tr><td rowspan="5">Arguments</td><td>padding</td><td>56</td></tr>
<tr><td>Batch size</td><td>4</td></tr>
<tr><td>Predict background</td><td>True</td></tr>
<tr><td>Test time augmentation</td><td>False</td></tr>
<tr><td>Tile size</td><td>224</td></tr>
<tr><td colspan="2">Processing Mode</td><td>Process as mosaicked image</td></tr>
</table>

The resulting classified raster provides valuable information for decision-making and resource allocation in waste management efforts within Kuala Lumpur and Gombak, Selangor.

vi. Accuracy Assessment

Using both qualitative and quantitative methods is essential to justify the performance of the U-Net in solid waste mapping. Accuracy assessment points was evaluate through visual inspection using Pleiades Neo images and field verification. This qualitative approach allows for the direct observation of the model's output against ground truth data, enabling the identification of any discrepancies or misclassifications.

Additionally, we conducted a quantitative evaluation by generating a confusion matrix and calculating overall accuracy for systematically check the classification errors. The confusion matrix provides a breakdown of the model's predictions compared to the ground truth across different classes, allowing for the calculation of metrics such as accuracy, precision, recall, and F1-score.

By combining both qualitative and quantitative methods, a comprehensive assessment of the U-Net model's performance in solid waste mapping can be achieved. This approach helps to ensure the reliability and validity of the results, guiding decision-making processes regarding the deployment or further refinement of the model.

Results and Discussion

a. Deep Learning Model Performance

Evaluating the performance of a deep learning model for image classification is crucial for making informed decisions about its deployment or identifying areas for further improvements using common metrics of accuracy, precision, recall and F1-score that generated in ArcGIS Pro processing result as illustrated in Figure 6 and Figure 7. By analyzing these metrics generated in Figure 7, we can gain insights into the model's performance. High accuracy, precision, recall, and F1-score indicate a well-performing model with good predictive capability. Evaluating these metrics helps in making informed decisions about deploying the model or refining it further to enhance its performance.

epoch	training loss	validation loss	accuracy	Dice
0	0.18649058043956757	0.07244016975164413	0.9831432700157166	0.05314129963517189
1	0.12447816133499146	0.04989007115364075	0.9846727848052979	0.1059970036149025
2	0.10176011174917221	0.04350045323371887	0.9849758744239807	0.20079518854618073
3	0.11586380004882812	0.04234811291098595	0.985554039478302	0.06291300803422928
4	0.10780447721481323	0.04687678813934326	0.9850688576698303	0.26322001218795776
5	0.08774566650390625	0.0344083271920681	0.986930787563324	0.21052424609661102
6	0.09383641183376312	0.038082681596279144	0.9863927960395813	0.30611780285835266
7	0.0909910500049591	0.03346140682697296	0.9875298738479614	0.21260587871074677
8	0.08274262398481369	0.032117582857608795	0.9878180623054504	0.2721317708492279
9	0.08439071476459503	0.031202230602502823	0.9881004691123962	0.25016161799430847
10	0.07868249714374542	0.029437052085995674	0.9880378842353821	0.329064279794693
11	0.08183260262012482	0.03350966051220894	0.987882673740387	0.3570863604545593
12	0.0794215202331543	0.02920479141175747	0.9889975786209106	0.32585519552230835
13	0.07767044007778168	0.04187764972448349	0.9859676361083984	0.41854915022850037
14	0.08143260329961777	0.039446551352739334	0.9872350692749023	0.4089355170726776
15	0.0769980400800705	0.03956082835793495	0.9862547516822815	0.44282442331314087
16	0.0918150320649147	0.029283640906214714	0.9879776239395142	0.16107657551765442
17	0.07409576326608658	0.02976093254983425	0.987952709197998	0.42613887786865234
18	0.07389930635690689	0.03130460903048515	0.9879273772239685	0.4575040340423584
19	0.08090867847204208	0.039609216153621674	0.9880244135856628	0.42543256282806396
20	0.08083520829677582	0.02650773897767067	0.9895303845405579	0.3171592354774475
21	0.07479135692119598	0.027648689225316048	0.9891518354415894	0.4207685887813568
22	0.07894305139780045	0.026264451444149017	0.98972088098526	0.3055988550186157
23	0.08802620321512222	0.027727684006094933	0.9893372654914856	0.38172125816345215
24	0.0750589519739151	0.026150565594434738	0.9893935322761536	0.41336575150489807
25	0.07789242267608643	0.026518279686570168	0.9897301197052002	0.3894649147987366
26	0.06936025619506836	0.027015676721930504	0.9891783595085144	0.437017023563385
27	0.08016005903482437	0.02527076192200184	0.9900172352790833	0.3647089898586273
28	0.06954433768987656	0.02825113944709301	0.9890387654304504	0.4281854033470154
29	0.0714821070432663	0.025372346863150597	0.989722728729248	0.4109700620174408
30	0.07854928821325302	0.024636302143335342	0.9900537133216858	0.3825480341911316
31	0.07248861342668533	0.024854609742760658	0.990210235118866	0.37062618136405945
32	0.07298969477415085	0.024559032171964645	0.9900950193405151	0.4244540333747864
33	0.07461000233888626	0.024447232484817505	0.9901384115219116	0.387856125831604
34	0.06930574774742126	0.02542819455265999	0.9897416830062866	0.4532972276210785
35	0.07460850477218628	0.02422523684799671	0.9903284907341003	0.4100799560546875
36	0.07099995017051697	0.024266822263598442	0.9902197122573853	0.3976060748100281
37	0.06852775812149048	0.02442575991153717	0.9901907444000244	0.4116169214248657
38	0.07109063118696213	0.024131949990987778	0.990271806716919	0.39003127813339233
39	0.07087703794240952	0.02442026138305664	0.9902822971343994	0.41814330220222473

{'accuracy': '9.9027e-01'}

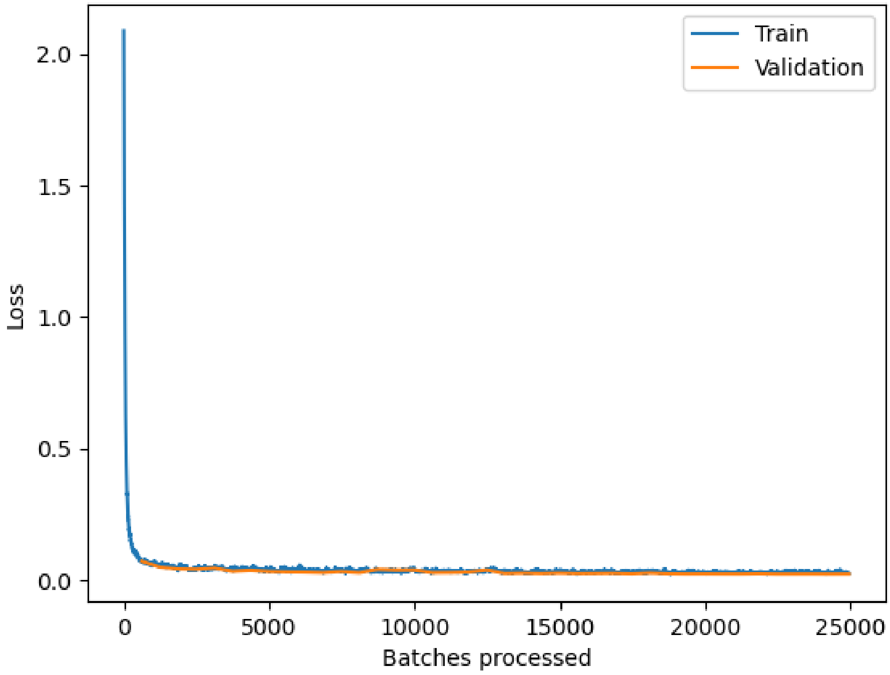
Figure 6: Model performance accuracy

UnetClassifier

Backbone: resnet34

Learning Rate: slice('3.0200e-06', '3.0200e-05', None)

Training and Validation loss



Analysis of the model

Per class metrics:

	NoData	1
precision	0.993367	0.728855
recall	0.996778	0.565434
f1	0.995070	0.636827

Figure 7: Analysis of the model

From the result obtained for Shah Alam, the model achieved satisfactory performance with an accuracy of 99.03%. In most deep learning frameworks, the train loss and validation loss serve as crucial indicators of model performing during training. The train loss reflects the error or disparity between the predicted output of the model and the actual target output, calculated on the training dataset. A decreasing train loss shows that the model is learning and enhancing its performance on the training data. On the other hand, validation loss assesses the model's performance on a separate dataset called the validation dataset, which the model has not encountered during training. It helps to measure how well the model generalizes to new, unseen data. A decreasing validation loss indicates that the model not only learns from the training data but also generalizes well to new data.

Interpreting these losses involves monitoring their trends during training. Since both train and validation losses are steadily decreasing, it indicates that the model is effectively learning without overfitting. In summary, the goal is to minimize both train and validation losses simultaneously to ensure effective learning effectively and good generalization to new data.

Subsequently, the model was deploy to detect solid waste areas in Kuala Lumpur and Gombak, Selangor. Figure 8 illustrates prediction errors, where other land covers mostly cemeteries are misclassify as solid waste sites. To address this classification error, we utilized supporting data such as cemetery area borders from OpenStreet Map and MYSA database.

Figure 8: Several of classification errors

Figure 9 below shows output map of 609 solid waste location after the removal of classification errors.

Figure 9: Mapping results of solid waste sites in Kuala Lumpur and Gombak, Selangor

b. Accuracy Assessment Results

Visual identification is utilize to evaluate the performance of solid waste mapping qualitatively. ArcGIS Pro offers tools to generate confusion matrices, which are valuable for assessing classification models. A confusion matrix displays the counts of true positive, true negative, false positive, and false negative predictions, allowing to compute metrics such as accuracy, precision, recall, and F1-score. Confusion matrix shows the distribution of predictions and actual labels for each class, and it can help identify the sources of errors and confusion.

The tool computes the user's accuracy and producer's accuracy for each class, along with an overall kappa index of agreement. These accuracy rates range from 0 to 1 where 1 denotes 100 percent accuracy. User's accuracy highlights false positives where pixels incorrectly classified as a known class when they should have classified as something else. This also referred to as errors of commission, or type 1 error with the data compute this error rate read from the rows of the table. Producer's accuracy addresses false negatives in which pixels of a known class classified as something other than that class. This known as errors of omission, or type 2 error with the data to compute this error rate read in the columns of the table. Kappa index of agreement offers an overall assessment of the classification accuracy. Table 5 depicts the confusion matrix resulting in an overall accuracy of 80.62% for 609 detected locations, which is slightly lower than model performance accuracy. This difference in accuracy underscores the importance of ongoing refinement and adaptation to address varied environmental contexts and challenges. Future iterations of the model will aim to mitigate these limitations and enhance its effectiveness across diverse landscapes, ensuring more comprehensive waste management solutions.

Table 5: Confusion matrix

OBJECTID *	ClassValue	C_0	C_1	Total	U_Accuracy	Kappa
1	C_0	0	0	0	0	0
2	C_1	118	491	609	0.80624	0
3	Total	118	491	609	0	0
4	P_Accuracy	0	1	0	0.80624	0
5	Kappa	0	0	0	0	0

c. Exposure Risk Analysis of Solid Waste

Based on the results of solid waste classification, an exposure risk map is generated using Kernel Density estimation method. This approach helps to identify regions with high level of exposure to solid waste sites.

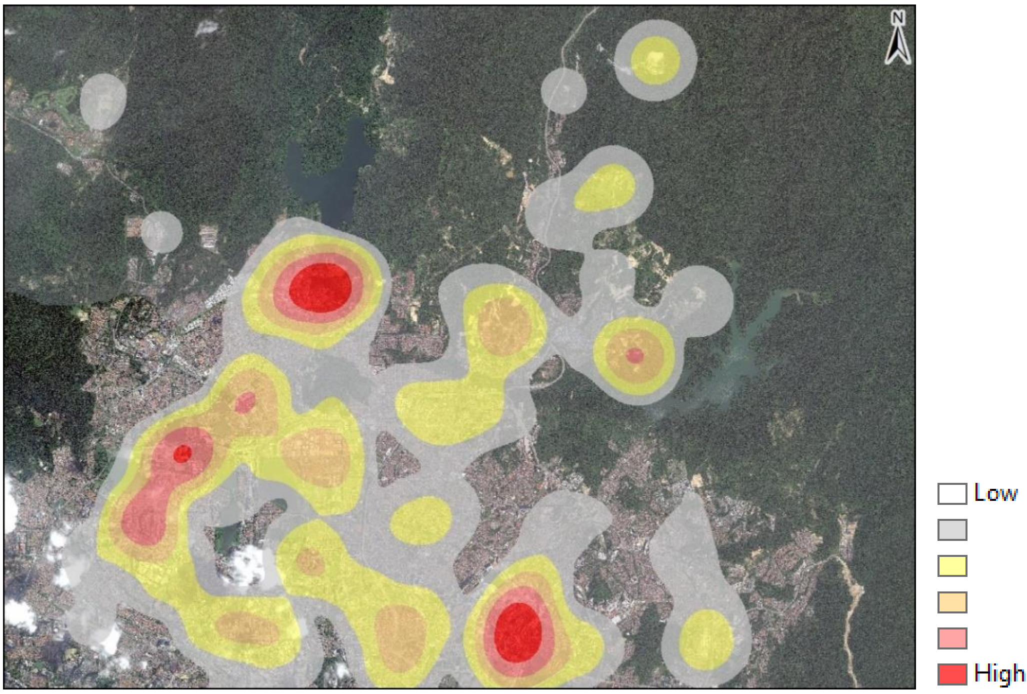


Figure 10: Exposure risk map

The resulting raster displays density values across the study area, with deeper colours indicating areas of higher risk. Each cell in the raster represents the estimated density of solid waste area within a defined neighbourhood. The colour ramp applied to the raster helps in visualizing the density values. Warmer colours signify areas of higher density, while cooler colours or absence of colour denotes areas of lower density. High-density regions on the raster indicate hotspots or concentrations of the solid waste. Conversely, low-density areas represent regions with fewer occurrences. These patterns serve to identify spatial trends, clusters, or areas of interest for further analysis or intervention.

The high risk regions are prodominantly situated in industrial areas, near rivers and cleared land area, posing potential risks to water quality. Figure 11 shows some areas within these high risk regions.

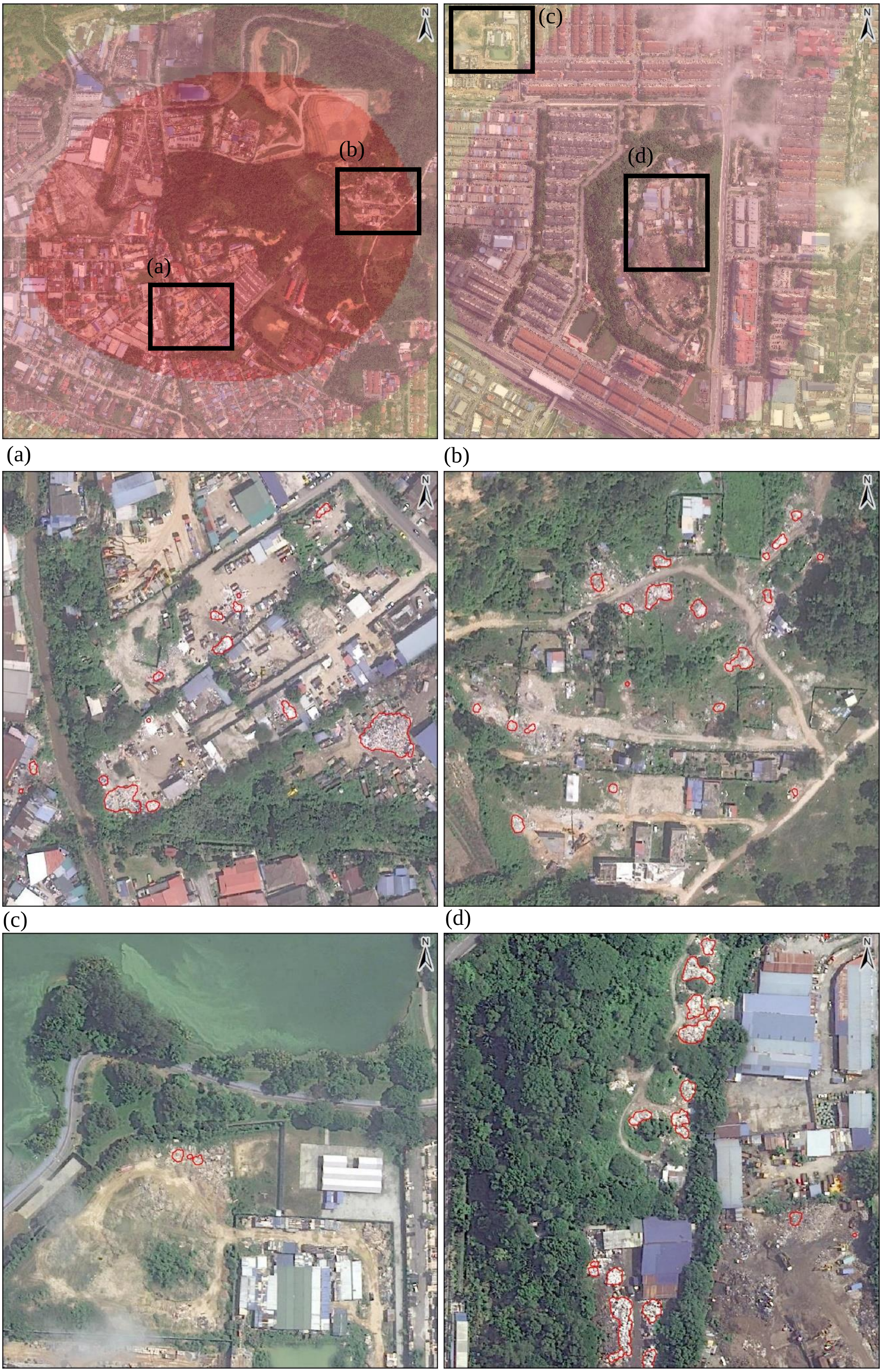


Figure 11: Some areas within high-risk regions

Conclusion and Recommendation

The primary focus of this study was the automatically mapping of solid waste sites using Convolutional Neural Networks (CNN) and U-Net, leveraging the ResNet34 backbone model with Pleiades Neo satellite imagery. The results indicate that the developed model achieves high accuracy for solid waste mapping in Malaysia. We obtained satisfactory outcomes after field verification and tested the model across different areas.

It is worth noting, however, that prediction error primarily occurred in distinguishing between solid waste sites and cemetery areas. An exposure risk map has also generated to highlight the locations of the high-risk regions.

To improve the model performance, it could be beneficial to tailor it to detect specific types of waste rather than detect waste in general. Furthermore, integrating data on reserved areas such as forests, rivers and roads could aid in detecting illegal dumping sites and curbing solid waste pollution.

In terms of future work, MYSA intends to disseminate this deep learning model through an application system called *Sistem Pemantauan Potensi Lokasi Pelupusan Sisa* (*e-Sisa*), accessible to local authorities for enforcement purposes.

Acknowledgement

The authors acknowledge Mr. Mohd Hakimi Abdul Rahman for his significant contribution to data preparation, which played a crucial role in the success of this research. We also express our heartfelt thanks to the MYSA Management for their unwavering support, providing not only resources but also greatly facilitated throughout our research journey. Their commitment and encouragement during the process were invaluable and deeply appreciated.

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