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Smart Mirror Controller

Final Project

by

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İZMİR

THESIS EVALUATION FORM

We certify that we have read this thesis and that in our opinion it is fully adequate, in scope and qualify as an undergraduate thesis, based on the result of the oral examination taken place on ____/____/____

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ABSTRACT



ÖZET



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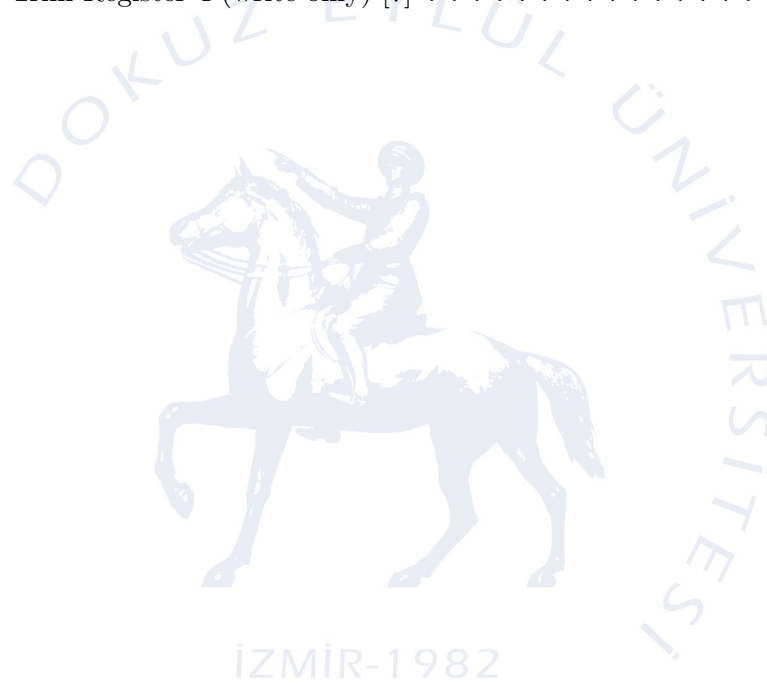
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1. INTRODUCTION



2. TECHNICAL BACKGROUND

2.1 Introduction to Artificial Neural Networks

2.2 Model Architecture for LE-NET5

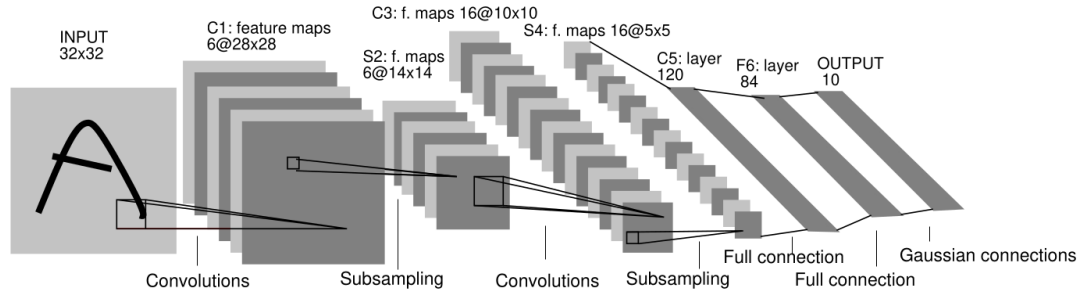


Figure 2.1: Architecture of LeNet-5, a Convolutional Neural Network, here for digits recognition. Each plane is a feature map, i.e. a set of units whose weights are constrained to be identical.

LeNet-5 A total of seven layers, each with no input with trainable parameters; each layer has multiple FeatureMap, which is a property of each of the FeatureMap inputs extracted via a convolution filter, and then each FeatureMap has multiple neurons.

C1 layer-convolutional layer:

The first convolution operation is performed on the input image (using 6 convolution kernels of size 5*5) to obtain 6 feature maps of C1 (6 feature maps of size 28 28, $32-5 + 1 = 28$). The size of the convolution kernel is 5, and there are 6 ($5 * 5 + 1$) = 156 parameters in total, where +1 indicates that a kernel has a bias. For convolution layer C1, each pixel in C1 is dependent on 5 of 5 pixels and 1 aberration in the input image, so there are $156 * 28 * 28 = 122304$ links in total. [5]

S2 layer-pooling layer (downsampling layer):

The pooling is done immediately after the first convolution. Pooling is done using 2 cores and S2, 14x14 ($28/2 = 14$) 6 feature maps are obtained. S2's pooling layer is a weighting coefficient plus an offset multiplied by the sum of the pixels in the 2*2 area in C1, and then the result is remapped. So each pooling core has two training parameters i.e. $2*6 = 12$ training parameters but there are $5*14*14*6 = 5880$ connections. [5]

C3 layer-convolutional layer:

After the first pooling, the second convolution, the output of the second convolution is C3, 16 pieces of 10x10 feature maps, and the size of the convolution kernel is 5. The first 6 feature maps of C3 (corresponding to column 6 of the first). red box) connects to 3 feature maps connected to S2 layer and next 6 feature maps are connected to S2 layer 4 feature maps are connected, next 3 feature maps are connected to 4 feature maps are unconnected in S2 layer and last one is linked to all feature maps in S2 layer. The convolution kernel size is still 5x5, so there are $6 (3*5*5 + 1) + 6 (4*5*5 + 1) + 3 (4*5*5 + 1) + 1 (6*5*5 + 1) = 1516$ parameters. The image size is 10 10 so there are 151600 connections. [5]

S4 layer-pooling layer (downsampling layer):

S4 is the pooling layer, the window size is still 2*2, a total of 16 feature maps and 16 10x10 maps of the C3 layer are pooled in units of 2x2 to get 16 5x5 feature maps. This layer has a total of 32 training parameters, $2*16, 5*5*5*16 = 2000$ connections. [5]

C5 layer-convolution layer:

The C5 layer is a convolution layer. Since the size of the 16 images of the S4 layer is 5x5, the size of the image formed after convolution is 1x1, which is the same as the size of the convolution kernel. This results in 120 convolution results. Each is linked to 16 maps from the previous level. So there are $(5*5*16 + 1) * 120 = 48120$ parameters and there are also 48120 connections. [5]

F6 layer-fully connected layer:

Layer 6 is a fully connected layer. The F6 layer has 84 nodes corresponding to a 7x12 bitmap, -1 means white, 1 means black, so the black and white of each symbol's bitmap corresponds to a code. The training parameters and number of connections for this layer is $(120 + 1) * 84 = 10164$. [5]

2.3 Python Libraries for Project

2.3.1 OpenCV

2.3.2 Python-Peripheral

2.3.3 Numpy

3. MATERIALS AND METHODS

3.1 Htpa32x32d Thermopile Infrared Array

The sensor chosen to be used in the project is HTPA32x32d thermopile array sensor. HTPA32x32d thermopile array sensor 32x32 pixel, operates between -10 and 70 degrees, provides I2C communication, has an internal EEPROM and provides an 8-bit data set. EEPROM data contains calibration data for each pixel of the sensor.

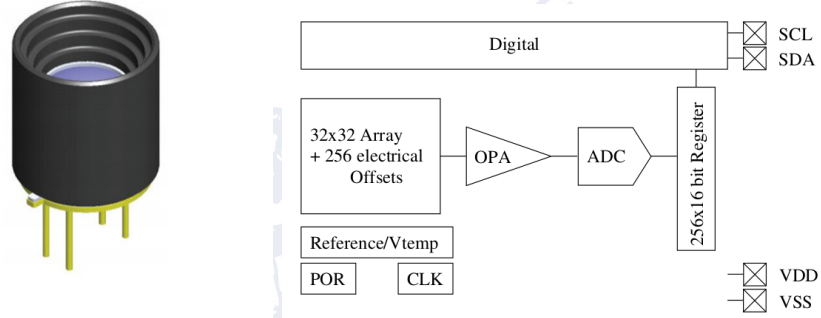


Figure 3.1: Schematic for HTPA32x32d

Table 3.1: Genaral Features HTPA32x32d

Features\{}	Sensitivity	Therm. Pix. Time Const.	Digital Interface	EEPROM Size
	450V/W	$< 4ms$	I2C	64kBit
Features\{}	Max Frame	Field of View	Selectable Clock	Storage Temperature
	60 Hz	33*33 deg	1 to 13 Mhz	-40/85 Deg.C

3.2 Sensor and MCU Communication PCB Design

A mini card has been designed between the sensor and the Raspberry pi card to communicate. However, the card could not be printed. The card that will connect the sensor and the motherboard has been designed completely according to the standards recommended by Heimann company.

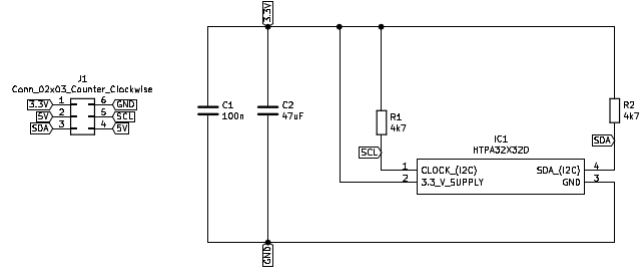


Figure 3.2: Schematic Design of Communication PCB

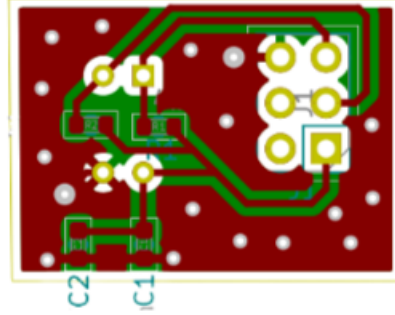


Figure 3.3: PCB Design of Communication PCB

In addition to this, we have produced a product suitable for a schematic on a mini perforated plate for use in communication with the card. In addition, we designed a protective cage from a 3d printer to protect the sensor.

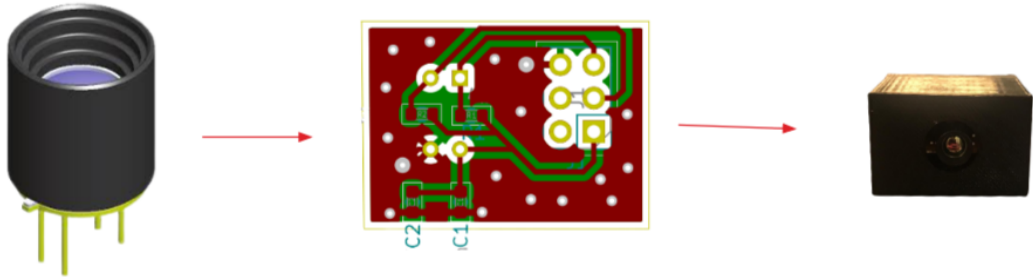


Figure 3.4: Mini Sensor Board

3.3 Dataset

3.3.1 Multi-Modal Hand Gesture Dataset for Hand Gesture Recognition

This dataset was created to validate a hand-gesture recognition system for Human-Machine Interaction (HMI). It is composed of 15 different hand-gestures (4 dynamic

and 11 static) that are split into 16 different hand-poses, acquired by the Leap Motion device. Hand-gestures were performed by 25 different subjects (8 women and 17 men). Every gesture has 20 instances (repetitions) per subject, performed in different locations in the image. [2]

for static and dynamic gestures:

This set contains 16 hand-poses, used for both static and dynamic hand-gestures:

A: L B: fist moved C: index D: ok E: C F: heavy G: hang H: two I: three J: four K: five
L: palm M: down N: palm moved O: palm up P: up

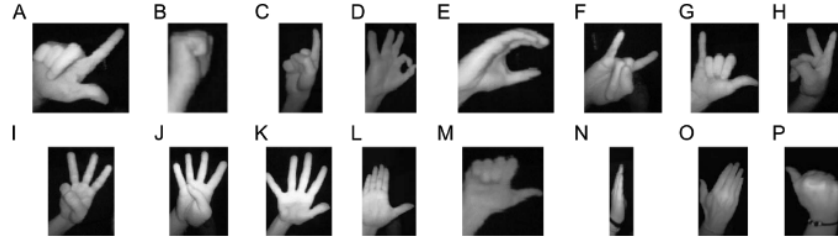


Figure 3.5: Hand Gesture Dataset

3.4 Data Augmentation

Using this dataset, a new train and test set was created for the static gestures in the project. A total of 8000 and 2000 train and test sets were created with randomly selected images. However, both resizing and data augmentation were done in order to make the data set suitable for the project. [6]

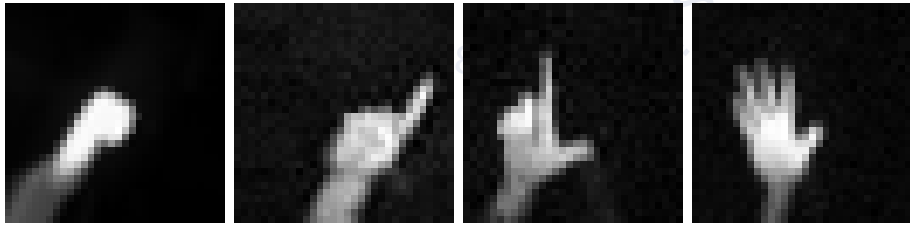


Figure 3.6: Close-Index-Last Page-Open Gestures

4. PROGRESS AND RESULT

In this section, the methods to be applied in the project are included.

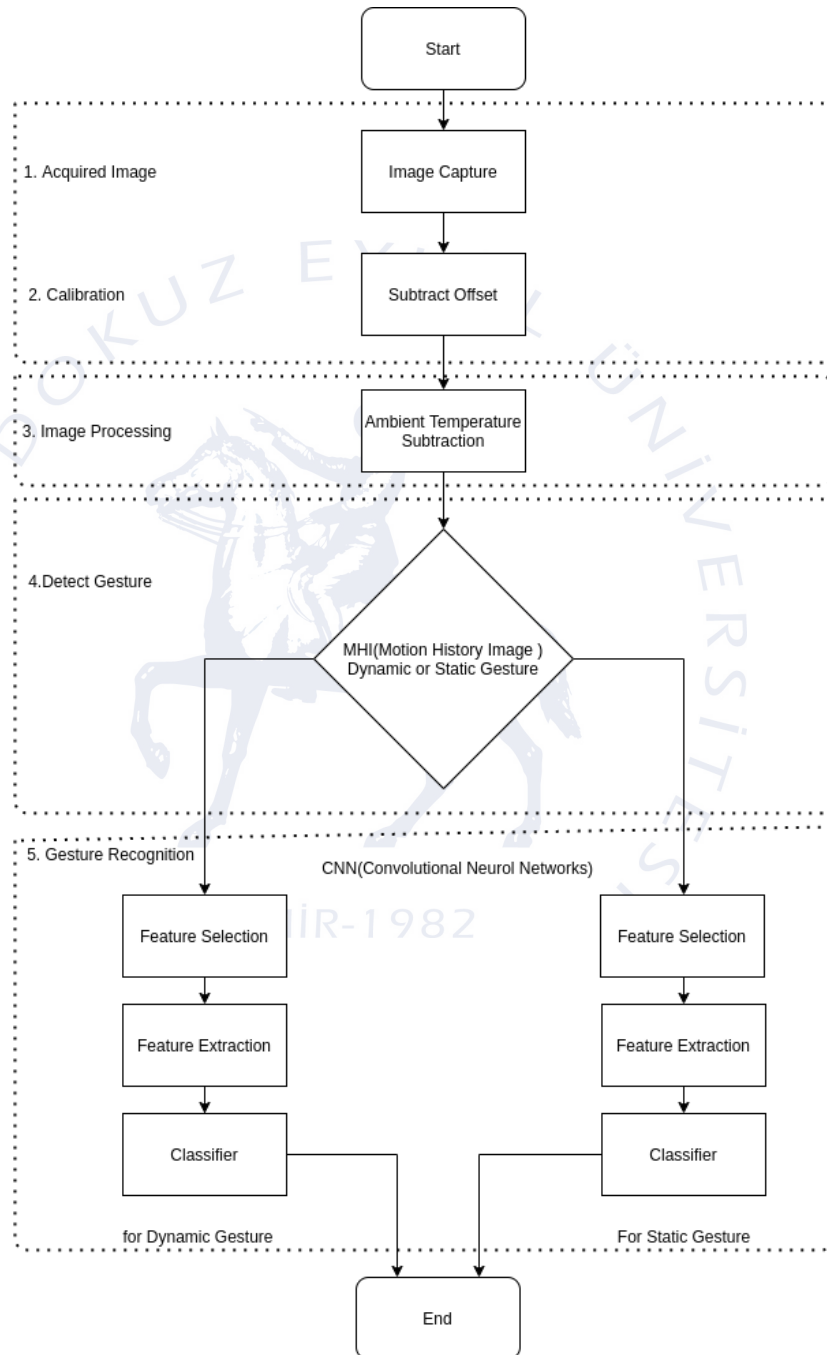


Figure 4.1: Software Flowchart

4.1 Capture Thermopiles Image

4.1.1 Heimann Thermopile Array Sensor communication

First, I provided the connections between the sensor and the Raspberry Pi in order to receive the image. I provided the communication with the mini card I made in 4.2 using the I2C protocol.

With the device connected to a Raspberry Pi, and with the Pi configured. [1] correctly for I2C, I was able to see the devices connected with the `i2cdetect` command.

```
pi@raspberrypi:~ $ i2cdetect -y 1
    0  1  2  3  4  5  6  7  8  9  a  b  c  d  e  f
00:  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --
10:  --  --  --  --  --  --  --  --  --  --  1a  --  --  --  --  --
20:  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --
30:  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --
40:  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --
50: 50  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --
60:  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --
70:  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --  --
```

Figure 4.2: Thermopile Infrared Array Device and EEPROM Addresses

In order to be able to read the data properly, the `python-periphery` [4] library was used. The sensor is divided into two parts (Top and Bottom Half), which are also divided into 4 blocks. The reading order is shown below for different blocks. When a conversion is initiated, the X Block of the upper and lower half are measured simultaneously. Each block consists of 128 Pixels sampled entirely in parallel. The reading order in the lower half is mirrored compared to the upper half so the center lines are always read last.

Table 4.1: Read Data 1 Command (Top Half of Array)

Addr/CMD	0x1A (7 Bit!) / 0x0A							
Read Data	7	6	5	4	3	2	1	0
1. Byte / 2. Byte	PTAT 1 MSB / LSB or Vdd 1 MSB / LSB							
3. Byte / 4. Byte	Pixel (0+BLOCK*128) MSB / LSB							
5. Byte / 6. Byte	Pixel (1+BLOCK*128) MSB / LSB							
...								
257. Byte / 258. Byte	Pixel (127+BLOCK*128) MSB / LSB							

Table 4.2: Read Data 2 Command (Bottom Half of Array)

Addr/CMD	0x1A (7 Bit!) / 0x0B							
Read Data	7	6	5	4	3	2	1	0
1. Byte / 2. Byte	PTAT 2 MSB / LSB or Vdd 2 MSB / LSB							
3. Byte / 4. Byte	Pixel (992-BLOCK*128) MSB / LSB							
5. Byte / 6. Byte	Pixel (993-BLOCK*128) MSB / LSB							
...								
65. Byte / 66. Byte	Pixel (1023-BLOCK*128) MSB / LSB							
65. Byte / 66. Byte	Pixel (1023-BLOCK*128) MSB / LSB							
67. Byte / 68. Byte	Pixel (960-BLOCK*128) MSB / LSB							
69. Byte / 70. Byte	Pixel (961-BLOCK*128) MSB / LSB							
...								
129. Byte / 130. Byte	Pixel (991-BLOCK*128) MSB / LSB							
131. Byte / 132. Byte	Pixel (928-BLOCK*128) MSB / LSB							
...								
257. Byte / 258. Bytes	Pixel (927-BLOCK*128) MSB / LSB							

Each block is checked before it is read. The python-opencv [3] library was used to visualize the obtained result.

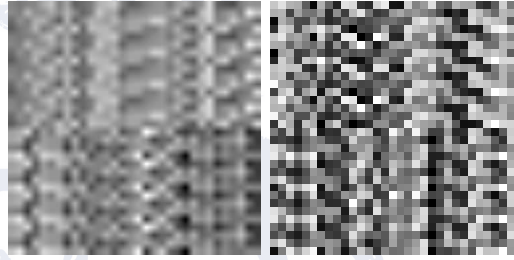


Figure 4.3: Thermal Image

Each pixel (or each analog-to-digital converter, given the repeating structure corresponding to each "block" of the sensor) has its own offset and sensitivity to incident light. Without calibrating it, this constant "noise" suppresses the signal from changing IR/temperature conditions. By subtracting the two frames in quick succession, this common noise signal is removed.

However, it is still quite noisy, as this frame subtraction increases random noise (since we now have contributions from two frames) and does not correct pixel-dependent sensitivity. Only fabrication calibration will be done with EEPROM data in the next step.

4.1.2 Calibrating images from Heimann Thermopile Array Sensor

After reading an image off a Heimann thermopile array, the pixel values can be converted to temperature readings through the use of calibration parameters stored on the device. To extract the calibration parameters, it is easiest to first read off the entire EEPROM on the thermopile array.

0x00	0x01	0x02	0x03	0x04	0x05	0x06	0x07	0x08	0x09	0x0A	0x0B	0x0C	0x0D	0x0E	0x0F
PixGain (float)		PixGain (float)				gradScale				TN as 16 bit unsigned		epsilon			
0x0000									MBIT(calib)		BIAS(calib)	CLK(calib)	BPA(calib)	PU(calib)	
0x0010							VDDTH1		VDDTH2						
0x0020	Arraytype								PTAT-gradient (float)		PTAT-offset (float)		PTAT (Th1)		PTAT (Th2)
0x0030													VddScGrad		VddScOff
0x0040															
0x0050					GlobalOff		GlobalGain								
0x0060	MBIT(user)	BIAS(user)	CLK(user)	BPA(user)	PU(user)										
0x0070					DeviceID									NrOfDefPix	
0x0080	DeadPixAdr as 16 bit unsigned values														
0x0090															
0x00A0															
0x00B0	DeadPixMask														
0x00C0	DeadPixMask								free to use						
0x00D0	free to use														
...															
0x0330															
0x0340	VddCompGrad _i stored as 16 bit signed values														
0x0530															
0x0540	VddCompOff _i stored as 16 bit signed values														
0x0730															
0x0740	ThGrad _i stored as 16 bit signed values														
0x0F30															
0x0F40	ThOffset _i stored as 16 bit signed values														
0x1730															
0x1740	P _i stored as 16 bit unsigned values														
...															
0x1F30															

Figure 4.4: EEPROM overview 32x32d [7]

Then, parameters and calibration values can be extracted from this array, as described in the Heimann datasheet. [7]

Calibration for only one pixel is done as follows.

$$PTAT_{av} = \frac{\sum_{i=0}^7 PTAT_i}{8} = 38152 Digits$$

$$PTAT_{gradient} = 0.0211 dK/Digit \text{ and } PTAT_{offset} = 2195.0 dK$$

$$V_{00} = 34435 Digits$$

$$elOffset[0] = 34240$$

$$gradScale = 24$$

$$ThGrad_{00} = 11137$$

$$ThOffset_{00} = 65506$$

$$VDD_{av} = 35000$$

$$VDD_{TH1} = 33942$$

$$VDD_{TH2} = 36942$$

$$PTAT_{TH1} = 30000$$

$$PTAT_{TH_2} = 42000$$

$$VddCompGrad[0] = 10356$$

$$VddCompOff[0] = 51390$$

$$VddScGrad = 16$$

$$VddScOff = 23$$

$$PixC_{00} = 1 \cdot 087 \cdot 10^8$$

$$PCSCALEVAL = 1 \cdot 10^8$$

Calculation of ambient temperature:

$$T_a = PTAT_{av} \cdot PTAT_{gradient} + PTAT_{offset} = 38152 \cdot 0.0211 + 2195.0dK = 3000dK$$

Compensation of thermal offset:

$$V_{00_Comp} = V_{00} - \frac{Th_{Grad00} \cdot T_a}{2^{gradScale}} - Th_{Offset00} = 34439$$

Compensation of electrical offset:

$$V_{00_Comp}^* = V_{00_Comp} - elOffset[0] = 199$$

Compensation of supply voltage:

$$V_{00-VDDComp} = V_{00_Comp}^* - \frac{\frac{VddCompGrad[0] \cdot PTAT_{av}}{2^{VddScGrad}} + V_{VddCompoff}[0]}{2^{VddScOff}} \cdot (VDD_{av} - VDD_{TH1} - (\frac{VDD_{TH2} - VDD_{TH1}}{PTAT_{TH2} - PTAT_{TH1}}) \cdot (PTAT_{av} - PTAT_{TH1})) = 199 - 1 = 198$$

The sensitivity coefficients (PixC ij) are calculated:

$$PixC_{00} = (\frac{P_{00} \cdot (PixC_{Max} - PixC_{Min})}{65535} + PixC_{Min}) \cdot \frac{epsilon}{100} \cdot \frac{GlobalGain}{100000} = 1 \cdot 087 \cdot 10^8$$

Leading to a compensation of the pixel voltage:

$$V_{00PixC} = \frac{V_{00-VDDComp} \cdot PCSCALEVAL}{PixC_0} = 182$$

All operations are applied for 1024 pixels. Application result images are as in figure 4.4.

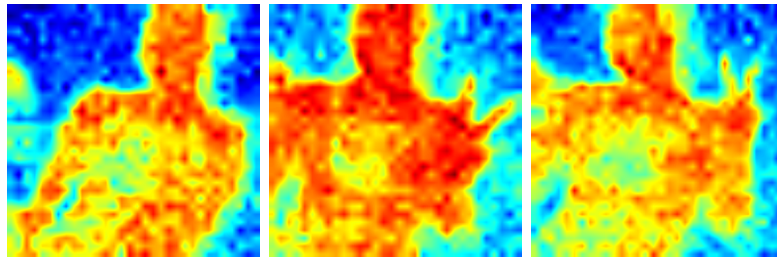


Figure 4.5: Thermal Images with EEPROM Calibration Data

NOTE:All steps to acquired the image are made with reference to the datasheet [7].

4.2 Hand Thermal Image Isolation

The hand was isolated from the background without using any image processing method. For this, it has been arranged in a way that can remove the ambient temperature of the device from the image before giving a command. First, the average of 10 images was taken and given to all images. Thus, the background temperature was isolated.

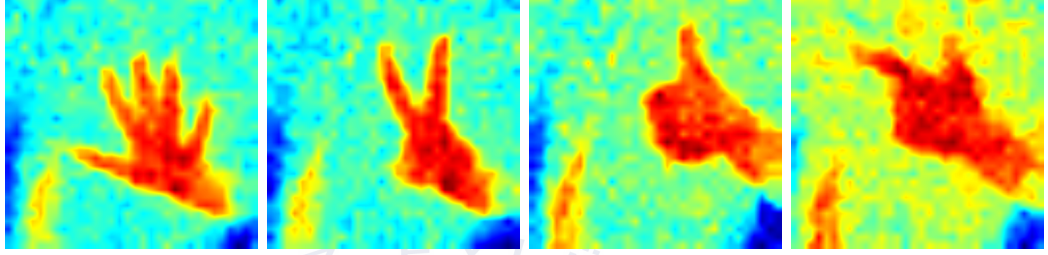


Figure 4.6: Thermal Images with Background

4.3 Hand Gesture Recognition

4.3.1 Static Gesture Recognition

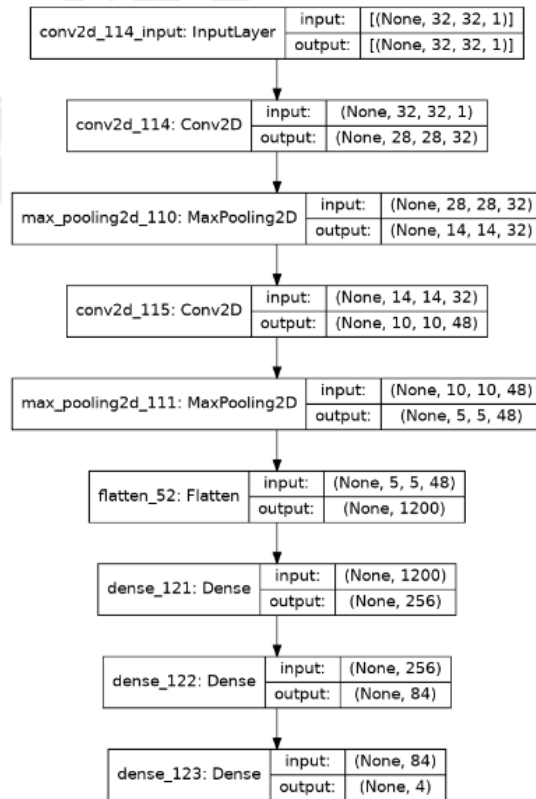


Figure 4.7: Software Flowchart

Model Architecture for LE-NET5

Test Sets and Results

4.3.2 Dynamic Gesture Recognition

Table 4.3: Trim Register 1 (write only) [7]

Addr / CMD	0x1A (7 Bit!) / 0x03							
Trim Reg 1	7	6	5	4	3	2	1	0
Name	RFU		REF_CAL		MBIT_TRIM			

REF_CAL: selectable amplification

MBIT_TRIM: $m = 4$ to 12 ($m+4$) bit as ADC resolution

In order to get the maximum efficiency from the sensor, to set the ADC Resolution to 16 bits, m of 12 was determined according to the data in the table. Since the framerate was too low, it was decided to speed up by sacrificing quality, but the quality was too low, revealing that ADC resolution should not be compromised. According to the resolutions, the images are as in figure 2.

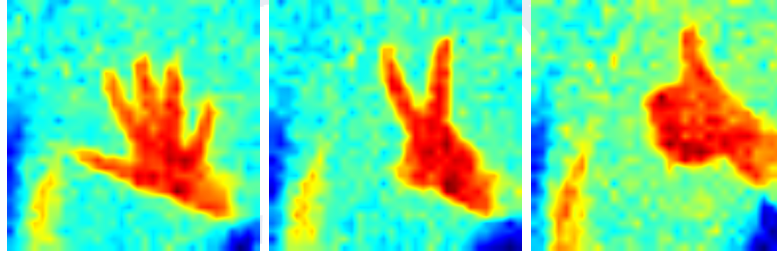


Figure 4.8: Thermal Images 8Bit-12Bit-16Bit ADC Resolution)

Table 4.4: Trim Register 2 (write only) [7]

Addr / CMD	0x1A (7 Bit!) / 0x04							
Trim Reg 1	7	6	5	4	3	2	1	0
Name	RFU			BIAS_TRIM_TOP				

BIAS_TRIM_TOP:0 to 31 $\rightarrow 1\mu A$ to $13\mu A$

Table 4.5: Trim Register 3 (write only) [7]

Addr / CMD	0x1A (7 Bit!) / 0x05							
Trim Reg 1	7	6	5	4	3	2	1	0
Name	RFU			BIAS TRIM BOT				

BIAS_TRIM_BOT: 0 to 31 $\rightarrow 1\mu A$ to $13\mu A$

This setting is used to adjust the bias current of the ADC. A faster clock frequency requires a higher bias current setting. [7]

Having ADC resolution 16 made us think that it did not affect us much. Afterward, it was said that if the BIAS current value is set to the maximum, its speed may increase. However, as a result of this experiment, almost no change was observed in the framerate.

Table 4.6: Trim Register 4 (write only) [7]

Addr / CMD	0x1A (7 Bit!) / 0x06							
Trim Reg 1	7	6	5	4	3	2	1	0
Name	RFU			CLK TRIM				

CLK_TRIM:0 to 63 $\rightarrow 1MHz$ to $13MHz$

The point where we could most easily observe the increase in Frame Rate was the Clock Trim set. Although I set the maximum value, I could not get the desired result here.

4.4 Matching Gesture to Commands of Smart Mirror

In the project carried out by Vestel, friends who are interested in the smart mirror part are expected to define the gestures for the android side of the smart mirror.

5. COST ANALYSIS



6. CONCLUSION



7. APPENDIX

7.0.1 Capture Image from Htpa32x32d Thermopile Array Sensor

htpa32x32d Library

```
from periphery import I2C
import time
import numpy as np
import copy
import struct

class HTPA:

    def __init__(self, address):
        self.address = address
        self.i2c = I2C("/dev/i2c-1")
        print("Grabbing EEPROM data")
        eeprom = self.get_eeprom()
        self.extract_eeprom_parameters(eeprom)
        self.eeprom = eeprom
        wakeup_and_blind = self.generate_command(0x01, 0x01)
            # wake up the device

        # ~ adc_res = self.generate_command(0x03, 0x0C) # set
        #     ADC resolution in eeprom
        # ~ pull_ups = self.generate_command(0x09, 0x88 ) #pu
        #     value in eeprom
        # set ADC resolution to 16 bits
        adc_res = self.generate_command(0x03, self.mbit_value
        )
        pull_ups = self.generate_command(0x09, self.pu_value)

        print("Initializing capture settings")

        self.send_command(wakeup_and_blind)
        self.send_command(adc_res)
        self.send_command(pull_ups)

        self.set_bias_current(self.bias_value) # bias value
            on eeprom
        self.set_clock_speed(0x050) # clk value on eeprom
            self.clk_value
        self.set_cm_current(self.bpa_value) # BPA value in
            eeprom

        # initialize offset to zero
        self.offset = np.zeros((32, 32))

    def get_eeprom(self, eeprom_address=0x50): #Talking EEPROM
        query = [I2C.Message([0x00, 0x00]), I2C.Message(
```

```

        [0x00]*8000, read=True))] # 8 Kbit Data from
        EEPROM
    self.i2c.transfer(eeprom_address, query)
    return np.array(query[1].data)

def extract_eeprom_parameters(self, eeprom): #EEPROM Data
    self.VddCompgrad = eeprom[0x0340:0x0540:2] + (eeprom
        [0x0341:0x0540:2] << 8)
    self.VddCompoff = eeprom[0x0540:0x0740:2] + (eeprom[0
        x0541:0x0740:2] << 8)

    ThGrad = eeprom[0x0740:0x0F40:2] + (eeprom[0x0741:0
        x0F40:2] << 8)
    ThGrad = [tg - 65536 if tg >= 32768 else tg for tg in
        ThGrad]
    ThGrad = np.reshape(ThGrad, (32, 32))
    ThGrad[16:, :] = np.flipud(ThGrad[16:, :])
    self.ThGrad = ThGrad

    ThOffset = eeprom[0x0F40:0x1740:2] + (eeprom[0x0F41:0
        x1740:2] << 8)
    ThOffset = np.reshape(ThOffset, (32, 32))
    ThOffset[16:, :] = np.flipud(ThOffset[16:, :])
    self.ThOffset = ThOffset

    P = eeprom[0x1740::2] + (eeprom[0x1741::2] << 8)
    P = np.reshape(P, (32, 32))
    P[16:, :] = np.flipud(P[16:, :])
    self.P = P

    epsilon = float(eeprom[0x000D])
    GlobalGain = eeprom[0x0055] + (eeprom[0x0056] << 8)
    Pmin = eeprom[0x0000:0x0004]
    Pmax = eeprom[0x0004:0x0008]
    Pmin = struct.unpack('f', reduce(
        lambda a, b: a+b, [chr(p) for p in Pmin]))[0]
    Pmax = struct.unpack('f', reduce(
        lambda a, b: a+b, [chr(p) for p in Pmax]))[0]
    self.PixC = (P * (Pmax - Pmin) / 65535. + Pmin) * \
        (epsilon / 100) * float(GlobalGain) /
        100
    self.gradScale = eeprom[0x0008]
    self.VddCalib1 = eeprom[0x0046] + (eeprom[0x0047] <<
        8)
    self.VddCalib = eeprom[0x0046] + (eeprom[0x0047] <<
        8)
    self.VddCalib2 = eeprom[0x0048] + (eeprom[0x0049] <<
        8)
    self.Vdd = 3000.0
    self.VddScaling = eeprom[0x004E]
    self.Vddoff = eeprom[0x004F]

    self.PtatCalib1 = eeprom[0x003C] + (eeprom[0x003D] <<
        8)
    self.PtatCalib2 = eeprom[0x003E] + (eeprom[0x003F] <<
        8)
    PTATgradient = eeprom[0x0034:0x0038]
    self.PTATgradient = struct.unpack('f', reduce(
        lambda a, b: a+b, [chr(p) for p in PTATgradient]))
        [0]

```

```

PTAToffset = eeprom[0x0038:0x003c]
self.PTAToffset = struct.unpack('f', reduce(
    lambda a, b: a+b, [chr(p) for p in PTAToffset]))
    [0]
self.clk_value = eeprom[0x001C]
self.bias_value = eeprom[0x001B]
self.pu_value = eeprom[0x001E]
self.mbit_value = eeprom[0x001A]
self.bpa_value = eeprom[0x001D]
self.subt = np.zeros((32, 32))

def set_clock_speed(self, clk):#set clock speed
    if clk > 63: # Max 64 Hz
        clk = 63
    if clk < 0:
        clk = 0
    clk = int(clk)
    print(clk)
    # The measure time depends on the clock frequency
    settings.(optimal value)
    clk_speed = self.generate_command(0x06, clk)
    self.send_command(clk_speed) # send clock data

# This setting is used to adjust the common mode voltage of
the preamplifier.

def set_cm_current(self, cm):
    cm = int(cm)
    cm_top = self.generate_command(0x07, cm)
    cm_bottom = self.generate_command(0x08, cm)

    self.send_command(cm_top)
    self.send_command(cm_bottom)

def set_bias_current(self, bias):
    bias = int(bias)
    # This setting is used to adjust the bias current of
    the ADC. A faster clock frequency requires a
    higher bias current setting.
    bias_top = self.generate_command(0x04, bias)
    # This setting is used to adjust the bias current of
    the ADC. A faster clock frequency requires a
    higher bias current setting.
    bias_bottom = self.generate_command(0x05, bias)
    self.send_command(bias_top) # send bias top data
    self.send_command(bias_bottom) # send bias bottom
    data

def temperature_compensation(self, im, ptat):#Thermal Offset
Calculate
    comp = np.zeros((32,32))
    Ta = np.mean(ptat) * self.PTATgradient + self.PTAToffset
    # temperature compensated voltage
    comp = ((self.ThGrad * Ta) / pow(2, self.gradScale)) +
    self.ThOffset
    Vcomp = np.reshape(im,(32, 32)) - comp
    return Vcomp

```

```

def offset_compensation(self, im):#general environment offset
    send offset data
    return im-self.offset

def sensitivity_compensation(self, im):#object temperature
    return (im*100000000)/self.PixC

def measure_observed_offset(self):#Measuring observed offsets
    mean_offset = np.zeros((32, 32))
    for i in range(10):
        print("    frame " + str(i))
        (p, pt) = self.capture_image()
        im = self.temperature_compensation(p, pt)
        mean_offset += (im-10)/10.0
    self.offset = mean_offset

def Vdd_Comperasition(self,im,ptat):#Vdd Comperasition
    calculate
    VVddComp=[]
    for i in range(16):
        for j in range(32):
            VVddComp.append((((self.VddCompgrad[(j+i*32)%128]*np.mean(ptat))/pow(2, self.VddScaling)+self.VddCompoff[(j+i*32)%128])/pow(2, self.Vddoff))*(self.Vdd-self.VddCalib1-((self.VddCalib2-self.VddCalib1)/(self.PtatCalib2-self.PtatCalib1))*(np.mean(ptat)-self.PtatCalib1)))
    for i in range(16,32):
        for j in range(32):
            VVddComp.append((((self.VddCompgrad[(j+i*32)%128+128]*np.mean(ptat))/pow(2, self.VddScaling)+self.VddCompoff[(j+i*32)%128+128])/pow(2, self.Vddoff))*(self.Vdd-self.VddCalib1-((self.VddCalib2-self.VddCalib1)/(self.PtatCalib2-self.PtatCalib1))*(np.mean(ptat)-self.PtatCalib1)))
    self.VVddComp=VVddComp
    return im-np.reshape(self.VVddComp,(32, 32))

def measure_electrical_offset(self, blind=True):#
    measure_electrical_offset
    pixel_values = np.zeros(256)
    ptats = np.zeros(8)

self.send_command(self.generate_expose_block_command(0, blind=blind), wait=False)

    query = [I2C.Message([0x02]), I2C.Message([0x00], read=True)]

    read_block = [I2C.Message([0x0A]), I2C.Message([0x00]*258, read=True)]
    self.i2c.transfer(self.address, read_block)
    top_data = np.array(copy.copy(read_block[1].data))

```

```

        read_block = [I2C.Message([0x0B]), I2C.Message([0x00
            ]*258, read=True)]
        self.i2c.transfer(self.address, read_block)
        bottom_data = np.array(copy.copy(read_block[1].data))

        top_data = top_data[1::2] + (top_data[0::2] << 8)
        bottom_data = bottom_data[1::2] + (bottom_data[0::2]
            << 8)
        # bottom data is in a weird shape
        pixel_values[0:128] = top_data[1:]
        # bottom data is in a weird shape
        pixel_values[224:256] = bottom_data[1:33]
        pixel_values[192:224] = bottom_data[33:65]
        pixel_values[160:192] = bottom_data[65:97]
        pixel_values[128:160] = bottom_data[97:]
        ptats[block] = top_data[0]
        ptats[7-block] = bottom_data[0]

    self.elloff=pixel_values;

    def electrical_offset(self,im):#electrical offset calculate
    V_new = np.zeros((32,32))
        for i in range(16):
            for j in range(32):
                V_new[i,j]=self.elloff[(j+i*32)%128]
        for i in range(16,32):
            for j in range(32):
                V_new[i,j]=self.elloff[(j+i*32)%128+128]
    self.V_new=V_new
        return im - self.V_new
    def capture_image(self, blind=False):
        pixel_values = np.zeros(1024)
        ptats = np.zeros(8)

        for block in range(4):
            print("Exposing block " + str(block))
            self.send_command(self.
                generate_expose_block_command(block, blind
                    =blind), wait=False)

            query = [I2C.Message([0x02]), I2C.Message([0
                x00], read=True)]
            expected = 1 + (block << 4)

            done = False

            while not done:
                self.i2c.transfer(self.address, query
                    )

                if not (query[1].data[0] == expected)
                    :
                    # print("Not ready, received
                        " + str(query[1].data[0])
                        + ", expected " + str(
                            expected))
                    #time.sleep(0.03)#Wait 30 ms
                else:
                    done = True

```

```

        read_block = [I2C.Message([0x0A]), I2C.
            Message([0x00]*258, read=True)]
        self.i2c.transfer(self.address, read_block)
        top_data = np.array(copy.copy(read_block[1].
            data))

        read_block = [I2C.Message([0x0B]), I2C.
            Message([0x00]*258, read=True)]
        self.i2c.transfer(self.address, read_block)
        bottom_data = np.array(copy.copy(read_block
            [1].data))

        top_data = top_data[1::2] + (top_data[0::2]
            << 8)
        bottom_data = bottom_data[1::2] + (
            bottom_data[0::2] << 8)

        pixel_values[(0+block*128):(128+block*128)] =
            top_data[1:]
        # bottom data is in a weird shape
        pixel_values[(992-block*128):(1024-block*128)
            ] = bottom_data[1:33]
        pixel_values[(960-block*128):(992-block*128)]
            = bottom_data[33:65]
        pixel_values[(928-block*128):(960-block*128)]
            = bottom_data[65:97]
        pixel_values[(896-block*128):(928-block*128)]
            = bottom_data[97:]

        ptats[block] = top_data[0]
        ptats[7-block] = bottom_data[0]

        pixel_values = np.reshape(pixel_values, (32, 32))

        return (pixel_values, ptats)

def generate_command(self, register, value): #periphery
    library register activate
    return [I2C.Message([register, value])]

def generate_expose_block_command(self, block, blind=False): #
    read data command
    if blind:
        return self.generate_command(0x01, 0x0B)
    else:
        return self.generate_command(0x01, 0x09 + (
            block << 4))

def send_command(self, cmd, wait=True): #send data to
    registers
    self.i2c.transfer(self.address, cmd)
    if wait:
        time.sleep(0.005) # sleep for 5 ms

def close(self): #closed device
    sleep = self.generate_command(0x01, 0x00)
    self.send_command(sleep)

```

Capture Image

```
import numpy as np
import cv2
from htpa import *
import pickle
i = 0
k = 0
dev = HTPA(0x1A)

while(True):
    if (i == 5):
        dev.measure_observed_offset()
        dev.measure_electrical_offset()

    (pixel_values, ptats) = dev.capture_image() # Capture Image
    im = dev.temperature_compensation(pixel_values, ptats) #
        thermal offset
    im = dev.offset_compensation(im) # general offset
    if(k>5):
        im=dev.electrical_offset(im)#electrical offset
    im=dev.Vdd_Comperasition()#Vdd Comperasition
    im = dev.sensitivity_compensation(im)#Sensitivity

    # resize and scale image to make it more viewable on
    raspberry pi screen
    im = cv2.resize(im, None, fx=12, fy=12)
    im -= np.min(im)
    im /= np.max(im)
    imcolor=cv2.applyColorMap(im,cv2.COLORMAP_JET)

    cv2.imshow('frame', im)
    cv2.imshow('frame1', imcolor)

    i += 1

    if cv2.waitKey(1) & 0xFF == ord('q'):
        break

dev.close()

cv2.destroyAllWindows()
```

7.0.2 Creating Dataset

Resize Dataset

```
import cv2
import os
from PIL import Image
import numpy as np

src='/open_train/five/'
filenames_train=os.listdir(src)

print(len(filenames_train))
for f_name in filenames_train:
    im=Image.open(src+f_name)
```

```

# Size of the image in pixels (size of original image)
# (This is not mandatory)
# width, height = im.size

# Setting the points for cropped image
# Setting the points for cropped image
left = 120
top = 45
right = 390
bottom = 240

# Cropped image of above dimension
# (It will not change original image)
#im1 = im.crop((left, top, right, bottom))
im1=im1.resize((32, 32))
im1.save('/open_train/five_new/'+f_name)

```

Dataset Augmentation

```

import cv2
import os
from PIL import Image
import numpy as np

# example of random rotation image augmentation
from numpy import expand_dims
from keras.preprocessing.image import load_img
from keras.preprocessing.image import img_to_array
from keras.preprocessing.image import ImageDataGenerator
from matplotlib import pyplot

# Passing the path of the image directory
src='/data2/closem/'
path1='/data2/close1/';
filenames_train=os.listdir(src)

print(len(filenames_train))
for f_name in filenames_train:
    im=Image.open(src+f_name)
    # convert to numpy array
    data = img_to_array(im)
    # expand dimension to one sample
    samples = expand_dims(data, 0)
    # create image data augmentation generator
    datagen = ImageDataGenerator(rotation_range=70)
    # prepare iterator
    it = datagen.flow(samples, batch_size=9, save_to_dir=path1,
        save_prefix='close_train1', save_format='png')

```

7.0.3 Static Gesture Learning Algorithm

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