A Study of Methods for Power Lines Monitoring

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by

Lalit Saini

Roll no. 180070030

Supervisor: Prof. V. Rajbabu

Department of Electrical Engineering

Indian Institute of Technology Bombay

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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.

I would like to thank Prof. V. Rajbabu and Prof. Biplab Banerjee for their guidance throughout the course of the project. I would also like to mention about Kaggle and Google Colab where I trained and tested all the models.

Date: 20^{th} November, 2021	Student name: Lalit Saini
	Roll no.: 180070030

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Lalit Saini

Abstract

Power line corridor monitoring consumes great amount of manpower and resources. Aim to automate the monitoring by producing deductions using images captured by UAV, drones or satellites. The detection and segmentation of power lines is quite similar to that of roads. Both in there respective images are smaller in width. We tried to transfer the techniques used in road detection to detection and segmentation of power lines. The study presented focus both on traditional non-learning based algorithms and learning based techniques. Most of the work done is based on roads which we aspire to extend to power lines. The power line corridor monitoring task has sub tasks such as vegetation detection and detection of change in growth of vegetation. We were not having a dataset particularly for power line corridors so we tried out techniques on nearest possible dataset. In the report I am going to talk about data acquisition techniques, methods currently used to perform power line corridor monitoring, will provide discussion on segmentation models that can be used for power line segmentation and their results on road dataset. Later I will provide a fairly simple change detection model with results.

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Chapter 1

Motivation

Every city today is heavily power dependent. The lines which carry electricity to power grids of cities from power generation plants passes through forests, hills, small cities and open areas. Constant surveillance and inspection of transmission lines is important to prevent any possible power outage. Each fault comes with a huge cost, early fault detection and prediction of future anomaly can save severe cost and damage. Currently the common methods for power line inspections are manual foot patrolling and helicopter assisted investigation. The problem with foot patrolling is that it is highly time consuming, human dependent and prone to inaccuracies. In terms of time helicopter assisted investigation is better but it comes with higher operating cost and it is less accurate than manual operations.

We aim to come up with a technique to detect conditions of power lines from images captured using satellite images and drone images. This will reduce the area that need to be looked manually. A typical power lines is under constant threat from vegetation growing nearby and any construction taking place within its corridor. Our aim is to first detect area where the power lines corridor is infiltrated by growing vegetation or any human based activity. Later we aim to predict the growth rate so that patrolling can be scheduled based on that.

The power line monitoring is not widely studied problem in the literature. This give us an opportunity to explore all already existing methods to solve similar problems and transfer the techniques from know domain to power line domain. It is quite interesting to explore first the non-learning based techniques and analyse the short comes of those algorithm. The analysis give a better understanding of how and why one should take help from learning based methods to solve a particular problem. The task majorly includes segmentation. The past of change detection is also very close to segmentation task.

Chapter 2

Background and Prior Work

In this chapter, we review the existing literature and provide the preliminaries that form the basis for the study of different techniques that can be used to detect power lines and roads. In the beginning we will see various methods by which we can generate dataset for remote sensing task and what are problems associated with each method. Following it we will see different power line detection and segmentation techniques available in the literature. Power line detection is not a well studied problem primarily due to lack of a bench marking dataset. Later on we will see techniques for road detection and change detection.

2.1 Data Acquisition Techniques

In remote sensing the type and the resolution of data plays a big role. Depending on the type of data the techniques to perform same task are done differently. For example to perform change detection on optical image data requires learning approach where same is done on data captured using LiDar using fairly complex method. Following is discussion on various data acquisition techniques.

2.1.1 Synthetic Aperture Radars

Active imaging sensors, operating in the microwave region of the electromagnetic spectrum. A SAR system transmits microwave signals and records backscattered signals to create a 2D like image. Geometrical deformation and multipath scattering makes the analysis of SAR images very challenging. Carande et al. [1] showed that using the height and coherence data obtained from SAR images power line poles can be identified.

2.1.2 Optical Satellite Images

Satellite images taken in the visible and near infrared region. These imaging sensors are passive, so they only receive energy reflected from the Earth's surface and cannot be obtained in darkness. Clouds, fog, and resulting shadows impact the satellite image quality and can prevent the use of the images. Weather conditions hinder image acquisition. Due to limited resolution the major focus is on the surrounding rather than the line itself. The optical satellite images are widely used for vegetation monitoring, the height information can be derived from these images if stereo images are available. Ahmad et al.[2] studied the problem of vegetation encroachment in power lines corridor.

2.1.3 Optical aerial images

Aerial images collected with a manned helicopter or fixed wing aircraft mainly in the visible and near-infrared wavelengths. Due to the passive nature of the imaging method, aerial images in general can be collected only when there is enough sunlight present and, for example, cloudy and foggy weather may prevent collection of useful images. Ye et al.[3] used optical aerial images and applied particle filtering to track the power lines

2.1.4 Thermal images

The principle of thermal imaging is based on the phenomenon that objects emit infrared radiation depending on their temperature. The energy emitted is given by Stefan Boltzmann law which states that the total energy emitted by an object is product of the Stefan-Boltzmann constant and the absolute temperature raised to power 4. The method is used for long time to conduct aerial as well as ground survey.

2.1.5 Airborne laser scanner data

Airborne Laser Scanning (ALS) technique can give high resolution 3D map of a scene. Airborne Laser Scanning (ALS) is an active remote sensing technique based on Light Detection and Ranging (lidar) measurements from an aircraft. Using ALS the coordinates of reflecting object can be determined. In addition to the coordinate information, the intensity of the returned pulses is normally available. McLaughlin [4] classified the obtained laser points into three classes namely vegetation, transmission line and surface. Liu et al. [5] used the intensity data and Hough transform to detect contours of lines.

2.2 Power Lines detection Techniques

The power line detection problem is not studied in a great detail in the literature mostly due to lack of a central dataset for bench marking newly formulated algorithms. Below are few of the techniques tried and tested in detection and segmentation of power lines.

2.2.1 Power line extraction using improved Radon Transform

Y. Chen el al. [6] proposed a new algorithm to identify and extract power lines from high resolution satellite images. Theoretically the problem of power lines detection is quite a difficult problem due to sup-pixel, weak target, discrete and complicated background. The authors proposed an improved radon transform, Cluster Radon Transform (CRT), to extract linear features from satellite images. CRT has less number of false alarm as compared to conventional Radon transform. CRT is followed by applying set of rules to detect power lines among other linear features. CRT offers a strong capability to detect short linear segments in an image. The authors tested the techniques on synthetically generated images in which the power lines are drawn by hands, they also tested it on areas cropped from google earth view. Radon transform is given by,

$$R(\rho, \theta) = \int_{x_{min}}^{x_{max}} \int_{y_{min}}^{y_{max}} f(x, y)\delta(\rho - x\cos\theta - y\sin\theta)dxdy$$

In CRT each pixel is weighted based on the presence of linear feature to eliminate any noise due to non linear features. The weight for each pixel at a distance ρ and the direction θ with x_m, y_n pixel value $f_{\rho,\theta}(x_m, y_n)$, is given by $I_{\phi,r}$

$$I_{\phi,r} = 1 - \frac{\Sigma_{m=i,n=j}^{r(r-1)/2} |f_{\rho,\theta}(x_m, y_n) - f_{\rho,\theta}(x_{m'}, y_{n'})|}{\Sigma_{m=i,n=j}^{r(r-1)/2} f_{\rho,\theta}(x_m, y_n) + f_{\rho,\theta}(x_{m'}, y_{n'})} \times (m' > m, n' > n, \phi = \frac{\pi}{2} + \theta$$

Using this weight the modified radon transform is given by,

$$R(\rho, \theta) = \int_{x_{min}}^{x_{max}} \int_{y_{min}}^{y_{max}} I_{\phi,r} f(x, y)\delta(\rho - x\cos\theta - y\sin\theta)dxdy$$

To summarize at some r, θ if the pixels are having high intensity value and at the $r, \frac{\pi}{2} + \theta$ if the pixels are having low intensity value then there can be a line at r at an angle θ. The algorithm provided by authors is given in 1

2.2.2 Power line extraction using Convolutional Neural Networks

Using optical images captured by Unmanned Aerial Vehicle (UAV) Saurav et al. [7] training various deep learning models to segment the power lines. They carried out experimentation using state of the art segmentation models available in the literature. They compared the results for U-Net [8] (figure 2.1) and Nested U-Net [9] (figure 2.2). They used transfer

Algorithm 1 Power line distinguishing algorithm

Input: $R,\ \theta,\ \rho$
Output: M_{pl} power line matrix
for each two successive lines $p(R,\theta,\rho)$ of all $\mathbf{L}$(all detected lines, sorted by R) **do**
    if $0 < |\Delta\theta| \leq m\&\&|\Delta\rho| \leq n$//*remove parasitic light point* **then**
        set $p(R,\theta,\rho) = 0$
    end if
end for
for each line $p(R,\theta,\rho)$ of $\mathbf{L}$(sorted by θ) **do**
    if line **parallel** $p(R,\theta,\rho) = true$ **then**
        Keep $p(R,\theta,\rho)$
    else
        remove $p(R,\theta,\rho)$
    end if
    for each outmost parallel lines in set **S do**
        Compute each part of the vertical section line of **S**
        if similar **then**
            S = power line
        else
            S = other linear feature, **remove** S
        end if
    end for
end for

learning for weights of the encoder unit of UNet.

2.3 Road Detection Techniques

Road detection is well studied problem in literature. From non-learning based algorithms to learning based models everything is tried upon road detection and segmentation part. Road detection and power lines detection are similar problems. To derive any useful information from road detection I explored existing road detection and segmentation techniques.

2.3.1 Road using color features

Beril and Cem [10] demonstrated a techniques using CIELab color space on high resolution aerial and satellite images. CIELab color space separates the illumination and the chroma

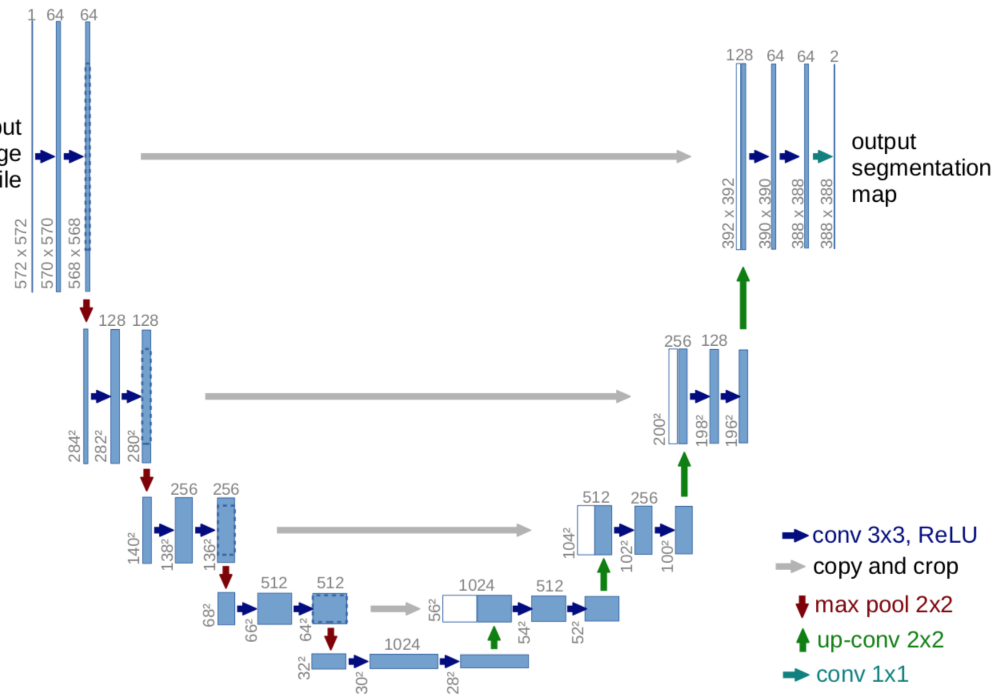


Figure 2.1: Original UNet Architecture [8]

features from each other. The authors discarded the illumination part and used only chroma features to detect similar pixels for road. The technique requires few labeled road images. Using those images the algorithm models chorma features for a road, using euclidean distance as the criteria it identifies possible pixels for a road. This is followed by Otsu thresholding to eliminate any false pixels. The algorithm described by the authors is given in 2.

Algorithm 2 Road detection using CIELab color space features

Input: TrainingSet, TestImage, Threshold
Output: LabeledImage

$a^* = 0,\ b^* = 0$
for each image in TrainingSet **do**
    $L, a, b = convertColorSpace(image, RGB\_TO\_CIELab)$
    $a^*, b^* = updateEstimate(a, b)$
end for
$a_{test}, b_{test} = convertColorSpace(TestImage, RGB\_TO\_CIELab)$
$distances = EuclideanDistance((a_{test}, b_{test}), (a^*, b^*))$
$distances = distances/max(distances)$
$LabeledImage = OtsuThresholding(distances, Threshold)$

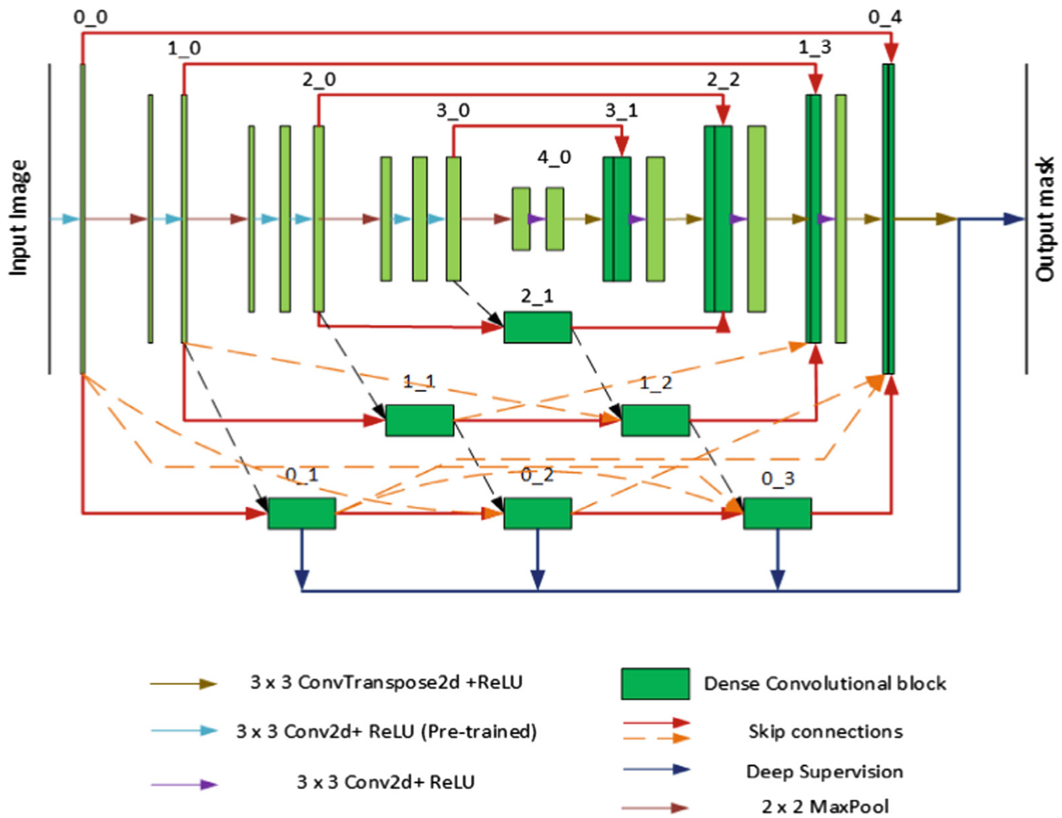


Figure 2.2: Nested-UNet Architecture as used in [7]

2.3.2 Road Detection using UNet and its variants

UNet [8] (figure 2.1) was introduced and used mainly for medical image segmentation. Due to its success in the field it is now widely used for general segmentation problem. The model consist of a encode unit which mainly extracts features , followed by a bottleneck which process the features and then a upsampling layer which segment the image. Using transfer learning UNet can be trained on smaller dataset. Zhang et al. [11] (figure 2.3) proposed an architecture Resunet, combining advantages of residual unit into UNet to perform road segmentation.

2.4 Change Detection

While monitoring a power line corridor it is necessary to pay attention to vegetation growing nearby. The rate at which vegetation is growing is also important. We tried and tested change

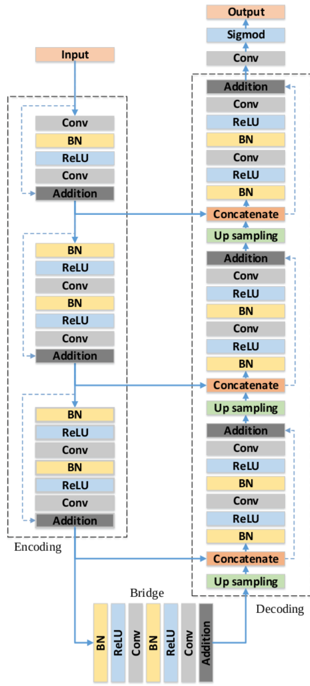


Figure 2.3: Residual Net Architecture [11]

detection techniques on landscape dataset using the following techniques.

2.4.1 Change Net

The model for change detection is different from UNet as it requires two image input. In change detection multi level features are extracted for both the images and then upscaled to same size. Where they are summed and then passed through a convolution layer followed by assigning probabilities to different classes. In [12] author did similar thing but instead of concatenating multi level features of same image they concatenated same level feature of both images together. In the model the features are extracted using ResNet backbone due to which there is restriction over the size of feature map we can obtain. The architecture we implemented is given in the figure 2.5.

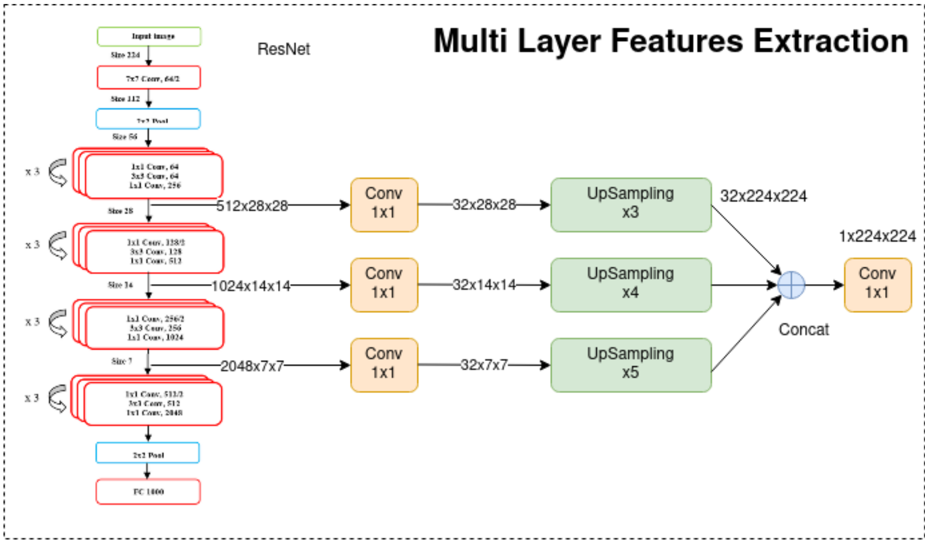


Figure 2.4: Multi layer features extraction for Change Net

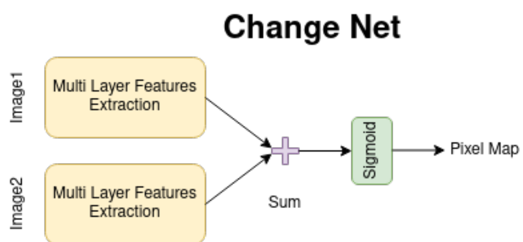


Figure 2.5: Change Net as implemented in [12]

2.5 Datasets Used

In few experimentation we used dataset created by us using various sources. Apart from that we mainly used two datasets Massachusetts Roads Dataset and Levir-CD Dataset.

2.5.1 Massachusetts Roads Dataset

The dataset was created by Volodymyr Mnih [13] and was introduced in chapter 6 of his thesis. The Massachusetts Roads Dataset consists of 1171 aerial images of the state of Massachusetts. Each image is 1500×1500 pixels in size, covering an area of 2.25 square kilometers. The dataset consist of a training set of 1108 images, a validation set of 14 images and a test set of 49 images. The dataset covers a wide variety of urban, suburban, and rural regions and covers an area of over 2600 square kilometers. The test set alone covers over 110 square kilometers. The target maps were generated by rasterizing road centerlines obtained from the OpenStreetMap project. A line thickness of 7 pixels and no smoothing was used in generating the labels. All imagery is rescaled to a resolution of 1 pixel per square meter.

2.5.2 Levir-CD

The dataset was introduced in a paper Hao Chen and Zhenwei Shi [14]. LEVIR-CD consists of 637 very high-resolution (VHR, 0.5m/pixel) Google Earth (GE) image patch pairs with a size of 1024 $\times$ 1024 pixels. These bitemporal images with time span of 5 to 14 years have significant land-use changes, especially the construction growth. LEVIR-CD covers various types of buildings, such as villa residences, tall apartments, small garages and large warehouses. Here, the dataset focus on building-related changes, including the building growth (the change from soil/grass/hardened ground or building under construction to new build-up regions) and the building decline. These bitemporal images are annotated by remote sensing image interpretation experts using binary labels (1 for change and 0 for unchanged). Each sample in the dataset is annotated by one annotator and then double-checked by another to produce high-quality annotations. The fully annotated LEVIR-CD contains a total of 31,333 individual change building instances.

Chapter 3

Our Results

We first look into the application of CRT in detecting lines. Our first aim was to figure out how well non-learning based algorithm works on remote sensing dataset in detecting power lines and roads. Once we were done with traditional algorithms we shifted our focus to learning based approaches. We started with simple UNet which performed poorly on road dataset. Later we tried to make model deeper by adding dense and residual blocks. We experimented to see minimum dataset size required to train UNet for acceptable accuracy. At the end we explored the problem of change detection.

3.1 Improve Radon Transform

We tested the algorithm on a small dataset collected from google images. The images we first cropped and then resized. Larger dimension images long time to process. Radon transform was obtained using function provided in skimage.transform. We found that the technique work well for high resolution images where power lines are clearly visible and the pixel intensity is sufficiently high as compared to nearby pixels. Some of the results are provided in figure 3.1. The technique is highly sensitive to the hyper parameters like the distance between the lines and criteria to reject lines. The technique tend to fail for images in which the power lines are in parabolic shape. In that case for multiple angles and distance value we will get high intensity. Due to imposed conditions for rejecting lines we will get only few points out of these many points in a cluster which on taking inverse radon transform will give straight lines. In figure 3.1b we can see that in group of lines only two lines are detected. In figure 3.1c many lines rejected due to non parallel nature of lines in the image.

(a) (b) (c)

Figure 3.1: Power lines detection using improved radon transform. Tested on custom made dataset using Google Images. The lines in blue are detected power lines. In (a) the lines are parallel and are at suitable distance so they are detected correctly, (b) many lines packed within small distance not properly detected by the algorithm, (c) lines are intersecting so they fail the condition imposed on the minimum angle deviation for parallel lines.

3.2 Road detection using color features

The algorithm was tested on a subset of Massachusetts Roads Dataset [13]. Few labeled images were passed initially to extract the chroma feature values describing the road (a^*, b^* in 2). After getting the values for chroma feature testimages are passed and processed one by one. Few results for this are given in the figure 3.2. The algorithm is sensitive to the a, b feature of the color space. If in image there is surrounding with similar feature values that is classified as part of the road. Value of threshold in Otsu thresholding is also important that is a hyper parameter in the algorithm. If we increase the training samples the prediction tends to become more accurate. In post processing connected component analysis can be done to improve the segmentation results.

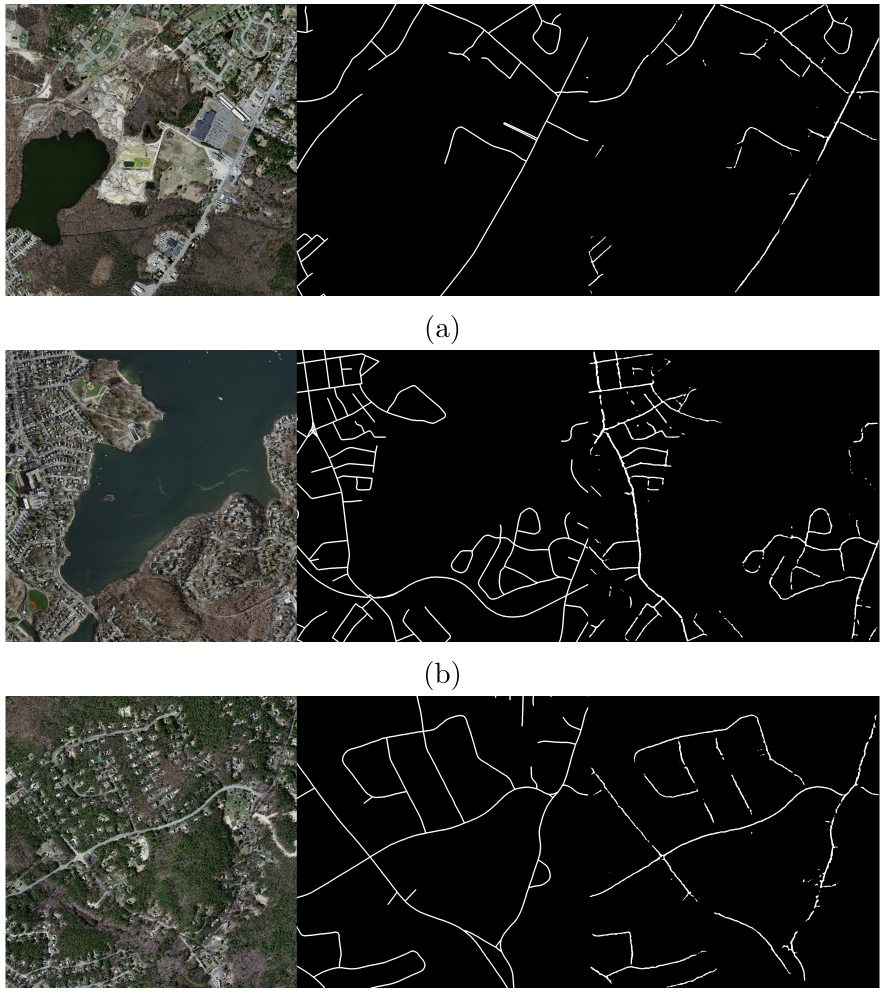
(a) (b) (c)

Figure 3.2: Roads detection using CIELab color space chroma features. The detected patches of road are marked in red. The algorithm is not able to detect roads when the road feature matches with surrounding's features.

3.3 Road detection using UNet

The model was trained and tested on Massachusetts Road Dataset [13]. For the encoder part of UNet we used pre trained weights of resnet50. Resnet have a identity connection from input to output from a series of convolution layers. The identity connection ensures that there is always significant gradient to flow backwards. Using Resnet allow us to train deeper neural networks. We trained UNet for complete training set of the dataset for 5 epochs. The model was trained on random crop parts of the input images and prediction was taken on complete image. We used Adam optimizer with initial learning rate 8×10^{-5}. Cosine Annealing Warm Restarts was used as learning rate scheduler with restart after 1 iteration, factor increasing initial time as 2 and minimum learning rate as 5×10^{-5}. Dice Loss was used as loss function during training and validation score was obtained using IoU (intersection over union or Jaccard's index). We obtained a mean IoU score of **0.9033** and mean dice loss **0.1309** on test dataset which is higher as compared to IoU score of 0.7091 reported in [15] on the same dataset. Few results are shown in the figure 3.3, we can see that at some place the model fails to predict a continuous road.

It was observed that when we used Binary cross entropy loss during training there were



(a)

(b)

(c)

Figure 3.3: Road Detection using UNet with ResNet50 backbone. (left-right) Image, Ground Truth and Predicted mask.

a lot of noisy lines in predictions which lowered the IoU score. Dice loss worked best with UNet having Resnet50 as backbone.

To overcome problem of smaller dataset which is very much a possibility in task like power line detection, we experimented training the model on very small dataset (see figure 3.4) and later passing the input through conditional random field (CRF) model to refine the predictions. CRF require parameters like variance for spatial gaussian, color gaussian and weight of these gaussians, which make it hard to generalize over a large set of examples.

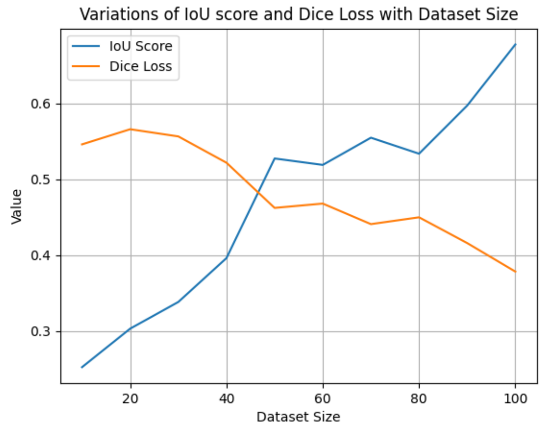


Figure 3.4: Study of variations of dice loss and IoU score with dataset size. The values are before passing it to CRF layer.

The output of CRF didn't improve the IoU score significantly. Out of all the scores were improved more for smaller dataset size and kept on decreasing as the dataset size increased. This is mainly because of non optimal parameters provided to CRF layer and lot of false positives and false negatives in the prediction of the model.

3.4 Road detection using Deep Residual UNet

The problem with UNet is its uneven loss function landscape due to which it tends to stuck in local minimum which was often observed while using Dice loss. The use of residual connections smoothen this landscape and make it easier for a model to find global minimum [16]. The model comes with two advantages the residual unit ease the process of training and the skip connections ensure backwards gradient flow, preventing gradient vanishing problem. We trained the network from scratch no pretrained weights were used. We trained the network with batch size of 4 and gradient accumulation of 4 batches for 100 epochs. Adam was used as the optimizer with initial learning rate of 8×10^{-5}. The learning rate scheduling was done using Step Learning Rate scheduler with step size 20 and gamma 0.05 . We obtained very good performance for this model attributed to residula connections. We obtained a mean IoU score of **0.9129** and mean dice loss **0.0475** on test dataset which is higher as compared to IoU score of 0.7447 reported in [15] on the same dataset. Few results are shown in the figure 3.5. The road predicted are more continuous then the ones predicted by UNet.

(a)

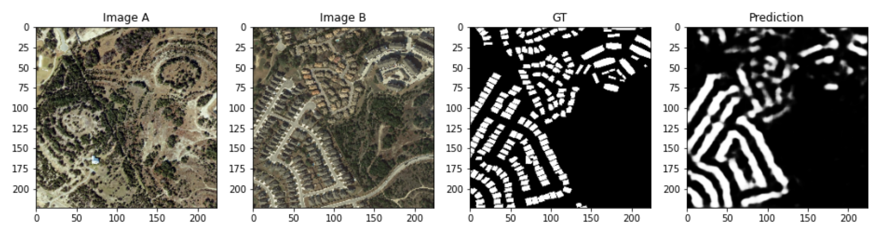
(b)

(c)

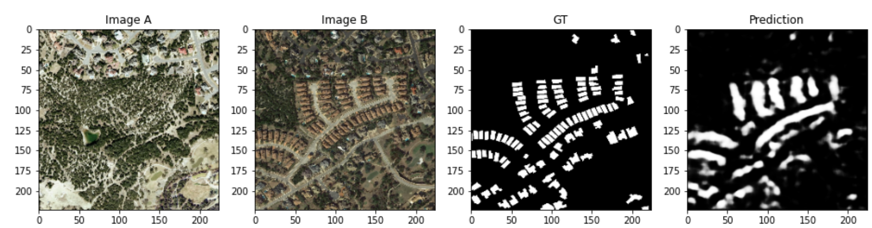
Figure 3.5: Road Detection using Deep ResUNet. (left-right) Image, Ground Truth and Predicted mask. Continuity of the roads maintained as compared to 3.3

3.5 Change Detection

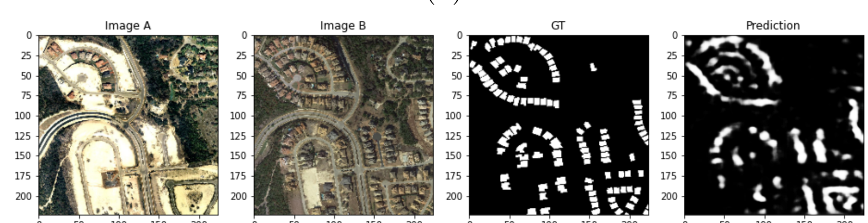
The model was trained and tested on Levir-CD dataset. For feature extraction we used ResNet50 pre trained weights. The model extracts features on different scales, this helps to extract both global information to resolve semantics and local information to resolve location. The motivation to concatenate these features was to get all the information at a place so that it can be weighted by convolution filter. The model was trained for 50 epochs with batch size 4. We used Adam optimizer with initial learning rate 8×10^{-5}. Cosine Annealing Warm Restarts was used as learning rate scheduler with restart after 1 iteration, factor increasing initial time as 2 and minimum learning rate as 5×10^{-5}. Dice Loss was used as loss function during training and validation score was obtained using IoU . We obtained a mean IoU score of **0.3159** and mean dice loss **0.5525** on test dataset which is lower as compared to IoU score of 0.7735 reported in [12] on a different dataset but using a very similar model. The results are given in the figure 3.6. In the images we can see that there is no clear boundary distinction, the predicted areas are merged within each other. The problem can be tackled with more refinement in the model.



(a)



(b)



(c)

Figure 3.6: Change Detection using multi layer features. (left-right) Image, Ground Truth and Predicted mask. The boundaries in the predictions are not very clear.

Chapter 4

Conclusion

Due to heavy dependencies on hyperparameter the non-learning based techniques cannot be generalised on a complete dataset for power lines detection. The number of pixels describing power lines in an image as supposed to be low which make the work for these techniques a bit tougher. It was observed that the learning based techniques as expected performed better. For segmentation of power lines we can conclude from results on road dataset that Deep Residual UNet will work better as compared to a plain UNet. When we get a proper dataset for power lines the model can tuned for the dataset. The achieved IoU score was better than the comparison made in the cited paper. More work is required to make change detection model better. Its current results are good enough to detect an approximate changed area, but when the clear distinction of boundaries become important the model will need improvements. For detecting change in vegetation under a power line current model is expected to work as in that case we don't need any sharp boundary information. The problem to work with very small dataset is still to be looked on in more depth. Few shot segmentation is the best candidate to look for segmentation using small dataset.

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