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Road Extraction from Satellite Images using DNN on HPC Platform

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Abstract: The concept of road extraction from VHR satellite images or remotely sensed images, plays a very prominent role for management of traffic, navigation systems, monitoring, or roads. With a rise in popularity of Artificial Intelligence in recent years, Road Extraction has become a main topic for many researchers. In this project, we studied many different papers and saw different algorithms and datasets used. Some of the algorithms are Deep Residual Network, Dense Global Residual Network, U-Net, U-Net++, CNN, ResNet. The pros and cons of various algorithms were further reviewed. Upon that study we decided to use U-Net for our project. We worked on an existing dataset using U-Net, while trying to make our own dataset.

Keywords - **Roads Extraction, Satellite Images, U-Net, Residual Network (ResNet), Convolutional Neural Network (CNN)**

I. INTRODUCTION

Extraction of roads from satellite images plays a key role in traffic management, city planning, forming maps, navigation, etc. The importance of maps in everyday life is a good indicator to show how important it is. The benefits of the technology do not end at everyday convenience but have a valuable impact on a country's defense as well. The technology can be used to get a good idea of the layout of enemy territory. Consequently, it should come as no surprise that there have been various attempts to get as good of a tool as possible to extract roads. In our paper, we went through several research papers to find the best method(s) possible to extract roads. Various challenges need to be overcome to extract roads, these depend heavily on the dataset, in cities it can be hard to distinguish roads from the surrounding considering the color is similar while in rural areas trees break the line of sight. As such, just numbers are not enough to find the best algorithm, nuance is necessary. In the research papers we studied we went through various algorithms and preprocessing methods used, the advantages and disadvantages. Based on our study we decided. to use U-Net as it was fast and gave some of the best results. It was also very easy to work with as the input and the output were the same.

II. LITERATURE REVIEW

1. **Literature Review of Roads extraction from satellite images**
   After our study, we find that most of the proposals suggested multiple algorithms among these: Deep Residual (U-net), Dense Global Residual Network, Atrous Spatial Pyramid Pooling, U-net, U-net++, D-LinkNet, AD-LinkNet, DeepLabV3+, Coord-Dense-Global (CDG), CNN, ResNet, ResNeXt, RCNN-Unet, Generative Adversarial Network.

2. **Classification**
   In the early attempts to work out the classical extraction of roads from remotely sensed images, simple classification-based techniques were implemented, which used texture and photometric features of a road. In comparison with the modern and most accurate model, the accuracy is much lesser since the classification techniques misclassified the road with other similar structures like building blocks, parking indicators, water canals, etc. These commonly implemented classification algorithms are the Artificial Neural Network, Support Vector Machine, Markov Random Fields, and the Maximum Likelihood Classifier. The earliest proposal was from the early 1990s by Heermann & Khazenie [1] who suggested the implementation of Artificial Neural Networks with back propagation (BP) algorithm or BP Neural Networks. Later in 2007, Mokhtarzade et al. [2] implemented the same, but passing additional parameters boosted the accuracy. This BP Neural Network was again employed by Kirthika & Mookambiga [3]. They took on various criteria like the spectrum information, texture-wise the entropy; contrast energy and uniformity of every pixel were computed with Gray Level Co-Occurrence Matrix (GLCM) [3]. These texture parameters were lastly merged with the spectrum information. However, at the latter stages, the use of the BP Network became obsolete as it started giving numerous problems like the need for more training data, slow convergence speed, and faster declination in performance with increasing classes [3].

The Naive Bayes is also one of the most implemented classification algorithms in the case of road extraction from satellite images. Present-day, with the aim to improve the accuracy of classification, integration of multiple classification algorithms has become significant. The crux is that given training samples, different classification algorithms or models must be trained or tested on these.

3. **Overview of Literature Analysis**

Table 1: Literature Survey Table

Authors	Advantages	Disadvantages
Yongyang Xu 1, Zhong Xie, Yaxing Feng and Zhanlong Chen [1]	Design has good performance in image classification, and can alleviate the vanishing gradient problem. It is very powerful and can strengthen feature propagation. It is based on dense-net which can reduce the number of parameters, which makes it easy to be trained. It has U-Net-based blocks that provide pixel-level attention to features extracted.	The dataset used for training contains small images with fewer roads; hence the accuracy might be inflated.
Z. Zhang, Q. Liu, Y. Wang, [2]	It is easy to train; It will also allow information propagation like U-Net without degradation. This allows the possibility to decrease the number of parameters, while still maintaining good results.	The method of evaluation was relaxed hence, the numbers might be higher. While it manages to identify the roads, the error is more prone when it comes to the width of the road.
LC. Chen, G. Papandreou, I. Kokkinos, K. Murphy, A. Yuille [3]	This method allows control over the resolution where feature responses are computed, It also increases the field of view which adds more context without increasing the parameters or computations	There are problems with identifying the exact boundaries of objects. The model is used to detect objects and not roads. The numbers are less relevant and its merits to identify roads are unknown.
L. Zhou, C. Zhang, M. Wu [4]	The proposed model is both time and memory-efficient. It can increase the receptive field of feature points without compromising the resolution of the image	The model has a false positive problem. Roads are detected when there are none. The performance is not constant all the time.
CA. Cira, R. Alcarria, MA Manso-Callejo, F. Serradilla [5]	The model leverages the advancements in computer vision to achieve better results on secondary roads. It is quite successful in detecting roads with different widths. It can also detect roads under obstructions like trees	Some obstacles like dry riverbeds or railroads can be detected as roads While actual roads detectable to humans might not be detected. Sometimes connection points can be missed resulting in unconnected roads. The model is more fallible to the imperfections present in the map
P. Deepan, S. Abhinaya, G. Haritha, V. Iswarya [9]	This model works end to end Removes the need for annotation tools that are required in most other model approaches	No numerical accuracy is published for the samples shown Not all the roads are detected contrary to their claims

4. **Overview of Performance**

The results of methods used in literature are shown in table II.

Algorithm	Accuracy
U-Net++ ResNeXt	0.943
DRU-Net	0.9187
U-Net	0.905
Mnih-CNN	0.887
DeepLabV3+	0.7040
D-LinkNet	0.6342

III. PROPOSED METHODS

1. **Dataset Description**

We have used the Massachusetts road dataset for our project. It has 1171 aerial images of resolution 1024X1024. It is the most widely used dataset as it has good resolution roads along with accurate masks

2. **Problem Statement**

   a) **Project Scope**
   The project aims to detect roads from satellite images making it easier to make accurate maps easily with minimal human input. Reducing government spending on such tasks.

   b) **Project Limitations**
   The model is unable to detect roads under occlusions and obstacles like trees.

   c) **Project Objective**
   The main objective of the project is to detect roads from satellite images accurately.

3. **Experimental Setting**

   a) **Methodology**

   We used TensorFlow and Keras as bases to make our code, split-folders were used to split the dataset in train and test folders. The ratio of the train to test was 9:1. The images and masks from the train folder were set to 128X128 size and fed to the U-Net model. The trained model was tested on 10% of the images in the test folder.

   b) **Algorithm (U-Net)**

   Firstly, it is shaped as a "U". It has a symmetric architecture and has two major parts: the left part, which is also known as the contracting path, consists of the general convolutional process; and the right path which is also known as the expansive path, consists of the transposed 2d convolutional layers.

   A crucial modification in UNET is that it consists of multiple feature channels in the up-sampling part, it allows the network to propagate context information to higher-resolution layers. As a result of this, the expansive path is symmetric to the contracting part and creates architecture in a U-shape. The network uses only the valid part of every convolution without any completely connected layers. To predict the pixels in the border region of the image, the missing context is expanded by mirroring the input image. This strategy is crucial to apply the network to large images, or else the resolution would be limited by the GPU memory.

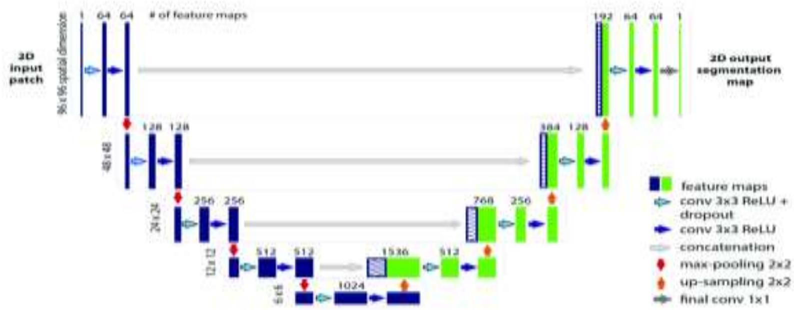

Fig.1. Structure of the U-Net Architecture

Because of the U shape the input and output received are of the same format. The depth of the model is also alterable. Greater the depth the more parameters the model covers. Depth is very much connected to the size of the input. Increasing the depth can increase the accuracy at the cost of training time.

IV. RESULTS AND DISCUSSION

1. **Results**

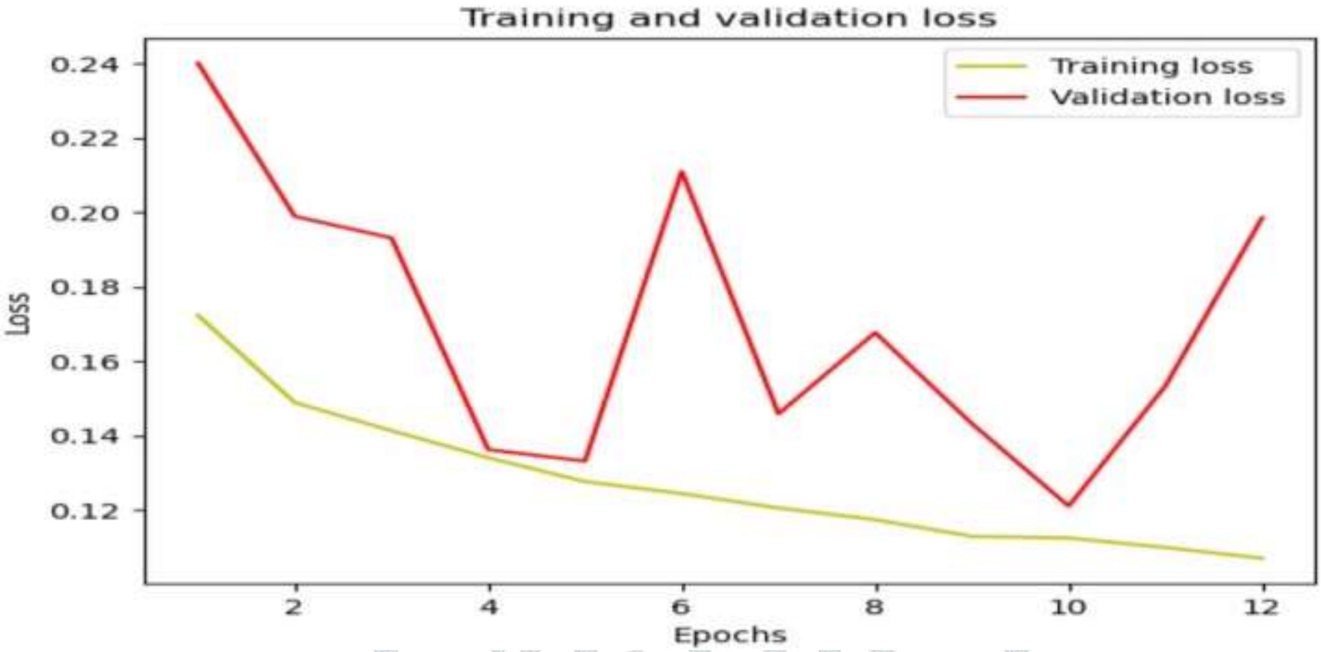

Fig.2. Training and Validation Loss

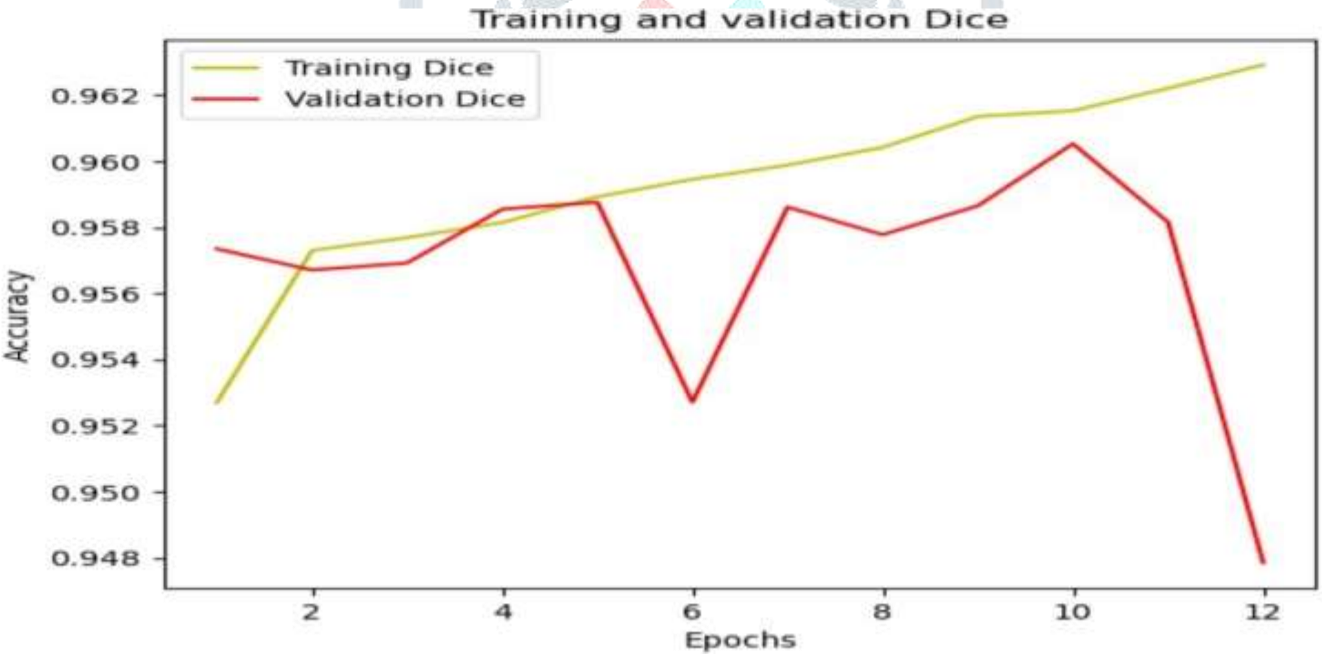

Fig.3. Training and Validation Dice

2. **Analysis of Results and Discussion**

These results were obtained on the big dataset as observed the results peak at 10 epochs at a very good accuracy of 0.958, after which overfitting happens, plummeting the accuracy. As observable from the masks made, the algorithm can detect most of the roads but there are small patches of roads that are missed, while at other times false roads are detected. It is noticeable that these false positives or negatives happen around noise, the area of these patches is different from the rest, and sometimes it is a clearing in a forest or dust patches that look like roads.

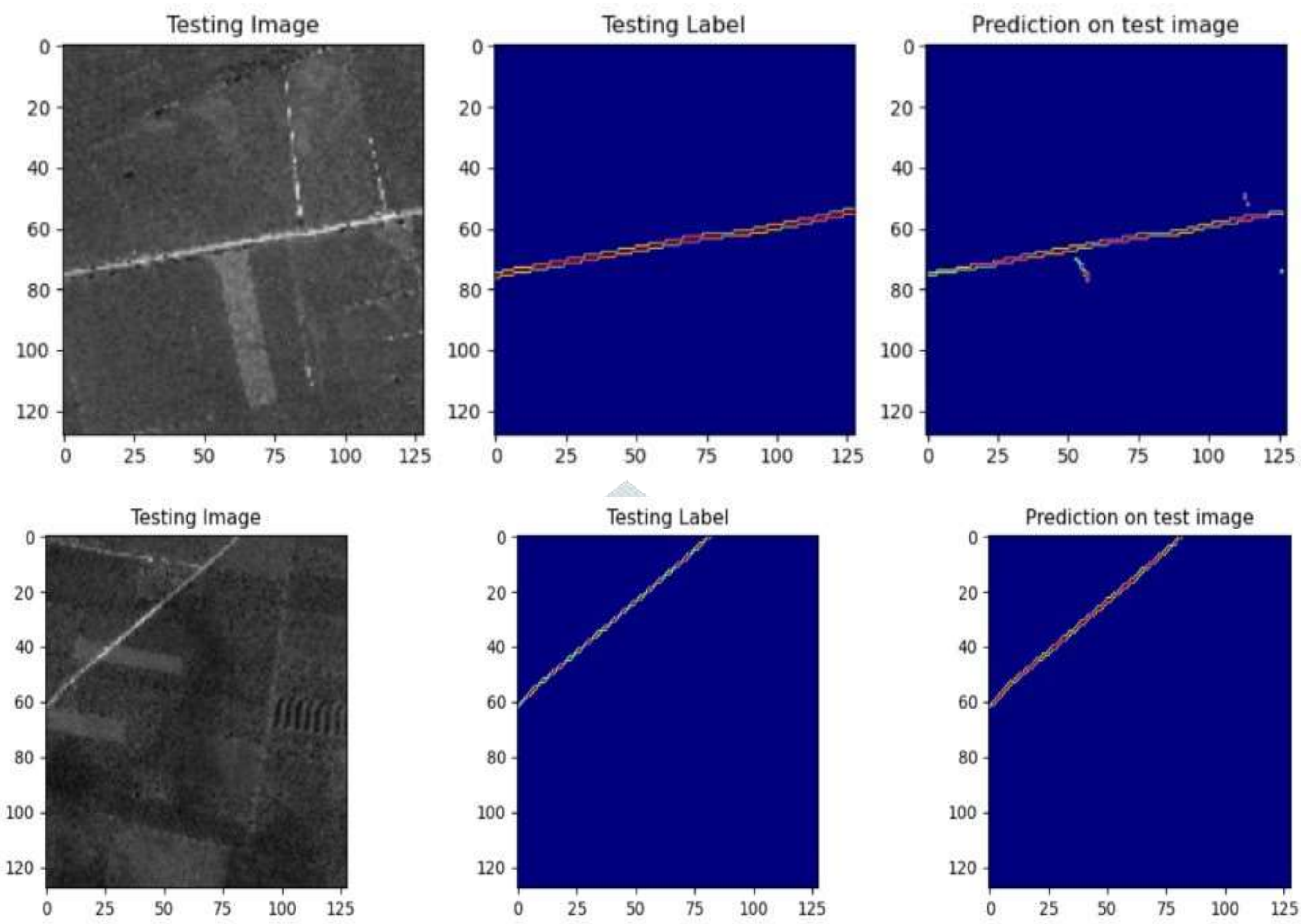

Fig.4. Single Road – Testing Image, Testing Label and Prediction

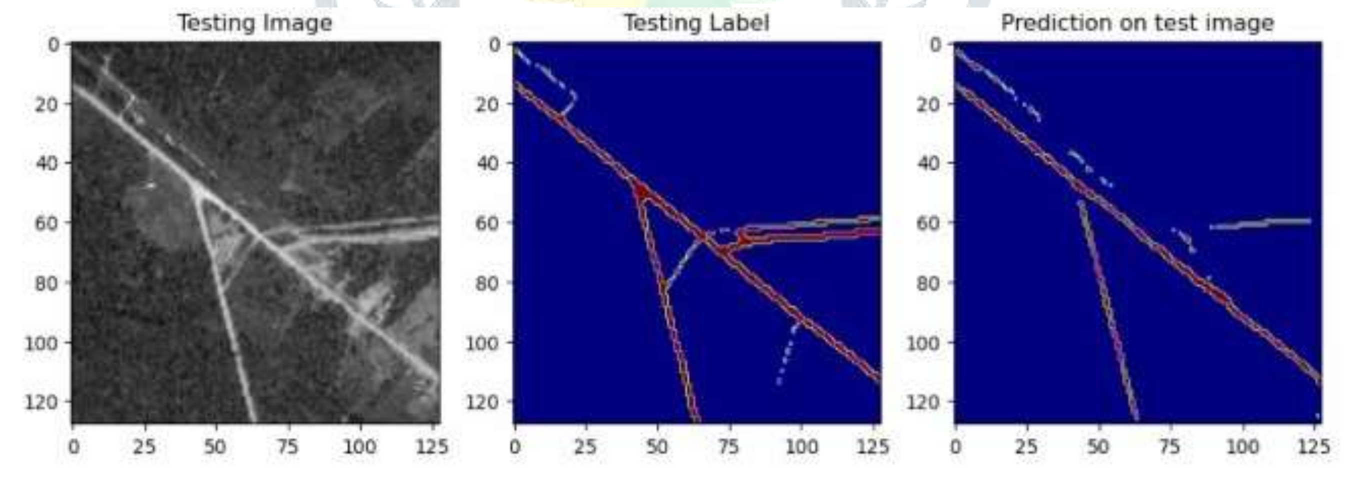

Fig.5. Multiple Roads – Testing Image, Testing Label and Prediction

V. CONCLUSION

In this paper, the methods concerned with the extraction of roads from remotely sensed images researched in recent years are summarized. This paper has covered several different approaches, techniques, methods and models that aim at solving this problem using various ML/DL algorithms namely U-net, ResNet, RCNN, DRU-net, FCN, ASPP, etc. Most of these approaches can recognize road regions using various distinct road features, which show an analogous surface or layout. However, in some cases of roof occlusions of roofs of trees or buildings, the models often fail resulting in some voids and disconnections between the partly extracted roads. Therefore, the way of extracting the roads from remote sensing images with speed and efficiency is very significant.

Hence, it is still a hassle to obtain an ideal methodology to solve the problem of road extraction. The newer models that employ the use of U-net and its family of models and ResNet seem to be more promising. On the other hand, the Recurrent Convolutional Neural Network also proved to be suitable in this problem domain. Several other proposals also introduced the new approaches of using an encoder-decoder type of network to enhance the road with the promising Atrous Spatial Pyramid Pooling (ASPP) Technique which was used by the most modern researchers.

I. Future Work

One of the main gaps found by our group was that the datasets for roads are very localized and hardly include any variations in terrain. We are already working on making a new dataset that is based in India. This dataset will be diverse like India and include roads from all around the country. Roads from plains and mountains, forests and deserts, cities and villages, highways and unpaved roads are all present. We are in the process of making masks for these images. The dataset once done can be used to check the versatility of any algorithm, to check for performance for all types of roads.

VI. ACKNOWLEDGEMENT

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