**Instituto Tecnológico**

**y de Estudios Superiores de Occidente**

Reconocimiento de validez oficial de estudios de nivel superior según acuerdo secretarial 15018, publicado en el Diario Oficial de la Federación del 29 de noviembre de 1976.

Departamento de Electrónica, Sistemas e Informática

Maestría en Sistemas Computacionales



**Performance comparison of Deep Learning Models applied for Satellite Image Classification**

Trabajo recepcional que para obtener el grado de

Maestro en Sistemas Computacionales

Presenta: Carlos Alberto Cordero Robles

Asesor Dr. Iván Esteban Villalón Turrubiates

Tlaquepaque, Jalisco. Julio de 2020.

[La portada se deberá actualizar con la versión oficial disponible en: <https://www.iteso.mx/titulacionposgrados>]

[SI EL DOCUMENTO ES ESCRITO EN INGLES, se debe colocar la portada principal en inglés, y una segunda portada en español.]

Acknowledgments

I would like to acknowledge to:

My thesis advisor Ivan Villalón, who suggested me the topic for this document and always tried to find the way to unblock me with any blocker that appeared during the investigation.

The engineer Victor Martinez who provided good guidance in many aspects to improve the quality of this effort.

Luxoft that is the enterprise where I work and provided resources and flexibility to let me continue with my professional development.

Oracle for all the support in resources that made the realization of this project possible.

The "Instituto Tecnológico y de Estudios Superiores de Occidente (ITESO)" for the resources provided for the development of this research. Additionally, to the "Consejo Nacional de Ciencia y Tecnología (CONACYT)" for the financial support received through the grant number 498325.

AGRADECIMIENTOS

El autor desea dar las gracias a:

Mi asesor de tesis Ivan VIllaón, quien sugirió el tema de tesis para este documento y siempre busco maneras de desbloquearme en todos los contratiempos que surgieron durante la investigación.

Al ingeniero Víctor Martínez quien proveyó buenos consejos y guía en muchos aspectos para mejorar la cualidad de este esfuerzo.

A Luxoft que es la empresa donde laboro que proveyó recursos y flexibilidad que me permitió continuar con mi desarrollo profesional.

A Oracle por todo el soporte en recursos que hicieron posible la realización de este proyecto.

Al "Instituto Tecnológico y de Estudios Superiores de Occidente (ITESO)” por los recursos provistos para el desarrollo de esta investigación. Adicionalmente, al "Consejo Nacional de Ciencia y Tecnología (CONACYT)" por el soporte financiero recibido a través del número de autorización 498325.

Dedication

I would like to dedicate this project to:

My great family that has always supported my ideas and projects.

Dedicatoria

Me gustaría dedicar este proyecto a:

Mi gran familia que siempre ha apoyado mis ideas y proyectos.

Abstract

Satellite images and its classification is important for many applications that involve the distribution of the human activities. Such distribution helps the governments to determine the best places to construct in one specific area and avoid problems related with natural disasters or legal constrains. Currently there are not too many agencies in charge of this image classification and the area to cover is enormous then an automation of this process is necessary for this task. This will take an eternity to perform this task manually. On the other hand, the algorithms for detection and classification used before Machine Learning have not shown good result classifying this specific sort of images. One method that has shown in later studies to be quite accurate in the task of image classification are the Convolutional Neural Networks (CNN). In this research we analyses the performance of four different CNN models for this specific task of satellite image classification. The dataset that is going to be used is the one provided by in 2017 by IARPA fMoW. This dataset contains more than two thousand images that belong to 62 classes and are already separated in Train and Validation.

The solution was implemented in Python using the Keras libraries integrated to Tensorflow. The research was divided in two parts. The first part was using a sample of the dataset near to one thousand images to determine the best hyperparameters for the models and the metrics for every one of them with the help of the tool Tensorboard. After having these results, the models that showed good performance where trained using the previous hyperparameters and the entire dateset.

The last part of the system is a dense layer that gather the output of the CNN model and attach it to the image metadata in order to get even more accuracy.

The model selected after the analysis was XXXXX with a final accuracy of XX.

Resumen

Las imágenes satelitales y su clasificación son importantes en diversas aplicaciones que involucran la distribución de las actividades humanas. Dicha distribución ayuda a los gobiernos a determinar la mejor ubicación para la construcción en áreas específicas para evitar problemas relacionados con desastres naturales o conflictos legales. Actualmente no existen muchas agencias destinadas a este propósito y considerando lo enorme que es el área por cubrir se llega a la conclusión que es necesario automatizar el proceso para esta tarea. Esta tarea seria eterna si se realiza manualmente. Por otra parte, los algoritmos de detención y clasificación usados antes de “Machne Learning” no han mostrado buenos resultados en la clasificación de este tipo de imágenes. Un método que ha mostrado ser bastante preciso en tareas de clasificación son las Redes Neuronales Convolucionales (CNN). En esta investigación analizo el desempeño de cuatro diferentes modelos de CNN para esta tarea específica de clasificación de imágenes satelitales. El “dataset” utilizado es uno provisto el 2017 por IARPA fMoW. Este “dataset” contiene más de doscientas mil imágenes pertenecientes a 62 clases y ya previamente separadas en Entrenamiento y Validación.

La solución fue implementada en Python usando la librería de Keras ya integrada a Tensorflow. La investigación se divide en dos partes. La primera parte es usando una muestra del “dataset” original cercana a las mil imágenes, para así determinar los mejores hiperparametros y los métricos de cada modelo, con la ayuda de la herramienta Tensorboard. Después de tener los resultados, los modelos que mostraron tener buenos resultados fueron entrenados usando el dataset completo y los hiperparametros antes encontrados, para al final solo quedar con el mejor candidato.

La última parte del sistema es una capa densa que conjunta la salida del modelo CNN y adjunta los metadatos de la imagen con el objetivo de dar aún más precisión.

El modelo seleccionado después del análisis fue XXXXX con una eficiencia final de XX.

TABLA DE CONTENIDO

[Dar clic en el menú de Referencias/ Dar clic en Tabla de Contenido/ Seleccionar Tabla de Contenido Personalizada/ Seleccionar Formato Formal, 4 Niveles, Dar Clic en Opciones. En la ventana de Opciones, asignar Nivel de TDC 1 a Título Intro. Dar clic en Aceptar, y de nuevo en Aceptar].

[AGRADECIMIENTOS 3](#_Toc451186816)

[DEDICATORIA 3](#_Toc451186817)

[RESUMEN 3](#_Toc451186818)

[TABLA DE CONTENIDO 3](#_Toc451186819)

[LISTA DE FIGURAS 3](#_Toc451186820)

[LISTA DE TABLAS 3](#_Toc451186821)

[LISTA DE ACRÓNIMOS Y ABREVIATURAS 3](#_Toc451186822)

[1. INTRODUCCIÓN 3](#_Toc451186823)

[1.1. Antecedentes 3](#_Toc451186824)

[1.2. Justificación 3](#_Toc451186825)

[1.3. Problema 3](#_Toc451186826)

[1.4. Hipótesis 3](#_Toc451186827)

[1.5. Objetivos 3](#_Toc451186828)

[1.5.1. Objetivo General: 3](#_Toc451186829)

[1.5.2. Objetivos Específicos: 3](#_Toc451186830)

[1.6. Novedad científica, tecnológica o aportación 3](#_Toc451186831)

[2. ESTADO DEL ARTE o de la TÉCNICA 3](#_Toc451186832)

[2.1. Tema relacionado 1 3](#_Toc451186833)

[2.2. Tema relacionado 2 3](#_Toc451186834)

[3. MARCO TEÓRICO/CONCEPTUAL 3](#_Toc451186835)

[3.1. Concepto básico 1 3](#_Toc451186836)

[3.2. Esquema básico 2 3](#_Toc451186837)

[3.2.1. Si se requiere subtema 3](#_Toc451186838)

[3.2.1.1. Subsubtema 3](#_Toc451186839)

[4. DESARROLLO METODOLÓGICO 3](#_Toc451186840)

[4.1. Levantamiento de requerimientos 3](#_Toc451186841)

[5. RESULTADOS Y DISCUSIÓN 3](#_Toc451186842)

[5.1. Resultados 3](#_Toc451186843)

[5.2. Discusión 3](#_Toc451186844)

[6. CONCLUSIONES 3](#_Toc451186845)

[6.1. Conclusiones 3](#_Toc451186846)

[6.2. Trabajo Futuro 3](#_Toc451186847)

[BIBLIOGRAFÍA 3](#_Toc451186848)

LISTA DE FIGURAS

[Figura 1. Ventana que se abre para insertar una imagen. 3](#_Toc451189394)

[En el menú de Referencias, seleccionar Insertar Tabla de Ilustraciones. Si se desea insertar para Figuras, solo se debe seleccionar el rótulo de Figura.]

LISTA DE TABLAS

[Tabla 1. Presentación de información en tablas. 3](#_Toc451189447)

[En el menú de Referencias, seleccionar Insertar Tabla de Ilustraciones. Si se desea insertar para Tablas, solo se debe seleccionar el rótulo de Tabla.]

LISTA DE ACRÓNIMOS Y ABREVIATURAS

[Del lado izquierdo va el acrónimo o abreviatura y del lado derecho su significado. La columna de en medio se deja en blanco. Al final, se deben quitar los bordes de la tabla]

|  |  |  |
| --- | --- | --- |
| IARPA fMoW |  | Functional Map of the World |
| ML |  | Machine Learning |
| DL |  | Deep Learning |
| CNN |  | Convolutional Neural Networks |
| SVM |  | Support Vector Machine |
| PCA |  | Principal Component Analysis |
| LDA |  | Linear Discrimination Analysis |
| SURF |  | Speeded Up Robust Features |
| SIFT |  | Scale Invariant Feature Transform |
| HOG |  | Histogram of Gradients |
| POP |  | Province of Manitoba |
| OLI |  | Operation Land Imager |
| TIRS |  | Thermal Infrared Sensor |
| IR |  | Infra-Red |
| UAV |  | Unmanned Aerial Vehicle |
| MSG |  | Meteosat Second Generation |
| NN |  | Neural Network |
|  |  |  |
|  |  |  |
|  |  |  |

[5 SALTOS DE LÍNEA CON ESTILO NORMAL ANTES DE PONER EL TITULO]

# INTRODUCCIÓN

Many of the applications for the satellite images are related with public works. Public works are strictly necessary to the develop of the civilization and its life quality, although they are extremely expensive. One construction can cost easily thousands of millions of dollars and a well planification can be de difference between a good usage of the building or a waste of money that can be lost because the accessibility or a natural disaster.

In order to be able plan and determine correct strategy for the public works construction it is required a classification of the current public works and land use distribution.

The methodologies used before ML have not shown good results classing this specific sort of images that is why in this research we are going to use and compare the behavior of four different DL models in order to find the best accuracy possible.

The dataset that is going to be used is the one provided for the challenge fMoW in 2017 that contains 62 classes already labeled and separated in training and validation. I shall clarify that such dataset is multispectral, but the goal of this investigation is to work only with the classic RGB bands. Nevertheless, a dataset preparation is required. Using more bands will be left for future investigations.

## Background

This research is based mainly in 2 previous investigations. The first one is entitled “Satellite Image Classification with Deep Learning” [7]. In this paper Mark Pritt and Gary Chern used the dataset provided from IARPA fMoW. The got an accuracy of 83% using a hybrid model were four models Resnet-152 [8], InceptionV3[9], Xcepetion [10] and DenseNet-121[11]. The models were trained using one epoch the dataset expanded by eight by flipping the image horizontal a vertically and rotating the image 90°, 180° and 270° degrees. The output of the model was attached to the model’s outputs to create a hybrid model that categorize the images.

The second paper entitled “Functional Map of the World” [12] is the paper related with the dataset itself. This paper describes the characteristics of the dataset. As it is explained in this paper the dataset is multispectral and the images goes from three to eight bands. In addition, the dataset contains a metadata with valuable geographic information as well as the sensor information.

## Justification

Satellite images and its classification is important for many applications that involve the distribution of the human activities. Public works is one of the most representative and expensive responsibilities of the governments and in some cases for some investors. At the same time, they represent an important factor for the population development and distribution. Unfortunately, these sorts of investments are overwhelmingly expensive, just here in México the construction of the Mayan train[1] and the “Dos Vocas” refinery[2] will cost together more than 150,000 million of Mexican pesos (more than 7.5 hundreds of millions of dollars), this is just to give an example of the cost that can take a public work of this magnitude. Although, as I have mentioned the public works have a purpose and if they are well planned and the benefits for the enclosed population and the life quality tends to improve, on the other hand if the public work is not well planned and geographically well distributed it will directly impact the enclosed population as well as the economy of the country.

Another controversial example is the “Nuevo Aeropuerto Internacional de México (NAIM)” that was recently cancelled because floods probabilities. We can even confirm this information and many other environment hazardous impacts in the document resolutive analysis SGPA/DGIRA/DG/09965 [3] that shows that in some periods of the year the airport remains covered by water, in addition the airport would be near to areas were endemic and extinction endangered species lives. The cost for the cancellation of this airport was 120 thousand millions of Mexican pesos (6 thousand millions of dollars approximately), those are the kind of mistakes related with constructions allocation that can be avoid with good planification and distribution of public works.

Nevertheless, this kind of situation are not only limited to government public works, many private constructions focused for recreation are also involved. One example is the Mercedez-Benz stadium in New Orleans also called the superdome. This stadium is located in the state of Louisiana that in 2005 suffered the floods caused by the hurricane Katrina and that was granted with a renovation that will cost 450 millions of dollars [5].

This take us to other important point when a construction is planned, as we have seen this investments costs millions of dollars and well applied they will retrieve a lot of incomes to the population and the nation in general, on the other hand if they are not well located or geographical distributed or if they are endangered for any natural disaster this will result in one enormous catastrophe for the invertors and the people affected by the people that inhabit in the area.

Then, after clarifying the necessity of a well panning it is important to mention that in order to be able to plan it is required to detect on time and understand the current distribution of the public works and constructions. One powerful resource that can be used is the satellite images, although the task of classification is most of the time performed manually and in order to categorize all the entire earth surface will be quite exhausting. The importance of this task has triggered many challenges [6] that are not limited to any technology and the objective is to obtain the higher performance in detection and classification of many kind of images including satellite images.

The latest years one technology that has shown good results when categorizing images has been the Neural Networks, specifically Deep Learning models that involve many layers of neurons. This technology is costly and involve hours or even weeks of computing, that is why it is highly valuable to determine if this technology has good result with a specific dataset in this case in particular a dataset of satellite images.

## Problem

The problem faced in this research is a classic classification problem related with satellite images and the method of classification is DL. The dataset that is going to be classified is IARPA fMoW that provides 62 classes. The CNN models that are going to be used are the ones proposed in [18]. To classify satellite images to obtain the land use is quite important for the civilization distribution. The latest years DL is a state-of-the-art technology that has show outstanding results in many areas as classification. In the actuality many DL architectures and models are accessible, and the goal of this paper is to compare the behavior of four different architectures used in [18] to determine which one is the most appropriated for this sort of datasets related with satellite images.

## Hypotesis

[Si la investigación lo justifica]

## Objective

#### General Objetive:

To find the heights accuracy using four different CNN models and working with a labeled Satellite images dataset with 3 bands.

#### Specific Objective:

In order to get the general objective, it is required first to accomplish some specific objectives that are:

\* To obtain a labeled dataset to be able to stimulate the CNN models with such information.

\* To preprocess the dataset to accomplish the specifications of every Model.

\* To construct or get every model and adapt it to the number of classes that are handled in our dataset.

\* To define a strategy to manage the dataset, maybe it is required to separate the images in tiles or maybe it is a good idea to start working with a small batch of images.

\* To find the best hyperparameters for every CNN model.

\* Evaluate the behavior of every CNN using metrics as F1-Score, Hamming Loss, Jaccard Score and Log loss.

## Scientific or technologic share/innovation

This document will share the different behavior of four different CNN architecture using a satellite images dataset.

# State Of Art or the technique

We can find in recently researches related to the classification of satellite images using DL. Some of them are focused in a specific area of study like land usage or bodies of water. Some of them are even more specific and would focus their work in a specific topic like areas for agriculture and cropping. On the other hand, we can find paper related with a more general detection of human construction that not only detect land usage areas but also public works.

One particularity that have the satellite images is that some images contain multispectral information, that means that the image is not having only the classic RGB layers but also near and far infrared that have shown good result making visible bodies of water. Some other images have eight layers and some of them have the capacity to trespass some centimeters the surface of the earth, nevertheless not all the investigations are using such layers, most of them are still using only the classic RGB layers.

One common problem that exist for the satellite images that only work with the classic RGB layers are the clouds. It is something that cannot be removed an always going to be a problem of the classic layers. Some papers have even focused their investigation on the detection of clouds and categorizing its shape and texture.

Another aspect that we can find in previous works are the usage of hybrid models. Sometimes it is possible to option more accuracy if we add to the system not only the image but also the geographical information or any other post processing that can be performed with dense layers or SVM.

## Satellite Image classification based on unsupervised methods

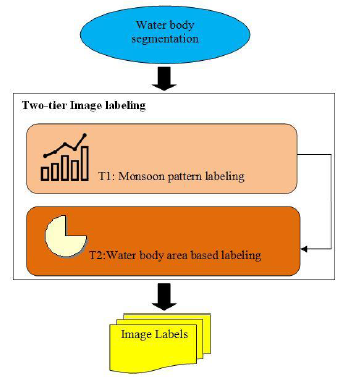
## A novel two-tier paradigm for labeling water bodies [13]

In 2017 Janice Aroma and Kumudha Raimond from the University of Karunya described the steps required to label satellite images. Labeling is an unsupervised method of clustering required to perform supervised training. The study doesn’t end just with the labeling, it also applies a supervised classifier to recognize seasonal water bodies.

In this paper is explained the necessity of intelligent models to determine and measure the damage and post hazard because the surveys and field works insitu represent a heavy time consumption. Satellite images are the opposite problem, they contain a lot of information at every band and the task now is to extract the features with accuracy and in the shortest time possible.

Currently the traditional methods for classification PCA and LCA are dependent of statistical color features although the satellite images commonly come from different satellites that have different sensors then using local discriminators instead of global discriminators have shown been more robust. The local discriminators used for image classification are SURF, SIFT and HOG.

Unfortunately, the process to obtain the features is still not efficient. In general, the most highly used labeling methods are pixel based that are laborious and complex. Then this paper proposes a method named Two-tier labeling scheme. One specific water body was taken for this study and the first tier was the Local monsoon pattern the second one was the water body area. Obtaining descriptors provided from these two tiers they were able to label different states of the water body including disasters or hazardous events.



## Satellite Image classification based on supervised Machine learning

## Pattern Recognition Scheme for Large-Scale Cloud [17]

In 2018 Adrian Pérez-Suay and Jordi Muñoz-Marí used machine learning for cloud detection over landmarks using MSG satellites images. MSG SEVIRI takes an image every 15 min with 12 spectral channels and the size of the images is 3712x3712. The dataset used was from the year 2010 with 200 landmarks and 7 million of images.

The labels used for this experiment were Space/no data (0), water (50), land (100), cloud (200) and the ML classifier method was SVM.

The features extracted were related with reflectance, brightness and temperature. IR channels provide information about the temperature of clouds, surface, and land. Some NIR channels helps separating between cloud and land and some IR channels help to detect fog and log clouds. At the end only 16 features were used.

|  |  |  |  |
| --- | --- | --- | --- |
| Number | Features | Day | Night |
| 1 | R1 VIS 0.6 µm | Yes | No |
| 2 | R2 VIS 0.8 µm | Yes | No |
| 3 | R3 NIR 1.6 µm | Yes | No |
| 4 | R4 IR 3.9 µm | Yes | Yes |
| 5 | BT7 IR 8.7 µm | Yes | Yes |
| 6 | BT9 IR 10.8 µm | Yes | Yes |
| 7 | BT10 IR 12.0 µm | Yes | Yes |
| 8 | Cloud Test: R2/R1 | Yes | No |
| 9 | Snow Test: (R1-R3)/(R1+R3) | Yes | No |
| 10 | NDVI: (R2-R1)/(R2-R1) | Yes | No |
| 11 | *mean3x3*(R1) | Yes | No |
| 12 | *std3x3*(R1) | Yes | No |
| 13 | *mean5x5*(R1) | Yes | No |
| 14 | *std5x5*(R1) | Yes | No |
| 15 | *mean3x3*(BT9) | Yes | Yes |
| 16 | *std3x3*(BT9) | Yes | Yes |

In order to give more accuracy to the problem it was divided in different scenarios depending on the time of the day and the zone. The day was divided in four ranges and the landmarks were assigned to twelve zones. The results are presented below.

Kappa Statistics and Overall Accuracy [k (OA%)] for the Selected Landmarks

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Name | #LM | High Light Sza<=szam | Medium Light szam<=sza<=80 | low light 80<=sza<=90 | night sza>=90 | global |
| Ad Dakhla (Morocco) | 0 | 0.62 (83.24) | 0.71 (87.03) | 0.63 (83.51) | 0.65 (85.78) | 0.66 (85.35) |
| aqaba2 (saudi arabia) | 14 | 0.50 (82.74) | 0.56 (83.34) | 0.57 (84.95) | 0.65 (90.06) | 0.59 (86.65) |
| azores5 (portugal) | 17 | 0.72 (87.61) | 0.64 (86.20) | 0.56 (80.98) | 0.56 (79.86) | 0.61 (82.94) |
| chad2 (chad) | 48 | 0.76 (87.94) | 0.74 (87.09) | 0.64 (81.97) | 0.58 (78.75) | 0.65 (82.83) |
| danger (south africa) | 63 | 0.82 (90.89) | 0.81 (90.36) | 0.68 (84.22) | 0.63 (81.57) | 0.71 (85.64) |
| grampian (scotland) | 83 | 0.70 (89.99) | 0.69 (88.90) | 0.57 (81.92) | 0.48 (78.32) | 0.57 (82.95) |
| libreville (gabon) | 107 | 0.69 (87.93) | 0.73 (89.52) | 0.69 (87.34) | 0.68 (88.25) | 0.69 (88.40) |
| messina (sicilia) | 120 | 0.80 (90.09) | 0.80 (89.92) | 0.73 (86.47) | 0.71 (85.73) | 0.75 (87.61) |
| nasser2 (egypt) | 131 | 0.57 (89.16) | 0.59 (88.33) | 0.63 (90.08) | 0.71 (94.17) | 0.64 (91.52) |
| rhodes (greece) | 154 | 0.80 (91.54) | 0.77 (88.73) | 0.72 (86.44) | 0.72 (86.50) | 0.75 (88.05) |
| tenerife (spain) | 177 | 0.77 (88.46) | 0.71 (85.41) | 0.63 (81.30) | 0.67 (83.18) | 0.69 (84.68) |
| Valencia (spain) | 190 | **0.83 (91.59**) | **0.84 (92.18)** | **0.76 (87.88)** | **0.73 (86.72)** | **0.78 (89.01)** |

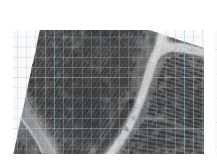
Best Results are highlighted in bold.

## Improved Machine Learning Methodology for High Precision Agriculture [16]

In 2018 Jérôme Treboux and Dominique Genoud members of the Institute of Information Systems of the University of Applied Sciences, Valais Sierre, Switezerland developed a method using ML to improve from 89.6% of accuracy (using methods based in color analysis) to 94.27% in classification of vineyards and roads. These sorts of analysis are important to increase the productivity in agriculture and determine the correct amount of inputs (water, fertilizer, etc.) in the correct place.

The research used infrared images taken from a UAV that in this case was a drone that can fly over the fields carrying treatment products.

The dataset were five images of five different vineyards in Valais, Switzerland taken by a drone. An expansion of the dataset was performed dividing the images in tiles of 30x33 pixels to end up with 13, 005 images manually labeled. The categories to classify were: Road, Vineyard or Other.



The dataset was divided 90% for training and 10% for validation. Only 16 features were taken from the images from the following three categories, First Order Statistics (Min, max, mean, geometric mean, sum, variance, etc.), Tamura (Granularity, Contrast, kurtosis of directional, etc.) and Haralick (Statistical features based on gray-level).

The final overall accuracy of the algorithm is of 94.275%. The local accuracies are shown below.

|  |  |  |  |
| --- | --- | --- | --- |
|  | Best detection within the study | local vineyar 1 | local vineyar 2 |
| Accuracy Std err | 96.06% N/D | 90.02% ± 1.17% | 89.6% ± 1.01% |

## Satellite Image classification based on Deep Learning

## DEEP LEARNING NEURAL NETWORKS FOR LAND USE LAND COVER MAPPING [14]

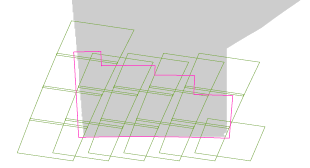
This research performed in 2018 by Christopher D. Storie and Chrisotpeh J. Henry from the University of Winnipeg, had the objective to classify the land use/land cover of Manitoba Canada. GeoManitoba that is department of POM requested such classification and continue doing it human bases semi-automated showed to be an unsustainable task (as much as 4800 work hours) because it has to be performed yearly.

The stakeholders had interest in this sort of research because it is possible to get information related with flood forecasting, urban and rural land use planning, resource management, and disaster management and planning.

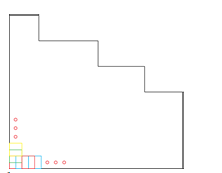
POP provided a multispectral (6 bands) Landsat database provided by GeoManitoba of 19,039 images belonging to 18 classes for the years 1993, 2000 and 2004. The requirement was to use the model to tag all the not tagged regions of those years.

The model used was VGG-16 that has an input layer of 224x244.

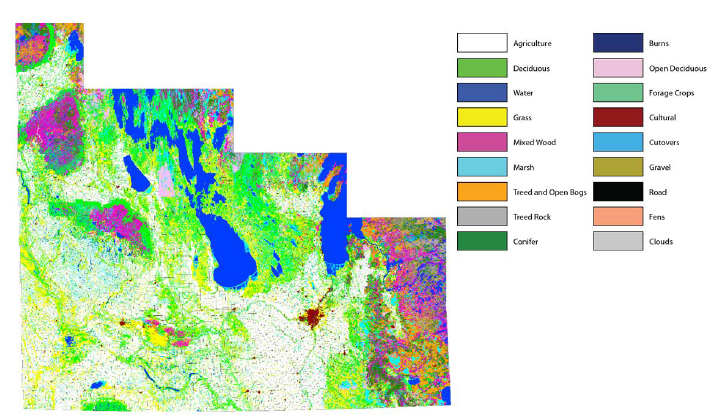
The first step was to construct the region of Manitoba using satellite images and matching them to construct an image with the entire map.



After that the map was divided in tiles of the size of the input layer of the model (224x224) but overlapped the half size of the window (112 pixels).

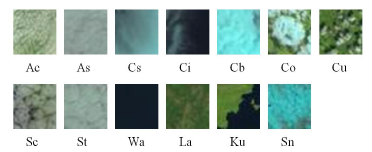


The dataset was divided in 18,054 images for training and 958 for validation. Since the dataset was too small it was required to apply transfer learning. The training plus the mapping process took near to 10 days and the accuracy was the following: 82.5% (1993), 81.2% (2000) and 79.5% (2004).



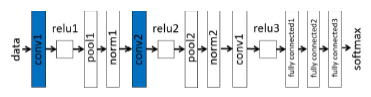
## Dense Cloud Classification on Multispectral [15]

In this research by University of Dortmund by the Image Analysis Group a methodology to categorize 13 cloud classes (also called genera) was performed based on a small dataset (147 images) of Landsat 8 satellite images. The images provided by the dataset used two different sensors OLI that has nine band from 435nm to 2294nm and TIRS that has two bands from 1060nm to 1251nm.



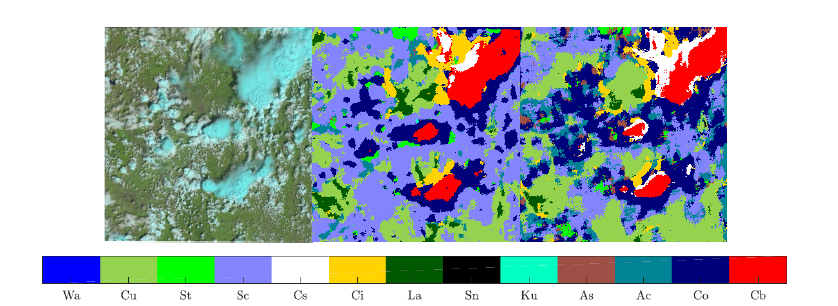
The dataset of 147 images (every image with a range between 6000 and 8000 pixels) was expanded cropping it in squares of 320x320 pixels and down sampling the squares to 32x32 pixels to end up with an expanded dataset of 9578 images. This expanded dataset was augmented with rotations and mirroring to obtain one thousand images per class, thirteen images in total that were distributed 90% for training and 10% for validation. The labeling was performed manually in few sessions.

For the CNN they used a customized Alex-Net. The customization consisted in removing all the layers excepting the first two Convolutional layers and their polling. Transfer learning was applied for these two layers from imageNet database. Finally, they added an untrained Convolutional Layer and a fully connected layer and used Adagrad optimizer for the training, they called this model CloudNet. About training time, they reported that the training of 10,000 epochs took near to ten minutes.



For the SVM they used SURF and one additional input for the SVM was the color histogram of the image, this final training took between 30 and 60 min.

The accuracy using RGB layers was 85.8% after adding the IR layer the accuracy slightly rised to 86.1% and finally adding the SVM classification the final accuracy was 95.4%.

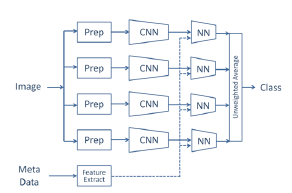


## Satellite Image Classification with Deep Learning [18]

In 2017 Mark Pritt and Gary Chern from Lockhead Martin Co. developed a classification DL system in python using Keras and Tensorflow libraries and a GPU NVIDIA Titan X. They are classifying satellite images, because the geographic expanses to be covered are great and the analyst available to conduct the searches reduced it is required to automate the process.

The dataset used was the one provided by the Intelligence Advanced Research Projects Agency (IARPA), the dataset is named the Functional Map of the World (fMoW) that contain 62 classes already labeled. The images contain from 3 to 8 bands and include metadata, although for this experiment only 3 bands were used. The dataset already comes divided in training and validation. For training the dataset was augmented eightfold by flips and 90°, 180° and 270°degree rotations.

They system that they proposed is an ensemble of CNNs that receive a processed (preprocessed) image and followed by a classic NN at the end the maximum probability determines de classification.



The preprocessing is needed because the satellite images in general don’t match the CNN input size of 224x224 or 299x299 then they have to be cropped and adjusted. The bonding box is part of the metadata information and it is used to perform the cropping.

The CNN models selected were DenseNet-161, ResNet-152, Inception-v3 and Xception. The metadata was normalized and used as an input for the NN models. Transfer learning was applied from ImageNet.

For training, the CNN models were trained only one epoch and for the NN twenty epochs were needed. The final results showed an accuracy of 83% and F1 score of 0.797.

## Deep Learning for Cloud Detection [19]

In this research performed in the University of Toulouse a comparison between DL methods used with classical handcrafted features and classical CNN is performed for cloud detection.

The detection consists in labeling every pixel of an image indicating if that pixel belongs to a cloud or not. The first detectors took the descriptors from the morphology of the shadow or from dedicated spectral bands, although they showed a lack of generalization and low robustness, the next generation of detectors used handcraft features that the engineer itself select for DL this is not required and the results are even better.

The dataset is 10,000 images from SPOT 6 satellite that provide 4 band (RGB and NIR) granted by the Airbus Defense and Space.

The comparison was made between the CNN solution against four classic methods: RGBI raw pixel values, band ratios, Gabor coefficient and discrete cosine transform (DCT) coefficients.

The selection of features critical form the classic methods, some of these features are noise sensitive, require neighboring information and many times need physical correction, nevertheless band ratios have shown good results. Band-ratios were processed at three different spatial resolutions (60m, 120m, 240m). Gabor is more used for textual features of the image, for this study 48 features were taken and for DCT 192 features that were the input for a classic NN to determine de classification. For the CNN this is not required but instead of having features it is required to take an input of 32x32 (patch) were the pixel to analyze is just at the center. The CNN used was like the one used in CIFAR-10. The results are shown below.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Input Type | Network | accuracy | Recall | Precision |
| Gabor | ANN | 77% | 43% | 66% |
| Raw pixels | ANN | 83% | 68% | 77% |
| featrues | ANN | 81% | 68% | 80% |
| SueprPixels | ANN | 83% | 69% | 80% |
| dct | ANN | 83% | 75% | 80% |
| pathches | CNN | 86% | 75% | 81% |

In general, the CNN (patches) got slightly better results 86%, we have to consider that the work to identify the features is not required when working with CNN.

# Theoric/conceptual framework

**Resumen:** En este capítulo se presentan las bases teóricas y conceptuales sobre [el objeto de estudio].

## Accuracy

In general, accuracy is the number of items well classified over the total number of inputs. If we want to evaluate the accuracy over a class, we need to evaluate the number of items of such class well classified over the total of inputs of such class.

## Precision

The precision is evaluated over the class and it is the number of items that were well classified of such class over the total of predictions that denoted this class.

## Recall

The Recall is evaluated over the class and it is the number of items that were well classified of such class over the real number of inputs of this class.

## F1-Score

Normally a model in the way how it gets more precision it starts reducing the recall the ideal is to have a balance. F1-Score follows the following formula:

F1-Score = 2 \* (precision \* recall) / (precision + recall)

The highest value will be F1-Score = precision = recall. In other words, F1-Score measure the valance between precision and recalls of a class prediction.

## Macro-F1

Macro-F1 is the average value of all the F1-Score values of all the classes to predict.

## Hamming Loss

Hamming Loss is the number of items wrong predicted over the total of inputs.

## Jaccard Score

Jaccard Score or Jaccard similarity coefficient score is the relationship for a class between the times that it was well predicted against all the times that class appears in the classifications. For example if we have one input like {0,1,2,2} and the prediction is the following {0,2,1,2} for the class number 2 the correct predictions is just one, and the times that appear in the classification as input or as prediction is 3 then the Jaccard score for the class 2 is 1/3. We can get the average Jaccard score for all the classes and get a value for the entire model called Jaccard Score macro. Understanding this we can understand Jaccard score as the similarity between the inputs and the predictions considering 0% the minimum when inputs and predictions are totally different and 100% when the accuracy is 100%.

## Log loss

Log loss or cross-entropy is a metric quite useful when the prediction is based in probabilities. In general, log loss is the error between the input and the output. Even if the accuracy is 100% if we use prediction based on probabilities there will always be a gap between the input and the output for example if have one image that is dog and a classifier that differs between cat and dogs and it says that the image is 90% dog and 10% cat, then it will be well classified but the error is of 10%. It is applied a log function to avoid handling too small numbers.

## Deep Learning Models

## ResNet-152 [8]

## InceptionV3 [9]

## Xception [10]

## DenseNet-161 [11]

# DESARROLLO METODOLÓGICO

**Resumen:** [En este capítulo se presenta en detalle el desarrollo metodológico que incluye [pasos o proceso a seguir] un resumen de los trabajos relacionados con [el objeto de estudio].]

## Levantamiento de requerimientos

[En esta sección se incluye la metodología de trabajo elegida para el desarrollo de la propuesta. Si el trabajo es un desarrollo de software, se podría elegir una metodología como “agile”, cascada, espiral, prototipado, incremental, RAD (Rapid Application Development, u otra relacionada con el desarrollo de software. Si es para el desarrollo de aplicaciones web podría utilizarse RMM (Relationship Management Methodology), OOHDM (Object Oriented Hypermedia Design Method), UWE (UML-Based Web), entre otros. y en esta sección se pondrían los títulos y subtítulos con los tipos XXXXX. Metodologías de Investigación podrían contener la definición teórica, metodologías o métodos formales de solución, métodos de simulación, entre otros DEFINIDOS Y SELECCIONADOS POR LOS TUTORES.]

# RESULTADOS Y DISCUSIÓN

**Resumen:** [En este capítulo se presentan los resultados obtenidos del desarrollo de este trabajo y una discusión sobre [el objeto de estudio]].

## Resultados

[Teclee los resultados en pasado. Ponga título a sus tablas y gráficos. Hacer referencia explícita utilizando la numeración. Ejemplo: …, como se muestra en la Figura 10. NO referenciar mencionado: como en la siguiente figura, o similar.]

## Discusión

[resultados más relevantes de este trabajo, los más relevantes de otros trabajos, comparar, referir a nuevos trabajos que puedan surgir de aquí, o problemas.

# CONCLUSIONES

**Resumen:** [En este capítulo se presentan las conclusiones y trabajo futuro en relación a [el objeto de estudio]].

## Conclusiones

[Las conclusiones deben responde a los objetivos establecidos]

## Future Works

1) In the section of methodology subsection Hyperparameter are described some steps that where execute manually in order to find the best learning rate per model, such model can be automated.

2) This investigation was performed using only the three basic bands RGB as suggested by [7] but may papers in the State of the Art section shows that it is also possible to use more band to obtain even more information, then for future work it is planed to use more bands starting with ones that detects water in order to improve the classification hoping to also improve significantly the classification of disasters.

BIBLIOGRAFÍA

[Bibliografía Estilo IEEE: <http://www.ieee.org/documents/ieeecitationref.pdf>

El orden de la bibliografía debe ser el orden en el que aparece en el documento. Toda bibliografía puesta en esta sección deberá estar citada dentro del texto. La forma de hacer la cita cuando es una sola es [1], si son varias y salteadas es [3], [5], [8]. Si son varias consecutivas es [5]-[8]. Combinadas es [2]-[6], [9].

El formato de la bibliografía es como lista numerada simple, sin tabla.

El formato de cada una es como se describe a continuación y dependiendo del tipo:

*[Book Article*

* *For an article in an edited book, use practice similar to that for*[*author w/ editor or translator*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#auth-ed/trans)*above, inserting article title between author[s] names and book title.*
* *[Citation Number] Author name[s], "*[*article title*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#title-art)*," in*[*book title*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#title)*,*[*editor names*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#auth-ed/trans)*, publication location: publisher, year,*[*pages.*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#pages)
* *Examples:]*

1. E.D. Lipson and B.D. Horowitz, "Photosensory reception and transduction," inSensory Receptors and Signal Transduction, J.L. Spudich and B.H. Satir, Eds. New York: Willey-Liss, 1991. pp. 1-64.
2. J. Lacan. "The insistence of the letter in the unconscious," in Psychoanalysis and Language, David Lodge, Ed., J. Rose, Trans., Ithaca, NY: Cornell University Press, 1992, pp. 123-34.

*[Journal*

* *[Citation Number] Author name[s], "*[*article title*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#title-art)*,"*[*journal title*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#title-per)*,*[*volume number, issue number, month (abbrv.)*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#volume)*,*[*pages*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#pages)*, publication year.*
* *Only include information which is pertinent to your source.  For example, many professional and academic journals do not have an issue month.  In that case, or when it seems unnecessary, do not include it in your citation.*
* *Examples:]*

1. K.A. Nelson, R.J. Dwayne Miller, D.R. Lutz, and M.D. Fayer, "Optical generation of turntable ultrasonic waves," Journal of Applied Physics, vol. 53, no. 2, Feb., pp. 1144-1149.
2. J. Allemang, "Social studies in gibberish," Quarterly Reviews of Doublespeak, vol. 20, no. 1, pp. 9-10.

*[Popular Periodical Article (monthly or bimonthly)*

* *In the case of popular monthly or bimonthly periodicals, omit volume number and issue, identifying instead by month and year of publication.*
* *[Citation Number] Author name[s], "*[*article title*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#title-art)*,"*[*periodical  title*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#title-per)*,*[*month (abbrv.)*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#volume)*,*[*pages*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#pages)*, publication year.*
* *Examples:]*

1. J. Fallows, "Network technology," Atlantic Monthly, Jul., pp. 34-36, 1994.

*[Popular Periodical Article (Biweekly, weekly, or daily)*

* *In the case of more frequently published periodicals, use day, month, and year to identify.*
* *[Citation Number] Author name[s], "*[*article title*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#title-art)*,"*[*periodical  title*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#title-per)*,*[*day number month (abbrv.)*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#volume)*,*[*pages*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#pages)*, publication year.*
* *Examples:]*

1. B. Metcalfe, "The numbers show how slowly the Internet runs today," Infoworld, 30 Sep., p. 34, 1996.
2. J. Turner, "Disorder 'kills without warning,'" The Toronto Star, 26 Jun., pp. F1-F2, 1998.

*[Paper Published in Conference Proceedings or Presented at Conference*

* *Treat a presentation in conference proceedings like an article in an edited book, including all available publication information.  Conference proceedings are often published by the organization holding the conference; in that case, do not cite the publisher.*
* *Example:]*

1. Paez-Borrallo, I.A. Perez-Alavarezz, and S.Z. Bello, "Adaptive foltering in data communications with self improved error reference," in Proc. IEEE ICASSP '94, 1994, pp. 65-68.

*[Treat an unpublished paper presented as a conference in the following manner: [Citation Number] Author name[s], "*[*article title*](http://www.edshare.soton.ac.uk/77/1/bbieee-help.html#title-art)*," presented at conference title. conference location, year.*

* *Example:]*

1. M. Lai, B. Chen, and S. Yuan, "Toward a new educational environment," presented at 4th Int. World Wide Web Conf. Boston, MA, 1995.

*[Web Page*

* *Give the author, title, type of medium (enclosed in brackets), volume and issue number (if on-line journal), page number (if relevant or given), and the year and the month of publication (in parentheses).  Then give the full internet address or the name of the online service provider prefaced by "Available at ".  If not an on-line journal, also put [cited year month day] before "Available at".*
* *Examples:]*

1. A. Harnack and G. Kleppinger, "Beyond the MLA Handbook: Documenting Electronic Sources on the Internet." Kairos, [Online serial] 1 (2), (1996 Sum), Available at HTTP: http://english.ttu.edu.kairos/1.2/
2. P. Curtis, "Mudding: Social Phenomena in text-based virtual realities," [Online document] Aug. 1992, [1996 Aug 30], Available at FTP: parcftp.xerox.com/pub/MOO/papers/DIAC921992.

**\*\*\*\*\*\*\*\*El estilo es Referencia**]

[1]<https://www.eleconomista.com.mx/estados/Fonatur-establece-el-costo-del-rentable-Tren-Maya-en-139072-millones-de-pesos-20200108-0081.html>

[2]<https://www.eleconomista.com.mx/empresas/Otorgarian-41300-millones--de-pesos-a-Dos-Bocas-20190909-0020.html>

[3] Documento de gus

[4] <https://imco.org.mx/nuevo-aeropuerto-internacional-mexico-proyecto-indispensable-riesgos-oportunidades/?gclid=Cj0KCQjwoub3BRC6ARIsABGhnyaN_vz4zxgkBnO6F3yAd4wnMyOKJSef3mj3_6oBdoxmFo8RlrTva7EaAk6JEALw_wcB>

[5]<https://www.neworleanssaints.com/news/construction-firm-for-renovations-to-mercedes-benz-superdome-approved-renderings>

[6]<http://www.image-net.org/challenges/LSVRC/>

[7] Satellite Image Classification with Deep Learning

Resnet-152 [8],

InceptionV3[9],

Xcepetion [10]

DenseNet-121[11].

[12] Functional Map of the World

[13] A novel two-tier paradigm for labeling water bodies

[14] DEEP LEARNING NEURAL NETWORKS FOR LAND USE LAND COVER MAPPING

[15] Dense Cloud Classification on Multispectral

[16] Improved Machine Learning Methodology for High Precision Agriculture

[17] Pattern Recognition Scheme for Large-Scale Cloud

[18] Satellite Image Classification with Deep Learning

[19] Deep Learning for Cloud Detection

**APÉNDICE A. Título**

**APÉNDICE B. Título**