A Mini Project Synopsis

On

Land cover classification with Deep Learning

Submitted in partial fulfillment of the requirement of
University of Mumbai for the Degree of

Bachelor of Engineering

In

Information Technology

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SYNOPSIS APPROVAL FOR B.E

This TE Mini Project Synopsis entitled "**Land cover classification with Deep Learning**" by **Raj Rajeshwari Bajre, Lovkesh Sharma, and Mahesh Mahajan** are approved for the degree of B.E. in **Information Technology**.

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Declaration

We declare that this written submission for TE Mini Project Synopsis Declaration entitled "**Land cover classification with Deep Learning**" represent our ideas in our own words and where others' ideas or words have been included. We have adequately cited and referenced the original sources. We also declared that we have adhere to all principles of academic honesty and integrity and have not misrepresented or fabricated or falsified any ideas / data / fact / source in our submission. We understand that any violation of the above will cause for disciplinary action by institute and also evoke penal action from the sources which have thus not been properly cited or from whom paper permission have not been taken when needed.

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Abstract

Recognizing the physical aspect of the Earth's surface as well as how it is used is a challenging problem in environment monitoring. This can be done by analysing Satellite images, Drone images or Very High Resolution (VHR) Satellite images, or through field surveys. With recent development in the space technology machine learning and deep learning have shown some promising results in the field of land cover classification. In this project satellite or drone images are used to classify the land cover into some classes namely residential, forest area, roads, water bodies, vegetation, slum etc. Objective is to use an ensemble of convolutional neural network (CNN) as deep learning framework approach for land cover mapping. The VHR satellite images are given as input to CNN layers for land classification.

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Chapter 1

Introduction

1.1 Fundamentals

Machine Learning

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. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves.

Deep learning

Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, semi-supervised or unsupervised.

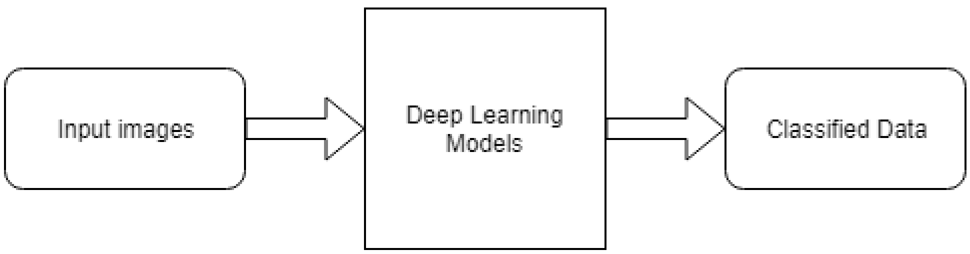


Figure 1.1 Concept of Deep Learning

1.2 Objectives

- To classify land cover using Deep Learning methods.
- To help organizations in finalizing appropriate location for placing their project.
- To help support the social cause “Swachh Bharat Abhiyan” by detecting the garbage heaps.
- Checking cracks in the existing projects (i.e. bridges, buildings and roads).

1.3 Scope

Land cover land use classification helps us to classify the images into several categories like forest, residential areas, water bodies, roads, etc. Aerial images give bird eye view which will help our application to detect cracks in buildings, bridges and roads. Aerial images can also be used to detect objects like garbage heaps, dustbins, etc.

1.4 Outline

Chapter 1 gives us introduction to the concept of land cover and land use classification. Chapter 2 consists of literature survey wherein we have studied various other previous works done in land cover classification domains. The techniques and methodologies used by them helps us to determine their shortcomings and overcome them in our project. It describes the pros and cons of each technique. The Chapter 3 presents the Theory and proposed work. The proposed approach or solution to the problems is discussed in brief. Applications of this classification of land in different domains are specified. The summary of the report is presented in Chapter 5.

Chapter 2

Literature Survey

2.1 Introduction

Recognizing the physical aspect of the Earth's surface as well as how it is used is a challenging problem in environment monitoring. Land cover classification deals with the classification of how much region is covered by forest, wetlands, impervious surfaces, agriculture, and other land and water types.

2.2 Summary of Literature Survey

Machine Learning

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. Machine learning focuses on the development of computer programs that can access data and use it learn for themselves.

Maximum likelihood

Maximum Likelihood Classification used by Author Nur Anis Mahmon [**citation**] is a statistical decision criterion to assist in the classification of overlapping signatures, pixels are assigned to the class of highest probability. The Maximum Likelihood classifier are considered to provide more accurate results compare the minimum distance classification, but it is slower due to the extra calculation. It was found that the maximum likelihood method gives more accurate result and both Minimum distance and Mahalanobis distance method trivia agricultural land and urban areas.

Support Vector Machine

SVM is used by supervised classification system SVM is based on statistical learning. SVM is used for classification and regression. Different applications of SVM are face identification, text categorization, bioinformatics, database mining, handwritten character recognition and time series analysis [2]. Testing and training is separated by SVM classifier. Several attributes and one target value is present in each instance in training set. Concept of decision surface is used in SVM. It is used to separate the classes in order to maximize the class margin. The decision surface is also known as optimal hyperplane. Support vectors are defined as data points close to decision surface. In training sample set creation key elements are support vectors.

Some variations of SVM are:

1) SVM can be modified by using nonlinear kernels to obtain a nonlinear classifier and

2) It can also be modified as multiclass classifiers by clubbing large number of SVM classifiers that are binary [10]. It minimizes number of misclassification. It is independent of feature dimensionality and produces accurate result. In SVM solution depends upon selection of kernel.

Deep Learning

Deep learning (also known as deep structured learning or hierarchical learning) is part of a broader family of machine learning methods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, semi-supervised or unsupervised.

CNN

In deep learning, a **convolutional neural network** (**CNN**, or **ConvNet**) is a class of deep neural networks, most commonly applied to analyzing visual imagery.

CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.

Machine learning techniques [1] such as nearest neighbor algorithm, decision tree, support vector machine, random forest, naïve bayes classifier has been used for land cover prediction from satellite imagery. The input features are collected from satellite image using time-series normalized difference vegetation index (NDVI). The output for six class classifications is impervious, forest, orchard, farm, grass and water. To balance the data in each class synthetic minority over- sampling technique (SMOTE) has been used. All the work has been carried out using python software. The highest accuracy is obtained using k-NN.

Google Earth [2] is a source of high spatial resolution images. The freely available Google Earth (GE) images are utilized to generate Land use/Land cover thematic map of the highly heterogeneous landscape of typical urban scene. In this paper, we have presented Euclidean

Distance and Average Pixel Intensity based K-NN classification to classify five different land objects (Building, Water Body, Vegetation, Road Network, Bare Land). The study area chosen for this case study is Bangalore city, India. Both the methods exhibit classification error because of poor spectral reflectance properties of google earth imagery. Google maps downloader is used to download the google earth imagery. Erd as Imagine is used for mosaicking number of tiles of GE imagery. Arc map is used for geo referencing.

The different image classification methods [3] have been used to classify the Land Use and Land Cover map of Selangor district. From different three classifiers, Maximum Likelihood classification techniques produced the highest overall accuracy with 88.88% of accuracy and also the kappa coefficient which is 0.8216. Compare with the Mahalanobis and Minimum classifier give the overall accuracy and kappa value lowest which are 74.44% and 78.88%. For classes to cover the land use and land cover for this study are, five features from the image have been classified. The features are Forest, Agriculture, Water bodies, Urban and Open Land. The high resolution images gave more detail information of the classified map. The classified images could be used for Natural Resource management planning and development purposes in the future.

After analysing and comparing supervised classifiers namely minimum distance, support vector machine, maximum likelihood, and parallelepiped [4] , it is indicated that for different types of images maximum likelihood classifier gives better results in terms of kappa coefficient and overall accuracy than minimum distance and parallelepiped classifier. Overall accuracy is greater than 88% and kappa statistics is greater than 0.82 for maximum likelihood classifier for all types of images except Landsat MSS images. Overall accuracy for SVM is more than 92% for both kernels.Sigmoid function and radial basis function can be used to improve accuracy of SVM. A

The system consists of an ensemble of CNNs [5] with post-processing neural networks that combine the predictions from the CNNs with satellite metadata. On the IARPA fMoW dataset of one million images in 63 classes, including the false detection class, the system achieves an accuracy of 0.83 and an F1 score of 0.797. It classifies 15 classes with an accuracy of 95% or better and beats the Johns Hopkins APL model by 4.3% in the fMoW TopCoder challenge.

In this paper, we have addressed the challenge of land use and land cover classification. For this task, we presented a novel dataset based on remotely sensed satellite images [6]. To obtain this dataset, we have used the openly and freely accessible Sentinel-2 satellite images provided in the Earth observation program Copernicus. The proposed dataset consists of 10 classes covering 13 different spectral bands with in total 27,000 labeled and geo-referenced images. We provided benchmarks for this dataset with its spectral bands using state-of-the-art deep Convolutional Neural Network (CNNs). For this novel dataset, we analyzed the performance of the 13 different spectral bands. As a result of this evaluation, the RGB band combination with an overall classification accuracy of 98.57% outperformed the shortwave-infrared and the color- infrared band combination and leads to a better classification accuracy than all single-band evaluations.

Traditionally, semantic segmentation of aerial and satellite images [7] crucially relies on manually labeled images as training data. Generating such training data for a new project is costly and time consuming, and presents a bottleneck for automatic image analysis. The advent of powerful but data-hungry deep learning methods aggravates that situation. Here, we have explored a possible solution, namely, to exploit existing data, in our case open image and map data from the Internet for supervised learning with deep CNNs. Such training data are available in much larger quantities, but "weaker" in the sense that the images are not representative of the test images' radiometry, and labels automatically generated from external
maps are noisier than dedicated ground truth annotations.

The objective of paper was to classify and map land use - land cover (LULC) of the study area using Remote Sensing and GIS techniques [8] and also to carry out accuracy assessment in order to assess how well a classification worked. The supervised classification was performed using Non Parametric Rule. The image was classified into six classes; Agriculture (4638 km2), water body (283km2), built up areas (1309 km2), mixed forest (372 km2), shrubs (499 km2), and Barren/bare land (37 km2). Agriculture was the dominant type of Land use classified which covers about 65.0% of the total study. In addition classified image need to be assessed for accuracy, before the same could be used as input for any applications. Individual accuracy assessment parameters are useful to assess the model performance in respect of a particular category/class of specific interest for the study. In this study, accuracy assessment was performed using error matrix. The study had an overall classification accuracy of 81.7% and kappa coefficient of 0.722. The kappa coefficient is rate as substantial and hence the classified image found to be fit for further research.

Table 2.1 Literature Review

PP R No	Paper name with author.	Technique	Best Accuracy (%)	Dataset
1	Land Cover from Satellite Imagery using ML Techniques.	K Nearest Neighbour(data process with SMOTE) Decision Tree Support Vector Machine Random Forest Naive Bayes Classifier	83.33	UCI ML Database
2	Land Use Land Cover Classification of Google Earth.	KNN(Euclidean Distance & Average Pixel Intensity) Generic KNN	76.38	Google Images
3	Differences of Image Classification Techniques for Land Use and Land Cover Classification.	Maximum Likelihood, Mahalanobis Distance, Minimum distance	88.88%	Landsat MSS, Landsat TM and Landsat ETM+
4	Supervised Classification of Satellite Images.	minimum distance, support vector machine, maximum likelihood, and parallelepiped	92%	Landsat 8
5	Satellite Image Classification with Deep Learning	1. CNN(Inception-V3, DenseNet, etc) 2. Ensemble Learning 3. Transfer learning 4. Data Augmentation	Accuracy - 83% F1 Score - 0.766	
6	EuroSAT: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification	1. CNN(ResNet-50, GoogLeNet) 2. Transfer Learning 3. RGB Band combination	Accuracy - 98.57%	

7	Learning Aerial Image Segmentation From Online Maps	1. CNN 2. FCN 3. Transfer Learning (VGG16)	F1 score - 0.645	
8	Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS	1. ERDAS IMAGINE 2015 software 2. ArcGIS 10.3 software 3. Non Parametric rule used	Accuracy - 81.7 % Kappa coefficient - 0.722	

Chapter 3

Proposed System

3.1 Existing System Architecture

There have been many researches in the field of remote sensing and Land Use Land Cover (LULC) classification. The classification is done using Remote Sensing, Machine learning and Deep Learning algorithms. The research is mainly focusing on classifying the basic classes such as land, water, grassland, roads, etc. The data used for LULC are Synthetic-aperture radar (SAR) Imagery, Very High Resolution (VHR) Satellite imagery.

Nur Anis Mahmon [1] have used Maximum likelihood classifier and other remote sensing technique for classifying the Landsat-8 Satellite imagery into classes like agriculture, open land, urban, water bodies, etc. The block diagram of the research is given below:

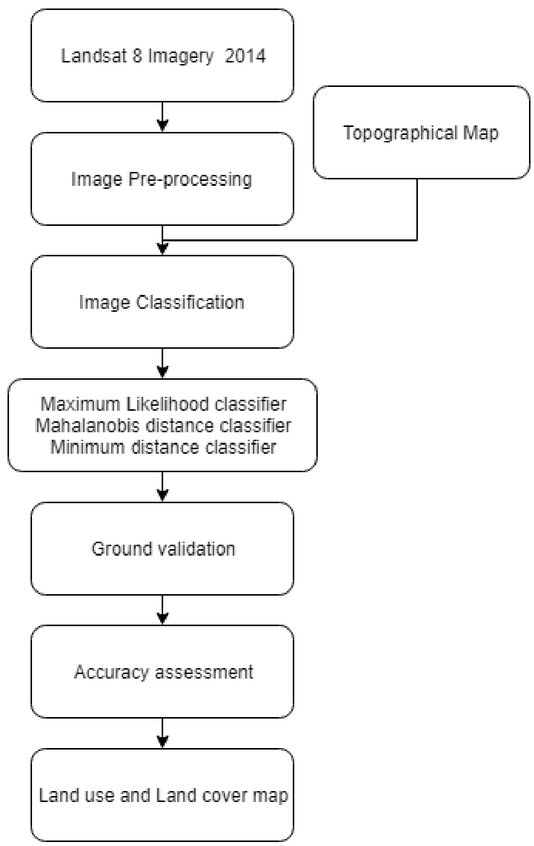


Figure 3.1 Existing Structure of research methodology [1]

Sowmya D R have used google earth imagery for land cover classification getting best accuracy of 75.04% using K-NN algorithm.

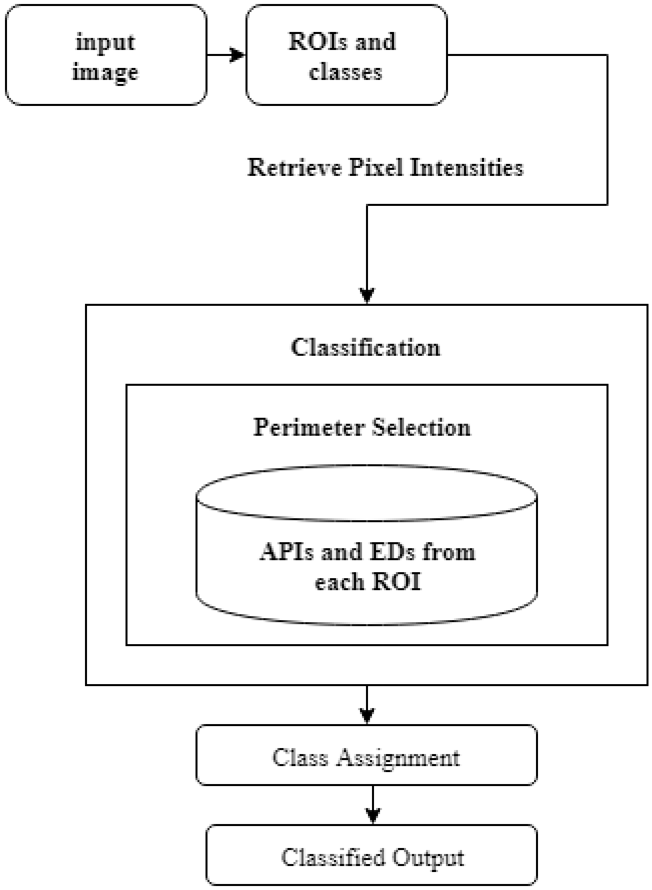


Figure 3.2 Structure of research [4]

Patrick Helber [7] have provided benchmarks for their dataset with its spectral bands using state-of-the-art deep Convolutional Neural Network (CNNs). For their novel dataset, we analyzed the performance of the 13 different spectral bands. As a result of this evaluation, the RGB band combination with an overall classification accuracy of 98.57% outperformed the shortwave-infrared and the color- infrared band combination and leads to a better classification accuracy than all single-band evaluations.

3.2 Proposed System Architecture

The previous sections discussed the strengths and weaknesses of existing system. In order to achieve better domain results, we will be using Deep Learning technique Convolutional Neural Network and Transfer Learning in order to improve the accuracy.

The proposed architecture is shown in Figure 3.3

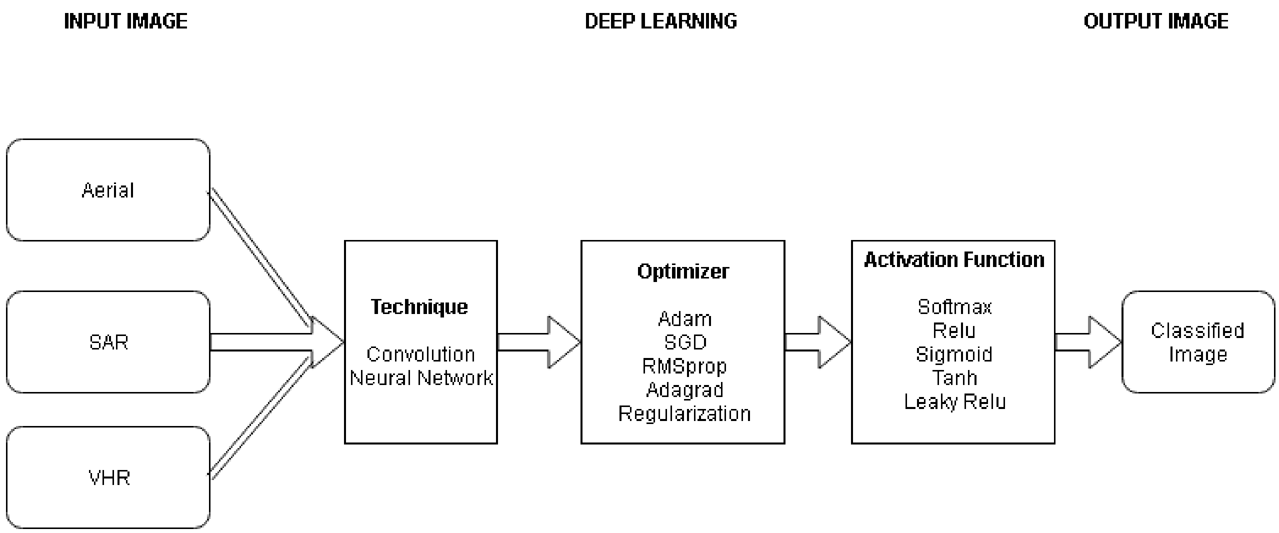


Figure 3.3 Proposed system architecture

Components of the Proposed System:

- Input Image - The input image can be of any of the three types:
    1. Aerial image: An aerial image is a projected image which is "floating in air", and cannot be viewed normally. It can only be seen from one position in space, often focused by another lens.Aerial photography is the taking of photographs from an aircraft or other flying object. Platforms for aerial photography include fixed-wing aircraft, helicopters, unmanned aerial vehicles, balloons, blimps and dirigibles, rockets, pigeons, kites, parachutes, stand-alone telescoping and vehicle-mounted poles.
    2. SAR image: Synthetic-aperture radar (SAR) is a form of radar that is used to create two-dimensional images or three-dimensional reconstructions of objects, such as landscapes. SAR uses the motion of the radar antenna over a target region to provide finer spatial resolution than conventional beam-scanning radars.
    3. VHR image: Very High Resolution (VHR) Satellite Imagery offers sub-meter resolution – one of the highest image qualities currently available from commercial remote sensing satellites.

- Deep Learning - Deep learning is a subset of machine learning in artificial intelligence (AI) that has networks capable of learning unsupervised from data that is unstructured or unlabeled. Also known as deep neural learning or deep neural network.

    1. Technique: In deep learning, a convolutional neural network (CNN, or ConvNet) is a class of deep neural networks, most commonly applied to analyzing visual imagery. CNNs use a variation of multilayer perceptrons designed to require minimal preprocessing. They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.

        A convolutional neural network consists of an input and an output layer, as well as multiple hidden layers. The hidden layers of a CNN typically consist of convolutional layers, RELU layer i.e. activation function, pooling layers, fully connected layers and normalization layers.

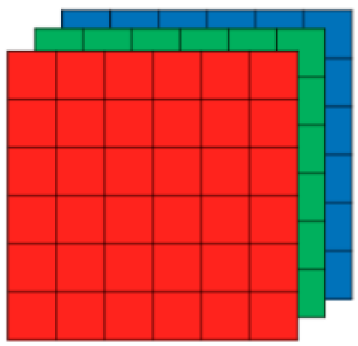
    2. Optimizer : Optimization algorithms helps us to minimize (or maximize) an Objective function (another name for Error function) E(x) which is simply a mathematical function dependent on the Model's internal learnable parameters which are used in computing the target values(Y) from the set of predictors(X) used in the model.
    3. Activation Function: Activation function decides, whether a neuron should be activated or not by calculating weighted sum and further adding bias with it. The purpose of the activation function is to introduce non-linearity into the output of a neuron.
- Output Image - The model gives well classified image according to the application it is being used for.

3.3 Implementation Details

Convolutional Neural Network

In neural networks, Convolutional neural network (ConvNets or CNNs) is one of the main categories to do images recognition, images classifications. Objects detections, recognition faces etc., are some of the areas where CNNs are widely used.

CNN image classifications take an input image, process it and classify it under certain categories (Eg., Dog, Cat, Tiger, Lion). Computers sees an input image as array of pixels and it depends on the image resolution. Based on the image resolution, it will see h x w x d (h = Height, w = Width, d = Dimension). In Figure 3.4 an image of 6 x 6 x 3 array of matrix of RGB (3 refers to RGB values) and an image of 4 x 4 x 1 array of matrix of grayscale image is shown.



6 x 6 x 3

Figure 3.4 Array of RGB Matrix [9]

Technically, deep learning CNN models to train and test, each input image will pass it through a series of convolution layers with filters (Kernels), Pooling, fully connected layers (FC) and apply Softmax function to classify an object with probabilistic values between 0 and 1. Figure 3.5 is a complete flow of CNN to process an input image and classifies the objects based on values.

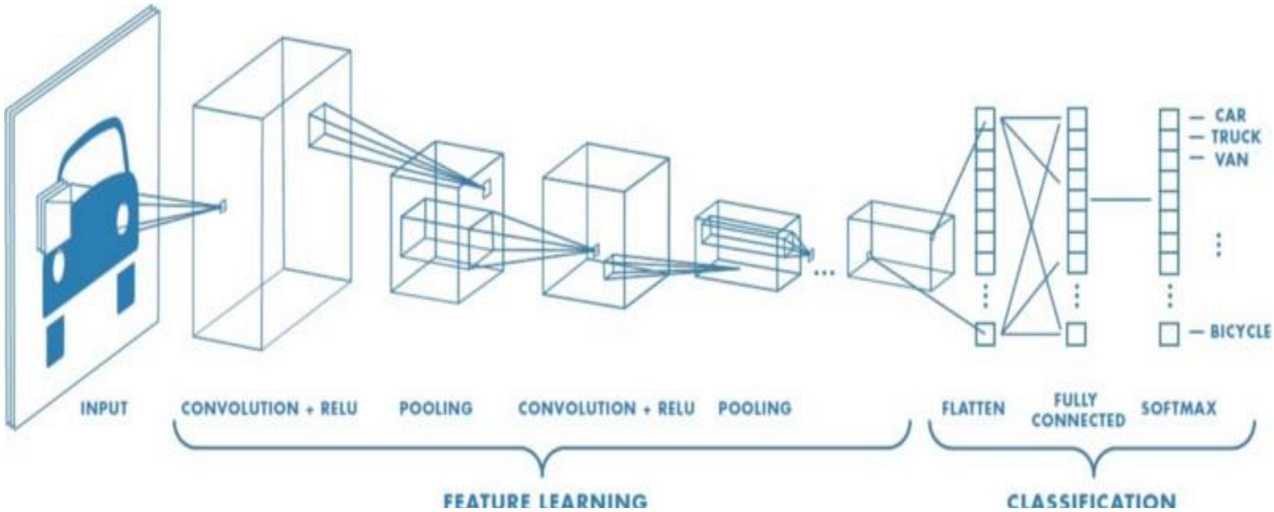


Figure 3.5 Neural network with many convolutional layers [9]

Convolution Layer

Convolution is the first layer to extract features from an input image. Convolution preserves the relationship between pixels by learning image features using small squares of input data. It is a mathematical operation that takes two inputs such as image matrix and a filter or kernel. See Figure 3.6

- An image matrix (volume) of dimension **(h x w x d)**
- A filter **(f_h x f_w x d)**
- Outputs a volume dimension **($h - f_h + 1$) x ($w - f_w + 1$) x 1**

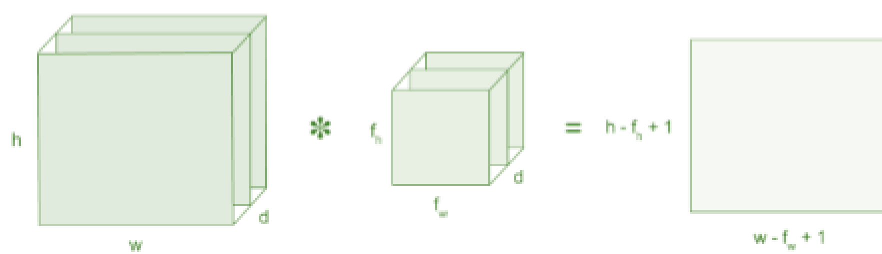


Figure 3.6 Image matrix multiplies kernel or filter matrix [9]

Consider a 5 x 5 whose image pixel values are 0, 1 and filter matrix 3 x 3 as shown in Figure 3.7

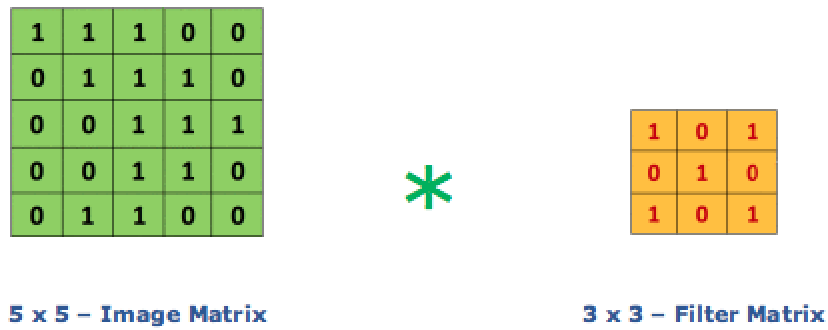


Figure 3.7 Image matrix multiplies kernel or filter matrix [9]

Then the convolution of 5 x 5 image matrix multiplies with 3 x 3 filter matrix which is called **"Feature Map"** as output shown in Figure 3.8

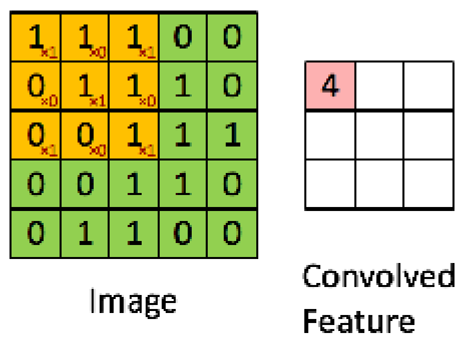
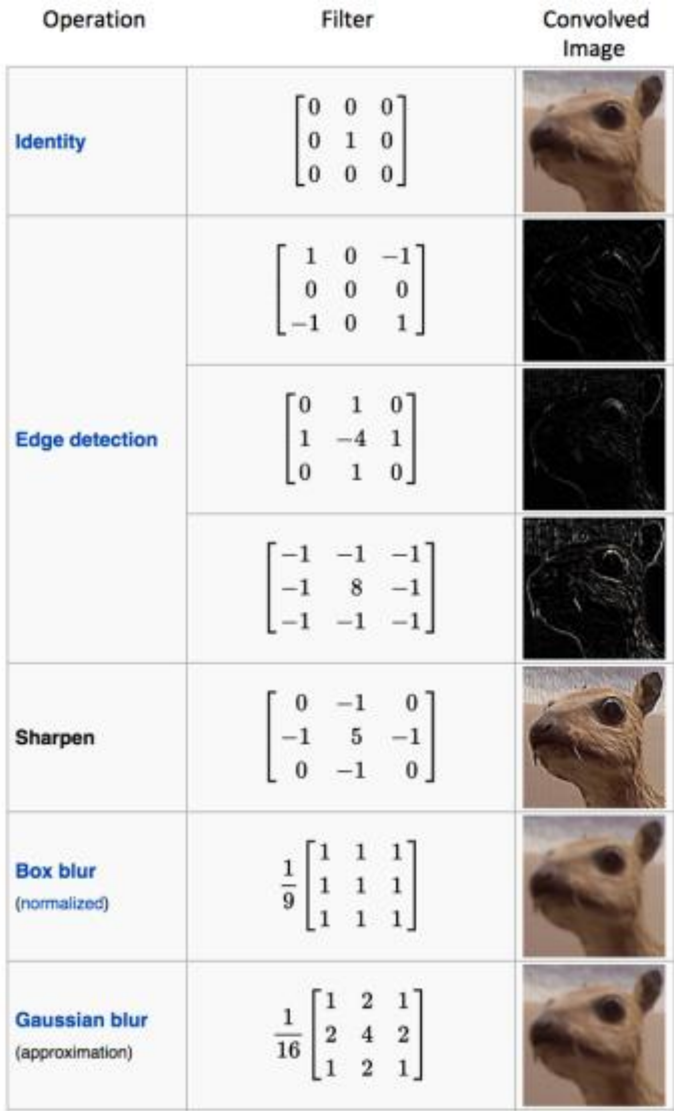


Figure 3.8 - 3 x 3 Output matrix [9]

Convolution of an image with different filters can perform operations such as edge detection, blur and sharpen by applying filters. Figure 3.9 shows various convolution image after applying different types of filters (Kernels).



Operation	Filter	Convolved Image
Identity	$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix}$	
Edge detection	$\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{bmatrix}$	
	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & -4 & 1 \\ 0 & 1 & 0 \end{bmatrix}$	
	$\begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix}$	
Sharpen	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 5 & -1 \\ 0 & -1 & 0 \end{bmatrix}$	
Box blur (normalized)	$\frac{1}{9}\begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}$	
Gaussian blur (approximation)	$\frac{1}{16}\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$	

Figure 3.9 Some common filters (Masks) [9]

Strides

Stride is the number of pixels shifts over the input matrix. When the stride is 1 then we move the filters to 1 pixel at a time. When the stride is 2 then we move the filters to 2 pixels at a time and so on. Figure 3.10 shows convolution would work with a stride of 2.

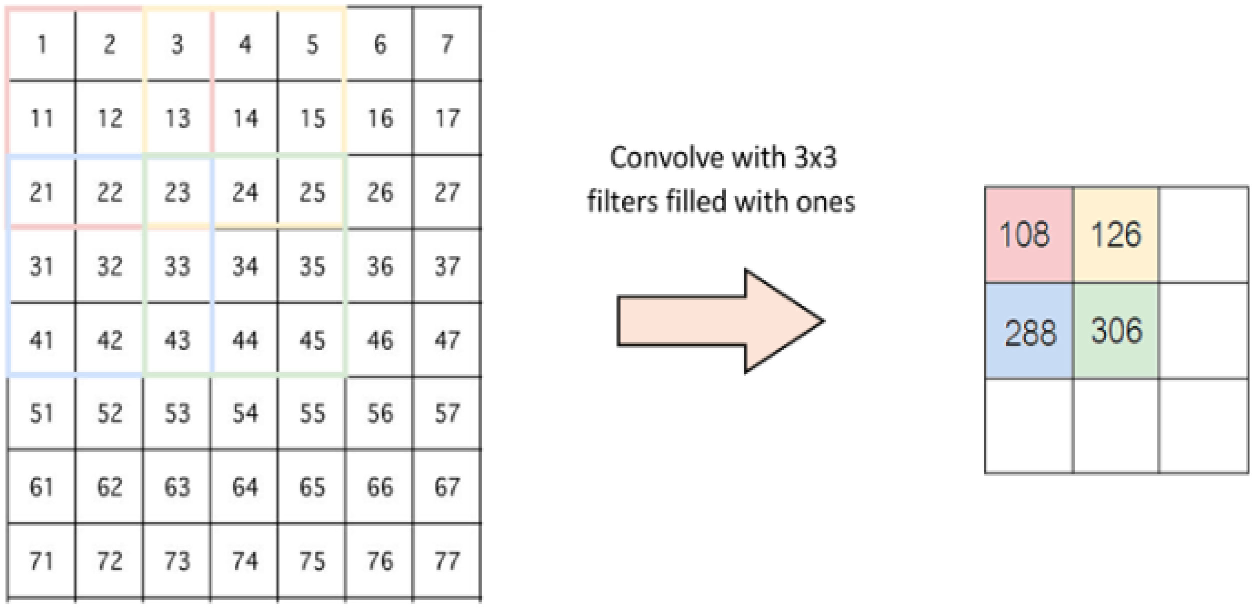


Figure 3.10 Stride of 2 pixels [9]

Padding

Sometimes filter does not fit perfectly fit the input image. We have two options:

- Pad the picture with zeros (zero-padding) so that it fits
- Drop the part of the image where the filter did not fit. This is called valid padding which keeps only valid part of the image.

Non Linearity (ReLU)

ReLU stands for Rectified Linear Unit for a non-linear operation. The output is $f(x) = max(0,x)$.

Why ReLU is important: ReLU's purpose is to introduce non-linearity in our ConvNet. Since, the real world data would want our ConvNet to learn would be non-negative linear values. Figure 3.11 shows the transformation of negative values.

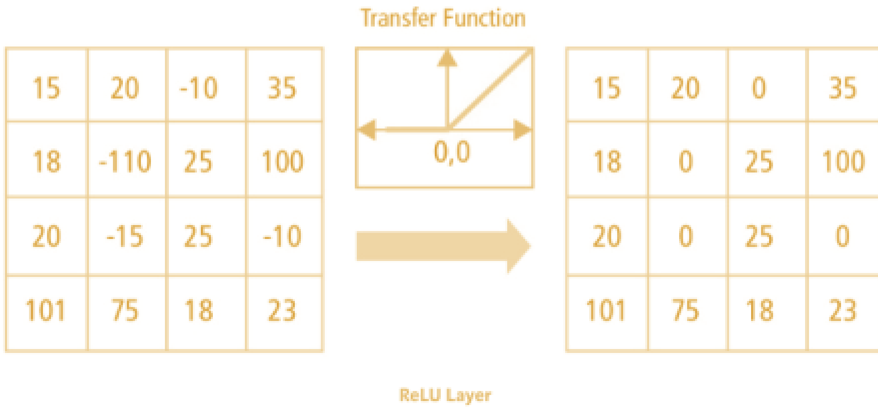


Figure 3.11 ReLU operation [9]

There are other non-linear functions such as tanh or sigmoid can also be used instead of ReLU. Most of the data scientists uses ReLU since performance wise ReLU is better than other two.

Pooling Layer

Pooling layers section would reduce the number of parameters when the images are too large. Spatial pooling also called subsampling or downsampling which reduces the dimensionality of each map but retains the important information. Spatial pooling can be of different types:

- Max Pooling
- Average Pooling
- Sum Pooling

Max pooling take the largest element from the rectified feature map. Taking the largest element could also take the average pooling. Sum of all elements in the feature map call as sum pooling. Figure 3.12 shows the max pooling operation with 2x2 matrix and stride = 2

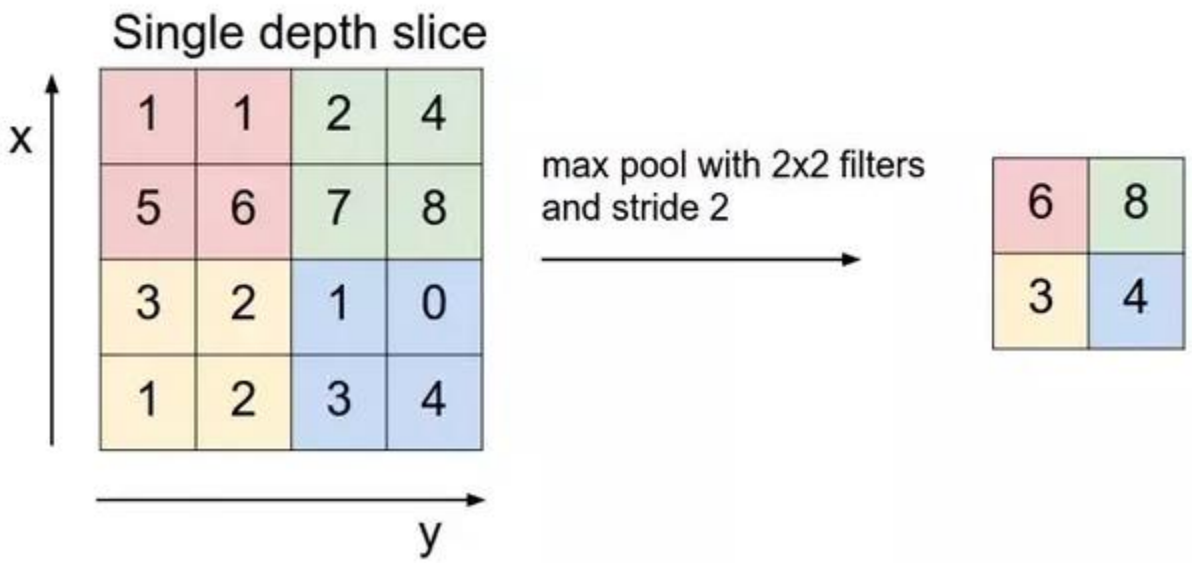


Figure 3.12 Max Pooling [9]

Fully Connected Layer

The layer we call as FC layer, we flattened our matrix into vector and feed it into a fully connected layer like neural network.

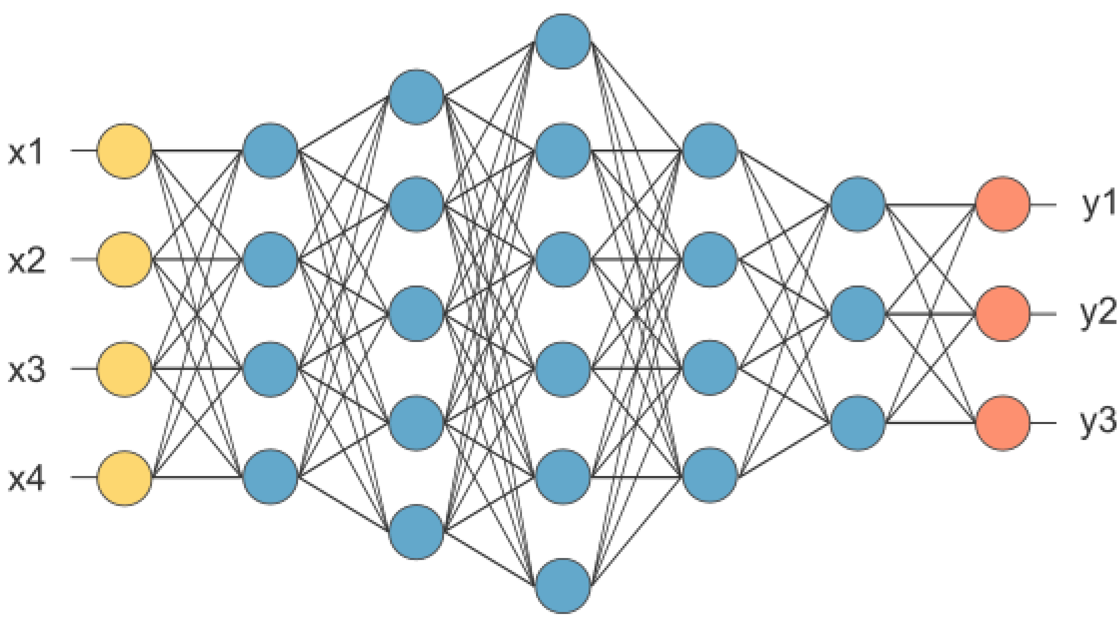


Figure 3.13 Layer, flattened as FC layer [9]

In Figure 3.13, feature map matrix will be converted as vector (x1, x2, x3, …). With the fully connected layers, we combined these features together to create a model. Finally, we have an activation function such as softmax or sigmoid to classify the outputs as cat, dog, car, truck etc.,

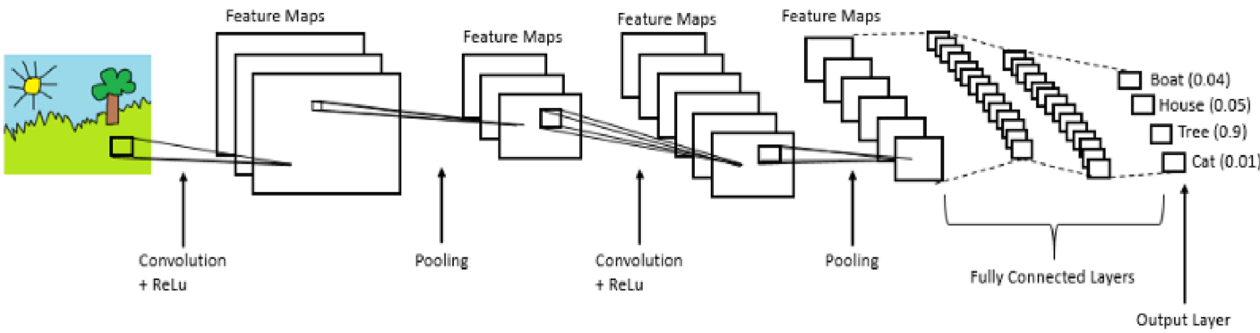


Figure 3.14 Complete CNN architecture [9]

The input images can be Aerial, SAR, VHR these image will be provided to the Deep learning algorithm for model training and feature identification. Then the model will provide classified imaged which can be further used in other applications in real time. The accuracy of the model trained in based on the quality of the dataset we give and the optimizer and activation functions we use in the layers of the convolution neural network. Figure 3.14 represents a complete architecture of CNN.

3.3.1 Classification using Transfer Learning

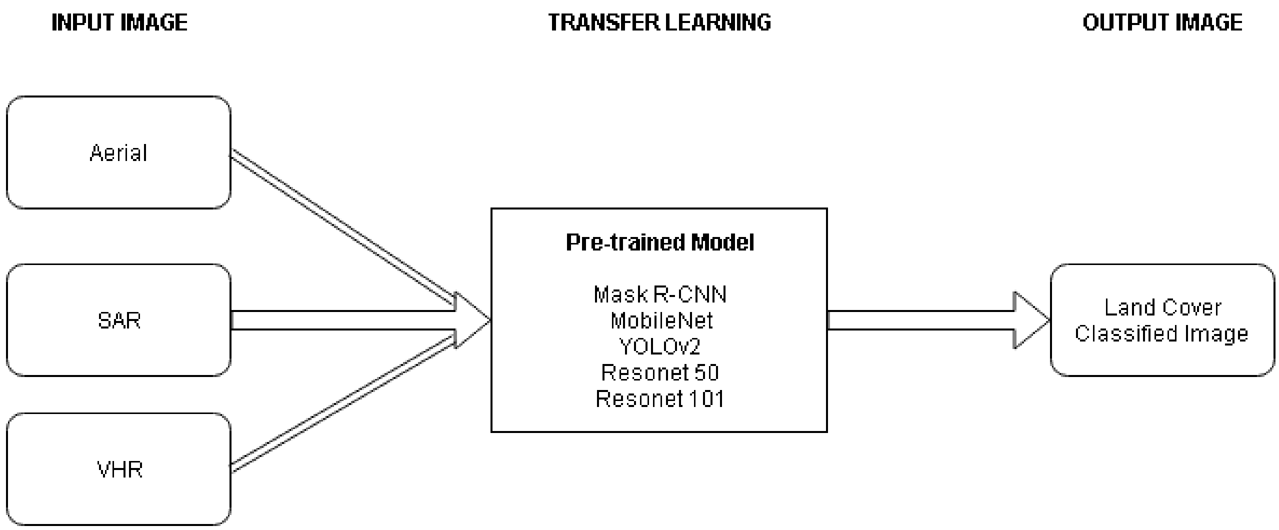


Figure 3.15 Proposed system architecture using Transfer Learning

The input images can be Aerial, SAR, VHR these image will be given to the Deep learning pre-trained model using transfer learning. Then the pre-trained model will provide classified imaged which can be further used in other applications in real time. The accuracy of the model trained in based on the type of the model we give. Figure 3.15 shows the use of transfer learning.

Activity Diagram

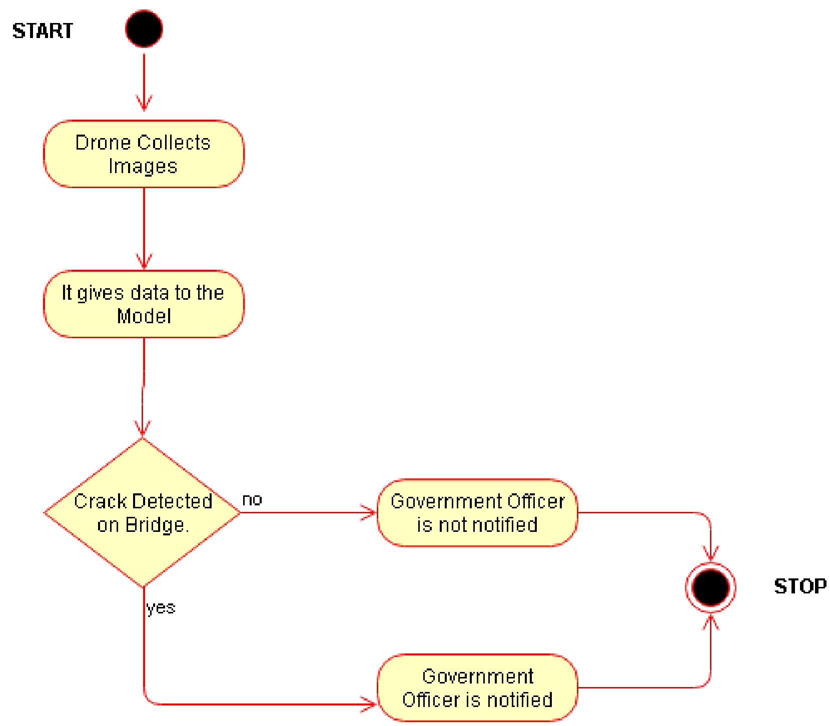


Figure 3.16 (a) Crack detection application activity diagram

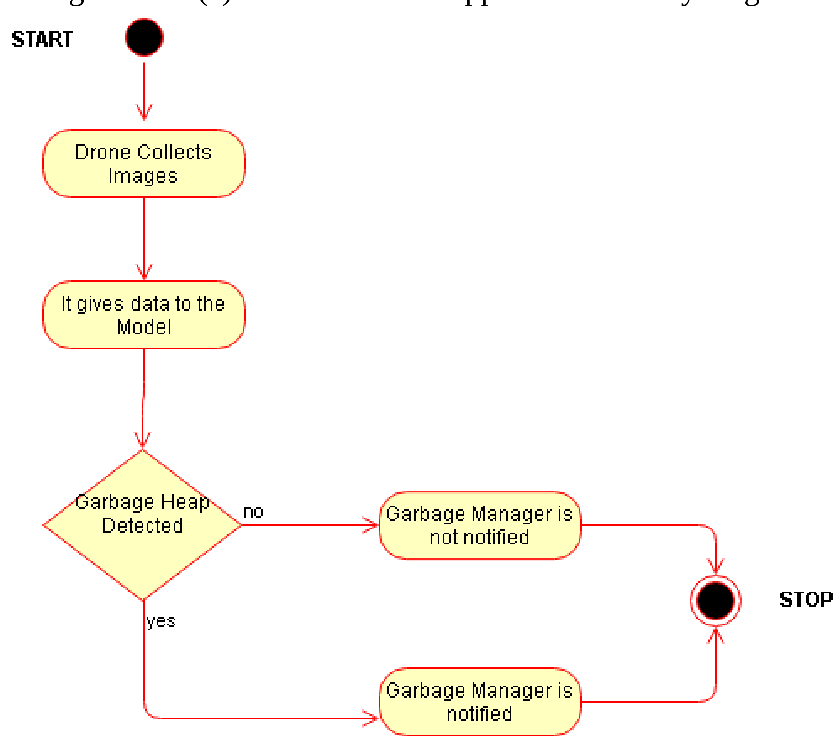


Figure 3.16 (b) Garbage monitoring application activity diagram

3.3.2 Sample Dataset Used

The Dataset used in existing system is based on satellite imagery but we will be using aerial imagery. The data will be collected live in real time application but for experimental purpose we will be using the Inria Aerial Image dataset. Which have good quality aerial imagery which can be used in training and classification of model.

3.3.3 Hardware and Software Specifications

The experiment setup is carried out on a computer system which has the different hardware and software specifications as given in Table 3.1 and Table 3.2 respectively.

Table 3.1 Hardware details

Processor	Intel(R) Core(TM) i7-8550U CPU @ 1.80GHz, 1992 Mhz, 4 Core(s), 8 Logical Processor(s)
HDD	1TB
RAM	16 GB
VRAM	2GB
Total virtual memory	9.75GB

Table 3.2 Software details

Operating System	Microsoft Windows 10 Home Single
Programming Language	Python, JavaScript, CSS
Database	SQL,MongoDB

Chapter 4

Applications

There are various applications of Land Cover Classification. The application is listed here.

4.1 Land Use and Land Cover Change Detection

The land cover land use classification helps us to analyse the changes that take over a period of time. These changes help us to understand the varying land use time to time. Increasing residential complexes and buildings in the classification with reduced forest cover denotes acquisition of forest lands for concrete jungle.

4.2 Assistance in Mapping

Google Maps is used on a large scale everyday by a large number of users. Navigation systems need to be updated on a regular basis. This classification helps the road maps to be updated time to time to avoid the false road guidance. The analysis of traffic on roads helps the traffic police departments to declare announcements regarding alternative routes.

4.3 Help in government's Swachh Bharat initiative

The classification of the land cover in small patches will help to recognize a garbage patch on the roads. This will make the task for local cleaning and sanitation authorities to maintain a healthy surrounding by regular garbage collection. The detection of a garbage dump used by the people as local dumping spot can cause outbreak of diseases. Thus we can educate people and spread awareness of a healthy environment.

4.4 Maintenance of roads

Detection of small cracks on road are difficult to be detected and not of a much problem. But ignorance to these cracks can make them wider over a period and thus needs to be repaired. Failure of such problems can lead to increased number of cracks and potholes in the road affecting the transportation, traffic and majorly risk of lives due to accidents.

4.5 Site identification for new project setup

The land use classification will give us an information of what percentage of land is unused in a particular area. This will help us to locate an empty site for a new project setup. This ensures that no allocation of forest areas for project site is done illegally reducing the forest cover.

4.6 Count of residential buildings

The classification can help us to keep a count of residential buildings in a particular area. This will help us to guess the population growth in that area and study how feasible is the area to survive.
who took keen interest on our project work and guided us all along, till the completion of our project work by providing all the necessary information for developing a good system.

4.7 Disaster Management

With a real time classification of the land cover, we can understand the rate at which the land cover of a particular type is changing which will help us to plan disasters well as well as identify the at earliest. For example, the outbreak of fire will rapidly change the land cover with fire patches alarming the fire station quickly to take immediate actions.

Chapter 5

Summary

In this report, the study of different techniques used for land cover and land use detection are presented. The different techniques such as deep learning, machine learning, transfer learning, ensemble techniques are implemented by maximum referenced research papers. The different hybrid approaches also described. Hybrid combination of deep learning models combined with machine learning models produce different results. Some hybrid combination includes combination of different pre-trained models like ResNet and GoogLeNet. The performance measures like accuracy and F1 score are described in this report. The inputs to these models needs proper image processing which helps the model to accurately classify the land use and cover. Various datasets have been identified for satellite images. The source to prepare a manual dataset are identified. The applications of this project are discussed in detail.

References

[1] Panda, A., Singh, A., Kumar, K., Kumar, A., Uddeshya, & Swetapadma, A. (2018). Land Cover Prediction from Satellite Imagery Using Machine Learning Techniques. 2018 Second International Conference on Inventive Communication and Computational Technologies (ICICCT).doi:10.1109/icicct.2018.8473241

[2] Sowmya, D. R., Hegde, V. S., Suhas, J., Hegdekatte, R. V., Shenoy, P. D., & Venugopal, K. R. (2017). Land Use/ Land Cover Classification of Google Earth Imagery. 2017 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE). doi:10.1109/wiecon-ece.2017.8468898

[3] Mahmon, N. A., Ya'acob, N., & Yusof, A. L. (2015). Differences of image classification techniques for land use and land cover classification. 2015 IEEE 11th International Colloquium on Signal Processing & Its Applications (CSPA). doi:10.1109/cspa.2015.7225624

[4] Jog, S., & Dixit, M. (2016). Supervised classification of satellite images. 2016 Conference on Advances in Signal Processing (CASP).doi:10.1109/casp.2016.7746144

[5] Pritt, M., & Chern, G. (2017). Satellite Image Classification with Deep Learning. 2017 IEEE Applied Imagery Pattern Recognition Workshop (AIPR).doi:10.1109/aipr.2017.8457969

[6] Helber, P., Bischke, B., Dengel, A., & Borth, D. (2018). Introducing Eurosat: A Novel Dataset and Deep Learning Benchmark for Land Use and Land Cover Classification. IGARSS 2018 - 2018 IEEE International Geoscience and Remote Sensing Symposium.doi:10.1109/igarss.2018.8519248

[7] Kaiser, P., Wegner, J. D., Lucchi, A., Jaggi, M., Hofmann, T., & Schindler, K. (2017). Learning Aerial Image Segmentation From Online Maps. IEEE Transactions on Geoscience and Remote Sensing, 55(11), 6054–6068.doi:10.1109/tgrs.2017.2719738

[8] Sophia S. Rwanga, J. M. Ndambuki,"Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS",International Journal of Geosciences, 2017, 8, 611-622 http://www.scirp.org/journal/ijg ISSN Online: 2156-8367 ISSN Print: 2156-8359

[9] Prabhu, "Understanding of Convolutional Neural Network (CNN)—Deep Learning." [Online].Available: https://medium.com/@RaghavPrabhu/understanding-of-convolutional-neural-network-cnn-deep-learning-99760835f148 [Mar 4, 2018]

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