1. INTRODUCTION

Image classification is the primary domain, in which deep neural networks play the most important role of medical image analysis. The image classification accepts the given input images and produces output classification for identifying whether the disease is present or not. In our model we mainly classify the different types of organs and predict the accuracy.

of the most imperative problems faced in the domain area of image recognition is the classification of medical images. The major intention of medical image classification is to classify medical images into several elements to assist medical practitioners or physicists in diagnosing disease. Hence, medical image classification is split into two steps. The first and foremost step of medical image classification is to extract the essential features from the acquired input image. The second step in medical image classification is utilizing the features to construct models that classify the image data set. In the recent past, medical practitioners customarily utilized their specialized experience to extract features so that classification of medical images could be performed into several classes. However, this manual medical image classification was found to be highly cumbersome and time consuming.

Medical image classification involves the process of segregating medical-related information into a useful form. Classification of medical images is based on placing image pixels with similar values into groups. With the placement of similar values into groups, common pixels are identified and are denoted by these pixels. Hence, a correctly classified image usually denotes the areas on the ground that share specific features as specified in the classification scheme.

Image classification is where a computer can analyse an image and identify the ‘class’ the image falls under. (Or a probability of the image being part of a ‘class’.) A class is essentially a label, for instance, ‘car’, ‘animal’, ‘building’ and so on. For example, you input an image of a sheep. Image classification is the process of the computer analysing the image and telling you it’s a sheep. (Or the probability that it’s a sheep.) For us, classifying images is no big deal. But it’s a perfect example of Moravec’s paradox when it comes to machines. (That is, the things we find easy are difficult for AI.)

Early image classification relied on raw pixel data. This meant that computers would break down images into individual pixels. The problem is that two pictures of the same thing can look very different. They can have different backgrounds, angles, poses, and etcetera. This made it quite the challenge for computers to correctly 'see' and categorise images.

Deep learning is a type of machine learning; a subset of artificial intelligence (AI) that allows machines to learn from data. Deep learning involves the use of computer systems known as neural networks. In neural networks, the input filters through hidden layers of nodes. These nodes each process the input and communicate their results to the next layer of nodes. This repeats until it reaches an output layer, and the machine provides its answer.

There are different types of neural networks based on how the hidden layers work. Image classification with deep learning most often involves convolutional neural networks, or CNNs. In CNNs, the nodes in the hidden layers don't always share their output with every node in the next layer (known as convolutional layers). Deep learning allows machines to identify and extract features from images. This means they can learn the features to look for in images by analysing lots of pictures. So, programmers don't need to enter these filters by hand.

Image classification has a few uses — and vast potential as it grows in reliability. Here are just a few examples of what makes it useful. Self-driving cars use image classification to identify what's around them. I.e., trees, people, traffic lights and so on. Image classification can also help in healthcare. For instance, it could analyse medical images and suggest whether they classify as depicting a symptom of illness. Or, for example, image classification could help people organise their photo collections.

2. LITERATURE REVIEW

Q. Zhu, B. Du, and P. Yan: Accurate segmentation of the prostate from magnetic resonance (MR) images provides useful information for prostate cancer diagnosis and treatment. However, automated prostate segmentation from 3D MR images still faces several challenges. The complex background texture and large variation in size, shape and intensity distribution of the prostate itself make segmentation even further complicated. Since large-scale dataset is one of the critical components for the success of deep learning, lack of sufficient training data makes it difficult to fully train complex CNNs. To tackle the above challenges, in this paper boundary-weighted domain adaptive neural network (BOWDA-Net) is proposed. To make the network more sensitive to the boundaries during segmentation, a boundary-weighted segmentation loss (BWL) is proposed.

Summary: In this paper boundary-weighted domain adaptive neural network (BOWDA-Net) is proposed. To make the network more sensitive to the boundaries during segmentation, a boundary-weighted segmentation loss (BWL) is proposed. . Furthermore, an advanced boundary-weighted transfer leaning approach is introduced to address the problem of small medical imaging datasets. We evaluate our proposed model on the publicly available MICCAI 2012 Prostate MR Image Segmentation (PROMISE12) challenge dataset.

Q. Zhu, B. Du, P. Yan, H. Lu, and L. Zhang: Bladder wall segmentation from Magnetic Resonance (MR) images plays an important role in diagnosis. Since the thickness of the bladder wall is a key indication of bladder cancer. There are several methods that have been used for bladder wall segmentation, such as level sets and Active Shape Model (ASM). However, the weak boundaries, the artifacts inside bladder lumen and the complex background outside the bladder wall make the bladder wall segmentation very challenging. To overcome these difficulties and obtain accurate bladder walls, in this paper, a shape prior constrained particle swarm optimization (SPC-PSO) model is proposed to segment the inner and outer boundaries of the bladder wall. The bladder walls are divided into two categories: strong boundaries and weak boundaries by the proposed model.

Summary: In this paper, a shape prior constrained particle swarm optimization (SPC-PSO) model is proposed to segment the inner and outer boundaries of the bladder wall. The bladder walls are divided into two categories: strong boundaries and weak boundaries by the proposed model. For the strong boundaries, the proposed model can reserve it. For the weak boundaries, the model applies the shape prior to guide the process of segmentation**.**

Q. Zhu, B. Du, B. Turkbey, P. Choyke, and P. Yan: Segmentation of the prostate from Magnetic Resonance Imaging (MRI) plays an important role in prostate cancer diagnosis. However, the lack of clear boundary and significant variation of prostate shapes and appearances make the automatic segmentation very challenging. In the past several years, approaches based on deep learning technology have made significant progress on prostate segmentation. However, those approaches mainly paid attention to features and contexts within each single slice of a 3D volume. As a result, this kind of approaches faces many difficulties when segmenting the base and apex of the prostate due to the limited slice boundary information. To tackle this problem, in this paper, we propose a deep neural network with bidirectional convolutional recurrent layers for MRI prostate image segmentation.

Summary: A deep neural network is proposed with bidirectional convolutional recurrent layers for MRI prostate image segmentation. In addition to utilizing the interslice contexts and features, the proposed model also treats prostate slices as a data sequence and utilizes the interslice contexts to assist segmentation. The experimental results show that the proposed approach achieved significant segmentation improvement compared to other reported methods.

K. Kranthi Kumar and T.V. Gopal: Content Based Image Retrieval (CBIR) is a prominent research area in effective retrieval and management process for large image databases. Which was a bottleneck in reducing semantic gap issue to solve, many approaches have been proposed. Among them, Relevance Feedback (RF) is a technique absorbed into CBIR systems to improve retrieval accuracy using user given feedback. One of the traditional methods to enact relevance feedback is Feature Reweighting (FRW), it is useful technique to enhance retrieval performance based on the acquired feedback from user. The assumption for previous FRW approaches are that the length of feature vectors for images are fixed and use only the information from the set of images send back in the early query result for feature reweighting. **Summary:** In this article, examined systematically the proposed system with various weight update strategies and compared output retrieval results and proposed a new self-order feature reweighting approach in CBIR to reduce semantic gap using relevance feedback which we experimented with COREL database with 25 different categories and each category containing 100 number of relevant images.

R. Ashraf, K.B. Bajwa, and T. Mahmood: Segmentation of the images is considered as a solution but there isn't any technique which can guarantee the object extraction in a robust way. Another limitation of the segmentation is that, most of the image segmentation techniques are very slow and still their results are not reliable. To overcome these problems a Bandelets transform based image representation technique is presented in this paper, which reliably returns the information about the major objects found in an image. For image retrieval purposes Support Vector Machine are applied and the performance of the system is evaluated on three standard data sets used in the domain of content-based image retrieval.

Summary: To overcome the problems which are in the existing method, a Bandelets transform based image representation technique is presented in this paper, which reliably returns the information about the major objects found in an image. For image retrieval purposes Support Vector Machine are applied and the performance of the system is evaluated on three standard data sets used in the domain of content-based image retrieval.

G. Wu, W. Lu, G. Gao, C. Zhao, and J. Liu: Deep learning has been successfully applied to visual tracking due to its powerful feature learning characteristic. However, existing deep learning trackers rely on single observation model and focus on the holistic representation of the tracking object. When occlusion occurs, the trackers suffer from the contaminated features obtained in occluded areas. In this paper, we propose a regional deep learning tracker that observes the target by multiple sub-regions and each region is observed by a deep learning model. In particular, we devise a stable factor, modelled as a hidden variable of the Factorial Hidden Markov Model, to characterize the stability of these sub-models. The stability indicator not only provides a confidence degree for the response score of each model during inference stage, but also determines the online training criteria for each deep learning model.

Summary: When occlusion occurs, the trackers suffer from the contaminated features obtained in occluded areas. In this paper, we propose a regional deep learning tracker that observes the target by multiple sub-regions and each region is observed by a deep learning model. In particular, we devise a stable factor, modelled as a hidden variable of the Factorial Hidden

Markov Model, to characterize the stability of these sub-models. The stability indicator not only provides a confidence degree for the response score of each model during inference stage, but also determines the online training criteria for each deep learning model.

2.1. References

Reference 1. Boundary-weighted domain adaptive neural network for prostate MR image segmentation.

Accurate segmentation of the prostate from magnetic resonance (MR) images provides useful information for prostate cancer diagnosis and treatment. However, automated prostate segmentation from 3D MR images faces several challenges. The lack of clear edge between the prostate and other anatomical structures makes it challenging to accurately extract the boundaries. The complex background texture and large variation in size, shape and intensity distribution of the prostate itself make segmentation even further complicated. Recently, as deep learning, especially convolutional neural networks (CNNs), emerging as the best performed methods for medical image segmentation, the difficulty in obtaining large number of annotated medical images for training CNNs has become much more pronounced than ever. Since large-scale dataset is one of the critical components for the success of deep learning, lack of sufficient training data makes it difficult to fully train complex CNNs. To tackle the above challenges, in this paper, we propose a boundary-weighted domain adaptive neural network (BOWDA-Net). To make the network more sensitive to the boundaries during segmentation, a boundary-weighted segmentation loss is proposed. Furthermore, an advanced boundaryweighted transfer leaning approach is introduced to address the problem of small medical imaging datasets. We evaluate our proposed model on three different MR prostate datasets. The experimental results demonstrate that the proposed model is more sensitive to object boundaries and outperformed other state-of-the-art method.

Reference 2. A novel approach to self-order feature reweighting in CBIR to reduce semantic gap using relevance feedback

Content Based Image Retrieval (CBIR) is a prominent research area in effective retrieval and management process for large image databases. Which was a bottleneck in reducing semantic gap issue to solve, many approaches have been proposed. Among them, Relevance Feedback (RF) is a technique absorbed into CBIR systems to improve retrieval accuracy using user given feedback One of the traditional methods to enact relevance feedback is Feature Reweighting (FRW), it is useful technique to enhance retrieval performance based on the acquired feedback from user. The assumption for previous FRW approaches are that the length of feature vectors for images are fixed and use only the information from the set of images send back in the early query result for feature reweighting. In this article, we examined systematically the proposed system with various weight update strategies and compared output retrieval results and proposed a new self-order feature reweighting approach in CBIR to reduce semantic gap using relevance feedback which we experimented with COREL database with 25 different categories and each category containing 100 number of relevant images. The experimental results demonstrated the advantage of our method in terms of precision and recall. The results show the success of the proposed approach and it is shown that our perspective outperforms previous work.

Reference 3. Content-based Image Retrieval by Exploring Bandletized Regions through Support Vector Machines

One of the major requirements of the Content Based Image Retrieval (CBIR) systems is to ensure the meaningful image retrieval against query images. CBIR systems provide potential solutions of retrieving semantically similar images from large image repositories against any query image. The performances of these systems severely degrade by the inclusion of image contents which do not comprise the objects of interest in an image during the image representation phase. Segmentation of the images is considered as a solution but there isn’t any technique which can guarantee the object extraction in a robust way. Another limitation of the segmentation is that, most of the image segmentation techniques are very slow and still their results are not reliable. To overcome these problems a Bandelets transform based image representation technique is presented in this paper, which reliably returns the information about the major objects found in an image. For image retrieval purposes Support Vector Machine are applied and the performance of the system is evaluated on three standard data sets used in the domain of content-based image retrieval.

Reference 4. Deep Learning for Content-Based Image Retrieval: A Comprehensive Study

Learning effective feature representations and similarity measures are crucial to the retrieval performance of a content-based image retrieval (CBIR) system. Despite extensive research efforts for decades, it remains one of the most challenging open problems that considerably hinders the successes of real-world CBIR systems. The key challenge has been attributed to the well-known ``semantic gap'' issue that exists between low-level image pixels captured by machines and high-level semantic concepts perceived by human. Among various techniques, machine learning has been actively investigated as a possible direction to bridge the semantic gap in the long term. Inspired by recent successes of deep learning techniques for computer vision and other applications, in this paper, we attempt to address an open problem: if deep learning is a hope for bridging the semantic gap in CBIR and how much improvements in CBIR tasks can be achieved by exploring the state-of-the-art deep learning techniques for learning feature representations and similarity measures. Specifically, we investigate a framework of deep learning with application to CBIR tasks with an extensive set of empirical studies by examining a state-of-the-art deep learning method (Convolutional Neural Networks) for CBIR tasks under varied settings. From our empirical studies, we find some encouraging results and summarize some important insights for future research.

Reference 5. Shape Prior Constrained PSO Model for Bladder Wall MRI Segmentation

Bladder wall segmentation from Magnetic Resonance (MR) images plays an important role in diagnosis. Since the thickness of the bladder wall is a key indication of bladder cancer. There are several methods that have been used for bladder wall segmentation, such as level sets and Active Shape Model (ASM). However, the weak boundaries, the artifacts inside bladder lumen and the complex background outside the bladder wall make the bladder wall segmentation very challenging. To overcome these difficulties and obtain accurate bladder walls, in this paper, a shape prior constrained particle swarm optimization (SPC-PSO) model is proposed to segment the inner and outer boundaries of the bladder wall. The bladder walls are divided into two categories: strong boundaries and weak boundaries by the proposed model. For the strong boundaries, the proposed model can reserve it. For the weak boundaries, the model applies the shape prior to guide the process of segmentation. Compared with some stateof-the-art methods, better results were obtained on bladder MR images from 11 patients by our proposed method.

2.2. EXISTING SYSTEM

This model emphasizes an existing method that which is designed using the machine learning architecture which is used to classify the various medical images. With an extensive utilization of digital images as information in the hospitals, the archives of medical images are growing exponentially. Digital images play a vigorous role in predicting the patient disease intensity and there are vast applications of medical images in diagnosis and investigation. To make this in the easier way Support Vector Machine (SVM) is used that which can classifies the various medical images for various body organs. The block diagram of the existing method is shown in the below figure.

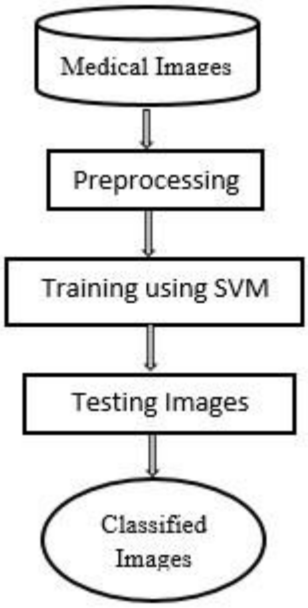


Fig 1. Block diagram of existing method

2.2.1 Disadvantages:

- Low efficiency.
- Time consuming.
- High complexities.
- No accurate classification

2.3.Proposed system.

The proposed model emphasizes a deep network architecture which is used to classify the various medical images. With an extensive utilization of digital images as information in the hospitals, the archives of medical images are growing exponentially. Digital images play a vigorous role in predicting the patient disease intensity and there are vast applications of medical images in diagnosis and investigation. Hence, we are proposing our model where the algorithm is trained for classifying medical images by deep learning technique. A pre-trained deep convolution neural network (GoogleNet) is used that which can classifies the various medical images for various body organs. The block diagram of the proposed model is shown in the below figure.

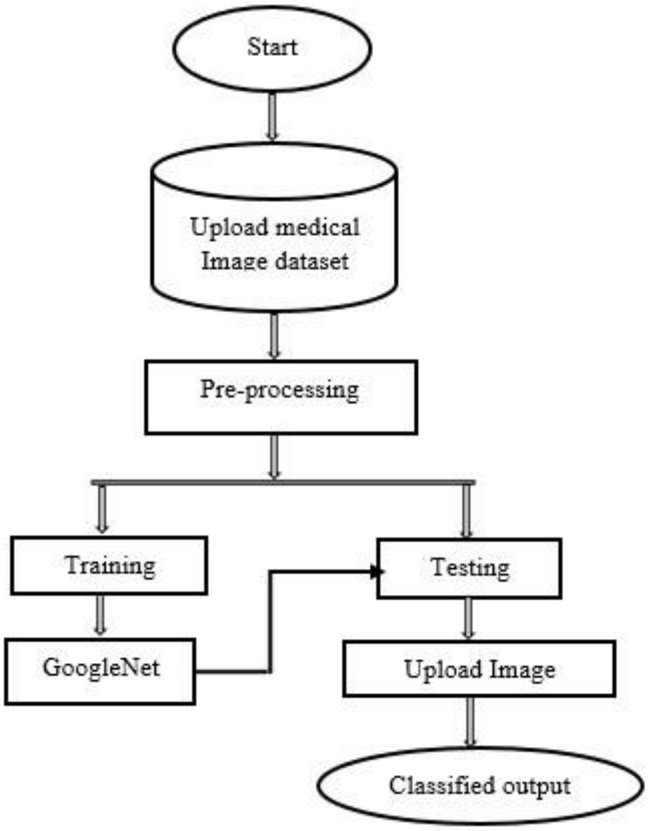


Fig 2. Block diagram of proposed method

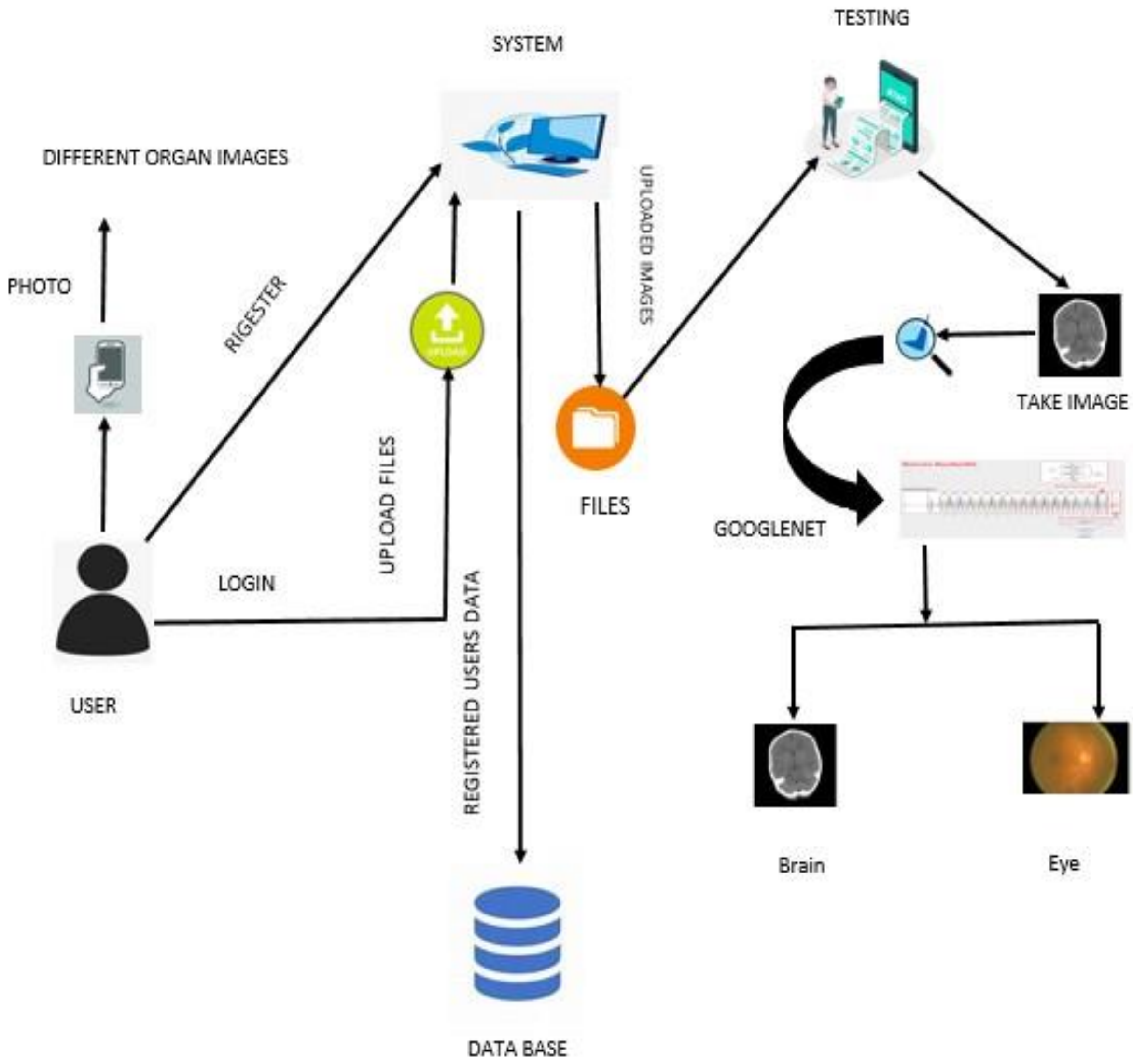
2.3.1 ADVANTAGES

- High efficiency.
- Time Saving.
- Inexpensive.
- Low complexities.

2.3.2 APPLICATIONS

Useful for the hospitals to detect brain strokes using this application.

2.4 ARCHITECTURE



2.5 Modules

System User:

2.5.1. System:

Create Dataset:

The dataset containing images of the desired objects to be recognize is split into training and testing dataset with the test size of 20-30%.

Pre-processing:

Resizing and reshaping the images into appropriate format to train our model.

Training:

Use the pre-processed training dataset is used to train our model using CNN algorithm.

2.5.2. User:

Register

The user needs to register and the data stored in MySQL database.

Login

A registered user can login using the valid credentials to the website to use a application.

About-Project

In this application, we have successfully created an application which takes to classify the images.

Upload Image

The user has to upload an image which needs to be classify the images.

Prediction

The results of our model is displayed as either Rice Blast, Leaf Blight, Healthy & Brown Spot.

Logout

Once the prediction is over, the user can logout of the application.

2.6 SYSTEM NARRATION

Software Development Life Cycle – SDLC:

In our project we use waterfall model as our software development cycle because of its step-by-step procedure while implementing.

- **Requirement Gathering and analysis** − All possible requirements of the system to be developed are captured in this phase and documented in a requirement specification document.
- **System Design** − The requirement specifications from first phase are studied in this phase and the system design is prepared. This system design helps in specifying hardware and system requirements and helps in defining the overall system architecture.
- **Implementation** − With inputs from the system design, the system is first developed in small programs called units, which are integrated in the next phase. Each unit is developed and tested for its functionality, which is referred to as Unit Testing.
- **Integration and Testing** − All the units developed in the implementation phase are integrated into a system after testing of each unit. Post integration the entire system is tested for any faults and failures.
- **Deployment of system** − Once the functional and non-functional testing is done; the product is deployed in the customer environment or released into the market.
- **Maintenance** − There are some issues which come up in the client environment. To fix those issues, patches are released. Also, to enhance the product some better versions are released. Maintenance is done to deliver these changes in the customer environment.

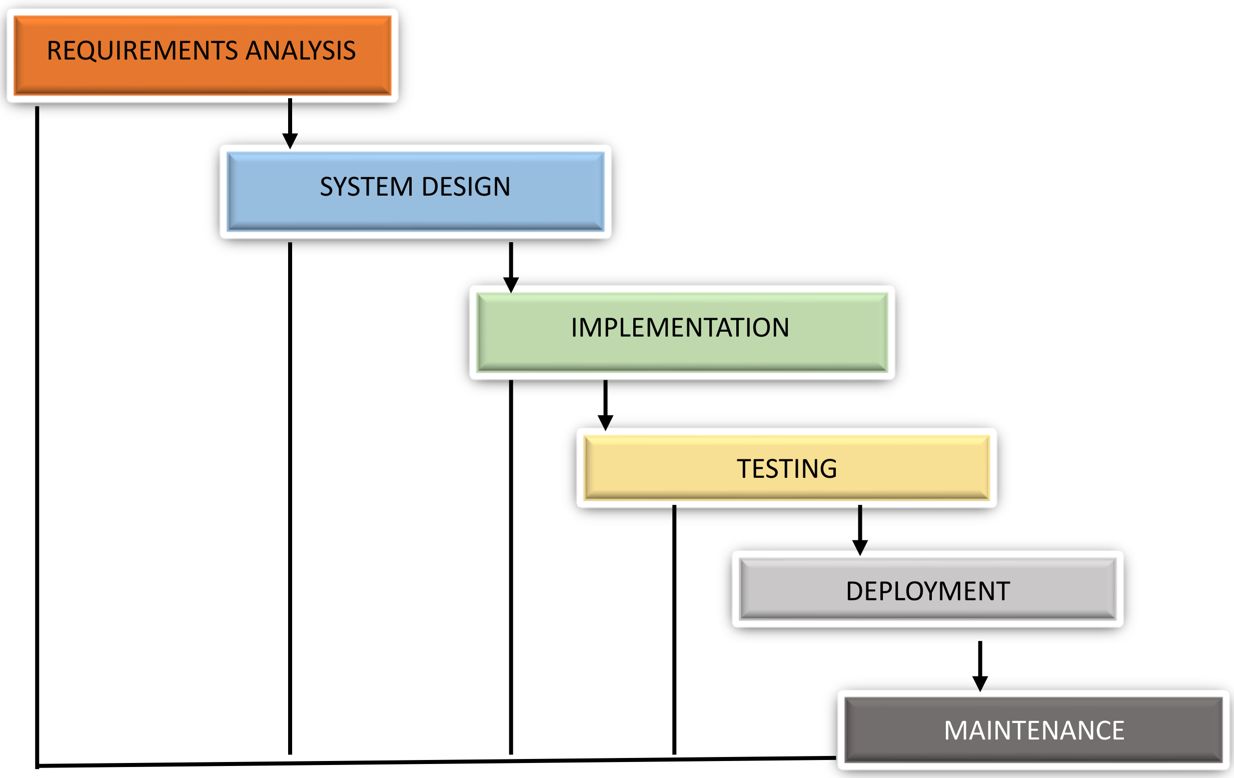


FIG:4 Waterfall Model

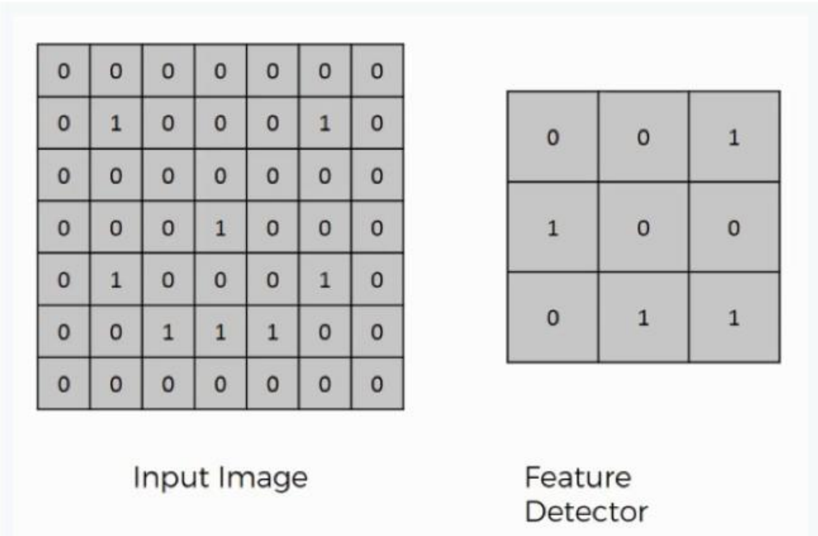
2.7 ALGORITHM

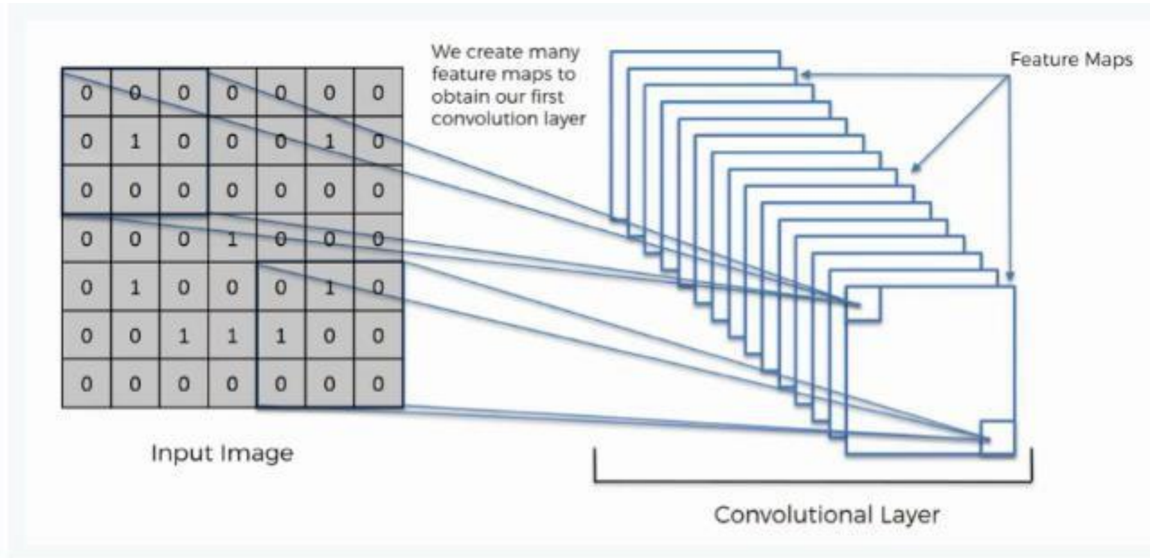
Convolutional Neural Network

Step1: Convolutional Operation

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out.

The Convolution Operation



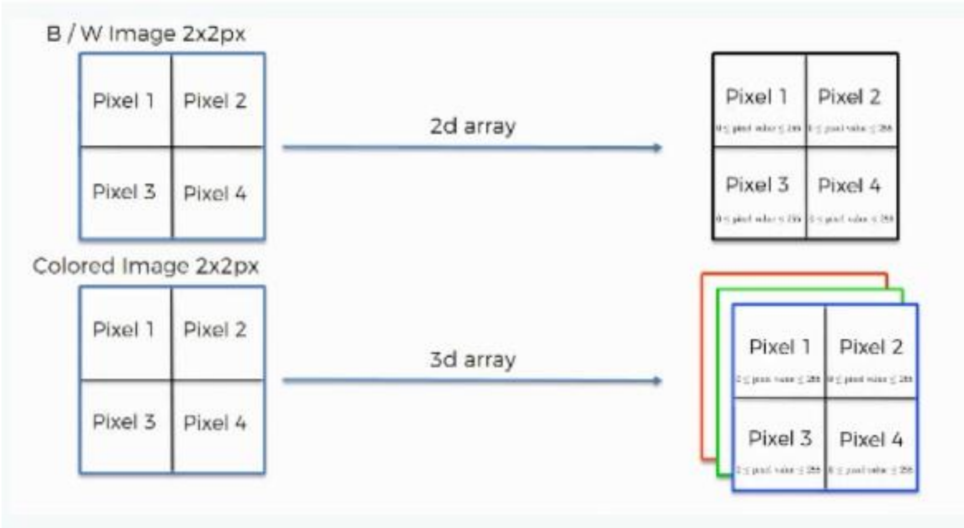


Step (1b): ReLU Layer

The second part of this step will involve the Rectified Linear Unit or Relook. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks.

Not necessary for understanding CNN's, but there's no harm in a quick lesson to improve your skills.

Convolutional Neural Networks Scan Images



Step 2: Pooling Layer

In this part, we'll cover pooling and will get to understand exactly how it generally works. Our nexus here, however, will be a specific type of pooling; max pooling. We'll cover various approaches, though, including mean (or sum) pooling. This part will end with a demonstration made using a visual interactive tool that will definitely sort the whole concept out for you.

Step 3: Flattening

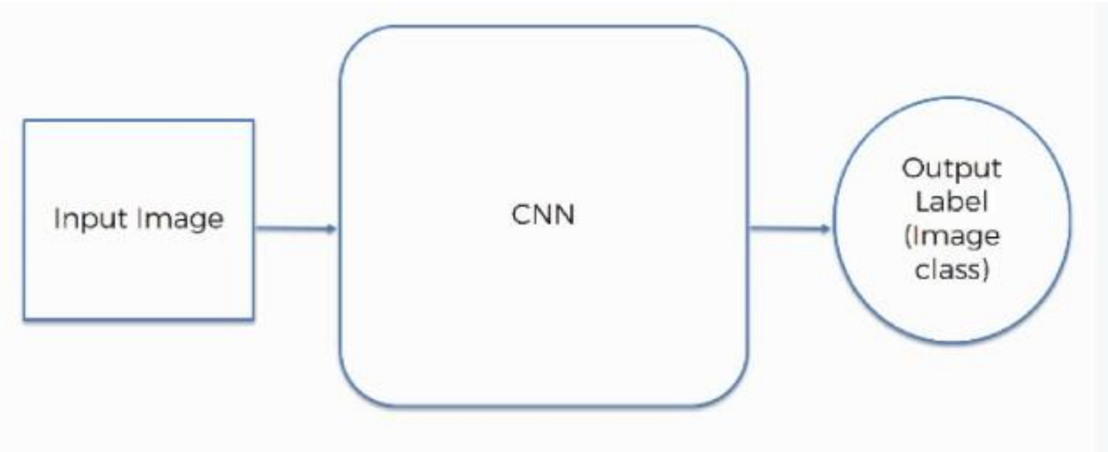
This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks.

Step 4: Full Connection

In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how Convolutional Neural Networks operate and how the "neurons" that are finally produced learn the classification of images.

Summary

In the end, we'll wrap everything up and give a quick recap of the concept covered in the section. If you feel like it will do you any benefit (and it probably will), you should check out the extra tutorial in which Soft as and Cross-Entropy are covered. It's not mandatory for the course, but you will likely come across these concepts when working with Convolutional Neural Networks and it will do you a lot of good to be familiar with them.



2.7.1 Google Net:

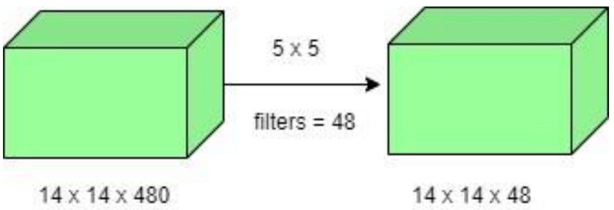
Google Net (or Inception V1) was proposed by research at Google (with the collaboration of various universities) in 2014 in the research paper titled “Going Deeper with Convolutions”.

This architecture was the winner at the ILSVRC 2014 image classification challenge. It has provided a significant decrease in error rate as compared to previous winners AlexNet (Winner of ILSVRC 2012) and ZF-Net (Winner of ILSVRC 2013) and significantly less error rate than VGG (2014 runner up). This architecture uses techniques such as 1×1 convolutions in the middle of the architecture and global average pooling.

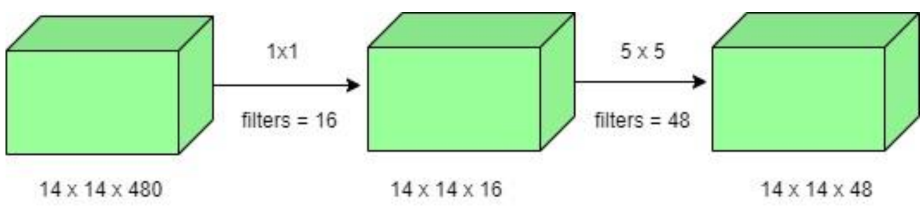
- **Features of GoogleNet:**

The GoogLeNet architecture is very different from previous state-of-the-art architectures such as AlexNet and ZF-Net. It uses many different kinds of methods such as 1×1 convolution and global average pooling that enables it to create deeper architecture. In the architecture, we will discuss some of these methods:

- **1×1 convolution:** The inception architecture uses 1×1 convolution in its architecture. These convolutions used to decrease the number of parameters (weights and biases) of the architecture. By reducing the parameters we also increase the depth of the architecture. Let's look at an example of a 1×1 convolution below:
- For Example, If we want to perform 5×5 convolution having 48 filters without using 1×1 convolution as intermediate:



- Total Number of operations : (14 x 14 x 48) x (5 x 5 x 480) = 112.9 M • With 1×1 convolution :



- (14 x 14 x 16) x (1 x 1 x 480) + (14 x 14 x 48) x (5 x 5 x 16) = 1.5M + 3.8M = 5.3M which is much smaller than 112.9M.

- **Global Average Pooling:**

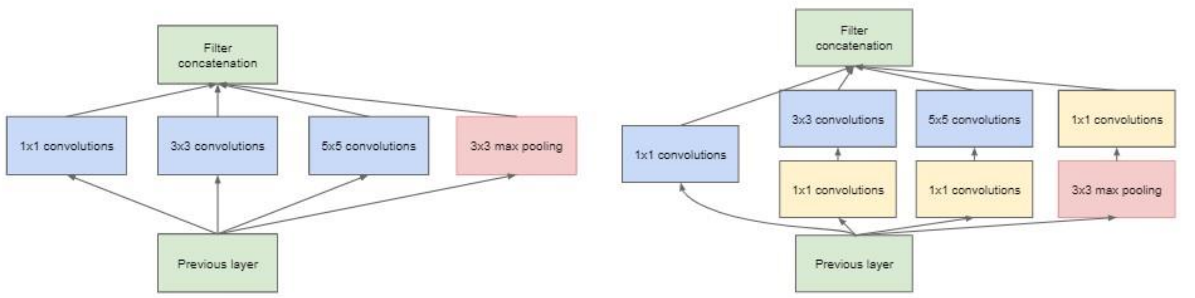
In the previous architecture such as AlexNet, the fully connected layers are used at the end of the network. These fully connected layers contain the majority of parameters of many architectures that causes an increase in computation cost.

In GoogLeNet architecture, there is a method called global average pooling is used at the end of the network. This layer takes a feature map of 7×7 and averages it to 1×1. This also decreases the number of trainable parameters to 0 and improves the top-1 accuracy by 0.6%

• **Inception Module:**

The inception module is different from previous architectures such as AlexNet, ZF-Net. In this architecture, there is a fixed convolution size for each layer.

In the Inception module 1×1, 3×3, 5×5 convolution and 3×3 max pooling performed in a parallel way at the input and the output of these are stacked together to generated final output. The idea behind that convolution filters of different sizes will handle objects at multiple scale better.



(a) Inception module, naïve version (b) Inception module with dimension reductions

• **Auxiliary Classifier for Training:**

Inception architecture used some intermediate classifier branches in the middle of the architecture, these branches are used during training only. These branches consist of a 5×5 average pooling layer with a stride of 3, a 1×1 convolutions with 128 filters, two fully connected layers of 1024 outputs and 1000 outputs and a Softmax classification layer. The generated loss of these layers added to total loss with a weight of 0.3. These layers help in combating gradient vanishing problem and also provide regularization.

3. SYSTEM DESIGN

3.1 UML Diagrams

UML stands for Unified Modeling Language. UML is a standardized general-purpose modeling language in the field of object-oriented software engineering. The standard is managed, and was created by, the Object Management Group.

The goal is for UML to become a common language for creating models of objectoriented computer software. In its current form UML is comprised of two major components: a Meta-model and a notation. In the future, some form of method or process may also be added to; or associated with, UML.

The Unified Modeling Language is a standard language for specifying, Visualization, Constructing and documenting the artifacts of software system, as well as for business modeling and other non-software systems.

The UML represents a collection of best engineering practices that have proven successful insists the modeling of large and complex systems.

The UML is a very important part of developing objects-oriented software and the software development process. The UML uses mostly graphical notations to express the design of software projects.

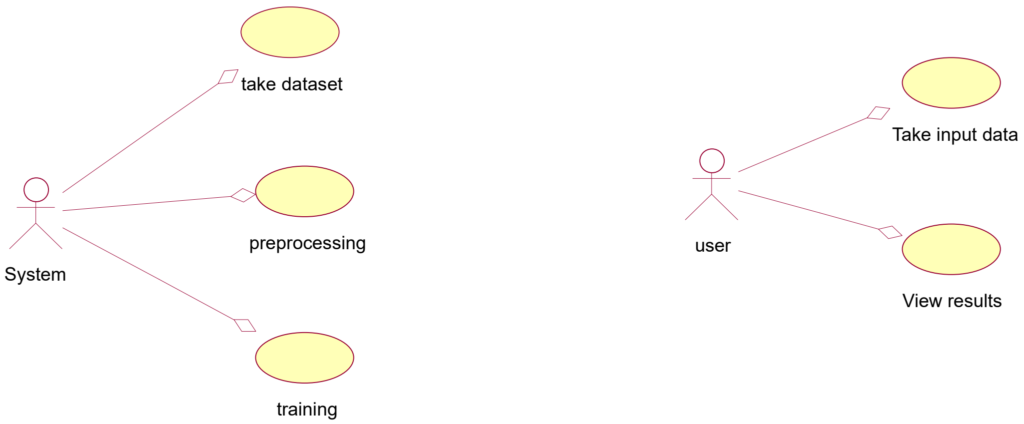
Goals:

The Primary goals in the design of the UML are as follows:

1. Provide users a ready-to-use, expressive visual modeling Language so that they can develop and exchange meaningful models.
2. Provide extendibility and specialization mechanisms to extend the core concepts.
3. Be independent of particular programming languages and development process.
4. Provide a formal basis for understanding the modeling language.
5. Encourage the growth of OO tools market.
6. Support higher level development concepts such as collaborations, frameworks, patterns and components.
7. Integrate best practices.

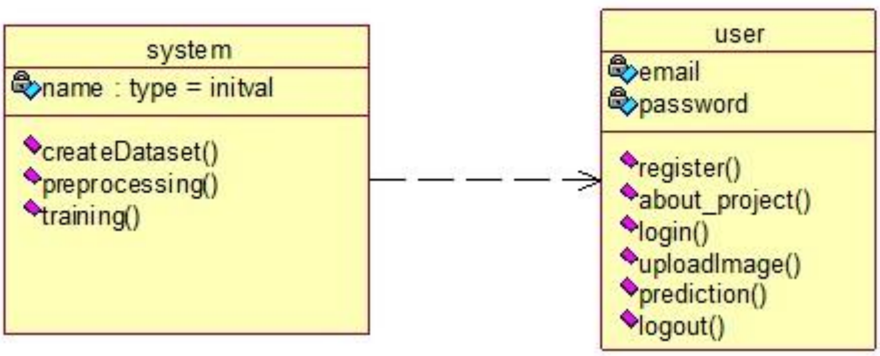
Use Case Diagram:

A use case diagram in the Unified Modeling Language (UML) is a type of behavioral diagram defined by and created from a Use-case analysis. Its purpose is to present a graphical overview of the functionality provided by a system in terms of actors, their goals (represented as use cases), and any dependencies between those use cases. The main purpose of a use case diagram is to show what system functions are performed for which actor. Roles of the actors in the system can be depicted.



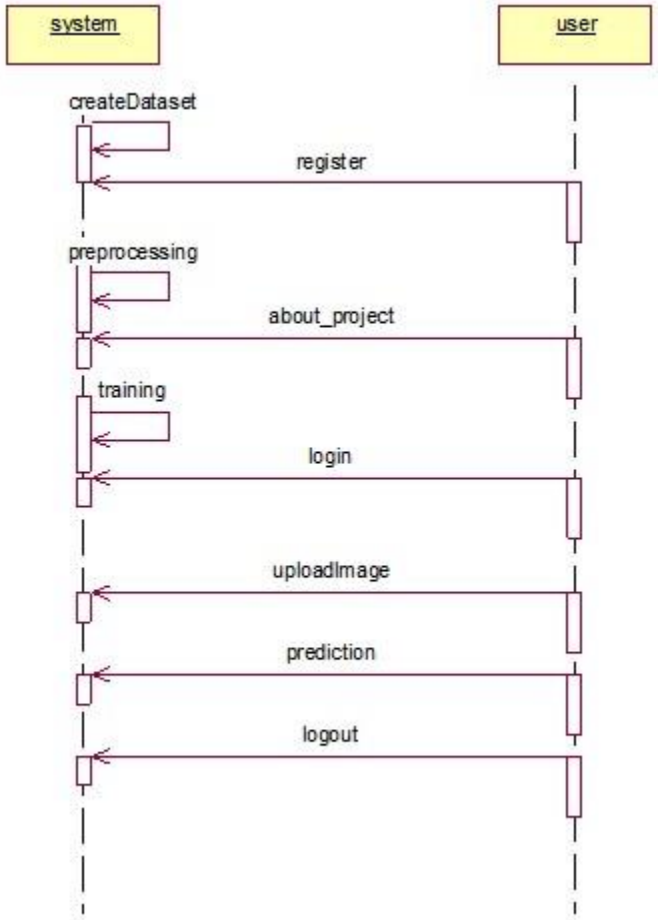
3.1.1 Class Diagram:

In software engineering, a class diagram in the Unified Modeling Language (UML) is a type of static structure diagram that describes the structure of a system by showing the system's classes, their attributes, operations (or methods), and the relationships among the classes. It explains which class contains information.



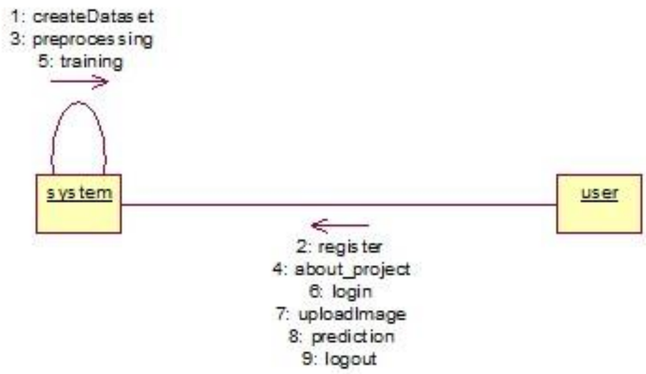
3.1.2 Sequence Diagram:

A sequence diagram in Unified Modeling Language (UML) is a kind of interaction diagram that shows how processes operate with one another and in what order. It is a construct of a Message Sequence Chart. Sequence diagrams are sometimes called event diagrams, event scenarios, and time diagrams.



3.1.3 Collaboration Diagram:

In collaboration diagram the method call sequence is indicated by some numbering technique as shown below. The number indicates how the methods are called one after another. We have taken the same order management system to describe the collaboration diagram. The method calls are similar to that of a sequence diagram. But the difference is that the sequence diagram does not describe the object organization whereas the collaboration diagram shows the object organization.

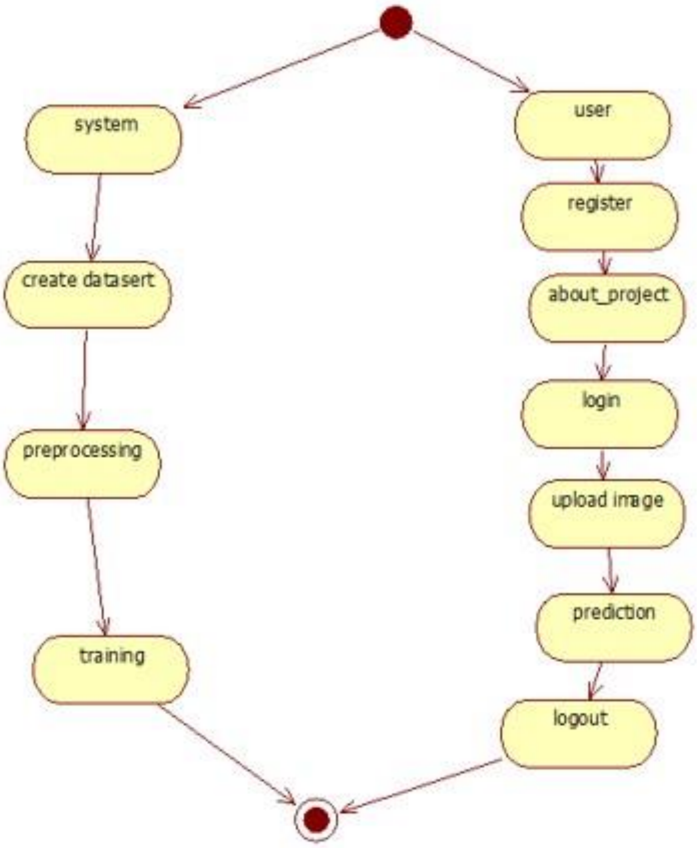


3.1.4 Deployment diagram:

Deployment diagram represents the deployment view of a system. It is related to the component diagram. Because the components are deployed using the deployment diagrams. A deployment diagram consists of nodes. Nodes are nothing but physical hardware's used to deploy the application.

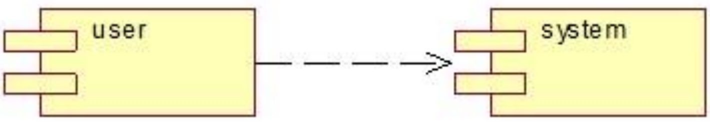
3.1.5 Activity Diagram:

Activity diagrams are graphical representations of workflows of stepwise activities and actions with support for choice, iteration and concurrency. In the Unified Modeling Language, activity diagrams can be used to describe the business and operational step-by-step workflows of components in a system. An activity diagram shows the overall flow of control.



3.1.6 Component diagram:

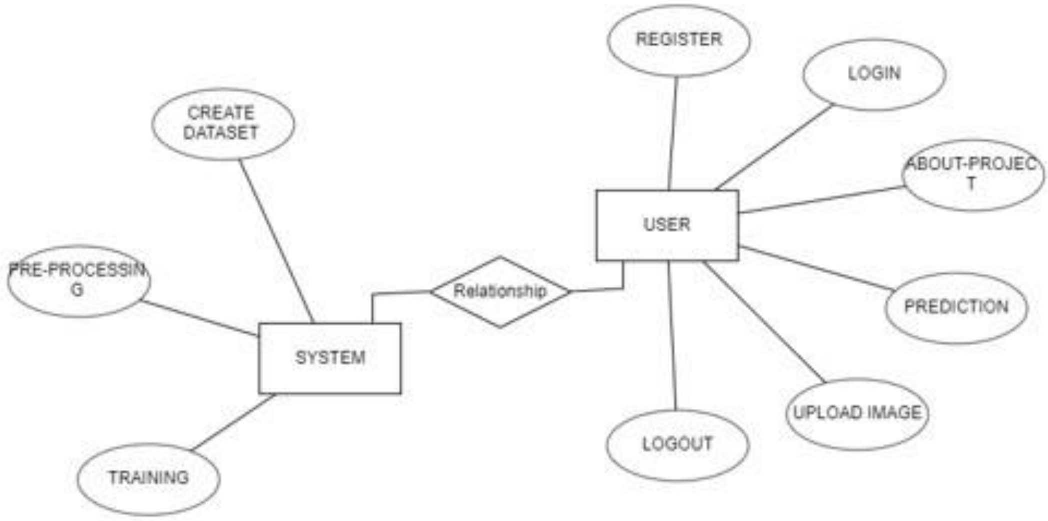
A component diagram, also known as a UML component diagram, describes the organization and wiring of the physical **c**omponents in a system. Component diagrams are often drawn to help model implementation details and double-check that every aspect of the system's required functions is covered by planned development.



3.1.7 ER Diagram:

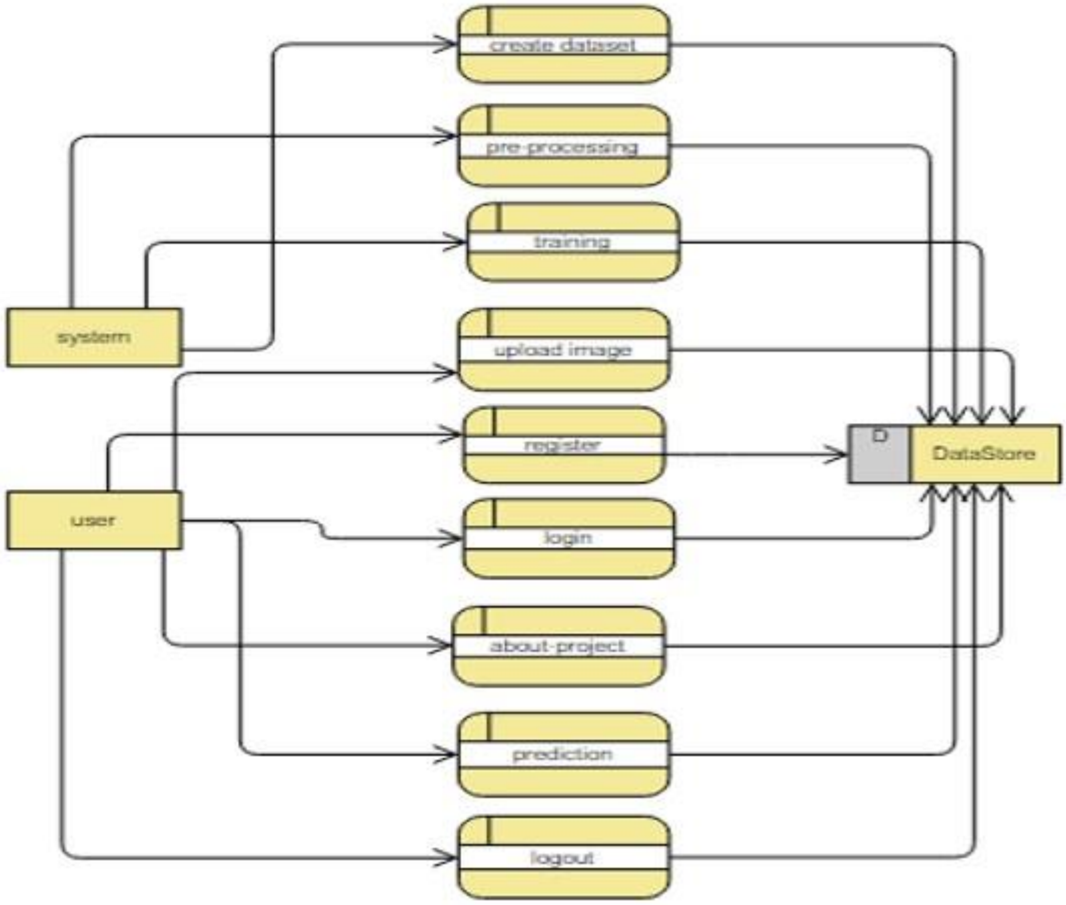
An Entity–relationship model (ER model) describes the structure of a database with the help of a diagram, which is known as Entity Relationship Diagram (ER Diagram). An ER model is a design or blueprint of a database that can later be implemented as a database. The main components of E-R model are: entity set and relationship set.

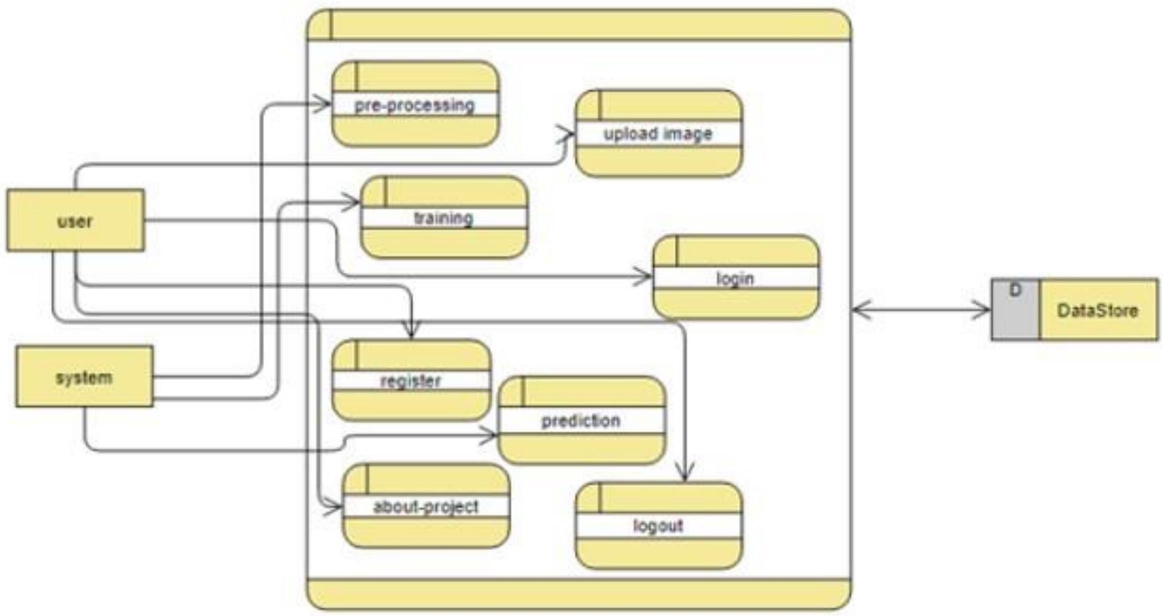
An ER diagram shows the relationship among entity sets. An entity set is a group of similar entities and these entities can have attributes. In terms of DBMS, an entity is a table or attribute of a table in database, so by showing relationship among tables and their attributes, ER diagram shows the complete logical structure of a database. Let's have a look at a simple ER diagram to understand this concept.



3.1.8 DFD Diagram:

A Data Flow Diagram (DFD) is a traditional way to visualize the information flows within a system. A neat and clear DFD can depict a good amount of the system requirements graphically. It can be manual, automated, or a combination of both. It shows how information enters and leaves the system, what changes the information and where information is stored. The purpose of a DFD is to show the scope and boundaries of a system as a whole. It may be used as a communications tool between a systems analyst and any person who plays a part in the system that acts as the starting point for redesigning a system.


create dataset
pre-processing
training
system
upload image
register
D
DataStore
user
login
about-project
prediction
logout


pre-processing
upload image
user
training
login
D
DataStore
system
register
prediction
about-project
logout

3.2 SYSTEM STUDY

3.2 Feasibility Study

The feasibility of the project is analysed in this phase and business proposal is put forth with a very general plan for the project and some cost estimates. During system analysis the feasibility study of the proposed system is to be carried out. This is to ensure that the proposed system is not a burden to the company. For feasibility analysis, some understanding of the major requirements for the system is essential.

Three key considerations involved in the feasibility analysis are

- Economical Feasibility
- Technical Feasibility
- Social Feasibility

3.2.1 Economical Feasibility

This study is carried out to check the economic impact that the system will have on the organization. The amount of fund that the company can pour into the research and development of the system is limited. The expenditures must be justified. Thus, the developed system as well within the budget and this was achieved because most of the technologies used are freely available. Only the customized products had to be purchased.

3.2.2 Technical Feasibility

This study is carried out to check the technical feasibility, that is, the technical requirements of the system. Any system developed must not have a high demand on the available technical resources. This will lead to high demands on the available technical resources. This will lead to high demands being placed on the client. The developed system must have a modest requirement, as only minimal or null changes are required for implementing this system.

3.2.3 Social Feasibility

The aspect of study is to check the level of acceptance of the system by the user. This includes the process of training the user to use the system efficiently. The user must not feel threatened by the system, instead must accept it as a necessity. The level of acceptance by the users solely depends on the methods that are employed to educate the user about the system and to make him familiar with it. His level of confidence must be raised so that he is also able to make some constructive criticism, which is welcomed, as he is the final user of the system.

3.3 SYSTEM SPECIFICATIONS

HARDWARE & SOFTWARE REQUIREMENTS

HARDWARE REQUIREMENTS

- Processor : I3/Intel Processor
- Hard Disk : 160GB
- RAM : 8Gb

SOFTWARE REQUIREMENTS

- Operating System : Windows 7/8/10 .
- Server side Script : HTML, CSS & JS.
- IDE : PyCharm.
- Libraries Used : NumPy, IO, OS, Flask, keras.
- Technology : Python 3.6+.