WEB APPLICATION: SATELLITE IMAGERY FOR LAND CLASSIFICATION IN GREATER MANILA AREA USING CONVOLUTIONAL NEURAL NETWORK

A Project Study Presented to the Faculty of

Electronics Engineering Department

College of Engineering

Technological University of the Philippines

In Partial Fulfilment of the Course Requirements for the Degree of

Bachelor of Science in Electronics Engineering

Submitted by:

Agoylo, Shiela Mae P.

Bultron, Mary Joy A.

Clamor, Ailyn Joyce O.

Monzaga, Jaishree Keith M.

Rosales, Catherine Rose R.

Salvador, Cleodelaine S.

Adviser:

Engr. Romeo L. Jorda, Jr

August 2020

APPROVAL SHEET

This project study entitled "**WEB APPLICATION : SATELLITE IMAGERY FOR LAND CLASSIFICATION IN GREATER MANILA AREA USING CONVOLUTIONAL NEURAL NETWORK**", has been prepared and submitted by the following proponents:

Agoylo, Shiela Mae P.	Monzaga, Jaishree Keith M
Bultron, Mary Joy A	Rosales, Catherine Rose R.
Clamor, Ailyn Joyce O.	Salvador, Cleodelaine S.

In partial fulfillment of the requirements for the degree of **Bachelor of Science in Electronics Engineering** is hereby recommended for approval.

ENGR. ROMEO L. JORDA, JR
Project Adviser

E-signature of LEAN KARLO S. TOLENTINO signed August 12, 2020 @ 9:35 PM UTC+8

ENGR. EDMON O. FERNANDEZ Panel Member	**ENGR. LEAN KARLO S. TOLENTINO** Panel Member

Digital signature of ENGR. JESSICA S. VELASCO signed August 12, 2020 @ 21:37H UTC+8

08-13-2020

ENGR. JESSICA S. VELASCO Panel Member	**ENGR. MARIA VICTORIA C. PADILLA** Panel Member

Accepted and approved in partial fulfillment of the course requirements for the degree of **Bachelor of Science in Electronics Engineering.**

ENGR. EDMON O. FERNANDEZ Head, ECE Department	**ENGR. BENEDICTO N. FORTALEZA** Dean, College of Engineering

ACKNOWLEDGEMENT

The proponents express their deepest gratitude for the support and guidance of the people who have contributed to make this study possible:

To the thesis adviser, Engr. Romeo L. Jorda, Jr., for guiding the researchers and giving valuable comments, suggestions, and provisions for the betterment of the study.

To all the panel members, Engr. Lean Karlo S. Tolentino, Engr. Jessica Velasco, Engr. Maria Victoria Padilla, and Engr. Edmon O. Fernandez, for adept recommendations for the benefit and development of the platform.

To the DOST Advance Science and Technology Institute and the Manila City Hall and Valenzuela City Hall, for the cooperation, valuable suggestions and providing the researchers their needed information.

To the experts who have evaluated and have given their constructive recommendations for the improvement of the platform.

To the friends and family of the proponents and to everyone who always give their unconditional support and motivate the researchers all throughout, given all the difficulties and challenges that they have faced in the course of this study.

And most especially to our Lord Almighty, for giving the researchers inspiration, strength, and determination in accomplishing this study amid the obstacles along the way. Without His graces and blessings, the achievement of this study would not have been possible.

ABSTRACT

Land Use Classification aims at achieving standardized landform categorization at different scales. Such classification is an important component in the development of structured maps which aids in processes of decision-making and planning. Local Government Units are mandated to conduct Land Classification mapping of their areas which bring up issue on time-consuming and expensive data gathering.

This study proposes the use of satellite imagery to correlate with the traditional way of mapping. Machine Learning is used to help predict the Land Classification of Greater Manila Area. The proponents used satellite imagery and pre-trained patches for the Land Use Classification (Agricultural, Commercial, Industrial, and Residential) that will be processed through the use of Convolutional Neural Network (CNN). The classification will depend on the screen size of the device used. Color coding is used to show the classification of an area - green, yellow, purple, and red as agricultural, residential, commercial, and industrial, respectively.

The website is used and evaluated by IT experts based on the aesthetics, user-friendliness, and accuracy of the system. The results show that the system can be an improvement in the traditional way of land use mapping.

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

City planners create a "land utilization" chart to define areas of a town to understand the purpose of the different areas in the city. The land use relates to the land cover, whether in the form of trees, metropolitan facilities, water, bare ground or other. For worldwide surveillance research, resource management and planning operations, the identification, delineation, and mapping of territory is a significant factor. Land classification is performed by trained professionals that can be costly. Guidelines for the inventory and identification of lands and sites for socialized housing stated that the inventory of lands can be conducted through ocular inspection, aerial photo interpretation and data collection from tax maps, cadastral maps, current property use maps and other documents. Urban mapping could be very helpful, but such information is very limited for a developing country like the Philippines.

In this study, the researchers will utilize satellite imagery to classify land use in the Greater Manila Area. A study in Germany uses radar SAR for optical and artificial eye (OBIA) picture assessment which has been commonly used to map Land Use and Land Cover (LULC), because it can use temporal data, decrease salt and pepper effects, and delineate limits of LULC. They proved how their Sentinel-2 satellite standardized testing scheme LULC is used to detect land use and modifications in the soil coverage, and how it can contribute to the improvement of geographical data.

1.2 Statement of the Problem

The Philippines has a law about land classification and urban planning. In the Republic Act No. 7279 Article 4, “Land Use, Inventory, Acquisition and Disposition” (Republic of the Philippines, GOVPH, 1992), land use for every city and municipal governments requires an inventory. Frequent monitoring can help local government units to have immediate action for problems like appropriate settlement allocation. Greater Manila Area has several municipalities. As a result, every local government unit should monitor the land use over their area for proper distribution in their cities’ resources. Every three years, urban classification is performed by trained professionals that could be costly and time consuming. Urban mapping may be useful, but for an emerging nation like the Philippines, the availability of information is very limited. People who are not aware about urban planning could be helped through a system that provides the land use surrounding their areas or the areas that they want to choose.

1.3 Objectives

1.3.1 General Objective

The main objective of this study is to determine the land classification of Greater Manila Area through satellite images using machine learning.

1.3.2 Specific Objectives

In specificity, the proponents plan to meet the following for the development of the system and the web application:

1. To collect dataset of satellite images with 10m spatial resolution from available open sources.
2. To gather reference map/ground truth from e.g., OpenStreetMap (OSM) or Local Government Units (LGUs).
3. To design and implement a Convolutional Neural Network that would classify land into residential, commercial, industrial, and agricultural areas.
4. To develop a web application that can visualize the land area classification.
5. To test and evaluate the web application.
6. To test and evaluate the accuracy of the system.

1.4 Significance of the Study

The study focuses on providing the local/national government a map of land areas to be classified as residential, commercial, industrial, and agricultural areas. With this study, proper authorities' urban planners may use the map for proper zoning which can be accessed through a web application.

The study aims to introduce a web application that can be utilized by the Local Government Units (LGUs) or the public with the purpose of providing land classification for zoning reference.

1.5 Scope and Limitation

This research focuses on the development of a land classification system in the Greater Manila Area on a web application with the use of satellite images from Google Maps to provide the public with the land use/land classification information. Limited information about the land maps in Greater Manila led to the proponents in using an open-source dataset from Europe. The website that is developed will classify the land use (Commercial, Agricultural, Residential, and Industrial) of an area depending on the screen size of the device that will be used. Another is the website can only be accessed through an internet connection.

1.6 Technical Definition of Terms

The following are terms and definitions that is used in the discourse of the study for easier understanding:

- ❖ **Convolutional Neural Network** is a Deep Learning algorithm that can take in an info photograph to give significance (learnable loads and predispositions), to different perspectives / objects in the image and can be distinguished between one view and the other.

- ❖ **Fine Tuning** is the process where we fine-tune existing networks (also known as Transfer Learning) that are already trained on a larger dataset by continuing training it on smaller datasets.

- **Database** is an accessible accumulation of data. In library research, a database is the place you discover journal articles. Every database contains a large number of articles which you can look for at the same time and quickly discover articles with higher pertinence than seeking in individual diaries.

- **Deep learning** is a part of machine learning that instructs computers to do what works out easily for people: learn from experience. Deep learning is particularly appropriate for image identification, which is significant for taking care of issues, for example, facial acknowledgement, movement recognition, and many propelled drivers help advancements, for example, free driving, path discovery, pedestrian identification, and autonomous parking.

- **Greater Manila Area** generally refers to the adjacent urbanization encompassing Metro Manila. Greater Manila spills more prominently into the neighboring areas of Laguna, Cavite, Rizal, Nueva Ecija, Tarlac, Bulacan, Batangas, Metro Manila and Pampanga.

- **Image patching** offers the capacity, alongside with artificial noise compound, to select areas of arbitrary form on a picture and replace them with surfaces that match other areas of arbitrary form. For cosmetic reasons, this is an optimal way to remove unwanted flaws from a picture.

- **Machine Learning** is an artificial intelligence application (AI) that enables systems to learn from and improve experience automatically without being specifically programmed. Machine learning focuses on enhancing PC programs that can access information and learn for their own benefit. Machine Learning algorithms utilize computational techniques to "learn" information directly from the data without depending on a foreordained equation as a model.
- **Python** is a high-level, deciphered, object-ordered, dynamic semantics state programming language. Its high-level built-in information structures, combined with dynamic composition and dynamic binding, make it allure to Rapid Application Development as well as to be used as a scripting or glue language to interface existing segments.

- **R** is a statistical computing environment and graphics language environment. It is highly extensible and provides a broad range of statistical and graphical techniques, including (linear and nonlinear modeling, classical statistical testing, analyzing time series, classification, classification, etc.) and graphic.

- **Satellite Imagery** may allude to various types of digitally transmitted pictures taken by artificial satellites circling the Earth. In addition to the military applications, satellite imagery has been utilized for mapping, ecological observing, archeological studies, and climate prediction.

- **Zoning** is a system of codes used for developing a municipality, generally a city or county, in which various geographic areas are branded a Zone containing different allowances and restrictions. Zoning is the key to future development within the municipality and adapts to current and future predicted trends within different zones.

CHAPTER 2

REVIEW OF RELATED LITERATURE AND STUDIES

2.1 Conceptual Literature

2.1.1 Satellite Imagery

The satellite images nowadays are one of the tools of the meteorologist to study the different events in the sky. Without satellites, it is hard to forecast weather and conduct research. It provides true data to analyze everything that is seen in the images and there is no chance to error about the images from that. There is a lot of application of satellite imagery that has a great impact in our society. Also, it has different kinds of satellite images, these are the visible imagery, infrared imagery, and water vapor imagery.

There are a number of kinds of satellite images, but the three common types of these are the visible imagery, infrared imagery, and water vapor imagery. Visible Imagery is based only through the amount of reflected sunlight. It could define the thunderstorm through different types of clouds because the amount of reflected sunlight and the thickness or depth of a cloud is proportional to each other. Second is Infrared Imagery, it can deduce the maximum height of cloud and temperature via IR radiation measurement. Since the IR radiation is not dependent through sunlight it can be measured anytime of the day. Last is Water Vapor imagery, this type of satellite imagery is designed to measure the atmospheric moisture from space (Milrad, 2018).

Before, satellite was used only for military activities. But today, due to advanced technology satellite images are also used for different applications. Satellite imaging with radar can be used now for climate monitoring, coastal monitoring, land use, forestry and agriculture, natural resources exploitation, map updating and compiling, marine environment, natural disaster etc. These show that satellite imagery has a wide range of applications that have great impact on our daily lives. Without those applications we do not have any idea for the things that happen in our surroundings (Inggs & Lord, 2000).

Figure 2.1: *Sample of Satellite Imagery* (Erwin, 2018)

2.1.1.1 Open Access Satellite Images

Governmental programs such as European Space Agency (ESA) Copernicus and National Aeronautics and Space Administration (NASA) Landsat are taking significant efforts to make such data freely available for commercial and noncommercial purposes with the intention to fuel innovation and entrepreneurship. With access to such data, applications in the domains of agriculture, disaster recovery, climate change, urban development, or environmental monitoring can be realized. (Helber, et al., 2019).

The following are some of the available open sources of satellite data:

❖ **Copernicus Open Access Hub** is an open access portal that provides freely available data of Sentinel satellites which are mostly used for land and coastal waters. This satellite Copernicus Open Access Hub is managed by the European Space Agency (ESA).

Figure 2.2: *Copernicus Open Access Hub GUI*

❖ **USGS Earth Explorer** this user interface is developed by United States Geological Survey provides online search, browse display, metadata export, and data download of satellite, aircraft, and other remote sensing inventories.

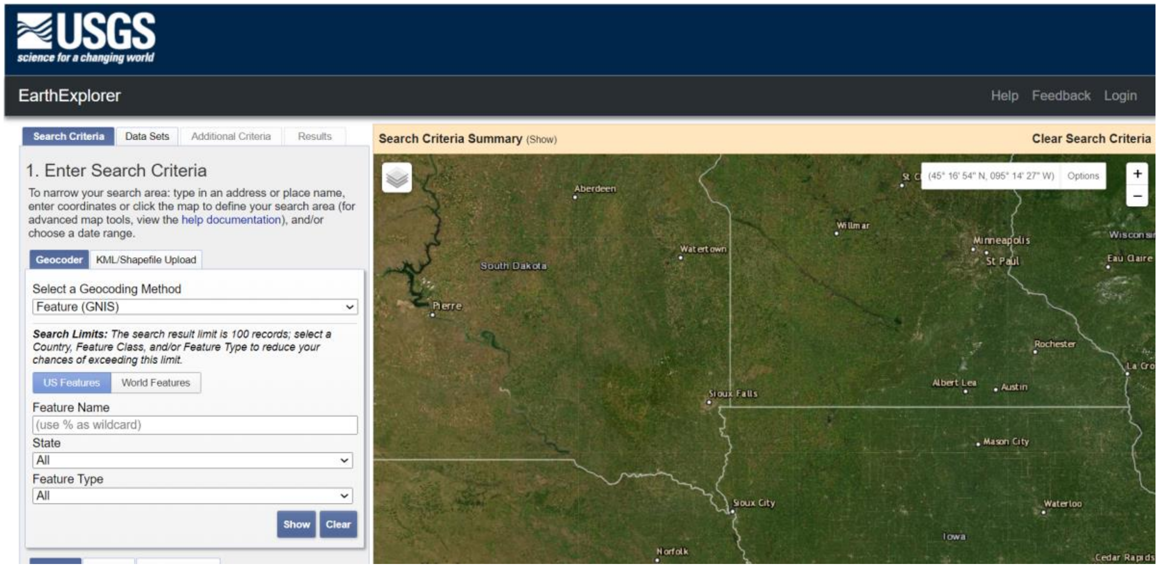


Figure 2.3: *USGS Earth Explorer UI*

Name	High-Level Description	Production & Distribution	Data Volume
Level-1C	Top-Of-Atmosphere reflectances in cartographic geometry	Systematic generation and online distribution	~600 MB (each 100km x 100km^2)
Level-2A	Bottom-Of-Atmosphere reflectances in cartographic geometry	Systematic and on-User side (using Sentinel-2 Toolbox)	~800 MB (each 100km x 100km^2)

Figure 2.4: *Land area of a tile (256x256 pixels) of Sentinel satellite products from both Copernicus Open Access Hub and USGS Earth Explorer (https://sentinel.esa.int/web/sentinel/missions/sentinel-2/data-products)*

❖ **Google Maps** is a Web-based service developed by Google that provides detailed information about geographical regions and sites around the world. Google Maps application program interface (API) makes it possible for the maps to be embedded on external or third-party websites. Google Maps API provides many features for manipulating maps and adding content to the map through a variety of services that allows to create a mapping application (Windarni, et al., 2016).

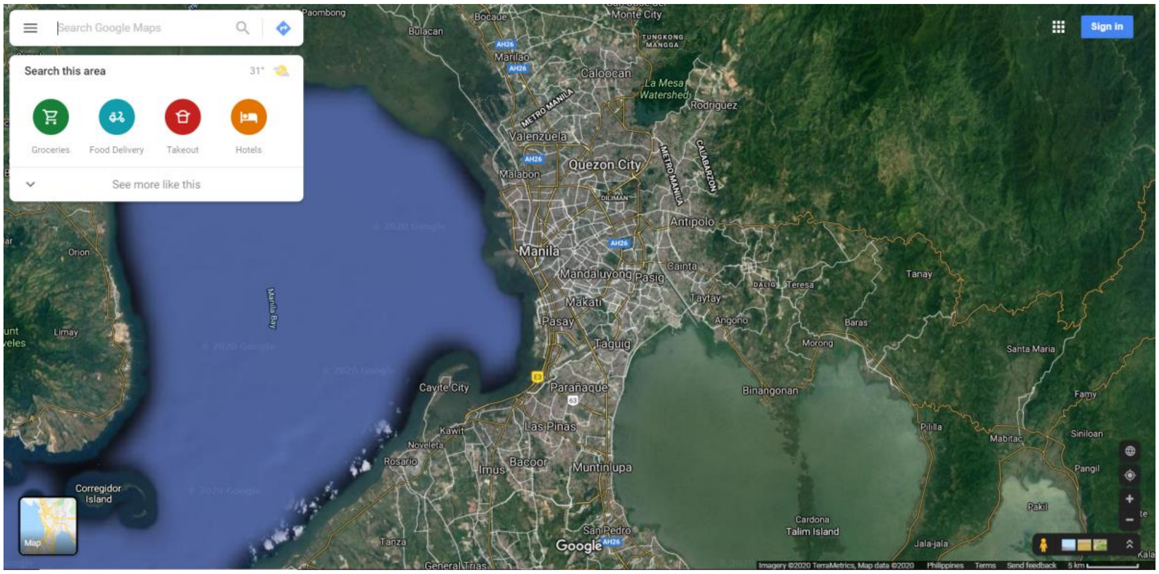


Figure 2.5: *Google Maps*

Folders, Tiles, and File Size by Zoom Level for a Sample Google Maps Tile Overlay (1-m Orthoimage Mosaic of a US State)

(see Technical Guide entitled *Tilesets: Understanding Sizes*)

Source image size: **352 GB** (uncompressed)

Image area: 109,185 square kilometers

Tile Size: 256 x 256 Pixels (required)

Tile Formats: JPEG + PNG for edge tiles

Coordinate Reference System:
WGS84 / Spherical Web Mercator (required)

Zoom Level	Number of Folders	Number of Tiles	Size on Disk
5*	1	2	32 KB
6	2	5	92 KB
7	2	7	308 KB
8	3	18	0.98 MB
9	4	43	2.86 MB
10	7	143	6.96 MB
11	13	516	17.1 MB
12	25	1,871	58.8 MB
13	49	7,236	201 MB
14	96	28,388	750 MB
15	192	112,485	2.88 GB
16	382	447,836	10.6 GB
17†	762	1,786,429	40.5 GB

* minimum zoom level: lowest level requiring more than one tile to cover the image area

† maximum zoom level: pixel size equal to or less than the spatial resolution of the input image

Total Number of Folders: **1,551**

Total Number of Tiles: **2,384,979**

Total Size on Disk: **55.1 GB**

Figure 2.6: *Table showing the image area of a 256x256 pixel tile from Google Maps*

2.1.1.2 Benchmark Datasets

Development and testing of computational methods are dependent on experimental data. Only in comparison to existing knowledge can method performance be assessed. For that purpose, benchmark datasets with known and verified outcome are needed (Sarkar, et al., 2020). Benchmark dataset is used as a standard, which solution can be compared and is used both in training and testing.

The following are some types of benchmark datasets that is publicly available:

- ❖ **UC Merced Land Use Dataset** is a 21-class land use image dataset meant for research purposes with each image measuring 256x256 pixels. The images were manually extracted from large images from the USGS National Map Urban Area Imagery collection for various urban areas around the country. The pixel resolution of this public domain imagery is 1 foot. (Yang & Newsam, 2010)

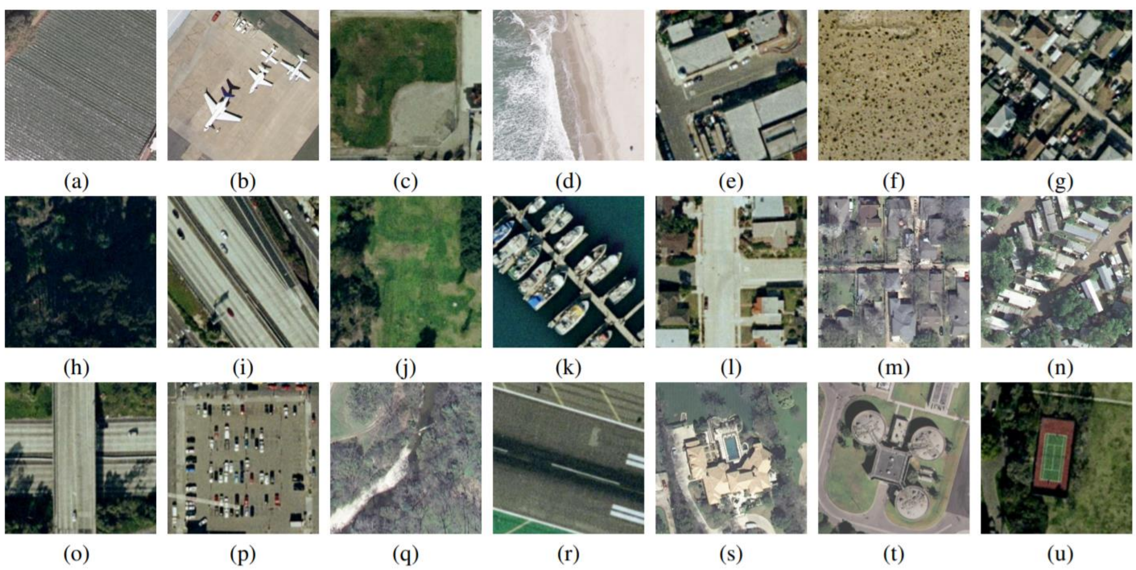


Figure 2.7: *Sample patches from the UC Merced dataset. (a) agricultural; (b) airplane; (c) baseball diamond; (d) beach; (e) buildings; (f) chaparral; (g) dense residential; (h) forest; (i) freeway; (j) golf course; (k) harbor; (l) intersection; (m) medium residential; (n) mobile home park; (o) overpass; (p) parking lot; (q) river; (r) runway; (s) sparse residential; (t) storage tanks; (u) tennis court (Castelluccio, 2015)*

❖ **EuroSAT Dataset** is a land use dataset that is based on Sentinel-2 satellite images covering 13 spectral bands and consisting of 10 classes with 27000 labeled and geo-referenced samples.

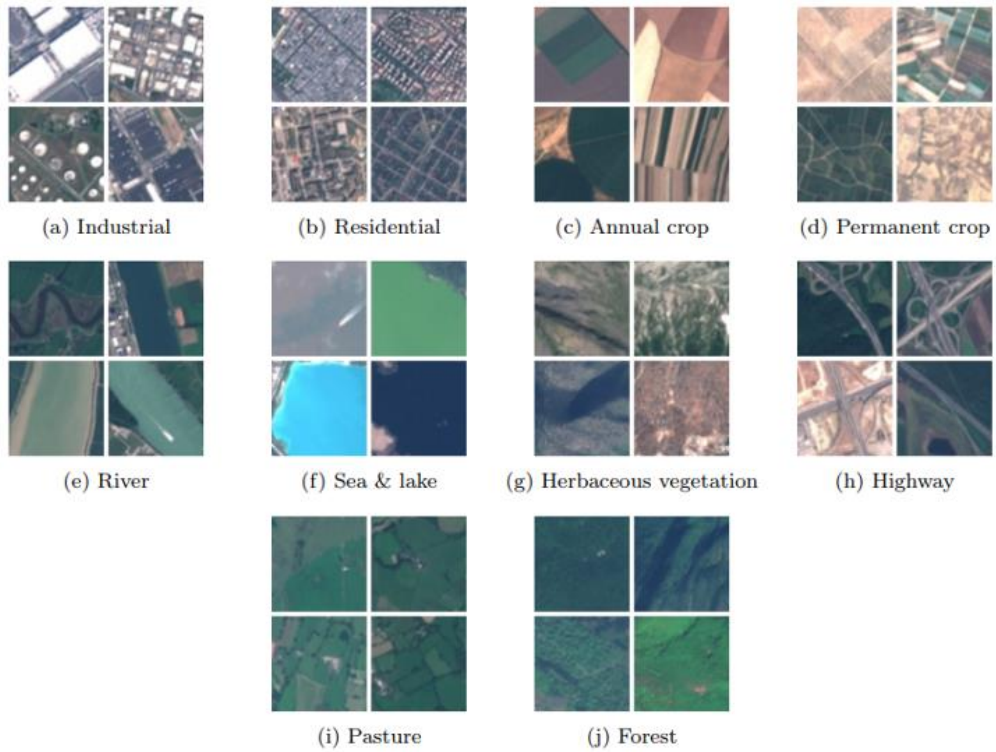


Figure 2.8: *Overview of sample image patches from EuroSAT dataset (Sharma, 2019)*

2.1.2 Machine Learning for Pattern Recognition

Pattern recognition is the process of recognizing the patterns using machine learning. It can be defined as the classification of data based on knowledge already gained or on statistical information extracted from the patterns. Its applications such as data mining, knowledge discovery in databases, fast emerging areas such as biometrics, bioinformatics, multimedia data analysis and most of all data science. Pattern recognition is a mature but exciting and fast developing field, which underpins developments in cognate fields such as computer vision, image processing, text and document analysis and neutral networks. An example of pattern recognition in the Study of Multivariate Data Clustering Based on K-Means and Independent Component Analysis is shown in Figure 2.

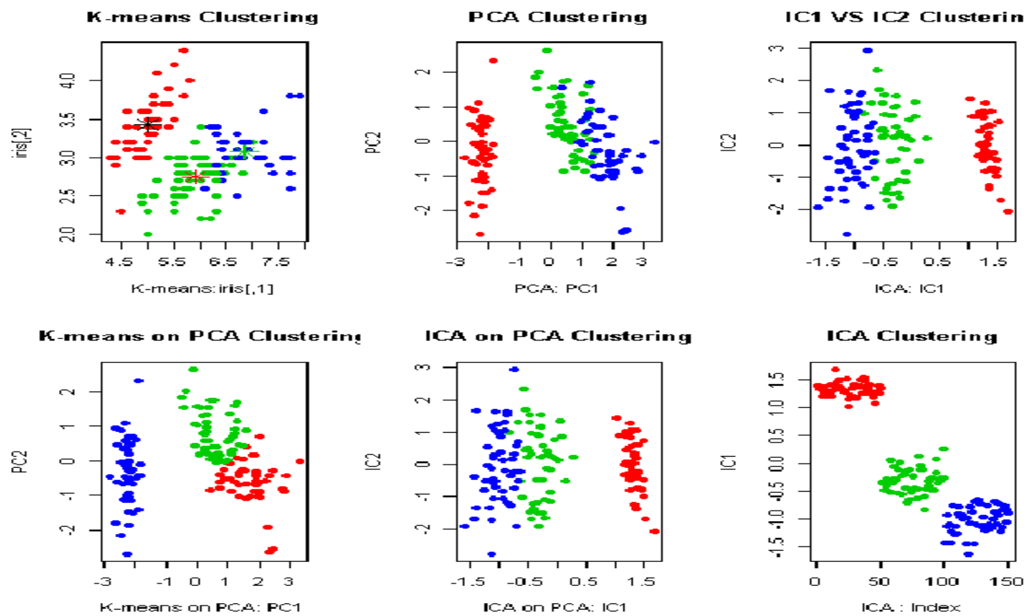


Figure 2.9: *Pattern recognition result to identify multivariate data cluster includes K-Means, PCA and ICA* (Reza & Ruhi, 2015).

2.1.3 Convolutional Neural Network

Convolutional Neural Network (CNN) became famous way back 2012 because of Alex Krizhevsky (computer scientist) won the ImageNet competition it is a competition of image classification (Krizhevsky, Sutskever, & Hinton, 2012). And because of the improvement of it every year, it's used today for different services. It is used in Facebook for automatic tagging algorithms, in searching a photo in Google, for recommendations of products in Amazon site, for infrastructure of Instagram, etc. But today it is prominent for the programmer in the aspect of image processing because of the accuracy of an artificial intelligence of it to recognize everything.

For the deep CNN it has a basic concept of it which is receptive field, it is called this as field of view. Receptive field is a very important concept of deep Convolutional Neural Network for the understanding and analyzing of an image. When it has an input image, it doesn't affect the quality of the image, but it ensures that the system cover the whole image region in processing. This is very useful also in any kind of prediction of an image like stereo, optical flow estimation and semantic image segmentation. It is doing prediction in every pixel in every input of an image (Luo, et al., 2016).

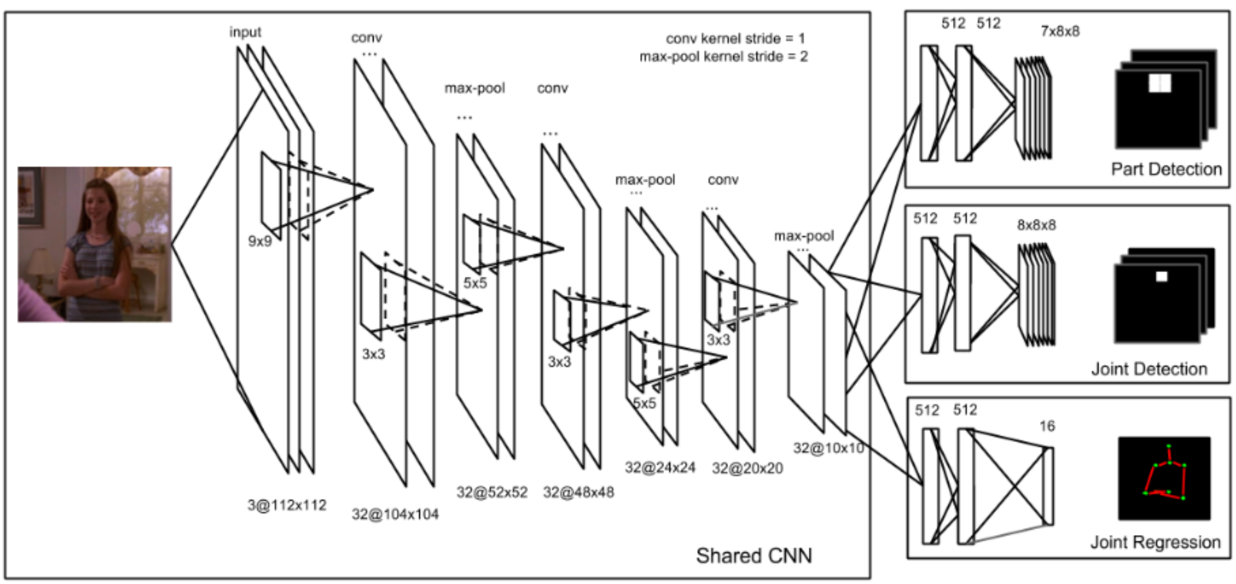


Figure 2.10: *Convolutional Neural Network which evaluates the pose of humans*

(Chan, 2019)

The following are some types of Convolutional Neural Network:

- **SegNet**

It is intended to be a systematic architecture for pixel-wise semantic division It is mainly driven by road scene understanding applications which require the capacity to demonstrate appearance (road, building), shape and comprehend the spatial-relationship (context) between various classes such as road and sidewalk. SegNet is composed of encoders and decoders layers. Each encoder applies convolution, group standardization and a non-linearity, then applies max pooling on the outcome, while putting away the list of the esteem extracted from each window. Decoders are like the encoders, the difference is that they don't have a non-linearity, and they sample their data, utilizing lists stored from the encoding stage. After the last decoder, the output is supplied to a softmax classifier which gives the last prediction. The prediction will be a n channel image, so we need to compose a different function to transform it into a RGB (Red Green Blue) image to subjectively look at the outcomes (Badrinarayanan, et al., 2017). Figure 4 shows the illustration to understand SegNet.

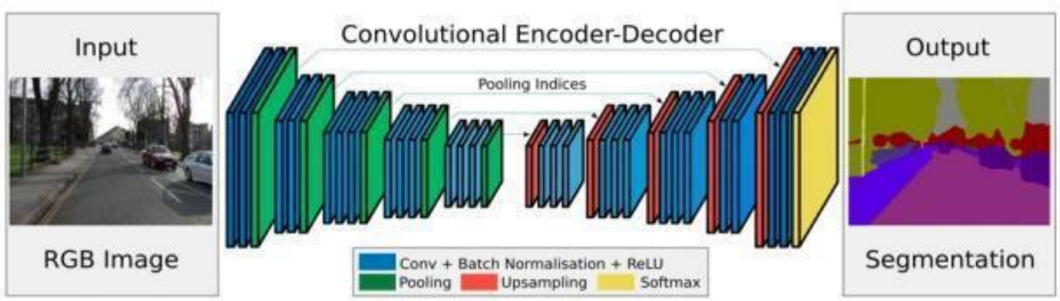


Figure 2.11: *Segnet architecture illustration* (Badrinarayanan, et al., 2017)

- ❖ **VGGNet**

This kind of CNN has 16 convolutional layers and is engaging a direct result of its extremely uniform architecture. It is like AlexNet, it is just a 3x3 convolutions with a lot of of filters. Trained on 4 GPUs for 2–3 weeks. Trained for 2-3 weeks on 4 GPUs. Currently, it is the network's preferred choice for extracting image features. The VGGNet's weight design is freely accessible and has been utilized as a benchmark feature extractor in several different applications and challenges. However, VGGNet comprises of 138 million parameters, which can be somewhat challenging to deal with (Das, 2017).

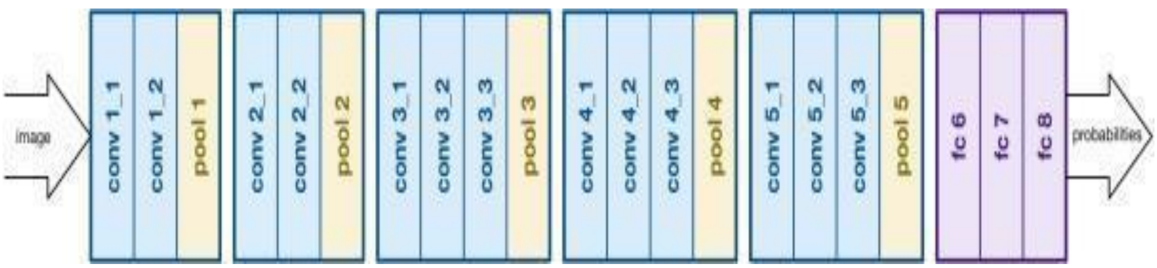


Figure 2.12: *VGGnet parameters* (Das, 2017)

- ❖ **ResNet**

ResNet (Residual Neural Network) by Kaiming He et al gave a novel structure "skip affiliations" and features generous gathering institutionalization. These skip affiliations are generally known gated units or gated discontinuous units and have a strong likeness to later productive segments in RNNs. As a result of this methodology, they had the alternative to set up a NN with 152 layers. But it was still less multifaceted than VGGNet. It achieves a principle 5 error rate of 3.57% which beats human-level execution on this dataset. Let’s see figure 6, the residual connection of ResNet layers.

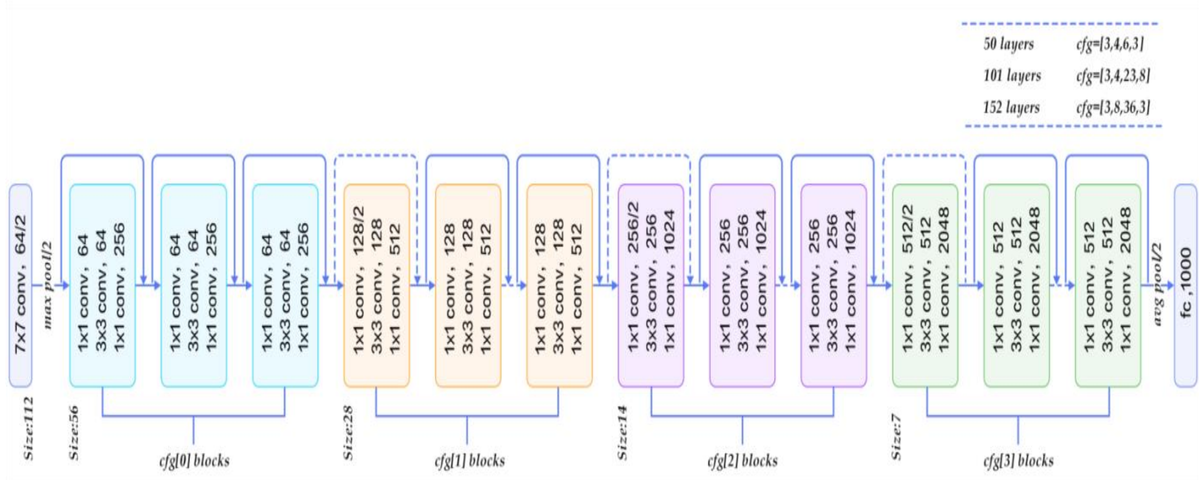


Figure 2.13: *Residual connection of ResNet layer* (Das, 2017)

2.1.4 Land Use/Land Cover

Land Use/Land Cover data files are a result of characterizing raw satellite data into "land use and land cover" (LULC) classifications dependent on the return value of the satellite image. There is not much of a dataset because; a) getting satellite images data. are very expensive, and b) The characterization procedure is time consuming and expensive. The LULC satellite image data products are outdated when released. However, LULC provides a very important way to verify the broad uses of different land uses and cover types, such as cities, forests, shrubs, agriculture, etc. Land use/land cover data are most commonly in a raster or network data structure, with every cell having an esteem that relates to a specific characterization. This structure considers making outline tables and performing suitability analyses. LULC data is sometimes changed to a vector format, although file dimensions become exceptionally large. The term "land use/land cover" (LULC) is a general term, while an early USGS project, which is discussed below, uses the name "Land Use and Land Cover" (LULC) (D. H. Hill Jr., J. B. Hunt Jr., 2017).

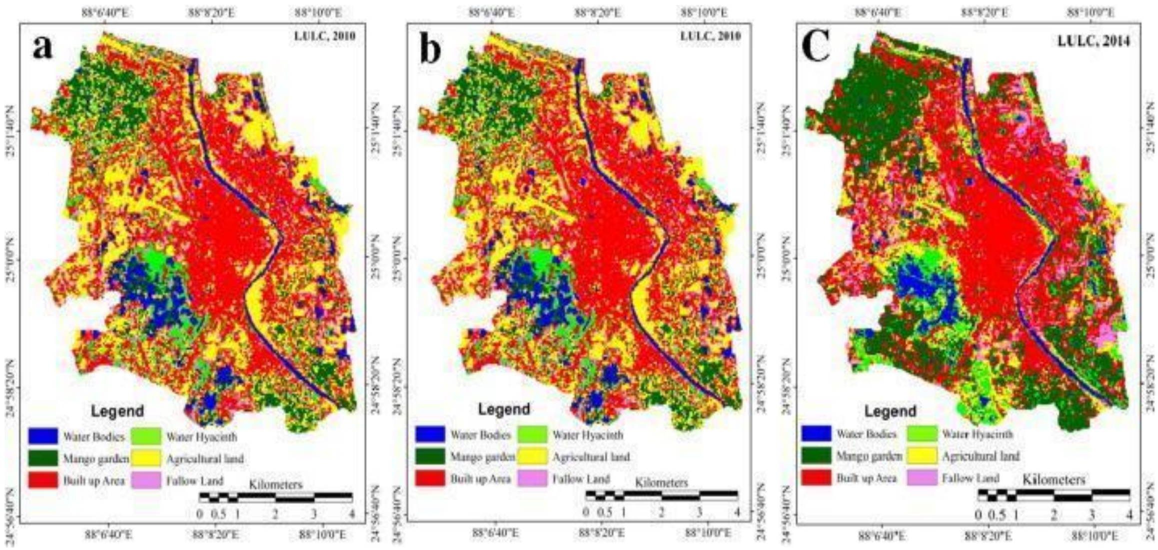


Figure 2.14: *LULC map in English Bazar urban centre, India of different year* (D. H. Hill Jr., J. B. Hunt Jr., 2017)

The following are some of the land use/land cover classifications:

❖ **Commercial Area**

Commercial area refers to land or buildings that are used for any business or enterprise done with the sole motive of generating a profit for the investor or conducting operations for living purposes. There are circumstances where the investor can live on the property and still make benefit from it. Locations with at least five different units and residences are normally classified as commercial properties. Office buildings are also considered commercial property (Koshal, 2011).

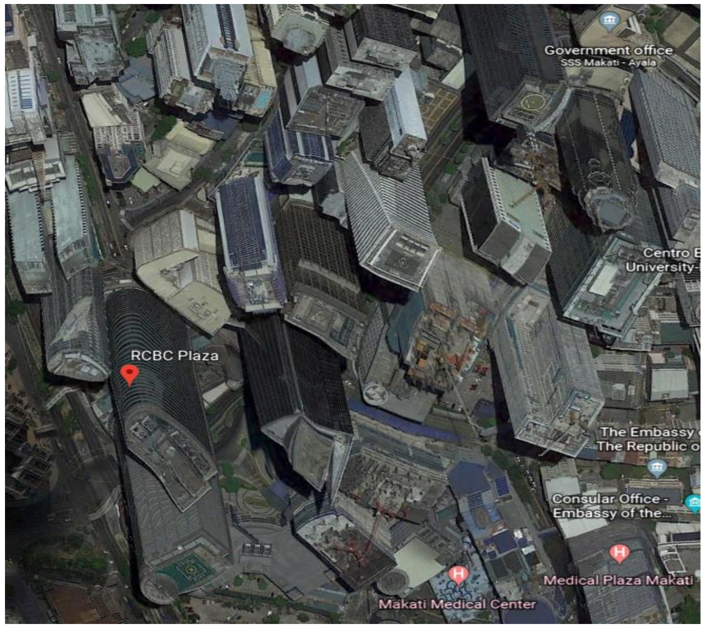


Figure 2.15: *RCBC Plaza Commercial Property in Bonifacio Global City* (Google Earth, n.d.).

❖ **Agricultural Area**

Agricultural lands consist of three main types: (1) land under temporary crops, temporary meadows for mowing or for pasture, land under market or kitchen gardens, and land that is temporarily fallow (2) land under permanent crops, and (3) pastures and hayfields. The total area of agricultural lands in the world is 4973.4 million ha. They cover 33.3% of terrestrial surface (2003), including 10.3% of arable land and land under permanent crops and 23% of pastures and hayfields (Lyuri, 2008), see the figure 10 below the sample of Agricultural land in Greater Manila Area.

Figure 2.16: *Agricultural land in Natatas Tanauan Batangas* (Google Earth, n.d.)

- **Residential Area**

The residential area alludes to living arrangements which can accommodate up to four different units, investment properties or homes for individual families. It is an association with homes, condos, or wherever individuals live. You may allude to a residential structure, neighborhood, or a block. Something that is considered "for residential use" is intended for use at home or as opposed to for business use. Any business being worked from a home, condo, or other place where individuals live on the property is considered as a residential area (Property Management ACES, n.d.), see the residential area in Figure 11.

Figure 2.17: *Clark View Subdivision in Clark Pampanga* (Google Earth, n.d.).

2.2 Related Studies

2.2.1 Related Studies on Economic Prediction using Satellite Images

The key factors being considered in poverty mapping are poverty planning, provision of government products, political responsibility, and outcome assessment, essentially considering the geographic dispersion of the existing bottom billion people in the developing world. In this journal, we train Convolutional Neural Networks (CNNs) to estimate poverty instantly from satellite 1 pictures of high and medium resolution. Spatial resolutions covering all 2 million square kilometers of Mexico are both used with Planet and Digital Globe imagery. MCS-ENIGH 2014 with Inter Census 2015 is used to predict poverty levels for 2,456 counties in Mexico, while CNNs will be trained with 896 countries using the MCS-ENIGH 2014. As a final design, GoogleNet is used to perfectly tune weights from ImageNet. They discovered that in MCS-ENIGH municipalities, the finest models incorporate about 10 percent variation in poverty. They found, although much research needs to be undertaken to know how the method of learning affects sample validity, that CNNs can be trained in satellite imaging to assess poverty (Babenko, Newhouse, & Ramakrishnan, 2017).

This article presents a technique of correlating light intensity from pictures with state-wide poverty, demographic, GDP, and coverage of forests, and forecasting potential levels of the same in each State, given Indian census night-time satellite pictures. We use the model-based prediction technique for the assessed information, the multivariate light intensity and the census information correlation regression evaluation and the ARIMA census data predicting model. To predict the validity of accessible population data, we compare outcomes from the ARIMA template and a regression approach. We outline a technology in the field of poverty that can assist formulate currency strategy, international assistance, or channel other types of assistance in a prompt manner (Nischal, et al., 2015).

In the emerging globe, reliable information on livelihoods stay rare, hampering attempts for the research and development of strategies to enhance them. Here we show a precise approach to estimating usage and the assets of high-resolution satellite imaging that would be cost-effective and scalable. We demonstrate how a convolutional neural network can be educated to define picture characteristics that can account for as little as 75% of the variance in financial results at local level using study information and satellite information from five African countries – Nigeria, Tanzania, Uganda, Malawi, and Rwanda. Our approach, which only needs openly accessible information, can turn attempts in emerging nations to monitor and target poverty. It also shows how strong machine learning methods can be implemented in an environment with restricted training information and suggests wide prospective applications in several science fields (Jean, et al., 2016).

Evaluating monetary and developmental parameters, for example, level of poverty of a locale from satellite imagery is a difficult issue that has numerous applications. We propose a two-stage way to deal with poverty prediction in a provincial locale from satellite imagery. First, we create a comprehensive and multi-task deep network, which simultaneously predicts the roof material, light, and water source from satellite images. Second, to assess poverty, we utilize the predicted developmental statistics. Our models can learn significant highlights including streets, water bodies and farmlands without pre-trained loads, and accomplish a performance that is near the ideal by utilizing full-measure satellite imagery as data. The fully convolutionary multi-task system model can identify various tasks and independent feature portrayals in addition to speeding up the training process (Pandey, et al., 2018).

It is essential to target aid and construct strategies for estimating local poverty in the demographic development that are restricted by household survey and census information collection expenses. The article will attempt to correctly predict poverty and financial well-being from elevated spatial-resolution satellite pictures. To assess median usage and poverty for 1,291 households, satellite images from Sri Lanka were collected. Regularization of Lasso is used to avoid median usage from being exceeded, and to utilize poverty headcount rates at the community stage. The construction density and the incidence of the shadow region were considered to be an option for high-rise structure, type of agricultural land, roofing material, car amount and road width and duration. Samples show the predictive capacity of the results are confirmed through the extrapolation to neighboring fields and the estimation of local poverty through decreased studies. They found that spatial modeling can change the estimates of poverty in a tiny region and that projections for derivative characteristics offer precise allocation of healthcare and significant benefits throughout the village's welfare allocation to current techniques which use satellite imagery to measure poverty (Engstrom, et al., 2017).

2.2.2 Related Studies about Accessible Data using Satellite Imagery

In this century, handling chains strive to solve the problems of memory and computer technology. Problems are dealt with Earth observation and meteorological survey to bring emerging cloud computing techniques into practice. The growing technology of satellite capture is producing larger information, and weather reports and forecasts are being handled through more complicated algorithms. This type of design is economically feasible as cloud suppliers offer affordable pay-per-use services. Cloud computation is capable of providing alternatives to the complexities of satellite information handling. Centralized information connectivity between localization limits processing funds and software optimization for scalable storage and shared computation capacity to minimize expenses and processing time (Sahl, et al., 2018).

In order to monitor the safety of the seashore, its residents and critical structures, this document integrates obtained information from various geospatial information facilities and distant sensing through the web-based Safe City & Coastal Area (SCCZ-GIS) where the evaluation findings are prepared in virtually actual time. Various distant information sources and facilities such as ESA Service Support Environment's satellite base station collaborate straight to use several creative techniques. In addition, authorized consumers can access the information via a browser-based private computer system or portable phones using a client-oriented request (Bruniecki, et al, 2014).

Ceaseless development in the utilization of innovation and portable applications implies more individuals approach web-distributed data, including geographic data. Nevertheless, interaction for visually impaired individuals is troublesome if maps aren’t accessible. In this paper, we break down webpage availability boundaries with the introduced geographic content on mobile phones. To demonstrate an alternative to enhance the availability of these pages, this study proposes the use of a procedure called crowdsourcing or publicly supporting. Scalable Vector Graphics Tiny (SVG Tiny) code composes this illustration. SVG Tiny is utilized to speak to geographic maps with HTML. Screen readers can translate the illustration to visually impaired people, eventually making maps progressively available (Calle-Jimenez & Luján-Mora, 2015).

Satellite imagery provides unparalleled possibilities to understand natural and cultural phenomena on a worldwide and regional scale. However, the task continues to scale those methods to very large regional levels, with essential issues assessed human and environmental sustainability by means of Satellite distant monitoring. Unmonitored techniques performance relies on functionality because removing the labels in satellite photos allows us to arrange pictures into a consistent cluster. The characteristics from which layer and network architecture are still uncertain to learn new tasks. The characteristics of latest research show that pre-trained networks can be used for the teaching in spatially and temporally vibrant information sources such as satellite imagery, pre-trained networks showed potential in current datasets. In this article, we present an assessment on the transferability of functionalities for satellite imaging from pre-trained Deep Convolutional Neural Networks. Their developed and trained features can be transferred from an unlabeled dataset to a distinct data set. The mix of characteristics taken from a multitude of profound network architectures is explored and evaluated, and more than 2,000 network-layer configurations systematically evaluated. This technique might be helpful when unlabeled pictures and other automated teaching assignments are clustered. The outcome is that these networks can be generalized to other datasets without or without a minimum of practice. Creating an information capacity issue in satellite mapping (Placeholder1) to identify the contents of pictures is now more spatially, spectrally, and temporally available (Hedayatnia, 2016).

Project Matsu is a joint effort between the Open Commons Consortium and NASA concentrated on innovating opensource technology for Earth satellite imagery cloud-based processing. A specific focus is on advancing fire and flood detection applications to help support calamity detection and ease. Project Matsu has built a cloud-based opensource foundation for processing, dissecting, and re-analyzing huge accumulations of hyperspectral satellite image data using OpenStack, Hadoop, MapReduce, Storm, and related technologies. We portray a system called the Matsu "Wheel for productive analysis of big data. Currently, the Matsu Wheel is used to process incoming hyperspectral satellite data generated daily by the NASA satellite Earth Observing-1 (EO-1). The system is intended to enable cloud computing applications such as, Hadoop and Accumulo to support scanning queries. A scanning query processes all, or most of the data, in a database or data repository. We also portray our basic Wheel analytics, including an irregularity indicator for unusual unearthly marks or thermal inconsistencies in hyperspectral data and a land cover classifier that can be used for water and flood recognition. Each of these analytics can create visual reports that are open by means of the web for people in general and intrigued decision makers or leaders. Additionally, the results of the analytics are made available for further conveyance through an Open Geospatial Compliant (OGC)-consistent Web Map Service (WMS). The Matsu Wheel permits many data services to be carried out together to effectively use assets to handle hyperspectral satellite image data and other, e.g., large ecological data sets that may be analyzed for many usages (Patterson, et al., 2016).

2.2.3 Related Study about Land Classification

We explored the potential for rapid land use/land cover (LULC) mapping using time-series Landsat satellite imagery and training data (for supervised classification) automatically extracted from crowdsourced OpenStreetMap (OSM) “land use” (OSM-LU) and “natural” (OSM-N) polygon datasets. The main challenge with using these data for LULC classification was their high level of noise, as the Landsat images all contained varying degrees of cloud cover (causes of attribute noise) and the OSM polygons contained locational errors and class labeling errors (causes of class noise). A second challenge arose from the imbalanced class distribution in the extracted training data, which occurred due to wide discrepancies in the area coverage of each OSM-LU/OSM-N class. To address the first challenge, three relatively noise-tolerant algorithms – naïve bayes (NB), decision tree (C4.5 algorithm), and random forest (RF) – were evaluated for image classification. To address the second challenge, artificial training samples were generated for the minority classes using the synthetic minority over-sampling technique (SMOTE). Image classification accuracies were calculated for a four-class, five-class, and six-class LULC system to assess the capability of the proposed methods for mapping relatively broad as well as more detailed LULC types, and the highest overall accuracies achieved were 84.0% (four-class SMOTE-RF result), 81.0% (five-class SMOTE-RF result), and 72.0% (six-class SMOTE-NB result). RF and NB had relatively similar overall accuracies, while those of C4.5 were much lower. SMOTE led to higher classification accuracies for RF and C4.5, and in some cases for NB, despite the noise in the training set. The main advantages of the proposed methods are their cost- and time-efficiency, as training data for supervised classification is automatically extracted from the crowdsourced datasets and no pre-processing for cloud detection/cloud removal is performed (Johnson & Iizuka, 2016).

Ecologically Valuable Areas play an important role in providing ecosystem services, however, human activities such as land conversion and urban sprawl pose pressures and threats to these areas. The study assessed the land use/land cover and urban sprawl in the Mount Makiling Forest Reserve (MMFR) Watersheds and Buffer Zone from 1992 to 2015 using remote sensing and Geographic Information System (GIS). Results showed that the land use/cover within the MMFR buffer zone has changed from 1992 to 2015 with built-up areas increasing by 117% despite Proclamation 1257, s. 1998 which regulates human activities in the zone. Based on the Shannon entropy analysis the land development in the MMFR buffer zone tends to be dispersed and sprawling. However, when the magnitude of change of urban sprawl in the buffer zone from 2002 to 2015 was calculated, a decrease in the entropy value was observed which implies a compacting pattern as the human settlement in the buffer zone increases over time. Proclamation 1257,

s. 1998 needs to be strengthened to protect MMFR and its buffer zone from further encroachment and pressure. Moreover, remote sensing and GIS proved to be useful tools for assessing urban sprawl in ecologically valuable areas such as MMFR (Soriano, et al., 2019).

In this paper, we address the challenge of land use and land cover classification using Sentinel-2 satellite images. The Sentinel-2 satellite images are openly and freely accessible provided in the Earth observation program Copernicus. We present a novel dataset based on Sentinel-2 satellite images covering 13 spectral bands and consisting out of 10 classes with, in total, 27,000 labeled and geo-referenced images. We provide benchmarks for this novel dataset with its spectral bands using state-of-the-art deep Convolutional Neural Network (CNNs). With the proposed novel dataset, we achieved an overall classification accuracy of 98.57%. The resulting classification system opens a gate towards a number of Earth observation applications. We demonstrate how this classification system can be used for detecting land use and land cover changes and how it can assist in improving geographical maps (Helber, et al., 2019).

Urban planning applications (energy audits, investment, etc.) require an understanding of built infrastructure and its environment, i.e., both low-level, physical features (amount of vegetation, building area and geometry etc.), as well as high-level concepts such as land use classes (which encode expert understanding of socioeconomic end uses). This kind of data is expensive and labor intensive to obtain, which limits its availability (particularly in developing countries). We analyze pasterns in land use in urban neighborhoods using large-scale satellite imagery data (which is available worldwide from third-party providers) and state-of-threat computer vision techniques based on deep convolutional neural networks. For supervision, given the limited availability of standard benchmarks for remote-sensing data, we obtain ground truth land use class labels carefully sampled from open-source surveys, in particular the Urban Atlas land classification dataset of 20 land use classes across 300 European cities. We use this data to train and compare deep architectures which have recently shown good performance on standard computer vision tasks (image classification and segmentation), including on geospatial data. Furthermore, we show that the deep representations extracted from satellite imagery of urban environments can be used to compare neighborhoods across several cities. We make our dataset available for other machine learning researchers to use for remote-sensing applications (Albert, Kaur, & Gonzalez, 2017).

The rapid development in deep learning and computer vision has introduced new opportunities and paradigms for building extraction from remote sensing images. In this paper, we propose a novel fully convolutional network (FCN), in which a spatial residual inception (SRI) module is proposed to capture and aggregate multi-scale contexts for semantic understanding by successively fusing multi-level features. The proposed SRI-Net is capable of accurately detecting large buildings that might be easily omitted while retaining global morphological characteristics and local details. On the other hand, to improve computational efficiency, depth wise separable convolutions and convolution factorization are introduced to significantly decrease the number of model parameters. The proposed model is evaluated on the Inria Aerial Image Labeling Dataset and the Wuhan University (WHU) Aerial Building Dataset. The experimental results show that the proposed methods exhibit significant improvements compared with several state-of-the-art

FCNs, including SegNet, U-Net, RefineNet, and DeepLab v3+. The proposed model shows promising potential for building detection from remote sensing images on a large scale (Liu, et al., 2019).

Urbanization is a fundamental trend of the past two centuries, shaping many dimensions of the modern world. To guide this phenomenon and support growth of cities that are competitive and sustainably provide needed services, there is a need for information on the extent and nature of urban land cover. However, measuring urbanization is challenging, especially in developing countries, which often lack the resources and infrastructure needed to produce reliable data. With the increased availability of remotely sensed data, new methods are available to map urban land. Yet, existing classification products vary in their definition of “urban” and typically characterize urbanization in a specific point (or points) in time. Emerging cloud based computational platforms now allow one to map land cover and land use (LC/LU) across space and time without being constrained to specific classification products. Here, we highlight the potential use of publicly available remotely sensed data for mapping changes in the built-up LC/LU in Ho Chi Minh City, Vietnam, in the period between 2000 and 2015. We perform a pixel based supervised image classification procedure in Google Earth Engine (GEE), using two sources of reference data (administrative data and hand-labeled examples). By fusing publicly available optical and radar data as input to the classifier, we achieve accurate maps of built-up LC/LU in the province. In today's era of big data, an easily deployable method for accurate classification of built-up LC/LU has extensive applications across a wide range of disciplines and is essential for building the foundation for a sustainable human society (Goldblatt, et al., 2018).

Monitoring and analysis of the land and rapid environmental change leads to the use of Land Use and Land Cover (LULC) classification approaches from remote sensing data. The main focus of this paper is to illustrate the practical approach to analysis and mapping of land use and land cover features using high resolution satellite images. The study is carried out for two different places, Basel and Tel Aviv. For this purpose, Quickbird satellite imagery is used for Basel and WorldView2 imagery for Tel Aviv. The classification method chosen for the Quickbird image is Support Vector Machine (SVM) classifier and Maximum Likelihood method for the WordView2 satellite imagery. Both of the methods are applied using ENVI 5.0 Remote Sensing software. An accuracy assessment is also applied to the classified results based on the ground truth points or known reference pixels (Cavur, et al., 2015).

In the emerging globe, reliable information on livelihoods stay rare, hampering attempts for the research and development of strategies to enhance them. Here we show a precise approach to estimating usage and the assets of high-resolution satellite imaging that would be cost-effective and scalable. We demonstrate how a convolutional neural network can be educated to define picture characteristics that can account for as little as 75% of the variance in financial results at local level using study information and satellite information from five African countries – Nigeria, Tanzania, Uganda, Malawi, and Rwanda. Our approach, which only needs openly accessible information, can turn attempts in emerging nations to monitor and target poverty. It also shows how strong machine learning methods can be implemented in an environment with restricted training information and suggests wide prospective applications in several science fields (Jean, et al., 2016).

Satellite imagery provides unparalleled possibilities to understand natural and cultural phenomena on a worldwide and regional scale. However, the task continues to scale those methods to very large regional levels, with essential issues assessed human and environmental sustainability by means of Satellite distant monitoring. Unmonitored techniques performance relies on functionality because the labelling of satellite photos allows us to arrange pictures into a consistent cluster. The characteristics from which layer and network architecture are still uncertain to learn new tasks. The characteristics of latest research show that pre-trained networks can be used for the teaching in spatially and temporally vibrant information sources such as satellite imagery, pre-trained networks showed potential in current datasets. In this article, we present an assessment on the transferability of functionalities for satellite imaging from pre-trained Deep Convolutional Neural Networks. Their developed and trained features can be transferred from an unlabeled dataset to a distinct data set. The mix of characteristics taken from a multitude of profound network architectures is explored and evaluated, and more than 2,000 network-layer configurations systematically evaluated. This technique might be helpful when unlabeled pictures and other automated teaching assignments are clustered. The outcome is that these networks can be generalized to other datasets without or without a minimum of practice. Creating an information capacity issue in satellite mapping to identify the contents of pictures is now more spatially, spectrally, and temporally available (Hedayatnia, et al., 2016).

Fez is the most ancient of the imperial cities of Morocco. In Fez, the rate of population growth has been spectacular in recent times (484,300 inhabitants in 1982 and 1,129,768 in 2014). The accelerated rate of population growth has generated a large urban sprawl in all its forms and serious environmental problems. In this research, we have analyzed the relationship between urbanization and land use changes and their impact on cityscape in Fez and the importance of the increase in impervious surface areas. Satellite imageries and census data have been used to identify different patterns of land use change and growth of the city for the period 1984–2013. Classification and analysis of the satellite imageries were performed using Erdas imagine and ArcGIS Software. Urban sprawl in Fez was assessed over 29 years (1984–2013). The overall accuracy of land cover change maps, generated from post-classification change detection methods and evaluated using several approaches, ranged from 78% to 87%. The maps showed that between 1984 and 2013 the amount of urban or developed land increased by about 121%, while rural cover by agriculture and forest decreased respectively by 11% and 3%. 2017 The Gulf Organisation for Research and Development. Production and hosting by Elsevier B.V. All rights reserved (El Garouani, et al., 2017).

CHAPTER 3

METHODOLOGY

3.1 Research Design

The proponents will gather satellite imagery data and utilize it to classify land areas of Greater Manila. The system is composed of the classification through Convolutional Neural Network which is written in Python programming language. A benchmark dataset is used in training and testing of CNN.

3.1.1 Input Process Output (IPO) Model

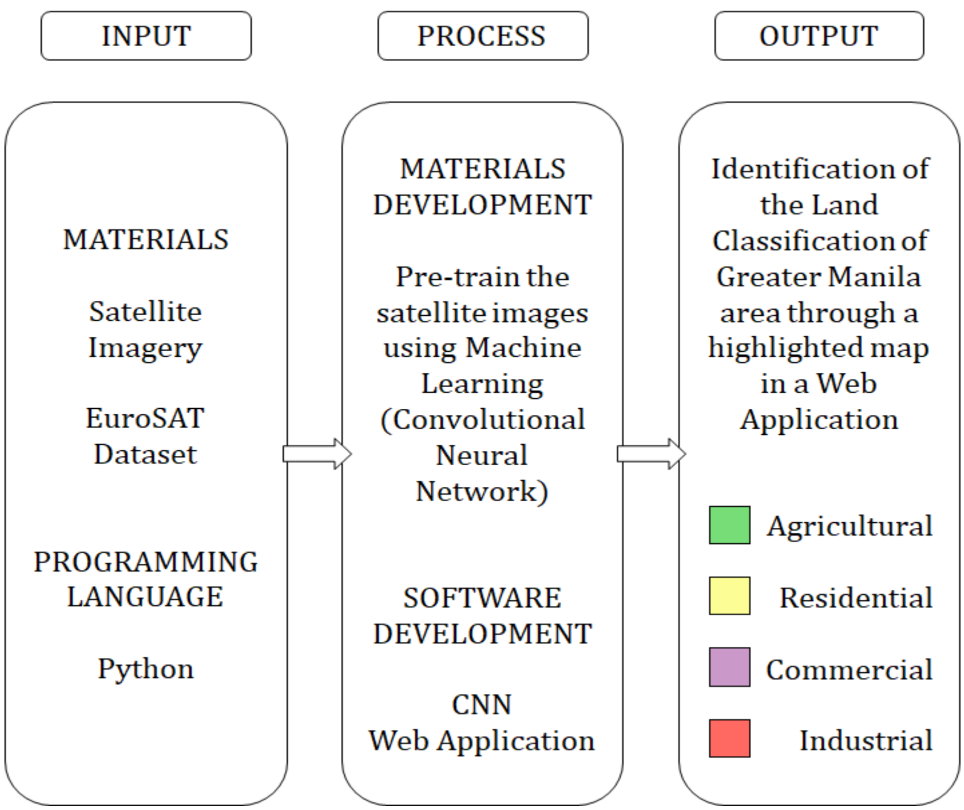


Figure 3.1: *Input Process Output (IPO) Model*

Figure 3.1 shows the input block which includes the materials and software needed for the process of the study. The second block is the process which includes the materials and software development. And the third block is the output, wherein the final result of land classification is included.

3.1.2 Satellite Images

The proponents used freely accessible sources in gathering satellite images and dataset. Google Maps is used for the satellite images with 256x256 pixels and a land area of about 100,000 sq. km. Google Maps has also an API that can be linked to the website that will be developed. EuroSAT dataset is used as the benchmark dataset to be trained and tested by the adapted Convolutional Neural Network, which is ResNet-50.

3.1.3 Convolutional Neural Network (CNN)

The CNN that is adapted in this study is the ResNet-50 which is an existing CNN which has already learned features that can be used in fine tuning/transfer learning. ResNet-50 is used in testing and training the benchmark dataset to be able to classify the satellite images gathered from Google Maps.

3.2 Software Development

The design of the project focuses on the web application and the integration of the CNN system with the satellite images from Google Maps. The website is developed using web programming tools such as HTML5 and CSS3. The system is publicly accessible through internet connection.

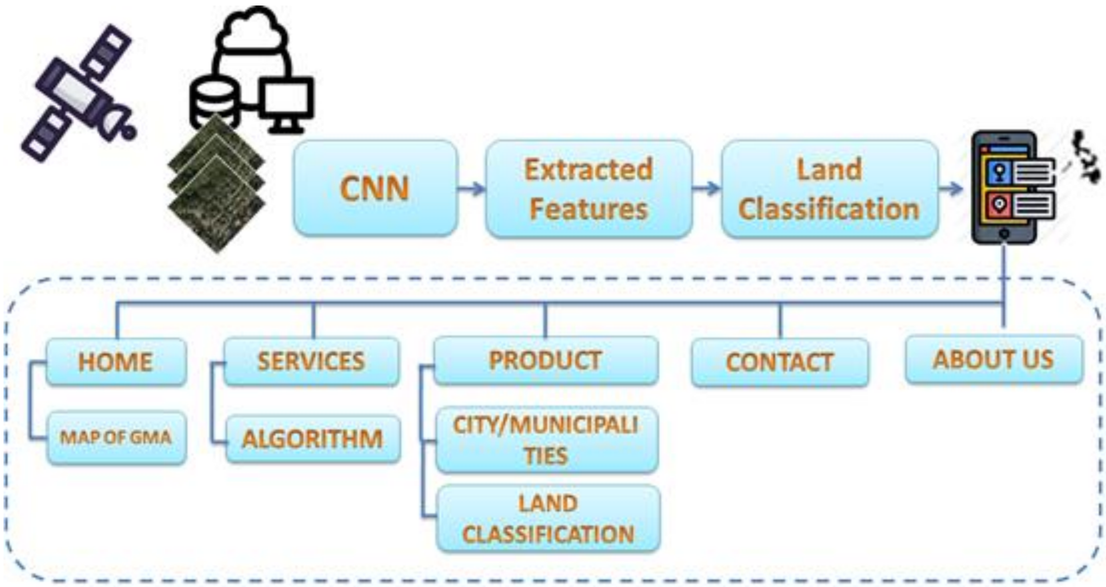


Figure 3.2: *Shows the step-by-step process of the proposed system.*

Figure 3.2 shows a concise main idea of the study, its flow from the beginning. Linked satellite images from Google Maps will be shown on the screen. A snapshot of a chosen area will be taken and will be classified using CNN. In this web application, users will see the visual map having a different color based on what kind of land use.

3.2.1 User Interface

The proponents used the following website developing tools in designing the web application:

3.2.1.1 Front-End (UI)

For the front-end user interface, HTML 5, CSS3, Bootstrap 3, JavaScript, and jQuery is used. HTML 5 is used to define the contents and the appearance of the web page and it works with CSS3 which is used to format structured content for the efficient performance of the site content. Bootstrap 3 helps with easier and faster designing of the website. HTML 5, CSS3 and Bootstrap 3 are used for the positioning of the elements of the webpage and aesthetics. jQuery is used to make the usage of JavaScript much easier. JavaScript and jQuery are assigned for the events of the page (e.g., what modal will show when a button is clicked), for the display of Google Maps, and for the data to be sent to the server for image processing and for the response to be received.

3.2.1.2 Back-End (UI)

For the back-end user interface, Python is used as the programming language with Python-based Django as the back-end framework, and Fast.AI which is a Python library for simplifying and making the training fast and accurate. Python and Django are responsible in running the main web server, and in receiving the data from the frontend to process the image (image that is captured from the map to the image processing) and to return the result to the website. Fast.AI is used for image processing.

3.2.2 Research Process Flow

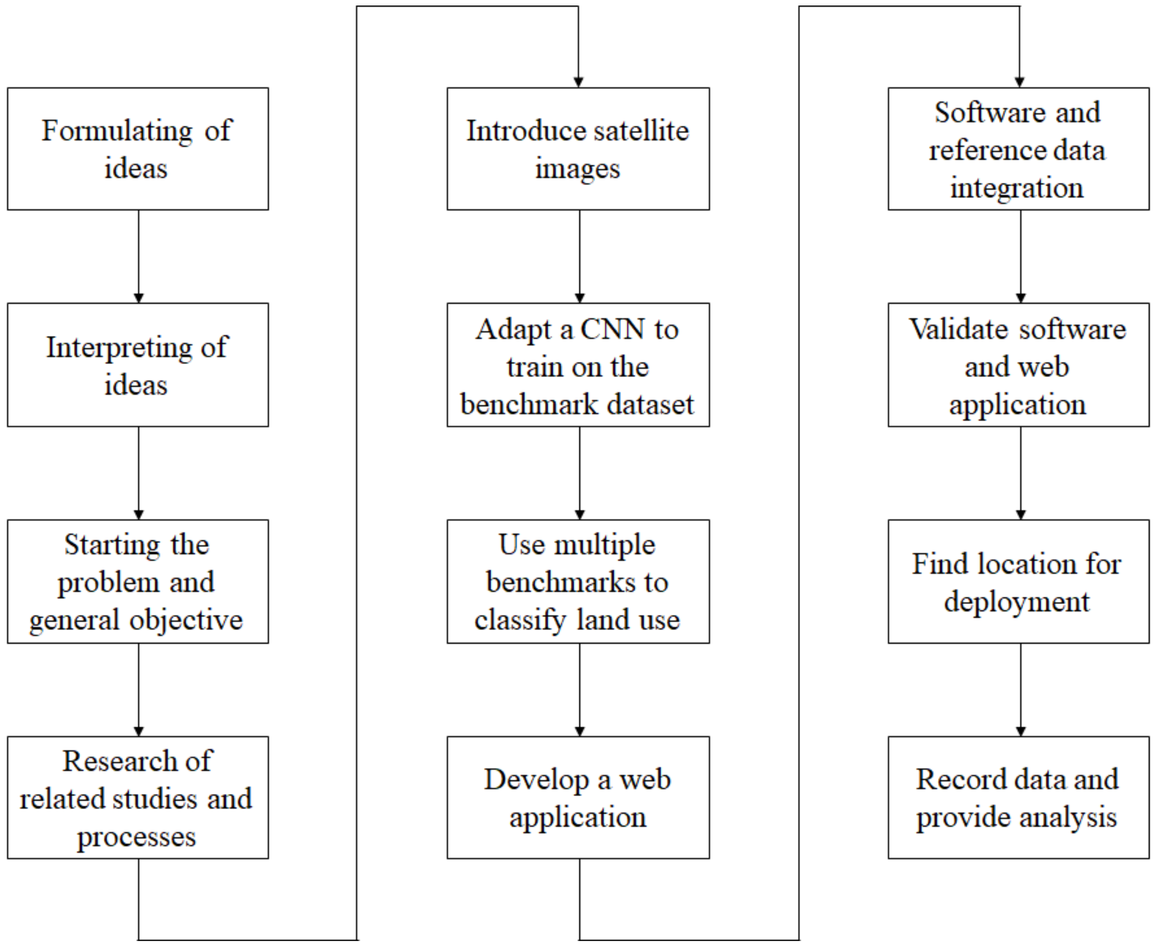


Figure 3.3: *Research Process Flow*

Figure 3.3 shows how the project progresses, starting with the formulation of the present problem in the society that will be given a solution by the conducted study. The study will be supported by previous related research. With the methods present in the past research, the integration of the system will be possible. After gathering the needed requirements for the system, the construction will proceed as well as the development of the program that will set the conditions to be met. In order to test the efficiency of the software, the project must be deployed to the target location.

3.2.3 Machine Learning System Flow Chart

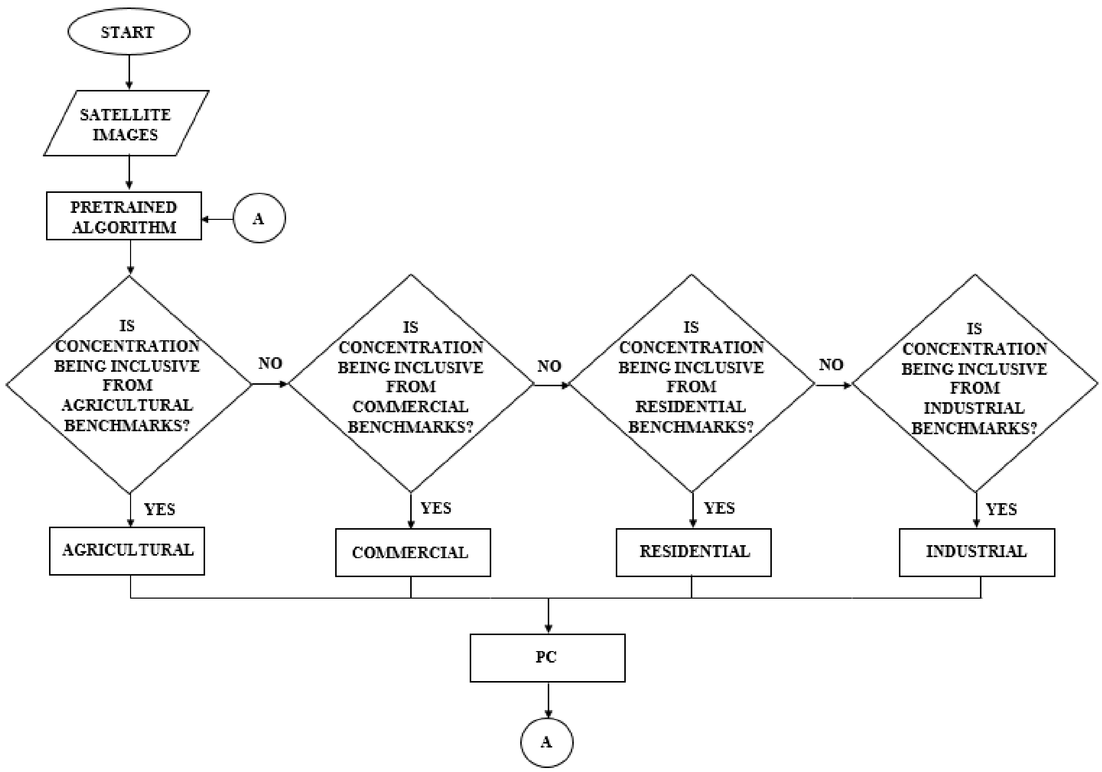


Figure 3.4: *Machine Learning Process Flow Chart*

Figure 3.4 shows the process of the proposed system. The satellite images will be the input of the algorithm for the image processing. The software will utilize the convolutional neural network to classify the images from the training of the benchmark dataset. Once the software detects the features, the system will simultaneously process the data to predict the land classification of the different municipalities in the greater manila area. The satellite images will be processed in the pre-trained algorithm for the machine learning to predict if the municipality belongs in the “Residential Area”, “Commercial Area”, “Industrial Area”, and “Agricultural Area” from different benchmarks to be specified.

3.3 Materials and Equipment

Table 3.1 shows the list of the bill of the materials which are needed to build of this web application on this study. Researchers decided to use a material that fits the specification needed on programming and developing a web application for the system to function properly. Proponents will use a laptop that has an i5 and 64-bit processor to run the Python codes and to make a software and web application. Benchmark dataset and high-resolution satellite images will be accessed freely through the internet.

Table 3.1 *Bills of Materials*

MATERIALS				
QUANTITY	UNIT	DESCRIPTION	UNIT COST (Php)	TOTAL COST (Php)
6	Month	Website subscription	615	3,690
6	Month	Internet Connection	1,500	9,000
9	Piece	Satellite Images	0	0
1	Piece	Laptop	0	0
GRAND TOTAL				12,690

3.4 Testing Procedure

The designed Convolutional Neural Network algorithm is used to train the benchmark dataset that will help the system to recognize land classifications (Residential, Commercial, Industrial and Agricultural) from the satellite images of the Greater Manila Area.

Feature extraction is applied to define each character by the presence or absence of key features, and to identify sub features to examine in the satellite image. CNN will sample 256x256 pixels in every image to identify pixel patterns in order to match them with the benchmarks used to pre-train the algorithm.

The proponents will choose the most accurate CNN architecture for this study. With the verified data, the proponents will develop a web application that can be accessed freely by everyone. The residents of Batangas, Bulacan, Cavite, Laguna, Pampanga, Metro Manila, Nueva Ecija, Tarlac, and Rizal will be able to assess their current living situation using this application.

3.5 Evaluation Procedure

The proponents will conduct interviews and online surveys of IT experts and professionals to evaluate the system and the web application. Evaluation sheets will be given for the interview and will be sent for the online survey through Google forms.

The Convolutional Neural Network will be evaluated based on its accuracy. The web application will be evaluated based on its speed, accuracy, aesthetics, and accessibility specially the user-friendliness of the system.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Technical Description of the System

TUPSI website has a system that can classify land use in different parts of the Greater Manila Area. Classifications are agricultural, residential, commercial, and industrial areas.

The system captures a screenshot of the map (satellite image) and the CNN will classify the said image and visualize it through highlighted patches of the area with being green, yellow, pink, and red, as the classifications of the areas indicated from the latter respectively.

4.2 Overview of the System Parts

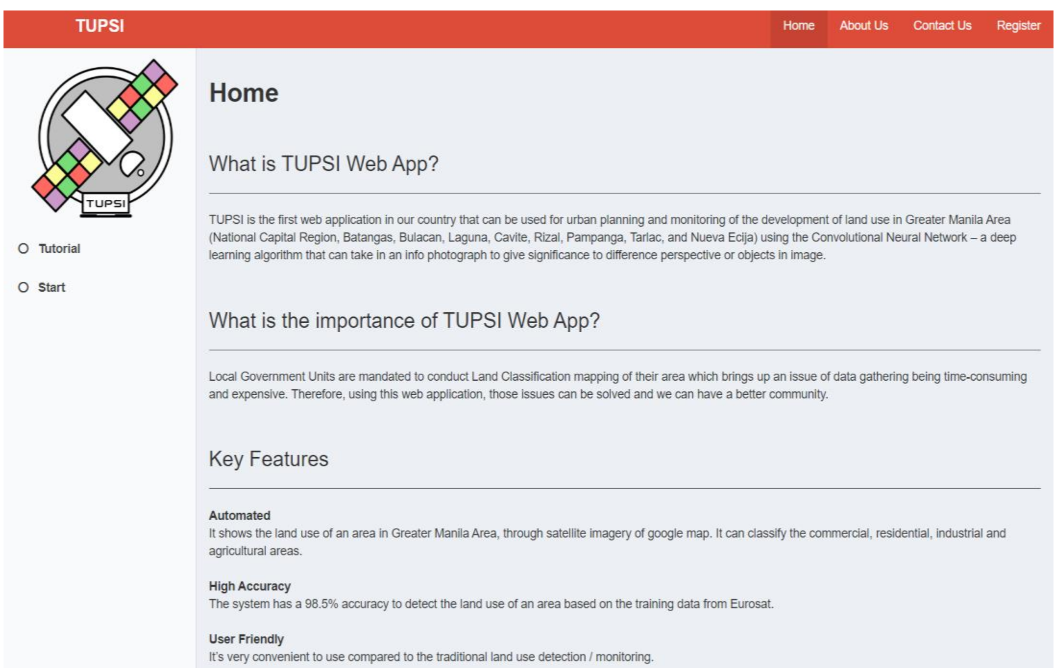


Figure 4.1: Main web page/Home page

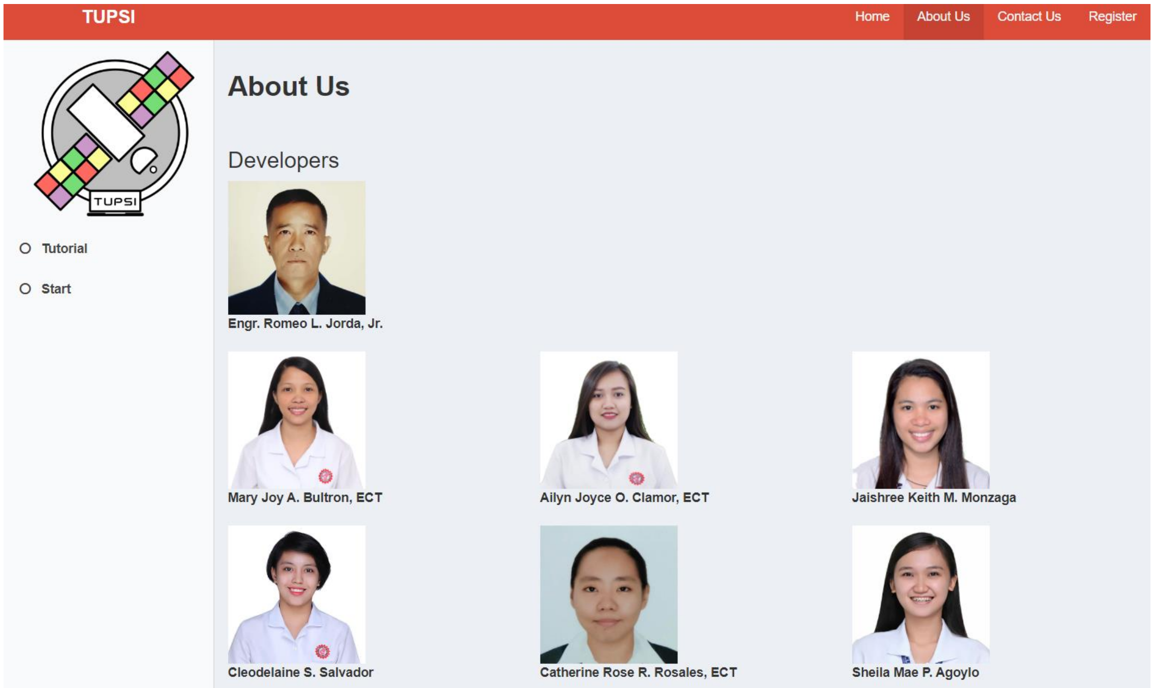


Figure 4.2: About Us page

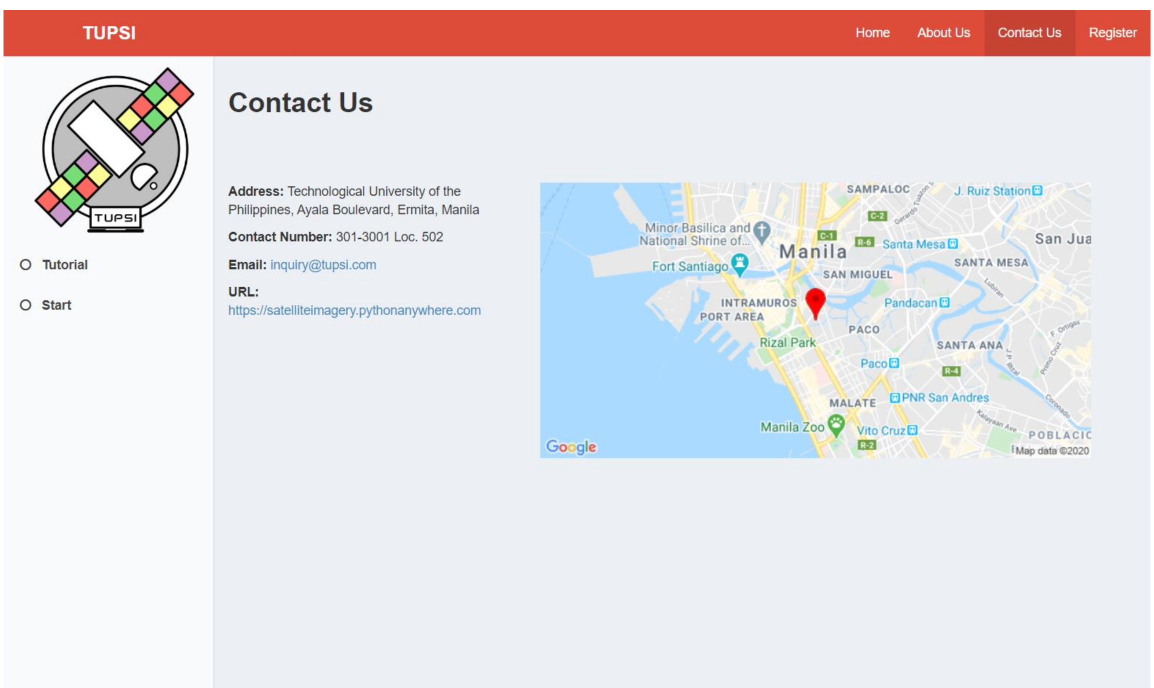


Figure 4.3: Contact Us page

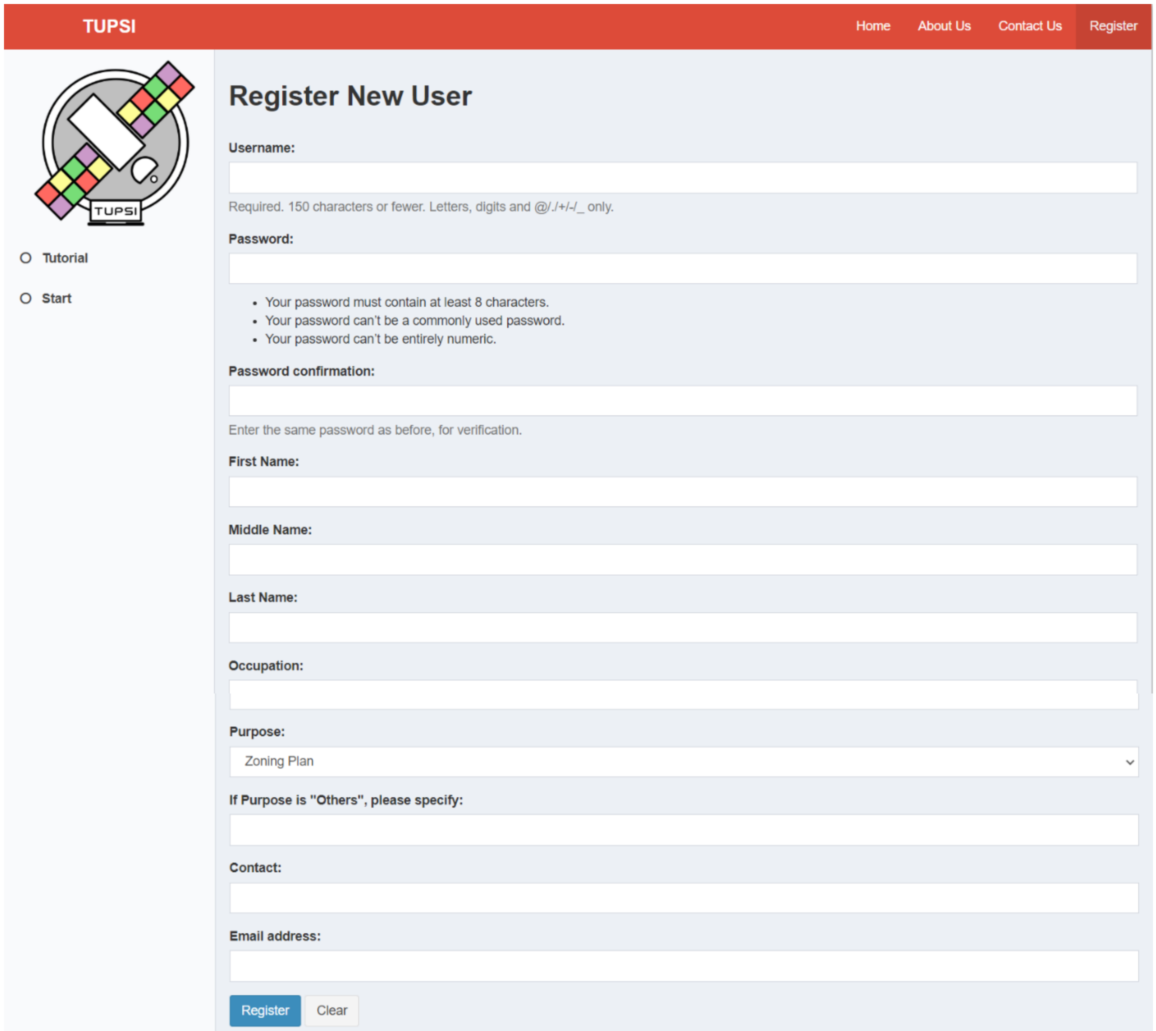


Figure 4.4: Registration Interface

Figure 4.4 shows the registration page where users can sign up by filling out the needed information.

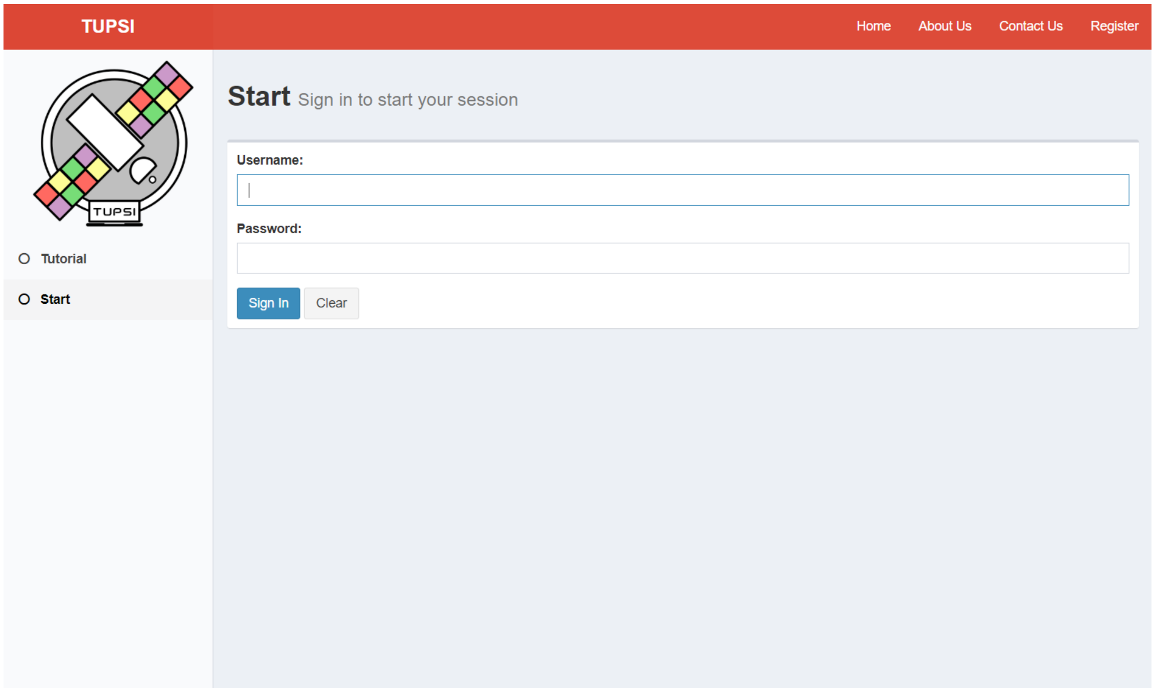


Figure 4.5: Sign in Interface

Figure 4.5 shows the sign in interface where users can sign in using the username and password from their registration.

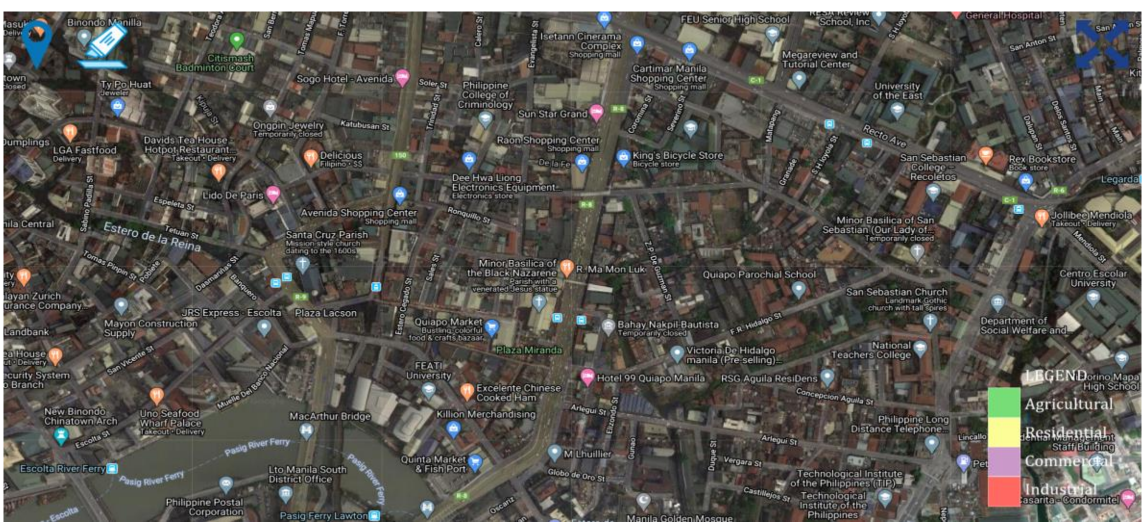
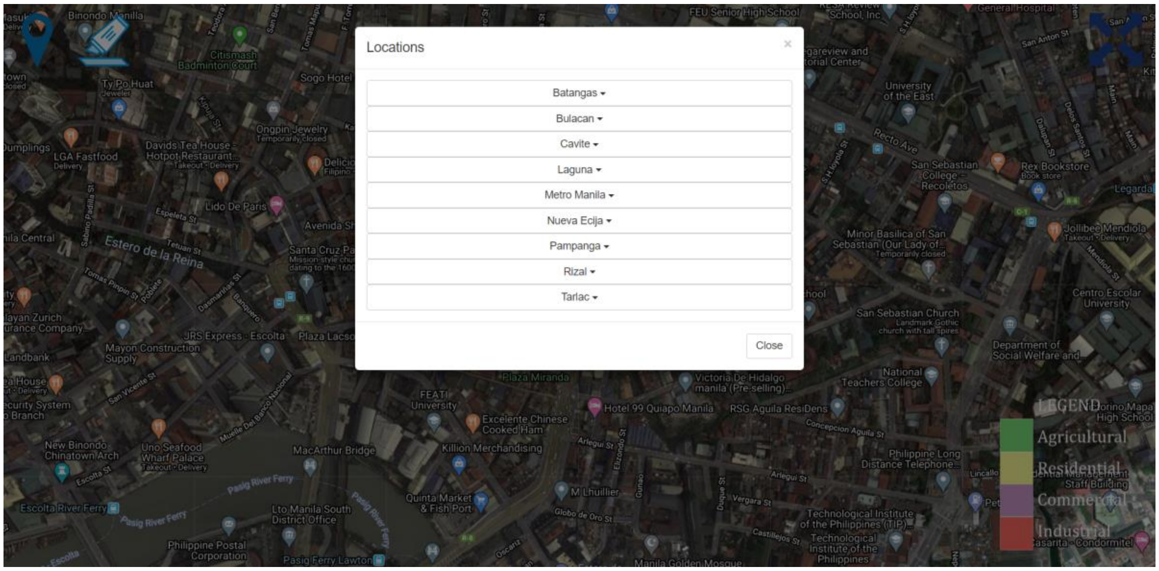
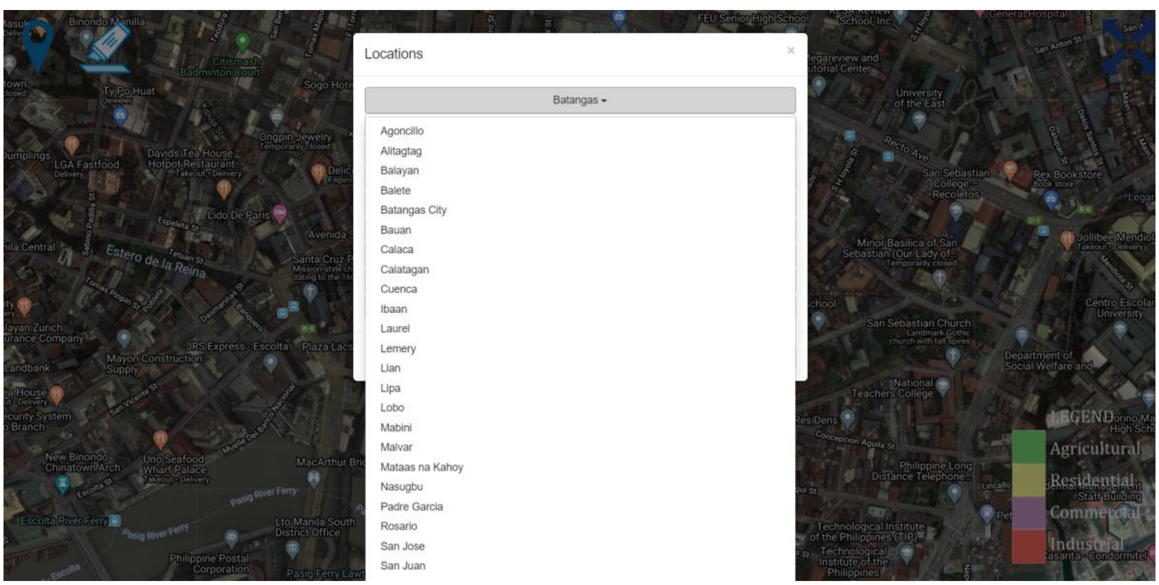


Figure 4.6: Map

Figure 4.6 shows the map from Google Maps with the upper left corner icons for the location and highlight and the upper right corner icon is for the full screen. The legend for classification is shown at the lower right corner of the screen.



(a)



(b)

Figure 4.7: (a) Location list; (b) Location list drop down menu

Figure 4.6a shows the location list of Greater Manila Area and Figure 4.6b shows the location list drop down menu for the specific areas of Greater Manila.

4.3 Project Scope and Limitation

The system has four classification or categories: agricultural, residential, commercial, and industrial and covers Greater Manila Area (Nueva Ecija, Tarlac, Pampanga, Rizal, Metro Manila, Cavite, Bulacan, Laguna and Batangas) which has 21,720.45 sq.km. of land area.

4.3.1 Satellite Images

In this study, three open sources of satellite images were considered: the Copernicus Open Access Hub, the USGS Earth Explorer, and Google Maps. Both Copernicus Open Access Hub and USGS Earth Explorer have data from the Sentinel satellite of satellite images of 10m to 20m resolution. Google Maps have data from various satellites from which the resolution varies depending on how the map is zoomed.

However, that Google Maps images have different resolutions than the objective of 10m which is from Sentinel satellite that is mostly used for land use classification, considering that it has an API that can be linked to the web application that is developed, the proponents have chosen this open source for the satellite images.

Table 4.1 *Difference between Copernicus Open Access Hub, Google Maps and USGS Earth Explorer*

	Copernicus Open Access Hub	Google Maps	USGS Earth Explorer
Resolution	10m; 20m; 60m	15cm; 30cm; 10m; 15m; 20m; 30m; 100m	10m; 20m; 60m
Land Area per tile size	100x100 sq. km	About 100,000 sq. km	100 x 100 sq. km
Download Time	More than an hour	Linked through API	1 hour
Cloud Cover Percent	0% to 100%	< 1 percent	0% to 100%
Satellite Used	Sentinel 2	Various satellite depending on the zoom (Landsat, Sentinel)	Sentinel 2
Availability	Publicly accessible	Publicly accessible	Publicly accessible

4.3.2 Benchmark Dataset

The proponents have considered the EuroSAT dataset which is a benchmark dataset for land use and land cover classification as the benchmark dataset for the training and testing of the CNN. This dataset consists of satellite images from over 34 European countries. Since the Philippines has a different urban structure from Europe, therefore, some differences with the accuracy of the classification can be seen in the results.

4.3.3 Convolutional Neural Network

The proponents have adapted the existing ResNet-50 CNN for this study since it has shown the best result for the accuracy of the system which is 98.5%.

Web Application System

There are two ways of classification that can be done in the web application. One is with the use of the Highlight icon which will show the color-coded classification of the land use, and the other one is with the use of the box cursor which will show the classification of the area within the box and the percentage of accuracy. Classification with the use of the box cursor is more accurate than the color-coded classification.

Occasionally, some functions fail when using internet browsers other than Google Chrome because of the languages used for web creation. Also, as the web application relies on the use of the internet, the loading time of the classification may be affected by slow internet connection.

Using the web application in mobile phones can affect the classification because of the smaller screen size.

4.4 Evaluation of the System

The interviewed IT experts evaluated the developed CNN and web application. The IT experts that answered the online survey (online evaluation form) evaluated the web application based on the end-user's experience.

4.4.1 Convolutional Neural Network

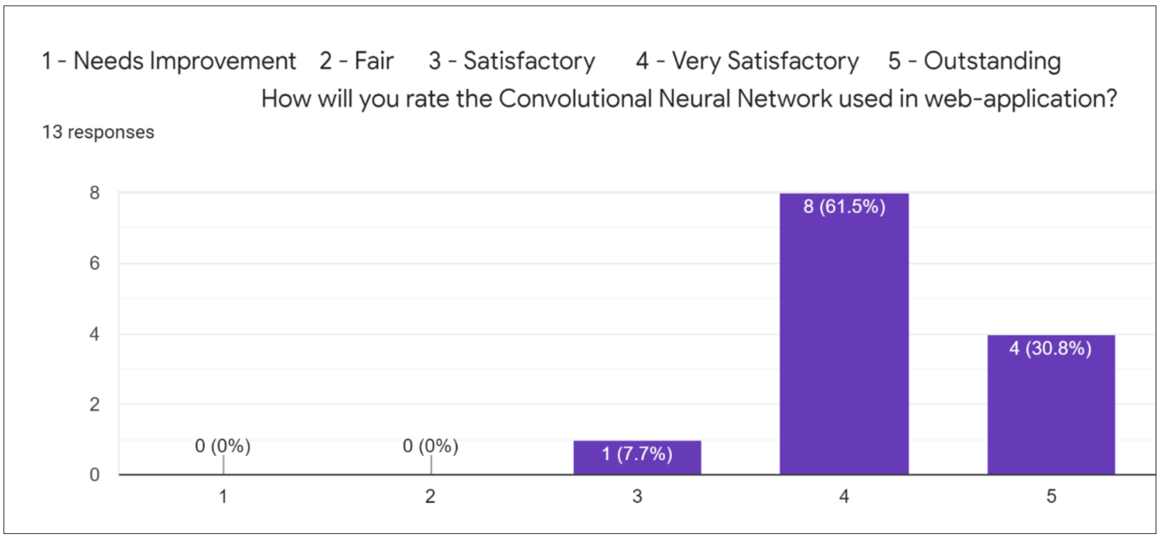


Figure 4.8: Evaluation of the Convolutional Neural Network used in the study

Figure 4.7 shows that 30.8% of the respondents rated the CNN as “Outstanding”, 61.5% rated “Very satisfactory” and 7.7% rated “Satisfactory” for the Convolutional Neural Network used in the web application.

4.4.2 Loading time of the Web Application

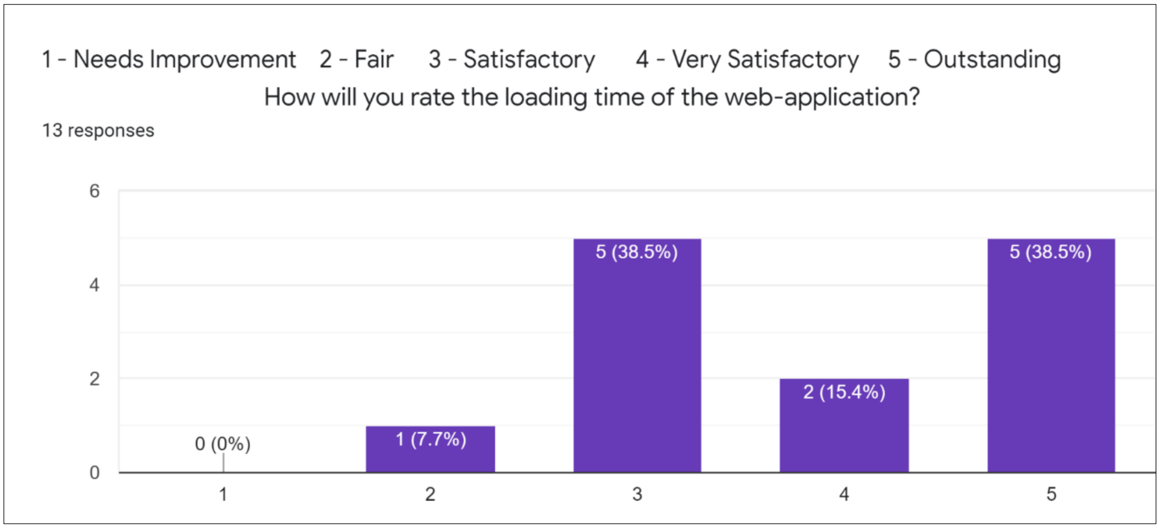


Figure 4.9: Evaluation on the loading time of the web application

Figure 4.8 shows that 38.5% of the respondents rated the loading time of the web application as “Outstanding”, 15.4% rated “Very satisfactory”, 38.5% rated “Satisfactory” and 7.7% rated “Fair” for loading time of the application

4.4.3 Accuracy of the Web Application

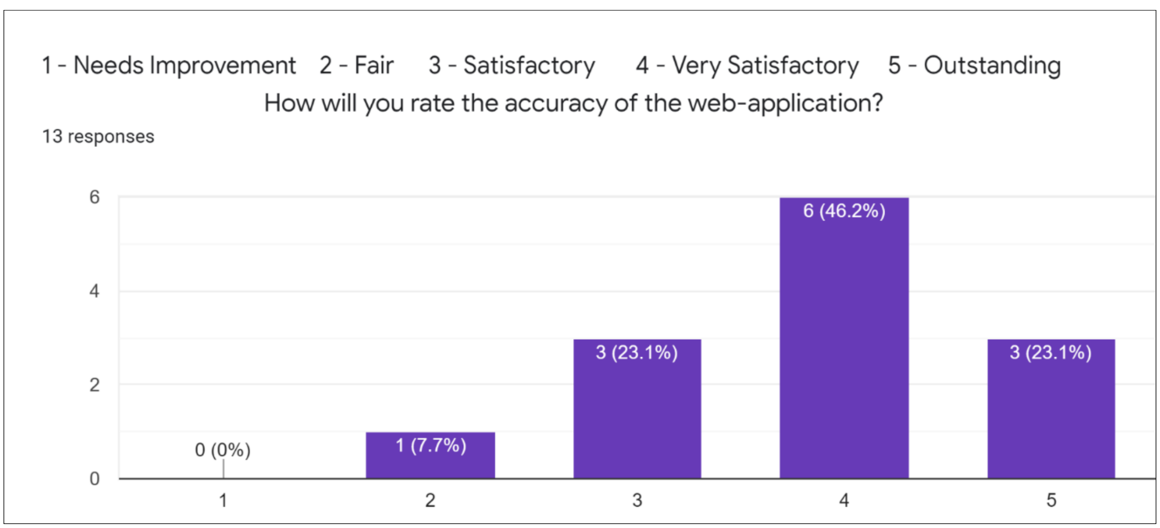


Figure 4.10: Evaluation on the accuracy of the web application

Figure 4.9 shows that 23.1% of the respondents rated the accuracy of the web application as “Outstanding”, 46.2% rated “Very satisfactory”, 23.1% rated “Satisfactory” and 7.7% rated “Fair” for the accuracy of the web application

4.4.4 Over-all Evaluation of the Web Application

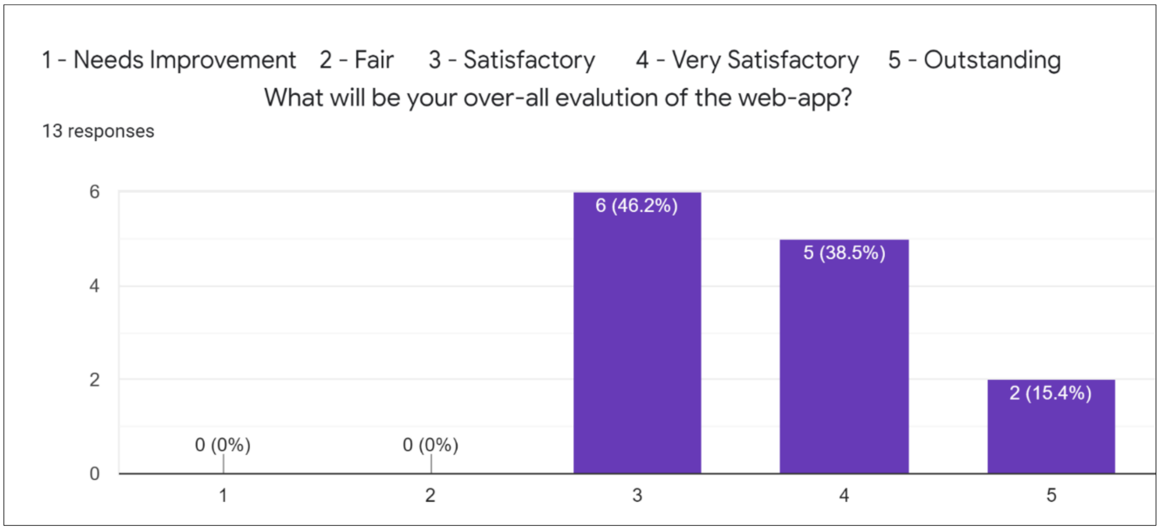


Figure 4.11: Over-all evaluation of the web app

Figure 4.10 shows that 15.4% of the respondents rated the over-all evaluation of the web application as “Outstanding”, 38.5% rated “Very satisfactory” and 46.2% rated “Satisfactory” for the over-all evaluation of the web application.

CHAPTER 5

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

This chapter includes the description of the study's results, its conclusion regarding the findings, and the recommendations made to support improvement of the study. The goal of this study is the creation of an efficient land use map accessible for the public use

5.1 Summary of Findings

Based on the gathered data from the online survey, most users **approved** the Convolutional Neural Network used in the classification as well as with the accuracy of the system. On the other hand, a **fair view** is given with the loading time and over-all evaluation of the web application. As with the opinion of the evaluators about the user-friendliness of the web application, **majority approves**, with some giving suggestions for the improvement of the system.

Evaluators' approval on the usage of the web application for the system could help in the mapping of different areas with the website being simple yet informative and efficient.

5.2 Conclusion

Satellite Imagery is proven to be more cost-effective and less time consuming than the traditional way of land-use mapping. In the research study conducted, proponents conclude that:

1. The collection of the dataset of satellite images with 10m spatial resolution from available open sources is done by using Google Maps with 15m spatial resolution of satellite images.
2. The reference map/ground truth utilized is from the EuroSat dataset which is used as the benchmark dataset.
3. The Convolutional Neural Network that is designed and implemented to classify land areas is adapted from ResNet-50.
4. The development of a web application that can visualize the land area classification is done using different website developing tools.
5. The web application is tested and evaluated by IT experts based on the user-friendliness, loading time and aesthetics.
6. The accuracy of the system is tested and evaluated by IT experts based the Convolutional Neural Network used and the over-all performance of the system.

5.3 Recommendation

Based on the interview that the proponents have conducted, the evaluators recommended the following:

1. The UI (User Interface) of the web application must be enhanced for better user experience (better viewing and navigation).
2. Collection of additional data and update in mapping details. Further studies could help identify other datasets for better classification of the different land use in the Philippines.

3. Additional information about the land areas classified/information about the categories of an area classified.
4. Search bar where users could specify an exact location in the map and details about the areas in the map e.g., the population size of the different municipalities, etc.
5. The system in an android application could make the study accessible to everyone.

References

Albert, A., Kaur, J., & Gonzalez, M. (2017). Using convolutional neural networks and satellite imagery to identify patterns in urban environments at a large scale. https://arxiv.org/abs/1704.02965

Babenko, B., Hersh, J., Newhouse, D., Ramakrishnan, A., & Swartz, T. (2017). Poverty mapping using convolutional neural networks trained on high and medium resolution satellite images, with an application in Mexico. *31st Conference on Neural Information Processing Systems Workshop on Machine Learning for the Developing World (NIPS 2017)*. https://arxiv.org/abs/1711.06323

Badrinarayanan, V., Kendall, A., & Cipolla, R. (2017). SegNet: A deep convolutional encoder-decoder architecture for image segmentation. In *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *39*(12), 2481-2495. doi: 10.1109/TPAMI.2016.2644615.

Bruniecki, K., Stepnowski, A., Moszyński, M., Łubniewski, Z., Drypczewski, K., Markiewicz, L., Kulawiak, M., & Bieliński, T. (2014). Using EO satellite data in safe city and coastal zone web-GIS. *2014 20th International Conference on Microwaves, Radar and Wireless Communications (MIKON)*, 1-4. doi: 10.1109/MIKON.2014.6899843.

Calle-Jimenez, T., & Luján-Mora, S. (2015). Using crowdsourcing to improve accessibility of geographic maps on mobile devices. *The Eighth International Conference on Advances in Computer-Human Interactions (ACHI 2015), Volume: 2015*, 150-154.

Castelluccio, M., Poggi, G., Sansone, C., & Verdoliva, L. (2015). Land use classification in remote sensing images by convolutional neural networks. https://arxiv.org/abs/1508.00092

Cavur, M., Kemec, S., Nabdel, L., & Duzgun, S. (2015). An evaluation of land use land cover (LULC) classification for urban applications with Quickbird and WorldView2 data. *2015 Joint Urban Remote Sensing Event (JURSE)*, 1-4. doi: 10.1109/JURSE.2015.7120486.

Chan, A. (2019). Pose Estimation with Deep Convolutional Neural Network. *VISAL*. http://visal.cs.cityu.edu.hk/research/hmlpe/

Chepkemoi, J. (2019, June 10). *The World's Largest Industrial Areas*. WorldAtlas. https://www.worldatlas.com/articles/world-s-largest-industrial-areas.html

Das, S. (2017, November 17). *CNN Architectures: LeNet, AlexNet, VGG, GoogLeNet, ResNet and more….* Medium: Analytics Vidhya. https://medium.com/analytics-vidhya/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5

Donges, N. (2018, Februrary 22). *The Random Forest Algorithm*. Towards Data Science. https://towardsdatascience.com/the-random-forest-algorithm-d457d499ffcd

El Garouani, A., Mulla, D. J., El Garouani, S., & Knight, J. (2017). Analysis of urban growth and sprawl from remote sensing data: Case of Fez, Morocco. *International Journal of Sustainable Built Environment*. http://dx.doi.org/10.1016/j.ijsbe.2017.02.003

Engstrom, R., Hersh, J. & Newhouse, D., (2017). Poverty from space: Using high-resolution satellite imagery for estimating economic well-being. *Policy Research Working Paper, No. 8284*. http://hdl.handle.net/10986/29075

Erwin, S. (2018, April 25). *Intelligence community, companies give out satellite imagery to motivate app developers*. Space News. https://spacenews.com/intelligence-community-companies-give-out-satellite-imagery-to-motivate-app-developers/

Goldblatt, R., Deininger, K., & Hanson, G. (2018). Utilizing publicly available satellite data for urban research: Mapping built-up land cover and land use in Ho Chi Minh City, Vietnam. *Development Engineering*, *Volume 3*, 83-99. https://doi.org/10.1016/j.deveng.2018.03.001

Google Earth. (n.d.). Map showing location of Clarkview Subdivision. https://earth.google.com/web/

Google Earth. (n.d.). Map showing location of Technological University of the Philippines. https://earth.google.com/web/

Google Earth. (n.d.). Map showing location of The Farm At San Benito. https://earth.google.com/web/

GrayCell Technologies. (n.d.). *Why Use HTML 5*. https://www.graycelltech.com/why-use-html-5/

Google Earth. (n.d.). Map showing location of Wyeth Nutrition Cabuyao Factory. https://earth.google.com/web/

GOVPH. (n.d.). Housing and Urban Development Coordinating Council. http://www.hudcc.gov.ph/content/laws-and-executive-issuances

Hedayatnia, B., Yazdani, M., Nguyen, M., Block, J., & Altintas, I. (2016). Determining feature extractors for unsupervised learning on satellite images. *2016 IEEE International Conference on Big Data (Big Data)*, 2655-2663. doi: 10.1109/BigData.2016.7840908.

Helber, P., Bischke, B., Dengel, A., & Borth, D. (2019). EuroSAT: A novel dataset and deep learning benchmark for land use and land cover classification. https://arxiv.org/abs/1709.00029

Hilvano, N., Garcia, R., Hao, A. J., Alegre, A., & Cristano, Jr. T. (2019). Land use/land cover change detection and urban sprawl analysis in the Mount Makiling Forest Reserve Water Sheds and Buffer Zone, Philippines. *Environments 2019*, 6(2), 9. https://doi.org/10.3390/environments6020009

Inggs, M. R., & Lord, R. T., (2000). Applications of Satellite Imaging Radar. *South African Institute of Electrical Engineers, SAIEE*. Available online: http://www.rrsg.ee.uct.ac.za/members/rlord/papers/saiee00.pdf.

Jean, N., Burke, M., Xie, M., Davis, W. M., Lowell, D. B., & Ermon, S. (2016). Combining satellite imagery and machine learning to predict poverty. *Science, 353*(6301), 790-794. doi: 10.1126/science.aaf7894.

Johnson, B. A., & Iizuka, K. (2016). Integrating OpenStreetMap crowdsourced data and Landsat time-series imagery for rapid land use/land cover (LULC) mapping: Case study of the Laguna de Bay area of the Philippines. *Applied Geography*, *67*, 140-149.

Koshal. (2011, October 25). *Difference Between Residential and Commercial*. Difference Between. https://www.differencebetween.com/difference-between-residential-and-vs-commercial/?fbclid=IwAR3B_WR-oJxxY3dJwKv-

Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. In *Proceedings of the 25th International*

Conference on Neural Information Processing Systems – Volume 1 (NIPS'12), 1097-1105. https://dl.acm.org/doi/10.5555/2999134.2999257

Liu, P., Liu, X., Liu, M., Shi, Q., Yang, J., Xu, X., Zhang, Y., & Liu, X. (2019). Building footprint extraction from high-resolution images via Spatial Inception Convolutional Neural Network. Remote Sens. 2019, 11(7), 830; https://doi.org/10.3390/rs11070830.

Llorito, D., & Zhang, J. (2017, May 29). *Philippines: Building Competitive, Sustainable and Inclusive Cities.* The World Bank. https://www.worldbank.org/en/news/press-release/2017/05/29/philippines-building-competitive-sustainable-and-inclusive-cities.

Luo, W., Li, Y., Urtasun, R., & Zemel, R. (2016). Understanding the Effective Receptive Field in Deep Convolutional Neural Networks. In *Advances in Neural Information Processing Systems 29 (NIPS 2016), 30th Conference on Neural Information Processing Systems (NIPS 2016)*. https://arxiv.org/abs/1701.04128.

Lyuri, D. (2008). *Agriculture*. In S. E. Jørgensen & B. D. Fath (Eds.), Encyclopedia of Ecology (pp. 76-84). Elsevier. https://doi.org/10.1016/B978-008045405-4.00838-7.

Milrad, S. (2018). *11 - Satellite Imagery*. Synoptic Analysis and Forecasting. In S. Milrad (Ed.), Synoptic Analysis and Forecasting (pp. 145-161). Elsevier. https://doi.org/10.1016/B978-0-12-809247-7.00011-9.

NC State University Libraries. (2017). *Land Use/Land Cover Data*. https://www.lib.ncsu.edu/gis/lulc

Nischal, K. N., Radhakrishnan, R., Mehta, S., & Chandani, S. (2015). Correlating night-time satellite images with poverty and other census data of India and estimating future trends. In *Proceedings of the Second ACM IKDD Conference on Data Sciences (CoDS 15)*. Association for Computing Machinery, 75-79. doi: https://doi.org/10.1145/2732587.2732597.

OECD. (2015). Institutional sectors and classifications for R&D statistics. In Frascati Manual 2015: Guidelines for Collecting and Reporting Data on Research and Experimental Development. OECD Publishing. https://doi.org/10.1787/9789264239012-5-en. Retrieved from OECDiLibrary: https://www.oecd-ilibrary.org/science-and-technology/frascati-manual-2015/institutional-sectors-and-classifications-for-r-amp-d-statistics_9789264239012-5-en;jsessionid=m9-g_5vc6GSUPWf19G6Tyn9u.ip-10-240-5-49

Pandey, S. M., Agarwal, T., & Krishnan, N. C. (2018). Multi-task deep learning for predicting poverty from satellite images. In *The Thirtieth AAAI Conference on Innovative Applications of Artificial Intelligence (IAAI-18)*, 7793-7798. Available at: https://www.aaai.org/ocs/index.php/AAAI/AAAI18/paper/view/16441/16388.

Patterson, M. T., Bennett, C., Grossman, R. L., Ly, V., Pederson, S., Powell, R., Anderson, N., Bruggemann, J., Handy, M., Mandl, D., Pivarski, J., Spring, J., & Xia, J. (2016). The Matsu Wheel: A cloud-based framework for efficient analysis and reanalysis of Earth satellite imagery. In *2016 IEEE Second International Conference on Big Data Computing Service and Applications (BigDataService)*, 156-165. doi: 10.1109/BigDataService.2016.39.

Philippine Statistic Authority. (2018, January 24). Transition to Electronic Data Collection for the Philippines Census 2020. Presentation for the UN ESCAP, Bankok. Available at: https://www.unescap.org/sites/default/files/Session3_Decision_making_process_Philippines_Census_WS_24-27Jan2018.pdf.

Property Management ACES. (n.d.). Difference Residential vs. Commercial Property Management. https://propertymanagementaces.com/difference-residential-vs-commercial-property-management/

Republic of the Philippines, GOVPH. (1992, March 24). *(Republic Act No. 7279) An Act to Provide for a Comprehensive and Continuing Urban Development and Housing Program, Establish the Mechanism for its Implementation, and for Other Purposes*. Official Gazette. Available at: https://www.officialgazette.gov.ph/1992/03/24/republic-act-no-7279/.

Reza M. S., & Ruhi S. (2015). Study of Multivariate Data Clustering Based on K-Means and Independent Component Analysis. In *American Journal of Theoretical and Applied Statistics*, 4(5), 317-321. doi: 10.11648/j.ajtas.20150405.11.

Rouse, M. (2013, February). *Google Maps*. WhatIs.com. https://whatis.techtarget.com/definition/Google-Maps

Sahl, R., Dupont P., Messager, C., Honnorat, M., & Vu La, T. (2018). High-resolution ocean winds: Hybrid-cloud infrastructure for satellite imagery processing. In *2018 IEEE 11th International Conference on Cloud Computing (CLOUD)*, 883-886. doi: 10.1109/CLOUD.2018.00127.

Samonte, J. (2015, September 22). 9 Reasons Why You Should Invest in a Commercial Property in BGC. *Hoppler*. https://www.hoppler.com.ph/blog/real-estate-tips/9-reasons-why-you-should-invest-in-a-commercial-property-in-bgc.

Sarkar, A., Yang,Y. & Vihinen,M. (2019). Variation benchmark datasets: update, criteria, quality and applications. *Database*, *2020*, 1-16. article ID baz117; doi:10.1093/database/baz117.

Segal, N. (n.d.). 10 Common Uses of Bootstrap. *HTMLGoodies*. https://www.htmlgoodies.com/html5/markup/10-common-uses-of-bootstrap.html

Sharma, S. (2019, February 11). *Hands-on-Experience on achieving State of the Art results on classifying EuroSAT satellite images using Keras*. Medium: Sachin Sharma. https://medium.com/@sachinsharma9780/hands-on-experience-on-achieving-state-of-the-art-results-on-classifying-eurosat-satellite-images-91a9897f7433.

TensorFlow. (n.d.). *eurosat*. https://www.tensorflow.org/datasets/catalog/eurosat

Web Unlimited. (2012, May 24). *What is CSS3 And Why Is It Used?*. https://www.webunlimited.com/css3-used

Windarni, V. A., Sediyono, E., & Setiawan, A. (2016). Using GPS and Google maps for mapping digital land certificates. In *2016 International Conference on Informatics and Computing (ICIC), Mataram*, *2016*, 422-426. doi: 10.1109/IAC.2016.7905756.

W3Schools.com. (n.d.). *jQuery Introduction*. https://www.w3schools.com/jquery/jquery_intro.asp

Yang, Y., & Newsam, S. (2010). Bag-of-visual-words and spatial extensions for land-use classification. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems (GIS '10)*, 270-279. https://doi.org/10.1145/1869790.1869829.

APPENDIX A

Evaluation Form

TECHNOLOGICAL UNIVERSITY OF THE PHILIPPINES

COLLEGE OF ENGINEERING

ELECTRONICS ENGINEERING DEPARTMENT

Name: Rolan Lambert Cordero Office: Sytian Position: Wordpress Developer

Listed below are some questions that could help us evaluate and improve this research project. The goal of this evaluation form is to learn more about the strengths and weaknesses of the proposed land-use mapping software in Greater Manila Area.

1. Is it user-friendly? If not, why?

No, needs a lot of front end work, most likely for UI/UX. The app must be built in consideration of the end user's perspective.

2. Is it the first land-use mapping web-app that you encountered? If not, why?

No, there are actually a lot of apps that uses the idea of land mapping, but not that identical to this app. We could take for example the apps that utilizes maps for detection of traffic and satellite weather forecast.

3. What problems could you see in the web-app?

Loading speed / performance.
User Interface, needs redesign.
Scalability, this app is complex, so proper planning, documentation, and programming is needed, else it can't handle future enhancements or features.

4. What improvements could you suggest for the betterment of the web-app?

UI/UX of the app must absolutely be enhanced for better viewing and navigation. Another thing is the data input. There must be some way for the user to manually input and update the mapping details.

5. What other testing /evaluation procedures could you recommend?

User acceptance testing, to be done by whoever will be using the app (end user) and/or Beta testing before deployment. Load testing is another way to determine the performance/speed of the app.

Rating Legend: 1 - Needs Improvement 2 - Fair 3 - Satisfactory 4 - Very Satisfactory 5 - Outstanding

6. How will you rate the accuracy of the web-application?

☐1 ☐2 ☑3 ☐4 ☐5

7. How will you rate the loading time of the web-application?

☐1 ☐2 ☑3 ☐4 ☐5

8. How will you rate the Convolutional Neural Network used in web-application?

☐1 ☐2 ☐3 ☑4 ☐5

9. What will be your over-all evaluation of the web-app?

☐1 ☐2 ☑3 ☐4 ☐5

TECHNOLOGICAL UNIVERSITY OF THE PHILIPPINES

COLLEGE OF ENGINEERING

ELECTRONICS ENGINEERING DEPARTMENT

Name: Christian Tagab   Office: Velprint Corp.   Position: Document Control Custodian

Listed below are some questions that could help us evaluate and improve this research project. The goal of this evaluation form is to learn more about the strengths and weaknesses of the proposed land-use mapping software in Greater Manila Area.

1. Is it user-friendly? If not, why?

   No. Guide or walkthrough could be provided to help user to access the web-app.

2. Is it the first land-use mapping web-app that you encountered? If not, why?

   Yes.

3. What problems could you see in the web-app?

   The update of land-use and its integration to the web-app.

4. What improvements could you suggest for the betterment of the web-app?

   The placement of Location List. It may place together w/ highlight button (on the right part of the screen).

5. What other testing /evaluation procedures could you recommend?

   Integration Testing.

Rating Legend: 1 - Needs Improvement 2 - Fair 3 - Satisfactory 4 - Very Satisfactory 5 - Outstanding

6. How will you rate the accuracy of the web-application?

   ☐1 ☐2 ☐3 ☑4 ☐5

7. How will you rate the loading time of the web-application?

   ☐1 ☐2 ☑3 ☐4 ☐5

8. How will you rate the Convolutional Neural Network used in web-application?

   ☐1 ☐2 ☐3 ☑4 ☐5

9. What will be your over-all evaluation of the web-app?

   ☐1 ☐2 ☐3 ☑4 ☐5

TECHNOLOGICAL UNIVERSITY OF THE PHILIPPINES
COLLEGE OF ENGINEERING
ELECTRONICS ENGINEERING DEPARTMENT

Name: Kevin C. Esguerra Office: City Planning & Development Office Position: Project Development Officer I

Listed below are some questions that could help us evaluate and improve this research project. The goal of this evaluation form is to learn more about the strengths and weaknesses of the proposed land-use mapping software in Greater Manila Area.

1. Is it user-friendly? If not, why?
   Yes, it needs just a little bit of revision on the UI.

2. Is it the first land-use mapping web-app that you encountered? If not, why?
   Yes, the mapping software I have encountered is the ArcGIS which is a desktop application and not web-based.

3. What problems could you see in the web-app?
   Since the program is web application, ~~it~~ ~~so~~ the user won't be able to use the software if there is no internet connection and the detection of map is not really sync on actual Philippine database.

4. What improvements could you suggest for the betterment of the web-app?
   Just a bit of UI revision and a login feature for data collection & reports purposes.

5. What other testing /evaluation procedures could you recommend?
   Let Manila City Hall employees without background on technology to see if the system is user-friendly on common people & ask for their suggestions.

Rating Legend: 1 - Needs Improvement 2 – Fair 3 – Satisfactory 4 – Very Satisfactory 5 – Outstanding

6. How will you rate the accuracy of the web-application?
   ☐1 ☐2 ☑3 ☐4 ☐5

7. How will you rate the loading time of the web-application?
   ☑1 ☐2 ☐3 ☐4 ☑5

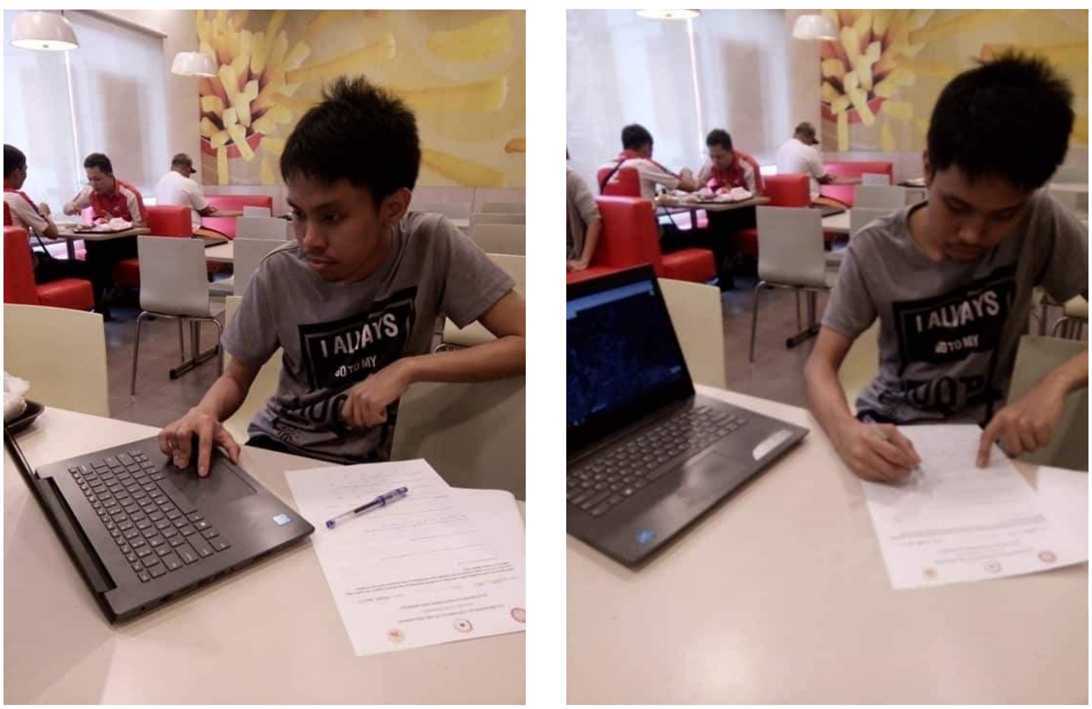
8. How will you rate the Convolutional Neural Network used in web-application?
   ☐1 ☐2 ☐3 ☑4 ☐5

9. What will be your over-all evaluation of the web-app?
   ☐1 ☑2 ☐3 ☑4 ☐5

APPENDIX B

Project Documentation

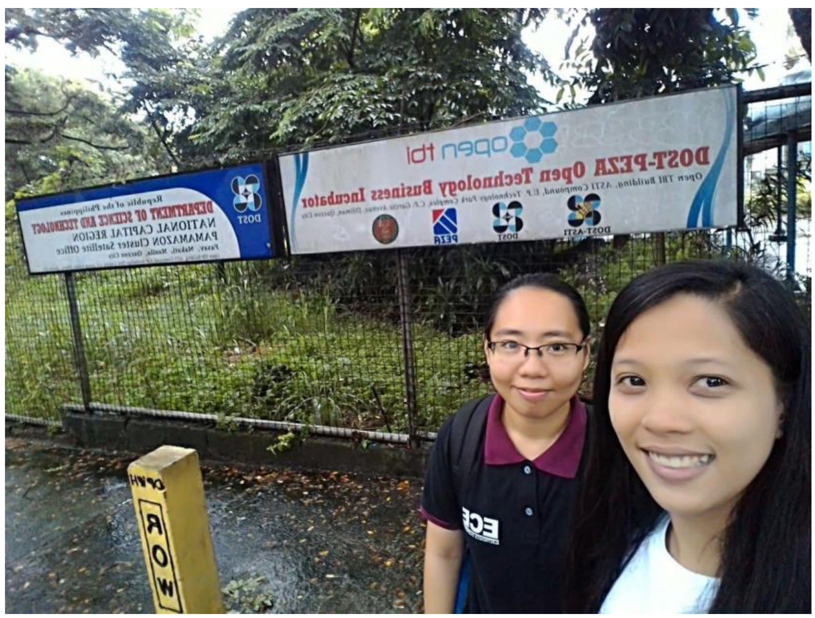
Interview with Mr. Kevin Escaro, City Planning and Development Department of Quezon City



IT Professionals Interview for the Evaluation of the Website (1)

IT Professionals Interview for the Evaluation of the Website (2)

Interview in the Planning Office of Quezon City



Request for satellite images from DOST-ASTI

Interview in the Planning Office of Valenzuela City

APPENDIX C

Source Codes

Codes for training the dataset

```
import fastai
import os
import zipfile
from pathlib import Path

from fastai.callbacks import SaveModelCallback
from fastai.vision import *
from fastai.metrics import error_rate


CHECKPOINT_STAGE_1_FILE_NAME = 'eurosat_stage_1_checkpoint'
CHECKPOINT_STAGE_2_FILE_NAME = 'eurosat_stage_2_checkpoint'
DATASET_URL = 'http://madm.dfki.de/files/sentinel/EuroSAT.zip'
EPOCH = 4
MODEL_STAGE_1_FILE_NAME = Path('eurosat_stage_1.pkl')
MODEL_STAGE_2_FILE_NAME = Path('eurosat_stage_2.pkl')

#   Download EuroSAT dataset
print("")
print("[1/7] Downloading EuroSAT dataset ZIP file...")
eurosat_dataset_file = download_data(DATASET_URL, ext='')

#   Unzip dataset in .ZIP format
print("")
print("[2/7] Unzipping downloaded EuroSAT dataset ZIP file...")
eurosat_dataset_folder = eurosat_dataset_file.with_suffix('')
with zipfile.ZipFile(eurosat_dataset_file, 'r') as zip_ref:
    zip_ref.extractall(eurosat_dataset_folder)
```

```
#   Prepare data from EuroSAT dataset file

print("")

print("[3/7] Preparing databunch...")

data_path = os.path.join(eurosat_dataset_folder, os.listdir(eurosat_dataset_folder)[0])

tfms = get_transforms()

data =
ImageList.from_folder(data_path).split_by_rand_pct(0.2).label_from_folder().transform(tfms,
size=224).databunch()


#   Start stage 1 of training

print("")

print("[4/7] Stage 1 of training...")

learner = cnn_learner(data, models.resnet50, metrics=error_rate)

learner.fit_one_cycle(EPOCH, callbacks=[SaveModelCallback(learner, every='epoch',

    monitor='accuracy', name=CHECKPOINT_STAGE_1_FILE_NAME)])


#   Save stage 1 of training as model file

print("")

print("[5/7] Saving stage 1 of training...")

learner.save(MODEL_STAGE_1_FILE_NAME.with_suffix(''))

learner.export(str(MODEL_STAGE_1_FILE_NAME))


#   Start stage 2 of training (train last layer)

print("")

print("[6/7] Stage 2 of training....")

learner.unfreeze()

learner.fit_one_cycle(EPOCH, max_lr=slice(3e-04,3e-03),
callbacks=[SaveModelCallback(learner, every='epoch',

    monitor='accuracy', name=CHECKPOINT_STAGE_2_FILE_NAME)])
```

```
#   Save stage 2 of training as model file
print("")
print("[7/7] Saving stage 2 of training...")
learner.save(MODEL_STAGE_2_FILE_NAME.with_suffix(''))
learner.export(str(MODEL_STAGE_2_FILE_NAME))

print("")
print("<<< END TRAINING >>>")
```

Codes for the classification

```
import base64
import re

import numpy as np
from fastai import *
from fastai.vision import *

from django.http.response import JsonResponse
from django.utils.decorators import method_decorator
from django.views.decorators.csrf import csrf_exempt
from django.views.generic import View
from django.views.generic import TemplateView


class IndexTemplateView(TemplateView):
    template_name = 'satellite_cnn/index.html'


class PredictionView(View):

    @method_decorator(csrf_exempt)
    def dispatch(self, request, *args, **kwargs):
        return super(PredictionView, self).dispatch(request, *args, **kwargs)

    def post(self, request, *args, **kwargs):
        def argNmax(a, N):
            return np.argpartition(a.ravel(), -N)[-N]
```

```
data = request.POST['img']

imgstr = re.search(r'data:image/png;base64,(.*)', data).group(1)
output = open('predict.png', 'wb')
decoded = base64.b64decode(imgstr)
output.write(decoded)
output.close()

learn = load_learner('', 'eurosat_stage_1.pkl')
img = open_image('predict.png')

cat, tensor, probs = learn.predict(img)
pro = probs.numpy() * 100
arg1max, arg2max, arg3max = argNmax(pro, 1), argNmax(pro, 2), argNmax(pro, 3)

print(cat)
print(tensor)

return JsonResponse({'class': str(cat), 'percent': str(round(pro[arg1max], 2))})
```

APPENDIX D

User Manual

TUPSI

Is the official web application of the project study entitled:

Web application: Satellite Imagery for the Land Classification of Greater Manila Area using Convolutional Neural Network

Visit the website:

https://satelliteimagery.pythonanywhere.com/#

Proponents:

Agoylo, Shiela Mae P.

Bulton, Mary Joy A.

Clamor, Ailyn Joyce O.

Monzaga, Jaishree Keith M.

Rosales, Catherine Rose R.

Salvador, Cleodelaine S.

Adviser

Engr. Romeo L. Jorda Jr.

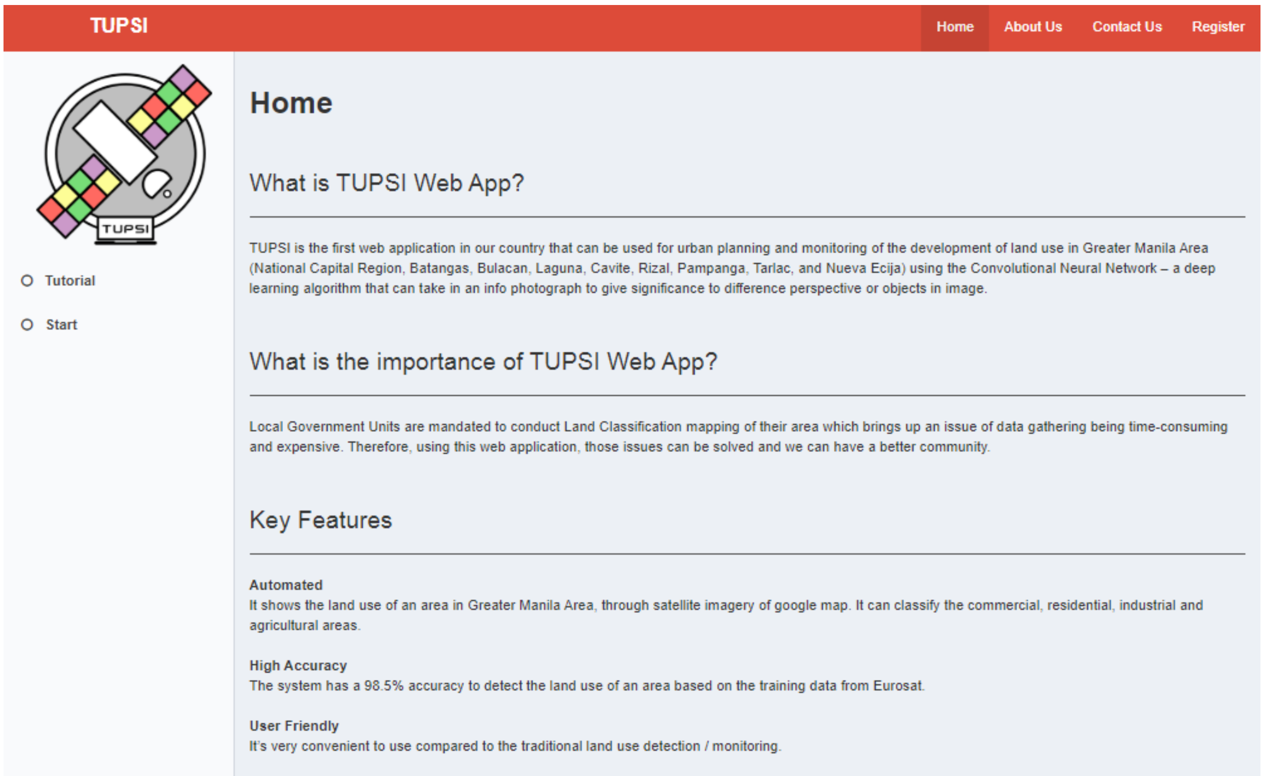
Contact us:

tup.satelliteimagery@gmail.com
Ayala Blvd., Ermita, Manila

Using the web app

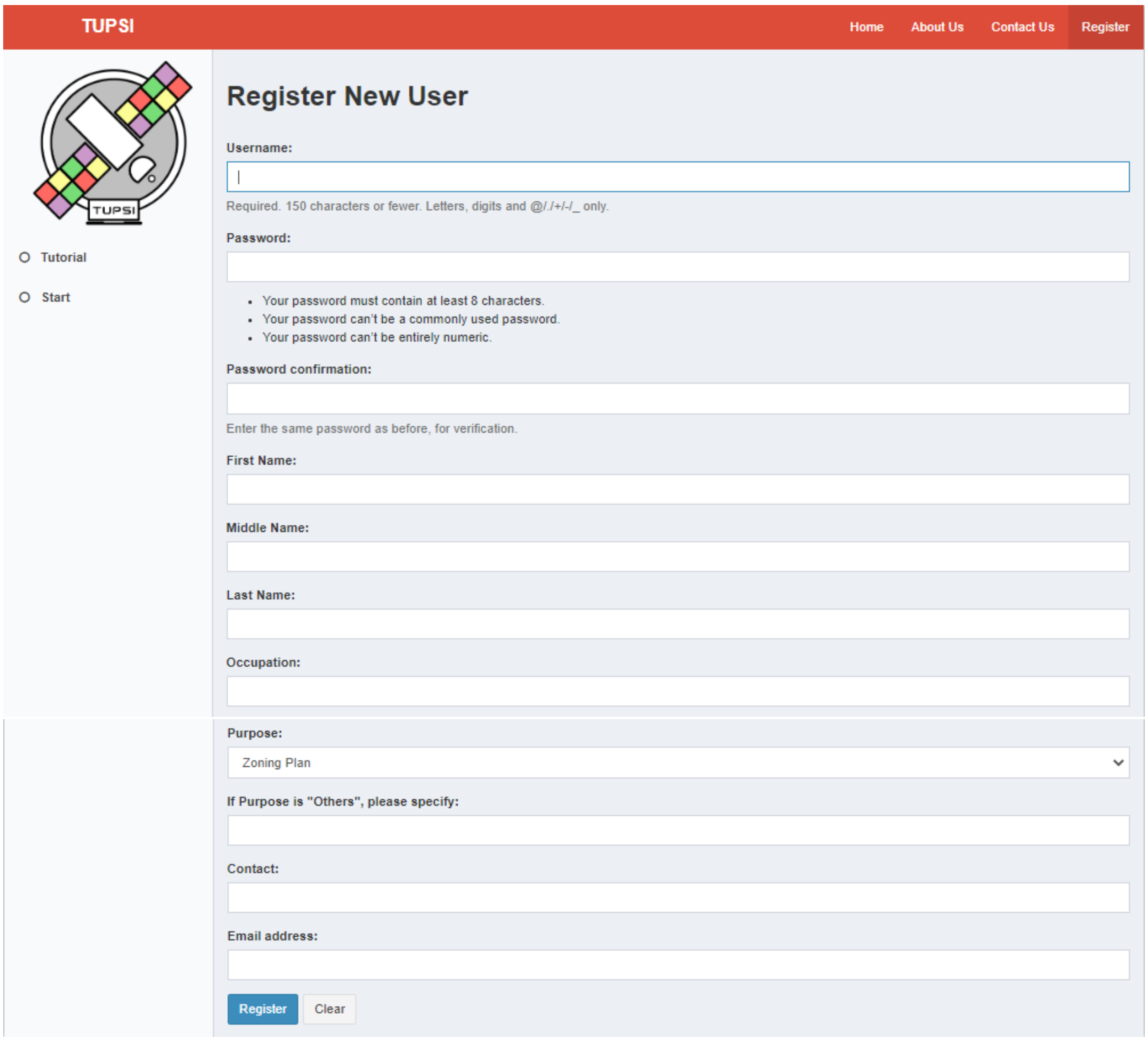
1. Go to https://satelliteimagery.pyhtonanywhere.com/#

   The website:

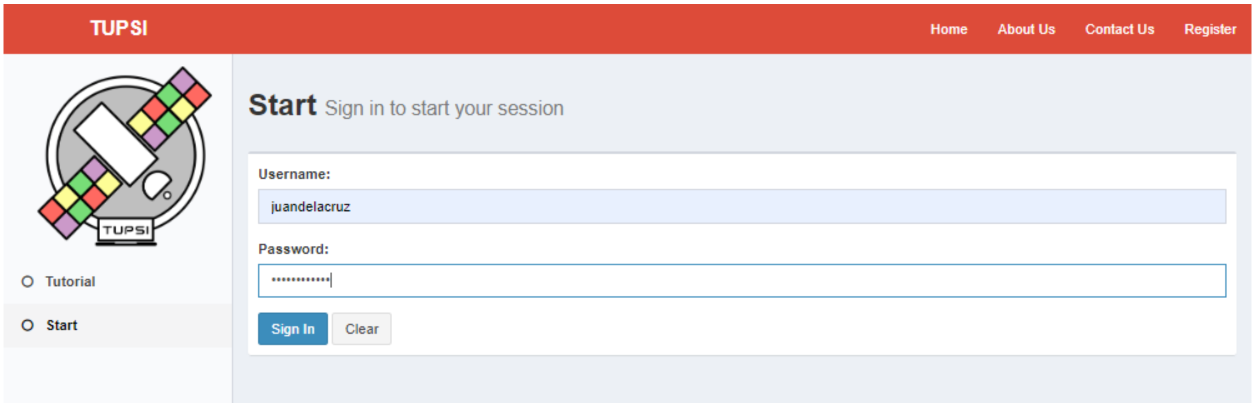


2. Click the “Register” button on the upper right corner of the website.

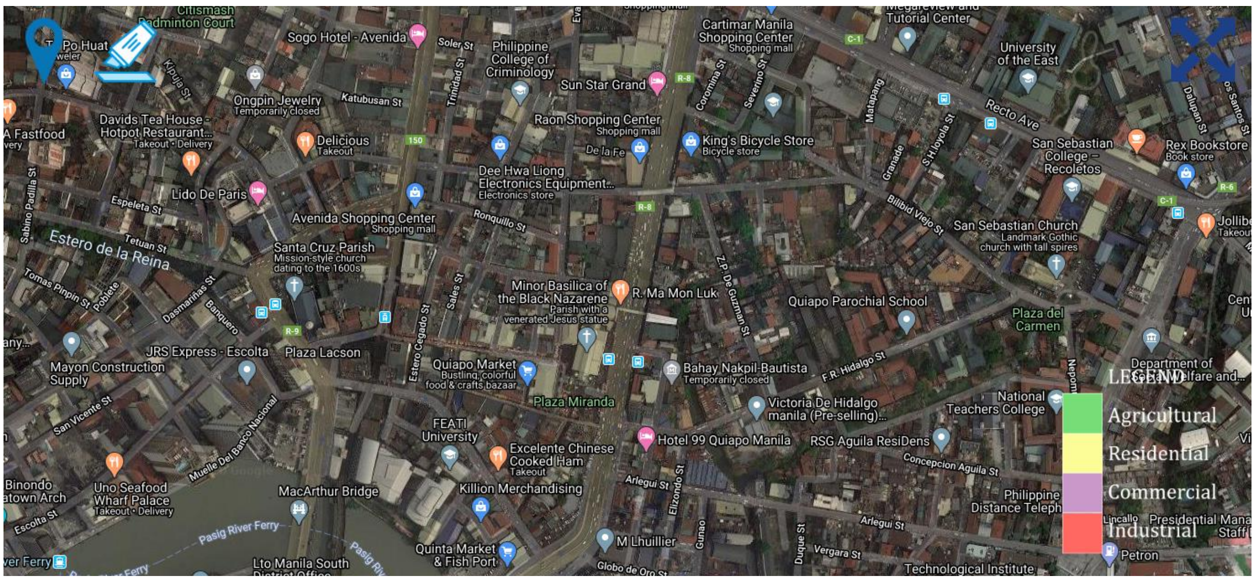
Enter the needed information for your account and click the blue “Register” button.



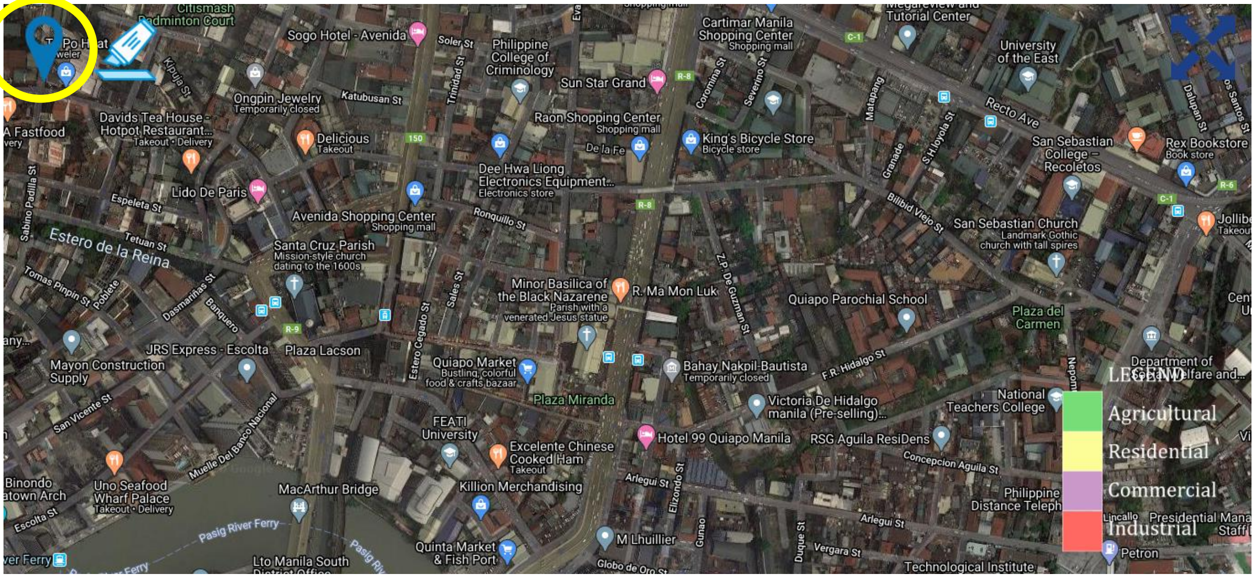
3. Sign in on your account.



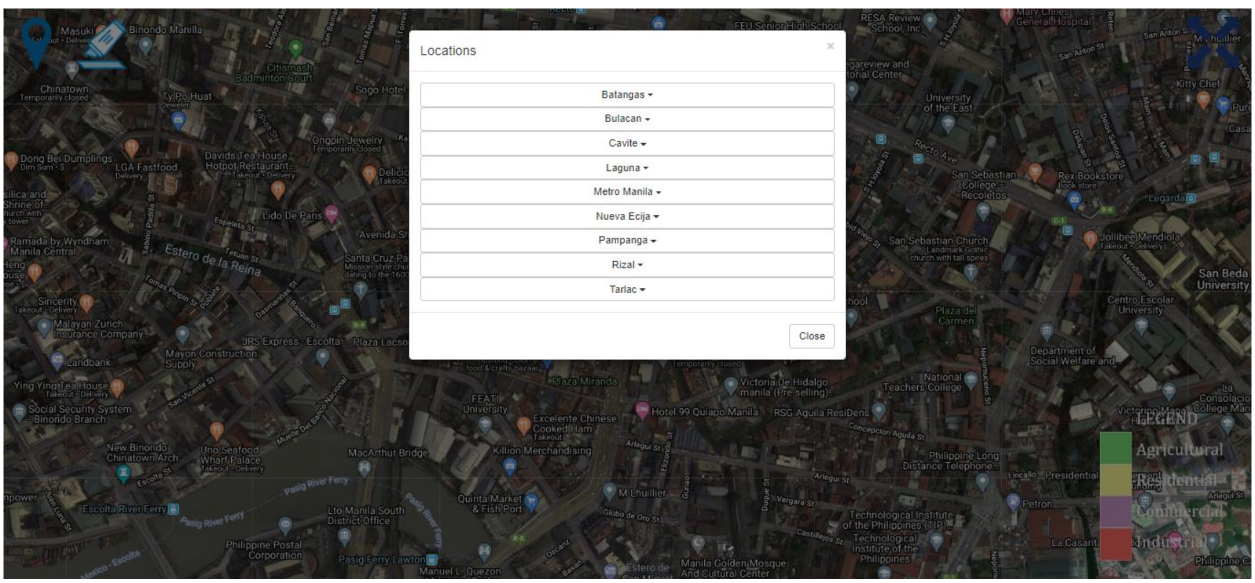
Web app map:



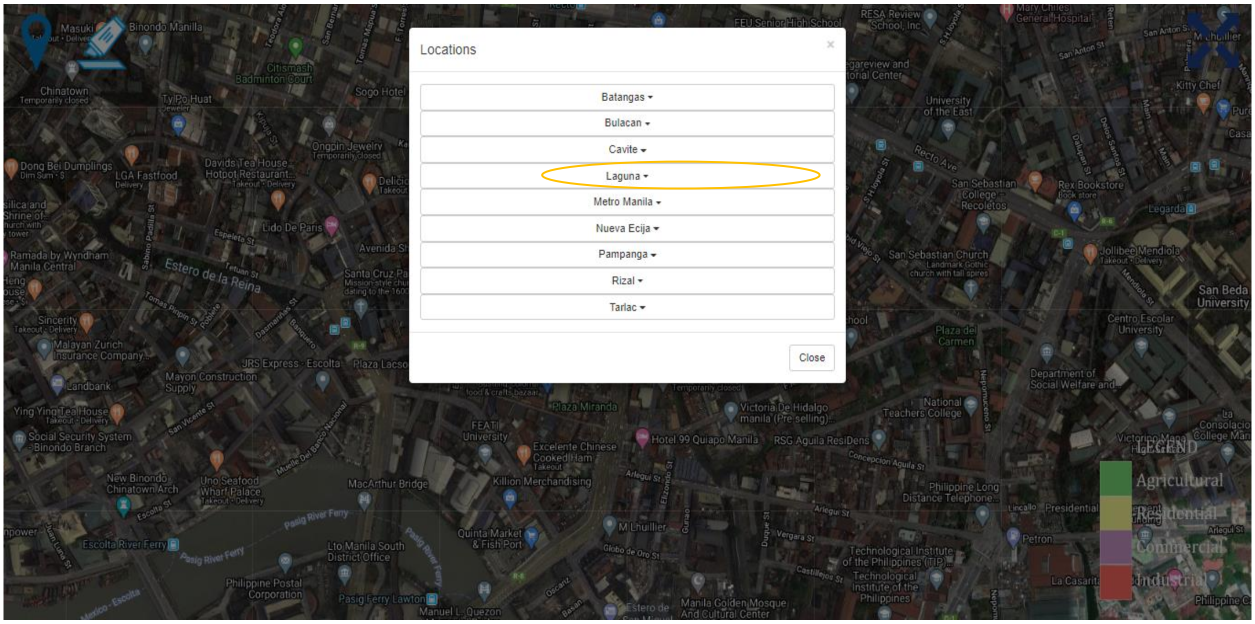
4. Click the location list button to open a drop-down menu of locations in Greater Manila Area.



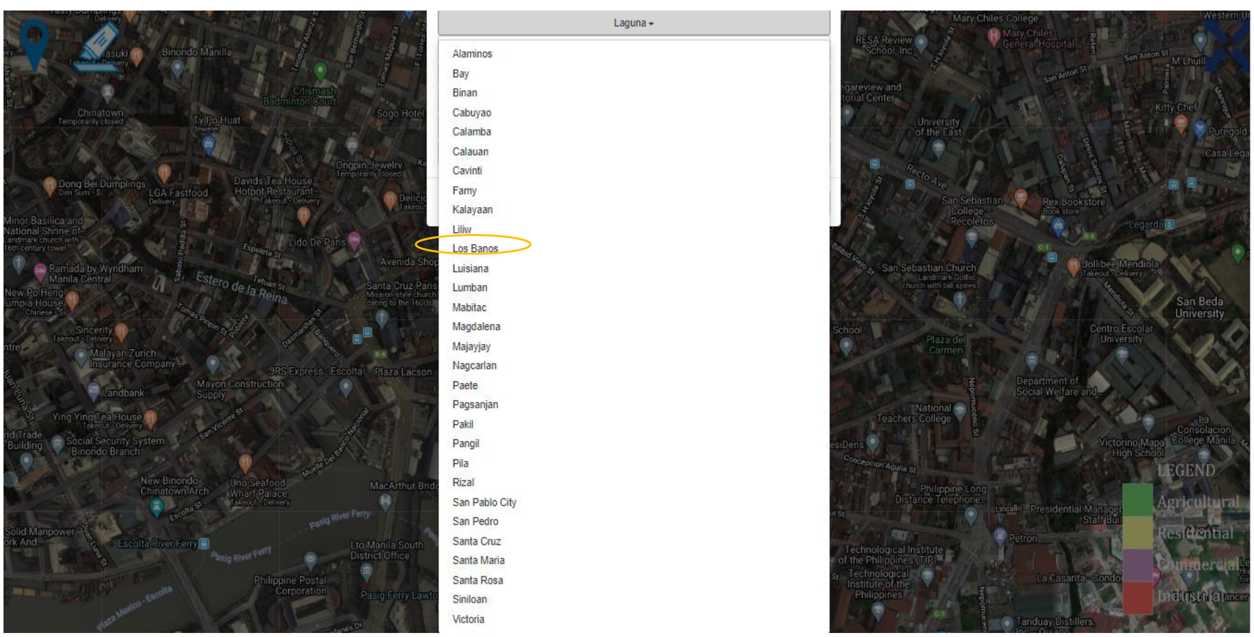
The drop-down menu location list:



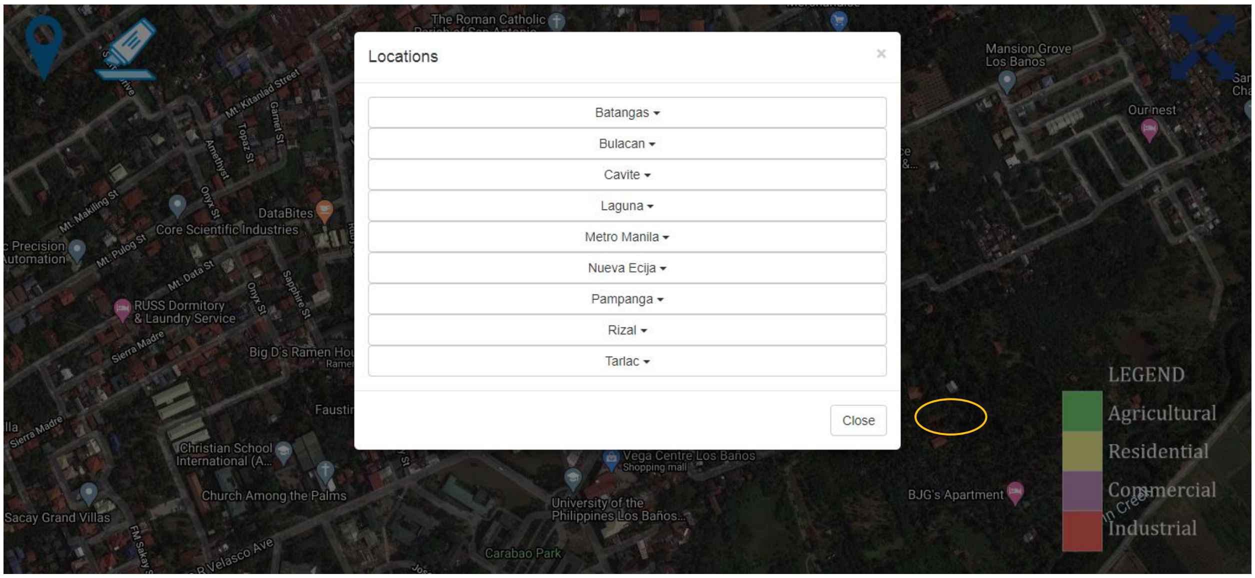
5. Click your desired location (here we chose Laguna).



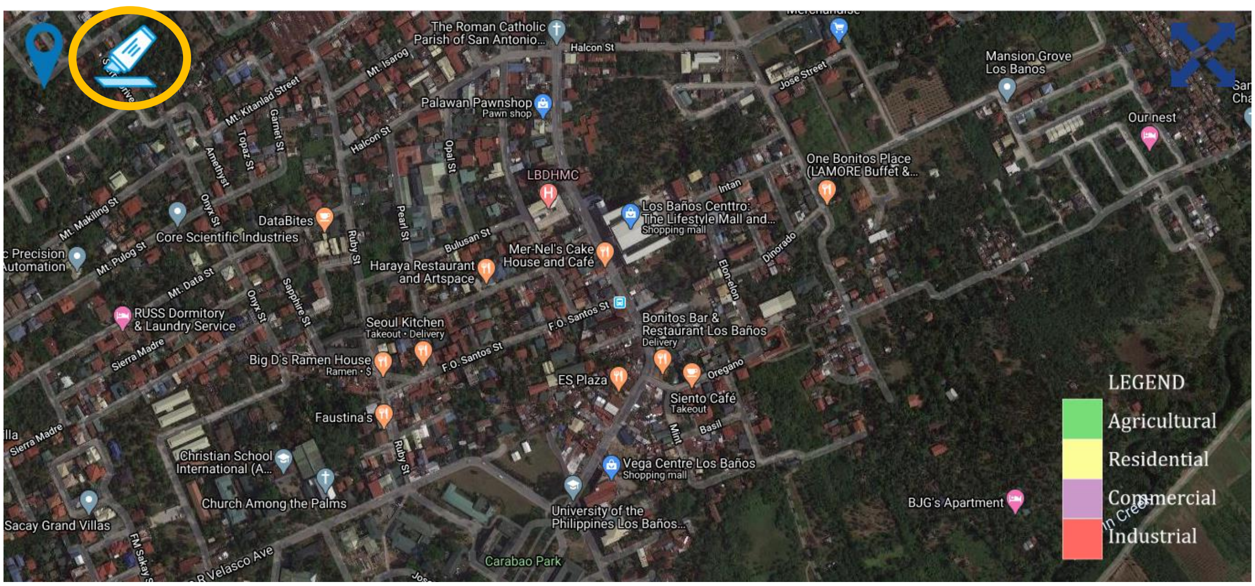
The dropdown location under Laguna:



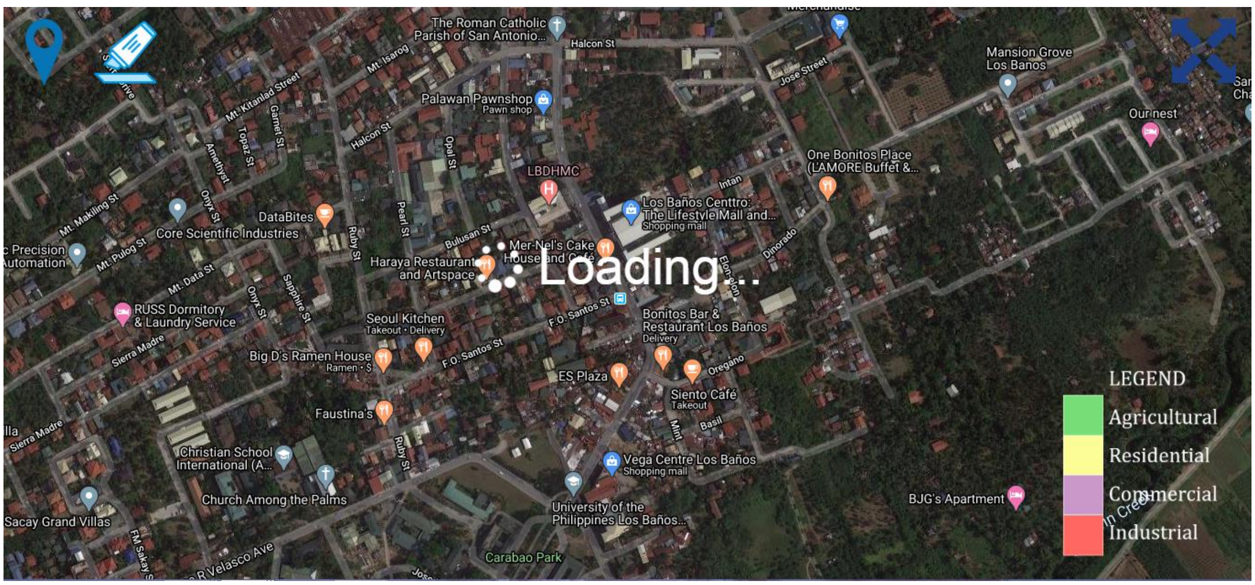
6. You will be generated to your chosen location. Close the drop-down menu to see the whole map of your area.

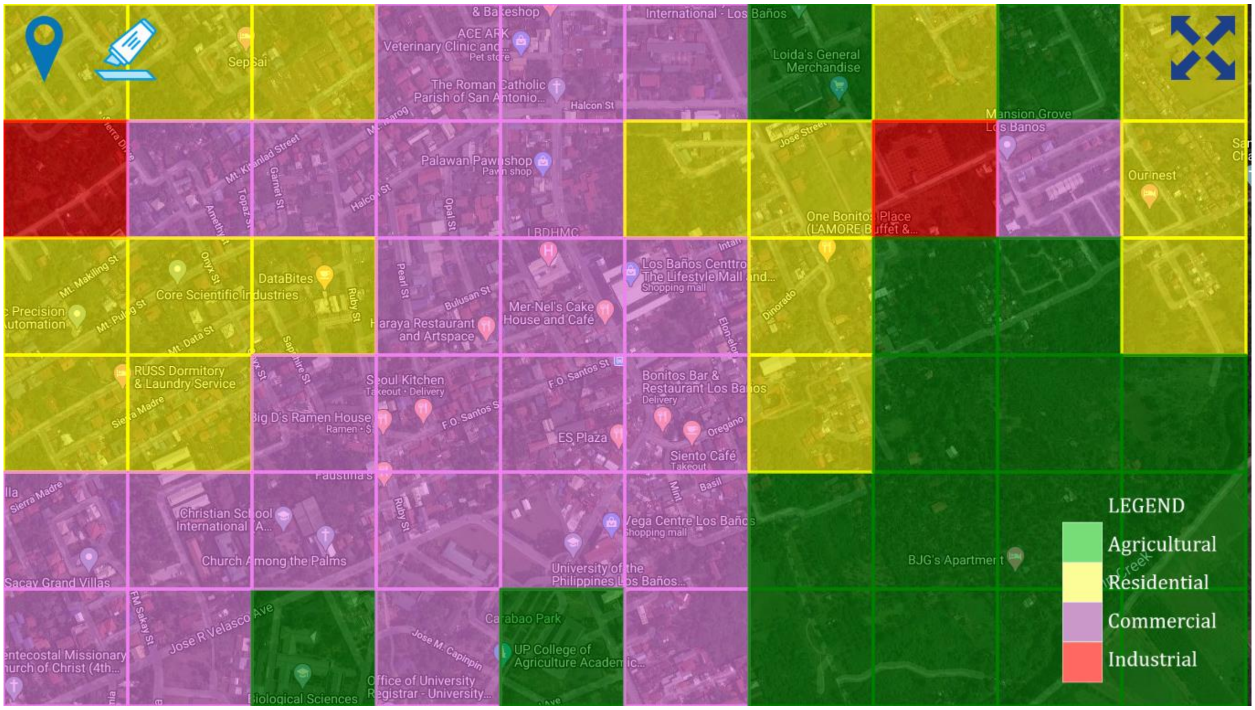


7. To start the prediction, click the “Highlight Map” Button at the upper right are of the map.



This will take a screenshot of the map and the prediction will load.





- You can toggle full screen/restore the view of the map by clicking the button at the upper right corner of the screen.

- The prediction is shown with colored tiles.

The map is divided into squares of 15x6* and the colored tiles indicates the land class of the areas in the map,

wherein:

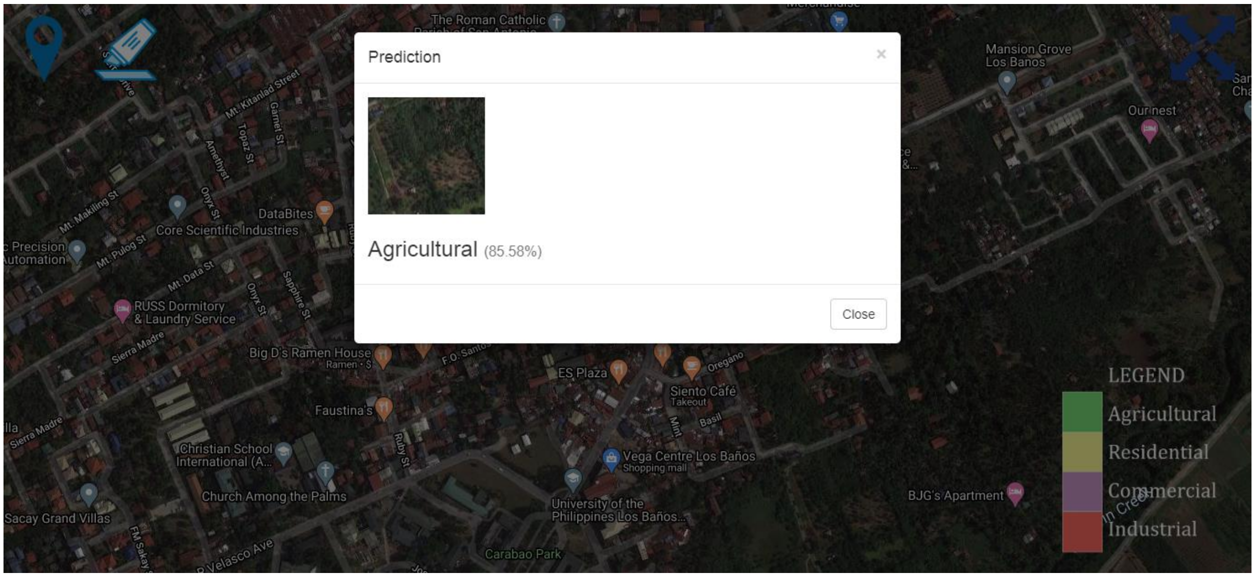
Green - Agricultural

Yellow - Residential

Purple – Commercial

Red – Industrial

*note: the number of tiles will depend on the size of the screen of your device



Clicking on the map with the square cursor can predict the land class of the are within the square cursor and the accuracy of the prediction is also shown: the area is “agricultural” and with 96.09% accuracy.

APPENDIX E

Proponents' Profile Layout

Shiela Mae P. Agoylo

Doña Consolacion Village 3 Malhacan, Meycauayan City, Bulacan
+639771632292
shielamaeagoylo@gmail.com

Personal Information

Birthday: December 11, 1997
Age: 22
Height: 5'5"
Weight: 104lbs
Citizenship: Filipino

Career Objective

"Seeking a challenging position in a reputable company to fully utilize my skills and gain practical knowledge while making a significant contribution to help achieve the goals of the company."

Educational Attainment

Tertiary: *Technological University of the Philippines – Manila*
Ayala Blvd., Ermita, Manila
Bachelor of Science in Electronics Engineering
SY: 2014 – 2020

Secondary: *Zambales National High School*
Iba, Zambales
SY: 2010 – 2014

Primary: *Amungan Elementary School*
Iba, Zambales
SY: 2004 – 2010

Seminars:

Packetworx: Internet of Things (IoT)
Engr. Arnaldo Bagabaldo, February 12, 2019

IECEP SUMMIT 2020 Career Pathways: Walk with Prominence through Profession Segment 1 – Redefining Success
IECEP-MSC, February 8, 2020

IECEP SUMMIT 2020 Career Pathways: Walk with Prominence through Profession Segment 2 – Graduate Studies: To Pursue or Not to Pursue
IECEP-MSC, February 8, 2020

IECEP SUMMIT 2020 Career Pathways: Walk with Prominence through Profession Segment 3 – How to Win Job Interview
IECEP-MSC, February 8, 2020

IECEP SUMMIT 2020 Career Pathways: Walk with Prominence through Profession Segment 4 – Career Pathways
IECEP-MSC, February 8, 2020

Organization Affiliations

Organization of Electronics Engineering Students

Member (2014 – 2020)

Institute of Electronics Engineers of the Philippines Manila
Member (2016 – Present)

MARY JOY BULTRON

14 Immaculate Concepcion St. Brgy. Holy Spirit Diliman,
Quezon City
09308225623 / 09060071779
Maryjoybultron@gmail.com

Personal Information

Birthday: December 15, 1995
Age: 24
Height: 4'11"
Weight: 45 Kg
Citizenship: Filipino

Personal Skills

- Mastery of core knowledge
- PCB design using multisim
- Analytical and Problem Solving
- Set-up designing using SketchUp
- Computer Literate

Achievements

OCTOBER 23, 2018
ELECTRONICS TECHNICIAN EXAM (PASSER)

Career Objective

To be able to work in a company when I can apply all the knowledge and skills I have learned from the academic and supervised-industrial training

Educational Attainment

COLLEGE:

Technological University of the Philippines
Ayala Blvd., Ermita, Manila
Bachelor of Science in Electronics Engineering
(S.Y. 2016 – AUGUST 2020)

Technological University of the Philippines
Ayala Blvd., Ermita, Manila
Electronics Engineering Technology
(S.Y. 2013 - 2016)

SECONDARY:

North Fairview High School
North Fairview Quezon City
(S.Y. 2009 - 2013)

PRIMARY:

Old Balara Elementary School
Old Balara Quezon City
(S.Y. 2003 - 2009)

Seminars:

DECEMBER 21, 2018 — **Introduction of Test Engineering and Basic ATE Instrument, Trends in Microcontrollers, & Fault Isolation**
MAXIM PHILIPPINES OPERATING CORPORATION

DECEMBER 10, 2018	**ECE Seminar: Industry Preparedness** St. Thomas Hall, Colegio de San Juan de Letran
NOVEMBER 24, 2018	**Electronics Engineering in the Philippines and the ASEAN Economics Community** Multipurpose Hall NU Annex Building

Organization Affiliations

Organization of Electronics Engineering Students
Member (2016– 2020)

Ailyn Joyce O. Clamor

Blk 29 Lot 7 San Manuel 1 Dasmariñas City
+63916-191-0513
ailynclamor@gmail.com

Personal Information

Birthday: June 5, 1997
Age: 23
Height: 5'3"
Weight: 122lbs
Citizenship: Filipino

Personal Skills

- Knowledgeable on basic hardware troubleshooting,
- Good in written Why-why analysis.
- Basic PCB Designing using multisim and proteus.
- Proficient in Microsoft Office Application (Word, Excel, PowerPoint).
- Basic knowlegde about programming (R, MATLAB, LABVIEW, Virtuoso Layout.
- Skilled in Soldering and Circuit Designs.
- Analytical and Problem Solving.
- Self-motivated and high level of energy.
- Adaptability and ability to work under pressure.

Achievements

Board Passer
Electronics Technician Board Examination 2017

Career Objective

"To be able to work in a comply when I can apply all the knowledge and skill I have learned from the academic and supervised-industrial training."

Educational Attainment

Tertiary: *Technological University of the Philippines – Manila*
Ayala Blvd., Ermita, Manila
Bachelor of Science in Electronics Engineering
SY: 2016 – 2020

Technological University of the Philippines – Cavite
Salawag, Dasmarinas City
Electronics Engineering Technology
SY: 2013 – 2016

Secondary: *Dasmariñas North National High School*
San Isidro Labrador Dasmariñas City
SY: 2009 – 2013

Primary: *San Miguel Elementary School*
San Miguel 1 Dasmariñas City
SY: 2003 – 2009

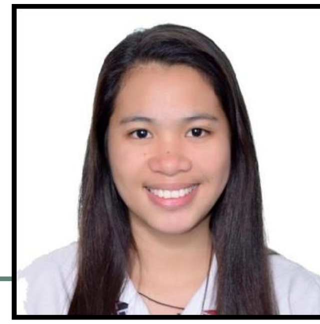
Organization Affiliations

Organization of Electronics Engineering Students
Member (2016 – 2020)

Institute of Electronics Engineers of the Philippines Manila
Member (2017 – Present)

Jaishree Keith M. Monzaga

Ph 2 Sec 4 Blk 5 Lot 20 Belvedere Towne Paradahan 1, Tanza, Cavite
0917-801-7211
jaishreekeith.monzaga@tup.edu.ph



Personal Information

Birthday: February 6, 1998
Age: 22
Height: 5'4"
Weight: 143lbs
Citizenship: Filipino

Personal Skills

Basic Electronics and Communication

Troubleshooting and soldering

Computer Literate: Microsoft Office Application (Word, Excel, Power point)

Basic knowledge in Adobe Photoshop

Basic Simulation and Design Software (Multisim, Express PCB)

Basic programming knowledge (Java, Python)

Leadership skills experienced as sports leader

Achievements

Scholar of Cong. Jon-jon Ferrer IV of City of General Trias (2014-2017)
Junior Committee Head of Sports (2016-2017)
3rd place in SCUAA Women's Basketball (2018)

Career Objective

"I am experienced in human skills which I gained during my high school and college days as I actively involved in sports. I posses values like discipline, diligence, being humble, hardworking and a sense of humor. I am a jolly person indeed I gained many friends in school and community. Moreover, I am a good follower and willing in learning new experience."

Educational Attainment

Tertiary: *Technological University of the Philippines – Manila*
Ayala Blvd., Ermita, Manila
Bachelor of Science in Electronics Engineering
SY: 2014 – 2021
Secondary: *Holy Nazarene Christian School*
Mulawin, Tanza, Cavite
SY: 2010 – 2014
Primary: *Bea Therese School*
Paradahan 1, Tanza, Cavite
SY: 2004 – 2010

Seminars:

Publishing Extension Outputs in Research Journals
Technological University of the Philippines, July 3, 2020

"Virtual Reality of Things"
National University, November 2018

"Internet of Things and Telecom: The New Golden Era"
National University, November 2018

"Impact and Benefits of Industry 4.0: A Smart Factory Automation"
National University, November 2018

Organization Affiliations

Organization of Electronics Engineering Students
Member (2014 – Present)

Institute of Electronics Engineers of the Philippines Manila
Member (2017 – Present)

Cleodelaine S. Salvador

1741 Bayanihan Village Bagbaguin, Caloocan CIty
+639238548747
cleodelainesalvador@gmail.com

Personal Information

Birthday: May 18, 1997
Age: 23
Height: 5’6”
Weight: 118lbs
Citizenship: Filipino

Personal Skills

Efficient, hardworking, versatile, and flexible
Good follower and listener
Highly motivated in learning new knowledge and skills
Knowledgeable in Microsoft Office Applications
Quick learner of advance technologies
Sense of Responsibility

Career Objective

“Seeking a challenging career that will utilize my fullest potential that will give opportunities to enhance my personality, and career growth that will commensurate with my abilities and qualifications, at the same time share and gain knowledge by performing the assigned task in the best interest of the company.”

Educational Attainment

Tertiary: *Technological University of the Philippines – Manila*
Ayala Blvd., Ermita, Manila
Bachelor of Science in Electronics Engineering
SY: 2013 – 2020
Secondary: *Caybiga High School*
Gen. Luis St. Caybiga, Caloocan
SY: 2009 – 2013
Primary: *Caybiga Elementary School*
Pleasant Vieew Subd. Bagbaguin, Caloocan
SY: 2003 – 2009

Seminars:

Careeer Pathway: Walk with Prominence through Profession
Segment 1 – Redefining Success
Segment 2 – Graduate Studies: To pursue or Not to Pursue
Segment 3 – How to Win Job Interview
Segment 4 – Career Pathways
Pamantasan ng Lungsod ng Manila/ IECEP-MSC, February 8, 2020

3D Printing Workshop
Technological University of the Philippines – Manila/ OECES, July 29-31, 2019

Organization Affiliations

Organization of Electronics Engineering Students
Member (2013 – 2020)

Institute of Electronics Engineers of the Philippines Manila
Member (2019 – 2020)

Association of Student Assistants
Secretary (2018-2020)

Commission on Student Elections
Working Committee Member (2019)

Catherine Rose R. Rosales

152 Malunggay St., CAA Compd. Phase – 4 Las Piñas City
+63 930 458 2264
catherinerose.rosales@tup.edu.ph

Personal Information

Birthday: August 22, 1996
Age: 24
Height: 4'8"
Weight: 119lbs
Citizenship: Filipino

Personal Skills

Efficient, hardworking, and flexible
Highly motivated in learning new skills
Adaptability to work in new environment
Ability to work under pressure
Good follower and listener

Achievements

Electronics Technician Board Exam Passer (October 2018)
DOST Scholar (2013 – 2016)

Career Objective

"To be able to use the knowledge and skills that I have acquired in my academic years as a student in a progressive organization and be able to have the opportunity to learn new things in my future work."

Educational Attainment

Tertiary: *Technological University of the Philippines – Manila*
Ayala Blvd., Ermita, Manila
Bachelor of Science in Electronics Engineering
SY: 2013 – 2020

Secondary: *Parañaque Science High School*
Parañaque City, Metro Manila
SY: 2009 – 2013

Primary: *Mary Immaculate School*
Parañaque City, Metro Manila
SY: 2003 – 2009

Seminars:

TechEx: Fundamentals of Data Science
Webinar/IEEE TUP Manila Student Branch, October 24, 2020

Role of Artificial Intelligence to Traffic Management
Webinar/IEEE Young Professionals, September 19, 2020

Leadership Tool: Project Management
Webinar/PUP ECESS, September 16, 2020

Access Denied: Understanding Modern Cybersecurity
Webinar/PUP ECESS, September 15, 2020

Internet of Everything: Readiness of the Philippines in the Road of Digitalization
Webinar/PUP ECESS, September 14, 2020

Role of Machine Learning in Smart Manufacturing
Webinar/IEEE Young Professionals, September 12, 2020

Cybersecurity: The New Normal
Cybertalk with CERT-PH – Segment 2
PKI and its role in the New Normal – Segment 3
Webinar/DICT Cybersecurity, June 24, 2020

Career Pathways: Walk With Prominence through Profession
Segment 1 – Redefining Success
Segment 2 – Graduate Studies: To Pursue or Not to Pursue
Segment 3 – How to Win Job Interview

Segment 4 – Career Pathways
Pamantasan ng Lungsod ng Ma/IECEP-MSC, February 8, 2020

Structured Cabling System and Design
Technological University of the Philippines - Manila, August - December 2019

MIT Iterative Innovation Process
Technological University of the Philippines - Manila, July 2019

Arduino Training Workshop
Technological University of the Philippines - Manila, July 2019

LoraWAN Technology Seminar
Technological University of the Philippines - Manila, February 2019

Organization Affiliations

Organization of Electronics Engineering Students
Member (2015 – 2020)

Association of Student Assistants – TUP Manila
Member (2018 – 2020)

Commission on Student Elections (COMSELEC) – TUP Manila
Volunteer (2018 – 2019)

DOST Scholar’s Club – TUP Manila
Member (2013 - 2016)

APPENDIX F

Turnitin Result

TUPSI 1A

ORIGINALITY REPORT

13%	7%	9%	5%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Maria T. Patterson, Nikolas Anderson, Collin Bennett, Jacob Bruggemann et al. "The Matsu Wheel: A Cloud-Based Framework for Efficient Analysis and Reanalysis of Earth Satellite Imagery", 2016 IEEE Second International Conference on Big Data Computing Service and Applications (BigDataService), 2016 Publication	1%
2	www.lib.ncsu.edu Internet Source	1%
3	www.econstor.eu Internet Source	1%
4	Mahmut Cavur, Serkan Kemec, Leili Nabdel, H. Sebnem Duzgun. "An evaluation of land use land cover (LULC) classification for urban applications with Quickbird and WorldView2 data", 2015 Joint Urban Remote Sensing Event (JURSE), 2015 Publication	1%
5	www.ecologycenter.us	