Zoning Classification using Machine Learning and Remote Sensing Data

Submitted in partial fulfillment of the requirements of the degree of

Bachelor of Engineering

by

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Internal Approval Sheet

CERTIFICATE

This is to certify that the project entitled **"Zoning Classification using Machine Learning and Remote Sensing Data"** is a bonafide work of

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Approval Sheet

Project Report Approval for B. E.

This project report entitled **" Zoning Classification using Machine Learning and Remote Sensing Data"** by

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Examiners

1.---

2.---

Date: / /2021

Place: Ulhasnagar – Thane

Declaration

I declare that this written submission represents my ideas in my own words and where others' ideas or words have been included, I have adequately cited and referenced the original sources. I also declare that I have adhered to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any idea/data/fact/source in my submission. I understand that any violation of the above will be cause for disciplinary action by the Institute and can also evoke penal action from the sources which have thus not been properly cited or from whom proper permission has not been taken when needed.

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Chapter 1

Introduction

1.1 Abstract

A huge percentage of the population worldwide now lives in crowded cities which have grown organically over the years, leading to a low quality of life. The solution proposed to this problem was years ago i.e. Zoning and Urban Planning. But today this process faces a lot of bottlenecks mainly due to human inefficiency, the 3 main steps in Zoning are Surveying, Auditing and Enforcing. We propose to automate the steps of Surveying and Auditing of cities zoning codes. We propose to do it using publicly accessible high resolution remote sensing satellite imagery of a city's structures and analysing them using a Deep Learning model. Also we intend to build an easy to use web interface to broadcast the results of the model to both, the concerned authorities and the citizens of a particular city.

1.2 Introduction

In urban planning where local governments like municipality or metropolitan level government, divide the city's land or localities in different divisions called zones. And each zone has some unique regulations for new construction and existing structures which are different from other zones. Zoning occupies a huge percentage of all of the work done by town planning and enforcement authorities. And surveying and auditing is the most prominent of all the work done by these organizations.

The method of auditing by municipal inspectors is not possible now because cities are getting bigger day by day, there is an emergence of super municipalities e.g. The Pearl River Delta Metropolitan Region which contains cities like Shenzhen, Hong Kong, Macau, Guangzhou which have a population of 78 million. In India the Mumbai Metropolitan Region Development Authority which is the authority for Mumbai, Thane, Kalyan-Dombivali, Navi-Mumbai etc, with a combined population of 29 million. It's difficult to survey this large population manually, it's also a waste of time and resources. And we intend to automate the process of surveying and inspecting the zones in any city, in any part of the world using machine learning and remote sensing data.

1.3 Problem Statement

This project aims to find, if the zoning codes of a land area of a city can be determined with the use of just the remote sensing satellite imagery data. And also create an end to end model to generate the zoning map of a region with the regions geographical coordinates as the input to the model. The interface created should be easy to use and inclusive with regards to it's support on different types of devices.

Hence, the aim is to develop an end-to-end machine learning pipeline with a web slippy map interface for generation of tiled zoning maps of urban areas using remote sensing satellite data.

1.4 Scope

All of the zoning codes are planned by the Town planning department of Municipal governments, and are enforced using different methods. First is, "construction permits" which are given by referring to the zoning codes of the city, but there is a lot of illegal construction in our cities. The second method is "complaints by citizens' '. In which Citizens can complain about violations of the zoning codes to the municipal government. But the problem in this approach is, citizens are unaware about how to complain or what the zoning codes are. The third method is auditing by municipal inspectors, which is very rare and infrequent, and given current Covid conditions or in future, if such a pandemic occurs it will be a dangerous approach.

The scope of this project is to develop a model which will help the Town Planning Department of municipal governments to overcome all the problems stated above. All of the above methods are mostly ineffective and non-reliable but it also consumes time, money and manpower. It will also help normal citizens. Before buying the property/plot they can analyse whether the surrounding is suitable or not through the web map.

Chapter 2

Literature Review

2.1 Introduction

Satellite remote sensing has been used successfully in a variety of fields, including categorization and change detection. However, in addition to classification and change detection, remote sensing image processing requires a few preprocessing operations, and it is highly dependent on the method used. As a result, the remote sensing community is constantly working to improve remote sensing algorithms for characteristics including preprocessing, segmentation, and classification. Deep learning (DL) methods are based on neural networks, which have been employed in the remote sensing sector for many years.

Prior to the introduction of DL, however, the remote sensing community had switched its focus away from neural networks and toward support vector machines (SVM) and ensemble classifiers, such as random forest, for image classification and other tasks (e.g. change detection). Random forest gained popularity due to its ease of use (e.g., relatively insensitive to classification parameters) and generally good accuracy, while SVM got more attention because of its ability to handle high dimensionality data and perform well with limited training samples, among other things. However, the development of deep learning (DL) has increased interest in neural networks in recent years.

Recently, the remote sensing community has shifted its focus to deep learning (DL), and DL algorithms have shown significant success in a variety of image analysis tasks, including Land Use and Land Classification, scene classification, and object detection. Below are some recent examples of advances in this field.

2.2 Survey of Existing systems

We have surveyed multiple research publications for this project following are some of the prominent methodologies that we have found during our research.

"A patch-based convolutional neural network for remote sensing image classification"- In this paper, we have seen a new patch-based CNN system tailored for medium-resolution remote sensing imagery classification. The proposed system uses new features to adapt it for remote sensing data classification. The proposed system is compared to the pixel based conventional neural network, the pixel-based CNN and the patch-based neural network. The classification results show that the proposed system achieves significant improvements in both the overall and categorical classification accuracies.

"Land-Use Classification Using Convolutional Neural Network with Bagging and Reduced Categories" - In this paper, 3 layered Convolutional Neural Network algorithms were used. And they proposed Bagging can improve the overall accuracy. Concerning the improvement of the classification accuracy of the target class "coniferous", it is considered that the Bagging based on CNN has an effect on improving the precision, and the RNC is effective in improving the recall. In addition, the combination of Bagging and RNC improves both recall and precision.

"MugNet: Deep learning for hyperspectral image classification using limited samples" - In this paper, we have seen a new deep learning method, MugNet, which aims at making full use of the spectral and spatial correlations. MugNet is constructed on the basis of a simplified network, PCANet, where required hyper-parameters have been significantly reduced. To better deal with the problem of limited samples, they introduce a semi-supervised method to MugNet. And The experiments have shown that MugNet outperforms some state-of-the-art HSI classification methods even in the case of small-scale training set

"Learning multiscale and deep representations for classifying remotely sensed imagery" - In this paper, the multiscale convolutional neural network was presented to extract multiscale deep features by considering multiscale contextual information. Comparisons were made between the proposed method, the EMP method and spectral–spatial kernel-based feature fusion approaches.

2.3 Limitations of existing systems

On surveying the above prominent papers, we have found some flaws that need to be nullified for the infrastructure to be beneficial to the general public. Following are the drawbacks that we have found, which we have attempted to overcome in our project.

In “A patch-based convolutional neural network for remote sensing image classification”, Unbalanced test images class size i.e. some classes in the dataset have more images than the rest of the classes which causes low efficiency and accuracy and adds a bias in the model. It has low accuracy because the LandSat-8 dataset is used, which has low resolution imagery. The data is not multi temporal i.e. data is collected at a single time which may lead to cloud interference or other interferences. The window size of $5 \times 5 \times 8$ which is not able to capture heterogeneous pixels in the case of Landsat 8.

On reviewing “Land-Use Classification Using Convolutional Neural Network with Bagging and Reduced Categories” we found that, The scope of the model is centered around forest areas which results in creation of a highly specific model. The dataset size is very small which results in a very low accuracy model, as it is trained on less data. The model uses various ensemble learning methods which lead to higher training time.

According to the “MugNet: Deep learning for hyperspectral image classification using limited samples” the computational efficiency of the model is comparatively lower than other such models, also the scope of the model is limited to farmlands and forested areas. This model fails on urban imagery. MugNet is not a completely end-to-end manner,

In “Learning multiscale and deep representations for classifying remotely sensed imagery”, the model leans towards the side of object detection rather than zoning classification, hence it is limited by the number of objects that it can detect. Also it uses the Worldview-II dataset which is a closed dataset. Hence the results of the model cannot be recreated.

Chapter 3

Description

3.1 Convolutional Neural Networks (CNNs)

A convolutional neural network (CNN) is a form of artificial neural network that is specifically intended to process pixel input and is used in image recognition and processing. CNNs are image processing, artificial intelligence (AI) systems that employ deep learning to do both generative and descriptive tasks, often including machine vision, which includes image and video recognition, as well as recommender systems and natural language processing(NLP).

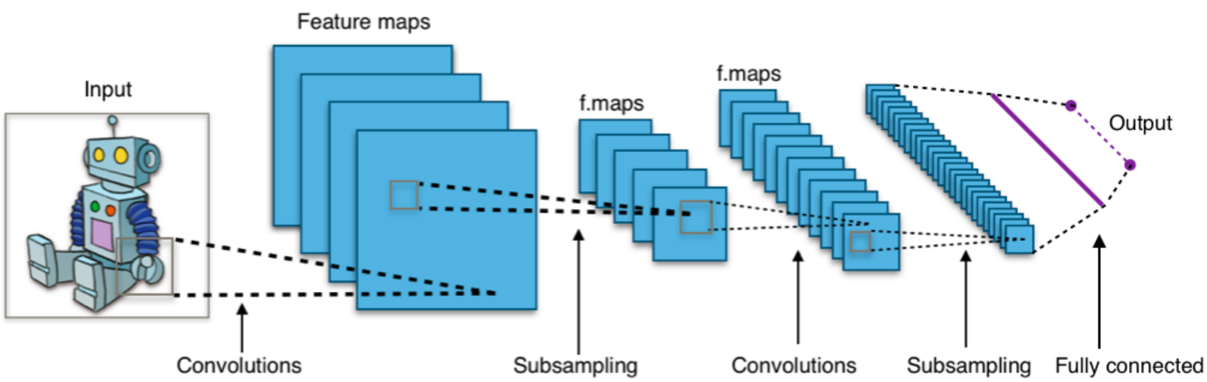

Fig : A typical CNN model for image related tasks

A CNN employs a technology similar to a multilayer perceptron that is optimised for low processing requirements. An input layer, an output layer, and a hidden layer with several convolutional layers, pooling layers, fully connected layers, and normalising layers make up CNN's layers. The removal of constraints and improvements in image processing efficiency result in a system that is significantly more effective and easier to train for image processing and natural language processing.

3.2 Remote Sensing

In contrast to on-site observation, remote sensing is the collecting of information about an object or phenomenon without making direct contact with it. The phrase is used to describe the process of gathering knowledge about the Earth and other planets. Remote sensing is used in a variety of fields, including geography, land surveying, and most Earth science disciplines (for example, hydrology, ecology, meteorology, oceanography, glaciology, and geology), as well as military, intelligence, commercial, economic, planning, and humanitarian applications.

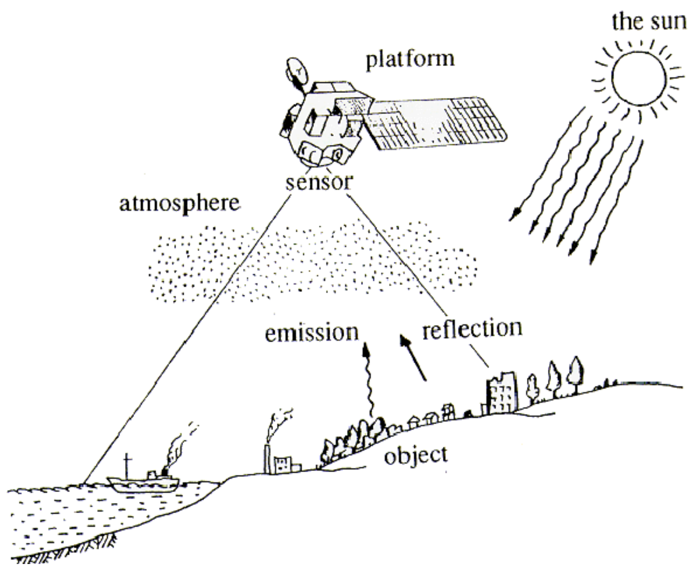

Fig : Satellite Remote Sensing Data Acquisition

The phrase "remote sensing" now refers to the detection and classification of objects on Earth using satellite or aircraft-based sensor technologies. Based on propagating signals, it includes the surface, atmosphere, and seas (e.g. electromagnetic radiation). It can be divided into "active" remote sensing (when a signal is emitted by a satellite or aircraft to the object and its reflection is detected by the sensor) and "passive" remote sensing (when a signal is emitted by a satellite or aircraft to the object and its reflection is detected by the sensor) (when the reflection of sunlight is detected by the sensor).

3.3 Web Maps

The technique of using maps given by geographic information systems (GIS) on the Internet, more especially the World Wide Web, is known as Web mapping or online mapping (WWW). A web map, often known as an online map, is both delivered and consumed, making it more than merely web cartography; it is a service that allows users to choose what the map will display. Web GIS places a greater emphasis on geodata processing parts of design, such as data gathering, and server software architecture, such as data storage and algorithms, than on end-user reports.

The terms web GIS and web mapping are still used interchangeably. End users who are web mapping gain analytical capabilities, and web GIS uses web maps. Web mapping of consumer goods and services is referred to as location-based services. A web browser or another user agent capable of client-server interactions is commonly used for web mapping. Its evolution is being driven by questions of quality, usefulness, social advantages, and legal limits.

3.4 Keras

Keras is an open-source software library for artificial neural networks that includes a Python interface. Keras serves as a user interface for TensorFlow. Keras supported a variety of backends up until version 2.3, including TensorFlow, Microsoft Cognitive Toolkit, Theano, and PlaidML.

Only TensorFlow is supported as of version 2.4. It is user-friendly, modular, and expandable, with the goal of allowing quick experimentation with deep neural networks. It was created as part of the ONEIROS (Open-ended Neuro-Electronic Intelligent Robot Operating System) research project, and François Chollet, a Google engineer, is the principal author and maintainer.

Keras includes many implementations of standard neural-network building blocks like layers, objectives, activation functions, optimizers, and a slew of other tools to make working with picture and text data easier while also reducing the amount of coding required to write deep neural network code. The code is maintained on GitHub, and community support forums include a Slack channel and a GitHub problems page.

Chapter 4

Proposed Methodology

4.1 Dataset

We will be creating a dataset with the given classes with at least 150 images per class, it will be suitable for classifying images of indian cities.

1. **Residential** which include single-family housing, multi-family residential or mobile homes.
2. **Commercial/ Institutional property** is real estate that is used for business activities.
3. **Industrial** is a group of structures that are related based on their primary production activities. e.g. Industrial sectors, factories, etc.
4. **Slums** consist of densely packed housing units of weak build quality.
5. **Open spaces** means unused grounds or barren land.
6. **Green spaces** means playground, gardens, park.
7. **Farmland** is an area of land that is devoted primarily to agricultural processes with the primary objective of producing food and other crops.
8. **Forest**, those ecosystems that have a tree crown density of 10% or more and are stocked with trees capable of producing timber or other wood products.
9. **Railway** is a means of transport, on vehicles which run on tracks(rails or railroads).
10. **Runways** are a paved strip of ground on a landing field for the landing and takeoff of aircraft.
11. **Highway** is the quickest route for driving between one city and another.
12. **Waterbody** is any significant accumulation of water. e.g. ocean, seas,lakes,ponds,rivers.

Fig : Images of from all 12 classes of the dataset

4.2 Model

We are aiming to use a Convolutional Neural Network architecture which will be trained on the created dataset. The CNN architecture has been validated on various Image Classification tasks. The input to the CNN model will be an image file of size 256x256 pixels, and the output value will be an integer denoting the class of the tile which the image represents.

We are also planning to deploy the model as a REST API for the general public to access it easily using cURL. Also this will provide an easy access point for the website to become interactive and generate the tiles for any land area, just by making an http request.

4.3 Web map Interface

We will be using bing maps api for creating the base map, because it is a geospatial mapping platform. Developers can use it to make apps that layer location-relevant data on top of licenced map images. Satellite sensors, aerial cameras (including 45 degree oblique "bird's eye" aerial imagery licenced from Pictometry International), streetside imagery, 3D city models, and topography are all included in the imagery. Bing Maps Platform also provides a point-of-interest database including a search capability. Microsoft uses the Bing Maps Platform to power its Bing Maps product.

We will also be using Python Image Library (PIL) for creating the color coded tiles on the zoning map. Python Imaging Library is a free and open-source extension library for Python that adds support for accessing, processing, and saving a wide range of image file types. It works on Windows, Mac OS X, and Linux. PIL 1.1.7, which was released in September 2009 and supports Python 1.5.2–2.7, is the most recent version. In 2011, the development of the original project, known as PIL, was halted. Following that, the Pillow team forked the PIL repository and introduced Python 3.x support. In Linux distributions such as Debian and Ubuntu, this derivative has been adopted as a substitute for the original PIL.

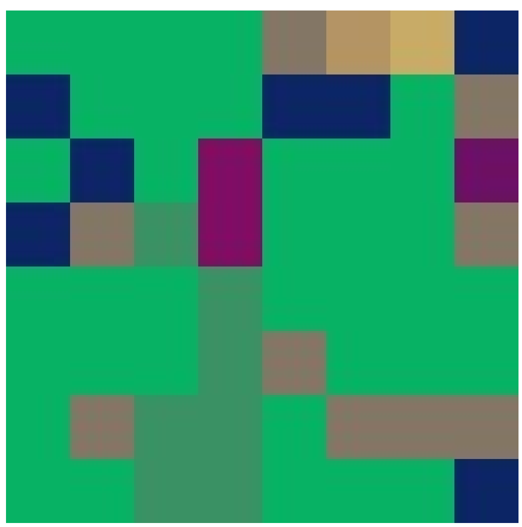

Fig : Color coded tile generated using the Python Image Library (PIL)

Chapter 5

Implementation

5.1 Dataset

The dataset we have used for developing the prototype of our model is UC Merced Landuse dataset. UC Merced is a land use remote sensing picture dataset with 21 classes and 100 photos per class. For various metropolitan regions around the country, the photos were manually extracted from huge photographs from the USGS National Map Urban Area Imagery collection. This public domain imagery has a pixel resolution of 0.3 m.

Fig: example images from all classes of the UC Merced Dataset

5.2 Model

VGG-16 is a Convolutional Neural Network (CNN) model, VGGNet-16 has 16 learnable layers and a fairly homogeneous architecture, making it quite appealing. It features only 3x3 convolutions, but a lot of filters, similar to AlexNet. It may be taught for 2–3 weeks on 4 GPUs. It is now the most popular method for extracting characteristics from photos in the community. The VGGNet's weight configuration is open source and has been utilised as a baseline feature extractor in a variety of other applications and challenges.

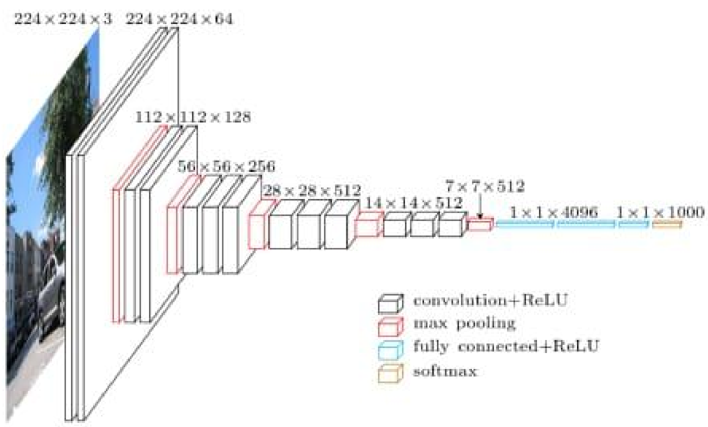

Fig : Architecture of the layers of vgg-16 model

16 Layers of VGG16

1.Convolution using 64 filters

2.Convolution using 64 filters + Max pooling

3.Convolution using 128 filters

4. Convolution using 128 filters + Max pooling

5. Convolution using 256 filters

6. Convolution using 256 filters

7. Convolution using 256 filters + Max pooling

8. Convolution using 512 filters

9. Convolution using 512 filters

10. Convolution using 512 filters+Max pooling

11. Convolution using 512 filters

12. Convolution using 512 filters

13. Convolution using 512 filters+Max pooling

14. Fully connected with 4096 nodes

15. Fully connected with 4096 nodes

16. Output layer with Softmax activation with 1000 nodes.

In [8]:

```
model.compile(loss="sparse_categorical_crossentropy",optimizer="adam",metrics=["accuracy"])
history = model.fit(train, epochs=5, validation_data=val,verbose=1)
```

```
Epoch 1/5
237/237 [==============================] - 69s 249ms/step - loss: 3.1339 - accuracy: 0.3903 - val_loss: 0.5157 - val_accuracy:
0.8349
Epoch 2/5
237/237 [==============================] - 42s 179ms/step - loss: 0.4498 - accuracy: 0.8553 - val_loss: 0.3007 - val_accuracy:
0.9021
Epoch 3/5
237/237 [==============================] - 43s 183ms/step - loss: 0.2682 - accuracy: 0.9162 - val_loss: 0.2124 - val_accuracy:
0.9333
Epoch 4/5
237/237 [==============================] - 40s 167ms/step - loss: 0.1881 - accuracy: 0.9419 - val_loss: 0.1584 - val_accuracy:
0.9556
Epoch 5/5
237/237 [==============================] - 41s 172ms/step - loss: 0.1411 - accuracy: 0.9634 - val_loss: 0.1214 - val_accuracy:
0.9677
```

Fig : Training parameters and process of vgg-16 model

We have used the pre-trained model of VGG-16 trained on the ImageNet Dataset. We used the transfer learning methodology to train the pre-trained model on the UC Merced Dataset. In the training process, It has used the sparse categorical cross entropy loss function. The optimization was done according to the Adam Optimization method. Adam optimization is a stochastic gradient descent method that is based on adaptive estimation of first-order and second-order moments.

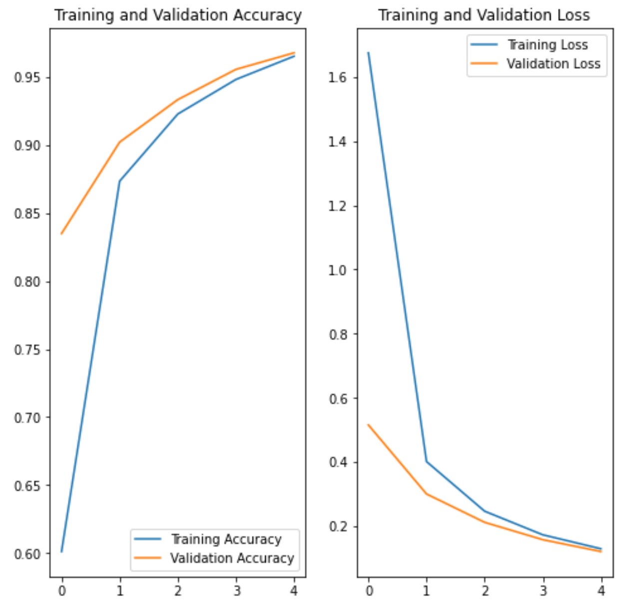

Fig : Training metrics for the vgg-16 model on GPU for 4 epochs

5.3 Interface

We have successfully created a tiled map for the current model. It has a base map created using the Bing Maps API and the Color coded images created using the Python Image Library (PIL) added as a layer to the webmap with a Opacity of 50%.

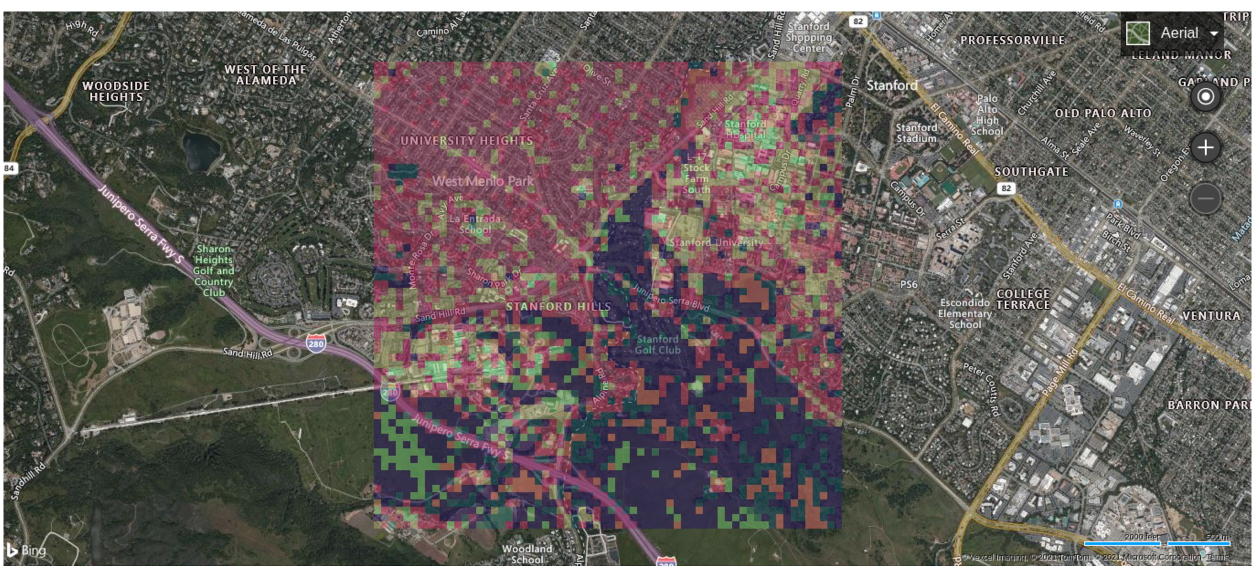

Fig : Screenshot of the color coded Zoning web map generated as a result of our model.

The web map generated clearly shows that our model successfully classifies most of the tiles correctly, the Sand Hill Road and Freeway 280 have been successfully classified as highways and most of the area of the Stanford Golf Course has been classified as a green field. Also the borders between the sparse residential regions, green spaces and the dense residential regions is very evident.

Chapter 6

Conclusion

This system has the potential to make the process of town planning and zoning highly efficient. It can also eradicate multiple bottlenecks that cause time delays in the process of Urban Governance. It will also help government officials to quickly survey and enforce zoning laws without the need to do on-ground surveys. If in the future lockdowns similar to the recent covid lockdowns are imposed, there will be no compromise on aesthetic and quality of living in our cities.

Our system has achieved low training and computation time by making adequate use of Parallel Processing using GPUs. It has demonstrated efficient processing of batches of high resolution images. The web interface developed is supported on all basic web browsers and all screen sizes.

6.1 Future Work

The web map generated by our model clearly shows the success and accuracy that our module has achieved. But still the web map looks a little bit cluttered. Hence the accuracy of the model could be increased further. Also the model currently in use is the VGG-16 model which has 13 convolution layers , 3 fully connected layers and several other activation and max-pooling layers. This model might not be the most efficient model for our task. The model could be tweaked and optimized further to achieve lower time and space complexity and a higher computational efficiency.

Chapter 7

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