SETTLEMENT CLASSIFICATION OF REMOTELY-SENSED IMAGES USING MULTI-SCALE BLOCK LOCAL BINARY PATTERN

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ABSTRACT

With the growing population and recurrent changes in climate and environment, there has also been continuous growth in the number of informal settlements in the country. These settlers are the most vulnerable when it comes to disasters because of the quality of housing materials they used. Thus, it would help to develop a tool to automatically classify between settlement types which can be used by decision makers to address specific concerns such as disaster risk management, urban planning, and monitoring the population of informal settler families. This study uses satellite images from Google Earth, which are then pre-processed for further analysis. Texture feature using Multi-scale Block Local Binary Pattern (MB-LBP) operator is computed from the pre-processed images and the cosine similarity function is applied in order to classify whether a particular area is informal or formal settlement. Results show that using a 15x15 MB-LBP operator gives the optimal value for overall accuracy (95.00\%) which therefore suggests that the use of MB-LBP operator for texture analysis is a promising method for settlement classification.

INTRODUCTION

Background of the Study

Over the years, infrastructures change in order to adapt to the climate, the economy, the environment, and the growing population. These changes affect the state of settlements, depending on how many times the settlers rebuild infrastructures, reform the lands, convert water forms to landforms, and get devastated by disasters. Because of these recurrent changes, these built infrastructures are prone to dangers caused by the degrading quality of the ground. With this, it will be difficult to plan and build houses, as well as infrastructures, resulting in unmet demands of the settlers. This will lead to a life with insufficient housing.

According to Housing and Urban Development Coordinating Council (2014), informal settlements are areas where groups of illegal housing units are established and where housing does not follow the planning and building regulations, affecting the quality of life of the settlers. Informal settlements in Metro Manila are usually dispersed, where houses are constructed whenever there are spaces and opportunities to do so. In terms of materials, informal settlement housing can be categorized as: temporary shelters made from salvage materials, semi-permanent shelters, and permanent shelters (Ragragio, 2003).

Due to the status of informal settlements, there are several negative consequences for the settlers. Informal settlements, in particular, are most vulnerable to disasters because they are located in areas with weak and unstable infrastructures and establishments. In 2016, almost half of the Informal Settler Families (ISFs) surveyed in Metro Manila (about 520,000 people) suffer from higher levels of flooding and disruption, including the inability of settlers to go to work or school. The poor road conditions of informal settlements in Metro Manila affect ISFs (around 250 in Manila and Muntinlupa, and around 350 in Quezon City). This can affect not only the settlers but also, the infrastructures may cause the blockage of sewers on waterways caused by the pollution of the surrounding environment. Criminal activities also affect ISFs (around 400 in Manila and Muntinlupa, and around 800 in Quezon City) because of insufficient security and lack of street lighting (World Bank, 2017).

Figure 1: Satellite Image of a Settlement in Metro Manila

Statement of the Problem

With the growing number of informal settlements in the Philippines, it would help to have a tool for easily identifying them. Several types of research about settlement classification were conducted in foreign countries but, only a few were written in the Philippine context. This study explores the use of a variant of Local Binary Pattern (LBP) texture operator called the Multi-scale Block Local Binary Pattern (MB-LBP) to classify whether a settlement taken from a satellite image from Google Earth is formal or informal.

Prior knowledge of the location of informal settlements and the area they cover is required in this study. One way to detect the area of the subject is by using image processing. According to Hofmann (2001), settlement classification on satellite images is possible through image processing, since there are distinctive physical features like the use of diverse materials for informal settlements. This depends on the resolution and the quality of the image areas. While Hofmann stated that the method for detecting informal settlements may vary and can even detect individual shacks, this study focuses on locating and spatially delineating the types of settlements as to formal or informal.

Significance of the Study

With the continuous growth in the number of informal settlements in the Philippines, there is a need for a representation of their physical demographics to understand more of their housing and environmental conditions. This study may serve as a tool for the initial classification of settlements which can be used by decision-makers to address specific concerns related to it, such as disaster risk management, urban planning, and monitoring the population of informal settler families.

Scopes and Limitations

The program was implemented in Python and was executed using the Windows Operating System. The images used were satellite images from Google Earth desktop application. The areas of interest used in the training and testing are within Metro Manila and were taken from a zoom of 100m. The image resolution of the training images was 320 x 180 pixels while testing images was 1980 x 1080 pixels.

Research Objectives

This study aims to develop a program that can classify settlements using satellite images from Google Earth. Specifically, the study aims to accomplish the following:

1. Collect formal and informal settlement areas from Google Earth;
2. Build a training data set of formal and informal settlements;
3. Extract MB-LBP feature on each type of settlement,
4. Classify formal between informal settlements, and;
5. Evaluate the performance of MB-LBP in classifying settlements.

REVIEW OF RELATED LITERATURE

Several studies have been conducted to detect settlements on remote-sensed images using image processing. Researchers have to consider the image quality, image scale, distance of the object (settlement) from the remote sensor (satellite), characteristics of the settlement, and the algorithm used to effectively classify settlements on satellite images.

Hoffman (2001) mentioned that information that helps to classify a settlement can be obtained from various characteristics of the image used. Detection of physical structures of settlements (shelters from informal settlements are usually made from various materials) is dependent on the spatial and spectral resolution of the sensor. Using a sensor with good resolution should classify and distinguish informal settlements from other forms of settlements. He also mentioned that detecting informal settlements may vary depending on the information of imaging and spatial scale: one way is to detect every single shack and another way is to just find and outline the informal settlement areas.

One of the widely used methods for mapping and analyzing land data is using remote sensing-based approach (Mugiraneza et al., 2019). Remote sensing is obtaining information, such as characteristics of an area using data acquired from sensors, usually satellites. This approach can be a notable alternative on field data collection since it records the status of informal settlements by using image processing techniques and Very High Resolution (VHR) images (Ballim, 2016).

The research of Caabay and Mercado (2013) applied image segmentation and recognition to detect settlements near waterways using remote-sensed images from Google Maps, a web mapping service by Google, which have available sources of satellite images on the Internet to find informal settlements in Metro Manila. Another research by Kohli et al. (2016) used satellite imagery, together with segmentation, followed by hierarchical classification, using object-oriented image analysis along with expert knowledge in the form of local slum ontology. A research article by Taubenböck et al. (2018) combined data sets from satellite imagery and twitter, to determine whether the structures based on the results of remote-sensing reflects the availability of the people to use social media, and to determine whether there are difference on how people from formal and informal settlements interact on social media (what they search and read, their behaviors, etc.).

There are various methods in classifying entities on satellite images but some methods does not show much accurate results and others requires a lot of resources. One method used to classify images that has proven to be a great yet simple texture descriptor is the Local Binary Operator (LBP).

Local Binary Operator (LBP) is a simple and efficient texture descriptor which thresholds the neighborhood of each pixel and labels the result of pixels of an image as a binary number. LBP is generally used in face recognition and texture analysis. In relative studies, LBP has shown exceptional performances in terms of speed and performance. LBP also supports multi-scale analysis (Mäenpää, 2003).

LBP is mainly used for biometrics, including facial recognition, fingerprint recognition, palmprint recognition, and facial age classification. LBP is also used for texture classification. The Local Binary Pattern is known to be a simple yet effective texture classifier. Not only can it be used as facial recognition, but it can also be used as a texture identifier on remote images. By applying further evaluation and extension methods, the algorithm can make the classification of settlements on satellite images more precise.

The research of Král et al. (2016) proposed automatic face recognition using Enhanced Local Binary Pattern (E-LBP). Since normal LBP is not robust to handle noise images and has different illumination conditions, they offered an enhanced descriptor that computes vector values while considering different neighborhoods and more pixels.

Another research of Mdakane and Bergh (2012) applied LBP with the extension of recognizing uniform patterns with rotational invariant variance, and then combined multiple operators to classify informal settlements on QuickBird images.

It has been discovered that LBP is a great texture descriptor due to its simplicity but high discriminative power. However, adding an extension to LBP will further improve the original LBP. The research of Liao et al. (2007) proposed MB-LBP to apply on image recognition. It was introduced to overcome the flaws of a regular LBP, such as the robustness, small spatial support areas and the inability to capture larger structure that may be a dominant feature of an image. Another research by Suri and Amit (2011) combined a concept called integral Haar histograms with circular MB-LBP to implement a real-life and robust facial detector which is proven accurate with varying face sizes, illumination, angle and face expressions.

With the claimed accuracy of using MB-LBP as a texture descriptor, this study explores the possibility of applying the said method to settlement classification.

METHODOLOGY

Materials

The program was developed using the following tools:

A. Hardware Tools:

1. Acer Aspire E5-473G-33RT 14 inch notebook
2. Intel Core i35005U Processor (3M Cache, 2.00GHz)
3. 2GB NVIDIA GeForce 920M DDR3 VRAM
4. 8gb DDL3R SDRAM
5. 1TB SATA HDD

B. Software Tools:

1. Windows 10 Home Single License
2. Text editor software
3. Python (programming language) software Version 3.7.3
4. OpenCV library version 4.1.1
5. Google Earth desktop application

Data Acquisition

Training and testing images were taken from Google Earth at a zoom level of 100m. The regions selected are within Metro Manila only. The chosen areas are those that have already been classified in a published article which will be used as the true value later in the comparison. Reference for map data of informal settlements on Metro Manila (Figure 2) was taken from research article of Taubenböck et al. (2018). They defined the physical characteristics of slums by conceptualizing spatial features such as 'highest building density', 'non-regular, complex alignment of buildings', 'homogeneity of the pattern', 'small building sizes', and 'low building heights'.

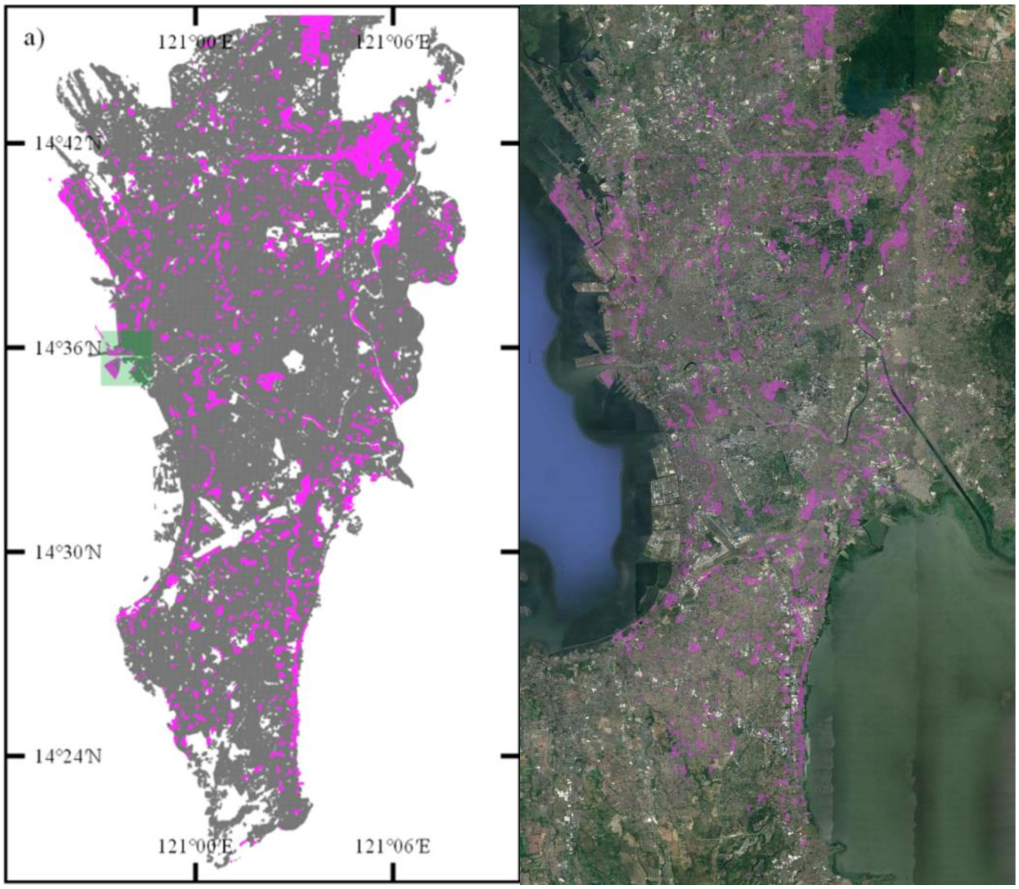


Figure 2: Map Data of Informal Settlements in Metro Manila (left) overlayed on Google Earth desktop application (right)

Training images were classified as two texture classes: formal settlement class and informal settlement class. Both classes contained 72 training images with a resolution of 320 x 180 pixels. Figures 3 and 4 show sample images of formal and informal settlements, respectively.

Figure 3: Images of Formal Settlements

Figure 4: Images of Informal Settlements

Testing images (Figure 5) have a resolution of 1920 x 1080 pixels.

Figure 5: Input Testing Image

Image Pre-Processing

Pre-processing methods are applied to both training and testing images to enhance the image for texture analysis. Figure 6 shows the pre-processing flowchart:

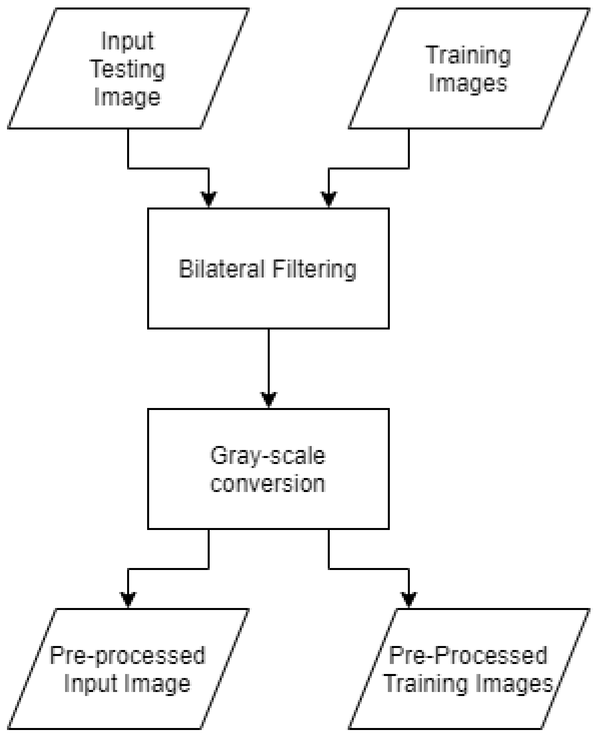


Figure 6: Image Pre-processing Flow Chart of the Input Image and Training Data Images.

Bilateral image filter was applied to the training and testing images in order to remove noise that affect the texture of the images while preserving edges. This helps in maintaining the edges of the settlements present in the images.

After bilateral filtering, all the images were converted into grayscale images. This method should be applied first before implementing MB-LBP because the operator only accepts grayscale pixels. Figure 7 shows sample images after the pre-processing phase.

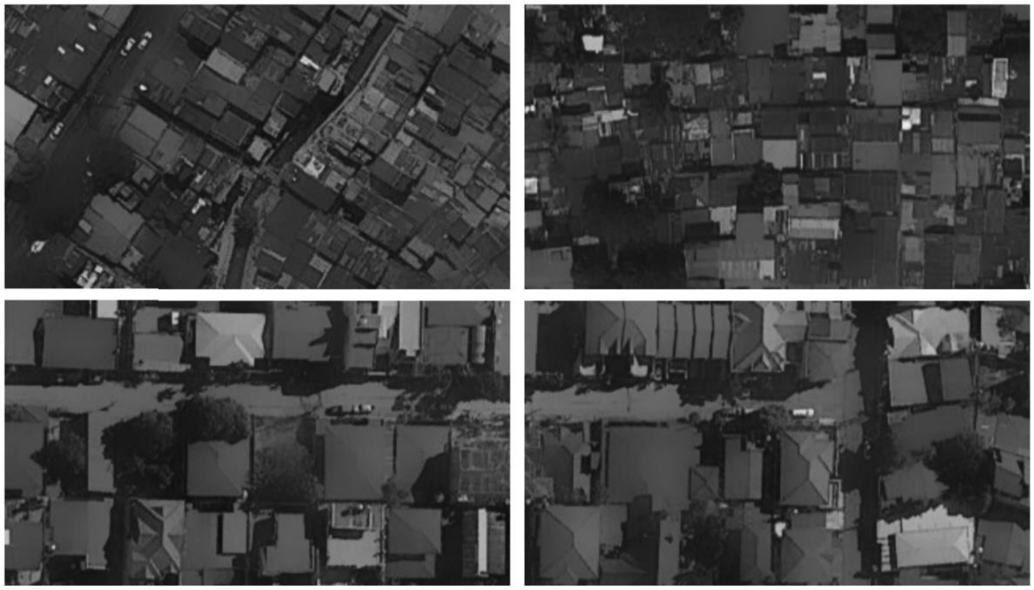


Figure 7: Images After Image Pre-processing

Image Analysis

After the pre-processing methods on the training and testing images were implemented, several steps were performed to generate the classified image as output. Figure 8 shows the flowchart of image analysis to be followed.

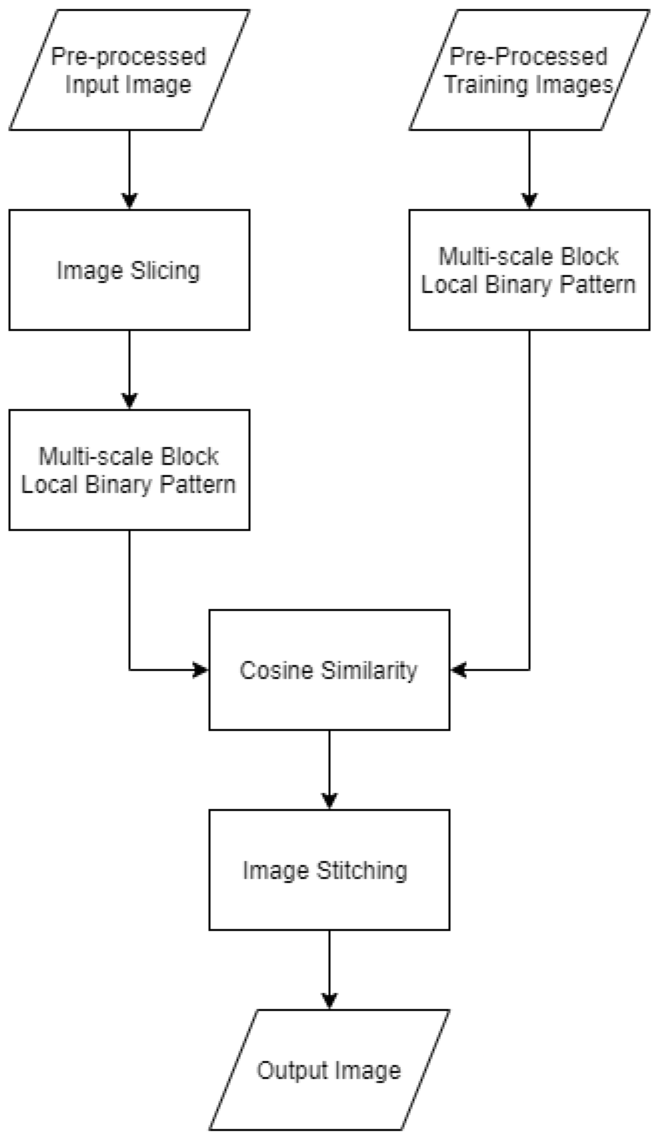


Figure 8: Image Analysis Flow Chart to Classify Settlements

1. Training Data Images

The texture operator Multi-scale Block Local Binary Pattern (MB-LBP) was applied to every image in the training data set.

In the computation of the MB-LBP, the sub-window size of the process is provided as a parameter and the square of the sub-window size indicates the scale of the MB-LBP operator. Figure 9 shows the image representation of MB-LBP feature.

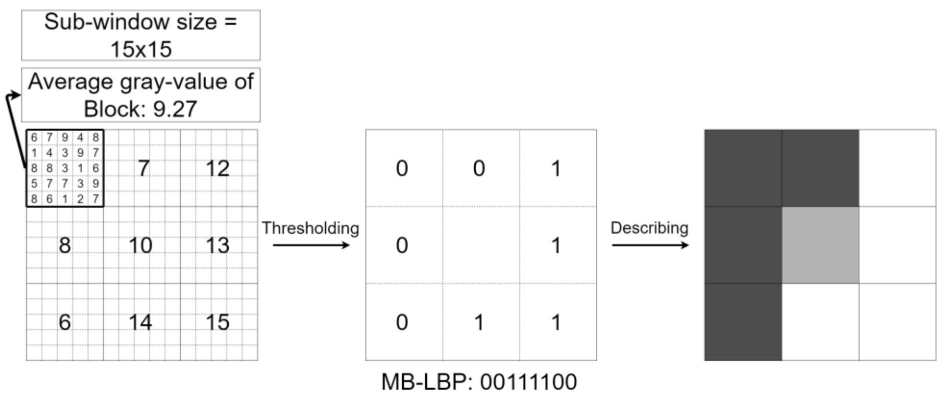


Figure 9: Image Representation for MB-LBP feature

In this research, the size of the sub-window used is 15. Since the MB-LBP process involves dividing the sub-window to 9 blocks, each block here is composed of 5x5 sub-regions. The average sum of image intensity was computed in each sub-region leaving a single value to represent each of the 9 blocks. The value of the center block is then used as a threshold for the next step. Following a clockwise rotation from the topmost left block, if the average value of the center block is greater than the neighborhood block value, write “0”, otherwise, write “1”. This gives an 8-digit binary number which is converted into decimal using the MB-LBP equation given by the following:

$$MB - LBP = \sum_{i=0}^{7} s(g_i - g_c)2^i$$

$$s(x)= \begin{cases} 1, & \text{if } x \geq 0 \\ 0, & \text{if } x < 0 \end{cases}$$

Where g_c is the Average Value of the Center Sub-window and g_i are the Neighborhood Sub-windows

The frequency of each value obtained from MB-LBP is stored to compute for the image histogram, this histogram can also be seen as a 256-dimensional feature vector.

The operator was implemented in all images from formal and informal settlement class to obtain the texture class of the training data images (Figure 10).

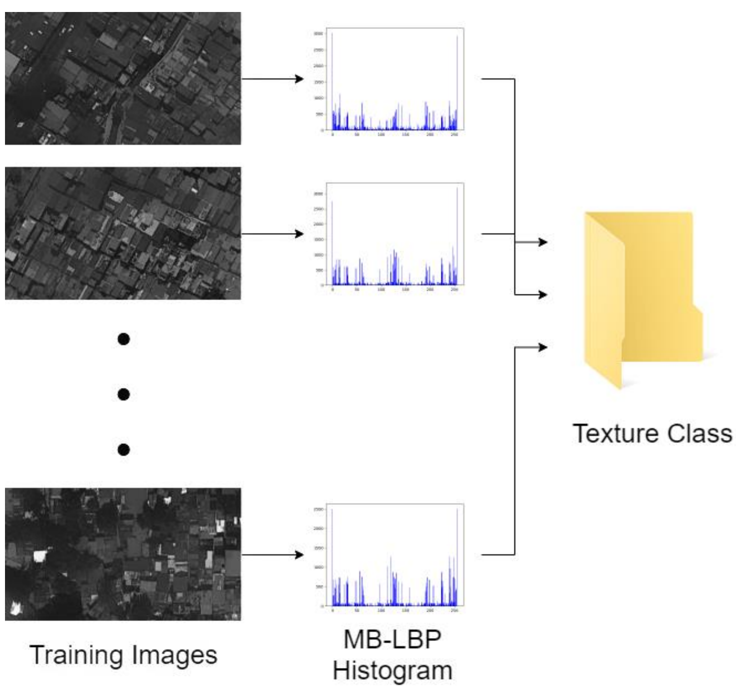


Figure 10: Training Images are Converted to a MB-LBP Histogram and Stored as a Texture Class

2. Testing Data Images

The testing image is firstly sliced into 36 320 x 180-pixel images, having the same resolution and numbers of pixels as the training images (Figure 11).

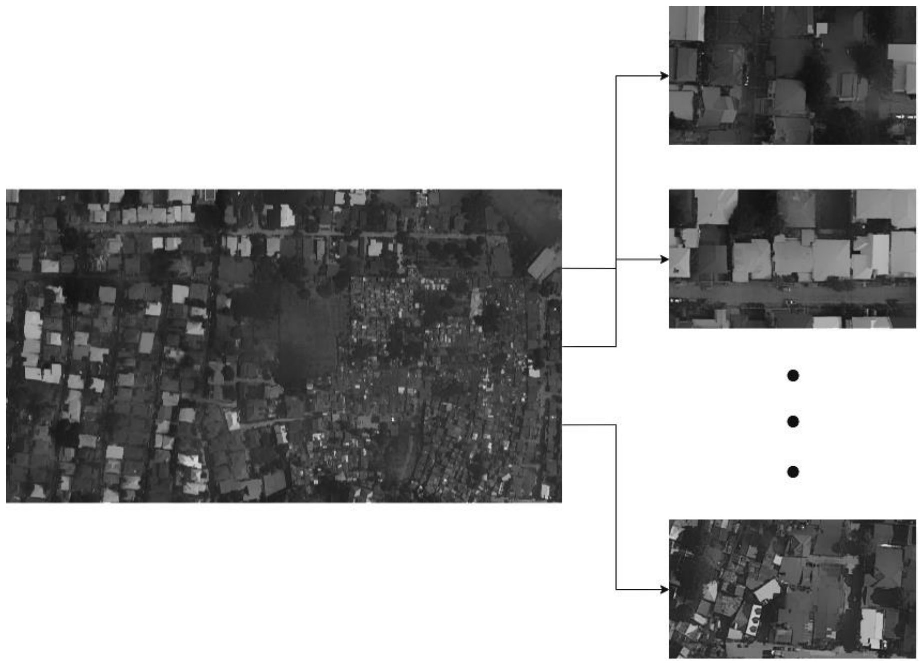


Figure 11: Testing Image Transformed Into Sliced Images

MB-LBP operator was then also applied to the 36 testing images to obtain a feature vector on each image. After obtaining feature vectors for the training and testing data images, classification can now be performed using a similarity measure function.

The similarity measure function used was the cosine similarity function. Cosine similarity measures the cosine of the angle between two vectors projected in a multi-dimensional space, which is our 256-dimensional feature vector of the images. The formula for cosine similarity is

$$\cos(\theta) = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} \mathbf{A}_i \mathbf{B}_i}{\sqrt{\sum_{i=1}^{n} \mathbf{A}_i^2} \sqrt{\sum_{i=1}^{n} \mathbf{B}_i^2}}$$

Where A_i and B_i are Components of Vector A and B Respectively.

The cosine similarity between the sliced testing images and the training images was computed, and then the similarity values were stored with its label if the feature vector attribute is from a formal or informal class. After all the similarity values between the vector from the sliced testing image and all the training images were obtained and stored, it was sorted to the highest similarity value to lowest, then only the top 50 values were considered. Finally, the sliced image is classified based on the majority of the settlement labels in the top 50 values. The sliced image is highlighted green if it is classified as formal settlement and red if it is classified as informal settlement (Figure 12). This was implemented on all the sliced testing images.

Figure 12: Settlement Classified as Formal (Green) and Informal (Red)

After the classification of sliced images is done, image stitching of the classified sliced images is applied and will be the output image.

RESULTS AND DISCUSSION

This study examined the use of Multi-scale Block Local Binary Pattern for the classification of settlements in selected areas in Metro Manila. The MB-LBP operator shows that textures can be a simple, yet powerful classifier in an image. Since most informal settlements are made up of salvage materials, have smaller houses, and are more compressed than formal settlements, which are also larger in house size, it significantly affects the image texture making the distinction between the formal and informal settlements considerably visible.

Figure 13: Output Image After Image Analysis

However, there are also several factors affecting the classification of settlements. One of the affecting factors is the resolution of the sliced images for classifying. Since the area is not controlled, other objects such as roadways, trees, open areas, and other infrastructures aside from settlements are also considered.

Figure 14: Areas Such as Open Space Affect the Classification of Settlement.

In Figure 14, despite the fact that the area of informal settlement is smaller and most of the area is an open space, it was still classified as informal, seeing that open spaces are not considered as a formal settlement in the training data.

There are also some images that are incorrectly classified. In Figure 15, since the program depends on textures to classify images, the image was classified as formal image because the housing quality is similar to formal areas whereas it should be classified as informal.

Figure 15: Informal Settlement that is Classified as Formal Due
to the Housing Quality is Similar to Formal Settlements.

The size of the sub-windows from the formula of MB-LBP can also affect the classification of images. A confusion matrix (Figure 16) was constructed to describe the performance of the classifier depending on the sub-windows.

	Predicted Positive	Predicted Negative
Actual Positive	**True Positive (TP)** - Informal Classified as Informal **TP = 69**	**False Negative (FN)** - Informal Classified as Formal **FP = 2**
Actual Negative	**False Positive (FP)** - Formal Classified as Informal **FN = 7**	**True Negative (TN)** - Formal Classified as Formal **TN = 102**

Figure 16: Confusion Matrix of Settlement Classifier using 15x15 Sub-window MB-LBP Operator.

Using the four outputs from the confusion matrix, precision, sensitivity and accuracy were calculated.

$$Precision = \frac{TP}{TP+FP}$$

$$Sensitivity = \frac{TP}{TP+FN}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

Precision is the ratio of correct positive predictions to the total predicted positives. Recall or sensitivity is the ratio of correct positive predictions to the total positive examples. Accuracy is defined as the ratio of correctly predicted examples by the total examples.

Classification Precision				
Images	3x3	9x9	15x15	21x21
1	0.8333	0.7333	0.8462	0.8462
2	1.0000	0.8421	1.0000	1.0000
3	1.0000	0.7500	1.0000	1.0000
4	0.6667	0.6190	0.7647	0.8000
5	1.0000	0.8182	0.9474	0.9375
TOTAL	0.8750	0.7527	0.9079	0.9155

Table 1: Classification Precision Obtained with Various Sub-window Sizes. The Higher the Value, The Higher the Precision

On table 1, the 21x21 sub-window sizes gave the best classification precision, for the precision value of the five images ranges from 0.8000 to 1.0000, with two images resulted in the highest value. Followed by 15x15 sub-window sizes, the precision value of the five images ranges from 0.7647 to 1.0000, with two images resulted in the highest value.

Classification Sensitivity				
Images	3x3	9x9	15x15	21x21
1	0.9091	1.0000	0.9091	1.0000
2	0.8824	0.9412	0.9412	0.8824
3	0.8333	1.0000	1.0000	1.0000
4	0.9231	1.0000	1.0000	0.9231
5	0.5000	1.0000	1.0000	0.8333
TOTAL	0.7887	0.9859	0.9718	0.9154

Table 2: Classification Sensitivity Obtained with Various Sub-window Sizes. The Higher the Value, The Higher the Sensitivity

On table 2, the 9x9 sub-window sizes gave the best classification sensitivity, for the sensitivity value of the five images ranges from 0.9412 to 1.0000, with four images resulted in the highest value. Followed by 15x15 sub-window sizes, the sensitivity value of the five images ranges from 0.9091 to 1.0000, with three images resulted in the highest value.

Classification Accuracy				
Images	3x3	9x9	15x15	21x21
1	0.9167	0.8889	0.9167	0.9444
2	0.9444	0.8889	0.9722	0.9444
3	0.9444	0.8889	1.0000	1.0000
4	0.8056	0.7778	0.8611	0.8889
5	0.7500	0.8889	0.9722	0.8889
TOTAL	0.8722	0.8667	0.9500	0.9333

Table 3: Classification Accuracy Obtained with Various Sub-window Sizes. The Higher the Value, The Higher the Accuracy

On table 3, the 15x15 sub-window sizes gave the best classification accuracy, for the accuracy value of the five images ranges from 0.8611 to 1.0000, with one image resulted in the highest value and two images resulted in the value of 0.9722. Followed by 21x21 sub-window sizes, the accuracy value of the five images ranges from 0.8889 to 1.0000, with one image resulted in the highest value.

It has shown that 15x15 sub-windows has the optimal values for accuracy, precision and recall. The 9x9 sub-window size has the most sensitive results but has lower accuracy and precision. On the other hand, 21x21 sub-window size has the most precise results but the sensitivity and accuracy is not great compared to 15x15 sub-windows. The 15x15 has more stable values in precision, sensitivity and accuracy.

Using smaller sub-window sizes makes the representation less robust, which leads to lower classification accuracy (3x3 MB-LBP is simply the regular 3x3 LBP operator). On the other hand, using larger sub-window sizes removes small information, which can also lowers accuracy.

SUMMARY AND CONCLUSION

The research proposed MB-LBP texture features as classifier to categorize formal and informal settlements. The texture feature used have already considered the density, housing quality and the house size, it does not need to be computed separately as additional features to be used for classification.

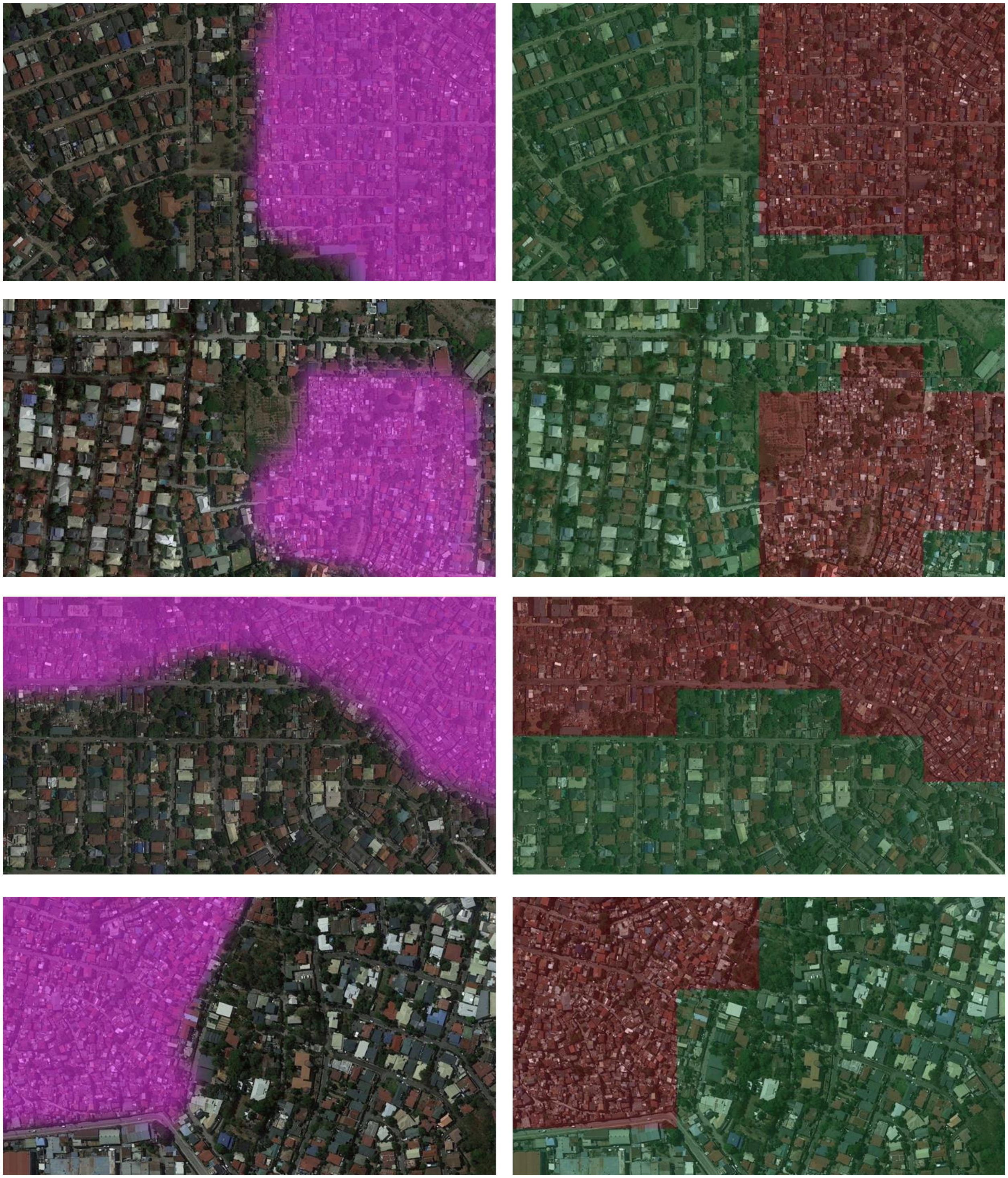
With proper pre-processing methods, using satellite images taken from Google Earth application can be an excellent input for both training and testing data. The use of MB-LBP operator for texture analysis is a promising method for classifying formal and informal settlements. Additionally, optimizing sub-window size to use in the operator can also improve classification accuracy.

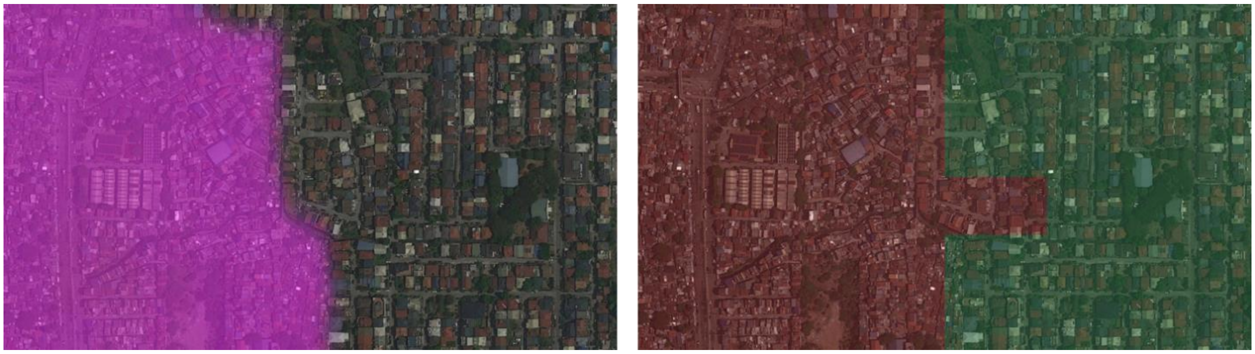
FUTURE WORKS

Using a simple, yet effective texture operator is a promising method for classifying settlements in satellite images. Pre-processing and image analysis methods can be improved for more accurate classification. Advanced satellite imaging can also be a factor for classifying small details or information that can be acquired from satellite image which can affect the output.

APPENDIX

Reference images (left) and output images using 15x15 sub-windows MB-LBP (right) of Metro Manila areas.





LITERATURE CITED

Housing, U.D.C.C.(HUDCC), and U.K. GHK Consulting Ltd. (2014) Developing a national informal settlements upgrading strategy of the philippines. [Online]. Available: http://hudcc.gov.ph/sites/default/files/styles/large/public/document/NISUS%20Final%20 Report July2014.pdf

J. Ragragio. (2003) The case of metro manila, philippines. [Online]. Available: http://www.ucl.ac.uk/dpu-projects/Global_Report/pdfs/Manila.pdf

W. Bank. (2017) Philippines urbanization review: Fostering competitive, sustainable and inclusive cities. [Online]. Available: http://documents.worldbank.org/curated/en/963061495807736752/pdf/ 114088-REVISED-PUBLIC-Philippines-Urbanization-Review-Full-Report.pdf

P. Hofmann, "Detecting informal settlements from ikonos image data using methods of object oriented image analysis an example from cape town (south africa)," Remote Sensing of Urban Areas, pp. 107–118, 01 2001.

T. Mugiraneza, A. Nascetti, and Y. Ban, "Worldview-2 data for hierarchical object-based urban land cover classification in kigali: Integrating rule-based approach with urban density and greenness indices," Remote Sensing, vol. 11, p. 2128, 09 2019.

K. Ballim, "Detecting informal settlements from high resolution imagery using an object-based image approach," 2016.

M. Caabay and R. Mercado, "Locating informal settlements near waterway areas using google maps," 2013

D. Kohli, R. Sliuzas, and A. Stein, “Urban slum detection using texture and spatial metrics derived from satellite imagery,” Journal of Spatial Science, vol. 61, no. 2, pp. 405–426, 2016. [Online]. Available: https://doi.org/10.1080/14498596.2016.1138247

H. Taubenb¨ock, J. Staab, X. X. Zhu, C. Geiß, S. Dech, and M. Wurm, “Are the poor digitally left behind? indications of urban divides based on remote sensing and twitter data.” ISPRS International Journal of Geo-Information, vol. 7, 2018.

T. M¨aenp¨a¨a, “The local binary pattern approach to texture analysis - extensions and applications,” 2003.

P. Kr´al, A. Vrba, and L. Lenc, Enhanced Local Binary Patterns for Automatic Face Recognition, 05 2019, pp. 27–36.

L. Mdakane and F. van den Bergh, “Extended local binary pattern features for improving settlement type classification of quickbird images,” 2012.

S. Liao, X. Zhu, Z. Lei, L. Zhang, and S. Li, “Learning multi-scale block local binary patterns for face recognition,” vol. 4642, 08 2007, pp. 828–837.

P. Suri and E. Amit, “Robust face detection using circular multi block local binary pattern and integral haar features,” International Journal of Advanced Computer Science and Applications, vol. 1, 01 2011.

S. Liao and A. Chung, “Texture classification by using advanced local binary patterns and spatial distribution of dominant patterns,” vol. 1, 01 2007, pp. 1221–1224

L. Zhang, R. Chu, S. Xiang, S. Liao, and S. Li, “Face detection based on multi-block lbp representation,” 01 2007, pp. 11–18.

G. Singh and G. Gadgil. (2017) Navigating informality: Perils and prospects in metro manila’s slums. [Online]. Available: http://pubdocs.worldbank.org/en/564861506978931790/Navigating-Informality-MetroManila-7-26-17web.pdf

UN-Habitat. (2015) Habitat iii issue papers 22—informal settlements. [Online]. Available: https://unhabitat.org/wpcontent/uploads/2015/04/HabitatIIIIssue-Paper22 InformalSettlements.pdf