

A PROJECT REPORT ON

MACHINE LEARNING MODEL FOR DETERMINING QUALITY OF SATELLITE IMAGES

in Optical Data Processing Division Of Space Applications Center (ISRO)

Submitted by

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In fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

in

Computer Engineering



SILVER OAK COLLEGE OF ENGINEERING AND TECHNOLOGY,
AHMEDABAD

Gujarat Technological University, Ahmedabad

2018-2019

Declaration of Authorship

I, PRIYANSHI SHAH, declare that this project titled, ‘Machine Learning Model For Determining Quality Of Satellite Images’ and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for an undergraduate degree at Silver Oak College Of Engineering And Technology.
- Where any part of this project has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.

Signed:

Date:

“There are two sides to every story.”

-Anonymous

Abstract

In this project, an automatic approach for detecting quality of remote sensing RESOURCESAT - 2A satellite images has been introduced. RESOURCESAT-2 series satellite images are used for urban planning, crop monitoring, finding vegetation index etc., so for these applications the quality of an image depends on amount of land present in the images. Image quality detection is helpful to scientists in improving the accuracy of land cover classification in satellite images. This algorithm is a Deep Learning Convolutional Neural Network model trained on RESOURCESAT-2A LISS 4 satellite images using Inception V3 transfer learning. The objective is to accurately predict quality of optical satellite images by rating them in categories from lowest to highest according to the land cover. This project has one CNN model trained on the available data set, it will classify images among 5 categories. The details are:

Rating 1-5:

- 1 - image with no land
- 2 - 1/4 th image with visible land features
- 3 - 2/4 th image with land feature
- 4 - images with 3/4 th or more land coverage
- 5 - image with only land features

Acknowledgements

This project gave me an opportunity to learn and develop deep learning algorithm by moving out of my comfort zone and I could not have done this project without the permission from my college, so I would like to thank T and P cell officer Mr. Nipen Shukla and HOD Mr. Satvik Khara for allowing me to do my internship at SAC(ISRO).

I would also like to extend my hearty thanks to SAC(ISRO) HR head Mr. Ravishankar for allowing me to work as an intern at their esteemed organization and for placing me in ODPD for my intership.

I would like to specially thank Mr. Debajyoti Dhar - Group Director SIPG, Head ODPD/SIPG and Mr. S M Moorthi - Scientist/Engineer-'SG' for allowing me to work in their division and for taking time to hear me out, for providing me guidance during my internship in spite of being extraordinarily busy with their duties.

I would also like to express my deepest and special thanks Mrs. Neha Gaur - Scientist/Engineer-'SE' and Mr. Ankur Garg - Scientist/Engineer-'SD' for providing an interesting project to work on, for providing best facilities, solving my doubts even the silly ones, giving necessary advice and precious guidance; which were extremely valuable for my project both theoretically and practically.

I would also like to thank internal guide Prof. Ati Garg from my college, who gave me guidance and insightful support during the project.

Last but not the least I would like to mention here that I am greatly thankful to each and everyone who has been associated with my project at any stage but whose name does not find a place in this acknowledgement.

Yours Sincerely,
Priyanshi Shah

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Chapter 1

Introduction

1.1 Problem Summary

Satellites capture multiple images every minute, and features like cloud, water in images captured by earth observation satellites like RESOURCESAT, CARTOSAT etc. are of major concern. Some applications only require images with land features, so for those applications images covered by cloud or images with water and snow are of no use. To predict quality of images for land based applications, users need to look at every image manually which require lots of human effort. As a consequence of the above problem, one of the possible approaches is to give information of the quality of the image by using automatic quality detection, then archiving this information with each individual image. This is a very useful process to enable users to select images that are appropriate for their application.

1.2 Technology And Literature Review

1.2.1 Machine Learning

Machine learning, in layman terms, is to use the data to make a machine make intelligent decision[11]. An important task of Machine learning is to extract, process, define, clean, arrange and then understand the data to develop intelligent algorithms[11]. Machine learning is an application of artificial intelligence (AI) that provides systems the ability to automatically learn and improve from experience without being explicitly programmed[11]. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves [10]. Machine learning is employed in a range of computing tasks where designing and programming explicit algorithms with good performance is difficult or infeasible; example applications include email filtering, detection of network intruders, and computer vision.

1.2.2 Deep Learning

Deep learning is a subset of machine learning where artificial neural networks, algorithms inspired by the human brain, learn from large amounts of data. Similarly to how we learn from experience, the deep learning algorithm would perform a task repeatedly, each time tweaking it a little to improve the outcome. We refer to deep learning because the neural networks have various (deep) layers that enable learning. Just about any problem that requires thought to figure out is a problem deep learning can learn to solve. Deep learning allows machines to solve complex problems even when using a data set that is very diverse, unstructured and inter-connected. The more deep learning algorithms learn, the better they perform[9]. Deep learning is the most interesting and powerful machine learning technique right now.

1.2.3 Machine Learning vs Deep Learning

1.2.3.1 Data Dependencies

The most important difference between deep learning and traditional machine learning is its performance as the scale of data increases. When the data is small, deep learning algorithms don't perform that well. This is because deep learning algorithms need a large amount of data to understand it perfectly[4].

1.2.3.2 Hardware Dependencies

Deep learning algorithms heavily depend on high-end machines, contrary to traditional machine learning algorithms, which can work on low-end machines. This is because the requirements of deep learning algorithm include GPUs which are an integral part of its working. Deep learning algorithms inherently do a large amount of matrix multiplication operations. These operations can be efficiently optimized using a GPU because GPU is built for this purpose[4].

1.2.3.3 Feature Engineering

In Machine learning, most of the applied features need to be identified by an expert and then hand-coded as per the domain and data type. For example, features can be pixel values, shape, textures, position and orientation. The performance of most of the Machine Learning algorithm depends on how accurately the features are identified and extracted. Deep learning algorithms try to learn high-level features from data. This is a very distinctive part of Deep Learning and a major step ahead of traditional Machine Learning. Therefore, deep learning reduces the task of developing new feature extractor for every problem. Like, Convolutional NN will try to learn low-level features such as edges and lines in early layers then parts of faces of people and then high-level representation of a face[4].

1.2.3.4 Problem Solving Approach

When solving a problem using traditional machine learning algorithm, it is generally recommended to break the problem down into different parts, solve them individually and combine them to get the result. Deep learning in contrast advocates to solve the problem end-to-end[4].

1.2.4 Where Is Machine Learning And Deep Learning Being Applied Right Now?

Computer Vision: for applications like vehicle number plate identification and facial recognition.

Information Retrieval: for applications like search engines, both text search, and image search.

Marketing: for applications like automated email marketing, target identification

Medical Diagnosis: for applications like cancer identification, anomaly detection

Natural Language Processing: for applications like sentiment analysis, photo tagging Online Advertising, etc [4].

1.2.5 Convolutional Neural Networks

In machine learning, a convolutional neural network (CNN, or ConvNet) is a class of deep, feed-forward artificial neural networks, most commonly applied to analyzing visual imagery. CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing. Convolutional networks were inspired by human brain neural structure. CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage of CNN [3].

1.2.6 Inception v3

Why Inception?

Inception is a deep learning convolutional neural network model. The Inception network was an important milestone in the development of CNN classifiers. Prior to inception most popular CNNs just stacked convolution layers deeper and deeper, hoping to get better performance, but very deep networks are prone to overfitting and naively stacking large convolution operations is computationally expensive. Also because of huge variation in the location of the information in images of dataset, choosing the right kernel size for the convolution operation becomes tough because a larger kernel is preferred for information that is distributed more globally, and a smaller kernel is preferred for information that is distributed more locally. To overcome all these problems Inception was developed to make network a bit wider rather than deeper with filters of multiple sizes to operate on the same level to reduce multiple computations[1].

Why Inception v3?

The popular versions of Inception are : Inception v1, Inception v2 and Inception v3, Inception v4 and Inception-ResNet. Inception v1 and Inception v2 didn't contribute much until near the end of the training process, when accuracies were nearing saturation. Inception v3 incorporated upgrades stated for Inception v2, and in addition used RMSProp Optimizer, factorized 7x7 convolutions, BatchNorm in the Classifiers and Label Smoothing (A type of regularizing component added to the loss formula that prevents the network from becoming too confident about a class, prevents overfitting). Inception v3 performs convolution on an input, with 3 different sizes of filters (1x1, 3x3, 5x5). Additionally, max pooling is also performed. The outputs are concatenated and sent to the next inception module. Inception v3 is better in performance compared to its earlier versions, it is faster and provides more accuracy and it provides many ways to overcome overfitting[1].

1.2.6.1 Architecture of Inception v3

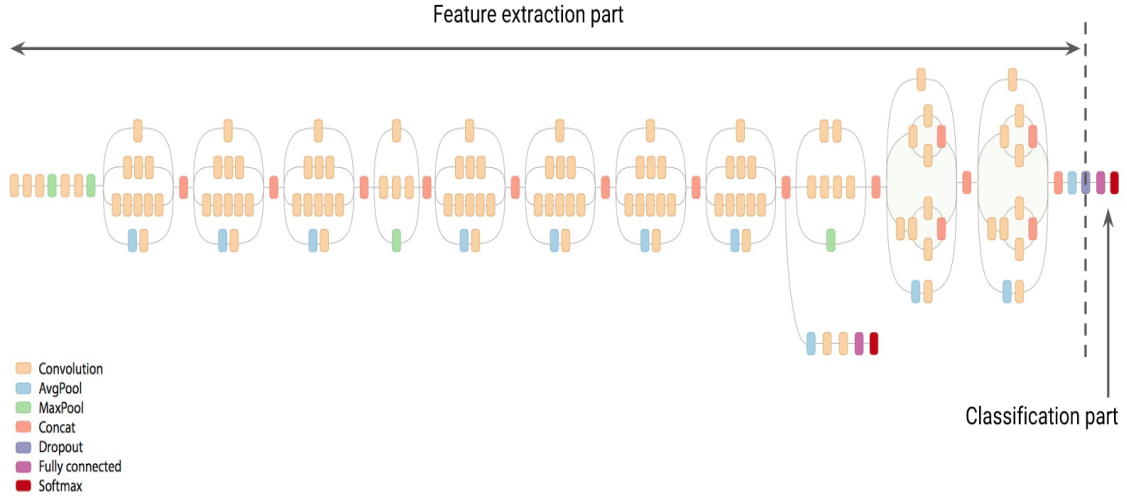


FIGURE 1.1: Inception-v3 Architecture

Inception-v3 model is trained on Imagenet dataset, which consists of 1000 classes like fish, bird, mammal, plant, sport, fabric, utensil, musical instrument, room etc. There are total 315 layers in the model. The architecture of the model is shown in the figure 1.1. Main layers of the model are Convolution, Average Pooling, Max Pooling, Dropout, Fully Connected and Softmax. Layers at the beginning extract features from the input image and final layers perform the classification task based on the classes of the dataset.

1.2.7 Python

Python is a high-level programming language for general-purpose programming. Created by Guido van Rossum and first released in 1991, Python has a design philosophy that emphasizes code readability, notably using significant whitespace [7]. Python is known for its readability and less complexity.

1.2.8 Pycharm

PyCharm is an integrated development environment (IDE) used in computer programming, specifically for the Python language. It is developed by JetBrains company. PyCharm is cross-platform, with Windows, macOS and Linux versions [6]. The simple UI of pycharm is its plus point.

1.2.9 Keras And Tensorflow

Keras

Keras is a neural networks API, written in Python and capable of running on top of TensorFlow, CNTK, or Theano. It was developed with a focus on enabling fast experimentation. Keras is a deep learning library that allows easy and fast prototyping (through user friendliness, modularity, and extensibility), supports both convolutional networks and recurrent networks, as well as combinations of the two. Keras is easy to learn and easy to use [5].

Tensorflow

TensorFlow is an open source software library for high performance numerical computation. Its flexible architecture allows easy deployment of computation across a variety of platforms (CPUs, GPUs, TPUs). Originally developed by researchers and engineers from the Google Brain team within Googles AI organization, it comes with strong support for machine learning and deep learning [2].

Chapter 2

Implementation

2.1 Lifecycle of Machine Learning Model

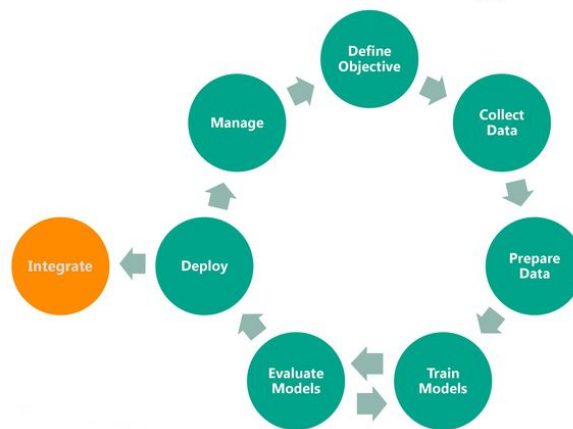


FIGURE 2.1: Lifecycle of Machine Learning Model

The main phases of the model are: 1) To define the objective of the model. 2) To collect RESOURCESAT-2A satellite data. 3) To prepare dataset for training and testing. 4) To train the model on the training dataset. 5) To evaluate the model. 6) To refine the dataset or code of the model to obtain desired accuracy. 7) Deploy the model and integrate it. The activities for development of the project using machine learning lifecycle are represented in the flow chart in Figure 2.2:

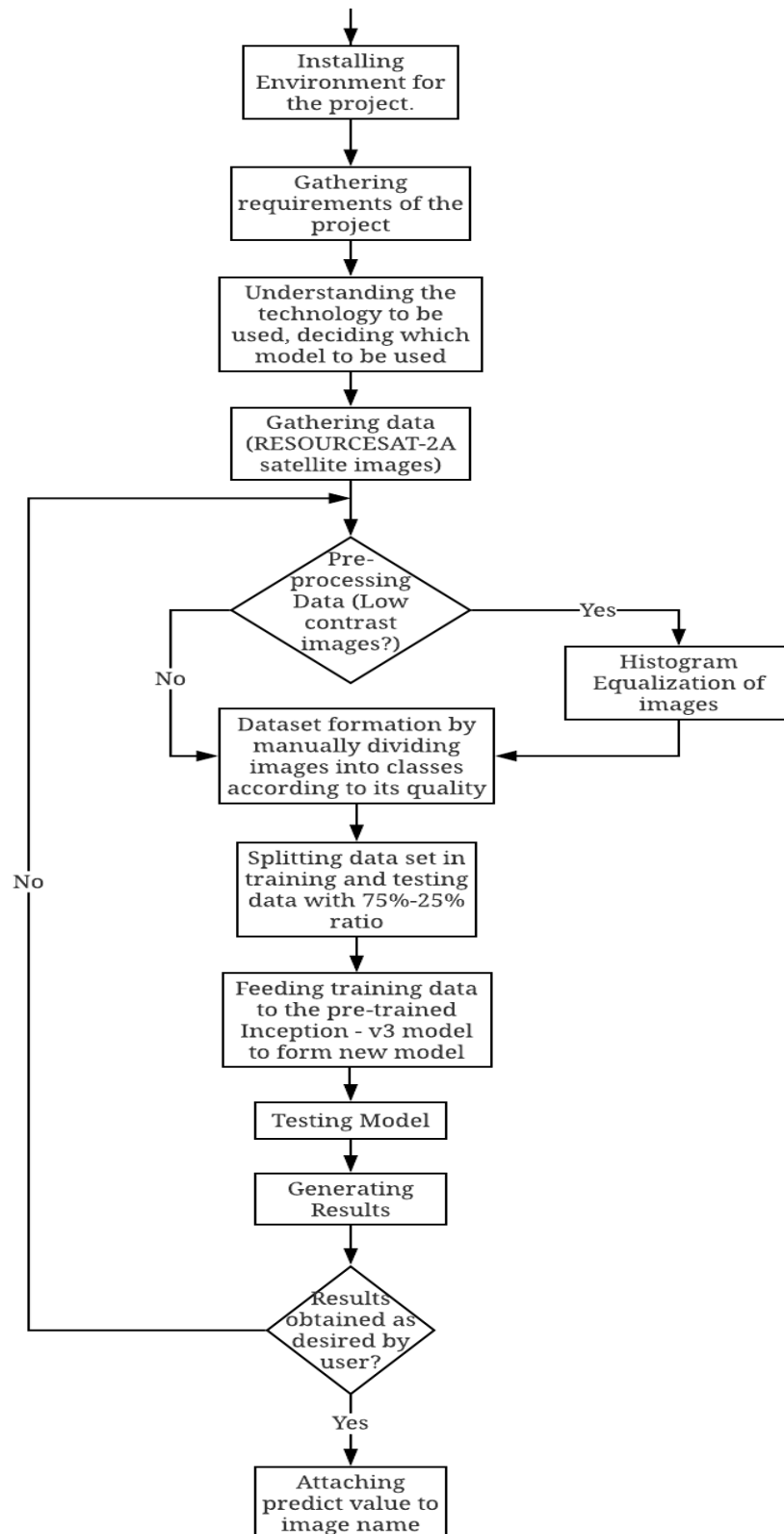


FIGURE 2.2: Flow chart of the model

2.2 Image Quality Detection Data

A dataset consisting of 1000 RESOURCESAT-2A satellite images from July, 2017 to Sept, 2017 has been used for this project. RESOURCESAT-2A is an Indian Remote Sensing satellite developed by ISRO intended for resource monitoring. RESOURCESAT-2A is a follow on mission to RESOURCESAT-1 and RESOURCESAT-2, launched in 2003 and 2011 respectively. RESOURCESAT-2A carries three payloads, they are a high resolution Linear Imaging Self Scanner (LISS-4) camera operating in three spectral bands in the Visible and Near Infrared Region (VNIR) with 5.8 m spatial resolution and steerable up to 26 deg across track to achieve a five day revisit capability. The second payload is the medium resolution LISS-3 camera operating in three-spectral bands in VNIR and one in Short Wave Infrared (SWIR) band with 23.5 m spatial resolution. The third payload is a coarse resolution Advanced Wide Field Sensor (AWiFS) camera operating in three spectral bands in VNIR and one band in SWIR with 56 m spatial resolution [8].

2.2.1 The Dataset Formation

For this project images with resolution 512 x 512 taken with RESOURCESAT-2A LISS-4 (Linear Imaging Self Scanner -4) sensor are used. Each image was carefully rated and was stored in an excel file with its name and its rating. All the images were manually rated on the basis of features mentioned below:

Rating 1-5:

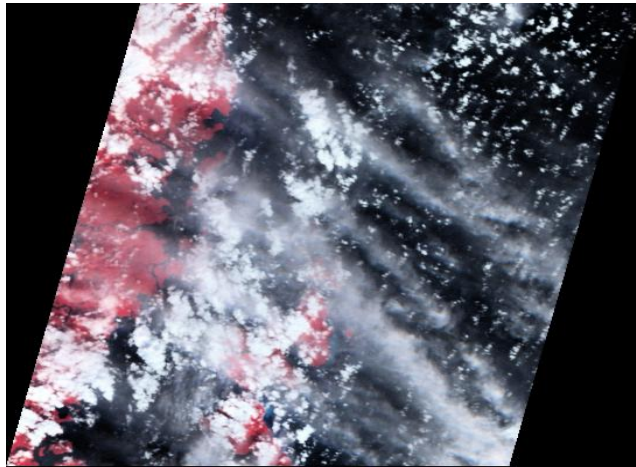
- 1 - image with no land
- 2 - 1/4 th image with visible land features
- 3 - 2/4 th image with land feature
- 4 - images with 3/4 th or more land coverage
- 5 - image with only land features

Using the python code to read excel file I divided images from Resourcesat-2A folder into 5 classes using the image name and its rating. Each class was formed with approximately 170 images. To evaluate the quality of images, dataset was randomly splitted into 75%-25% ratio for training and testing respectively, using python libraries like random, os and shutil.

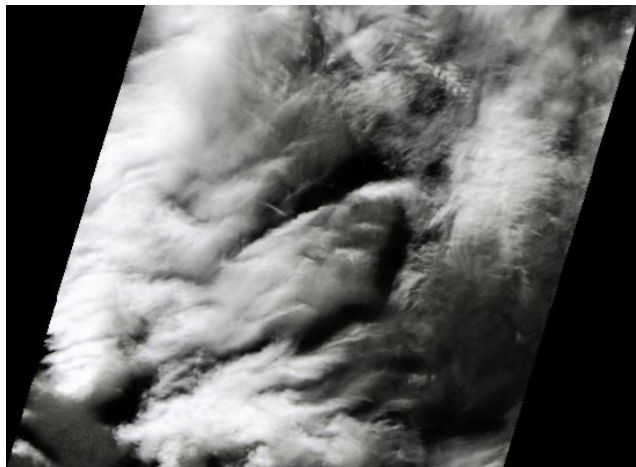
Here is the pseudo code for random splitting:

```
files = os.listdir(filepath)
os.mkdir(filepath)
index = random.sample(range(0,len(files)),no. of sample)
for i in range (0, len(index)):
shutil.copy(src,dest)
```

Here are few sample images of Resourcesat-2A satellite belonging to 5 classes:

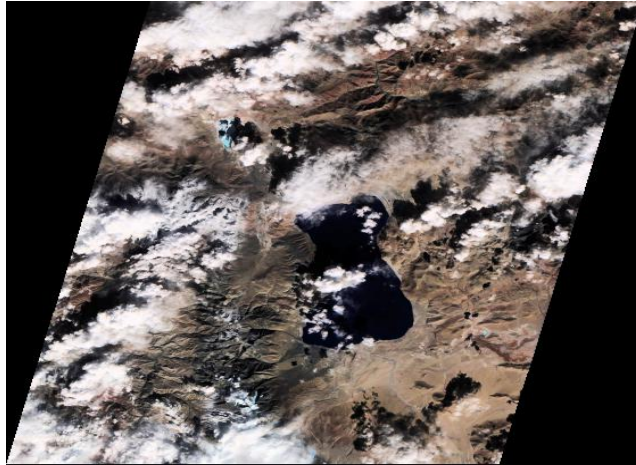


(a)

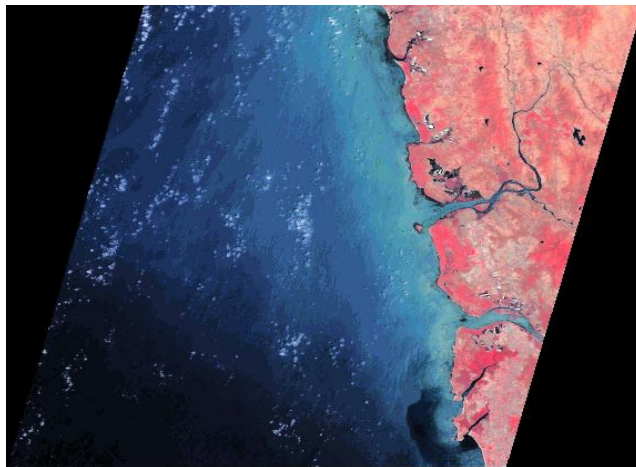


(b)

FIGURE 2.3: class 1: (a)Image with water and land covered by clouds, (b)Image with land covered by clouds

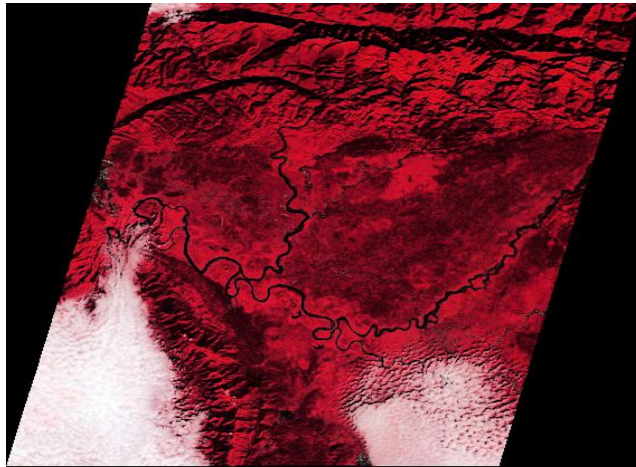


(a)

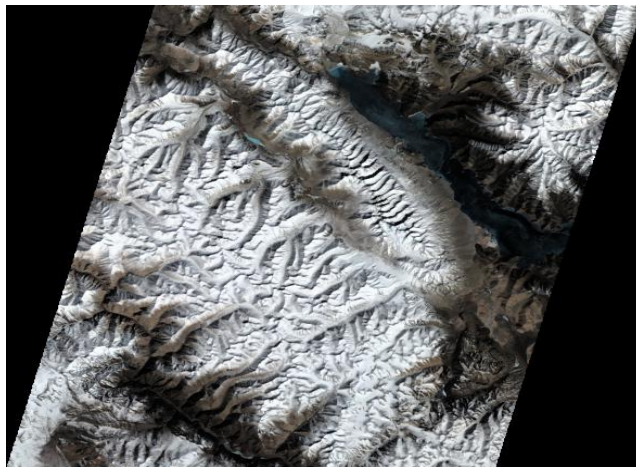


(b)

FIGURE 2.4: class 2: (a)Image with water and land covered by clouds, (b)Image with land covered by clouds

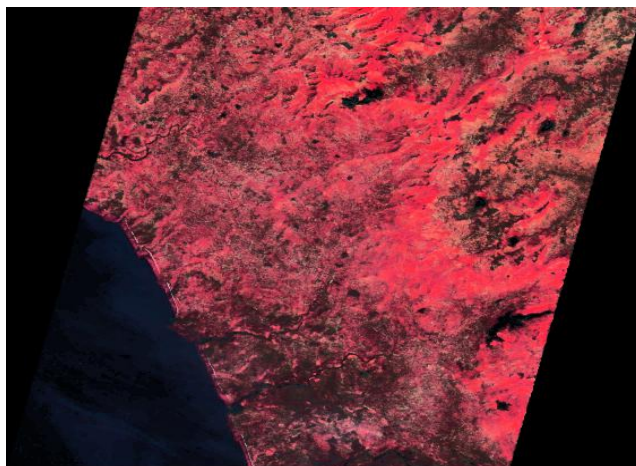


(a)

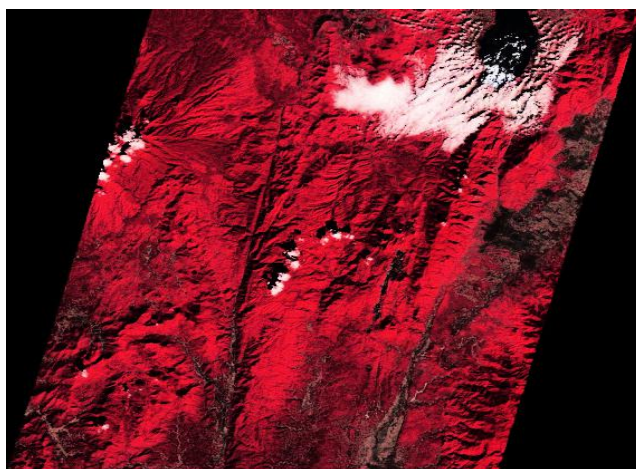


(b)

FIGURE 2.5: class 3: (a)Image with almost 1/2 portion of land covered by clouds,
(b)Image with land covered covered by snow

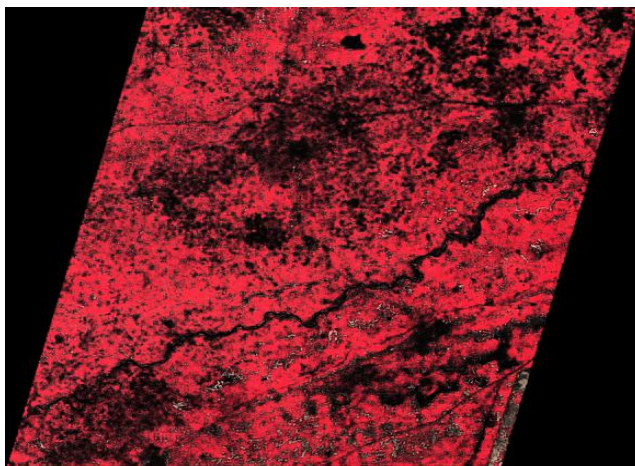


(a)

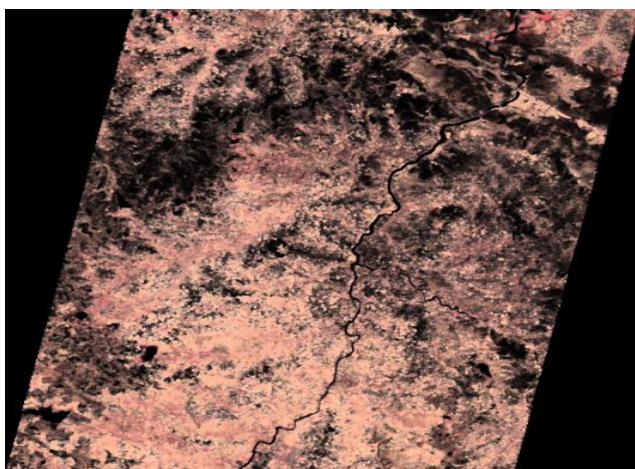


(b)

FIGURE 2.6: class 4: (a)Image with $3/4$ proportion of visible land and $1/4$ proportion of water, (b)Image with $1/4$ proportion of land covered by clouds



(a)



(b)

FIGURE 2.7: class 5: (a)Full image with visible land,(b)Full image with visible land

2.3 Training new classifier using Inception-v3 Transfer Learning

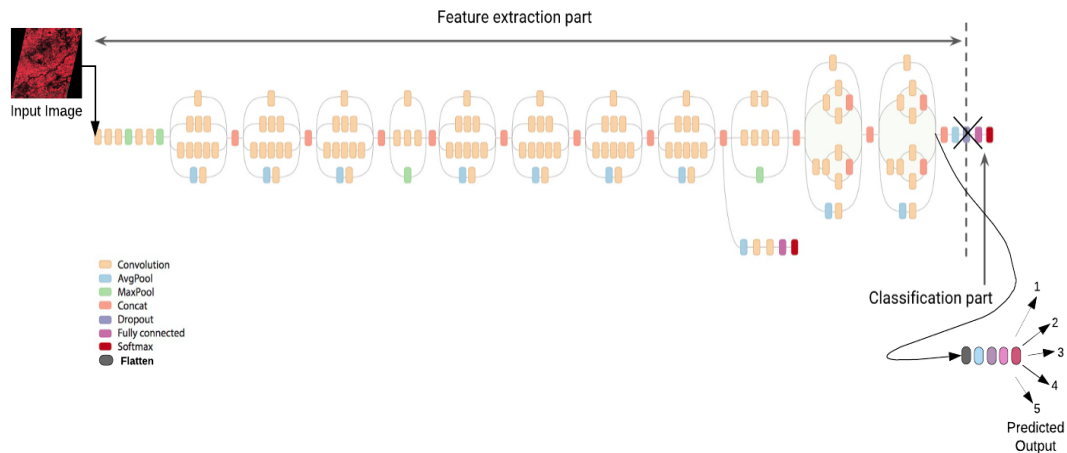


FIGURE 2.8: Inception-v3 Transfer Learning

As I had image data set, I used Convolutional Neural Network (CNN) to train the model. Among many CNN models, Inception - v3 is used because the network is a bit wider rather than deeper as compared to earlier CNNs. The RESOURCESAT-2A LISS 4 training set with each image having dimension 512 x 512 was used to train a model using Inception-v3 transfer learning. For training, 299 out of 315 layers were kept trainable and other layers were non trainable. Top most layers (concat, avg pool, dropout, fully connected, softmax with dense value 1000) were replaced by (flatten, avg pool, dropout, fully connected, softmax with dense value 5) as shown in figure 2.4. Experiments were made with the values of the hyper parameters like learning rate, dropout, batch size etc. When accuracy was not obtained as needed and when the model was overfitting, data pre-processing like histogram equalization was done. The schematics of using Inception-v3 for training and classification are shown on figure 2.9.

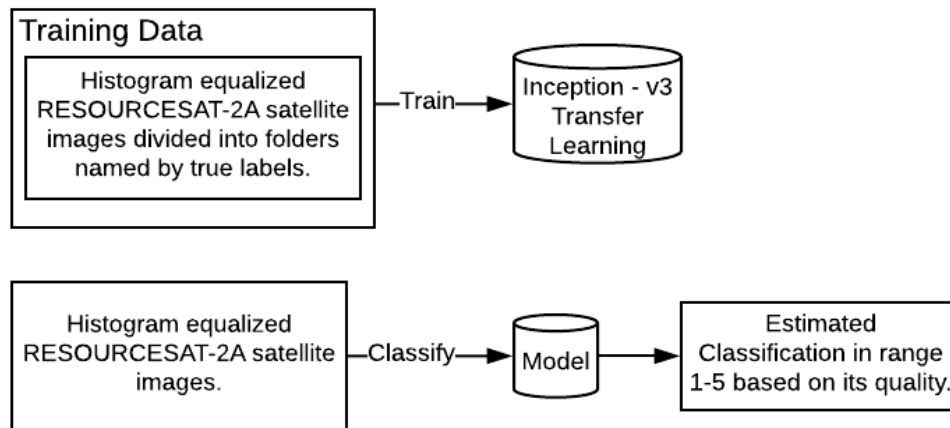


FIGURE 2.9: Once trained, the model can be used to perform classification on new images not belonging to the training set

To perform training, histogram equalized RESOURCESAT-2A images together with the labels, which are considered to be true, were used as an input to the Inception-v3 model. To perform classification, each image was first histogram equalized and then it was used as the input to the python prediction code.

2.4 Model Overfitting and How to reduce it?

2.4.1 What is Overfitting?

In statistics, goodness of fit refers to how closely a deep learning neural network models predicted values match the observed (true) values. A model that has learned the noise instead of the signal is considered overfit because it fits the training dataset but has poor fit with new datasets.

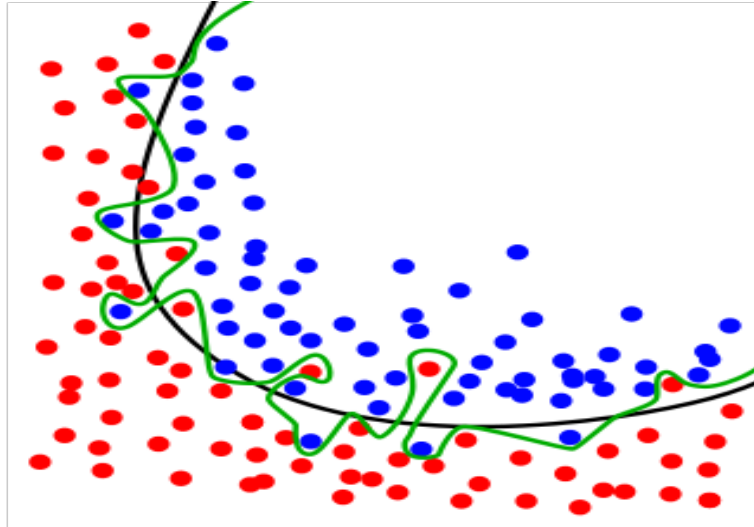


FIGURE 2.10: Black line fits the data well, the green line is overfit.

2.4.2 Methods Used To Reduce Overfitting

2.4.2.1 Histogram Equalization

RESOURCESAT-2A satellite images are having low contrast, so it is very difficult to see any features in them, so Deep Learning model is not able to extract features from those images. Because of this reason it is necessary to apply histogram equalization to these images to enhance contrast. I have made a code to apply histogram equalization to all the images using python opencv library. The pseudo code is mentioned below:

```
equalize(){  
H, S, V = cv2.split(cv2.cvtColor(image, cv2.COLOR_BGR2HSV))  
eq_v = cv2.equalizeHist(V)  
eq_image = cv2.cvtColor(cv2.merge([H, S, eq_V]), cv2.COLOR_HSV2RGB)  
}
```

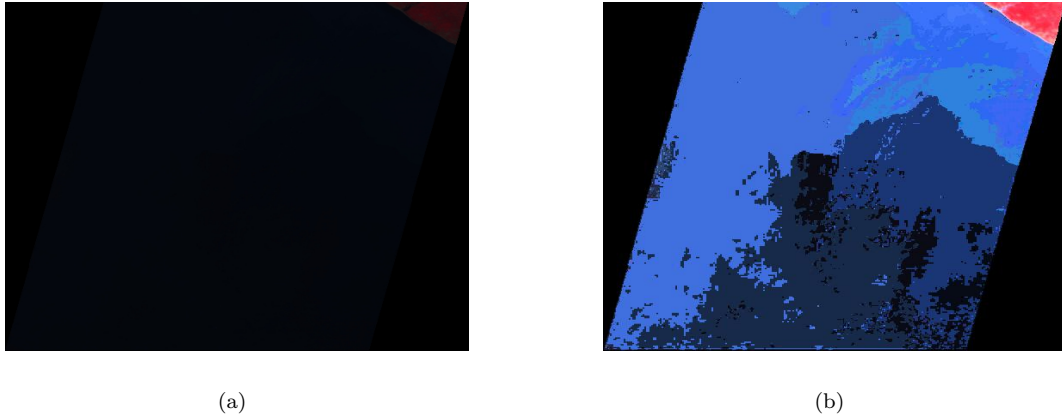


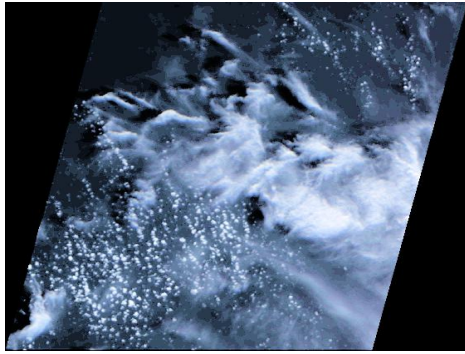
FIGURE 2.11: class 1: (a)Image before Histogram Equalization,(b)Image after Histogram Equalization

2.5 Details of Learning

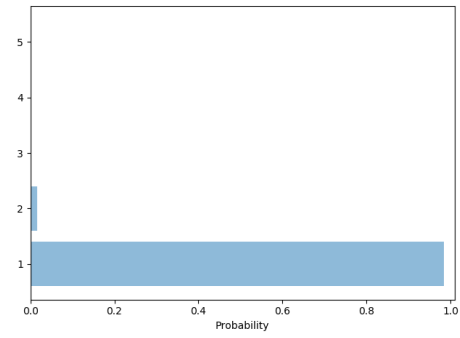
I trained my model using adam optimizer with a learning rate of 0.0014 and batch size of 100 examples. Keeping a smaller batch size helped in reducing training time per epoch. I made various experiments with the learning rate and 0.0014 learning rate was giving best accuracy. I trained the network for roughly 50 cycles through the training set consisting of 600 images.

2.6 Results

On training the model with RESOURCESAT - 2A LISS 4 satellite images as input and applying Inception-v3 transfer learning, the training accuracy was 83%, validation accuracy was 83% and testing accuracy was 80%. Figure 2.12 to Figure 2.16 show some sample images with predictions made by the model.

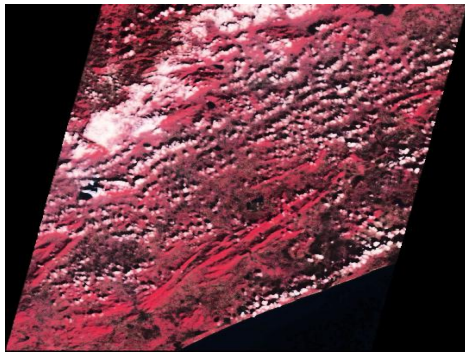


(a)

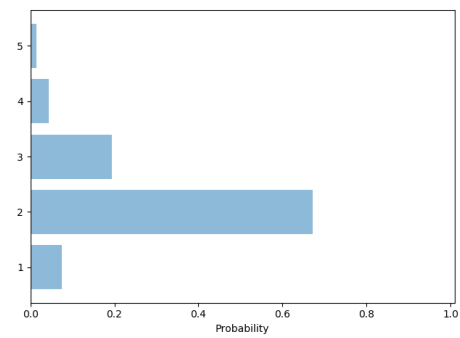


(b)

FIGURE 2.12: (a)Image belonging to class 1, (b)Model's predicted results in the form of Bar Graph showing probability of predicted classes

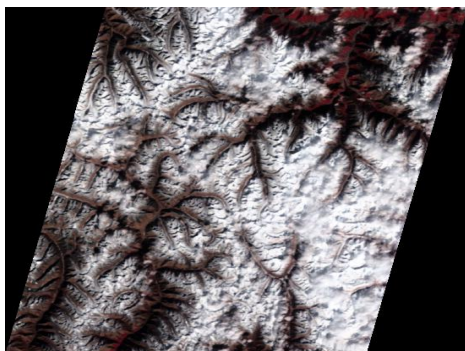


(a)

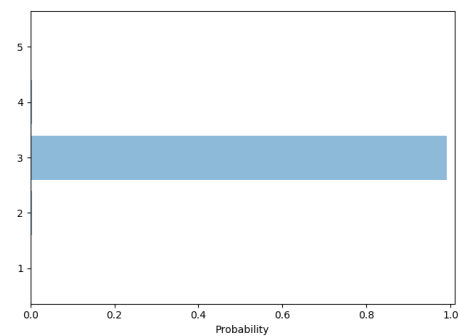


(b)

FIGURE 2.13: (a)Image belonging to class 2, (b)Model's predicted results in the form of Bar Graph showing probability of predicted classes

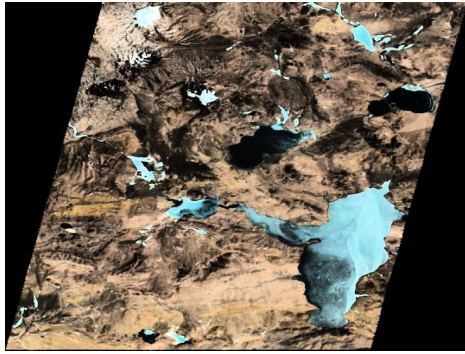


(a)

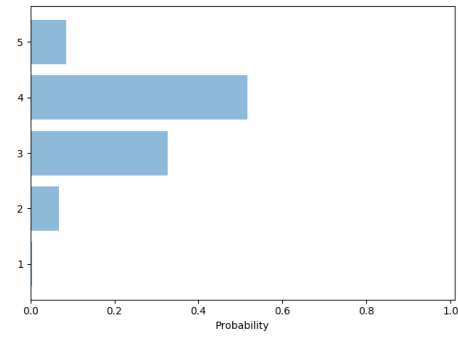


(b)

FIGURE 2.14: (a)Image belonging to class 3, (b)Model's predicted results in the form of Bar Graph showing probability of predicted classes

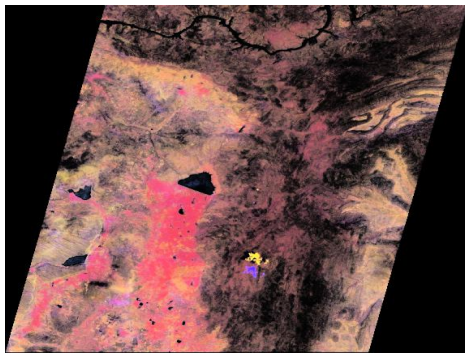


(a)

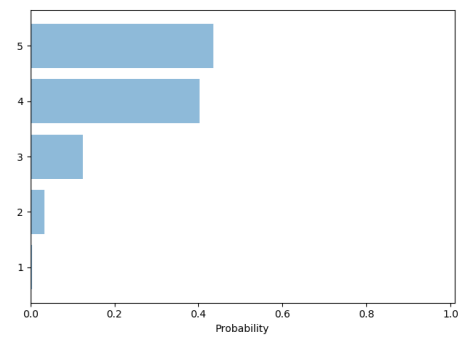


(b)

FIGURE 2.15: (a)Image belonging to class 4, (b)Model's predicted results in the form of Bar Graph showing probability of predicted classes



(a)



(b)

FIGURE 2.16: (a)Image belonging to class 5, (b)Model's predicted results in the form of Bar Graph showing probability of predicted classes

2.7 Confusion Matrix

2.7.1 What is a Confusion Matrix?

In the field of machine learning and specifically the problem of statistical classification, a confusion matrix, also known as an error matrix, is a specific table layout that allows visualization of the performance of an algorithm, typically a supervised learning one (in unsupervised learning it is usually called a matching matrix). Each row of the

matrix represents the instances in a predicted class while each column represents the instances in an actual class (or vice versa). The name stems from the fact that it makes it easy to see if the system is confusing two classes (i.e. commonly mislabeling one as another). It is a special kind of contingency table, with two dimensions ("actual" and "predicted"), and identical sets of "classes" in both dimensions (each combination of dimension and class is a variable in the contingency table).

2.7.2 Plotting the Confusion Matrix for the Model

The estimated quality classification were compared to the subjective classifications to measure the error. A Confusion Matrix has been plotted to detect confusion between the classes made by the model, which is shown in the figure 2.17.

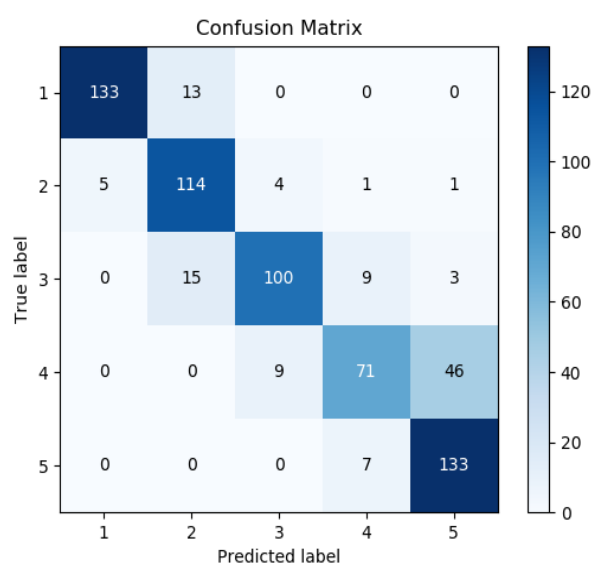


FIGURE 2.17: Confusion Matrix

Chapter 3

Summary

3.1 Advantages of model

Before this model was made, scientists used to manually classify satellite images on basis of quality which required lots of human effort and time, so this model will help them to automatically predict quality of images, thus saving their efforts and time. This model will help users to detect quality of satellite images within minutes(depends on the amount of images as input)by just running the python code for prediction.

3.2 Usefulness

The model predicts quality of Resourcesat-2A satellite images with an accuracy of 83%, so scientists can rely on this model to predict quality and extract required images for their work.

3.3 Future work

Future planning is to increase accuracy of the model by providing more images for training especially of class 4 and class 5, because the model is getting confused between classes 4 and 5 as seen in figure 2.17.

Appendix A

An Appendix

A.1 BUSINESS MODEL CANVAS

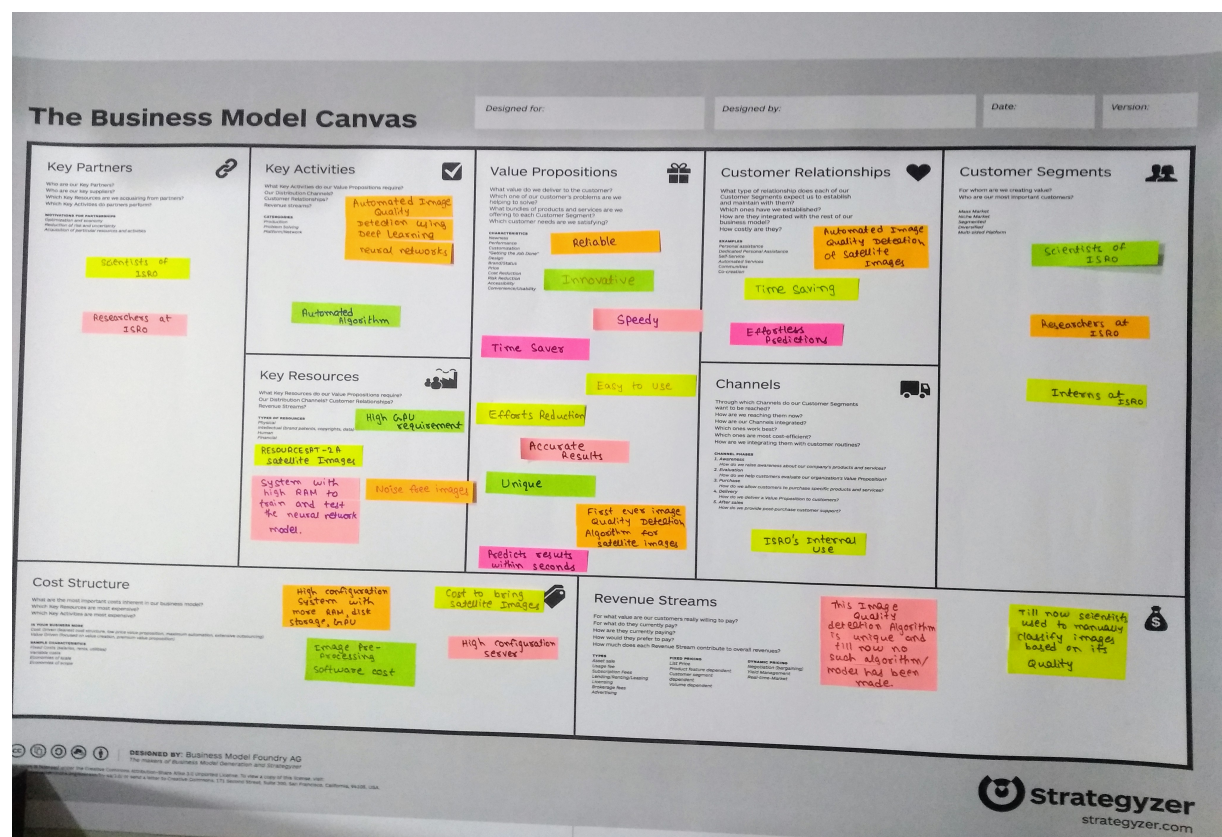


FIGURE A.1: Business Model Canvas

A.1.1 KEY PARTNERS

- Scientists at ISRO: Scientists will use this algorithm to detect the quality of satellite images.
- Researchers at ISRO: Researchers will use this algorithm to detect the quality of satellite images.

A.1.2 KEY ACTIVITIES

- Automated Image Quality Detection using Deep Learning Neural Networks.

A.1.3 KEY RESOURCES

- High GPU Requirement.
- RESOURCESAT-2A Satellite images.
- System with high RAM to train and test the neural network model.
- Noise free images.

A.1.4 COST STRUCTURE

- High configuration system with more ram, more disk storage and GPU.
- Image pre-processing software cost.
- Cost to bring satellite images.
- High configuration server.

A.1.5 VALUE PROPOSITIONS

- Reliable
- Innovative
- Speedy
- Time saver
- Easy to use
- Efforts reduction
- Accurate results
- Unique
- Predicts results within seconds

A.1.6 CUSTOMER RELATIONSHIPS

- Automated image quality detection of satellite images.
- Time saving.
- Effortless predictions.

A.1.7 CHANNELS

- For ISROs Internal use.

A.1.8 REVENUE STREAMS

- This image quality detection algorithm is unique and till now no such algorithm / model has been made.
- Till now scientists used to manually classify images based on its quality.

A.1.9 CUSTOMERS SEGMENTS

- Scientists at ISRO.
- Researchers at ISRO.

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