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A Project Report on

AUTOMATED ANALOG METER READING SYSTEM USING IMAGE PROCESSING AND MACHINE LEARNING

Submitted in partial fulfillment for the award of the degree of

BACHELOR OF ENGINEERING (B.E) IN ELECTRONICS AND COMMUNICATION

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CERTIFICATE

Certified that the project work entitled “AUTOMATED ANALOG METER READING SYSTEM USING IMAGE PROCESSING AND MACHINE LEARNING” carried out by Ranjan P(USN:4JC14EC081), Sushruth N(USN:4JC14EC113), Thejus P(USN:4JC14EC116), Vandana T(USN:4JC14EC117) bonafide students of SJCE, Mysuru for the partial fulfillment of the curriculum prescribed for the award of the degree of Bachelor of Engineering in Electronics and Communication by the Visvesvaraya Technological University, Belagavi, during the year 2017-18. It is certified that all corrections or suggestions indicated for Internal assessment have been incorporated in the final report. The project report has been approved as it satisfies the requirements in respect of project work prescribed for the degree.

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We also declare that, to the best of our knowledge and belief, the matter embodied in this project report has not been submitted previously by us for the award of any degree to any other institution or university.

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Abstract

Measuring devices are an integral part of any product. They are critical for managing and assessing the proper working of the products. Without them, it is impossible to tell if a device is working properly or not. There are basically two types of measuring devices. Analog meters and digital meters.

Today there are a lot of Analog meters measuring various parameters in different environments. They are used in various applications like electricity meters, industrial machines for measuring voltage, temperature, pressure, aircraft for measuring altitude, speed etc. One major problem is that these meters require on-site manual monitoring to know if the system is working correctly. This task requires a lot of human effort and becomes tedious as there are a lot of Analog meters. Another problem is that it is very expensive to replace an Analog meter with a digital meter, as the cost of digital meters is quite high. To overcome these problems, we propose a system which automates this process.

The existing projects just consider either the needle based analog meter or digits based analog meter. So one of the novelties of this project is considering different types of analog meters. Many of the existing projects just capture the analog meter images on-site and transmit them to the servers for processing. This is a costly process as a lot of bandwidth is required to transmit images. This project does all the processing part on the on-site microprocessor like Raspberry Pi and just transmit the detected values to the server.

Our System first classifies various types of Analog meters. Right now the classifier is trained to detect Analog meter with needle and Analog meter with text readings. After this, if the analog meter with a needle is detected, binary threshold, hough threshold are set appropriately so that the needle is detected properly. The readings corresponding to the needle position is found out by some basic trigonometric functions. Next, if the analog meter detected has digits, then each digit is segmented separately based on contour area. A trained classifier is used to recognize the digits individually. All the detected values are transmitted over Wi-Fi to the cloud database for further analytics.

Around 500 images were taken for training the analog meter classification model. Accuracy of around 95% was obtained. The needle in the analog meters was detected by setting hough threshold, binary threshold, and other image processing algorithms. The detection accuracy of this process is around 90 %. Recognition of digits was done by training a model with the dataset of around 300 images. The accuracy of digit recognition was around 97%. In order to implement the proposed system in real time environment, the accuracy of the whole system has to be further improved.

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Chapter 1

INTRODUCTION

1.1 Introduction

Measuring devices play a major role in our lives. Measuring devices are found everywhere. There are many analog measuring devices in the world. It's not feasible to replace them all with their digital counterparts.

So, we introduce a methodology based on image processing and machine learning to obtain an efficient and accurate reading of analog meters. Primarily, in order to detect the type of analog meter, machine learning algorithms will be used. We intend to use convolutional neural networks to detect the type of analog meter. As of now, the convolutional neural network has the highest correct detection rate of around 92%. Then various image preprocessing techniques like histogram equalization, image smoothening are applied to the frames to improve the interpretability of the captured images. There can be different types of analog meters: For ones with the dials, to measuring the angle of the dials, the system uses canny edge detection algorithm and Hough transform; for the ones with text readings, the text scene is segmented using contour detection algorithm and then a trained model for recognizing digit is used. The readings obtained at the Raspberry Pi are sent to the cloud-based server for further analytics.

1.2 Motivation

There are a lot of Analog measuring instruments in the whole world. A major problem is that manual monitoring of these instruments is not viable. Also, it is not practically possible to replace all of them with digital measuring instruments with IOT capability. That's because digital measuring instruments are a lot costlier compared to its Analog counterparts. Also in some time-critical equipment, it is not possible to shut down the equipment for changing Analog measuring instruments with digital measuring instruments.

So, designing a system which would sort of mimic the capabilities of Analog measuring instruments is a financially viable option. Our proposed idea using techniques of image processing and machine learning detects the readings of various kinds of Analog measuring devices and sends them over to a database.

1.3 Literature Survey

1. **Extraction of Energy Information from Analog Meters Using Image Processing-** This paper presents a solution that uses on-line data exchange of power consumption information to

- a cloud server without modifying the existing electromechanical analog meters. In this framework, a systematic approach to extract energy data from images is applied to replace the manual reading process. The drawback is that it is not generalized to different types of meters. The Thresholding for detection of lines is not always the same for different types of meters [1].
2. **Automatic Electricity Meter Reading Based on Image Processing-** This paper introduces a system based on image processing to obtain the reading of the electricity digital meter. In this system the back camera of the mobile phones is used to acquire the image of the electricity meter. The system then applies a sequence of image processing functions to automatically extract and recognize the digits of the meter reading image. This image goes through three main stages: preprocessing which ends up with cropping the numeric reading area, segmentation of individual digits using horizontal and vertical scanning of the cropped numeric area, and recognition of the reading by comparing each segmented digit with the digit's templates. The proposed system is implemented using Android Studio software with openCV library and has been tested on 21 images of electric meters captured smart-phone camera in Saudi Arabia, and results shows a recognition with the accuracy rate of 96,49% (per number digit) and 85.71% accuracy rate for the electricity meter readings. The drawback here is that the segmented digits are classified using template matching technique. The technique used here works well only with the meter for which the templates are predefined [2].
 3. **A Wireless Automatic Meter Reading System Based on Digital Image Process and ZigBee-3G** - In this paper, a new kind of wireless automatic reading system based on digital image processing technology, ZigBee and 3G network is proposed. This design mainly aims to apply in residential buildings or areas, and it uses digital image processing technology template matching method to get the meter data which is fast and really solves compatibility problems in meter reading system. At the end of the paper, securities of transmitting data to remote monitor center by 3G network are discussed. Virtual private network tunneling technology is used in this design which makes data transmission much more reliable and safer than the current meter reading system. The concentration is mainly on transmission of captured data, but there is not much of image processing part involved in this paper. It has been experimented only for a single type of residential meters. The accuracy is about 60%-70% which is quite low [3].
 4. **Image Processing for Automatic Reading of Electro-Mechanical Utility Meters** - Electro-mechanical meters are commonly employed to measure the consumption of utilities. Basically there exist two types of analog meters: the ones that use rotary dials (like an odometer) and the ones with pointer dials (like a speedometer). Former approaches to automated meter reading have dealt with the first kind of meters. Considering that automated reading of the latter ones can be confusing, in this work, a methodology based on image processing and segmentation to enable the image acquisition and processing of pointer dials to obtain efficiently and accurately readings is introduced. This methodology uses an image acquired with smart-phone and applying a sequence of image processing functions it finds and extracts dial images of such meter images. Then the methodology identifies the position of the pointers followed by a clever implementation that enables the reading. The database is composed with more than a hundred images taken under different light conditions, perspectives and angles. The method is able to extract the reading in an average of 3 seconds, with a 92% accuracy with images taken in-field. The method enables the use of a common smart-phone to acquire an automatically extract the reading of a pointer-type dial meter. This allows interesting applications that could help people to monitor their energy consumption and learn patterns to save energy. This could be one step ahead of energy saving policies that can be discovered though massive data analysis. The drawback is that the segmentation of dial part works perfectly for only one type of meter on which the algorithm is experimented upon [4].

5. **Automatic reading of domestic electric meter-** In this paper, an automatic reading system of the traditional household meter is designed on the basis of image processing and advanced DSP system. To identify the meter reading accurately, a regional average method is proposed to implement the image-scaling in order to avoid the distortion. In the image-filtering process, we raise an average-product method which is verified to attain good effects. For image segmentation, a new union thresholding method, based on the gray-scale transformation, is proposed to enhance the adaptability of uneven luminance. Although the segmentation does not work very well with the union segmentation, especially when different types of meters are used [5].
6. **Electricity Meter Reading Based on Image Processing-** This paper talks about automated Meter reading which reads the values of electrical meter by using a camera that takes a photo of the meter, recognizes the digits, and then stores the output in a text file. The meter image is captured by mobile phone back camera with some constraints: the camera has to be parallel to the meter, the meter reading area has to appear in the image without shadows, part of the meter black box must appear from left and right, and the right most digit must be entirely shown and clear. The reading area that is extracted from the image is further segmented for digit recognition. Digit recognition is the process where we match the segmented data with our predefined template which is itself is the drawback. These templates work only on the meter with which the templates are designed for [6].
7. **Method and apparatus for monitoring an analog meter-** A method and apparatus for remote monitoring of an analog meter is set out which employs a Hough Transform on the edge points of the meter scale to obtain the center of the meter scale. The graduation marks and the needle are detected from the intensity profile along various radii. Thereby, the Foreign Application Priority Data meter reading can be adopted to different meter scales during an easy training process. The method can be for oblique reading of the scale. One assumption that the system makes is that there is no black character, graphics or scale mark along the path of interest that can interfere with the black needle. The system also assumes that the position and orientation of the meter is fixed with respect to the imaging system [7].
8. **Machine Monitoring on Cloud using Raspberry Pi and Internet of Things-** This paper demonstrates a novel approach in industrial machine monitoring on cloud server using Internet of Things implemented on Raspberry Pi. The raspberry pi is a small credit card sized computer which can directly send data to the cloud server. Any kind of CNC or industrial machine can be connected to Raspberry pi giving logical inputs and can be monitored on the Internet based server so that the real time production data, the work currently going on, the employee who is working on a particular machine, the rate of production, causes of delays and downtimes everything can be monitored by the supervisory or authorities sitting at a remote location almost anywhere in the world. Moreover, the system is very simple which can be operated by unskilled workman working on the floor. In this project data is sent using HTTP protocol which is not as secure as the HTTPS protocol. This is one of the drawbacks of this system [8].
9. **PowerPi: Measuring and modeling the power consumption of the Raspberry Pi-** This paper presents PowerPi, a power consumption model for the Raspberry Pi which is used as a substitute to conventional home gateways to derive the impact of typical hardware components on the energy consumption. The different power states of the platform are measured and a power model is derived, allowing to estimate the power consumption based on CPU and network utilization only. The proposed power model estimates the power consumption resulting in a RMSE of less than 3.3%, which is slightly larger than the maximum error of the measurements of 2.5%. The limitation of this method is that it doesn't consider power loss due to heating and also the power consumed by the USB camera [9].

10. **Image analysis of Electrical Meter-** This paper talks about a method to manually segment the region of interest before recognizing the digits. The project is implemented in LabView. Relative size of digits in the reference image and relative location of the digits in the image to be read is made use of. Circular edge detection, pattern searches, and rotation detection are used to locate dials and segments and to determine their values. The limitation of this project is that digits are recognized using vertical and horizontal edge detection techniques. This is not ideal because the threshold required for detecting edges may vary from one image to another [10].
11. **An approach to extract text from water meter using Python-OpenCV-** This paper brings talks about an algorithm to extract the text from a water meter image. The meter image has same scales of the width and height of the target area which makes this algorithm suitable to recognize the numbers. The algorithm finds the region of interest of water meter using matplotlib, then all numbers are segmented. The segmented digit, each row value is added and stored as an array values from 0-9. To extract text from a water meter image, first segments the digits and each row value is added and compared with previous stored array values. The comparison is done by finding the Euclidean distance of two arrays and then computed the text information. The algorithm is able to extract text from the specified meter images using OpenCV-Python. The main drawback of this system is that recognition of digits is done through template matching. So this method doesn't work if the image is captured at different distances. Generally accuracy of these types of method are not as good as that of the systems that use machine learning. [11].
12. **Automated utility meter reading-** In this method, the algorithm used talks about reading meters with digits. Segmentation of the digits is done using distance change method and then the numbers are recognized using a trained classification model. This paper also uses template matching methods. It makes use of euclidean distance, mahalanobis distance. The limitation of this project is that all the computations are done on a remote server. The on-site microprocessor just transmits the images to the server. This is not an efficient method as lot of bandwidth is required for transmitting images [12].

1.4 Objective

There are different types of analog meters which are being used today. So there will be three steps in implementing our idea.

Frames are captured at regular intervals of around 5 seconds from cameras placed in front of different analog meters and will be transmitted over to the Raspberry Pi through local ZigBee network.

1. **Detecting the type of analog meter** - Primarily, in order to detect the type of analog meter, machine learning algorithms will be used. We intend to use convolutional neural networks to detect the type of analog meter. As of now convolutional neural network has the highest correct detection rate of around 92%.
2. **Applying particular image processing techniques to measure the analog values** - Various image pre-processing techniques like histogram equalization, image smoothening are applied to the frames to improve the interpretability of the captured images. There can be different types of analog meters: For ones with the dials, to measuring the angle of the dials, we use canny edge detection algorithm and Hough transform; for the ones with text readings, the text scene is segmented using contour detection algorithm and then we use OCR library for image to text conversion.
3. **The readings obtained at the Raspberry Pi are sent to the cloud based server for further analytics-** Right now the cloud server is simulated by SQL DB. Readings are sent to this

database at regular intervals. This helps in remote monitoring as the database can be accessed from anywhere.

1.5 Problem Statement

Measuring devices are an integral part of any products. They are critical for managing and assessing the proper working of the products. Without them it is impossible to tell if a device is working properly or not. There are basically two types of measuring devices. Analog meters and digital meters.

Today there are a lot of analog meters measuring various parameters in different environments. They are used in various applications like electricity meters, industrial machines for measuring voltage, temperature, pressure, aircrafts for measuring altitude, speed etc. One major problem is that these meters require on-site manual monitoring to know if the system is working correctly. This task requires a lot of human effort and becomes tedious as there are a lot of analog meters. Another problem is that it is very expensive to replace an analog meter with a digital meter as the cost of digital meters is quite high. To overcome these problems, we propose a system which automates this process. Our system captures the images of analog meters and applies some image processing techniques to measure the readings of the analog meters. This detected value is transmitted over Wi-Fi to the cloud database for further analytics.

1.6 Organization of report

Chapter 1 gives a brief introduction of the project. In chapter 2, softwares and hardwares used for the project are discussed. Design, implementation, system overview of the project are explained in Chapter 3. Results obtained are discussed and analyzed in chapter 4. In Chapter 5, conclusion, future enhancements, advantages, disadvantages are mentioned.

Chapter 2

HARDWARE AND SOFTWARE REQUIREMENTS

This chapter deals with discussion about the details of the hardware components and the software dependencies and software platforms that are made used in carrying out of this project.

2.1 Hardware requirements

This section deals with discussion about the details of hardware components that are used in this project. The components are discussed are as follows:

- Raspberry Pi 2 Model B
- iBall Face2Face C12.0

2.1.1 Raspberry Pi 2 Model B

It also has an upgraded ARMv7 multi-core processor. The processor speed has increased considerably in Raspberry Pi 2 Model B compared to the previous versions. One of the most important features is its small size compared to other microprocessors. It has the following specifications:

- 4 USB ports
- 40 GPIO pins
- Full HDMI port
- Ethernet port
- Combined 3.5mm audio jack and composite video
- Camera interface (CSI)
- Display interface (DSI)
- Micro SD card slot
- VideoCore IV 3D graphics core

The image of the Raspberry Pi used is shown in Figure 2.1. We can use Raspberry Pi Zero in future as it has small area and hence modules can be created easily

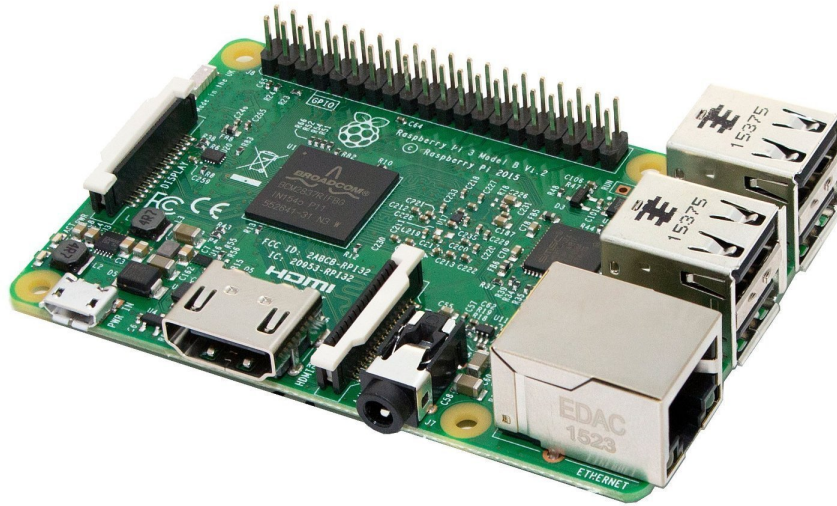


Figure 2.1: Raspberry Pi Model B

2.1.2 iBall Face2Face C12.0

This web camera is with interpolated 12.0MP Still Image resolution & 2.0 Mega Pixels Video resolution. This camera comes with the 5G Wide angle lenses which helps in providing the smooth video and lets you make quality video chat. So this camera is pretty good in capturing the needles and digits present in the analog measuring devices. It has the following Specifications:

- Interpolated 12.0 Mega Pixel Still Image Resolution
- Interpolated 2.0 Mega Pixel Video Resolution
- High quality 5G wide angle lens
- 6 LEDs for night vision, with brightness controller
- Snapshot button for still image capture
- Built-in high sensitive USB microphone
- Built-in 10 Photo frames and 16 special effects for more fun
- 4X Digital Zoom and Auto Face Tracking Function
- Multi-utility camera base for use on Monitors, LCD's and Laptops
- These all drivers are redirected to iBall website server for download & shared here for your ease to download.

The picture of the iBall camera used is shown in Figure 2.2. This camera also has additional lighting capacity which can be used at night.

2.2 Software requirements

We are implementing the system on Raspbian platform. We will be using Python as the coding language. Also many libraries like OpenCV, requests, flask, numpy will be used.



Figure 2.2: iBall Face2Face C12.0

2.2.1 OpenCV

The library has more than 2500 optimized algorithms, which includes a comprehensive set of both classic and state-of-the-art computer vision and machine learning algorithms. These algorithms can be used to detect and recognize faces, identify objects, classify human actions in videos, track camera movements, track moving objects, extract 3D models of objects, produce 3D point clouds from stereo cameras, stitch images together to produce a high resolution image of an entire scene, find similar images from an image database, remove red eyes from images taken using flash, follow eye movements, recognize scenery and establish markers to overlay it with augmented reality, etc.

It has C++, Python, Java and MATLAB interfaces and supports Windows, Linux, Android and Mac OS. OpenCV leans mostly towards real-time vision applications and takes advantage of MMX and SSE instructions when available. A full-featured CUDA and OpenCL interfaces are being actively developed right now. There are over 500 algorithms and about 10 times as many functions that compose or support those algorithms. OpenCV is written natively in C++ and has a templated interface that works seamlessly with STL containers.

2.2.2 Raspbian OS on Raspberry Pi

Raspbian is a Debian-based computer operating system for Raspberry Pi. Since 2015 it has been officially provided by the Raspberry Pi Foundation as the primary operating system for the family of Raspberry Pi single-board computers. Raspbian was created by Mike Thompson and Peter Green as an independent project. The initial build was completed in June 2012. The operating system is still under active development. Raspbian is highly optimized for the Raspberry Pi line's low-performance ARM CPUs.

Raspbian uses PIXEL, Pi Improved Xwindows Environment, Lightweight as its main desktop environment as of the latest update. It is composed of a modified LXDE desktop environment and the Openbox stacking window manager with a new theme and few other changes. The distribution is shipped with a copy of computer algebra program Mathematica and a version of Minecraft called Minecraft Pi as well as a lightweight version of Chromium as of the latest version.

2.2.3 Tkinter

The Tkinter module (“Tk interface”) is the standard Python interface to the Tk GUI toolkit from Scriptics (formerly developed by Sun Labs). Both Tk and Tkinter are available on most Unix platforms, as well as on Windows and Macintosh systems. Starting with the 8.0 release, Tk offers native look and feel on all platforms. Tkinter consists of a number of modules. The Tk interface is provided by a binary extension module named tkinter. This module contains the low-level interface to Tk, and should never be used directly by application programmers. It is usually a shared library (or DLL), but might in some cases be statically linked with the Python interpreter.

2.2.4 Flask

Flask is a micro web framework written in Python and based on the Werkzeug toolkit and Jinja2 template engine. It is BSD licensed. The latest stable version of Flask is 0.12.2 as of May 2017. Applications that use the Flask framework include Pinterest, LinkedIn, and the community web page for Flask itself.

Flask is called a micro framework because it does not require particular tools or libraries. It has no database abstraction layer, form validation, or any other components where pre-existing third-party libraries provide common functions. However, Flask supports extensions that can add application features as if they were implemented in Flask itself. Extensions exist for object-relational mappers, form validation, upload handling, various open authentication technologies and several common framework related tools. Extensions are updated far more regularly than the core Flask program.

2.2.5 MySQL

MySQL is offered under two different editions: the open source MySQL Community Server and the proprietary Enterprise Server. MySQL Enterprise Server is differentiated by a series of proprietary extensions which install as server plugins, but otherwise shares the version numbering system and is built from the same code base. Major features as available in MySQL 5.6 are

- A broad subset of ANSI SQL 99, as well as extensions
- Cross-platform support
- Stored procedures, using a procedural language that closely adheres to SQL/PSM[71]
- Triggers
- Cursors
- Updatable views
- Online DDL when using the InnoDB Storage Engine.
- Information schema
- Performance Schema that collects and aggregates statistics about server execution and query performance for monitoring purposes.[72]
- A set of SQL Mode options to control runtime behavior, including a strict mode to better adhere to SQL standards.
- X/Open XA distributed transaction processing (DTP) support; two phase commit as part of this, using the default InnoDB storage engine

- Transactions with save-points when using the default InnoDB Storage Engine. The NDB Cluster Storage Engine also supports transactions.
- ACID compliance when using InnoDB and NDB Cluster Storage Engines
- SSL support
- Query caching

MySQL queries are implemented in python using MySQLdb library. This is used to regularly update the SQL database with the detected reading values.

2.2.6 Wamp Server

WampServer refers to a software stack for the Microsoft Windows operating system, created by Romain Bourdon and consisting of the Apache web server, OpenSSL for SSL support, MySQL database and PHP programming language.

Here Wamp server is mainly used to host MySQL Database. A snippet of the wamp server console page is shown in Figure 2.3.

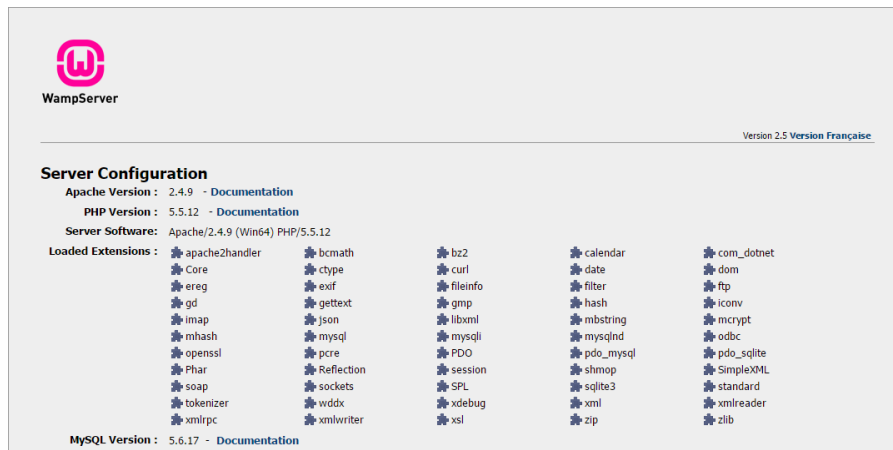


Figure 2.3: Various features offered by Wamp Server

Using all the hardware components and software tools mentioned in this chapter a system for automated analog meter reading was designed.

SYSTEM DESIGN AND IMPLEMENTATION

3.1 System Overview

3.1.1 Block Diagram

```

graph LR
    subgraph Units [ ]
        direction TB
        AM1[Analog meter]
        C1[Camera]
        RP1[Raspberry pi]
        AM1 -.->|Image capture| C1
        C1 -->|Frames transfer| RP1
        RP1 -->|Image processing| RP1
    end
    RP1 -.->|Data transfer| Cloud((Cloud db/server))
    Cloud --- DA[Data analytics]
    AM2[Analog meter]
    C2[Camera]
    RP2[Raspberry pi]
    AM2 -.->|Image capture| C2
    C2 -->|Frames transfer| RP2
    RP2 -->|Image processing| RP2
    RP2 -.->|Data transfer| Cloud
    AM3[Analog meter]
    C3[Camera]
    RP3[Raspberry pi]
    AM3 -.->|Image capture| C3
    C3 -->|Frames transfer| RP3
    RP3 -->|Image processing| RP3
    RP3 -.->|Data transfer| Cloud
    Cloud --- DA
    style Units fill:none,stroke:none
    style AM2 fill:none,stroke:none
    style C2 fill:none,stroke:none
    style RP2 fill:none,stroke:none
    style AM3 fill:none,stroke:none
    style C3 fill:none,stroke:none
    style RP3 fill:none,stroke:none

```

The major components required and used are Raspberry Pi 2.0 and Iball 20.0 HD web cam. The camera captures the images of the Analog measuring instruments at regular intervals and sends it to Raspberry Pi 2.0 for image processing and detection. The Raspberry Pi then sends the detected values along with other required parameters to the cloud server or database. We have used SQL DB here to simulate cloud server features and functions.

3.1.2 Hardware Overview

Raspberry Pi 2 Model B microprocessor offers a low cost solution. It also consumes very less power compared to other microprocessors. It has more RAM capacity compared to previous models of Raspberry Pi. It also has an upgraded ARMv7 multi-core processor. The processor speed has increased considerably in Raspberry Pi 2 Model B compared to the previous versions.

iBall Face2Face C12.0 web camera is with interpolated 12.0MP Still Image resolution & 2.0 Mega Pixels Video resolution. This camera comes with the 5G Wide angle lenses which helps in providing the smooth video and lets you make quality video chat. So this camera is pretty good in capturing the needles and digits present in the analog measuring devices.

3.1.3 Software Overview

OpenCV is an open source computer vision and machine learning software library. OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in the commercial products. Being a BSD-licensed product, OpenCV makes it easy for businesses to utilize and modify the code. The library has more than 2500 optimized algorithms, which includes a comprehensive set of both classic and state-of-the-art computer vision and machine learning algorithms.

MySQL is used for managing the SQL DB. MySQL is an open-source relational database management system (RDBMS). MySQL is written in C and C++. Its SQL parser is written in yacc, but it uses a homebrewed lexical analyzer. MySQL works on many system platforms, including AIX, BSDi, FreeBSD, HPUX, eComStation, i5/OS, IRIX, Linux, macOS Microsoft Windows, NetBSD, Novell NetWare, OpenBSD, OpenSolaris, OS/2 Warp, QNX, Oracle Solaris, Symbian, SunOS, SCO OpenServer, SCO UnixWare, Sanos and Tru64. A port of MySQL to OpenVMS also exists.

Python is a high level object oriented programming language used for general purpose. Python emphasizes a lot on code readability. Python uses dynamic typing, and a combination of reference counting and a cycle-detecting garbage collector for memory management. It also features dynamic name resolution (late binding), which binds method and variable names during program execution. We have used OpenCV in python. We have also made use of Flask on Python.

3.2 Working Principle

The block diagram of the flow of control in the proposed system is shown in Figure 3.2. After the end of process the readings are sent to the database. Each block is explained below.

First step is to capture the image through the iBall camera. This is done with the help of USB drivers and OpenCV. Next we have to detect the type of Analog meter. This is done with the help of Convolutional Neural Network (CNN).

3.2.1 Classification using CNN

The classification is a problem of identifying which of a set of categories the new data/observation belongs to. Classification is done by collecting the data called as training data and devising a pattern in the training data to further predict the category the test data belongs to. Here we have to classify image as image with needle reading or image with digit reading. In supervised learning, a classifier model is trained with a set of training features and their corresponding labels. This model generalizes on the training data and predicts the test labels on the test data. The process of categorizing the test

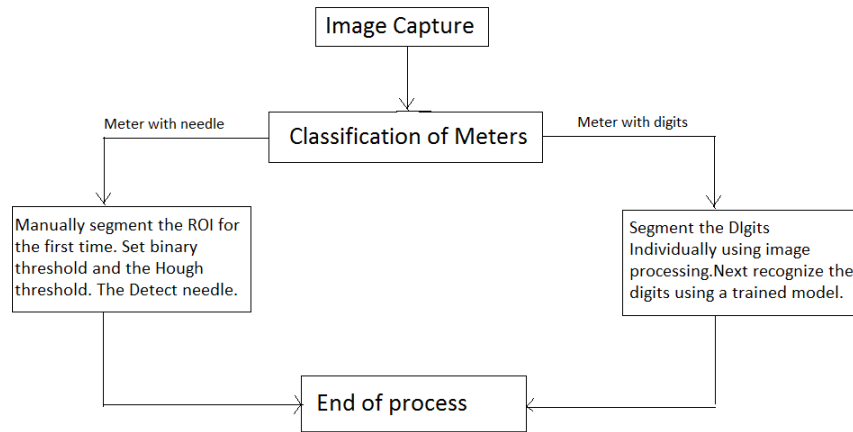


Figure 3.2: Basic working principle of Automated meter board reading

data on a previously learned model in a supervised classification problem is called as Classification. The classification problem in this scenario is a supervised classification. The different types of classifiers used for supervised classification are K-Nearest Neighbors Classifier, Support Vector Machines (SVM), Neural networks, etc.

Convolutional Neural Networks are very similar to ordinary Neural Networks. They are made up of neurons that have learnable weights and biases. Each neuron receives some inputs, performs a dot product and optionally follows it with a non-linearity. The whole network still expresses a single differentiable score function: from the raw image pixels on one end to class scores at the other. And they still have a loss function (e.g. SVM/Softmax) on the last (fully-connected) layer and all the tips/tricks we developed for learning regular Neural Networks still apply. Regular Neural Nets don't scale well to full images. In CIFAR-10, images are only of size $32 \times 32 \times 3$ (32 wide, 32 high, 3 color channels), so a single fully-connected neuron in a first hidden layer of a regular Neural Network would have $32 \times 32 \times 3 = 3072$ weights. This amount still seems manageable, but clearly this fully-connected structure does not scale to larger images. For example, an image of more respectable size, e.g. $200 \times 200 \times 3$, would lead to neurons that have $200 \times 200 \times 3 = 120,000$ weights. Moreover, we would almost certainly want to have several such neurons, so the parameters would add up quickly. Clearly, this full connectivity is wasteful and the huge number of parameters would quickly lead to overfitting.

Convolutional Neural Networks take advantage of the fact that the input consists of images and they constrain the architecture in a more sensible way. In particular, unlike a regular Neural Network, the layers of a ConvNet have neurons arranged in 3 dimensions: width, height, depth. (Note that the word depth here refers to the third dimension of an activation volume, not to the depth of a full Neural Network, which can refer to the total number of layers in a network.) For example, the input images in CIFAR-10 are an input volume of activations, and the volume has dimensions $32 \times 32 \times 3$ (width, height, depth respectively). As we will soon see, the neurons in a layer will only be connected to a small region of the layer before it, instead of all of the neurons in a fully-connected manner. Moreover, the final output layer would for CIFAR-10 have dimensions $1 \times 1 \times 10$, because by the end of the ConvNet architecture we will reduce the full image into a single vector of class scores, arranged along the depth dimension. The visualization is shown in Figure 3.3 and Figure 3.4.

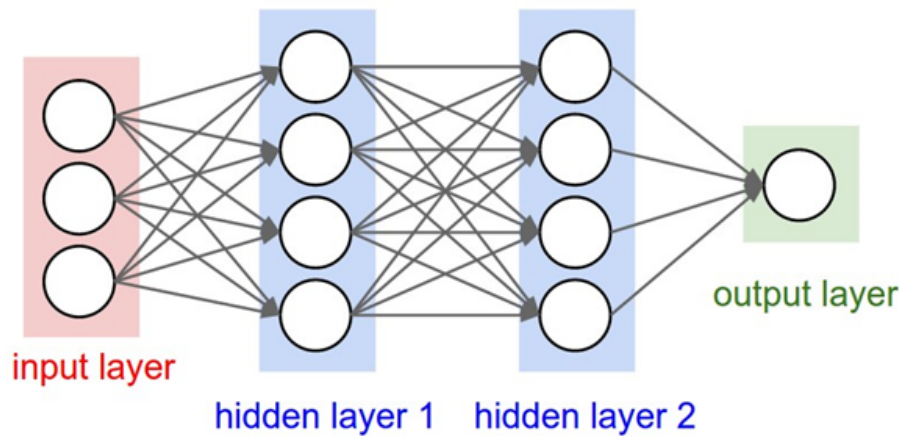


Figure 3.3: Generic Architecture of CNN

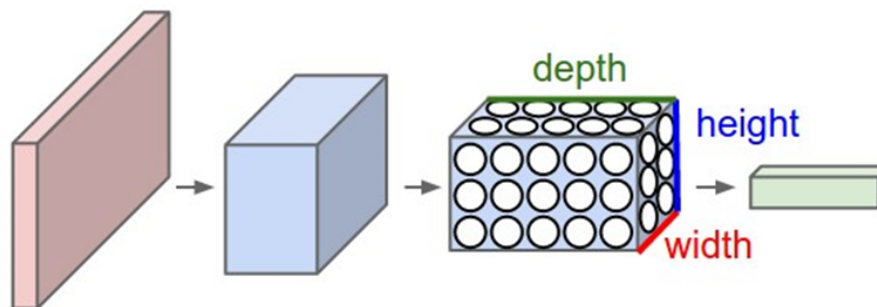


Figure 3.4: Layer neural network

3.2.2 Image preprocessing techniques for detecting needle.

Next step is to detect the needle in the analog meter. This is done using Gaussian Blur, thresholding methods and Hough transform. Gaussian Blur is used to remove low frequency noise in the image. It is a widely used effect in graphics software, typically to reduce image noise and reduce detail. The visual effect of this blurring technique is a smooth blur resembling that of viewing the image through a translucent screen, distinctly different from the bokeh effect produced by an out-of-focus lens or the shadow of an object under usual illumination. Gaussian smoothing is also used as a pre-processing stage in computer vision algorithms in order to enhance image structures at different scales—see scale space representation and scale space implementation.

After segmentation binary thresholding is used for setting a proper threshold to detect the needle. The Binary Thresholding function creates a raster output that divides your raster into two distinct classes. The algorithm behind the Binary Thresholding function, the Otsu method, was designed to distinguish between background and foreground in imagery by creating two classes with minimal intraclass variance (Otsu 1979). When working with a raster dataset that has a unimodal distribution, Binary Thresholding divides the data into two distinct classes. It creates a high-value class, displayed with white pixels, and a low-value class, displayed with black pixels.

After setting the binary threshold, Hough Transform is used to detect the needle. The Hough transform is a technique which can be used to isolate features of a particular shape within an image. Because it requires that the desired features be specified in some parametric form, the classical Hough transform is most commonly used for the detection of regular curves such as lines, circles, ellipses, etc. A generalized Hough transform can be employed in applications where a simple analytic description of a feature(s) is not possible. Despite its domain restrictions, the classical Hough transform (hereafter referred to without the classical prefix) retains many applications, as most manufactured

parts (and many anatomical parts investigated in medical imagery) contain feature boundaries which can be described by regular curves. The main advantage of the Hough transform technique is that it is tolerant of gaps in feature boundary descriptions and is relatively unaffected by image noise.

3.2.3 Digit segmentation and Recognition

Next to detect meters with digit readings, we have to segment the digits first. Next we have to recognize each of the digits. Segmentation is done using Otsu's thresholding, Adaptive thresholding, finding area of contours and Hough circles.

In Otsu's method we exhaustively search for the threshold that minimizes the intra-class variance (the variance within the class), defined as a weighted sum of variances of the two classes:

$$\sigma_w^2 = \omega_0(t)\sigma_0^2(t) + \omega_1(t)\sigma_1^2(t)$$

Adaptive thresholding typically takes a gray-scale or color image as input and, in the simplest implementation, outputs a binary image representing the segmentation. For each pixel in the image, a threshold has to be calculated. If the pixel value is below the threshold it is set to the background value, otherwise it assumes the foreground value.

There are two main approaches to finding the threshold:

1. The Chow and Kaneko approach
2. Local thresholding

The assumption behind both methods is that smaller image regions are more likely to have approximately uniform illumination, thus being more suitable for thresholding. Chow and Kaneko divide an image into an array of overlapping sub-images and then find the optimum threshold for each sub-image by investigating its histogram. The threshold for each single pixel is found by interpolating the results of the sub-images. The drawback of this method is that it is computationally expensive and, therefore, is not appropriate for real-time applications. An alternative approach to finding the local threshold is to statistically examine the intensity values of the local neighborhood of each pixel. The statistic which is most appropriate depends largely on the input image. Simple and fast functions include the mean of the local intensity distribution or average of maximum or minimum pixel values. Example of Threshold value where max is maximum pixel value and min is minimum pixel value.

$$T = (max + min)/2$$

The dot in the analog meters can be detected using the concept of Hough circles. In a two-dimensional space, a circle can be described by:

$$(x - a)^2 + (y - b)^2 = r^2$$

where (a,b) is the center of the circle, and r is the radius. If a 2D point (x,y) is fixed, then the parameters can be found according to (1). The parameter space would be three dimensional, (a, b, r). And all the parameters that satisfy (x, y) would lie on the surface of an inverted right-angled cone whose apex is at (x, y, 0). In the 3D space, the circle parameters can be identified by the intersection of many conic surfaces that are defined by points on the 2D circle. This process can be divided into two stages. The first stage is fixing radius then find the optimal center of circles in a 2D parameter space. The second stage is to find the optimal radius in a one dimensional parameter space.

Then the segmented digits are recognized using a trained CNN model. The dataset used for training is the Chars74 K dataset. This training is similar to the training employed in classifying the type of analog meter.

3.3 Method of Implementation

The project is implemented by collecting datasets required for classification of analog meters and also for recognizing the digits. Then either needle or digit is detected using some image processing algorithms. Corresponding readings are sent to the database.

3.3.1 Classification of analog meters

The classification of meters is achieved through various steps. They are

- Collection of the dataset
- Preprocessing and Augmentation
- Training the Convolutional Neural Network
- Testing and Validation of the Neural model

Two types of meters which are shown in Figure 3.5 and Figure 3.6 were considered for classification. One meter with a needle based reading and another with a digit based reading.



Figure 3.5: Analog meter with needle reading



Figure 3.6: Analog meter with digit reading

3.3.2 Dataset collection and preprocessing

The images of different types of digital and analog meters were collected from various sources. The dataset includes 200 images of analog meters and 250 images of digital meters contributing to a total of 450 images. The obtained images were preprocessed and cropped based on the requirement.

3.3.3 Layers used to build convnets

LeNet architecture was used to build the convolutional neural network.

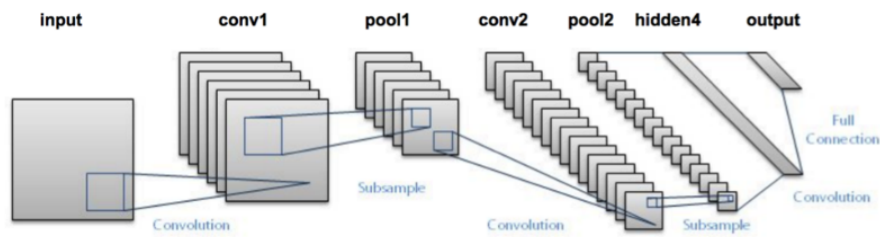


Figure 3.7: The LeNet architecture

The LeNet architecture is an excellent “first architecture” for Convolutional Neural Networks (especially when trained on the MNIST dataset, an image dataset for handwritten digit recognition).

LeNet is small and easy to understand — yet large enough to provide interesting results. Furthermore, the combination of LeNet + MNIST is able to run on the CPU, making it easy for beginners to take their first step in Deep Learning and Convolutional Neural Networks.

3.3.4 Training the convolutional network (CNN)

After the dataset is collected and preprocessed, the Neural Network model has to be trained in order to achieve the classification of meters.

To train a CNN, there are several hyper parameters which have to be tuned in order to perfectly train a model. Hyper parameters play a very important role in training a model perfectly.

The model which is being trained should attain a perfect fit to the trend/pattern in the data. There are two types of problems which can arise while training a model i.e over-fitting and under-fitting.

a) Over-fitting refers to a model that models the training data too well. Over-fitting happens when a model learns the detail and noise in the training data to the extent that it negatively impacts the performance of the model on new data. This means that the noise or random fluctuations in the training data is picked up and learned as concepts by the model. The problem is that these concepts do not apply to new data and negatively impact the models ability to generalize. Overfitting is more likely with nonparametric and nonlinear models that have more flexibility when learning a target function. As such, many nonparametric machine learning algorithms also include parameters or techniques to limit and constrain how much detail the model learns.

For example, decision trees are a nonparametric machine learning algorithm that is very flexible and is subject to overfitting training data. This problem can be addressed by pruning a tree after it has learned in order to remove some of the detail it has picked up.

b) Underfitting refers to a model that can neither model the training data nor generalize to new data. An underfit machine learning model is not a suitable model and will be obvious as it will have poor performance on the training data.

Underfitting is often not discussed as it is easy to detect given a good performance metric. The remedy is to move on and try alternate machine learning algorithms. Nevertheless, it does provide a good contrast to the problem of overfitting.

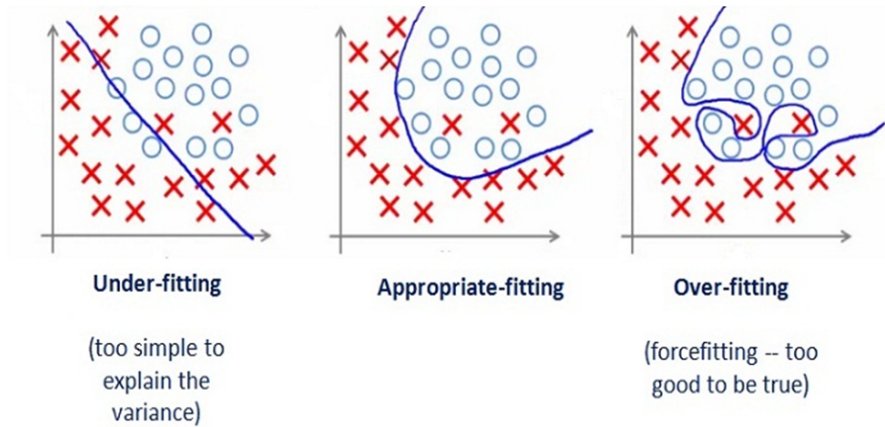


Figure 3.8: Examples of Under-fit, perfect-fit and Over-fit

3.3.5 Hyper-parameters in CNN

- Epoch – The number of iterations of back propagation for CNN required to train.
- Number of neurons – The number of neurons for input layer, hidden layers and the output layers.
- Batch size – The number of images to be considered for 1 back propagation.
- Number of filters – The number of filters in each convolutional layer to extract features.
- Pool size – The size of the kernel for max or min pool in the pooling layer.
- Convolution size – The size of the kernel for performing convolutions in the convolution layer.
- Drop out factor – The regularization factor to control overfitting and underfitting. This can be varied to achieve good fit.

3.3.6 CNN for Digit recognition

Once image segments are detected, recognizing the digits in each of them was the next step. This is done using a machine learning model trained using Convolutional Neural Network (CNN). The dataset used for training is CHARS74k dataset. In this dataset, symbols used in both English and Kannada are available.

In the English language, Latin script (excluding accents) and Hindu-Arabic numerals are used. For simplicity we call this the "English" characters set. Our dataset consists of:

- 64 classes (0-9, A-Z, a-z)
- 7705 characters obtained from natural images

- 3410 hand drawn characters using a tablet PC
- 62992 synthesized characters from computer fonts

This gives a total of over 74K images (which explains the name of the dataset). We have used 10 classes of numbers in the dataset for training. LeNet architecture is again used here for training.

Chapter 4

PERFORMANCE EVALUATION

The performance of the system was compared with manual readings. The overall performance of the system was satisfactory. There is scope for further improvements in the system which is discussed here.

4.1 Training CNN for classification of analog meters

The dataset of size 450 images is divided into train, test and validation sets. The test size was considered to be 12% of the total dataset (60 images). The validation size was considered to be 8% of the total dataset (30 images). First, the model is trained by taking random hyper parameters for CNN.

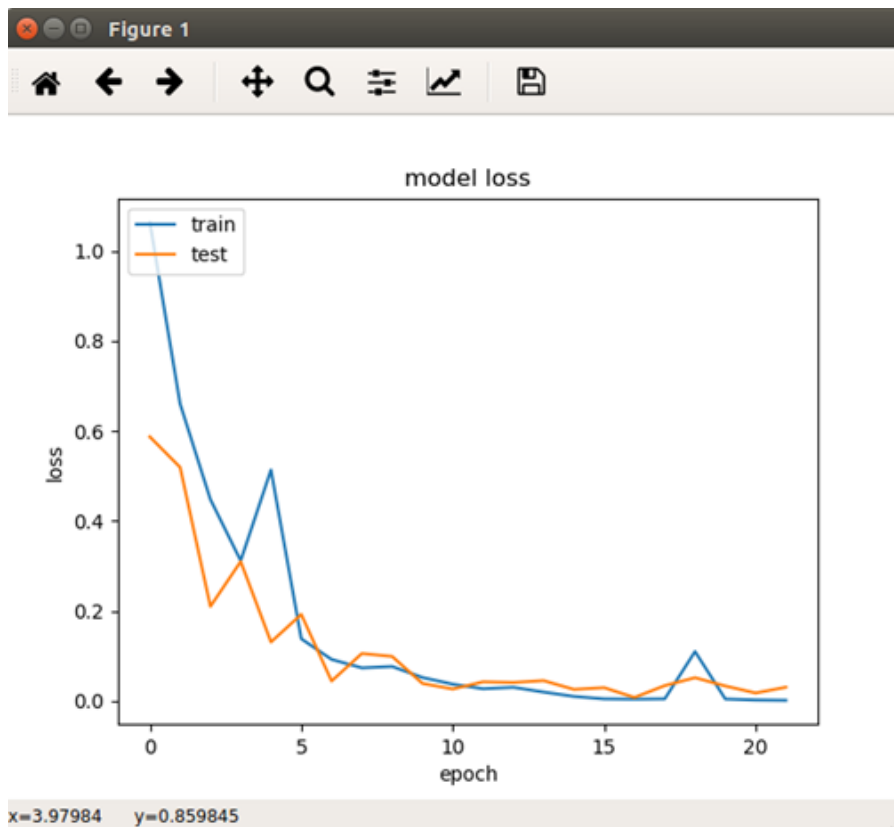


Figure 4.1: The learning curve of the model

The graph in Figure 4.1 shows that as though the training loss is decreasing with the increase in number of epochs, the validation loss is increasing after some epochs. This characteristic clearly shows that the model is overfitting and the hyper parameters must be tuned to reduce overfitting. The

parameters epoch, batch size can be chosen from the graph to ensure that the training loss and the validation loss are almost the same. This will train a good fit model. The parameter drop out factor also helps reduce the overfit and ensures that the training loss and the validation loss are less and almost equal. The model is saved after tuning the hyper parameters of the CNN. The good fit model is displayed in the Figure 4.2.

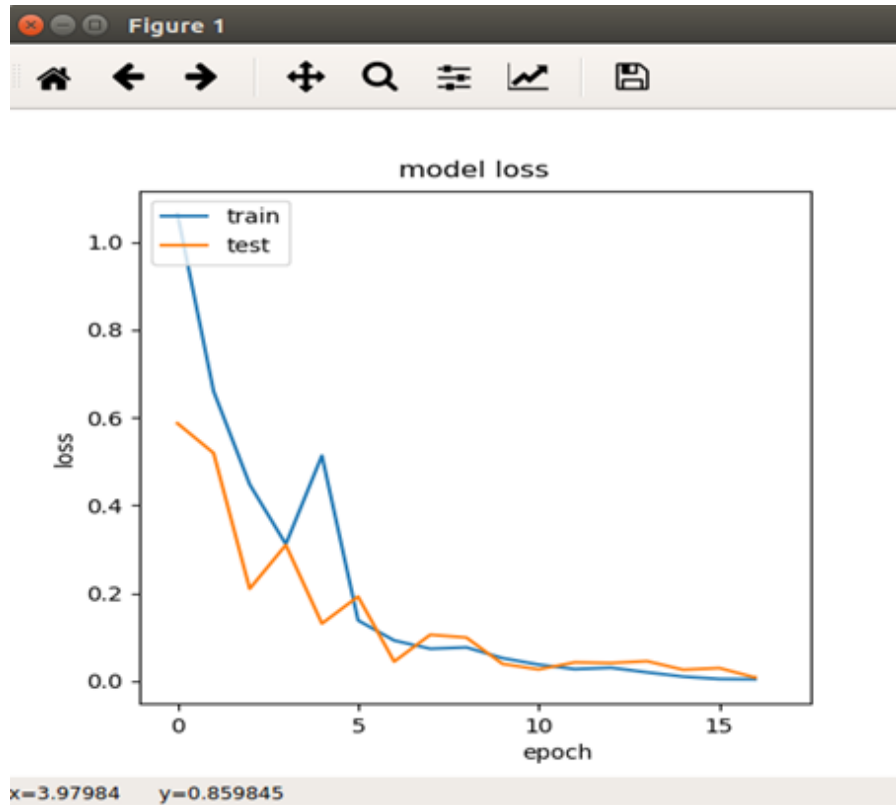


Figure 4.2: Learning curve of a good fit model

4.2 Testing and Validation

The model is tested by prediction on the test images which were generated at the beginning. Since, this is a supervised classification problem, the predictions on the test images are compared with the known test classes and further accuracy is computed on the test images. The accuracy however is a deterministic factor to determine if the model is performing correctly on the test images.

Also, 10 – fold cross validation is performed to ensure that the model is trained well for all kinds of analog and digital meters. In this process, the dataset is divided into 10 parts out of which 1 part is chosen as the validation set and the rest 9 parts of the dataset are chosen as the training set. The accuracy is computed with this as the constraint. This process is further repeated for 10 times with different testing sets. Hence, taking the average of all the accuracies is the average accuracy of the model. Cross validation ensures that the accuracy is determined accurately.

4.3 Detection of analog meter needle and its reading

After proper prediction of analog meter, if the detected meter is analog meter with needle readings, then the first step here is to manually segment the region of interest. This is done to remove the unwanted background images and to some extent the noise. This is done only once at the beginning.

The parameters involved in this segmentation is saved for further use. This procedure is shown in Figure 4.3 to Figure 4.6.

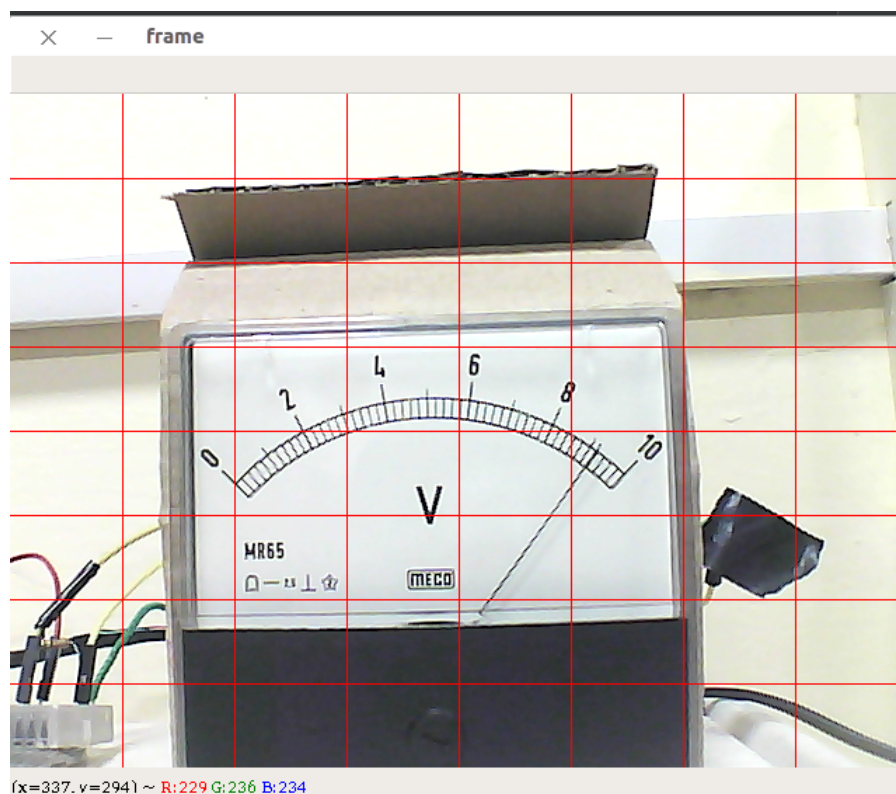


Figure 4.3: Initial Image before segmentation

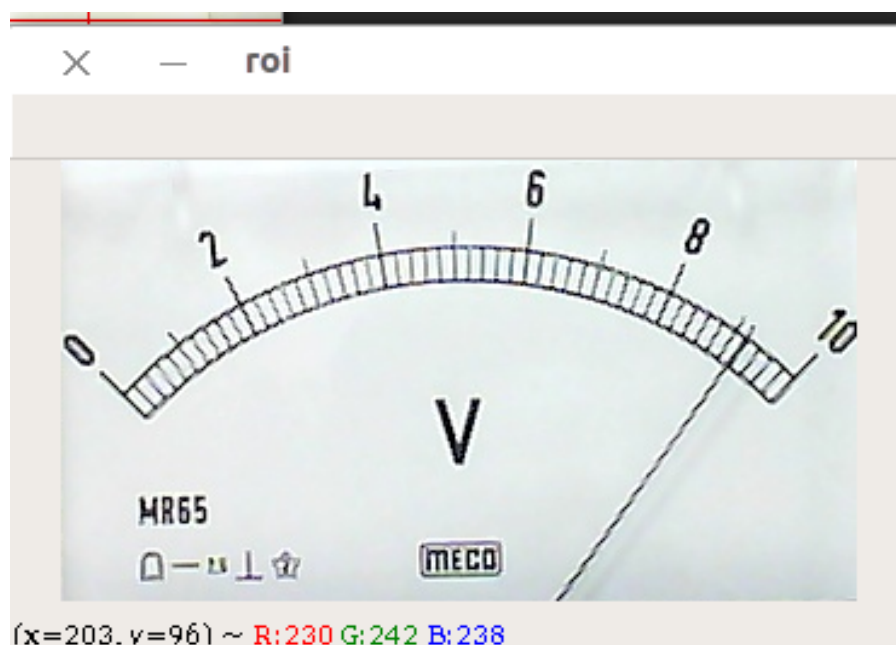


Figure 4.4: After segmentation

After some image processing like binary thresholding, Hough thresholding, the needle is detected as shown below.

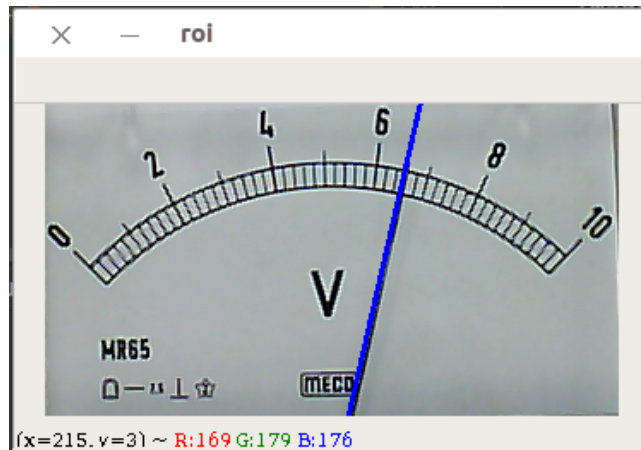


Figure 4.5: Needle detected image

Initially any two needle positions are detected without any readings. This is required for mapping output parameter to angle. The difference of the values of the two positions are calculated manually and then is divided by the angle between them. This gives the output value change for every degree of the needle.

All the binary threshold values and segmentation values are sent to the raspberry pi for use in further image capture. This is done through JSON object which is sent with the help of flask server.

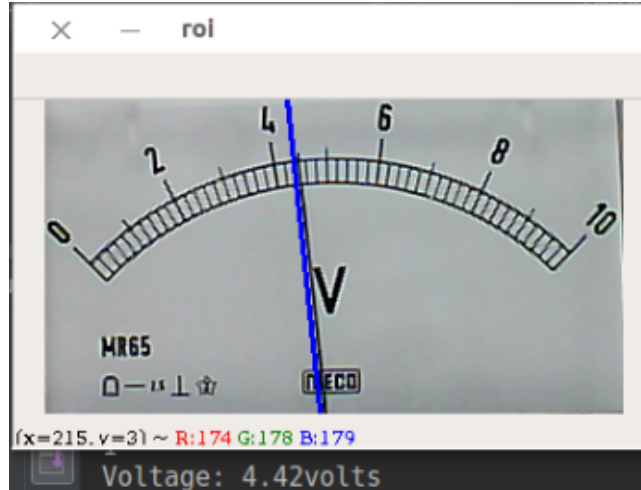


Figure 4.6: Image with detected reading.

4.4 Detection of digits in meters with digital readings

Initially the actual image(4.7) captured by the camera is cropped manually for getting the region of interest as in 4.8. This is done only once at the beginning. It is done when the camera is directly connected to the laptop. The dimensions and other specifications of the cropped region of interest is noted down. These values are then sent to Raspberry Pi in the form of JSON object using local flask server. So the Raspberry pi does the cropping automatically whenever it captures the images.

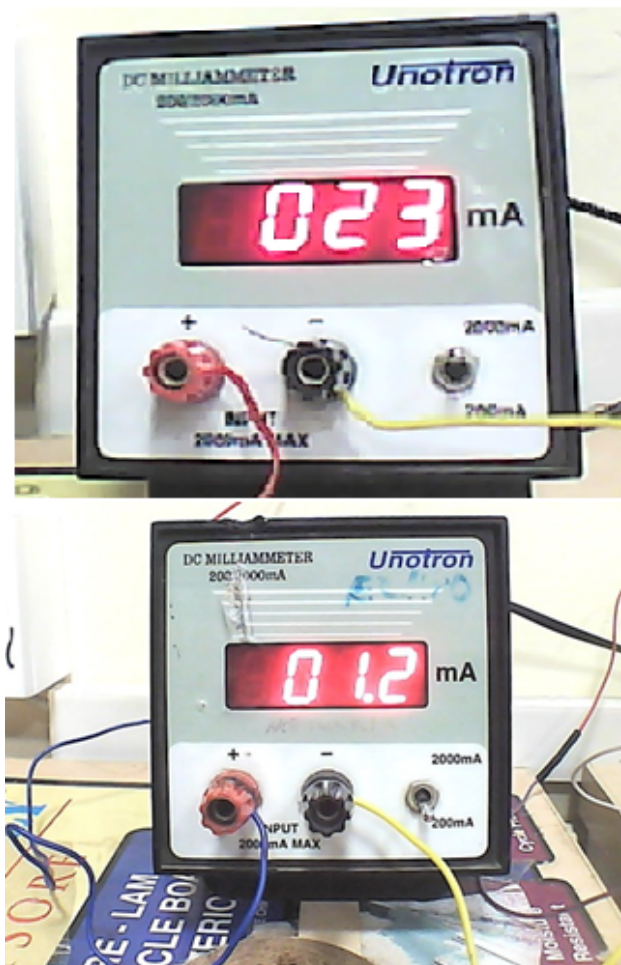


Figure 4.7: The original images of the analog meter with digital readings.



Figure 4.8: After cropping the original captured images

Next step is to detect the areas of individual digits in the cropped image. This can be done using various image preprocessing techniques.

First we need to detect the regions containing the digits. This is done with the help of Otsu's quantization, Adaptive quantization and then by finding the contours. Otsu's quantization and Adaptive

quantization help in reducing the noise present in the image. This reduces a lot of unwanted contours which may be detected in the image.



Figure 4.9: images obtained using Otsu's method

Adaptive thresholding produces output as in Figure 4.10.

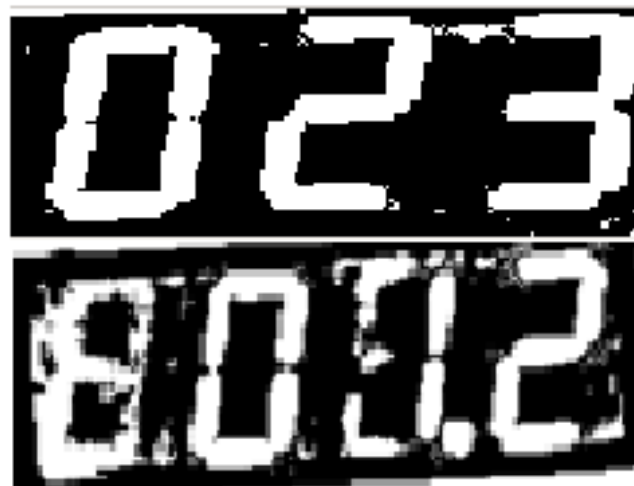


Figure 4.10: Images obtained using Adaptive threshold

Next bitwise AND of the image obtained after both types of thresholding is done which effectively reduces a lot of noise. The binary image after this step is shown in Figure 4.11.



Figure 4.11: Images with less noise

Next step is to detect the contours. This is done using an inbuilt OpenCV function. Contours detected is shown in Figure 4.12.

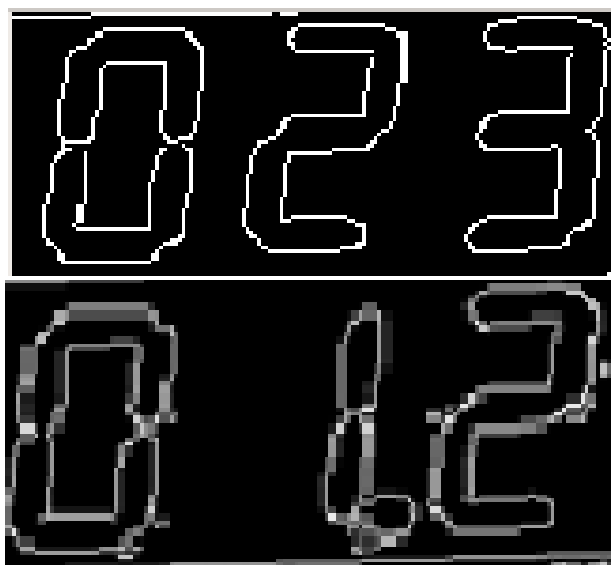


Figure 4.12: Edge detected images

Now based on position and area inside contours, only the required area is segmented. The DOT in the image is detected using the concept of Hough Circles as shown in Figure 4.13.

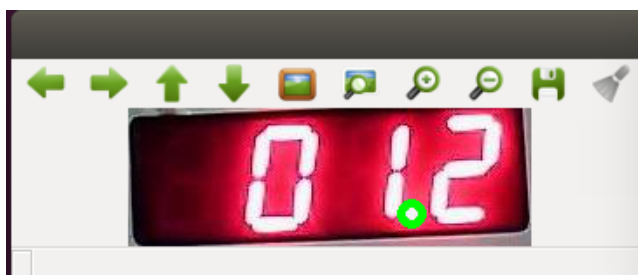


Figure 4.13: Circle detection

The final segmented area after including Hough Transform is bounded by a rectangle as shown in Figure 4.14.

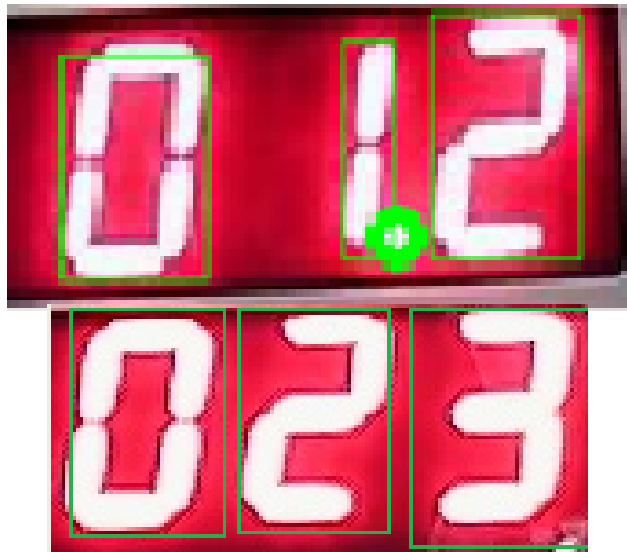


Figure 4.14: Segmented images

4.5 Recognition of digital image

10 Epochs with each of batch size 32 was used for training the model. Accuracy up to 70% was obtained. First the obtained image segments after segmentation was converted into a single channel image. This is required as the model has been trained for a single channel image. Converting three channel image to a single channel is done using binary thresholding. After this, prediction is done using the trained model. This is shown in Figure 4.15 and Figure 4.16.



Figure 4.15: Cropped images

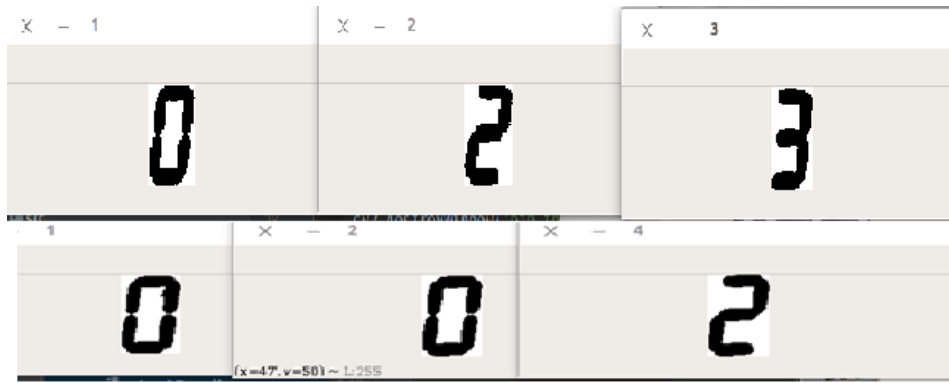


Figure 4.16: Segmented images

The accuracy of the trained model for recognizing the digits can be further improved. The values detected can be sent to the database hosted locally. The values can be read at regular intervals of 5 seconds, 10 seconds etc based on the requirements.

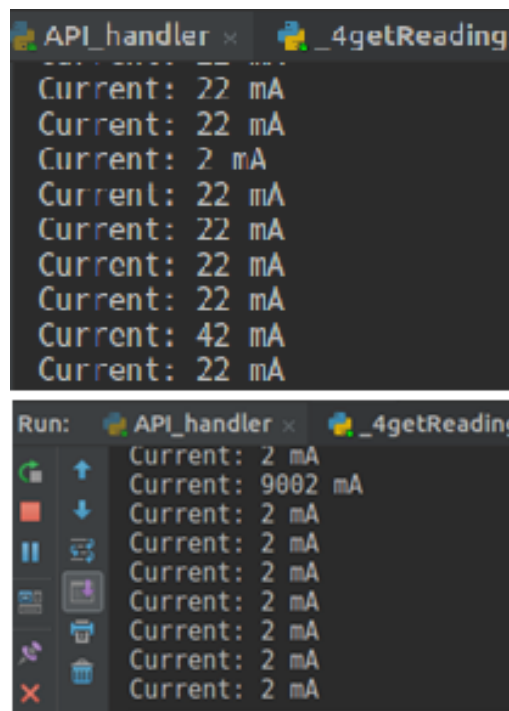


Figure 4.17: Detected readings

4.6 Results and accuracy

Accuracy of a classification system is given by:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where,

True Positive (TP) Observation is positive, and is predicted to be positive.

False Negative (FN) Observation is positive, but is predicted negative.

True Negative (TN) Observation is negative, and is predicted to be negative.

False Positive (FP) Observation is negative, but is predicted positive.

Here,

Class 1 Analog meter with needle.

Class 2 Analog meter with digital display.

4.6.1 Classification of analog meters

Two classes of images have been considered.

- Class 1 :Positive (In this case analog meter with needle reading)
- Class 2:Negative (In this case analog meter with digit reading)

Around 500 images were used for training the classification model. Testing accuracy is shown in Table 4.1

Table 4.1: Testing Accuracy

Type	Sample set	Accuracy
Analog meter with needle	150	96.2 %
Analog meter with digital display	200	94.3 %

4.6.2 Classification of segmented digits

300 images in total have been taken for training the model. This includes 30 images of each digit from 0 to 9. The dataset was collected from various meters with seven segment display. Testing was done on around 100 seven segment display digits. Accuracy of around 97 % was obtained.

4.6.3 Reading accuracy of analog meters with needle

The algorithm designed was tested on around 100 different readings of the analog meter with needle. The needle detection accuracy was around 90 %. After the needle is detected, its value was measured using trigonometric functions. This had an error of 1 to 2 %. This error is due to rounding of values during calculation.

Chapter 5

CONCLUSION AND FUTURE ENHANCEMENT

This chapter explains the conclusions drawn from the execution of the project and the details about the future enhancements that can be done to enhance the features and performances of this project.

Classification of Analog meters based on digits or needles was pretty much accurate. Very high accuracy of around 99.7% was obtained. Since this classification deals with only two datasets, it is easy to get high accuracy. Overfitting problem was dealt with by tuning the hyper parameters.

Next detecting analog meters with needle was done mainly with the use of Hough Transform. First manual segmentation of the Region Of Interest (ROI) was done. This is a onetime setup. Next needle and its value is detected using some mathematical concepts. Setting the threshold is one of the main problems here.

Next is the detection of digits in the meters. First segmentation of the digits is done using image pre processing techniques. Next a trained model is used for recognizing the digits. The main problem here is the accuracy of recognition of digits. Also the effects of lighting and glare was tried to reduce using adaptive equalization. But still the problem persists to an extent.

5.1 Advantages

1. This process will be eventually run on a Raspberry Pi. So very less power will be consumed.
2. Manual segmentation will help a lot in improving the accuracies of the trained models.
3. This method saves a lot of time as there is no need for manual inspection of the meters.

5.2 Disadvantages

1. Full automation is not yet achieved. All the manual segmentation and thresholding have to be automated.
2. The accuracies of the trained models can be improved further.
3. Environment conditions like lighting, glare affect the quality of image captured by the camera.

5.3 Applications

In many industries, wherein real-time monitoring of various parameters of machineries is crucial.

1. It is not efficient to manually monitor all the systems frequently. So our system provides a solution for this problem by automating the monitoring process.
2. It is not financially viable to replace the existing analog meters with the highly expensive digital meters.
3. This system can be used in mobile towers which are located in remote parts of the world. This would reduce the time and manpower required for measuring various parameters in the mobile towers.
4. This can also be used in nuclear power plants where one cannot go near the reactor core as it is highly radioactive. So various parameters of the reactor core can be easily measured.

Hence, our proposed system automates the process of monitoring the parameters. It is also economically feasible.

5.4 Future advancements

1. Image segmentation has to be automated. This will make the whole system fully automated.
2. Also we have to improve the accuracy of digit recognition. If the system is to be deployed in real time environment, accuracy of digit recognition should be high.
3. IR camera can be used instead of the normal camera. It may reduce the noise in the captured image.
4. Instead of Raspberry Pi Model B, a more compact Raspberry Pi Zero can be used. This helps in building proper modules.
5. Auto focus camera can be used so that region of interest can be properly captured.

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