Introduction

Good Afternoon everyone. First of all, Thank you MLT for giving me this opportunity. I am very happy today to share my research work with all of you.

I am Shreya Sharma from NEC corporation. I have been working as a data science researcher in the field of geospatial analytics since last 3 years. Today, I am going to introduce you to the fascinating world of geospatial intelligence and AI

What is Geospatial Intelligence (GI) ?

* Geospatial intelligence is a combination of three fields – remote sensing, computer vision and deep learning
* Remote Sensing is a technology to sense Earth’s surface from a distance in order to provide Earth observation images
* Computer vision is making computers see the world as we humans do
* And deep learning enables us to find patterns in data through learning from a lots of examples
* So, geospatial intelligence is to find patterns in earth observation images using computers
* But, why do we need earth observation images.

Why Earth Observation (EO)?

* Currently, only 25% of the earth’s surface can be seen by ground sensors. This limits are capability to monitor all the activities in earth
* Satellite earth observation is an ‘eye from the sky’. It helps us to see those areas of earth which are inaccessible or hidden. Such as oceans, mountains and forests…
* But how the satellite sees the earth? For that, let’s first understand how we see the earth

How we see Earth?

* This is the electromagnetic spectrum showing the several radiation types and their respective wavelengths
* We see the earth ‘only’ in the visible spectrum which allows us to see so many colours on this beautiful planet.

How satellite see Earth?

* But satellite sees the earth in the ‘ENTIRE’ spectrum, thus providing unique views of our planet.

For example, panchromatic which is a gray-scale image, visible, infrared, lidar, microwave and so on.

* Each wavelength highlights unique and useful information about Earth. For example, infrared highlights the vegetation, lidar provides the density of points and microwave is sensitive to surface material like metal or wood.

Applications

* Recently, with the launch of so many satellites, earth observation datasets have boomed
* In order to make sense of all this data and extract useful insights, deep learning plays a crucial role. It helps us to discover the patterns on our planet
* These datasets have high diverse applications across industries, such as…

My research work

* Today, I will share my research work on two very interesting applications
* First is ship classification which is recognizing different types of ships such as container, bulk-carrier and tanker for maritime surveillance, and
* Second is change detection, which is extracting changes automatically between two images taken at different times.
* For these applications, I work with microwave images because they are cloud free and deep learning algorithms
* Let’s start with ship classification

Ship classification – motivation

* With the increasing demand of global trade and sea food products, maritime surveillance has become extremely important.
* Ship classification is a key application in maritime surveillance. It helps to identify and track ships involved in illegal activities such as overfishing, oil spills, garbage dump, smuggling.
* Infact, in the past decade, the cases of illegal fishing in Japan have almost doubled
* on a global scale, it leads to a loss of 23 billion us dollars every year
* Thus, we need a reliable ship classification technology

Ship classification from space

* For ship classification, there are 3 major sources of information from space – AIS which stands for automatic identification system, visible images and microwave images
* AIS is a transponder which is installed on each ship and can be easily spoofed by the ship owner, so it’s not reliable
* Visible images cannot image under clouds and oceans are mostly covered with clouds
* But microwaves can penetrated clouds and cannot be spoofed by any ship owner
* Thus microwave images are highly reliable for ship classification

Conventional Methods

* Conventional methods can be divided into two categories
* First is hand-crafted feature based method. Here we manually compute features from each ship image and then based on those features classify the ships using traditional machine learning methods
* Second is convolutional-neural network based. Convolutional neural network is a deep learning method which is very useful for image analysis such as classification and segmentation.
* Here we input a stack of ship images into a CNN, which automatically extracts the features and outputs a ship class
* These methods classify a ship based on its appearance in the image

Problem

* But the problem is appearance is not constant. It varies with the viewing angle of the satellite
* For example, if a ship is viewed under two different angle, say at 30 degrees and 40 degrees. It looks very different. This leads to wrong classification
* In order to learn all such variations, we need a lot of labelled images which are not available in microwave
* Thus, only image information is not sufficient for robust classification

Proposed Method

* My idea is to use the satellite viewing angle as an additional information in a CNN
* This helps the network to learn a relationship between ship appearance and the vieweing angles and follow the change
* In the conventional method, we take a stack of ship images, input into the network and output a ship type
* In my method, I have utilized metadata which is an additional information available with images to extract a viewing angle map.
* This map shows the viewing angle at each pixel in the SAR image ranging from 25 degrees to 40 degrees
* This map is given as an additional input along with SAR images to train the network.

Experiments

* I evaluated this method for recognizing 3 types of ship using a benchmark dataset- OpenSARShip
* This data is captured by Sentinel-1 satellite and has 20 m resolution
* I used the hand-crafted feature method and cnn without angle information as baselines
* The evaluation metric is f-measure which is a very common metric used in image classification problems. The higher it is, the better is the classifier
* The second metric is amount of training data. Since microwave data is less, we want our method to perform well with less data so lower is better
* Here I show some examples from the dataset. As you can see, these ships are **so** difficult to recognize for humans

Experimental result

* The result shows that the proposed method outperforms the conventional methods
* It achieved 4.2% improvement in f-measure
* Also, the proposed method requires 25% less training data as compared to baseline to achieve same accuracy
* Next, I show a demo for this work

Demo

* So here you can see a satellite image
* First we detect all the ships in the image, here we see all the ships
* Next we can get more details about each ship
* We can also find the ships hidden in traditional sensing like AIS and can get information about them. Here you see probability of each class.

My research work- change detection

* Next I present my research work on change detection

Motivation

* Change detection helps us to understand the dynamics of our earth. That is, how the land surface is changing over time
* Here you see 2 examples of changes – first is dubai coastal expansion from 1984-2012
* and second is Saudi arabia irrigation from 1988-2012

Conventional method

* The conventional method of change detection is based on pixel-to-pixel difference between images. This is followed by classification of each pixel as change or no-change
* So we input a pair of images taken at different times, apply pixel-to-pixel difference and then classify each pixel into change or no-change. The final output we get is a change map.
* But, when we compare this map with ground truth, we see MANY false alarms.
* So how to get rid of them?

Proposed method

* So, in my proposed method, I eliminated the pixel difference. Instead I transformed the images into a feature space and then compute the difference between features.
* For feature transformation I use Siamese network which is a pair encoders sharing weights.
* Then we compute feature-to-feature difference and classify the pixels as change or no change
* So if the difference between features is greater than a threshold, the corresponding pixel is assigned change otherwise no-change
* Please check my paper for more details

Experiments

* To evaluate this method we conducted experiments for monitoring parking lots. In this case, the change are caused by movement of cars.
* For this, we selected images from 5 parking lots. The white dots show cars while the black shows the road
* We took a time-series of images with 10 dates. Then chronologically paired these images like t1-t2 forms pair 1, t2-t3 forma pair 2 and so on
* We used first 4 sites for training and the last site for testing
* For comparison, we selected 2 pixel-to-pixel based approaches as baseline
* And as evaluation metrics, f-measure for quantitative comparison and change maps for qualitative comparison

Results – fmeasure and change maps

* Here I show the results for two test pairs. As you can seen, the proposed method achieves 15% better f-measure than baselines
* Here I compare the change maps from the proposed and baseline methods with ground truth.
* As you can seen, the proposed method has significantly reduced the number of false alarms and is better interpretable.

Conclusion

* So, finally concluding my presentation.
* We learnt that geospatial intelligence is a combination pf three fields- remote sensing, computer vision and deep learning
* it is the technology for detecting patterns in earth observation images
* Then we learnt that earth observation data is highly valuable and provide unique patterns on our planet
* In order to understand those patterns, deep learning is a great tool
* and these data and tools have diverse applications across industries
* Finally presented my research work on ship classification and change detection

My final message is let’s curate the data more and more and make an impactful story.

Thank you very much.