# Artificial Intelligence Techniques for Extracting Impervious Surface Areas from Satellite Imagery

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**Key words**: Impervious Surfaces, Remote Sensing, Satellite Imagery, Artificial Intelligence, Caribbean Small Island Developing States.

**SUMMARY**

Small Island Developing States (SIDS) of the Caribbean are distressed by urbanization issues. Their small size, low elevation, and exposure to meteorological disasters exacerbate their socio-economic vulnerabilities. Moreover, they lack current and accurate geospatial datasets that are essential for planning a sustainable development. Information on impervious surface is a key quantifier of urbanization. These surfaces prevent water infiltration into the soil and result in several environmental issues and are considered a major trigger for natural disasters and climate change. In addition, they disturb the local ecological and economic systems by removing the natural land cover.

Artificial Intelligence (AI) techniques are increasingly being applied to effectively extract necessary spatial information from remotely sensed imagery with major breakthroughs being made through implementing Machine Learning and Deep Learning algorithms. Consequently, this phase of the research reviews the technical aspects and architectures for leading AI image processing techniques for extracting impervious surface areas from satellite imagery. Additionally, it compares AI-based methods against conventional methods to determine accuracies while considering cost, time, and feasibility.

The study’s hands-on experience in testing and executing the AI techniques displays preliminary results, highlights the involved challenges, and means to address them. The findings confirm that deep learning techniques are a promising area for unlocking unlimited capabilities to develop solutions for extracting impervious surface areas from satellite images. The deep learning U-Net architecture exhibited great potential for extracting impervious surface areas. This paper highlights the technical architectures of AI methods for extracting impervious surface and advises the most optimal technique to consider based on user applications. Ultimately, a methodological framework is proposed based on grasp of literature and early insights. This approach utilizes the available AI geospatial tools and freely available satellite imagery data to provide information critical for making informed decisions towards mitigating urbanization issues and tackling climate change impacts in the Caribbean SIDS.

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## 1. INTRODUCTION

Impervious surfaces are artificial hard covered areas that do not permit water to seep into the ground and, thus, restricting natural storm water run-offs. Most commonly recognized impervious surfaces features are pavements, buildings, roads, and other surface covers coated with concrete, metal, plastic, and glass. All these elements fall under the 'urban/built-up' land cover type (Yin, Dong, et al. 2021).

Construction and development of impervious surfaces usually includes removing the Earth's natural covers that disturbs the local ecological functions. This in turn cause deforestation, landslides, flooding, and water pollution. Besides being triggers of climate change, these adverse urban effects results in strains towards the environment and contributes to socio-economic detriment (Yin, Dong, et al. 2021). All of this negatively impacts the sustainability of a nation.

Therefore, being an indicator of urbanization and its environmental impacts, impervious surface must be constantly monitored. Information on impervious surfaces should be readily available for proper quantification, urban planning, and environmental management to ensure sustainability (Omurakunova, et al. 2020). Consequently, the focus of this study is to explore different techniques to extract impervious surface from satellite imagery. Special consideration will be given to the feasibility of implementing such techniques within the Caribbean small island developing states.

### 1.1 Background and Motivation

Small Island Developing States (SIDS) are recognized distinctively as a group of islands characterized by their small size, remoteness, narrow resource base, and exposure to global environmental challenges. Caribbean SIDS are low-lying coastal community located in a tropical location. While enduring similar challenges as the rest of SIDS, Caribbean SIDS face additional tropical challenges and limitations (Al-Tahir, Arthur and Davis 2011) such as rising temperature, sea level rise, flooding, drought, and hurricanes. Additional issues arise from the spread of urbanization that include unplanned development of urban settlements and poor building infrastructures. Finally, they lack the necessary resources for proper urban and sustainable planning. Specifically, they endure poverty and scarcity of geospatial resources and data (Baban, Ramlal and Al-Tahir 2004), limited experienced personnel with adequate training and knowledge, and outdated data in some cases.

Quantitatively capturing impervious surfaces has been a practice for decades using remote sensing technologies (Yin, Dong, et al. 2021). This stems from its reliable standing in Earth Observation applications and effectiveness in mapping land use land cover as well as mapping urban growth. When compared to ground surveying techniques, remote sensing has the advantage of saving operational cost and time, as well as eliminating accessibility problems (Xu, Mountrakis and Quackenbush 2016).

In the literature, the two medium resolution satellite images most commonly used to extract impervious surfaces areas are those of Landsat and Sentinel-2 due to their free availability and accessibility. Image processing techniques must be employed to extract the impervious surface areas. Immense number of literature and research documented the use of pixel-based classification, object-based approaches such as segmentation, urban spectral indices, and Artificial Intelligence (AI) based techniques (Wang, et al. 2021). Over the years, researchers in the remote sensing community resorted to AI methods considering that this fairly young area has endless possibilities. When compared to the other techniques, this technology has exhibited success in performing many implementations and adaptations. As one of such applications, AI-based methods have been applied to extract impervious surfaces in satellite imagery.

### 1.2 Research Objective and Justification

The previous discussion puts forward that urbanization problems hinder sustainability and that there is great need for a solution that provides information on impervious surface areas in an affordable and accessible manner. Also, considering the context-specific and region-specific needs formerly identified, this makes extracting impervious surface from satellite imagery more unique and desirous.

This paper is geared toward a critical review and analysis specifically on assessing AI image processing techniques for extracting impervious surface areas from satellite imagery. Specifically, this study answers the question: “what AI technique(s) can be uniquely chosen, adopted, and implemented for extracting impervious surface from satellite imagery to help solve the urbanization challenges within the Caribbean small island developing states?”

Beneficial to many people and organizations, assessing AI image processing techniques is a critical stage to determine the most optimal solution for extracting impervious surface areas based on fitness of purpose application. When adopted, this solution will provide accessibility to a wider population to provide impervious surface information to planners and environmental organizations to manage the environment and aid in addressing local challenges. Furthermore, this will provide useful information to model urban expansion and monitor natural resources for proper land utilization.

## 2. REVIEW OF AI-BASED EXTRACTION OF IMPERVIOUS SURFACES

### 2.1 Artificial Intelligence, Machine Learning, and Deep Learning

AI is demonstrated through machines in contrast to natural human intelligence. Models were designed to make predictions and regressions for decision-making and problem solving

(Janiesch, Zschech and Heinrich 2021). Generally, AI techniques fall into two distinct categories of machine learning (ML) and deep learning (DL) (Woschank, Rauch and Zsifkovits 2020). Both ML and DL are major AI breakthroughs today.

Machine Learning (ML) is a subset of AI that uses algorithms to program the system. The system learns from structured training data fed into it and makes a prediction based on the data. It can be either a supervised or unsupervised learning process that involves some human intervention but not explicit programming (Janiesch, Zschech and Heinrich 2021). It is used mostly in classification, clustering, and prediction for various image-based applications (Ma, Liu, et al. 2019).

Deep Learning (DL) is a subset of ML at a very advanced state. This uses Artificial Neural Network (ANN) as computing systems designed and layered with nodes that contains inputs, weights, and biases similar to the way the human brain works. Each layer performs complex operations like representation and abstraction, and it is a learning-representation model. It requires large datasets, thorough training, and powerful computing systems (Woschank, Rauch and Zsifkovits 2020). It is mostly used in application like object detection, classification, segmentation, and extraction.

When compared to DL, ML techniques have the advantages of being less complex and demand less training and time than DL models. However, they suffer from certain disadvantages such as that models can do classification but not feature extraction, often require human intervention, and cannot handle very large datasets compared to DL (Janiesch, Zschech and Heinrich 2021).

On the other hand, the advantages of Deep Learning (DL) techniques are that they are smarter than ML (Ma, Liu, et al. 2019), more robust (Wang and Li 2019), can process large datasets (Zhang, Zhou and Luo 2021), and have the ability to solve complex problems and discover hidden patterns in data for feature extraction and classification. Further, the DL models learn representations from the underlying data in the model in multiple level of abstraction to become more and more accurate (Parekh, Poortinga, et al. 2021) with minimal human intervention.

The major disadvantages of DL are that they require heavy computing hardware and software (Cresson 2020), imbalanced reference data can be conflicting, very tedious and requires substantial human effort to design and train program model (Xu, Mountrakis and Quackenbush 2016).

Classification ML techniques were used to extract impervious surface areas in several studies, most common were the maximum likelihood classifier, random forest, and support vector machines (Parekh, Poortinga, et al. 2021). From literature, the most relevant DL techniques used to extract impervious surface areas were convolutional neural networks, fully convolutional network, and U-Net. The following sections provide some details on these techniques.

## 2.2 Machine Learning Image Processing Techniques

### 2.2.1 Maximum Likelihood Classifier (MLC)

This supervised pixel-based classifier is one of the most used classifiers in remote sensing. This approach uses probability density function based on the Bayesian rule where pixels are assigned to a designated class with the highest probability occurring. The 'likelihood' is established from the training classes and treated as an optimization search through the image where each pixel is assessed for the best agreement of the appropriate belonging class (Huang, Yu and Feng 2019).

### 2.2.2 Random Forest (RF)

This non-parametric technique is used for classification and regression to predict which classes pixels belong to. The approach uses combined learning models to create a 'tree-like' structure known as decision trees forming the 'forest'. The decision trees are grouped, and multiple classification specific criteria are used to compare the trees. Trees send subsets of the original data known as branches and a random selection is done based on a vote to form the decision based on the average of their outputs. Prediction is done based on the majority voting of which class a feature belongs to (Guo, et al. 2020).

### 2.2.3 Support Vector Machines (SVM)

This non-parametric supervised learning model uses learning algorithms for data analysis and classification, and in some cases regression and outlier detection within the dataset. The pixels for each object to be classified are represented in a scatterplot as points in an n-dimensional space having coordinates for these features. Using the training set to create a best line known as a hyperplane between pixels it uses this as a separation boundary which represents the limits of different classes, respectively for each category. Categories are user-specified, and this is needed to realize the hyperplane. Margins are created using the points of maximum magnitude, where these marginal points are known as the supporting vectors (Faisal, et al. 2021).

## 2.3 Deep Learning Image Processing Techniques

### 2.3.1 Convolutional Neural Network (CNN)

This is an Artificial Neural Network (ANN) that is used in the analysis and classification problems and imitate the way humans think. Its architecture consists of hidden layers referred to as convolutional layers. Each convolutional layer has filters that operate as pattern detectors, based on the specified purpose (Huang, Yu and Feng 2019). There are three sets of layers, first being the convolutional layers which is responsible to convolve features in the imagery, the second set of layers in the middle are known as the pooling layer which reduces dimension of the feature map, and finally the third set of layers are where more sophisticated pattern recognition are performed whereby providing an output classification (Ma, Liu, et al. 2019). The model possesses the ability to learn filters/characteristics of imagery. It is designed for feature extraction in imagery data that promotes recognition, object detection, image enhancement and restoration, and semantic segmentation (Heipke and Rottensteiner 2020).

2.3.2 Fully Convolutional Network (FCN)

The main idea behind this technique is its design, where it's an end-to-end type of learning of the un-sampling algorithm, pixel-by-pixel manner. This is established through an encoder-decoder assembly which firstly down-samples the encoder's activation size and then un-samples it again (Yu, Yang and Chen 2018). Being fully convolutional, it allows images of random sizes to be used as input since there is no fully connected layer at the end to hinder activation. This is an upgrade to the CNN for segmentation uses where there are no fully connected layer, but replaced with convolutional layers (Yu, Yang and Chen 2018).

2.3.3 U-Net

This is based on the FCN, but primarily modified to perform better than FCN in image segmentation (Parekh, Poortinga, et al. 2021). This has a 'U-shaped' architecture hence the name and is designed to be very expansive with many layers and less symmetric to commissioning parts than other CNNs. The first half of the 'U' is known as the encoder, whereas the other half is the decoder (Parekh, Poortinga, et al. 2021). This modified FCN is designed to have extended architecture to work with fewer training samples and to generate segmentation more precisely and only valid parts of the convolution are used. The usual pooling operations in a CNN are replaced by un-sampling operations for the improvement of output resolution through its large number of feature channels in generating context information to higher resolution layers (Cresson 2020). The successive convolutional layers are used to learn to determine a more precise output with new data. This uses bounding box strategies to select boundaries in images and they are localized whereby preserving good resolution throughout.

## 3. AI TECHNIQUES IN THE EXTRACTION OF IMPERVIOUS SURFACES

The techniques reviewed have been applied in many studies, research, and even have been developed in industries and used by practitioners. Every day, state-of-the-art workflows and framework are being developed to extract impervious surface areas. For example, applied in most recent studies are extraction of impervious surface in China using Landsat and Sentinel imagery employing SVM, RF, and MLC (Feng and Fan 2021), achieving great accuracies for overall, user, and producer accuracies, with majority ranging between 75%-93%. SVM were used to classify land covers to highlight impervious surface. SVM was also used to extract impervious surface and compared against RF in Hong Kong (Lin, et al. 2019).

Machine learning-based supervised classification using SVM has been used to extract impervious surface areas in India for the national capital territory of Delhi using Sentinel-2 imagery. Other ML approaches to extract building footprints has been used in Makkah, Saudi Arabia from high-resolution imagery (Faisal, et al. 2021). Papers did reviews on DL to extract urban impervious surface features from remote sensing imagery, whereas others just reviewed general methods to extract impervious surface areas from satellite imagery specifically. Other studies like Feng and Fan 2021 systematically compared 12 methods to extract impervious surface for 4 types of spatial resolution images and documented their outcomes. Additionally, to extract impervious surface, applied are decision tree models, segmentation techniques (Wang, et al. 2021).

ML is used and was once popular such as RF and SVM, however researchers and practitioners has been switching to DL methods to overcome feature extraction issues. DL can facilitate large scale workflows, hence DL solutions will be promising for these 'bigdata' workflows, and it may be worthwhile in the long run. DL like CNN,VGG19, DeepLabV3+, and UNET architectures for automatic detection of impervious surface (Parekh, Poortinga, et al. 2021), while some used DL techniques to detect just rooftops, but others integrated DL ANN with LSMA to estimate and map impervious surface. Other researchers kept it simple and used SVM classification to extract impervious surface (Gao and Liu 2014).

In industry, Environmental Systems Research Institute, Inc. (ESRI) provides users with GIS tools within their software to perform many geospatial operations including extracting impervious surface in both ML and DL workflows and models through their ArcGIS suite (ESRI 2021). Other software providers are following along such as Radiant Solutions, Trimble's eCognition and Autodesk's AutoCAD.

ESRI developed DL pre-trained models to extract human settlements also knows as built-up areas or impervious surface areas for both Sentinel-2 and Landsat 8 imageries, however they were developed for certain countries like the US and Europe for those particular landscape and urban development patterns, using the UNET architecture achieving accuracies of 91.6% and 94.1% respectively (ESRI 2021).

## 4. METHODOLOGY

Based on this review, a general methodological approach was designed to further apply the chosen AI technique to implement impervious surface extraction using satellite imagery (Figure 1). This six-stage workflow can be used to develop a unique global or localized framework based on the objectives of the study. Stage 1 signifies the general data collection or acquisition of satellite imagery (or aerial imagery) of choice based on the study area. Stage 2 deals with the model design and development using the chosen AI image processing technique, whereas stage 3 is the execution of the model that encompasses the processing being executed, and stage 4 being the extracted impervious surface output. Next, stage 5 deals with testing the model's results through accuracy assessments and validating its performance. Finally, stage 6 analyses the statistics and test results to determine the main findings and concludes the contribution of the model as well as relevant application of use.

In relation to the choice of AI based image processing technique, this study found from the reviewed literature that the most common techniques used to extract impervious areas were classification-based. This is specially the case when using imagery from medium resolution sensors like Landsat 8 and Sentinel-2. Moreover, the most popular techniques with acceptable success factors were MLC, RF, and SVM for machine learning, and the U-Net architecture as the deep learning technique.

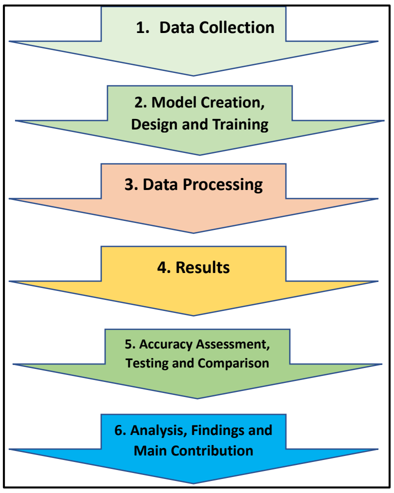



**Figure 1. Proposed general methodology.**

## 4.1 Data Collection and Study Area

A suitable study area in St. Augustine, Trinidad was chosen that comprises of mass urban features around a university campus (Figure 2). Freely available satellite imagery was sourced from the United States Geological Survey (USGS) website and the Copernicus Open Access Hub for Landsat 8 and Sentinel-2, respectively. Fortunately, imagery with low cloud cover and the same acquisition date of 18th January 2022 was retrieved.


**Figure 2. The 3km x 3km study area**

## 4.2 Model Creation, Design, and Training

Existing tools with built-in AI-based algorithms within the ESRI's ArcGIS Pro software were used to perform the classification operations. For ML techniques, MLC, RF, and SVM were performed using the software's classification wizard where less intense design of schema (for selection of land covers and spectral reflectance), training of sites and setting of parameters and setting up environments were done.

As a DL technique, this study employed the U-Net that is compacted in ESRI's Human Settlements Classification pre-trained DL model. This model has two separate versions that each is designed specifically for processing either Landsat 8 or Sentinel 2. This model uses a binary classification technique (1 and 0), where it only classes human settlements/urban areas, and no-data. The execution was performed using 'Classify Pixels Using Deep Learning' image geoprocessing tool, together with the relevant model, and the imageries were processed separately for individual outputs and comparison. In order to facilitate the comparison between ML and the U-Net's outputs, the ML techniques were applied to produce two-class binary output. Results of all four classification techniques were successfully obtained (Table 1). In this table, the buildings dataset was kept visual to better appreciate the conformity of the classification and orientation of the area.

### 4.3 Accuracy Assessment

To validate the performance of the AI classification techniques, reference (ground truthing) data were created. The Trinidad's National GIS datasets for buildings was obtained. This dataset was originally created in 2014, hence it had to be updated to match the situation in the specific date of the images. Updating that dataset was done by manually digitizing the new features using high-resolution world imagery data from ESRI's ArcGIS Pro (Figure 3).

**Figure 3. Developed/Impervious Reference/Validation Data (red) using National GIS building data (black).**

## 5. DISCUSSION AND ANALYSIS

From literature, pixel comparisons are the most effective approach for assessing classification results (Chang, et al. 2023). Thus, essential information and statistics were firstly obtained from the reference dataset, such as total pixel number, impervious pixels and non-impervious pixels counts (Table 2).

**Table 1. Extracted Impervious Surface Areas using ML and DL techniques.**

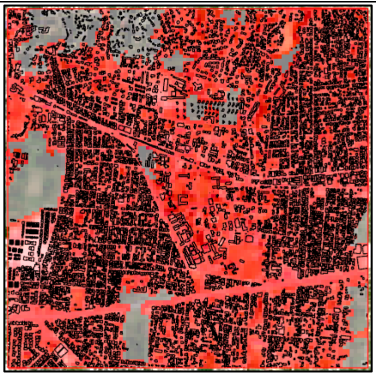
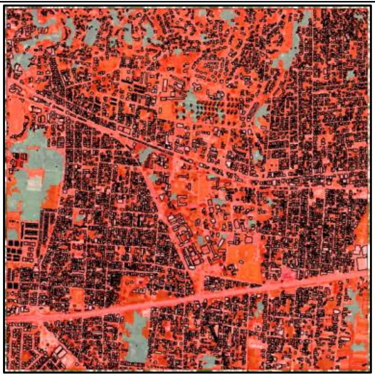
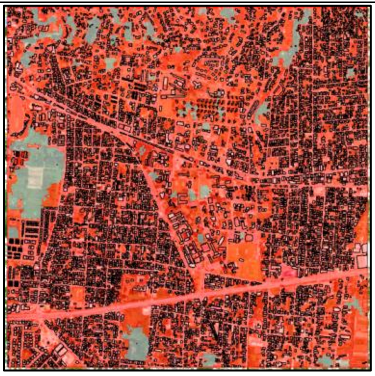
| **Classification Technique** | ***Landsat 8***   | ***Sentinel-2***   |
| --- | --- | --- |
| *Maximum Likelihood Classification (MLC)* |  |  |
| *Random Forest (RF)* |  |  |
| *Support Vector Machines (SVM)* |  |  |
| *U-Net* |  |  |

**Table 2. General Statistics of Ground Truthing data**

| Landsat 8 Reference Data | | Sentinel-2 Reference Data | |
|---|---|---|---|
| *Total pixels* | 9541 | *Total pixels* | 86382 |
| *Impervious* | 8636 | *Impervious* | 78420 |
| *Non-Impervious* | 905 | *Non-Impervious* | 7962 |

Further appreciation of the workflow accuracies lies within grasping the concept of the confusion matrix specific to this context. Here the general comparison and relation between actual labels (ground truth) and predicted labels can be discerned. True positive (TP) is where a pixel of impervious surface is correctly classified according to the ground truth; false positive (FP) is when a non-impervious surface is misidentified as impervious; false negative (FN) is where impervious pixel is actually misidentified as non-impervious; true negative (TN) is where non-impervious surfaces are classified correctly (Chang, et al. 2023). As such, pixel comparison results were obtained for all classifications (Table 3).

**Table 3. Pixel count arranged in the confusion matrix for Landsat and Sentinel**

| Landsat 8 | | | | | Sentinel 2 | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Method** | **TP** | **TN** | **FP** | **FN** | **Method** | **TP** | **TN** | **FP** | **FN** |
| **MLC** | 7481 | 715 | 190 | 1155 | **MLC** | 76802 | 5311 | 1470 | 2799 |
| **RF** | 8075 | 584 | 325 | 557 | **RF** | 77625 | 5071 | 1600 | 2086 |
| **SVM** | 8118 | 576 | 333 | 514 | **SVM** | 78420 | 5305 | 1470 | 1187 |
| **UNET** | 8047 | 588 | 318 | 588 | **UNET** | 64271 | 7250 | 395 | 14466 |

To assess the accuracy, additional computations were performed based on the values in Table 3 and using customary accuracy metrics. Specifically, Precision (= TP/TP+FP), Recall (= TP/TP+FN), Accuracy (= TP+TN/TP+FN+TN+FP), F-score (= 2*(Precision*Recall)/(Precision+Recall)), and Mean Intersection Over Union (MIOU) (= TP/FP+FN+TP) (Chang, et al. 2023). The calculated measures are presented in Table 4.

Results, both visually and statistically, proved the agreement of the models' classification and performance. Visually, both ML and DL classification of Landsat 8 image performed quite poor, where many urban areas were undetected, and many vegetation areas were misclassified as impervious (Table 1). Table 4 also highlights this poor performance of this through the accuracy, MIOU, F-score, recall and precision as well.

The U-Net DL pre-trained performed better in both Landsat 8 and Sentinel-2 images, however there is still room for improvement and training as some impervious areas were left out as well as non-impervious surface areas were classed as impervious. From Table 4, MLC performed the worst in the ML forum, but SVM performed the best followed by RF. However, it was noticed that MLC performed better using the Sentinel-2 imagery. Overall, classification of

Landsat 8 image performed worse than that of Sentinel-2 image. This should be expected due to the three-time difference of the spatial resolution of both images.

**Table 4. Statistical comparison of results from ML and DL classification**

| AI Method | Satellite | Technique | Accuracy | MIOU | F-Score | Recall | Precision |
|---|---|---|---|---|---|---|---|
| ***Machine Learning*** | Landsat 8 | *MLC* | 0.8590 | 0.8476 | 0.9175 | 0.8663 | 0.9752 |
| | | *RF* | 0.9076 | 0.9015 | 0.9482 | 0.9355 | 0.9613 |
| | | *SVM* | 0.9112 | 0.9055 | 0.9504 | 0.9405 | 0.9606 |
| | Sentinel-2 | *MLC* | 0.9506 | 0.9473 | 0.9730 | 0.9648 | 0.9812 |
| | | *RF* | 0.9573 | 0.9547 | 0.9768 | 0.9738 | 0.9798 |
| | | *SVM* | 0.9692 | 0.9672 | 0.9833 | 0.9851 | 0.9816 |
| ***Deep Learning*** | Landsat 8 | *U-Net* | 0.9050 | 0.8988 | 0.9467 | 0.9319 | 0.9620 |
| | Sentinel-2 | *U-Net* | 0.8280 | 0.8122 | 0.8964 | 0.8163 | 0.9939 |

## 6. CONCLUSION AND FINDINGS

This paper conducted a brief review of AI image processing techniques, specifically for the purpose of extracting impervious surfaces from satellite imagery. Three Machine Learning techniques were reviewed; MLC, RF and SVM. Additionally, the literature review indicated that the Deep Learning technique of U-Net, an image segmentation model, seems to be the most used technique to extract impervious surface areas from medium resolution satellite imagery.

Moreover, this study tested these three ML techniques where SVM proves to be the front-runner. The U-Net-based model was also tested through the ESRI's ArcGIS Pro pre-trained model for Human Settlements extraction and proved to be more ideal against the other ML techniques. From the findings, DL seems to perform satisfactorily, however ML especially SVM proves to be more reliable and robust. Further, Sentinel-2 imagery should be the imagery of choice in application such as these since Landsat 8 images are not only 3-times less in spatial resolution but will limits the application of feature classification and extraction.

On the other aspect of this study, the review and testing of AI ML and DL image classification techniques on satellite imagery confirmed that these techniques are effective and can be used in regions like the Caribbean SIDS. The adopted methodology is generic to AI classification techniques, yet it is a valid for acquiring essential impervious surface area information to aid dealing with urbanization issues and contribute towards the UN's 2030 SDGs.

One may recommend that several methods should be implemented (when possible) in pilot studies to assess and choose the most optimal one. Maybe a hybrid or novel approach can also be adopted by maintaining the benefits of some techniques and discarding the disadvantages. Additionally, using pre-trained DL seems very promising to where is today, however, there are many rooms for improvement such as doing more localized training for tropical landscapes, improving model's performance and accuracy, and even developing new models for context specific work. Finally, considering that ArcGIS Pro is a paid software service, the question is then “would implementing an open-source approach get similar or greater accuracies in the Caribbean SIDS of the limited resources?”

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