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Forest Fire Detection using Satellite Imagery

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Aim & Objectives

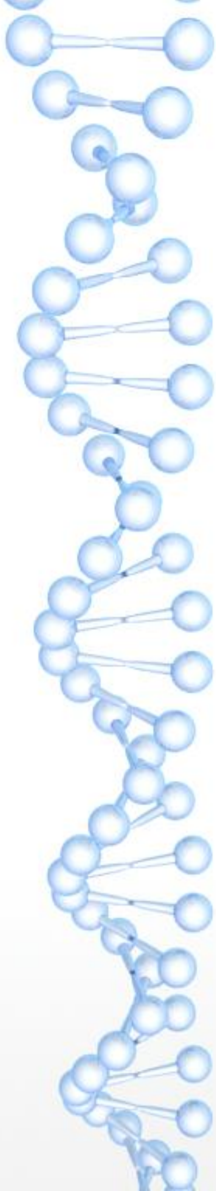
- Forest Fires are not a sudden incidents they occur in steps and the focus is to detect it in latest possible stage.
- Detecting features directly from a raw image is not so efficient as compared to doing same after applying image processing over it.
- The colour quantized image give us best extracted features from any raw image which leads to a better model performance.
- Detecting nearby local areas to find the sensitivity of incident.
- Providing an optimal solution recover the fire.

Project Introduction

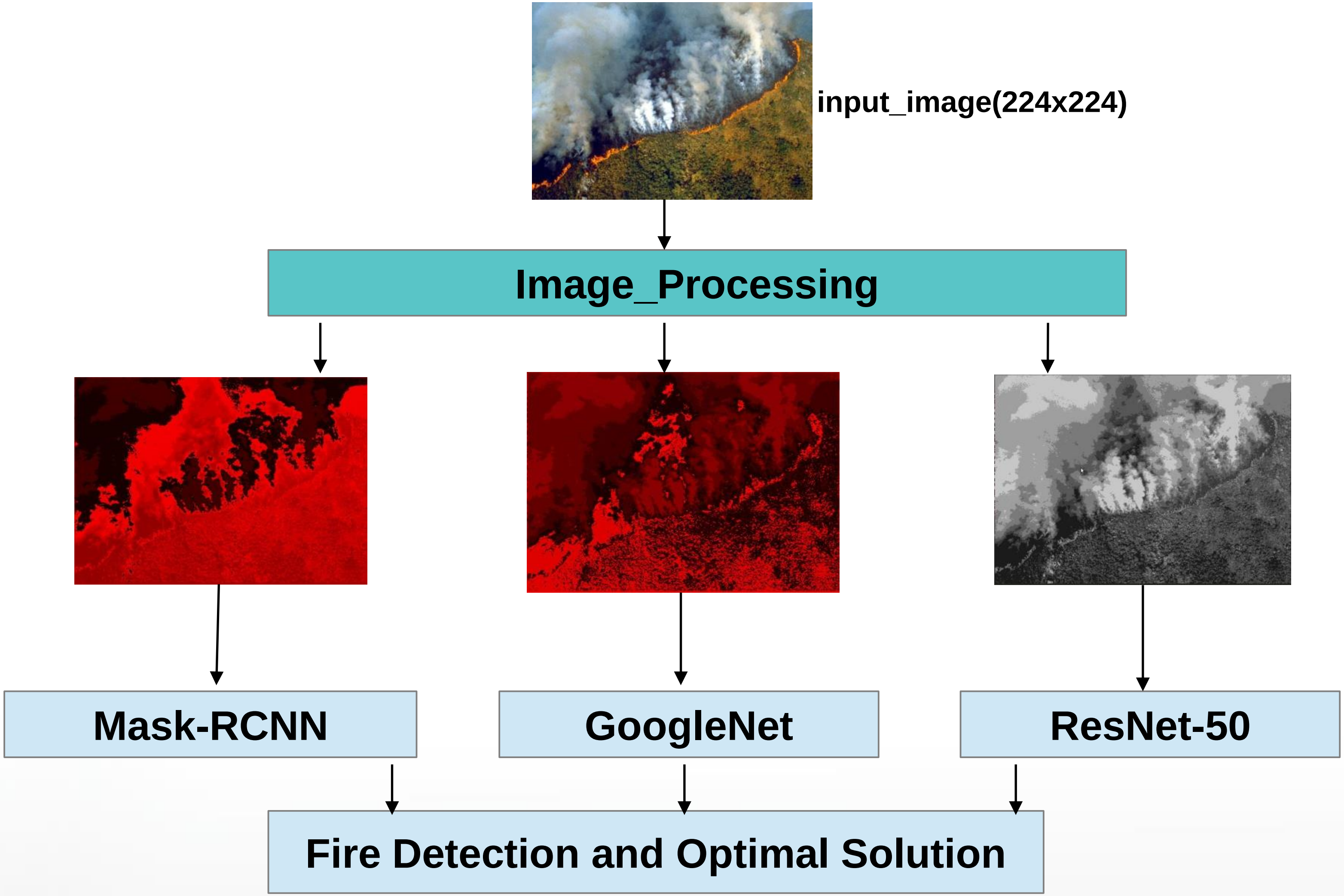
- Forest fire is a major concern as it causes huge damage to environment. Forest fire detection and coming up with optimal solution is a challenge.
- Technique that proved to be best for forest fire detection is pseudo-color processing for infrared forest-fire image.
- Imagery of the entire land surface of earth at 3-5 meter resolution are available and a coarse-resolution imagery from Landsat(30 meter pixels) or MODIS (250 meter pixels).

LITERATURE SURVEY

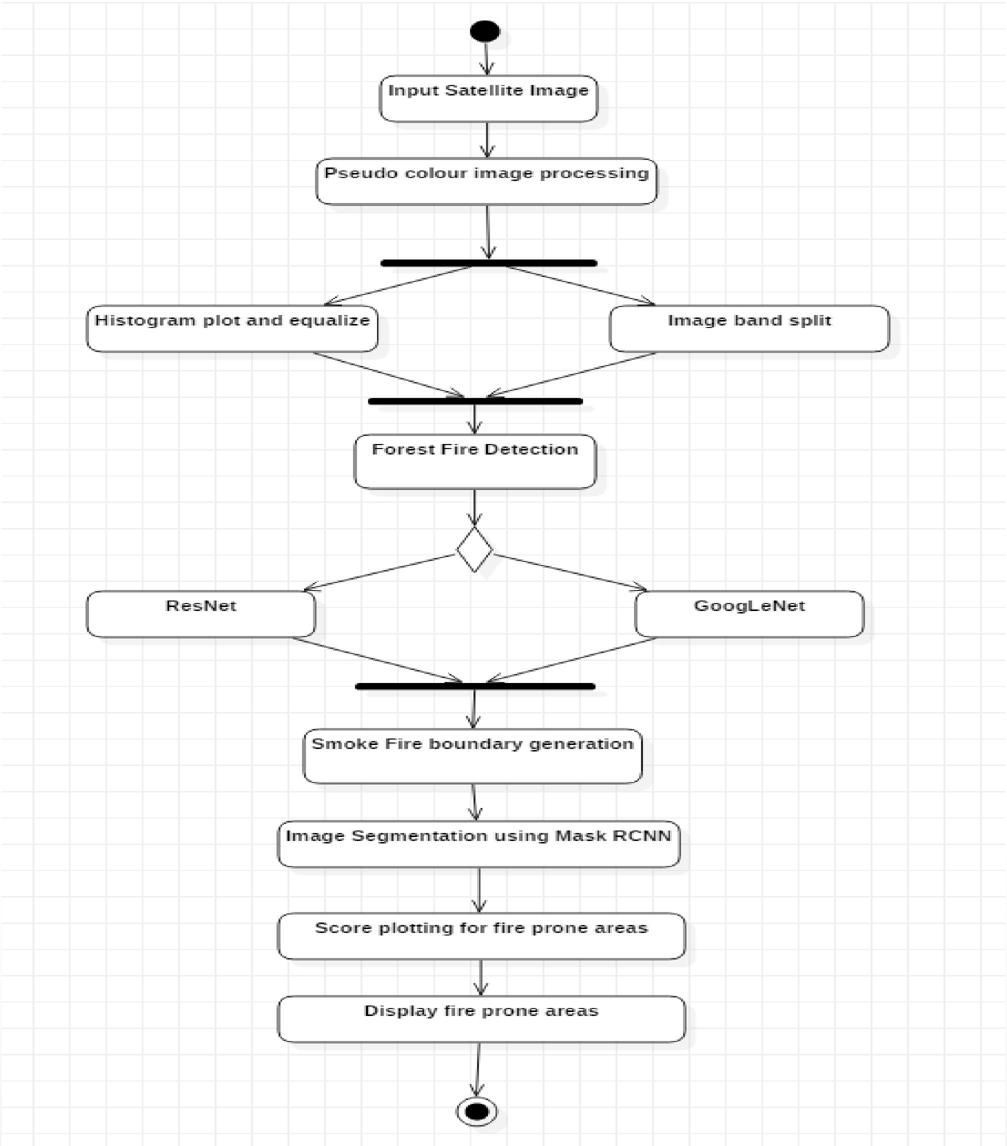
AUTHOR NAME	TITLE	MAJOR FINDING
Kaiming He , Georgia Gkioxari Piotr Dollár ,Ross Girshick	Mask R-CNN, Facebook AI Research (FAIR)	High-quality segmentation mask for each instance,extends Faster R-CNN
Daniel Gardner , David Nichols	Multi-label Classification of Satellite Images with Deep Learning , Stanford University	Convolutional Neural Network (CNN) model to perform multi-label classification of Amazon satellite images. Our model identifies the weather conditions and natural terrain features in the images as well as man-made developments such as roads, farming, and logging.
Anju Unnikrishnan , Sowmya V, Soman K P	Deep AlexNet with Reduced Number of of Trainable Parameters for Satellite Image Classification	Two Band AlexNet architecture for satellite image classification
Grant J. Scott,Matthew R. England,William A. Starms, Richard A. Marcum (Member of IEEE)	Training Deep Convolutional Neural Networks for Land–Cover Classification of High-Resolution Imagery	Deep convolutional neural network (DCNN), deep learning, high-resolution remote sensing imagery, land–cover classification, transfer learning (TL)
Shenquan Qu, Ying Wang, Gaofeng Meng, and Chunhong Pan (Institute of Automation, Chinese Academy of Sciences)	Vehicle Detection in Satellite Images by Incorporating Objectness and Convolutional Neural Network	Vehicle detection, Binary Normed Gradients (BING), Convolutional Neural Network (CNN), objectness
Adrian Albert , Jasleen Kaur , Marta C. González (Massachusetts Institute of Technology)	Using Convolution Networks and Satellite Imagery to Identify Patterns in Urban Environments at a Large Scale	Satellite imagery, land use classification, convolutional networks
Tingting Wang , Jianmin Su Yinglai Huang ,Yingshen Zhu (Harbin Institute of Technology)	Study of the pseudo-color processing for infrared forest-fire image	Processing the forest-fire image of detected by using the technology of pseudo-color to improve the amount of useful information is one of the most important of forest-fire detection.
Patrick Helber , Benjamin Bischke , Andreas Dengel , Damian Borth (TU Kaiserslautern, Germany)	EuroSAT: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification	Remote Sensing, Earth Observation, Satellite Images, Satellite Image Classification, Land Use Classification, Land Cover Classification, Dataset, Machine Learning, Dee Learning, Deep Convolutional Neural Network



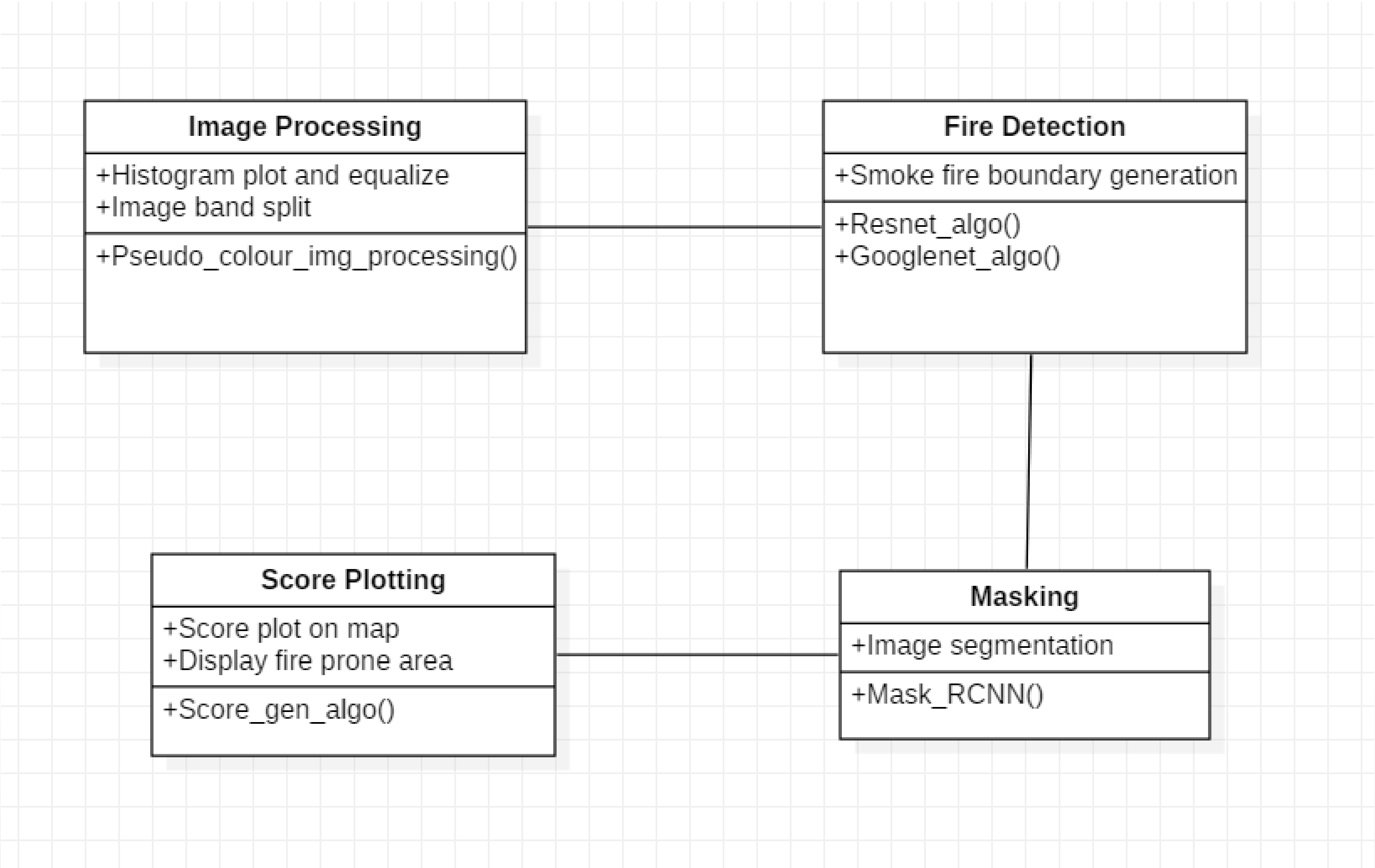
Project Workflow


input_image(224x224)
Image_Processing
Mask-RCNN
GoogleNet
ResNet-50
Fire Detection and Optimal Solution

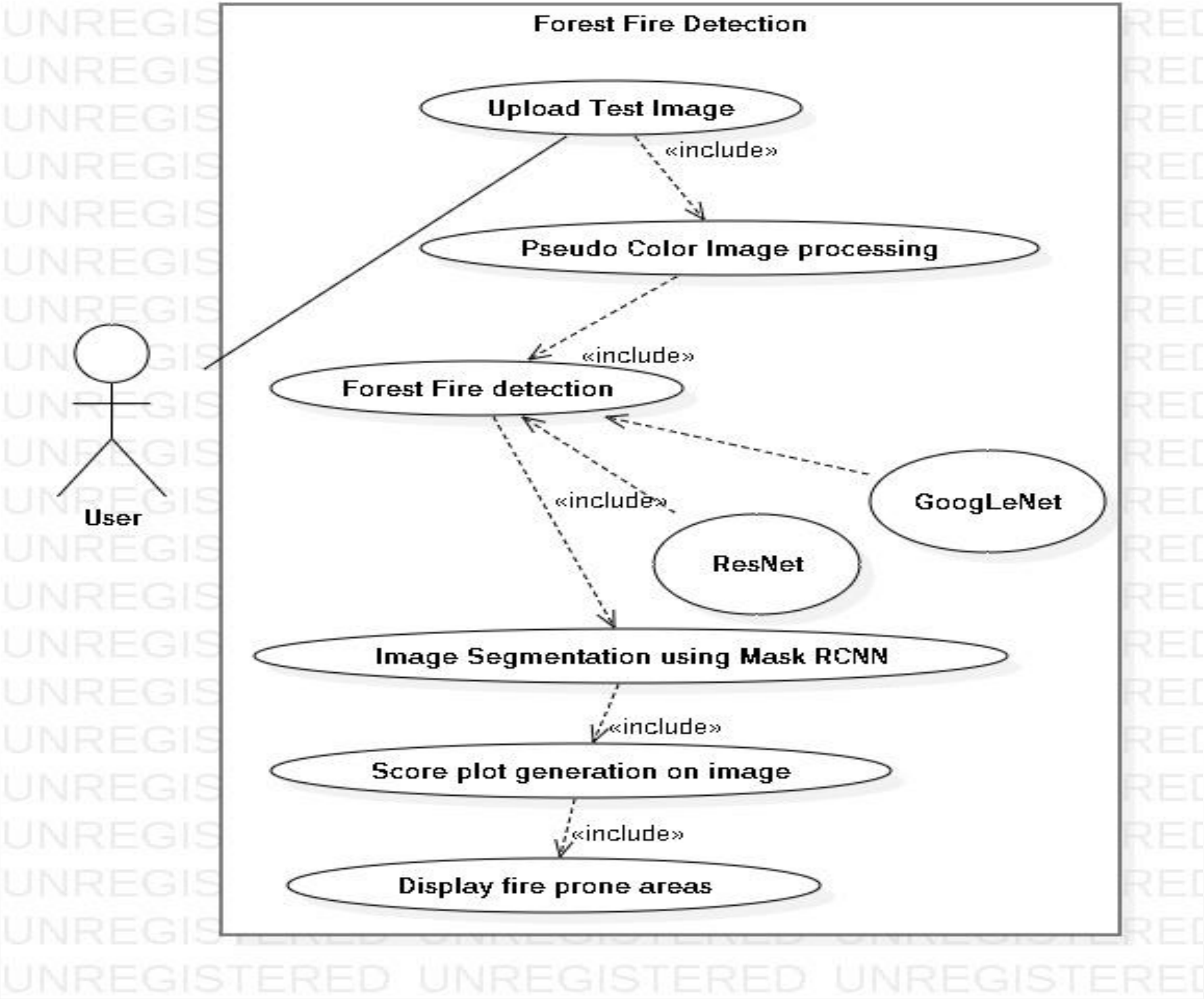
ACTIVITY DIAGRAM



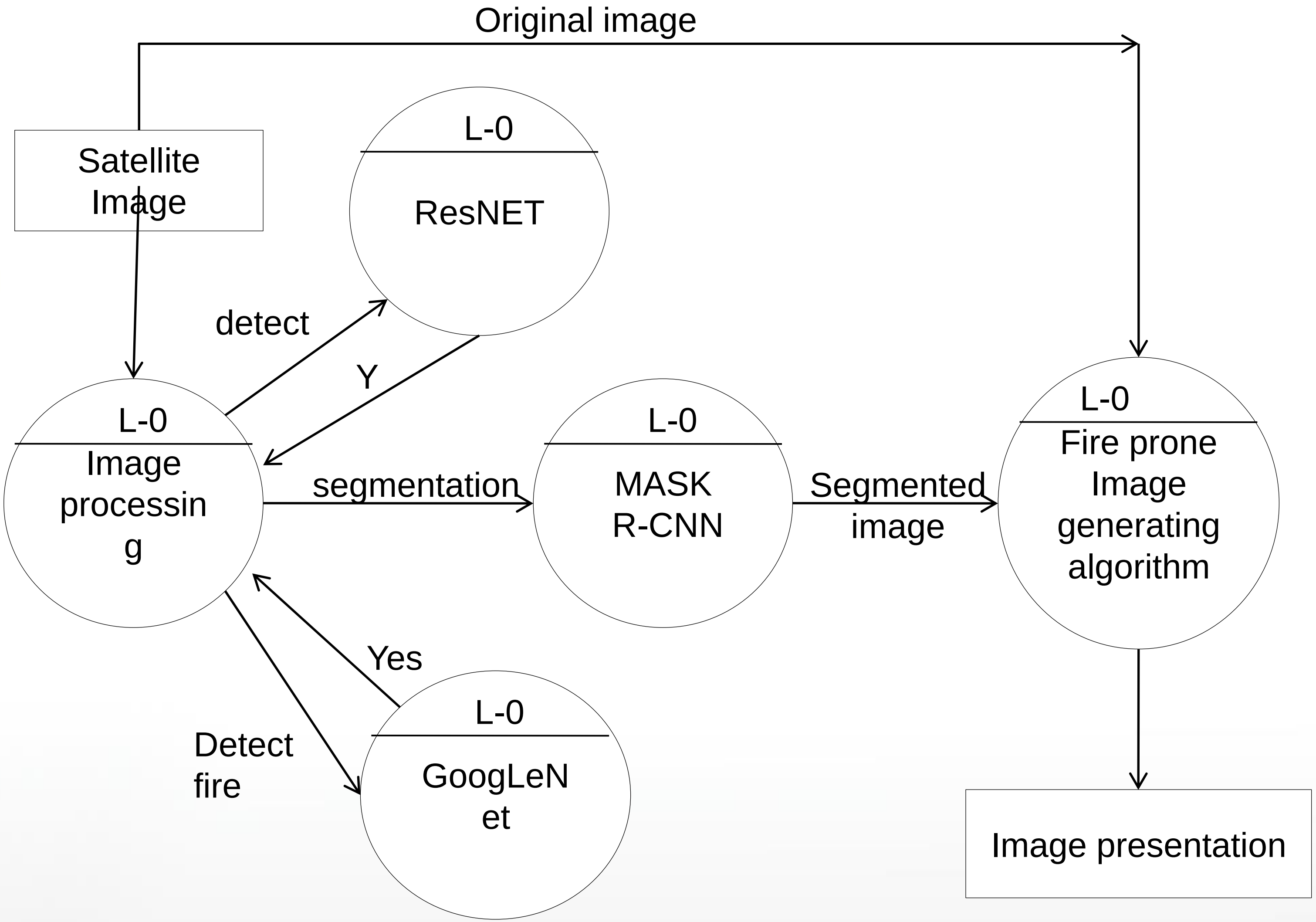
CLASS DIAGRAM

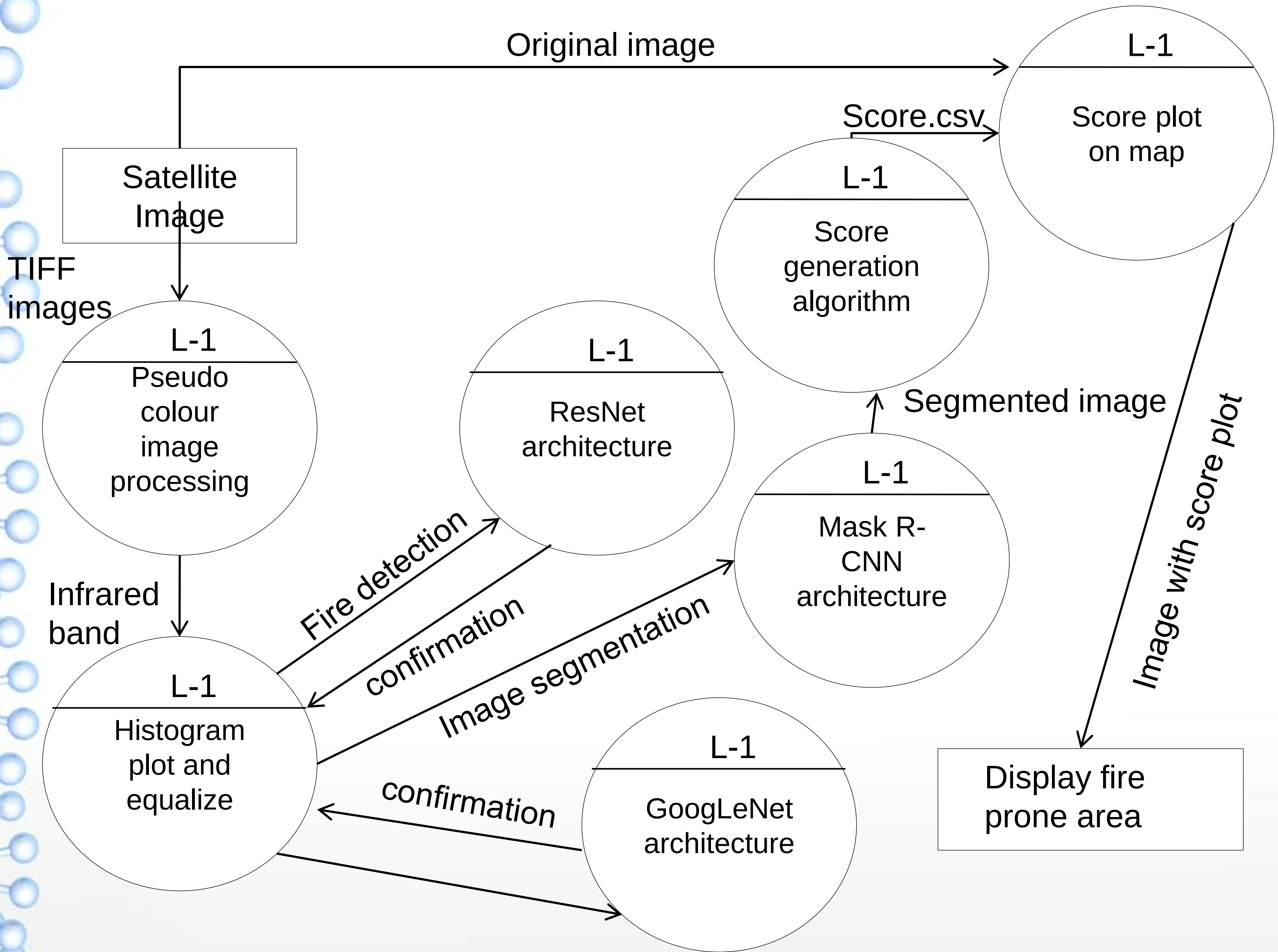


USE CASE DIAGRAM

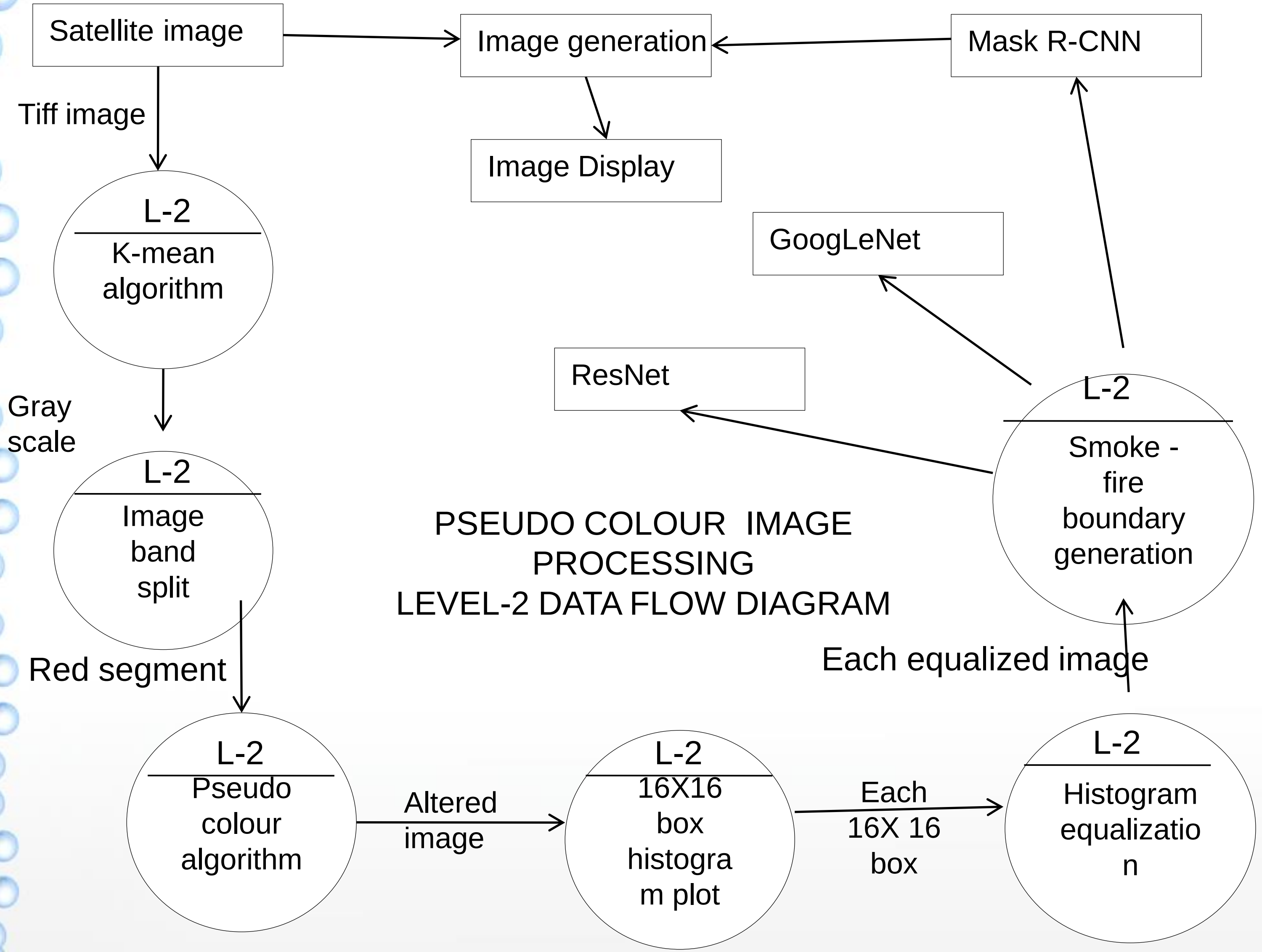


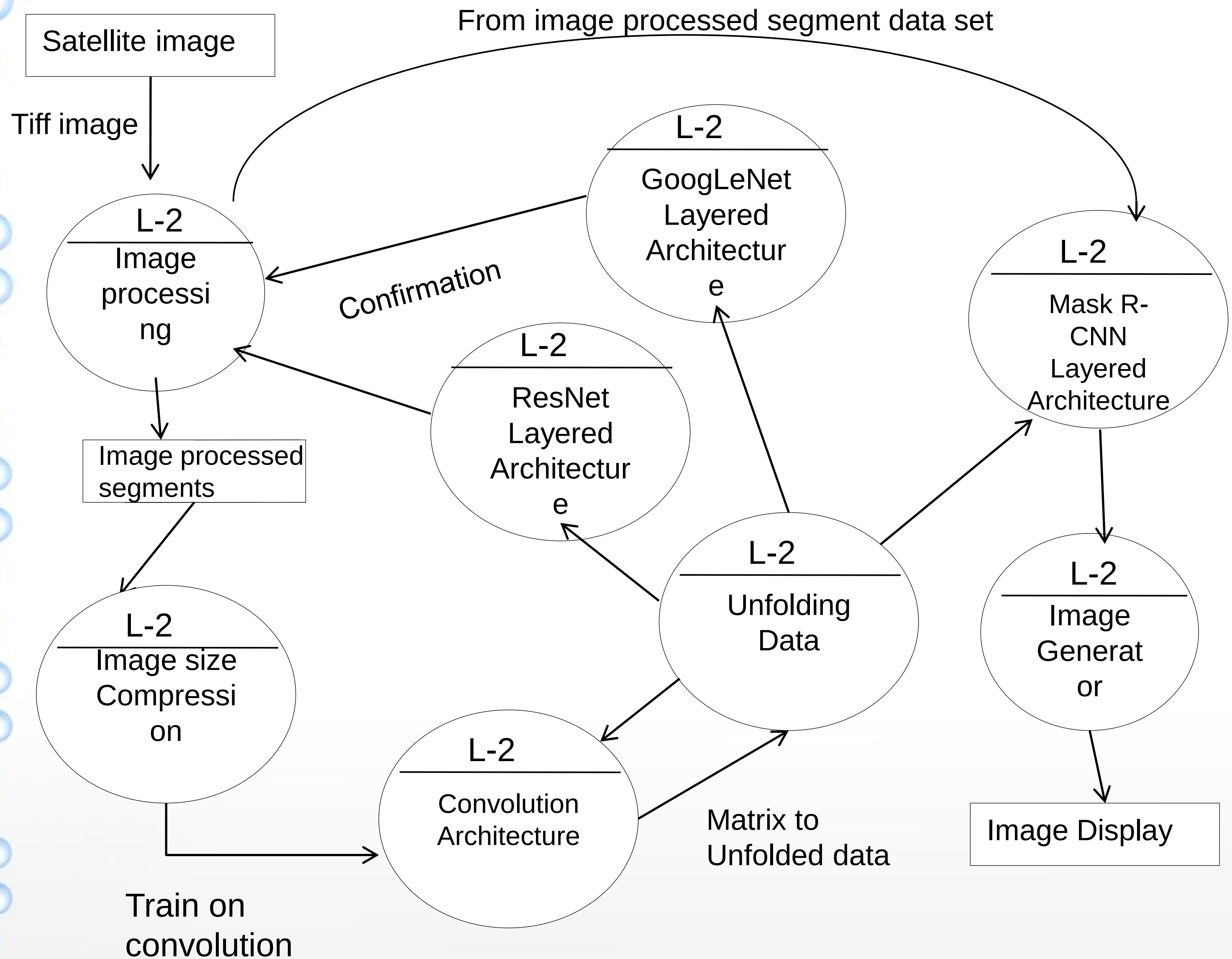
DATA FLOW DIAGRAM


Original image
Satellite Image
L-0
ResNET
detect
Y
L-0
Image processin g
segmentation
L-0
MASK R-CNN
Segmented image
L-0
Fire prone Image generating algorithm
Yes
Detect fire
L-0
GoogLeN et
Image presentation


Original image
L-1
Score plot on map
Score.csv
Satellite Image
L-1
Score generation algorithm
TIFF images
L-1
Pseudo colour image processing
L-1
ResNet architecture
Segmented image
L-1
Mask R-CNN architecture
Image with score plot
Infrared band
Fire detection
confirmation
Image segmentation
L-1
Histogram plot and equalize
L-1
GoogLeNet architecture
confirmation
Display fire prone area

PSEUDO COLOUR IMAGE PROCESSING
LEVEL-2 DATA FLOW DIAGRAM





Satellite image
Tiff image
From image processed segment data set
L-2
Image processing
Confirmation
L-2
GoogLeNet Layered Architecture
L-2
Mask R-CNN Layered Architecture
L-2
ResNet Layered Architecture
Image processed segments
L-2
Unfolding Data
L-2
Image Generator
L-2
Image size Compression
L-2
Convolution Architecture
Matrix to Unfolded data
Image Display
Train on convolution

Pseudo Color Image Processing

- It deals with **different grey-scale transforms of the grey image into different colours with different linear or nonlinear mapping functions.**

- The wild-fire image typically includes flame, some fire, smoke coverage area, the background.

- Flame can be divided into three parts: outer flame, inner flame, and centre of the flame.

- The temperature of outer flame is the highest, followed with in flame, then the centre of the flame, resulting in the gray level of flame image distributes in a certain form.

Principles of Forest-Fire Image Coloring

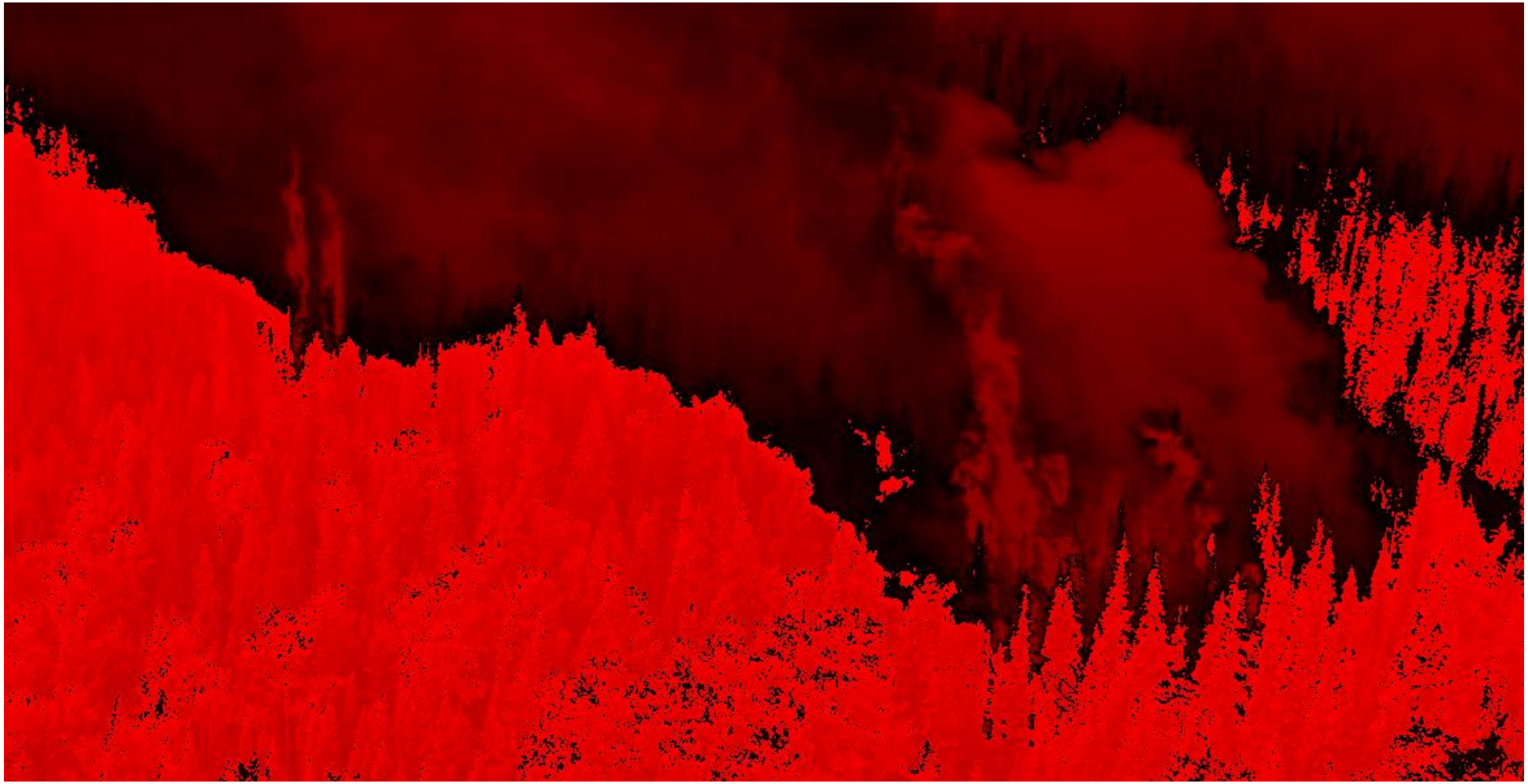
- We divide the image into two regions: the foreground of the image, areas covered by smoke, and the background.

- The gray values of the foreground concentrate between 0 and 128, according to gray value, we change the gray value of pixels into the values between white and yellow.

- The smaller of the grey value, the more light-coloured, the greater of the grey value, the more darken-coloured.

- The greater of the gray value the deeper of the red colour, the smaller of gray colour, the lighter of the red colour.

Fig 1 : R component of Normal image



Img 2 : Pseudo colour based filtered image

Histogram partial equalization

•**The background or burning parts of the forest - fire infrared images occupy most of the gray-scale. Flame, some fire, smoke parts occupy less.**

• When the contrast is weak, and the histogram distribution concentrates in the low gray level, background of the coded image is blur, and its details are loss seriously.

• The **gray levels of the area covered by smoke is in the middle gray-scale**, due to the impact of light and other factors, they may become higher.

• **The area covered by smoke may mistake for part of the flame.**

- For the above factors, **it proposes the partial histogram equalization to reduce the error** and increase the effect of pseudo-colour processing.

Histogram partial equalization

- Histogram statistical analysis is carried out, and based on the gray value distribution, we divide it into different local histograms.

- We analyze the rates of local histogram of the gray changing and its corresponding gray-scale, do **partial equilibrium to the histogram the gray value of which is at around 128.**

- **Using this algorithms for infrared image processing smoke, background and flames can be clearly distinguished.**

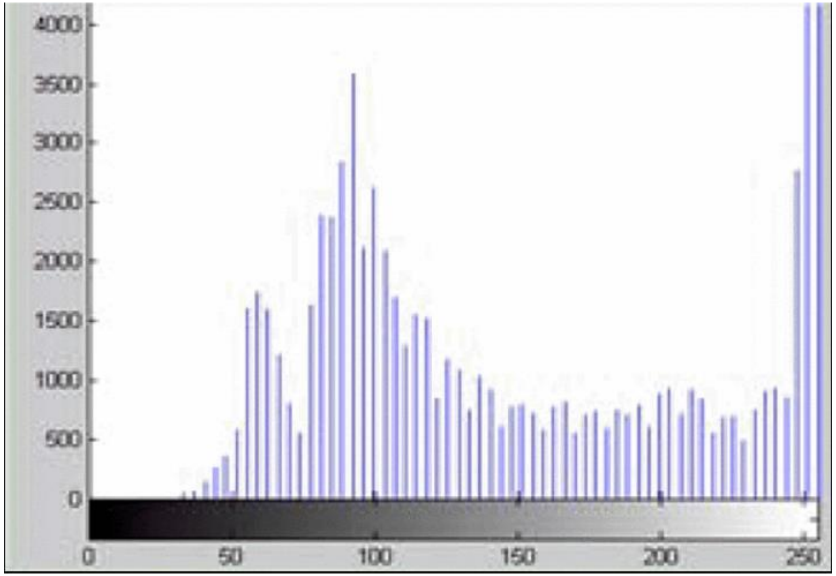
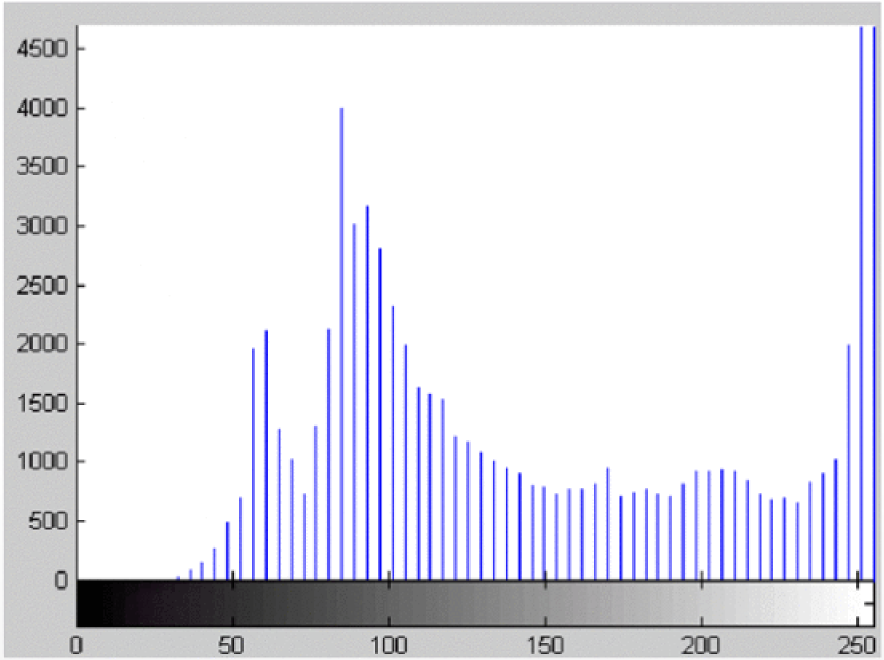


Fig 3 : Histogram distribution of Red colour after pseudo colour image processing [1]

Fig 4 : Histogram equalized b/w 120 to 150 of red colour[1]



MASK R-CNN

- Mask R-CNN extends Faster R-CNN to pixel-level image segmentation.
- Based on the framework of Faster R-CNN, it added a third branch for predicting an object mask in parallel with the existing branches for classification and localization.
- The mask branch is a small fully-connected network applied to each RoI , predicting a segmentation mask in a pixel-to-pixel manner.

MASK R-CNN NETWORK ARCHITECTURE

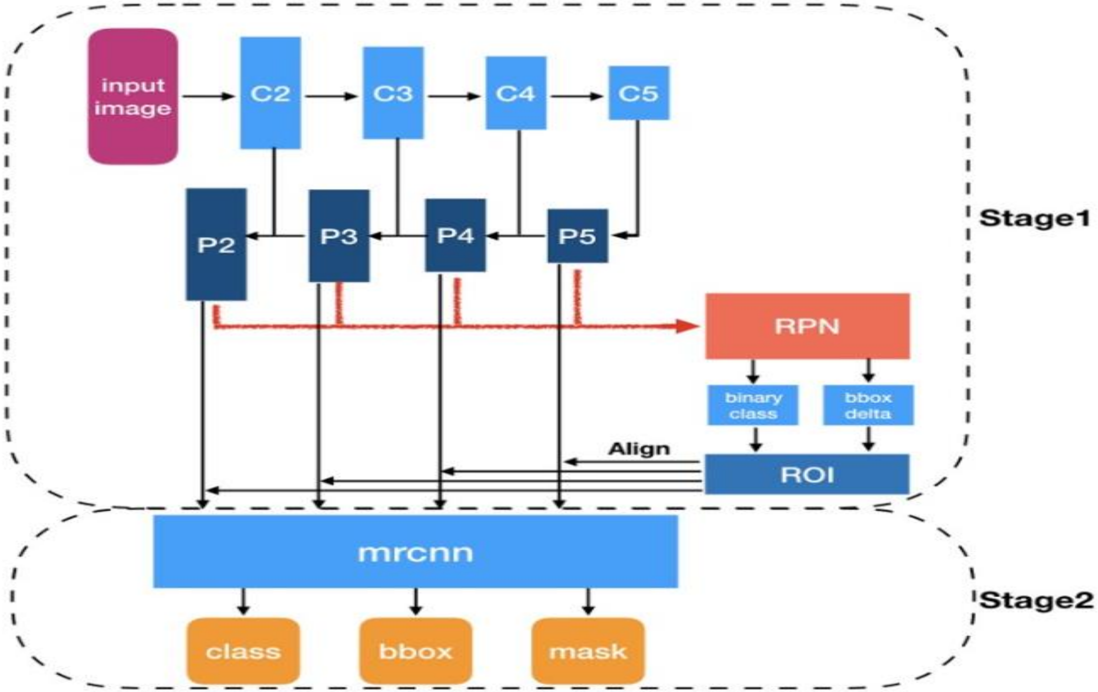


Fig 5: Two Stage Architecture[2]

MASK R-CNN RESULT

Fig 6: Masked Result [2]

GoogLeNet

- Main goal of using GoogLeNet is to detect the fire from satellite imagery.
- For faster and real time detection of fire on satellite imagery , GoogleNet ensures efficiency of computation.
- 12 times lesser parameters than AlexNet and significantly more accurate than AlexNet.
- Lower memory-use and lower power-use acutely important for mobile devices.
- Computational cost less than 2X compared to AlexNet.

Working of GoogLeNet

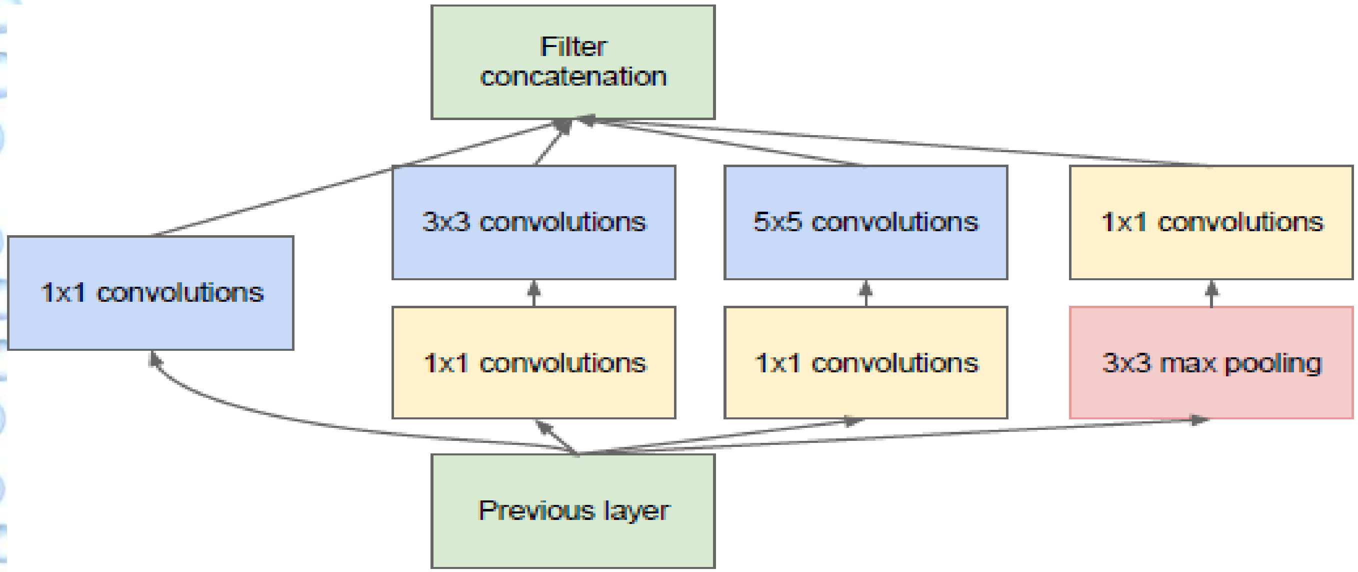


Fig 7. Inception module in GoogLeNet[3]

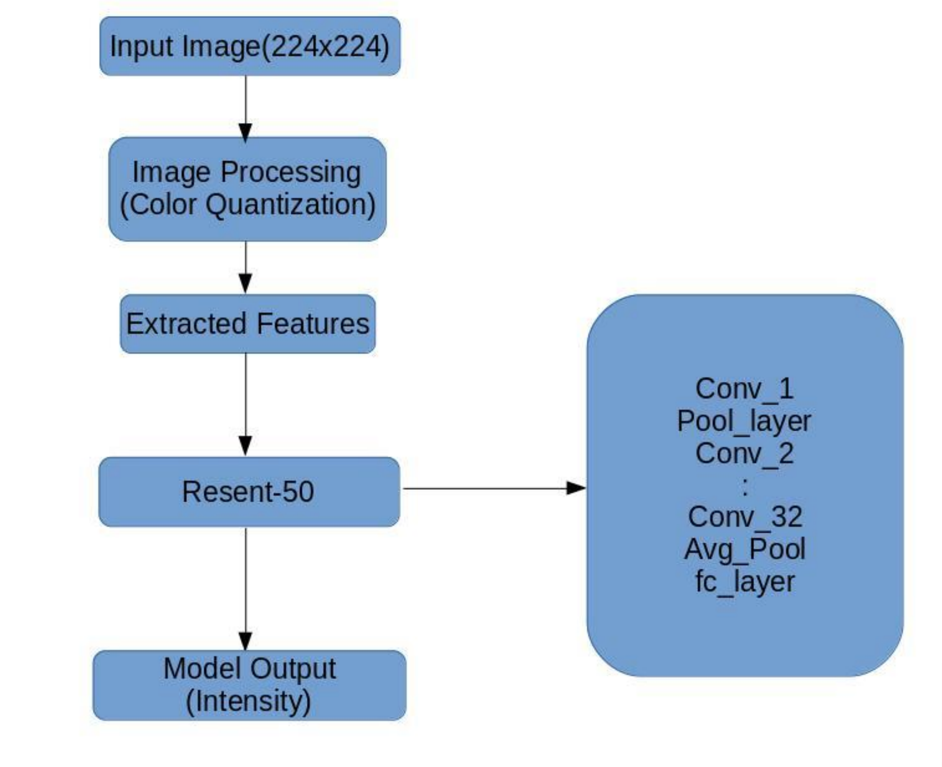
Resnet-50

- Instead of learning a direct mapping of x to y with a function H(x) (A few stacked non-linear layers). Let us define the residual function using F(x) = H(x)-x, which can be re-framed into H(x) = F(x)+x, where F(x) and x represents the stacked non-linear layers and the identity function(input=output) respectively.

- Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously.

- We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions.

Resnet-50 Model Architecture



Implementation

Satellites
KEEP CLAM
AND
CLICK IMAGES,
RESNET
is on
WORK.

Hyperparameter Tunning

- Learning rate
- No.of epochs
- Batch Size
- Activation Function
- No. of Hidden Layers
- Weight Initialization
- Feature extraction

Applications of Satellite Imagery

- There are currently over 4500 satellites orbiting the Earth. Over 600 of them are regularly taking pictures of the Earth's surface.
- Object Detection over earth's surface is an interesting task to keep an eye over activities.
- Traffic Monitoring, Intrusion Surveillance, Ship Detection on Oceans, Advancing Agriculture is huge field of study which enriches farmers activity.

CONCLUSION

The fire is detected using inception module over aerial video that contains real-time forest fire.

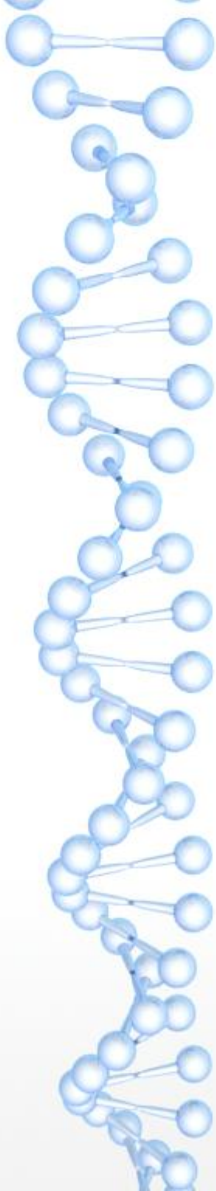
For feature extraction pseudo-color image processing is used and quantized images are generated. These methodology will reduce the computation time.

Future Plan:

Collecting the dataset of satellite forest fire images and train the model over quantized images.

REFERENCES

[1] Patrick Helber Et al. *A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification,IEEE Conference on Computer Vision and Pattern Recognition Workshops, 1 Feb 2019.*
[2] Grant J. Scott Et al., *Training Deep Convolutional Neural Networks for Landˆ aCover Classification of High-Resolution Imagery, IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, VOL. 14, NO. 4, APRIL 2017*
[3] KHAN MUHAMMAD Et al., *Convolutional Neural Networks Based Fire De- tection in Surveillance Videos, IEEE ACCESS, April 23, 2018.*
[4] Ziqi Zhu Et al., *Extreme Weather Recognition using A Novel Finetuning Strat- egy and Optimized GoogLeNet , International Journal of Computer Vision , 2016.*



THANK YOU!!