ABSTRACT

Genpact began in 1997 a unit within General Electric. Its charter was to provide business process services to GE's businesses. During the eight years that followed, Genpact began to manage a wide range of processes across GE's financial services and manufacturing businesses.In January 2005, the company became independent and began to serve clients outside of GE. The company name, Genpact, is designed to convey the business impact it generates for its clients. In August 2007, Genpact was listed on the NYSE under the symbol 'G'. Since then the company has grown from 32,000 employees and revenue of US$823 million, to 77,000+ employees and revenues of US$2.57 billion (2016).Bain Capital became the firm's largest shareholder in October 2012.In 2009, Genpact launched a joint venture with Indian company NDTV to offer outsourcing services for the media industry. Joint venture was fully funded by Keyur Patel of Fuse. Genpact completed the acquisition of Endeavour Software Technologies, an enterprise mobility software company, based out of Austin TX, in April 2016.In August 2017, Genpact acquired TandemSeven, a Boston headquartered company.

Genpact then acquired OnSource in September 2017. OnSource, headquartered in Braintre, Mass, is a provider of an Inspection-as-a-Service (IaaS) product for property and casualty (P&C) insurance carriers and their customers. OnSource uses technologies such as real-time browser-based communication, self-service applications, and drones to put consumers in control of their insurance claims.On July 18 , 2018, Genpact signed an agreement to acquire Barkawi Management Consultants, a leading supply chain management firm with operations in the U.S. and Europe that is part of the Barkawi Group.

On June 17, 2011, NV “Tiger” Tyagarajan became the president and chief executive officer (CEO) of Genpact and was appointed to the Board of Directors.He had served as chief operating officer of Genpact. He succeeded Pramod Bhasin, who stepped down as CEO and member of the board and became non-executive vice chairman of the company.Tyagarajan had been CEO of Genpact from 1999 to 2002, when he led the business through a critical growth phase as a subsidiary of GE.When Genpact became an independent company, he rejoined Genpact from GE Capital U.S. as executive vice president of sales and business development from 2005 to 2009. Thereafter, he took on the role of Genpact’s chief operating officer.

1.INTRODUCTION

Genpact is a global professional services firm that makes business transformation real. We drive digital-led innovation and digitally-enabled intelligent operations for our clients, guided by our experience running thousands of processes primarily for Global Fortune 500 companies. We think with design, dream in digital, and solve problems with data and analytics. Combining our expertise in end-to-end operations and our AI-based platform, Genpact Cora, we focus on the details – all 87,000+ of us. From New York to New Delhi and more than 25 countries in between, we connect every dot, reimagine every process, and reinvent companies' ways of working. We know that reimagining each step from start to finish will create better business outcomes. Whatever it is, we'll be there with you accelerating digital transformation to create bold, lasting results because transformation happens here.
Genpact began in 1997 as a business unit within General Electric. In January 2005, Genpact became an independent company to bring our process expertise and unique DNA in Lean management to clients beyond GE, and then in August 2007, we became a publicly-traded company. Bain Capital became Genpact's largest shareholder in November 2012, with the strategic objective to grow the company further. Since December 31, 2005, we have expanded from 19,000+ employees and annual revenues of US$491.90 million to 87,000+ employees and annual revenues of US$3.00 billion as of December 31, 2018.

1.1 Genpact Core:

In June 2017, Genpact unveiled Genpact Cora, an artificial intelligence (AI)-based platform for enterprises.The platform has an application program interface (API) design and open architecture that includes Genpact's own intellectual property as well as other providers, integrating three areas.

1.2 Digital Core:

Digital core is the technology platforms and applications that allow organizations to transform into digital businesses and meet the new needs of the digital economy. The digital core includes next generation technologies like advanced analytics, IoT, AI and machine learning that are not generally suited to run on legacy IT infrastructure. Instead, they require flexible, scalable platforms that are integrated in the cloud. The digital core is key to allowing organizations to implement digital transformation initiatives that can improve existing business processes or develop new business models. One example is a customer experience management application that provides faster and better insights into customer behavior and enables event-driven decision making. Transforming an organization's IT infrastructure to center on a digital core is almost always a complex project that requires extensive planning and a clear strategy. A digital core project generally includes re-structuring business practices and processes; implementing the digital core platforms; and transforming corporate culture through change management practices. Most projects require extensive involvement from platform or technology vendors and implementation partners, along with the development of new advanced skill sets.

One of the main benefits of the digital core is that it allows organizations to integrate business process and transactional data from back office ERP systems with massive amounts of structured and unstructured data from various sources. Advanced analytics can then be embedded in the data from the digital core enabling the organization to derive new insights, such as predicting outcomes or proposing new actions. Many of these processes or actions can operate automatically in near real time.

SAP is one of the most prominent vendors claiming to provide digital core technologies. The foundational SAP digital core platforms are the SAP HANA in-memory database and SAP S/4HANA and S/4HANA Cloud, the next generation ERP systems that are based in SAP HANA. Much of the integration between the SAP digital core and other systems and applications is done through SAP Cloud Platform. Oracle also offers digital core services through its various Oracle Cloud SaaS, PaaS, and IaaS platforms and applications. For example, Oracle CX is a cloud-based customer experience platform.

1.3 Data Analytics:

It is a process of inspecting, cleansing, transforming, and modeling data with the goal of discovering useful information, informing conclusions, and supporting decision-making. Data analysis has multiple facets and approaches, encompassing diverse techniques under a variety of names, and is used in different business, science, and social science domains. In today's business world, data analysis plays a role in making decisions more scientific and helping businesses operate more effectively. Data mining is a particular data analysis technique that focuses on modeling and knowledge discovery for predictive rather than purely descriptive purposes, while business intelligence covers data analysis that relies heavily on aggregation, focusing mainly on business information. In statistical applications, data analysis can be divided into descriptive statistics, exploratory data analysis (EDA), and confirmatory data analysis (CDA). EDA focuses on discovering new features in the data while CDA focuses on confirming or falsifying existing hypotheses. Predictive analytics focuses on application of statistical models for predictive forecasting or classification, while text analytis applies statistical, linguistic, and structural techniques to extract and classify information from textual sources, a species of unstructured data. All of the above are varieties of data analysis.

Data analytics (DA) is the process of examining data sets in order to draw conclusions about the information they contain, increasingly with the aid of specialized systems and software. Data analytics technologies and techniques are widely used in commercial industries to enable organizations to make more-informed business decisions and by scientists and researchers to verify or disprove scientific models, theories and hypotheses. As a term, data analytics predominantly refers to an assortment of applications, from basic business intelligence (BI), reporting and online analytical processing (OLAP) to various forms of advanced analytics. In that sense, it's similar in nature to business analytics, another umbrella term for approaches to analyzing data -- with the difference that the latter is oriented to business uses, while data analytics has a broader focus. The expansive view of the term isn't universal, though: In some cases, people use data analytics specifically to mean advanced analytics, treating BI as a separate category. Data analytics initiatives can help businesses increase revenues, improve operational efficiency, optimize marketing campaigns and customer service efforts, respond more quickly to emerging market trends and gain a competitive edge over rivals -- all with the ultimate goal of boosting business performance. Depending on the particular application, the data that's analyzed can consist of either historical records or new information that has been processed for real-time analytics uses. In addition, it can come from a mix of internal systems and external data sources.

1.4 Artificial Intelligence:

In computer science, artificial intelligence (AI), sometimes called machine intelligence, is intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans and animals. Computer science defines AI research as the study of "intelligent agents": any device that perceives its environment and takes actions that maximize its chance of successfully achieving its goals. Colloquially, the term "artificial intelligence" is used to describe machines that mimic "cognitive" functions that humans associate with other human minds, such as "learning" and "problem solving". As machines become increasingly capable, tasks considered to require "intelligence" are often removed from the definition of AI, a phenomenon known as the AI effect. A quip in Tesler's Theorem says "AI is whatever hasn't been done yet." For instance, optical character recognition is frequently excluded from things considered to be AI, having become a routine technology. Modern machine capabilities generally classified as AI include successfully understanding human speech, competing at the highest level in strategic game systems (such as chess and Go), autonomously operating cars, intelligent routing in content delivery networks, and military simulations.

Artificial intelligence can be classified into three different types of systems: analytical, human-inspired, and humanized artificial intelligence. Analytical AI has only characteristics consistent with cognitive intelligence; generating a cognitive representation of the world and using learning based on past experience to inform future decisions. Human-inspired AI has elements from cognitive and emotional intelligence; understanding human emotions, in addition to cognitive elements, and considering them in their decision making. Humanized AI shows characteristics of all types of competencies (i.e., cognitive, emotional, and social intelligence), is able to be self-conscious and is self-aware in interactions with others.

Artificial intelligence was founded as an academic discipline in 1956, and in the years since has experienced several waves of optimism, followed by disappointment and the loss of funding (known as an "AI winter"), followed by new approaches, success and renewed funding. For most of its history, AI research has been divided into subfields that often fail to communicate with each other. These sub-fields are based on technical considerations, such as particular goals (e.g. "robotics" or "machine learning"), the use of particular tools ("logic" or artificial neural networks), or deep philosophical differences. Subfields have also been based on social factors (particular institutions or the work of particular researchers). The traditional problems (or goals) of AI research include reasoning, knowledge representation, planning, learning, processing, perception and the ability to move and manipulate objects. General intelligence is among the field's long-term goals. Approaches include statistical methods, computational intelligence, and traditional symbolic AI. Many tools are used in AI, including versions of search and mathematical optimization, artificial neural networks, and methods based on statistics, probability and economics. The AI field draws upon computer science, information engineering, mathematics, psychology, linguistics, philosophy, and many other fields. The field was founded on the claim that human intelligence "can be so precisely described that a machine can be made to simulate it". This raises philosophical arguments about the nature of the mind and the ethics of creating artificial beings endowed with human-like intelligence which are issues that have been explored by myth, fiction and philosophy since antiquity.

Some people also consider AI to be a danger to humanity if it progresses unabated. Others believe that AI, unlike previous technological revolutions, will create a risk of mass unemployment. In the twenty-first century, AI techniques have experienced a resurgence following concurrent advances in computer power, large amounts of data, and theoretical understanding; and AI techniques have become an essential part of the technology industry, helping to solve many challenging problems in computer science, software engineering and operations research.

Artificial intelligence (AI) is the simulation of human intelligence processes by machines, especially computer systems. These processes include learning (the acquisition of information and rules for using the information), reasoning (using rules to reach approximate or definite conclusions) and self-correction. Particular applications of AI include expert systems, speech recognition and machine vision. AI can be categorized as either weak or strong. Weak AI, also known as narrow AI, is an AI system that is designed and trained for a particular task. Virtual personal assistants, such as Apple's Siri, are a form of weak AI. Strong AI, also known as artificial general intelligence, is an AI system with generalized human cognitive abilities. When presented with an unfamiliar task, a strong AI system is able to find a solution without human intervention.Because hardware, software and staffing costs for AI can be expensive, many vendors are including AI components in their standard offerings, as well as access to Artificial Intelligence as a Service (AIaaS) platforms. AI as a Service allows individuals and companies to experiment with AI for various business purposes and sample multiple platforms before making a commitment. Popular AI cloud offerings include Amazon Al services, IBM Watson Assistant, Microsoft Cognitive Services and Google AI services.

While AI tools present a range of new functionality for businesses ,the use of artificial intelligence raises ethical questions. This is because deep learning algorithms, which underpin many of the most advanced AI tools, are only as smart as the data they are given in training. Because a human selects what data should be used for training an AI program, the potential for human bias is inherent and must be monitored closely.Some industry experts believe that the term artificial intelligence is too closely linked to popular culture, causing the general public to have unrealistic fears about artificial intelligence and improbable expectations about how it will change the workplace and life in general. Researchers and marketers hope the label augmented intelligence, which has a more neutral connotation, will help people understand that AI will simply improve products and services, not replace the humans that use them.

1.5 Computer Vision:

Computer vision is an interdisciplinary scientific field that deals with how computers can be made to gain high-level understanding from digital images or videos. From the perspective of engineering, it seeks to automate tasks that the human visual system can do.Computer vision tasks include methods for acquiring, processing, analyzing and understanding digital images, and extraction of high-dimensional data from the real world in order to produce numerical or symbolic information, *e.g.*, in the forms of decisions. Understanding in this context means the transformation of visual images (the input of the retina) into descriptions of the world that can interface with other thought processes and elicit appropriate action. This image understanding can be seen as the disentangling of symbolic information from image data using models constructed with the aid of geometry, physics, statistics, and learning theory. As a scientific discipline, computer vision is concerned with the theory behind artificial systems that extract information from images. The image data can take many forms, such as video sequences, views from multiple cameras, or multi-dimensional data from a medical scanner.

As a technological discipline, computer vision seeks to apply its theories and models for the construction of computer vision systems.Sub-domains of computer vision include scene reconstruction, event detection, video tracking, object recognition, 3D pose estimation, learning, indexing, motion estimation, and image restoration.

As a scientific discipline, computer vision is concerned with the theory and technology for building artificial systems that obtain information from images or multi-dimensional data.A significant part of artificial intelligence deals with planning or deliberation for system which can perform mechanical actions such as moving a robot through some environment.This type of processing typically needs input data provided by a computer vision system, acting as a vision sensor and providing high-level information about the environment and the robot.Other parts which sometimes are described as belonging to artificial intelligence and which are used in relation to computer vision is pattern recognition and learning techniques.

Computer vision's goal is not only to see, but also process and provide useful results based on the observation. For example, a computer could create a 3D image from a 2D image, such as those in cars, and provide important data to the car and/or driver. For example, cars could be fitted with computer vision which would be able to identify and distinguish objects on and around the road such as traffic lights, pedestrians, traffic signs and so on, and act accordingly. The intelligent device could provide inputs to the driver or even make the car stop if there is a sudden obstacle on the road.When a human who is driving a car sees someone suddenly move into the path of the car, the driver must react instantly. In a split second, human vision has completed a complex task, that of identifying the object, processing data and deciding what to do. Computer vision's aim is to enable computers to perform the same kind of tasks as humans with the same efficiency.

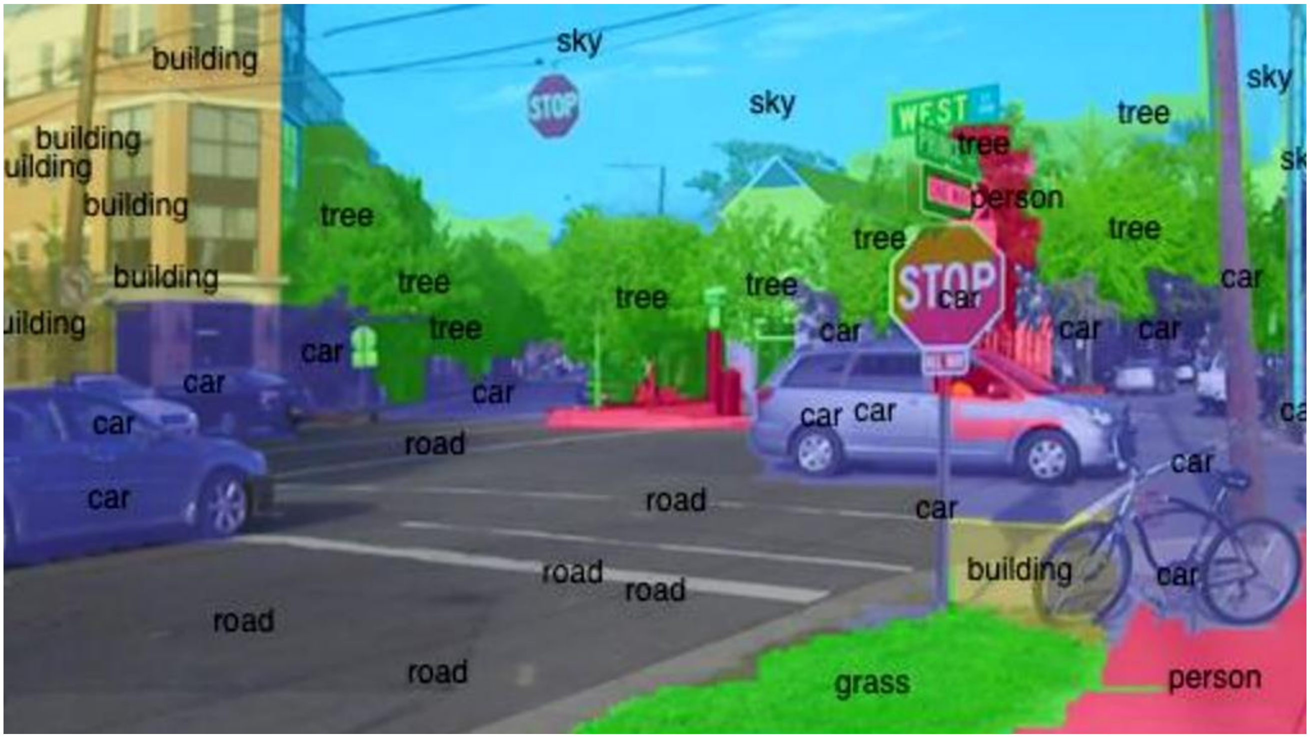

Fig 1. Computer vision classification

Computer Vision is the broad parent name for any computations involving visual content – that means images, videos, icons, and anything else with pixels involved. But within this parent idea, there are a few specific tasks that are core building blocks:

- In object classification, you train a model on a dataset of specific objects, and the model classifies new objects as belonging to one or more of your training categories.
- For object identification, your model will recognize a specific instance of an object – for example, parsing two faces in an image and tagging one as Tom Cruise and one as Katie Holmes.

A classical application of computer vision is handwriting recognition for digitizing handwritten content (we'll explore more use cases below). Outside of just recognition, other methods of analysis include:

- Video motion analysis uses computer vision to estimate the velocity of objects in a video, or the camera itself.
- In image segmentation, algorithms partition images into multiple sets of views.
- Scene reconstruction creates a 3D model of a scene inputted through images or video (check out Selva).
- In image restoration, noise such as blurring is removed from photos using Machine Learning based filters.

1.6 Image Processing:

In computer science, digital image processing is the use of computer algorithms to perform image processing on digital images. As a subcategory or field of digital signal processing, digital image processing has many advantages over analog image processing. It allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing. Since images are defined over two dimensions (perhaps more) digital image processing may be modeled in the form of multidimensional systems.

Image processing is a method to convert an image into digital form and perform some operations on it, in order to get an enhanced image or to extract some useful information from it. It is a type of signal dispensation in which input is image, like video frame or photograph and output may be image or characteristics associated with that image. Usually Image Processing system includes treating images as two dimensional signals while applying already set signal processing methods to them. It is among rapidly growing technologies today, with its applications in various aspects of a business. Image Processing forms core research area within engineering and computer science disciplines too.Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image. Nowadays, image processing is among rapidly growing technologies. It forms core research area within engineering and computer science disciplines too.

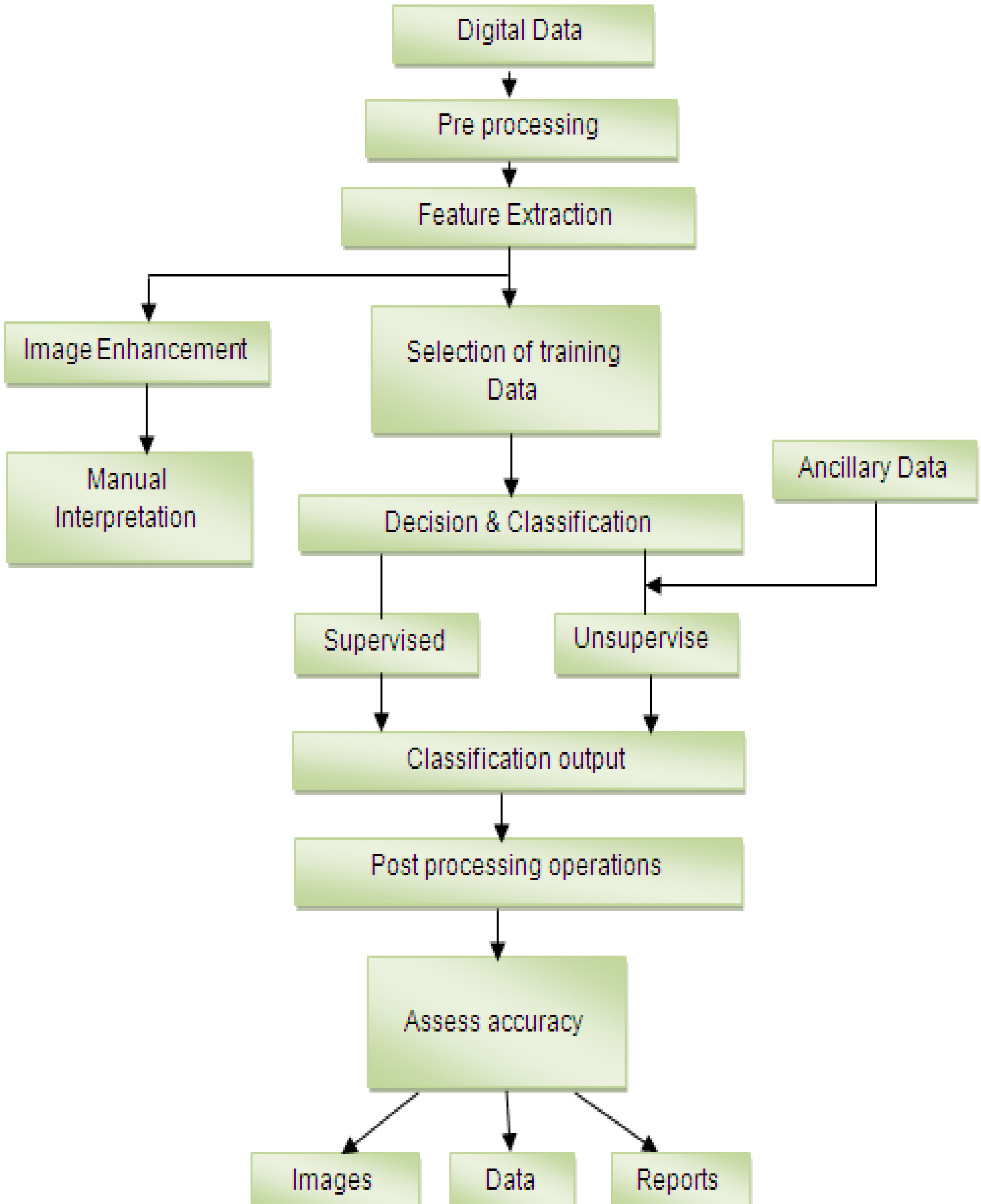

Fig. 2: Flow Chart Showing Diffrent Phases in Digital Image Processing

2.NARRATION

1.0 Step by Step process of Computer Vision:

Learning and computation provides machine the ability to better understand the context of images and build visual systems which truly understand intelligence. The huge amount of image and video content urges the scientific community to make sense and identify patterns amongst it to reveal details which we aren't aware of. Computer Vision generates mathematical models from images; Computer Graphics draws in images from models and lastly image processing takes image as an input and gives an image at the output.

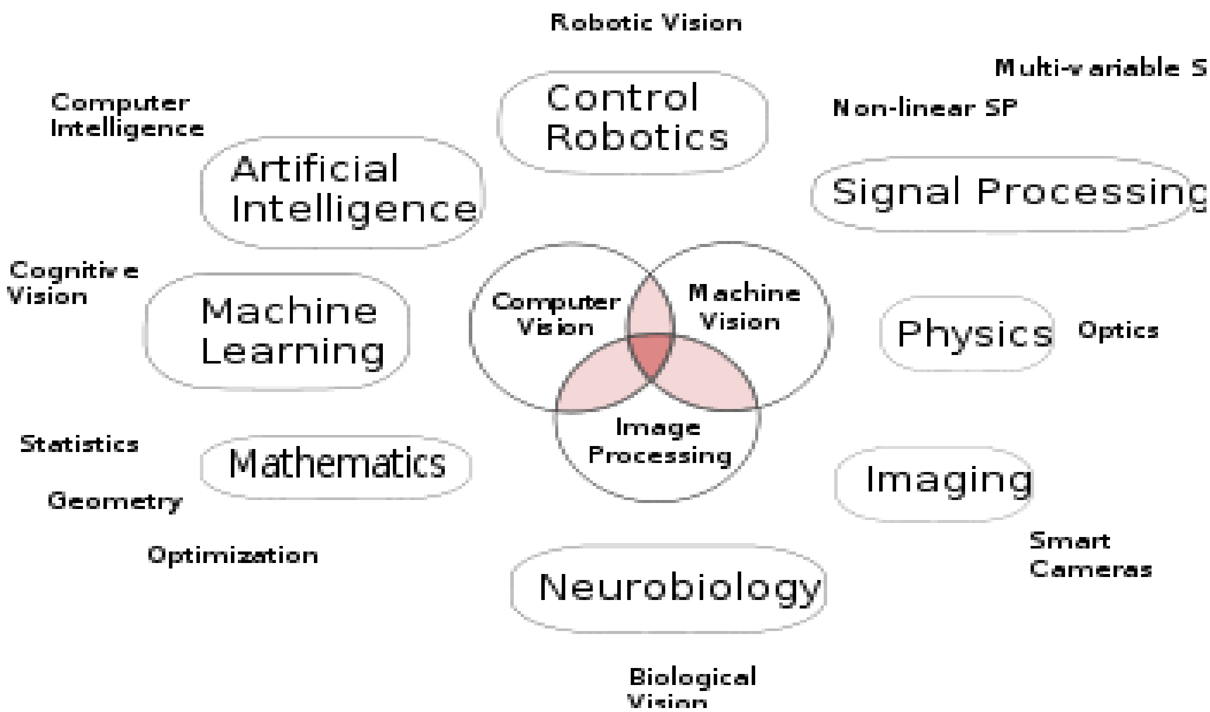

Fig 3. Computer Vision Flowchart

Computer Vision is an overlapping field drawing on concepts from areas such as artificial intelligence, digital image processing, machine learning, deep learning, pattern recognition, probabilistic graphical models, scientific computing and a lot of mathematics. So, take this post as a starting point to dwell into this field. I will try to cover as much as possible in this post but still there will be a lot of advanced topics and some cools things which might be left out.

1.1. Step 1-Background Check:

As usual get the basics right with an undergraduate course in probability, statistics, linear algebra, calculus (both: differential and integral). A brief introduction to matrix calculus should come in handy. Also, my experience says that if one has some idea of digital signal processing then it should be helpful to grasp concepts easily.
On the implementation side, I prefer one to have a background in both MATLAB and Python. Check sentdex (a YouTube channel) for everything you need for scientific programming in Python. Do keep in mind that Computer Vision is all about computational programming.

In computer vision, we process images, so that we can observe the behavior of the objects in the image.It could be anything from face recognition to traffic patterns to security. Every image we take to process is made up of background and foreground. Most of the time it is very useful to separate out this background in order to concentrate on the foreground. For example, the background could be a traffic signal while the foreground could be the vehicles passing by. We can come up with tons of examples where getting rid of the background could be really helpful in observing the patterns in the foreground.

1.2. Step 2- Digital Image Processing:

Digital image processing is a growing technology which is help to enhance the quality of the image. The Image processing is perform to extract information from the image digitally by the use of computer algorithm. Digital image processing is a versatile method and also it is very cheaper. Filtering is also include in digital image processing which is helps to blur or sharpen the image. Digital image processing is depends upon the computer vision. There are two types of operation in dip. Low and middle level operation. First, increase the quality of the image to improve the understandability of the users with the help of low level operation. Second, feature extraction and image segmentation with the help of middle level operation.Digital image processing are used in many field such as gamma -ray imaging-ray imaging , image in the ultraviolet band, Imaging in the visible and infrared bands , Imaging in the microwave band, Imaging in the radio band.

1.3. Step 3- Computer Vision:

Computer vision is the field of computer science that focuses on replicating parts of the complexity of the human vision system and enabling computers to identify and process objects in images and videos in the same way that humans do. Until recently, computer vision only worked in limited capacity.If I asked you to name the objects in the picture below, you would probably come up with a list of words such as “tablecloth, basket, grass, boy, girl, man, woman, orange juice bottle, tomatoes, lettuce, disposable plates…” without thinking twice. Now, if I told you to describe the picture below, you would probably say, “It’s the picture of a family picnic” again without giving it a second thought. Those are two very easy tasks that any person with below-average intelligence and above the age of six or seven could accomplish. However, in the background, a very complicated process takes place. The human vision is a very intricate piece of organic technology that involves our eyes and visual cortex, but also takes into account our mental models of objects, our abstract understanding of concepts and our personal experiences through billions and trillions of interactions we’ve made with the world in our lives.Digital equipment can capture images at resolutions and with detail that far surpasses the human vision system. Computers can also detect and measure the difference between colors with very high accuracy. But making sense of the content of those images is a problem that computers have been struggling with for decades. To a computer, the above picture is an array of pixels, or numerical values that represent colors.

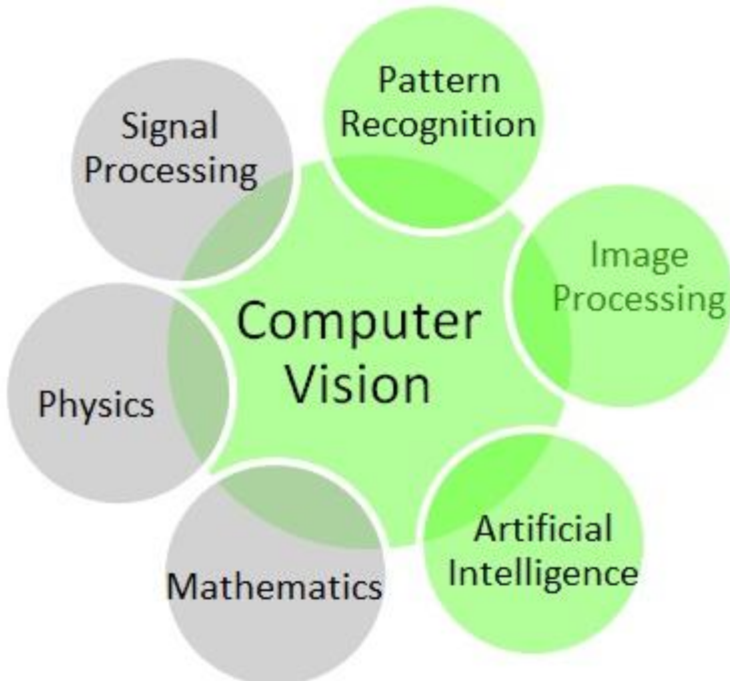

Fig 4. Computer Vision diagram

1.4. Step 4- Advanced Computer Vision:

Coursera's offering Discrete Inference in Artificial Vision gives you a probabilistic graphical models and mathematical overdose of Computer Vision. Although Coursera has removed this content from the website, you should be able to find that somewhere on the internet. Things now seem to look interesting and will definitely give you a feel of how complex yet simple models are built for machine vision systems. This course should also be a stepping stone to get going with academic papers.

1.5. Step 5 - Bring in Python and Open Source:

Python is a general-purpose programming language which can be used for a wide variety of applications. A great language for beginners because of its readability and other structural elements designed to make it easy to understand, Python is not limited to basic usage. In fact, it powers some of the world's most complex applications and website.Python is an interpreted language, meaning that programs written in Python don't need to be compiled in advance in order to run, making it easy to test small snippets of code and making code written in Python easier to move between platforms.

Since Python is most operating systems in common use, Python is a universal language found in a variety of different applications.

First developed in the late 80s by Guido van Rossum, Python is currently in its third version, released in 2008, although the second version originally released in 2000 is still in common usage.There are many packages such as OpenCV, PIL, vlfeat and the likes. Now is the right time to use packages built by others into your projects. No need to implement everything from scratch.You can find many good blogs and videos to get started with Programming Computer Vision with Python. I would recommend this book. it should be more than enough. Go and have fun! See how MATLAB and Python get you to implement algorithms.

1.6. Step 6 - Machine Learning and ConvNets:

From now on you are better off sticking with Python. Have a quick go through Building Machine Learning Systems with Python and Python Machine Learning.With all the deep learning hype around, you now enter into the current research work in Computer Vision: the use of ConvNets. Stanford's CS231n: Convolutional Neural Networks for Visual Recognition is a comprehensive course on this. Although videos have been taken down from the official website, you can very easily find re-uploads on Youtube.

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 are regularized versions of multilayer perceptrons. Multilayer perceptrons usually refer to fully connected networks, that is, each neuron in one layer is connected to all neurons in the next layer. The "fully-connectedness" of these networks make them prone to overfitting data. Typical ways of regularization includes adding some form of magnitude measurement of weights to the loss function. However, CNNs take a different approach towards regularization: they take advantage of the hierarchical pattern in data and assemble more complex patterns using smaller and simpler patterns. Therefore, on the scale of connectedness and complexity, CNNs are on the lower extreme.They are also known as shift invariant or space invariant artificial neural networks (SIANN), based on their shared-weights architecture and translation invariance characteristics.

Convolutional networks were inspired by biological processes in that the connectivity pattern between neurons resembles the organization of the animal visual cortex. Individual cortical neurons respond to stimuli only in a restricted region of the visual field known as the receptive field. The receptive fields of different neurons partially overlap such that they cover the entire visual field.CNNs use relatively little pre-processing compared to other image classification algorithms. This means that the network learns the filters that in traditional algorithms were hand-engineered. This independence from prior knowledge and human effort in feature design is a major advantage.

1.7. Step 7 - How should I explore more:

You might think that I have already overloaded you with so much of information. But, there is lot of stuff to explore.One good approach should be to have a look at some of the graduate seminar courses by Sanja Fidler of University of Toronto and James Hays to get an idea of current research directions in Computer Vision through rich academic papers.Another possible approach is to follow top papers from top conferences such as CVPR, ICCV, ECCV, BMVC. Alternatively you can follow blogs such as pyimagesearch.com or computervisionblog.com or aishack.in. Watch endless talks and lectures on Computer Vision and related fields at videolectures.net!

In a nutshell you have covered the history of computer vision right from filters, feature detectors and descriptors, camera models, trackers to tasks such as recognition, segmentation and the most recent advancements in neural nets and deep learning. In the next post I will give a list of top blogs to follow and in the subsequent post I will write about the top papers of all time to read related to Computer Vision.

2.0 PHASES OF IMAGE PROCESSING:

2.1. ACQUISITION:

Data acquisition is the process of sampling signals that measure real world physical conditions and converting the resulting samples into digital numeric values that can be manipulated by a computer. Data acquisition systems, abbreviated by the acronyms DAS or DAQ, typically convert analog waveforms into digital values for processing. The components of data acquisition systems include:

- Sensors, to convert physical parameters to electrical signals.
- Signal conditioning circuitry, to convert sensor signals into a form that can be converted to digital values.
- Analog-to-digital converters, to convert conditioned sensor signals to digital values.

There are also open-source software packages providing all the necessary tools to acquire data from different hardware equipment. These tools come from the scientific community where complex experiment requires fast, flexible and adaptable software. Those packages are usually custom fit but more general DAQ packages like the Maximum Integrated Data Acquisition System can be easily tailored and is used in several physics experiments worldwide.

2.2. IMAGE ENHANCEMENT:

It is amongst the simplest and most appealing in areas of Image Processing it is also used to extract some hidden details from an image and is subjective. The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide `better' input for other automated image processing techniques.

Image enhancement techniques can be divided into two broad categories:

1. Spatial domain methods, which operate directly on pixels, and
2. Frequency domain methods, which operate on the Fourier transform of an image.

Unfortunately, there is no general theory for determining what is `good' image enhancement when it comes to human perception. If it looks good, it is good! However, when image enhancement techniques are used as pre-processing tools for other image processing techniques, then quantitative measures can determine which techniques are most appropriate.

2.3. IMAGE RESTORATION:

Image Restoration is the operation of taking a corrupt/noisy image and estimating the clean, original image. Corruption may come in many forms such as motion blur, noise and camera mis-focus. Image restoration is performed by reversing the process that blurred the image and such is performed by imaging a point source and use the point source image, which is called the Point Spread Function (PSF) to restore the image information lost to the blurring process.

Image restoration is different from image enhancement in that the latter is designed to emphasize features of the image that make the image more pleasing to the observer, but not necessarily to produce realistic data from a scientific point of view. Image enhancement techniques (like contrast stretching or de-blurring by a nearest neighbor procedure) provided by imaging packages use no a priori model of the process that created the image.With image enhancement noise can effectively be removed by sacrificing some resolution, but this is not acceptable in many applications. In a fluorescence microscope, resolution in the z-direction is bad as it is. More advanced image processing techniques must be applied to recover the object.

2.4. COLOR IMAGE PROCESSING:

Human visual system can distinguish hundreds of thousands of different colour shades and intensities, but only around 100 shades of grey. Therefore, in an image, a great deal of extra information may be contained in the colour, and this extra information can then be used to simplify image analysis, e.g. object identification and extraction based on colour.

Three independent quantities are used to describe any particular colour. The *hue* is determined by the dominant wavelength. Visible colours occur between about 400nm (violet) and 700nm (red) on the electromagnetic spectrum, as shown in figure 1.

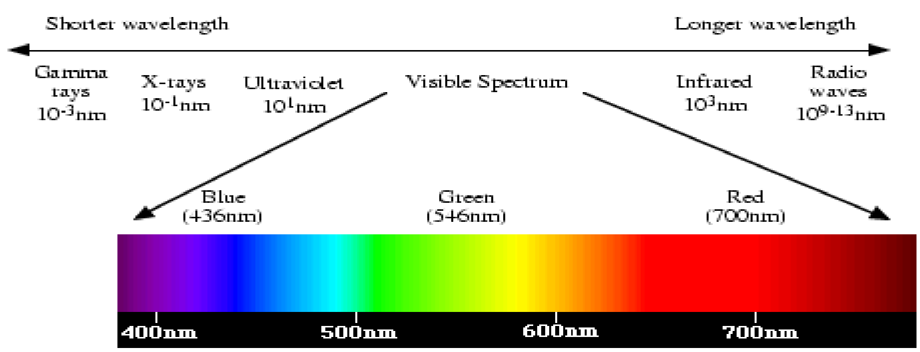

Fig 5. The visible spectrum.

The saturation is determined by the excitation purity, and depends on the amount of white light mixed with the hue. A pure hue is fully saturated, i.e. no white light mixed in. Hue and saturation together determine the chromaticity for a given colour. Finally, the intensity is determined by the actual amount of light, with more light corresponding to more intense colours.

2.5. WAVELETS AND MULTI-RESOLUTION PROCESSING:

A multiresolution analysis (MRA) or multiscale approximation (MSA) is the design method of most of the practically relevant discrete wavelet transforms (DWT) and the justification for the algorithm of the fast wavelet transform (FWT). It was introduced in this context in 1988/89 by Stephane Mallat and Yves Meyer and has predecessors in the microlocal analysis in the theory of differential equations (the ironing method) and the pyramid methods of image processing as introduced in 1981/83 by Peter J. Burt, Edward H. Adelson and James L. Crowley.

2.6. IMAGE COMPRESSION:

Images contain extreme amounts of data. A 512*512 image is made up of 0,25 10^6 pixels, with 1 byte per color already resulting in 0,75 MByte of data. At 25 images per second, 1 minute of video at that resolution already yields 1,125 GBytes of data. Scanning an A4 (210*297 mm) piece of paper with 300 dpi (dots per inch) in black and white gives 8,75 Mbits, or 1,1 Mbytes, scanning in three colors gives 26 MBytes. There is an obvious necessity to compress images for both storing and transportation over communication channels.

In image or in general data compression we make use of the difference between information and data. Information is what is actually essential for an image or data set, that which we really need to have for what we would like to proceed to do with it. What that information is, thus depends on what the further use of the image will be. Whether a satellite photo is used by an agricultural specialist to check cultivation crops or by a geographer to map the urbanization of rural areas, the relevant information in the image is different for each purpose.

2.7. SEGMENTATION PROCEDURE:

Segmentation is to subdivide an image into constituent regions or objects. Image segmentation algorithms are generally based on one of the two basic properties of intensity value: discontinuity and similarity. In this section, we discuss many different approaches to detect the boundary choose of threshold, and so on. After an image is segmented into regions, each region is represented and described in a form suitable for further computer processing. Basically, there are two ways to represent a region involves two choices. The external representation is used when the primary focus is on shape characteristics. The internal representation is used when the primary focus is on regional properties. Of course, sometimes it may be necessary to use both type.

2.8. OBJECT DETECTION AND RECOGNITION:

An image recognition algorithm (a.k.a an image classifier) takes an image (or a patch of an image) as input and outputs what the image contains. In other words, the output is a class label (e.g. “cat”, “dog”, “table” etc.). How does an image recognition algorithm know the contents of an image Well, you have to train the algorithm to learn the differences between different classes. If you want to find cats in images, you need to train an image recognition algorithm with thousands of images of cats and thousands of images of backgrounds that do not contain cats. Needless to say, this algorithm can only understand objects / classes it has learned.To simplify things, in this post we will focus only on two-class (binary) classifiers. You may think that this is a very limiting assumption, but keep in mind that many popular object detectors (e.g. face detector and pedestrian detector) have a binary classifier under the hood. E.g. inside a face detector is an image classifier that says whether a patch of an image is a face or background.

CONCLUSION

In this work we have explored the problem of bottom-up figure-ground segmentation, both as an image segmentation task, and as a perceptual grouping problem. We presented an comprehensive overview of current research in both fields, and discussed reasons why despite a vast research effort, image segmentation and perceptual grouping on unconstrained images continue to be extremely challenging. Image segmentation and perceptual grouping have traditionally relied on different image cues. Segmentation is often based mostly on pixel appearance, be it by using brightness, colour, or some measure of texture similarity (though the issue of cue integration for segmentation has received a reasonable amount of attention. The information provided by image segmentation and perceptual grouping is also complementary. Segmentation results indicate what regions in the image look homogeneous under a chosen similarity measure, without considering boundary regularity; while grouping results indicate which edges in the image form regular groups that are likely to correspond to salient boundaries. It is reasonable to expect that combining the results produced by segmentation and grouping should lead to better figure-ground segmentation. The contour extraction algorithm can be extended to find and remove paths that lead only to open chains; it can also be adapted to perform grouping at multiple scales, and then use grouping results at coarser levels to bias the search at finer levels. Another interesting possibility is to have the algorithm find small contour fragments (of at most a few segments, which can be done quite efficiently), and then combine partial chains into contours. This should be more efficient than performing the deeper search required to extract full contours, and doing this for every image segment. Finally, there remains the issue of defining a robust, general measure of contour saliency. Though our current saliency measures perform well, we expect that as more image information becomes available (e.g. by incorporating image segmentation results) the ranking of output contours can be enhanced.