International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 06 | June - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

Implementation of Deep Learning for Image-Based Potato Leaf Disease Detection

R. Ashish, M. Aditya, T. Samuel Raj, A. Vijaya Lakshmi

Abstract-

With the enhancement in agricultural technology and the use of artificial intelligence in diagnosing plant diseases, it becomes important to make pertinent research to sustainable agricultural development. Various diseases like early blight and late blight immensely influence the quality and quantity of the potatoes and manual interpretation of these leaf diseases is quite time-taking and cumbersome. As it requires tremendously a good level of expertise, efficient and automated detection of these diseases in the budding phase can assist in ameliorating the potato crop production. Previously, various models have been proposed to detect several plant diseases. In this paper, a model is presented that uses pre-trained models like VGG19 for fine- tuning (transfer learning) to extract the relevant features from the dataset. Then, with the help of multiple classifiers results were perceived among which logistic regression outperformed others by a substantial margin of classification accuracy obtaining 97.8% over the test dataset.

Keywords- feature extraction, logistic regression, inception V3, VGG16, VGG19, fine-tuning.

1 Introduction

There are various types of occupations in the world but majorly agriculture is the primary amidst all. Indian economy is not an exception to it, which depends on agriculture a lot. Potato is the most versatile crop which contributes to about 28.9% of total agricultural crop production in India. Potato is the fourth largest agricultural food crop in the world after maize, wheat, and rice. India is the 2nd largest country in the production of potatoes which produces 48.5 milliontons every year [23]. According to the

Agricultural and Processed Food Products Export Development Authority (APEDA), Uttar Pradesh is the largest producer state of potatoes as it accounts for more than 30.33% of the total production of India. Potato starch (farina) is used for sizing cotton and worsted in the textile industry. Potatoes are a rich source of potassium, vitamins (especially C & B6), and fibers. It reduces the total quantity of cholesterol in the blood and helps in curing diseases like blood pressure, heart disease, and cancer.

Diseases have adverse effects on plant and agricultural lands. The main causes of these diseases are microorganisms, genetic disorders, and infectious agents like bacteria, fungi, and viruses. Fungi and bacteria are mainly responsible for potato leaf diseases. Late blight and early blight are fungal diseases while soft rot and common scab are bacterial diseases [22]. So, spotting and diagnosing these diseases on such important vegetation motivates us to design an automated stratagem that could meliorate crop yield, enhance farmer's profit, and more contribution to the country's economy.

Earlier many researchers in the field of computer vision and image processing proposed to use traditional image processing techniques like LBP [14], K-means clustering [13] for detecting these leaf diseases. Deep learning models are better at mapping functions and hence are better feature generators. So, we created a deep learning model to detect potato leaf diseases that use several classifiers in this paper. The paper is divided into sections, where section I is an introduction, section II presents a review of literature, section III presents the data set description, section IV presents proposed model and in the end, conclusion is presented in section V

2 Related Work

There are many methods to detect the plant diseases and various researchers had suggested various techniques for detecting potato leaf diseases in their work. In this section, a summary of those approaches is presented.

P. Badar et. al. [2] have used an approach of segmentation using K Means Clustering [13] on various features of Potato leaf image samples such as colour, texture, area, etc. and applied Back Propagation Neural Network algorithm for identifying and classifying the disease in the leaf image in which they obtained a classification accuracy of 92%.

U. Kumari et. al. [4] have used an approach of image Segmentation in which they have extracted various features of an image like contrast, correlation, energy, homogeneity, mean, standard deviation, and variance, etc.

After extracting features, Neural Network is applied as a classifier to identify and classify diseases on the leaves of 2 plants i.e, Tomato and Cotton. Using this approach, they were able to achieve a classification accuracy of 92.5%.

M. Islam et. al. [3] have used the concept of image segmentation on potato leaf class of Plant Village dataset [1] and then they applied multiclass Support Vector Machine on that segmented image to classify the diseases in which they obtained 95% classification accuracy.

C. G. Li et. al. [5] have used an image segmentation approach for the identification and classification of fungal diseases on the grape leaves dataset. This work uses K Means clustering for extracting colour, texture, and shape features from the images, and SVM (Support Vector Machine) is applied to the extracted features for the classification of the diseases.

J chen et. al. [6] have used a CNN model named LeafNet [18] and DSIFT [19] for extracting features of an image. After that, a bag of visual words (BOVW) model is used to classify the tea leaf images using SVM and MLP (multi-layer perceptron) classifiers. Recently, Faster R- CNN [20] approach has been adopted for image identification and classification purposes [16,17]. A. Ramcharan et. al. [15] has used the concept of transfer learning for cassava diseaseimages

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 06 | June - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

3 Dataset Description

Kaggle is an open-source repository that provides Plant Village Dataset [1] for research purposes. The dataset comprises approximately 55,000 well-labelled images of healthy leaves and infected leaves of various fruits and vegetables like apple, blueberry, cherry, grapes, peach, pepper, orange, tomato, and potato, etc. Every folder of the fruit and vegetable has two types of images i.e. coloured and grayscale. Every crop contains more than one type of leaf disease and for classification, each type is considered as a separate class of disease. Dataset [1] is divided into two types in which each image has a leaf picture with background and without background.

Figure 1: Sample image of each class

The number of images in a particular class is not uniform, it varies from 152 images to 1000 images. We have used only potato images for our classification problem which comprises three classes i.e. Early Blight, Late Blight, and healthy leaf images. The train-test-split data is shownin table 1.

Table 1: Showing the number of samples in training and testing set of our model

Label	Category	Number	Training sample	Test sample
1	Early Blight	1000	787	213
2	Late Blight	1000	791	209
3	Healthy	152	122	30
Total		2152	1700	452

4 Platform Utilized

The machine over which this research has been accomplished is having an NVIDIA GeForce N16V-GMR1 graphic card. The feature extraction and classification work are done using an orange data mining tool using its image analytics add-on. Orange is an open-source python library used as a data visualization and analysis tool. which consists of a canvas interface onto which the user places the widgets and creates a data analysis workflow. Users can interactively explore visualization using the basic functionalities like showing the data table, feature selection, training predictors, visualizing data elements, etc.

V. PROPOSED APPROACH

A. FEATURE EXTRACTION USING VGG19:

VGG19 is a CNN based approach proposed by K. Simonyan and A. Zisserman [7]. The dataset used to train this model as ImageNet, which contains more than 15 million labelled high- resolution images belonging to 22000 categories.

This model was trained for a competition known as ImageNet LargeScale Visual Recognition Challenge (ILSVRC) in which this model used 1.3 million images for training purposes, 50000 for validation purposes, and 100000 for testing purposes. The Only preprocessing done in VGG19 [7] is just subtracting the mean RGB value from each pixel.

The VGG19 [7] model ameliorated the classification accuracy as compared to AlexNet as it replaced all the large Kernel-sized filters with various 3*3 kernel-sized pooling is carried out over the window size of 2*2 with a stride size of 2. The last layer of the model is the soft-maxlayer.

All the hidden layers of the model have been introduced with non-linearity with the help of the ReLU function [7]. sequentially arranged filters. even the model also included the 1*1 filters to utilize the linear transformation. To maintain the spatial resolution, the padding of 1 pixel is done. Spatial pooling is carried only at 5 convolution layers. VGG19 results were very competitive concerning the winner of the challenge i.e, Google Net having a 6.7% error and VGG19 had 6.8% in top 5 validation and test error.

B. ARCHITECTURE: CNN

Convolutional Neural network is one of the variants of artificial neural networks and is widely used for classification, image processing, segmentation tasks, etc. convolution means the sliding of the filter over the image to learn some important features of the input image. since we know that image is nothing but a matrix filled with some numerical value denoted using I in figure 2. So, with the help of these filters abbreviated as K in figure 2, which are convolved over the input image, learns the essential content or features at multiple stages.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 06 | June - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

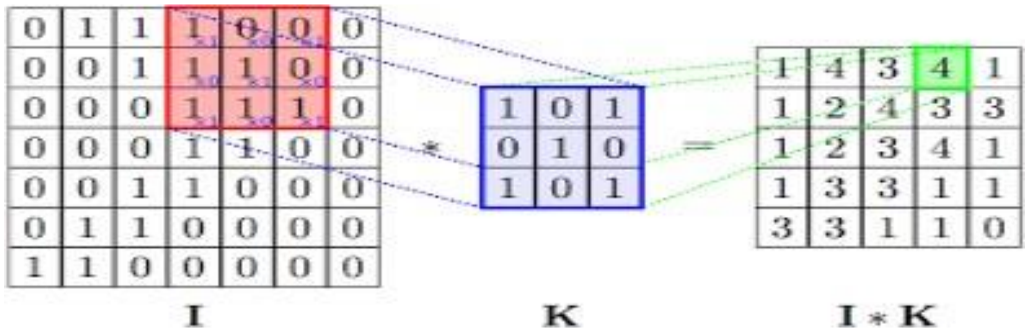

Figure 2. Represents the convolution using the filter K over the image.

The hidden layer of the CNN comprises convolutional layers, pooling layers, fully connected layers, and normalization layer. where the output of the hidden layers is fed to the activation function.

Activation function makes the network more powerful and adds the ability to it to learn something complex and complicated form data and represent non-linear complex arbitrary functional mappings between inputs and outputs. Hence using a nonlinear activation we were able to generate non-linear mappings from inputs to outputs. The activation function used in our case is relu in hidden layers and soft-max in output layers. convolution is stated above, pooling is used to down-sample or for reducing the dimensionality of input representation. Pooling is of various types like min pooling, max pooling, and average pooling where their respective name states their functionality like min pooling means extracting the minimum value from the matrix of some dimension, max-pooling means extracting the maximum value from the matrix. An example of max pooling through the 2*2 window is shown below in figure 3.

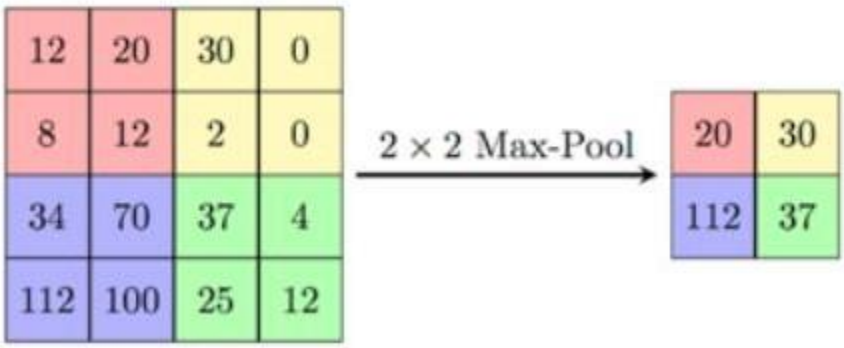

Figure 3. describes the max-pooling from the 2*2 window and reducing the dimension from 4*4 to 2*2.

Average pooling means taking the average of all the values present in that matrix. Fully connected layers represent that weights from the previous layer will act as input to all the neurons present in the next layer. The normalization layer is used to normalize the activations of the previous layer maintaining the mean activation close to 0.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 06 | June - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

C. MODEL

Nowadays, applications of Deep Convolutional neural networks are widely used in medical, agricultural fields etc for various purposes and we used the pretrained model like VGG19 in our case to extract the relevant features of the dataset.

This way we leverage previous learning and avoid starting from scratch. There are several pretrained models available such as VGG16 [7], VGG19 [7], InceptionV3 [11].

We extracted features from images by passing them into the pretrained models and the extracted features are now passed as input to various classifiers such as SVM [8], Neural Network [10], KNN [12], Logistic regression [9].

After evaluating results from all the above approaches, we found that VGG19 along with logistic regression gave the stateof-the-art solution.

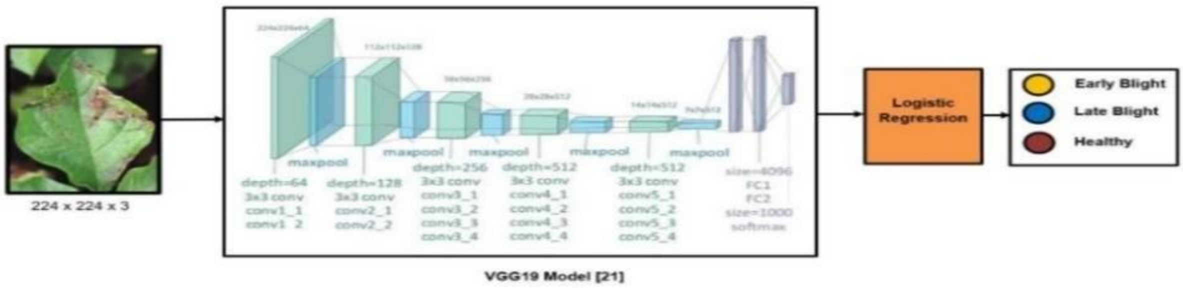

Figure 4 : Proposed Model

D. CLASSIFICATION

In this model logistic regression is used for classification. Logistic Regression [9] is a supervised algorithm used when the dependent variable(output) takes only discrete values for a given set of features (or inputs). In Logistic Regression Hypothesis Function is calculated and the output of the function is evaluated in terms of probability. After this, the output of the Hypothesis function is passed to Cost Function. Cost function converts the probabilistic results to categorical results. The flow of the model goes like the following:

(A)= Prob(B=1|A;a)__________________ (1)

The probability that given an event A, another event B=1 which is parameterized by variable 'a' is given in equation 1 above.

Prob(B=1|A;a)+Prob(B=0|A;a)=1 _____________ (2)

Prob (B=0|A;a) =1-Prob(B=1| A;a)

To convert probabilistic results to categorical results, a cost function is used which is shown by equation (3) below.

((A), B) = -B*log(**Ψ**(A)) - (1-B) *log(1-**Ψ**(A)) _ _ (3)

If B=1, (1-B) term will become zero, therefore

-log(**Ψ**(A)) alone will present.

If B=0, (B) term will become zero, therefore -

log(1-**Ψ**(A)) alone will present.

Domain classification for textual conversation was observed that domain recognition differs from emotion recognition and sentiment analysis because emotion recognition or sentiment analysis only reflects the mood or emotions while domain recognition recognizes its domain categories automatically for which the conversation has taken place. It is a relatively new classification and advancement in the field of machine learning.

VI. RESULTS AND DISCUSSION

In this proposed model 2152 images of potato leaves were taken from a plant village dataset which comprises 1000 images of early blight,1000 images of late blight, and 152 of healthy images of potato leaves. Dataset is divided into two parts:

The training part comprises 1700 images (70%) and the test part contains 452 images (30%). Various pre-trained models like inceptionV3 [11], VGG16 [7], and VGG19 [7] are used for feature extraction among which VGG19 gave the optimal result as shown in table 3 below.

Multiple classifiers namely KNN [12], SVM [8], Neural Network [10], and logistic regression are used for classification. Among which Logistic Regression gives the state-of-the-art solution with a classification accuracy of 97.7%.

To evaluate the efficiency of the model, performance parameters such as AUC (Area Under the Curve), CA (Classification Accuracy), Precision, Recall, F1- Score are calculated as shown in table 3

Table 2 comparison report with other models

Model Proposed	Classification Accuracy
Image segmentation + backpropagation neural network[2]	92%
Image segmentation + Support Vector Machine[3]	95%
Proposed Approach	**97.8%**

Table 3 Shows AUC (Area Under the Curve), CA (Classification Accuracy), Precision,Recall, F1-Score using VGG16, V19 and InceptionV3

Model	Classifier	AUC	CA	F1	Precision	Recall
VGG16 [7]	KNN	98.7	93.8	93.8	93.8	93.8
	SVM	99.3	93.8	93.7	94.1	93.8
	Neural Network	99.2	95.3	95.2	95.3	95.3
	Logistic Regression	99.7	97.7	97.7	97.7	97.7
VGG19 [7]	KNN	99.2	95.4	95.3	95.3	95.4
	SVM	99.6	94.7	94.6	95	95.4
	Neural Network	98.9	96.5	96.5	96.5	96.5
	Logistic Regression	99.9	**97.8**	97.8	97.8	97.8
Inception v3 [11]	KNN	98.3	93.1	93.2	93.7	93.1
	SVM	99.7	96.4	96.4	96.4	96.4
	Neural Network	99.6	96.2	96.2	96.2	96.2
	Logistic Regression	99.7	97.5	97.5	97.5	97.5

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 07 Issue: 06 | June - 2023 SJIF Rating: 8.176 ISSN: 2582-3930

Figure 5,6 and 7 show the ROC plots concerning multiple classes like Early Blight,Healthy and Late Blight

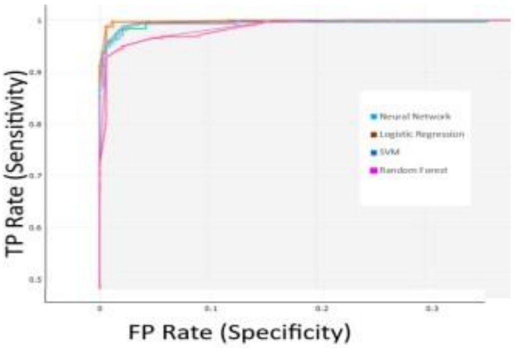

Figure 5. ROC Plot of Early blight class using VGG19 with Logistic Regression

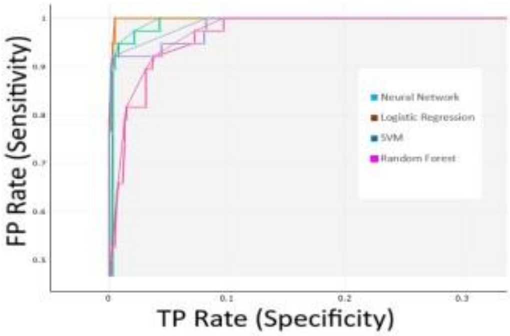

Figure 6. ROC Plot of Healthy class using VGG19 with Logistic Regression

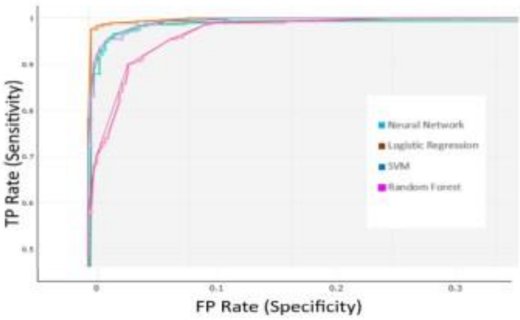

Figure 7. ROC Plot of Late Blight class using VGG19 with Logistic Regression

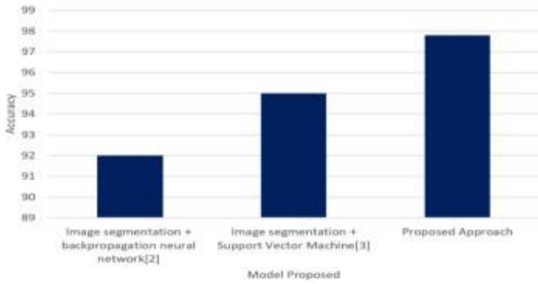

Figure 8 classification accuracy

VII. CONCLUSION

In this work, we have used the concept of transfer learning and have developed an automated system to diagnose and classify diseases in the potato leaves like early blight, late blight and healthy with a novel solution achieving classification accuracy of 97.8% over the test dataset, with 5.8% and 2.8% improvement with [2] and [3] respectively. Our technique can help farmers in detecting diseases in their early stages and in enhancing their crop yields. figure 8 shows the classification accuracy of the proposed approach in comparison with other implementations.

VIII. FUTURE SCOPE

Nowadays, It is very important to detect a disease in a plant in the budding stage so that productivity and quality of the yield can be upgraded. Since disease detection needs a lot of expertise so it would be very beneficial if we could implement this system on the smartphone in which farmers can click a picture of the leaf and send it to the server. The server will automatically identify and classify the type of disease and send results along with prescribed medicines back to the smartphone.

REFERENCES

[1] Abdallah Ali (2019, September) PlantVillage Dataset, Version 1, Retrieved 22 February 2020, https://www.kaggle.com/xabdallahali/plantvillage-dataset.

[2] Athanikar, . Girish and Ms. Priti Badar. “Potato Leaf Diseases Detection and Classification System Mr.” (2016).

[3] M. Islam, Anh Dinh, K. Wahid and P. Bhowmik, "Detection of potato diseases using image segmentation and multiclass support vector machine," 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE), Windsor, ON, 2017, pp. 1-4.

[4] C. U. Kumari, S. Jeevan Prasad and G. Mounika, "Leaf Disease Detection: Feature Extraction with K- means clustering and Classification with ANN," 2019 3rd International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2019, pp. 1095-1098.

[5] Li, Guanlin & Ma, Zhanhong & Wang, Haiguang. (2011). Image Recognition of Grape Downy Mildew and Grape Powdery Mildew Based on Support Vector Machine. IFIP Advances in Information and Communication Technology. 370. 151-162. 10.1007/978-3-642-27275-2_17.

[6] Chen, Jing & Liu, Qi & Gao, Lingwang. (2019). Visual Tea Leaf Disease Recognition Using a Convolutional Neural Network Model. Symmetry. 11. 343. 10.3390/sym11030343.

[7] Simonyan, K., and A. Zisserman. Very Deep Convolutional Networks for Large-Scale Image Recognition. Computational and Biological Learning Society, 2015, pp. 1–14.

[8] Evgeniou, Theodoros & Pontil, Massimiliano. (2001). Support Vector Machines: Theory and Applications. 2049. 249-257. 10.1007/3-540-44673-7_12.

[9] Peng, Joanne & Lee, Kuk & Ingersoll, Gary. (2002). An Introduction to Logistic Regression Analysis and Reporting. Journal of Educational Research - J EDUC RES. 96. 3-14. 10.1080/00220670209598786.

[10] Krizhevsky, Alex & Sutskever, Ilya & Hinton, Geoffrey. (2012). ImageNet Classification with Deep Convolutional NeuralNetworks. Neural Information Processing Systems. 25. 10.1145/3065386.

[11] Szegedy, Christian & Vanhoucke, Vincent & Ioffe, Sergey & Shlens, Jon & Wojna, ZB. (2016). Rethinking the Inception Architecture for Computer Vision. 10.1109/CVPR.2016.308.

[12] Peterson, Leif. (2009). K-nearest neighbor. Scholarpedia. 4. 1883. 10.4249/scholarpedia.1883.

[13] Li, Youguo & Wu, Haiyan. (2012). A Clustering Method Based on K-Means Algorithm. Physics Procedia. 25. 1104-1109. 10.1016/j.phpro.2012.03.206.

[14] Huang, di & Shan, Caifeng & Ardabilian, Mohsen & Chen, Liming. (2011). Local Binary Patterns and Its Application to Facial Image Analysis: A Survey. IEEE Transactions on Systems, Man, and Cybernetics, Part C. 41. 765-781. 10.1109/TSMCC.2011.2118750.

[15] Ramcharan, Amanda & Baranowski, Kelsee & McCloskey, Peter & Ahmed, Babuali & Legg, James & Hughes, David. (2017). Using Transfer Learning for Image-Based Cassava Disease Detection. Frontiers in Plant Science. 8. 10.3389/fpls.2017.01852.

[16] Oppenheim, Dor & Shani, Guy & Erlich, Orly & Tsror, Leah. (2018). Using Deep Learning for Image- Based Potato Tuber Disease Detection. Phytopathology. 109. 10.1094/PHYTO-08-18- 0288-R.

[17] Fuentes, Alvaro & Yoon, Sook & Kim, Sang & Park, Dong. (2017). A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition. Sensors. 17. 2022. 10.3390/s17092022.

[18] Barré, Pierre & Stöver, Ben & Müller, Kai & Steinhage, Volker. (2017). LeafNet: A computer vision system for automatic plant species identification. Ecological Informatics. 40. 10.1016/j.ecoinf.2017.05.005.

[19] Lindeberg, Tony. (2012). Scale Invariant Feature Transform. 10.4249/scholarpedia.10491.

[20] Ren, Shaoqing & He, Kaiming & Girshick, Ross & Sun, Jian. (2015). Faster R-CNN: Towards Real- Time Object Detection with Region Proposal Networks. IEEE Transactions on Pattern Analysis and Machine Intelligence. 39. 10.1109/TPAMI.2016.2577031.