Introduction

Good Afternoon everyone. First of all, thank you very much for giving me this opportunity. Today, I will present an overview of my projects with special focus on the research work done at NEC. After that, I will present a case study on one of the Rakuten's problem statements. So let's begin.

About me

- A brief introduction about myself. I am from India and I have been working in Japan since October 2016.
- I completed my education in India with Btech in electrical engineering and M.tech in geoinformatics engineering from IIT Bombay.
- During masters, I served as teaching assistant in image processing lab where I mentored 27 students in their course projects and conducted several image processing tutorials
- After that, I started my professional journey at NEC as a data science researcher where I worked on deep learning and satellite imagery.
- In my research career so far, I have filed 3 patents, 5 publications in top-level remote sensing conferences and initiated many foreign collaborations at NEC.
- In hobbies, I am very fond of blogging and maintain a blog where I share career tips. I also enjoy community activities and have been an active member of 2 groups in Tokyo: one is an NGO and second is a machine learning study group

Career Interests

- Based on my research experience so far, I divide my interest in four major areas- computer vision, image processing, deep learning and statistical analysis
- And I am interested in applying these research skills in different domains – geospatial, healthcare, e-commerce, agriculture and security for creating real-world solutions.
- However, my focus is always on impact. So, I can explore and learn new areas quickly as and when the need arises.

Overview of Projects

- Here I present an overview of my projects. At NEC, I have worked majorly on 3 research projects using deep learning- ship classification for maritime surveillance, change detection in time-series of satellite images and land-cover segmentation in large-size images. I will discuss in detail about 2 of these in the next slides
- During my masters, I worked on the problem of super-resolution on hyperspectral images. Hyperspectral images are those images which contain a lot of spectral bands like 200-300 bands which provides rich spectral resolution. But this spectral information comes at the cost of poor spatial resolution, so my goal was to enhance the spatial resolution. For this, I proposed a novel method based on ant colony optimization which was published in an international conference.
- In my academic projects, I worked on image processing and machine learning problems such dimensionality reduction, shape detection, feature extraction and so on.
- I have provided more details about these projects on my website

Contents

- Today I present two of my research projects done at NEC – first is ship classification and second is change detection
- After that I will discuss about my current work and challenges
- I will also present briefly the collaboration activities I started at NEC
- Finally, I will present a case study on Rakuten's brain tumor segmentation problem.
- Let's start with ship recognition.

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

Demo

- Next, I show a demo example for this work which was presented at International geoscience and remote sensing symposium, the largest conference in this field.
- So here you can see a satellite image
- First we detect all the suspicious ships in the image, here we see the ships which were hidden in AIS but can be seen by our system.
- And then by clicking on each ship, we can obtain the probability of each class it can belong.

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 the question is how to get rid of them?

Problem

- For that first we need to understand, why pixel-to-pixel difference cause false alarms
- There are mainly 3 reasons for this - first is camera jitter which cause many coregistration error at the pixel level
- Second is Speckle which is a characteristic property in microwave image and causes a noisy background
- Third is camouflage which results in non-defined shape and boundary. This make detection of very small and moving objects changes very difficult
- these three factors result in low change detection accuracy
- So we need a method which is robust to these conditions.

Solution

- This brings me to my solution that eliminates pixel-to-pixel difference and instead uses a feature-to-feature difference to compare the images
- For feature comparison, Siamese network has been widely employed in computer vision for image retrieval
- Siamese network is basically a twin-branch neural network where the two branches have exactly the same architecture and share weights
- Each branch inputs an image and transforms into feature vector and then the two feature vectors are compared through some distance measure
- Using this concept, I proposed a method for change detection in satellite images

Proposed method

- So, in my proposed method, I take a pair of images taken at different time.

- Then create patches as the images are too big to feed into a neural network
- Then transformed the patches into feature vectors using Siamese network and computed a distance loss between them which is used to train the network
- In the testing phase, I take a new pair of images, extract patches and use the trained Siamese to extract feature vectors
- Then compute the distance between feature vectors and threshold the distances to mark the patches as change or no-change
- Finally, collect the predicted labels of all patches and generate a change map.

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

- Here I show the results for two test pairs. As you can see, the proposed method achieves 15% better f-measure than baselines

Results-change Maps

- Here I compare the change maps from the proposed and baseline methods with ground truth.
- As you can see, the proposed method has significantly reduced the number of false alarms and is better interpretable.

Current work and challenges

- Now I will talk about my current work and the challenges I am facing
- So taking a step further, currently I am working on improving the proposed Siamese method
- For this, I created a colorized change map which shows all predictions including False positives and false negatives in different colors
- On comparing this map with ground truth, I found that there are many false negatives which shows that many foreground areas are undetected
- So the research question now is now can we improve the detection of foreground regions
- One possible solution is to use additional information that focus the network’s attention on foreground

- So I am developing a multitask Siamese network which along which change detection also does classification of foreground and background. Now I use three types of labels- change labels between images, classification labels of image 1 and classification labels of image 2
- The initial experiments have shown improvement in detection of foreground areas than the Siamese one
- However, the results have not published yet so I have not shown any here.

Collaboration Activities

- Next, I would like to highlight some of the collaboration activities
- I actively initiated several foreign and domestic collaboration during business trips, conferences and NEC internal events
- I started business collaboration with European remote sensing firm which is a leading maritime surveillance company to get feedback on our ship recognition technology and learn more about remote sensing business model
- I organized discussions with 2 well-known professors from INRIA France and University of Trento Italy to build strong connections with foreign academia and obtain useful references for future research
- I initiated cross-lab discussion between NEC labs Europe and Japan during business trip and NEC Open house. The discussion led to the idea of combining our ship recognition technology with theirs Graph AI technology
- Within Japan, I initiated collaboration with AIST by attending special lecture series and created an a business opportunity for our image analysis technology
- Finally, I collaborated with professor at Kyushu University for change detection project

Case Study : Brain tumor segmentation with MRI

- So that was all about my research work at NEC. Now I would like to present a case study on brain tumor segmentation.

Motivation

- Cancer is one of the deadliest disease of this century. In 2018 alone, 18.1 million cancer incidence cases have been reported around the world
- One the most complex type of cancer is brain tumor. If we focus on India, more than 50000 new cases are reported each year.
- Out of these 20% are children and it has been found that TUMOR kills more children than any other disease in the world
- To cure this, current treatments include surgery, radiation and chemotherapy. However these treatments have shown success in only 51% cases and are often very painful and expensive
- But a shocking fact is that, 90% lives would have been saved if detected early and correctly. So accurate and early detection of brain tumor is highly needed.

Brain Tumor and it types

- Before going into the detection process, let's first understand what is brain tumor and what are its types
- Brain tumor is a lump created by abnormal growth of cells in brain
- Based on the origin, tumor can be divided into two types – primary, if it originates in brain and secondary, if it originates somewhere else like lung or breast and then transfers to brain.
- The primary tumor can be further divided into three types – meningioma, pituitary adenoma and glioma
- The first two are fairly easy to detect for radiologists and are often non-cancerous. As shown in the figures, they have a well-defined structure
- It is the glioma which is cancerous and is very difficult to detect because of its diffused structure and poor contrast
- So to detect brain cancer, accurate glioma segmentation is needed

Role of MRI images

- So now the question is how to identify the glioma segments.
- For this purpose MRI images are very useful
- they provide unique information about different glioma segments such as edema, non-enhancing core, enhancing core and necrotic
- MRI images have high-resolution imaging quality and variety of modalities which highlight different glioma segments. For examples, FLAIR highlights the complete glioma, T2 highlights the core area while, T1 highlights the enhancing core
- These complementary information makes MRI images highly suitable for glioma segmentation

Challenges in MRI-based glioma segmentation

- However there are some challenges in MRI-based glioma segmentation
- Based on a short survey in this field, I divide the challenges into 3 categories
- First are MRI artifacts which are caused during acquisition and processing of MRI
- Second are Glioma features because of their diffused structure which makes their shape, size and location highly unpredictable. Moreover the glioma segments change the structure of nearby healthy cells, so incorporating the prior knowledge about healthy cells is very difficult
- Third are dataset related owing to the huge size of MRI images. Other challenges in this category are imblanced labels because generally on 5% brain cells have tumor while rest are healthy and variation in labelling by experts. So there is an inherent noise.
- So today I am going to propose a solution that will address these issues.
- But I would like to make a note here that this case study is not about finding a research gap, instead here I focus on presenting one possible solution.

MRI Pre-processing

- To deal with MRI artifacts, I will do some image pre-processing.
- First is the noise removal. This enables to increase the contrast between brain tissues and suppress noise and see brain cells more clearly

- Second in intensity homogeneity. In MRI images, due to varying magnetic field the image has distortions, so we need to apply a method to make the intensity homogeneous
- Third is intensity standardization. Due to different acquisition time and equipement, the scale of intensity is not same, so we need to standardize it for fair comparison between images
- After this pre-processing, most of the MRI artifacts would be removed and the images will be ready for detection process

Challenges slide again

- Next for extracting stable and discriminative Glioma features, I will use Convolutional Neural Network because of its location inavariance property
- For handling huge image, I will use patch extraction by extracting patches that fit in memory and easy to process by CNN
- To deal with imbalanced and noisy labels, I will use data augmentation.

Proposed Solution

- So combining all the blocks I discussed, here I present my proposed solution
- In the training phase we use the MRI images and their labels. The image are first pre-processed to remove artifacts. Then they are divided into patches
- The patches are augmented to reduce class imbalance. And all the patches are then fed into CNN for extracting robust glioma pattern of different glioma segments.
- In the testing phase, the test images are fed into the trained CNN and labels of all the patches are combined to output a segmentation map.

Experimental set-up for evaluation

- For experiment, I will start with a benchmark dataset – brain tumor segmentation which is released every year as a challenge in MICCAI. MiCCAI is the biggest conference in medical image analysis field
- In this dataset, each MRI image has 4 modalities – T1, T2, T1-enhanced and flair
- And the ground truth contains 5 segmentation labels
- For metrics, I will use dice coefficient, sensitivity and specificity as they are used most commonly in the research papers.

Future Directions

- As future work, I can see three possible directions
- First is incorporating additional data such as blood report and prescription data
- Second is glioma grading which tells the intensity of cancer. Currently, 4 grades have been defined by medical associations
- And finally using 3D CNN’s for handling 3D MRI images

So that’s all about this case study and here are some references I used for this work.

Thank you for your attention.