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Department of Electronics & Instrumentation Engineering

IMAGE CLASSIFICATION WITH LABVIEW

& INDUSTRY APPLICATIONS

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AIM & OBJECTIVE

Today we are surrounded by different technologies which are constantly developing. We are in an era of technological renaissance. With an increase in the technology we develop we are moving towards a world where everything is integrated and connected seamlessly.

Today to facilitate seamless adaption of technology across different domains of science, there has been development in various fields of science in many different areas like Neural Networks, Statistical Methods, Artificial Intelligence, Quantum Computation and different areas of Physics.

The Phase-2 of the project is intended to implement a highly dynamic field of study i.e. Image Classification and Identification used almost everywhere in ***Industry*** to classify materials based on their quality, using a highly interactive G-Programming Environment taught under the curriculum i.e. ***NI-LabVIEW***.

The projecct explains how the ***IEEE 802.11*** and ***SMTP Protocols*** are used by cameras to transfer our images and analyse them.

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NECESSITY

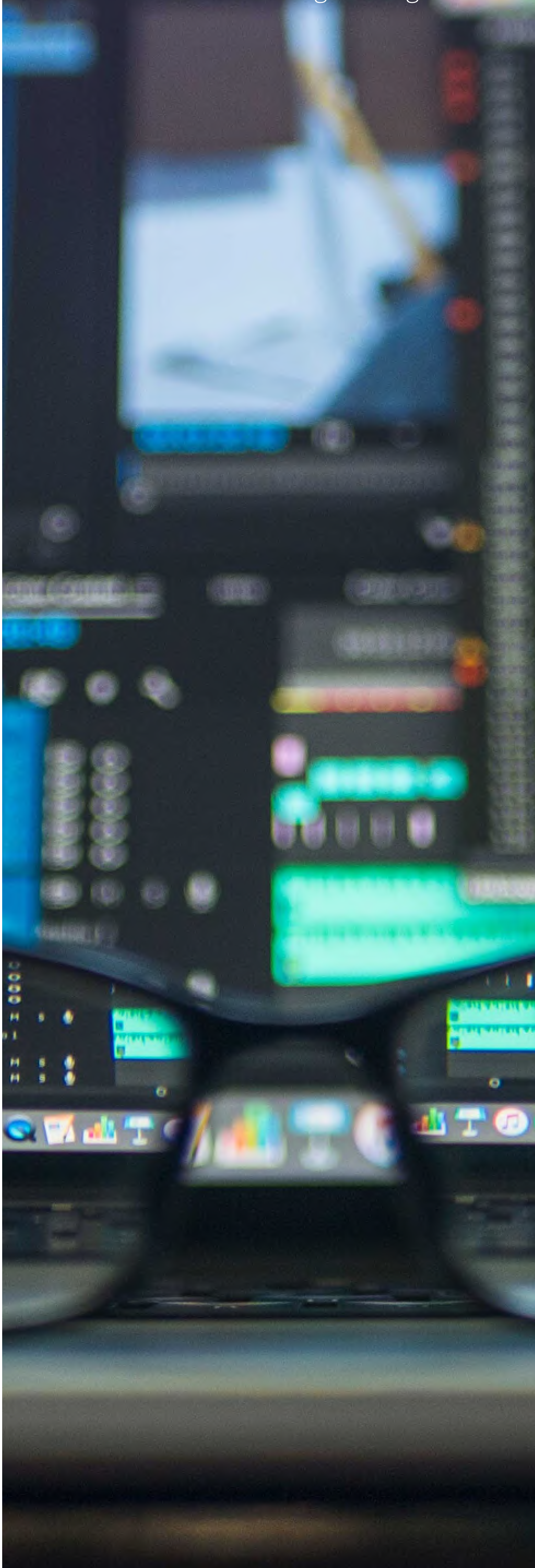
& IMPORTANCE

What is Image Classification and what is its need?

The first question we may have is what the difference is between computer vision and image recognition. Indeed, computer vision has been vigorously developed by Google, Amazon and many AI developers, and the two terms “computer vision” and “image recognition” may have used interchangeably. Computer vision (CV) is to let a computer imitate human vision and take action. For example, CV can be designed to sense a running child on the road and produces a warning signal to the driver. In contrast, image recognition is about the pixel and pattern analysis of an image to recognize the image as a particular object. Computer vision means it can “do something” with the recognized images. Because in this post I will describe the machine learning techniques for image recognition, I will still use the term “image recognition”.

Just like the phrase “What-you-see-is-what-you-get” says, human brains make vision easy. It doesn’t take any effort for humans to tell apart a dog, a cat or a flying saucer. But this process is quite hard for a computer to imitate: they only seem easy because God designs our brains incredibly good in recognizing images.

A common example of image recognition is optical character recognition (OCR). A scanner can identify the characters in the image to convert the texts in an image to a text file. With the same process, OCR can be applied to recognize the text of a license plate in an image.



What is graphical programming?

The graphical approach to programming allows a computer to process spatial representations in two or more dimensions. In contrast to text-based programming, which uses lines of code, graphical programming replaces text with pictures or symbols of physical things.Graphical programming provides an approach that's more intuitive and less cumbersome for some programmers. It also can be a more effective way to introduce computer programming to visual learners. For example, researchers at the Lifelong Kindergarten Group have created a program called Scratch, which uses graphical programming to help children learn math and engage in creative thinking.Graphical programming is often called visual programming or Visual Programming Language (VPL). It's different from Microsoft's Visual Basic, which defines pictures by using text-based language.

Laboratory Virtual Instrument Engineering Workbench (LabVIEW) is a system-design platform and development environment for a visual programming language from National Instruments.The graphical language is named "G"; not to be confused with G-code. Originally released for the Apple Macintosh in 1986, LabVIEW is commonly used for data acquisition, instrument control, and industrial automation on a variety of operating systems (OSs), including Microsoft Windows, various versions of Unix, Linux, and macOS.The latest versions of LabVIEW are LabVIEW 2019 SP1 and LabVIEW NXG 4.0, released in November 2019. NI released the free for non-commercial use LabVIEW and LabVIEW NXG Community editions on April 28th, 2020.

What is the use of Image Classification in Industry?

When machine learning and image classification get integrated, computers become capable of performing visual tasks that until recently could only be carried out by humans. Together, these technologies offer the potential for breakthroughs in automation, presenting new digital opportunities for companies in a variety of domains.

Let's begin by exploring some medical applications for image classification through machine learning. Image analysis, whether performed by a human or a machine, can literally influence life or death decisions, as doctors often depend on what they can see as much as anything else in identifying medical conditions and correct treatment for them.In fact, according to an article published by Healthcare Informatics last year, IBM researchers say images represent 90% of all data used in the medical field. Given that computers are not prone to stress, distraction, or fatigue, it's no great stretch of the imagination to see how imaging solutions can help medical professionals diagnose patients accurately and hence administer the most appropriate treatment.In addition to consistent accuracy, speed is another advantage of artificial intelligence systems, such as convolutional neural networks. Once trained, they can classify and analyze visual content more quickly than humans, which means faster as well as more accurate diagnosis and treatment.

Thus by analyzing images of people, places, objects, scenes, and documents, machine learning for image classification promises new levels of automation in just about every industry. If your business is not involved in the industries mentioned above (or even if it is), the examples presented here may inspire you to have your own ideas about using the technology in your company.

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RESEARCH GAP

The prevailing current problems in Image Recognition Technology:

Over the decades that we've spent as researchers and technical leaders in computer vision, there have been few developments as astounding as the rapid progress in image recognition. In the past several years, we have seen object detection performance skyrocket from approximately 30 percent in mean average precision to more than 90 percent today, on the PASCAL VOC benchmark. For image classification on the challenging ImageNet dataset, state-of-the-art algorithms now exceed human performance. These improvements in image understanding have begun to impact a wide range of high-value applications, including video surveillance, autonomous driving, and intelligent healthcare.The driving force behind the recent advances in image recognition is deep learning, whose success is powered by the formation of large-scale datasets, the development of powerful models, and the availability of vast computational resources. For a variety of image recognition tasks, carefully designed deep neural networks have greatly surpassed previous methods that were based on hand-crafted image features. Yet despite the great success of deep learning in image recognition so far, there are numerous challenges that remain to be overcome before it can be employed for broader use.

Improving model generalization

One of these challenges is in how to train models that generalize well to real-world settings that have not been seen in training. In current practice, a model is trained and evaluated on a dataset that is randomly split into training and test sets. The test set thus has the same data distribution as the training set, as they both are sampled from the same range of scene content and imaging conditions that exist in this data. However, in real-world applications, the test images may come from data distributions different from those used in training. For example, the unseen data may differ in viewing angles, object scales, scene configurations, and camera properties. A recent study shows that such a gap in data distribution can lead to significant drops in accuracy over a wide variety of deep network architectures [1]. The susceptibility of current models to natural variations in the data distribution can be a severe drawback in critical applications such as autonomous vehicle navigation.

Exploiting small and ultra-large-scale data

Another existing challenge is how to better exploit small-scale training data. While deep learning has shown great success in various tasks with a large amount of labeled data, current techniques generally break down if few labeled examples are available. This condition is often referred to as few-shot learning and it demands careful consideration in practical applications. For example, a household robot is expected to recognize a new object after being shown it just once. A human can naturally do so even if the object is manipulated, such as folding up a blanket. How to endow deep learning networks with such generalization ability is an open problem in research.At the other extreme is how the performance of recognition algorithms can be effectively scaled with ultra-large-scale data. For critical applications such as autonomous driving, the cost of recognition errors is very high.

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So enormous datasets, containing hundreds of millions of images with rich annotations, are built with hopes that the accuracy of the trained models can be dramatically improved. However, a recent study suggests that current algorithms cannot necessarily exploit such ultra-large-scale data as effectively [2]. On the JFT dataset containing 300 million annotated images, the performance of a variety of deep networks increases just logarithmically with respect to the amount of training data (Image 1). The diminishing benefits of greater training data at large scales present a significant issue to address.

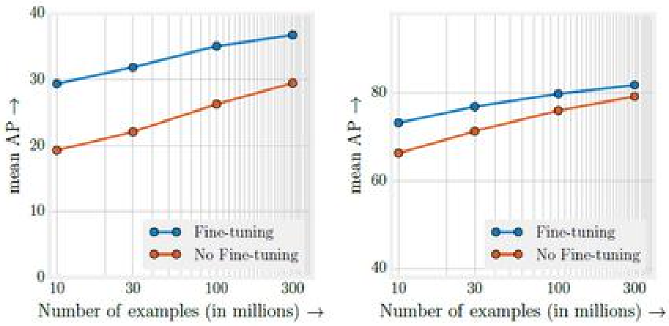


Image 1 The left graph uses the mAP @ [0.5, 0.95] metric on the COCO minival test set, and the right graph uses the mAP @ 0.5 metric on the PASCAL VOC 2007 test set.

Automating network engineeringA final challenge that we wish to mention is the need to automate network engineering. In recent years, the field has seen its focus shift from the crafting of better features to designing new network architectures. However, architecture engineering is a tedious process that deals with numerous hyperparameters and design choices. Tuning these elements requires a tremendous amount of time and effort by experienced engineers. What's more, the optimal architecture for one task may well be quite different for another task. Although investigations into automatic neural architecture search have begun, they are still at an early stage and have been limited only to image classification.

The search space of current approaches is rather narrow, as they seek a locally optimal combination of existing network modules (e.g., depth-wise convolutions and identity connections) and are unable to discover new modules (Image 3). Whether these current approaches are adequate for more sophisticated tasks is unclear.

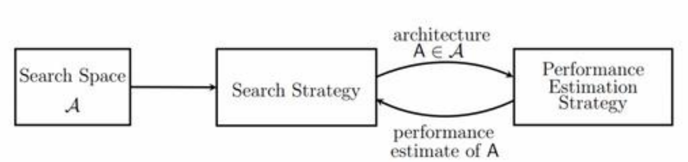


Image 3 Abstract diagram of the neural structure search algorithm.

Despite these challenges, we still believe in the huge potential of deep learning for image recognition. Opportunities abound for addressing these issues and rapidly pushing the field forward. Several of these directions are described below.

Integrating common sense

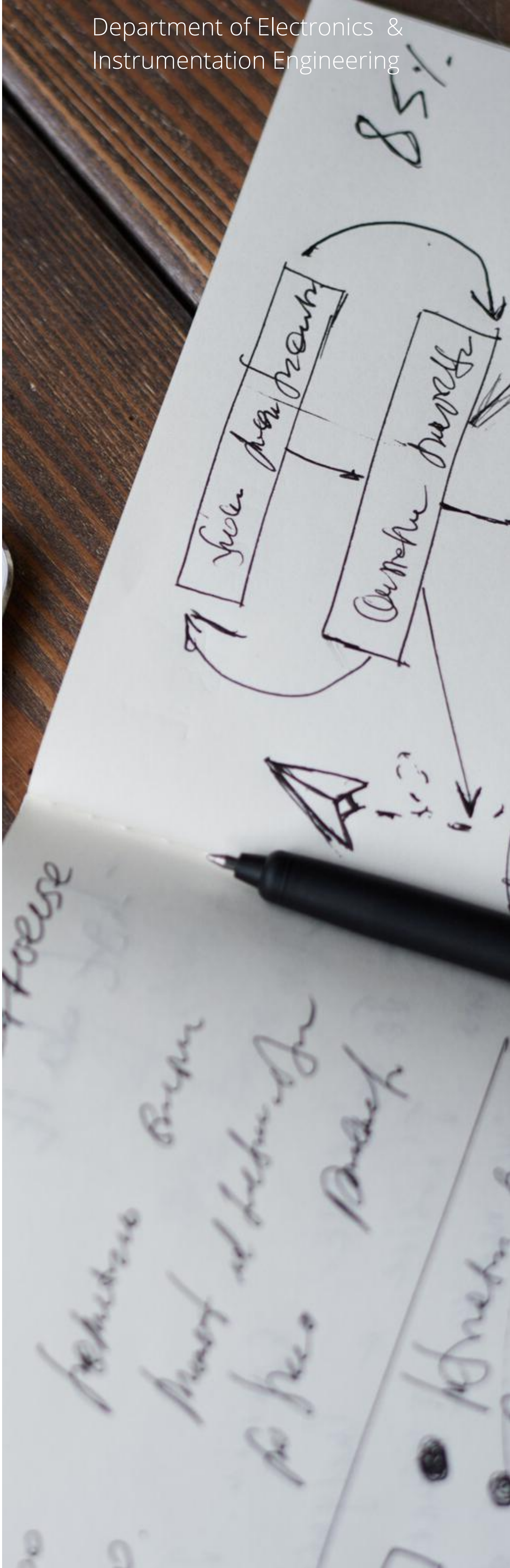
One important direction is to integrate common sense into deep learning. At present, deep learning is predominantly used as a purely data-driven technique, where the network fits a non-linear function to annotated samples given in the training set, and then applies the learned function to image pixels at test time. No knowledge outside of the training set is used. By contrast, humans conduct recognition not only based on samples they have seen before, but also based on their common-sense knowledge about the real world. People are able to reason about what they see to avoid illogical recognition results. Moreover, when they encounter something new or outside of their expectations, humans can quickly adapt their knowledge to account for this new experience. The challenge lies in how to acquire, represent, and reason with common knowledge within deep networks.

Reasoning geometrically

Another promising direction is to jointly perform image recognition and geometric reasoning. In the leading models for image recognition, only 2D appearance information is considered. By contrast, humans perceive 3D scene layouts together with inferring the semantic categories that exist within. A 3D layout may be derived not only from binocular vision, but also from geometric reasoning on 2D input, such as when people look at photos. Joint image recognition and geometry reasoning offers mutual benefits. The 3D layout determined from geometric reasoning can help to guide recognition in instances of unseen perspectives, deformations, and appearance. It can also eliminate unreasonable semantic layouts and help in recognizing categories defined by their 3D shape or functions. For example, there exist large intra-class appearance variation among sofas. However, they share common properties that can aid in identifying them, such as having a horizontal surface for sitting and a back surface for support. On the other hand, recognized semantics can regularize the solution space of geometric reasoning. For example, if a dog is recognized in a scene, its corresponding 3D configuration should fit the 3D shape model of dogs.

Modeling relationships

Relational modeling also holds great potential. To comprehensively understand a scene, it is vital to model the relationships and interactions among the object entities that are present (Images 4 and 5). Consider two images that each contain a person and a horse. If one displays the person riding the horse and the other exhibits the horse trampling the person, what is shown in these images has an entirely different meaning. Moreover, the underlying scene structure extracted through relational modeling can help to compensate when current deep learning methods falter due to limited data.



Though efforts are already underway for this problem, the research is still preliminary and there is much room for exploration.

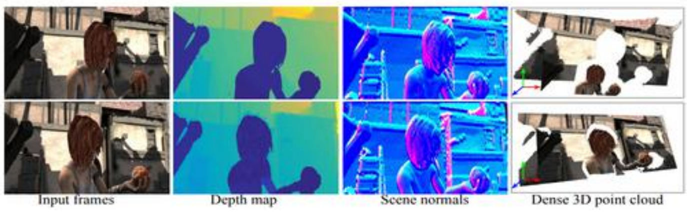


Image 4 Reconstruct the point clouds of complex dynamic scenes from two different frames of video.

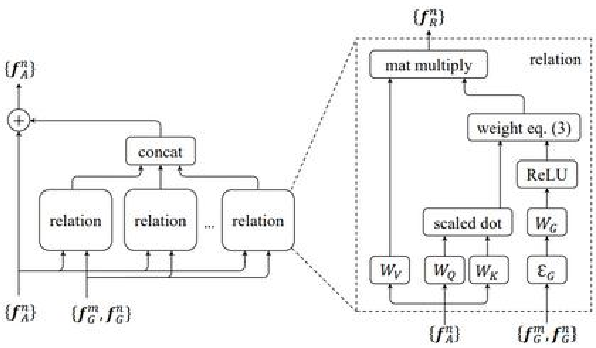


Image 5 Relational network in target detection. f_A represents the external features of objects, and f_G represents the geometric characteristics of objects.

The above mentioned and described problems are the open areas of research and development in the fields of science. Many Industry leading companies are struggling and finding ways to elevate these problems.

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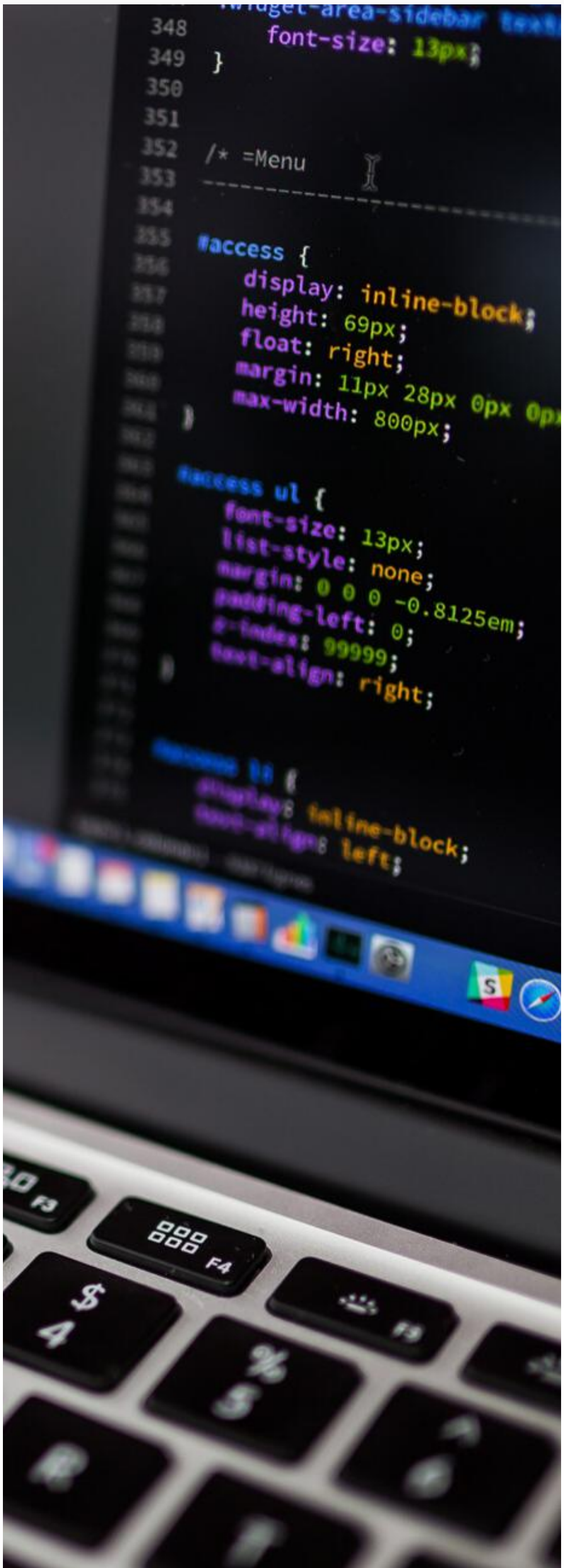
METHODOLOGY



- The project starts by Identifying an image using libraries in LabVIEW.
- The image acquired is then recognized using LabVIEW and then the processed recognized image is sent to a python program for Image Classification.
- The program takes the input from the camera via IEEE 802.11 protocol.
- The python program uses HAAR Algorithm for image classification and identification.
- The HAAR algorithm primarily is used for Face Detection.
- The camera of laptops uses IEEE 802.11 protocol.
- The python HAAR algorithm then uses camera to detect face.
- Then the image classification algorithm checks whether the detected face is present in the provided database.
- If it detects the presence of a familiar face while detection, then it outputs Face Present.
- If the face is not familiar then it outputs Face Not Present.
- This method of image classification is then used in many areas of industry like Steel, medical Sectors, MNC's, Quantum Research Fields.
- The program also sends an E mail via the SMTP protocol.

HAAR
CASCADE

Haar Cascade is a machine learning object detection algorithm used to identify objects in an image or video and based on the concept of features proposed by Paul Viola and Michael Jones in their paper "Rapid Object Detection using a Boosted Cascade of Simple Features" in 2001.It is a machine learning based approach where a cascade function is trained from a lot of positive and negative images. It is then used to detect objects in other images.

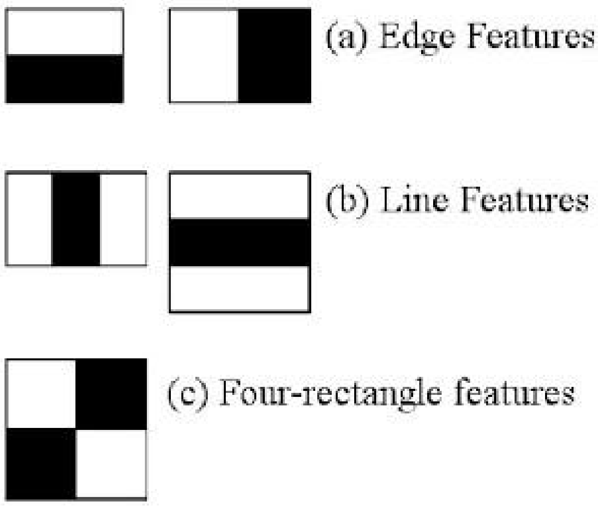
The algorithm has four stages:

- Haar Feature Selection
- Creating Integral Images
- Adaboost Training
- Cascading Classifiers

It is well known for being able to detect faces and body parts in an image, but can be trained to identify almost any object.Lets take face detection as an example. Initially, the algorithm needs a lot of positive images of faces and negative images without faces to train the classifier. Then we need to extract features from it. First step is to collect the Haar Features. A Haar feature considers adjacent rectangular regions at a specific location in a detection window, sums up the pixel intensities in each region and calculates the difference between these sums.

HAAR CASCADE

Integral Images are used to make this super fast.But among all these features we calculated, most of them are irrelevant. For example, consider the image below. Top row shows two good features. The first feature selected seems to focus on the property that the region of the eyes is often darker than the region of the nose and cheeks. The second feature selected relies on the property that the eyes are darker than the bridge of the nose. But the same windows applying on cheeks or any other place is irrelevant.



HAAR
CASCADE

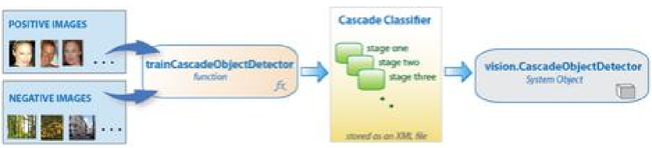
So how do we select the best features out of 160000+ features? This is accomplished using a concept called Adaboost which both selects the best features and trains the classifiers that use them. This algorithm constructs a “strong” classifier as a linear combination of weighted simple “weak” classifiers.

The process is as follows.During the detection phase, a window of the target size is moved over the input image, and for each subsection of the image and Haar features are calculated. You can see this in action in the video below. This difference is then compared to a learned threshold that separates non-objects from objects. Because each Haar feature is only a "weak classifier" (its detection quality is slightly better than random guessing) a large number of Haar features are necessary to describe an object with sufficient accuracy and are therefore organized into cascade classifiers to form a strong classifier.

HAAR
CASCADE

Cascade Classifier

The cascade classifier consists of a collection of stages, where each stage is an ensemble of weak learners. The weak learners are simple classifiers called decision stumps. Each stage is trained using a technique called boosting. Boosting provides the ability to train a highly accurate classifier by taking a weighted average of the decisions made by the weak learners.Each stage of the classifier labels the region defined by the current location of the sliding window as either positive or negative. Positive indicates that an object was found and negative indicates no objects were found. If the label is negative, the classification of this region is complete, and the detector slides the window to the next location. If the label is positive, the classifier passes the region to the next stage. The detector reports an object found at the current window location when the final stage classifies the region as positive.



HAAR
CASCADE

The stages are designed to reject negative samples as fast as possible. The assumption is that the vast majority of windows do not contain the object of interest. Conversely, true positives are rare and worth taking the time to verify.

- A true positive occurs when a positive sample is correctly classified.
- A false positive occurs when a negative sample is mistakenly classified as positive.
- A false negative occurs when a positive sample is mistakenly classified as negative.

To work well, each stage in the cascade must have a low false negative rate. If a stage incorrectly labels an object as negative, the classification stops, and you cannot correct the mistake. However, each stage can have a high false positive rate. Even if the detector incorrectly labels a nonobject as positive, you can correct the mistake in subsequent stages. Adding more stages reduces the overall false positive rate, but it also reduces the overall true positive rate.

Cascade classifier training requires a set of positive samples and a set of negative images. You must provide a set of positive images with regions of interest specified to be used as positive samples.

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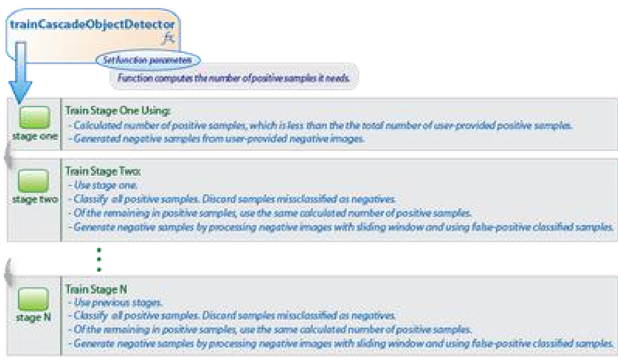
HAAR
CASCADE

You can use the Image Labeler to label objects of interest with bounding boxes. The Image Labeler outputs a table to use for positive samples. You also must provide a set of negative images from which the function generates negative samples automatically. To achieve acceptable detector accuracy, set the number of stages, feature type, and other function parameters.



Cascade classifier training requires a set of positive samples and a set of negative images. You must provide a set of positive images with regions of interest specified to be used as positive samples.

SMTP

& IEEE 802.11 PROTOCOL

IEEE 802.11 PROTOCOL

IEEE 802.11 is part of the IEEE 802 set of LAN protocols, and specifies the set of media access control (MAC) and physical layer (PHY) protocols for implementing wireless local area network (WLAN) Wi-Fi computer communication in various frequencies, including but not limited to 2.4 GHz, 5 GHz, 6 GHz, and 60 GHz frequency bands.They are the world's most widely used wireless computer networking standards, used in most home and office networks to allow laptops, printers, and smartphones to talk to each other and access the Internet without connecting wires. They are created and maintained by the Institute of Electrical and Electronics Engineers (IEEE) LAN/MAN Standard s Committee (IEEE 802). The base version of the standard was released in 1997, and has had subsequent amendments. The standard and amendments provide the basis for wireless network products using the Wi-Fi brand.

SMTP
& IEEE 802.11 PROTOCOL

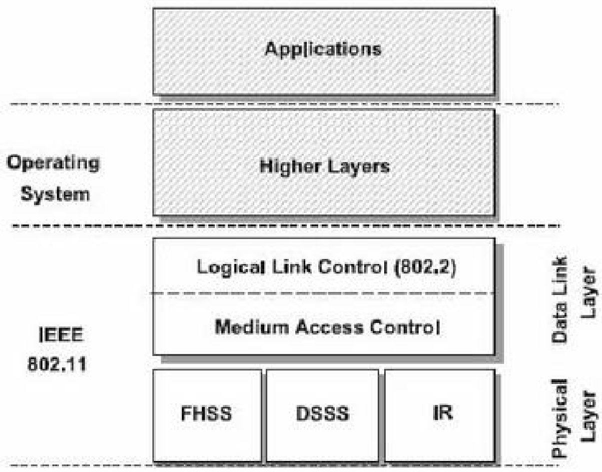
While each amendment is officially revoked when it is incorporated in the latest version of the standard, the corporate world tends to market to the revisions because they concisely denote capabilities of their products. As a result, in the marketplace, each revision tends to become its own standard.The protocols are typically used in conjunction with IEEE 802.2, and are designed to interwork seamlessly with Ethernet, and are very often used to carry Internet Protocol traffic.Although IEEE 802.11 specifications list channels that might be used, the radio frequency spectrum availability allowed varies significantly by regulatory domain.

The 802.11 family consists of a series of half-duplex over-the-air modulation techniques that use the same basic protocol. The 802.11 protocol family employs carrier-sense multiple access with collision avoidance whereby equipment listens to a channel for other users (including non 802.11 users) before transmitting each packet.802.11-1997 was the first wireless networking standard in the family, but 802.11b was the first widely accepted one, followed by 802.11a, 802.11g, 802.11n, and 802.11ac.

SMTP

& IEEE 802.11 PROTOCOL

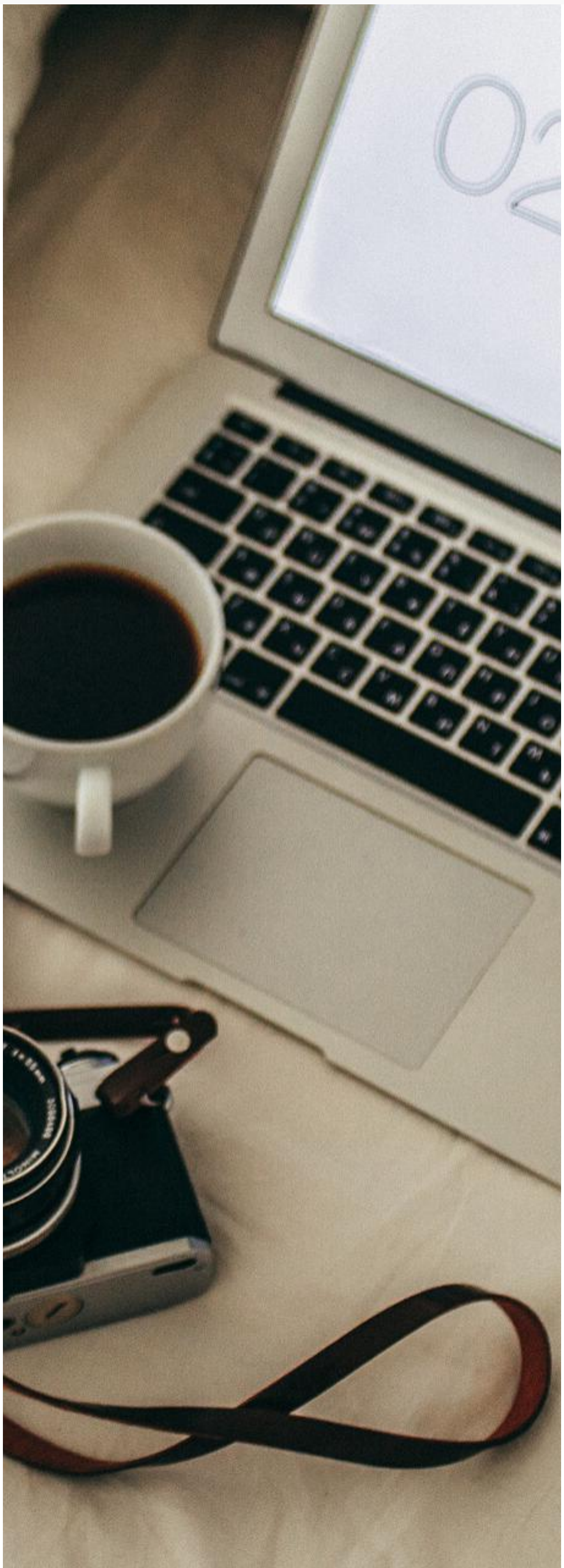
Other standards in the family (c–f, h, j) are service amendments that are used to extend the current scope of the existing standard, which may also include corrections to a previous specification. [1]802.11b and 802.11g use the 2.4 GHz ISM band, operating in the United States under Part 15 of the U.S. Federal Communications Commission Rules and Regulations; 802.11n can also use that band. Because of this choice of frequency band, 802.11b/g/n equipment may occasionally suffer interference in the 2.4 GHz band from microwave ovens, cordless telephones, and Bluetooth devices etc. 802.11b and 802.11g control their interference and susceptibility to interference by using direct-sequence spread spectrum (DSSS) and orthogonal frequency-division multiplexing (OFDM) signaling methods, respectively.



IEEE 802.11 Protocol Stacks

SMTP

& IEEE 802.11 PROTOCOL



SMTP

The Simple Mail Transfer Protocol (SMTP) is a communicatio protocol for electronic mail transmission. As an Internet standard, SMTP was first defined in 1982 by RFC 821, and updated in 2008 by RFC 5321 to Extended SMTP additions, which is the protocol variety in widespread use today. Mail servers and other message transfer agents use SMTP to send and receive mail messages. Proprietary systems such as Microsoft Exchange and IBM Notes and webmail systems such as Outlook.com, Gmail and Yahoo! Mail may use non-standard protocols internally, but all use SMTP when sending to or receiving email from outside their own systems. SMTP servers commonly use the Transmission Control Protocol on port number 25.User-level email clients typically use SMTP only for sending messages to a mail server for relaying, and typically submit outgoing email to the mail server on port 587 or 465 as per RFC 8314. For retrieving messages, IMAP and POP3 are standard, but proprietary servers also often implement proprietary protocols, e.g., Exchange ActiveSync.

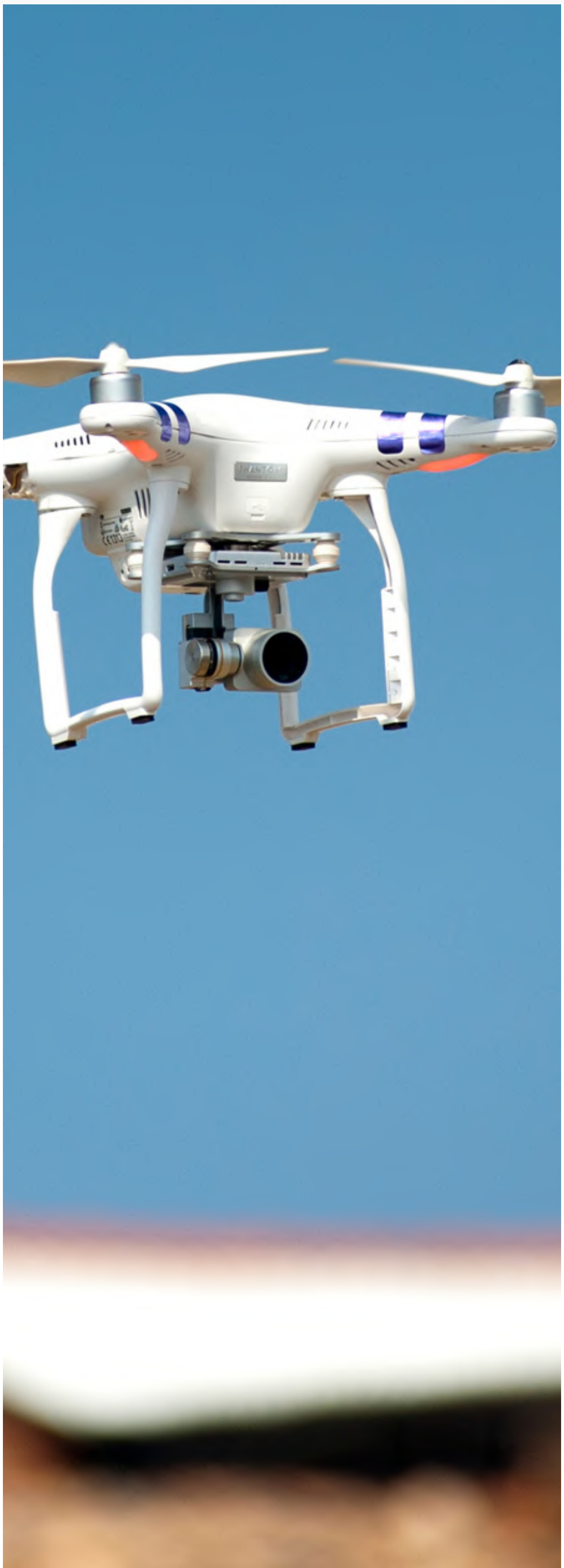
SMTP

& IEEE 802.11 PROTOCOL

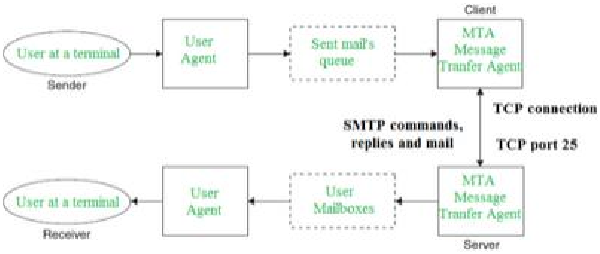
SMTP is a connection-oriented, text-based protocol in which a mail sender communicates with a mail receiver by issuing command strings and supplying necessary data over a reliable ordered data stream channel, typically a Transmission Control Protocol (TCP) connection. An SMTP session consists of commands originated by an SMTP client (the initiating agent, sender, or transmitter) and corresponding responses from the SMTP server (the listening agent, or receiver) so that the session is opened, and session parameters are exchanged. A session may include zero or more SMTP transactions. An SMTP transaction consists of three command/reply sequences:

- MAIL command, to establish the return address, also called return-path,[15] reverse-path,[16] bounce address, mfrom, or envelope sender.
- RCPT command, to establish a recipient of the message. This command can be issued multiple times, one for each recipient. These addresses are also part of the envelope.
- DATA to signal the beginning of the message text; the content of the message, as opposed to its envelope. It consists of a message header and a message body separated by an empty line.

SMTP
& IEEE 802.11 PROTOCOL



DATA is actually a group of commands, and the server replies twice: once to the DATA command itself, to acknowledge that it is ready to receive the text, and the second time after the end-of-data sequence, to either accept or reject the entire message.



Besides the intermediate reply for DATA, each server's reply can be either positive (2xx reply codes) or negative. Negative replies can be permanent (5xx codes) or transient (4xx codes). A reject is a permanent failure and the client should send a bounce message to the server it received it from. A drop is a positive response followed by message discard rather than delivery.The initiating host, the SMTP client, can be either an end-user's email client, functionally identified as a mail user agent (MUA), or a relay server's mail transfer agent (MTA), that is an SMTP server acting as an SMTP client, in the relevant session, in order to relay mail.

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LABVIEW
& IMAGE RECOGNITION

Image analysis combines techniques that compute statistics and measurements based on the gray-level intensities of the image pixels. You can use the image analysis functions to determine whether the image quality is good enough for your inspection task. You can also analyze an image to understand its content and to decide which type of inspection tools to use to handle your application. Image analysis functions also provide measurements you can use to perform basic inspection tasks such as presence or absence verification.Common tools you can use for image analysis include histograms and line profile measurements.

- Histogram:

A histogram counts and graphs the total number of pixels at each grayscale level. Use the histogram to determine if the overall intensity in the image is suitable for your inspection task. Based on the histogram data, you can adjust your image acquisition conditions to acquire higher quality images.You can detect whether a sensor is underexposed or saturated by looking at the histogram.

LABVIEW
& IMAGE RECOGNITION

- Machine Vision:

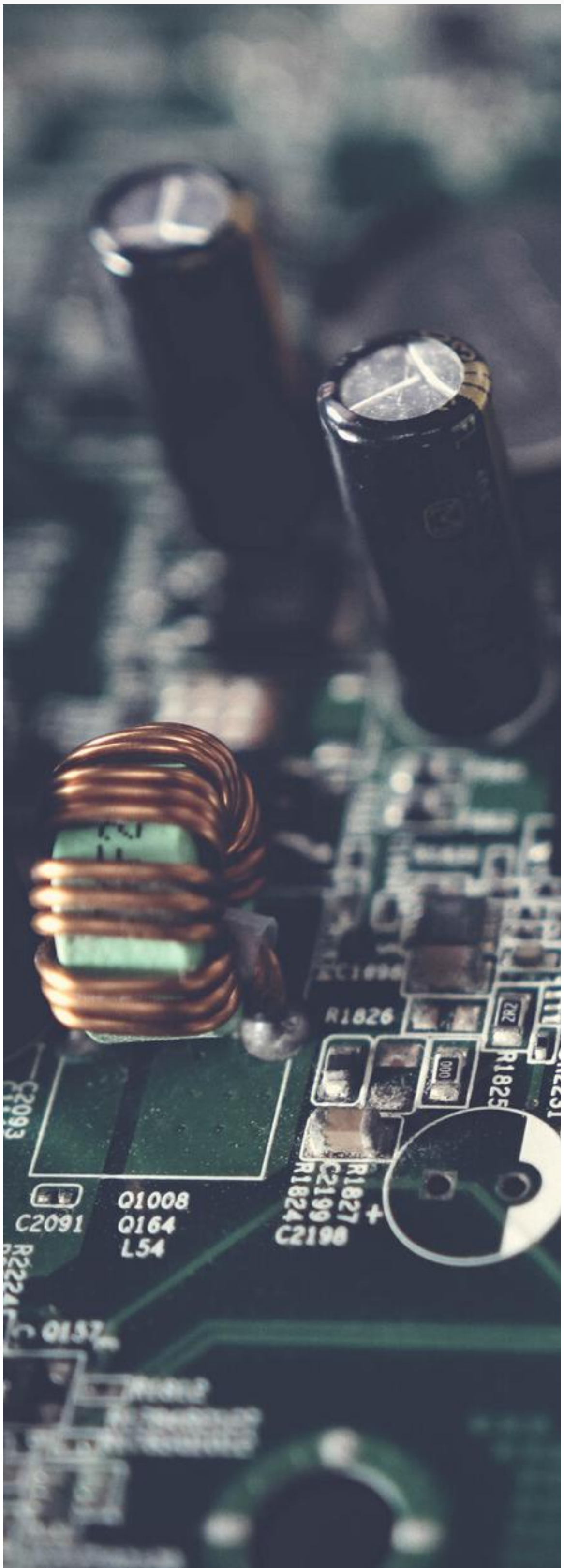
The most common machine vision inspection tasks are detecting the presence or absence of parts in an image and measuring the dimensions of parts to see if they meet specifications. Measurements are based on characteristic features of the object represented in the image. Image processing algorithms traditionally classify the type of information contained in an image as edges, surfaces and textures, or patterns. Different types of machine vision algorithms leverage and extract one or more types of information.Edge DetectionEdge detectors and derivative techniques, such as rakes, concentric rakes, and spokes, locate the edges of an object with high accuracy. An edge is a significant change in the grayscale values between adjacent pixels in an image. You can use the location of the edge to make measurements, such as the width of the part. You can use multiple edge locations to compute such measurements as intersection points, projections, and circle or ellipse fits.Edge detection is an effective tool for many machine vision applications.

LABVIEW
& IMAGE RECOGNITION

- Detection:

The objective of detection applications is to determine if a part is present or absent using line profiles and edge detection. An edge along the line profile is defined by the level of contrast between background and foreground and the slope of the transition. Using this technique, you can count the number of edges along the line profile and compare the result to an expected number of edges. This method offers a less numerically intensive alternative to other image processing methods such as image correlation and pattern matching.The most common machine vision inspection tasks are detecting the presence or absence of parts in an image and measuring the dimensions of parts to see if they meet specifications. Measurements are based on characteristic features of the object represented in the image. Image processing algorithms traditionally classify the type of information contained in an image as edges, surfaces and textures, or patterns. Different types of machine vision algorithms leverage and extract one or more types of information.

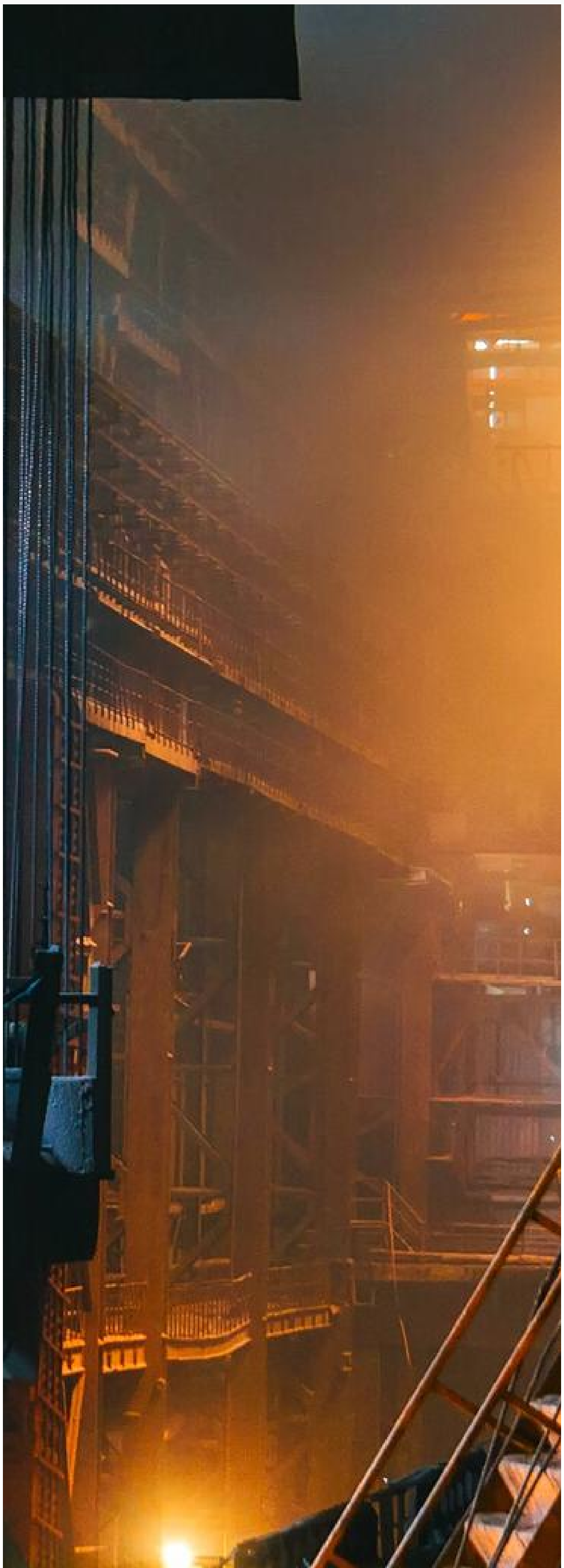
LABVIEW
& IMAGE RECOGNITION



- Pattern Matching:

Pattern matching locates regions of a grayscale image that match a predetermined template. Pattern matching finds template matches regardless of poor lighting, blur, noise, shifting of the template, or rotation of the template.Use pattern matching to quickly locate known reference patterns, or fiducials, in an image. With pattern matching you create a model or template that represents the object for which you are searching. Then your machine vision application searches for the model in each acquired image, calculating a score for each match. The score relates how closely the model matches the pattern found.Pattern matching algorithms are some of the most important functions in image processing because of their use in varying applications. You can use pattern matching in the following three general applications – alignment, gauging, and inspection.

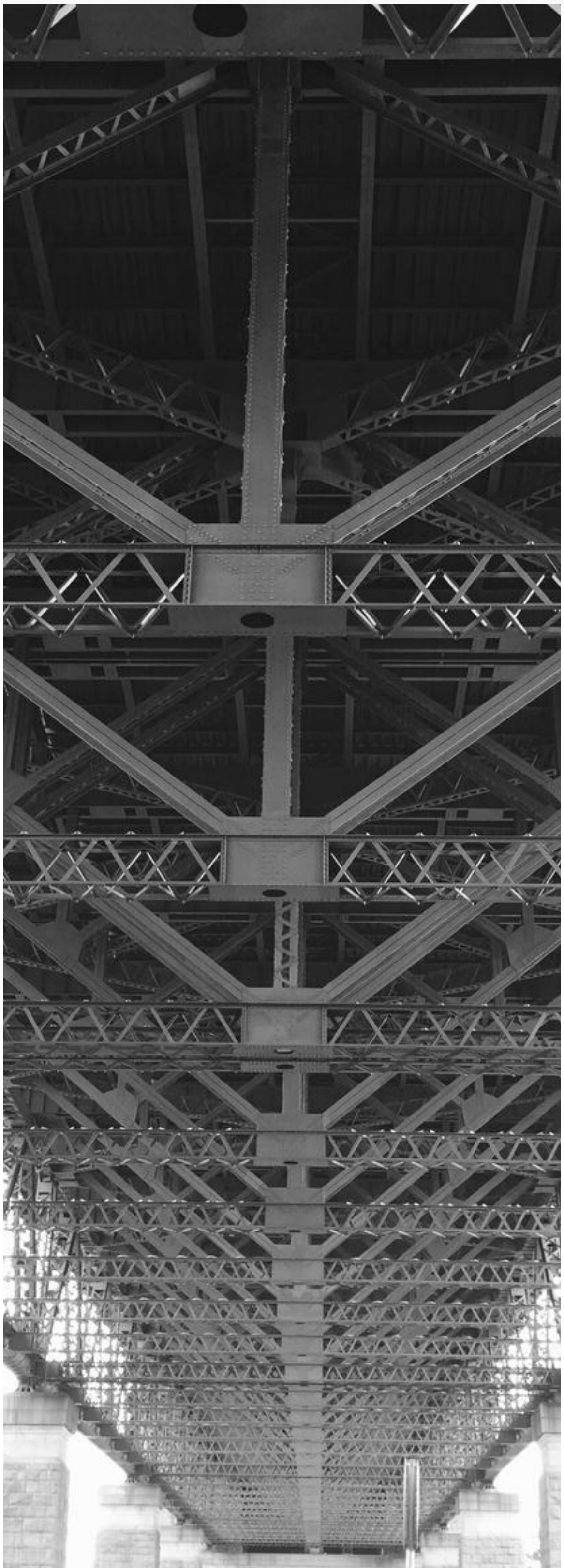
INDUSTRY
APPLICATIONS



- **FOOD SECTOR**

Vision systems are used in food industry for sorting and for quality inspection. The appearance of bakery products is an important quality attribute, which together with the product flavour significantly influence the purchase potential of the product by consumers. Internal and external appearance attributes contribute to the overall impression of the product's quality. Digital images of chocolate chip cookies were used to evaluate their size, shape, colour and the fraction of the top surface area that was chocolate chip. A number of four fuzzy models were developed in order to be able to predict consumer ratings based on the examined features. Visual inspection of muffins was also performed with the aid of a classification algorithm used for separating dark samples from light ones using graded and ungraded samples. The correct classification of 96% of graded muffins and 79% of ungraded muffins was achieved. Visual inspection is largely used in quality assessment of meat products.

INDUSTRY
APPLICATIONS



- **AUTOMATIVE SECTOR**

Ubiquitous computing has led to interconnection of cars with the internet and amongst themselves, thus transforming the driver assistance. Driver drowsiness monitoring is a method that uses IR cameras
mounted in front of the driver to monitor its behaviour like head and eye leads movement to detect and alert
the driver in case of inattentiveness. Driver assistive technologies based on cameras and/or radar sensors
are: Adaptive Cruise Control (ACC), Forward Collision Warning (FCW), Intelligent Speed Assistance
(ISA), Lane Departure Warning (LDW), Lane Keeping System (LKS), Lane Change Assistance, Night
Vision Systems, Parking Assistance and so on. Mobileye developed a system able to detect traffic-signs. Recently, apps have been developed so that smartphones can detect lane markers and assist in navigation
by displaying an overlay of graphical directions on top of the GPS maps. In latest models of cars many
vendors opted for digital display instead of analogue hand displays.

INDUSTRY
APPLICATIONS

- **STEEL INSPECTION**

Steel inspection is not a trivial task, as the strip is moving past the observer with speeds that exceed 20m/s. Another issue is the experience need for this kind of work and also the working conditions which involve high temperatures and noise levels. The simplest method requires simple optics and intensity thresholding, although laser devices have been developed in order to ease this process.

A wood inspection solution has been proposed by Bhandarkar (1999). CT image slices are acquired and segmented. Each of the segmented image is analysed and labelled as defect-free or defect-like.
Correlation among the CT sequences allows for 3D reconstruction of the log defects. Combining a decision tree with a modular neural network topology, results are far better the using a single neural network for classifying the wood veneer.

PROGRAM

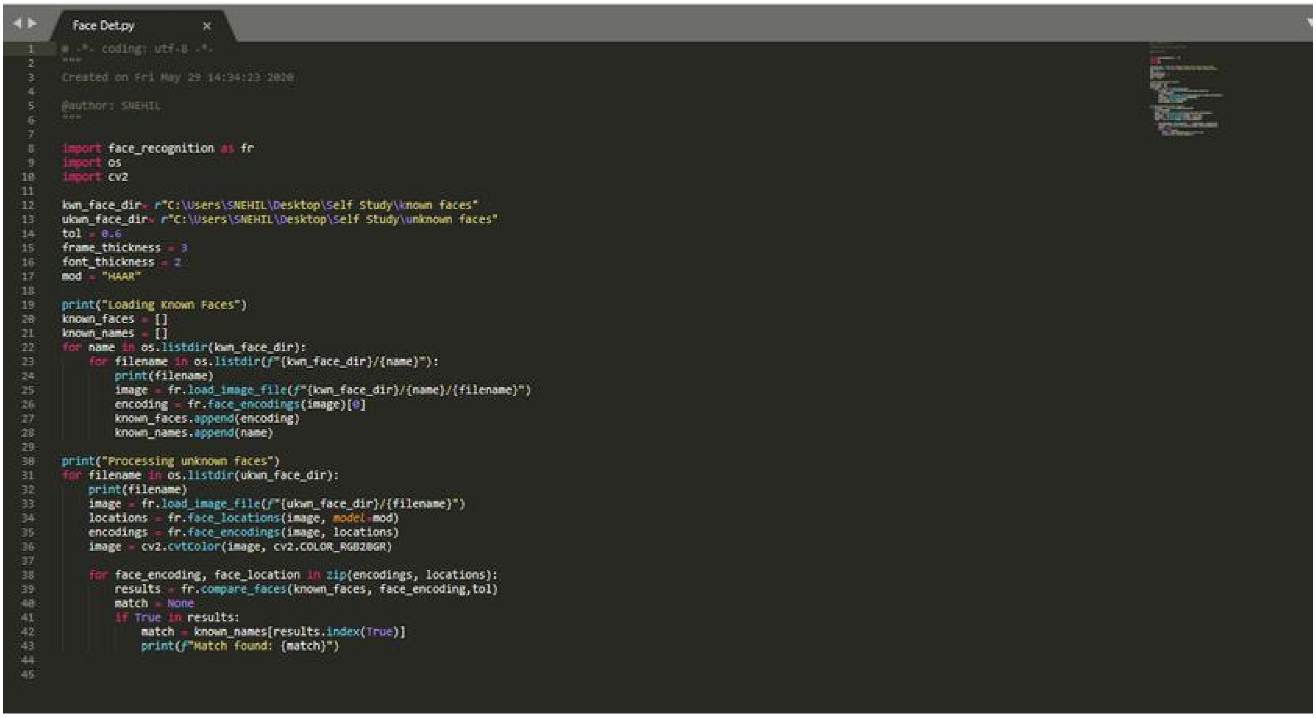
& CODE(PYTHON)

```
# -*- coding: utf-8 -*-
"""
@author: SNEHIL
"""

import face_recognition as fr
import os
import cv2

kwn_face_dir= r"C:\Users\SNEHIL\Desktop\Self Study\known faces"
ukwn_face_dir= r"C:\Users\SNEHIL\Desktop\Self Study\unknown faces"
tol = 0.6
frame_thickness = 3
font_thickness = 2
mod = "HAAR"

print("Loading Known Faces")
known_faces = []
known_names = []
for name in os.listdir(kwn_face_dir):
    for filename in os.listdir(f"{kwn_face_dir}/{name}"):
        print(filename)
        image = fr.load_image_file(f"{kwn_face_dir}/{name}/{filename}")
        encoding = fr.face_encodings(image)[0]
        known_faces.append(encoding)
        known_names.append(name)
```

PROGRAM

& CODE(PYTHON)

```
print("Processing unknown faces")
for filename in os.listdir(ukwn_face_dir):
print(filename)
image = fr.load_image_file(f"{ukwn_face_dir}/{filename}")
locations = fr.face_locations(image, model=mod)
encodings = fr.face_encodings(image, locations)
image = cv2.cvtColor(image, cv2.COLOR_RGB2BGR)

for face_encoding, face_location in zip(encodings, locations):
results = fr.compare_faces(known_faces, face_encoding,tol)
match = None
if True in results:
match = known_names[results.index(True)]
print(f"Match found: {match}")
```



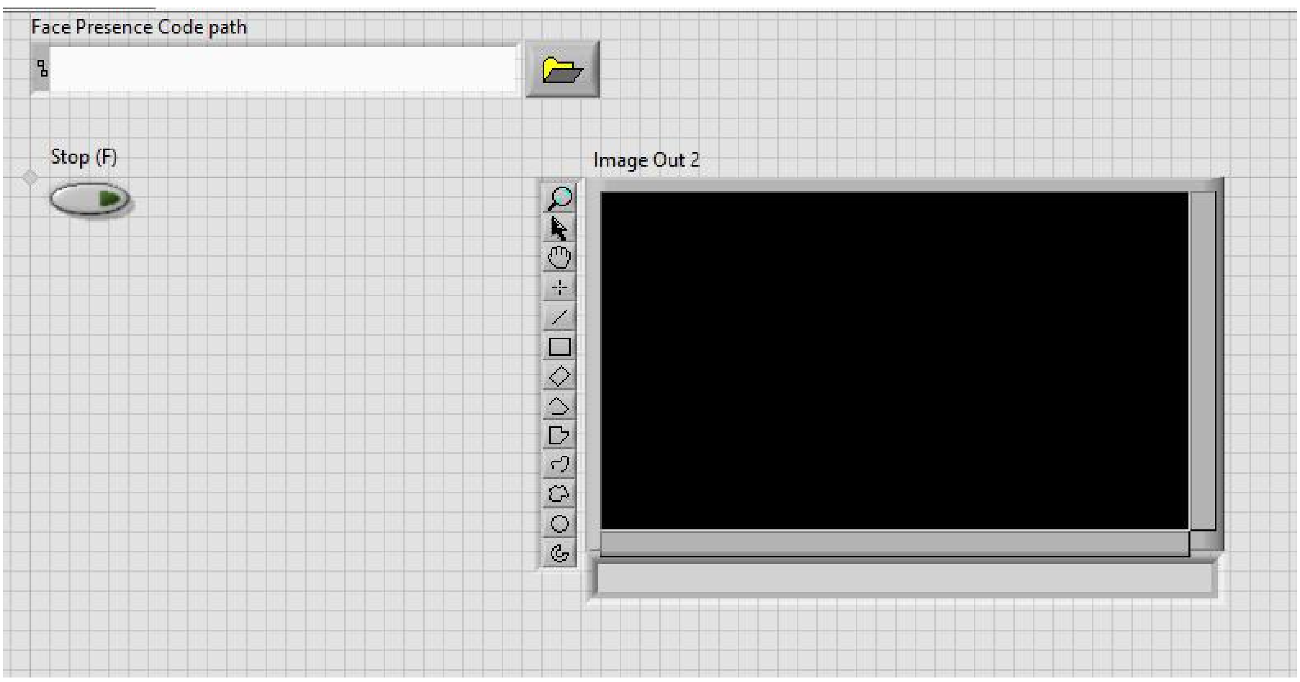
Face Det.py

```
# -*- coding: utf-8 -*-
"""
Created on Fri May 29 14:34:23 2020

@author: SNEHIL
"""

import face_recognition as fr
import os
import cv2

kwn_face_dir= r"C:\Users\SNEHIL\Desktop\Self Study\known faces"
ukwn_face_dir= r"C:\Users\SNEHIL\Desktop\Self Study\unknown faces"
tol = 0.6
frame_thickness = 3
font_thickness = 2
mod = "HAAR"

print("Loading Known Faces")
known_faces = []
known_names = []
for name in os.listdir(kwn_face_dir):
    for filename in os.listdir(f"{kwn_face_dir}/{name}"):
        print(filename)
        image = fr.load_image_file(f"{kwn_face_dir}/{name}/{filename}")
        encoding = fr.face_encodings(image)[0]
        known_faces.append(encoding)
        known_names.append(name)

print("Processing unknown faces")
for filename in os.listdir(ukwn_face_dir):
    print(filename)
    image = fr.load_image_file(f"{ukwn_face_dir}/{filename}")
    locations = fr.face_locations(image, model=mod)
    encodings = fr.face_encodings(image, locations)
    image = cv2.cvtColor(image, cv2.COLOR_RGB2BGR)

    for face_encoding, face_location in zip(encodings, locations):
        results = fr.compare_faces(known_faces, face_encoding,tol)
        match = None
        if True in results:
            match = known_names[results.index(True)]
            print(f"Match found: {match}")
```

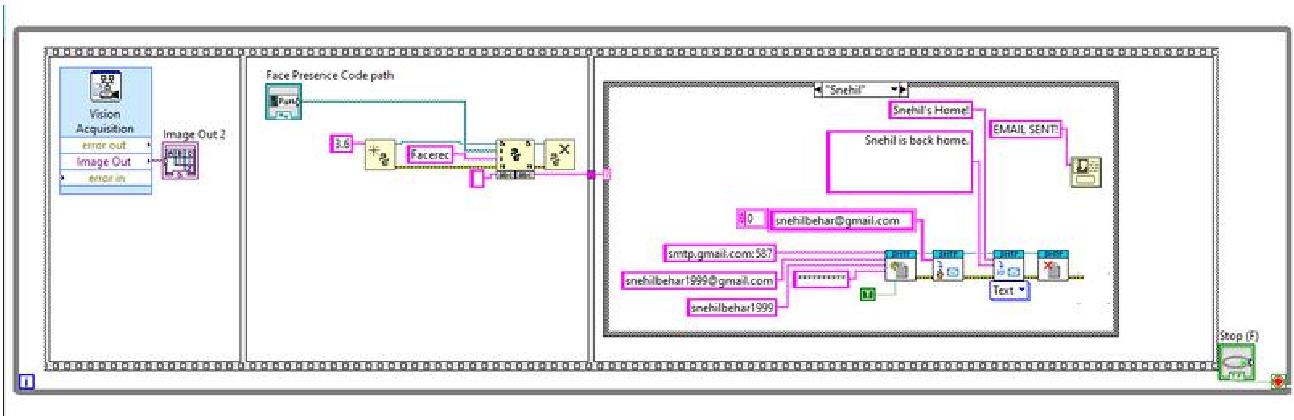
Python Code

PROGRAM

& CODE(LABVIEW)

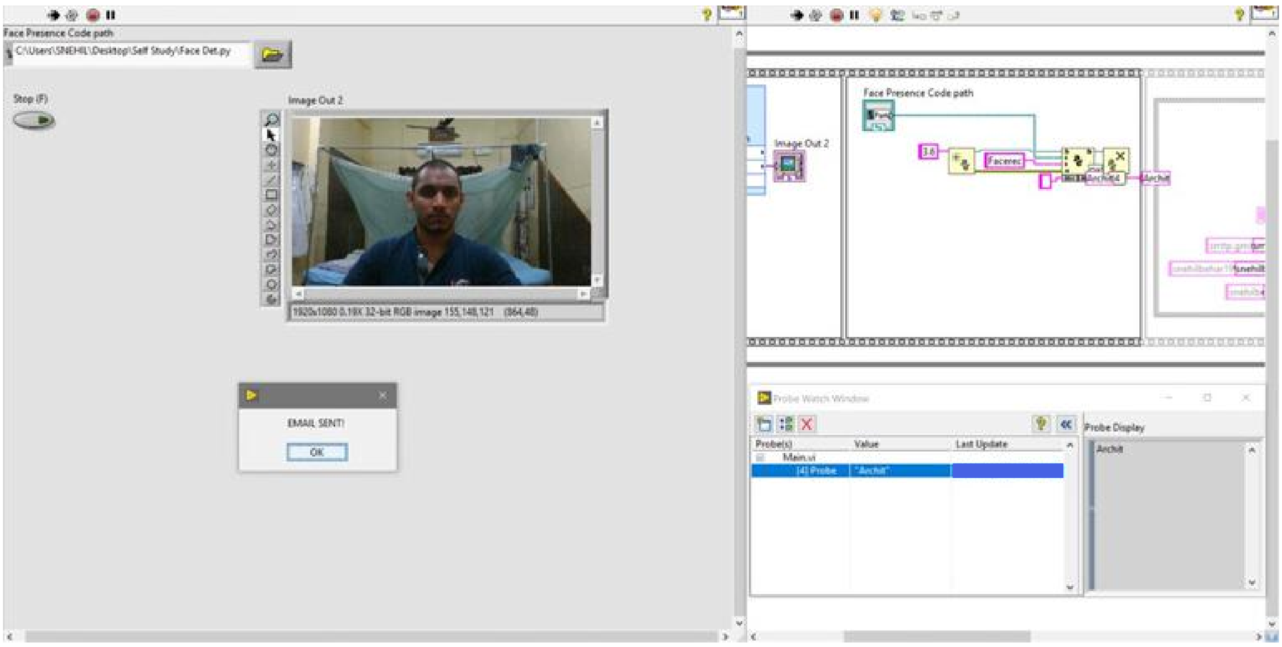


Front Panel

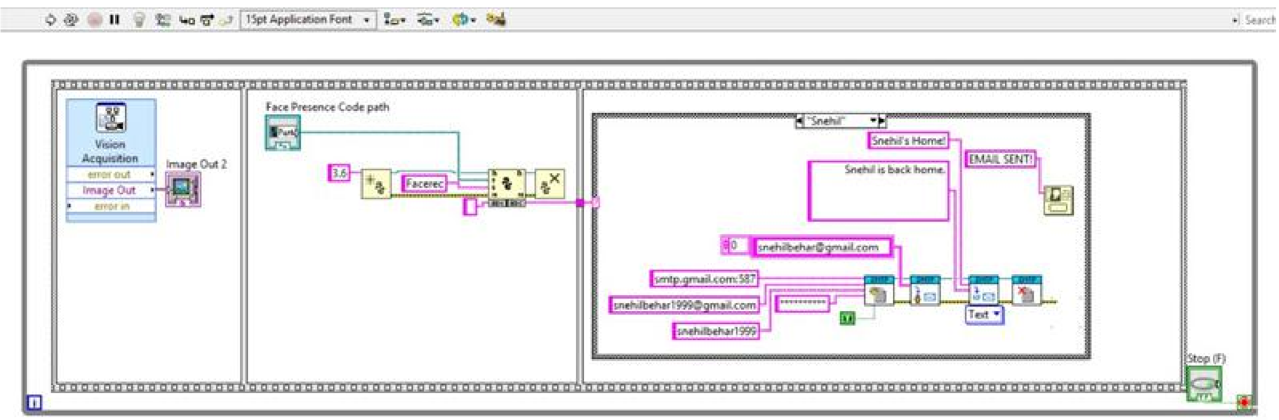


Block Diagram

RESULT



Front Panel



Block Diagram

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CONCLUSION

Thus we can conclude that we were able to successfully understand the working of image recognition using HAAR and LabVIEW via IEEE 802.11 and SMTP protocols for Industry applications.

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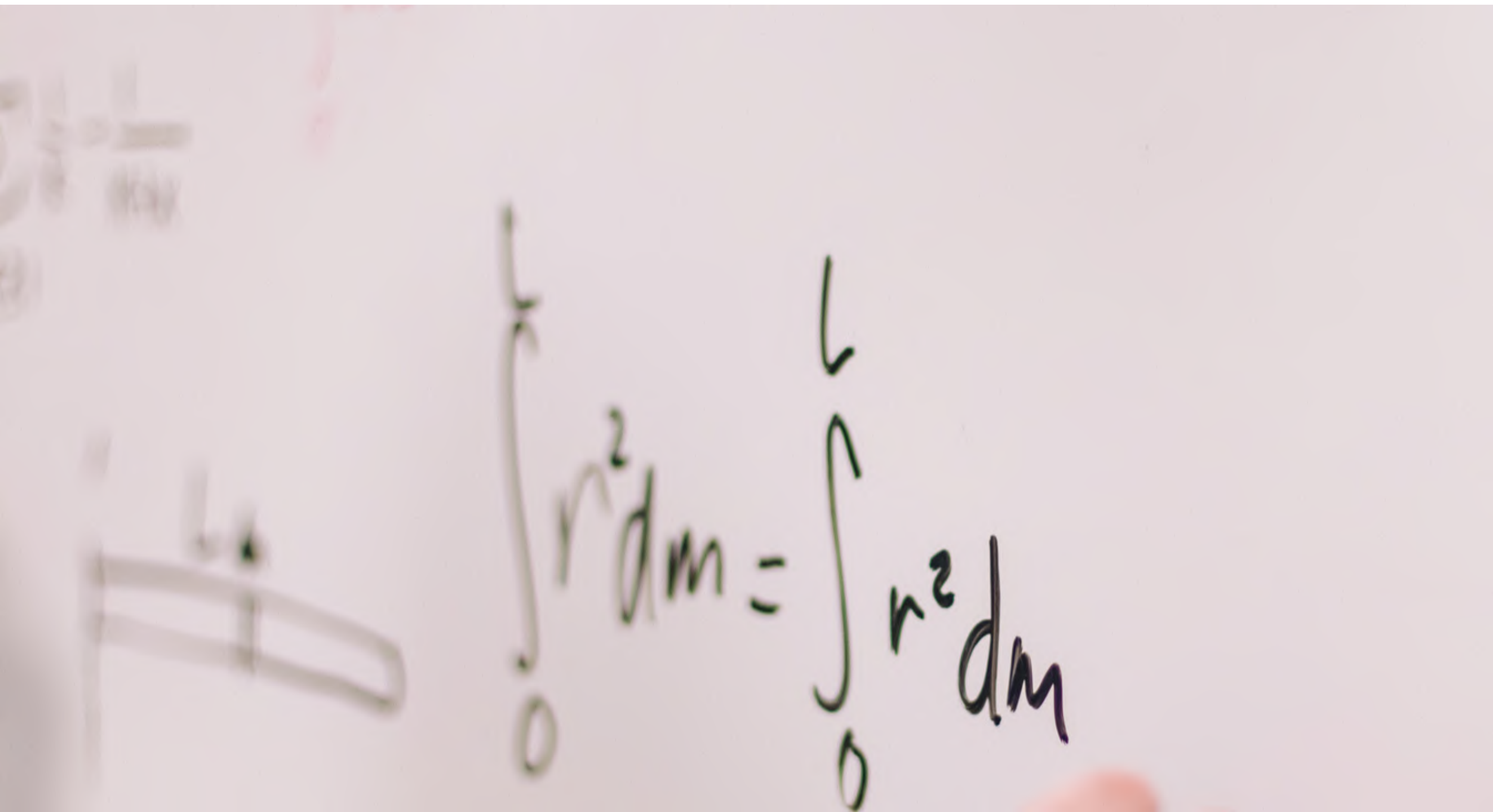
CO-MAPPING

SUBJECT	RELEVANCE
VI	Image recognition in Labview
APC	Industry Applicatons of Image Classification and recognition
CCN	IEEE 802.11 & SMTP Protocols



LITERATURE

SURVEY

- Bhandarkar, S.M., Faust, T. D., Tang, M. “CATALOG: A System for Detection and Rendering of
Internal Log Defects Using Computer Tomography,” Machine Vision and Applications, vol. 11,
pp. 171-190, 1999
- Brosnan, T., Sun D.W. (2004) Improving quality inspection of food products by computer vision–
–a review, Journal of Food Engineering, 61, p. 3-16
- Chaki, A and Chattopadhyay, T (2009) An Automatic Decision Support System for Medical
Instrument Suppliers Using Fuzzy Multifactor Based Approach. The fifth annual IEEE Conference
on Automation Science and Engineering (IEEE CASE 2009), 8,p. 158-163
- Chattopadhyay, T, et al. (2008). An Application for Retrieval of Frames from a Laparoscopic
Surgical Video Based on Image of Query Instrument. TENCON 2008, IEEE Region 10
Conference, 11, p. 1-5
- Chattopadhyay, T. (2012) Applications of Image Processing in Industries, CSI Communications,
July 2012, p. 8-11
- Davies, E.R. (2012) Computer and Machine Vision, 4th Edition: Theory, Algorithms, Practicalities
- Golnabi, H. (2007) Design and application of industrial machine vision systems, Robotics and
Computer-Integrated Manufacturing, 23,p. 630-637

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LITERATURE

SURVEY

- Jamieson, V. (2002) Physics raises food standards, Physics World, 1, p. 21,22
- Kim, S., Schatzki, T.F. (2000) Apple watercore sorting using X-ray imagery: I. Algorithm development. Transactions of the ASAE, 43 (6), p. 1695–1702
- Kondo, N., Ahmada, U., Montaa, M., Muraseb, H. (2000) Machine vision based quality evaluation of Iyokan orange fruit using neural networks. Computers and Electronics in Agriculture, 29 (1–2) p. 135–147
- Majumdar, S, Jayas, D.S. (2000) Classification of cereal grains using machine vision: IV. Combined morphology, colour, and texture models. Transactions of the ASAE, 43(6), p. 1689–1694

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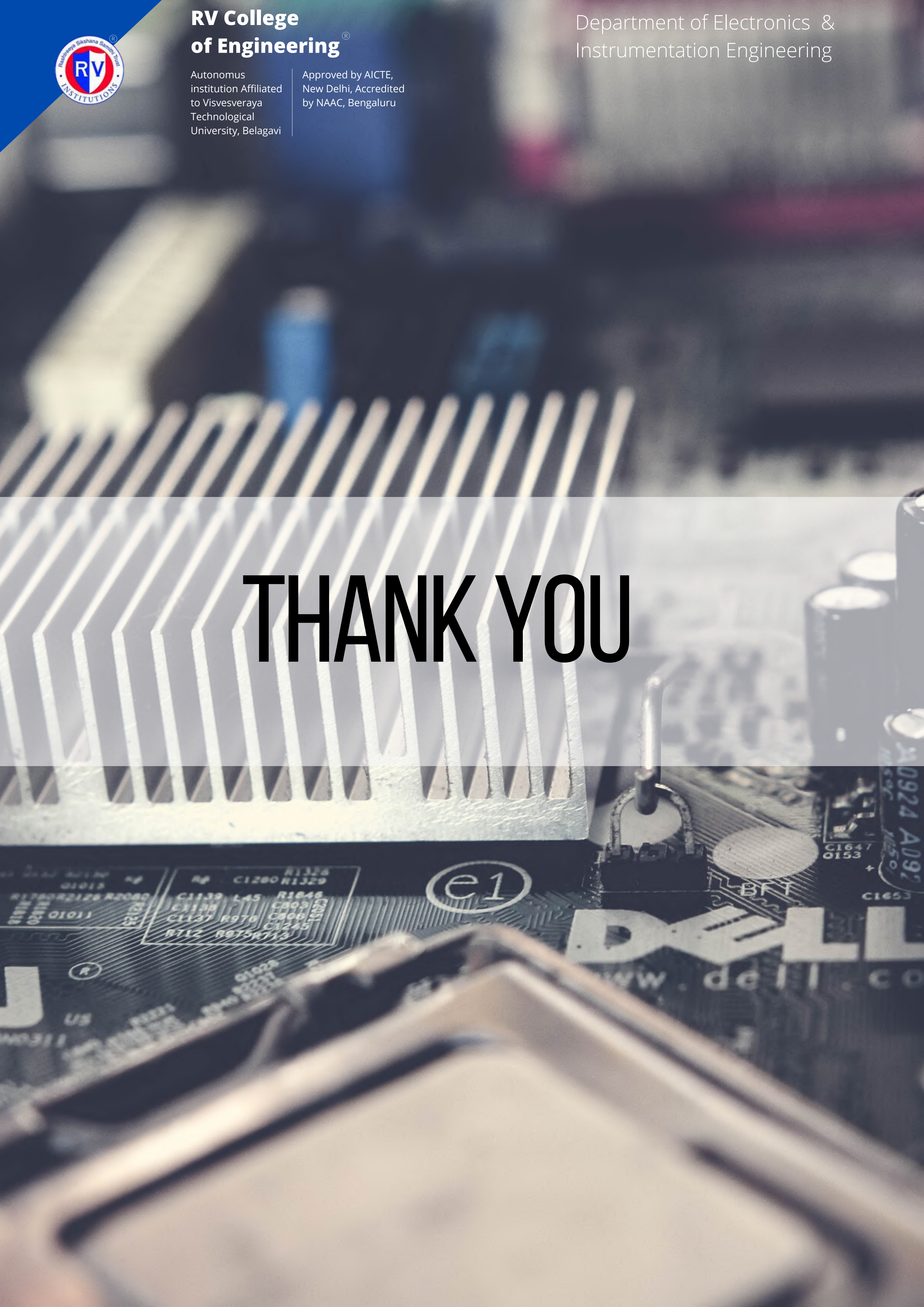

THANK YOU