EARLY DETECTION OF CHRONIC PODIATRIC DIABETIC FOOT ULCER

Submitted in partial fulfillment of the requirements for the
award of Bachelor of Technology degree in
biomedical engineering

by

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DEPARTMENT OF BIOMEDICAL ENGINEERING

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SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Marilyn Rija. W (38240014), Pavithra G.S (38240023)** who carried out the project entitled "**Early Detection of Chronic Podiatric Diabetic Foot Ulcer**" under our supervision from **September 2021 to March 2022**.

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DECLARATION

We **Marilyn Rija. W (38240014), Pavithra. G. S (38240023)** hereby declare that the Project Report entitled **"Early Detection of Chronic Podiatric Diabetic Foot Ulcer**" done by us under the guidance of Dr.**T. SUDHAKAR,** M.Sc., Ph. D., Department of Biomedical Engineering is submitted in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Biomedical Engineering.

DATE:23/04/2022

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ABSTRACT

Diabetes mellitus is a severe chronic disorder that affects millions of people worldwide. Patients with diabetes are more prone to foot ulceration. Early detection of diabetic foot ulcers (DFUs) is an effective strategy for preventing amputation in severe stages. The objective of this project is to measure the temperature in diabetic feet, which primarily contributes to identifying abnormal values that increase the risk for foot ulceration. Arduino mega board is used as the microcontroller, with ten temperature sensors LM35 to detect heat at different positions placed on a pair of insoles. A temperature difference greater than 2.2 ℃ is considered abnormal foot. Mobile applications were developed toview the monitored temperature data and stored in a text file for future studies, along with accurate machine language technique R-CNN (Region-Based Convolutional Neural Networks) was used to assess the wound infection stages. We collected a diabetic wound dataset of images in this proposed system and annotated them with wound depth and granulation tissue grades as labels for classification. We can detect and localize the type of foot ulcer, giving the patient the option for early detection of foot ulcers.

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LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
DM	Diabetic Mellitus
DFU	Diabetic foot ulcer
LCD	Liquid Crystal Display
CML	Conventional Machine Learning
LDA	Linear discriminant analysis
R-CNN	Region with convolutional neural networks
ROI	Regions of interest
K-NN	K-Nearest Neighbor
MATLAB	Matrix Laboratory
ATMEGA 2560	Arduino Mega 2560
VDD	Voltage Drain Drain
GND	Ground
VCC	Voltage common collector
TX	Transmitter
RX	Receiver
DC	Direct current
IC	Integrated circuit
I/O	Input / Output
IDE	Integrated Drive electronics
ICSP	In-circuit serial programming
PWM	Pulse width modulation
USB	Universal serial bus
SPP	Serial port protocol
PC	Personal computer
TXD	Transmitted serial data
RDX	Receiver data serially
SDK	Software development kit
RGB	Red Blue Green

CNN	Convolutional neural network
ORB	Oriented FAST and rotated BRIEF

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CHAPTER 1

INTRODUCTION

Diabetes Mellitus (DM) commonly known as Diabetes, is a lifelong condition resulting from hyperglycemia (high blood sugar levels), which leads to major life-threatening complications such, as kidney failure, blindness, and lower limb amputation which is often preceded by Diabetic Foot Ulcers (DFU). In the industrialized world, diabetic foot problems are the major cause of nontraumatic lower-extremity amputations. Diabetics have a 15 to 46 times higher risk of lower extremity amputation than individuals who do not have diabetes. Family physicians play an important role in ensuring that diabetic patients receive prompt and appropriate treatment for skin ulcers. According to the global report on diabetes, in 2018, 422 million people are living with DM compared to 108 million people in 1980. In current clinical practices, the evaluation of Diabetes Foot Ulcer comprises various important tasks in early diagnosis, and several lengthy actions are taken in the treatment and management of Diabetes Foot Ulcer for each particular case, the medical history of the patient is evaluated. Appropriate diabetic foot care necessitates an understanding of the most frequent risk factors for limb loss. Several of these risk factors can be recognized by looking at certain features of the patient's medical history and performing a quick but detailed examination of the foot. In the diabetic foot, there are several risk factors for lower-extremity amputation. Peripheral neuropathy causes a decline of sensitive touch, Insufficiency of the arteries, foot deformities, and callus formation arise in high-pressure zones, Reduced sweating and dry, fissured skin are symptoms of autonomic neuropathy. The main cause of diabetic foot complications is due to Poor circulation weakening the skin, contributing to the formation of foot ulcers, and impairing wound healing. thus, resulting in temperature fluctuations. Inflammation leads to ulceration and infection. The majority of diabetic foot ulcers develop over bony prominences, particularly when bunions, calluses, or hammer-toe formations result in unusually prominent bony points. By monitoring the temperatures of different candidates with diabetes and comparing them with normal feet temperature. As inflammation is present in affected areas of the foot, temperature differences can be observed in the same location on the contralateral foot. As studies show the cut-off value is about a 2.2℃ difference between the same spot-on contralateral location on the plantar surface of the foot. the temperature value will be displayed in LCD and the android application is developed for viewing foot temperature data and stored in the text file for analysis. In addition, the ulcer evaluation is carried out with the help of image processing algorithms would be basedon the exact assessment of these visual signs as color descriptors and texture features. The visual appearance of Diabetes Foot Ulcer and its surrounding skin depends upon the various stages i.e., redness, callus formation, blisters, significant tissues types like granulation, bleeding, and scaly skin. The major challenges that are involved with this classification task are large time in collection and expert labeling of the Diabetes Foot Ulcer images high inter-class similarity between the normal (healthy skin) and abnormal. In this work, we have tested several Conventional Machine Learning (CML) methods and R-CNN algorithms for the classification of ulcers and non-ulcer. Then, we propose and design a novel fast R-CNN architecture.

CHAPTER 2

LITERATURE SURVEY

- Bill Cassidy*, et al.* (2021) This paper makes use of advanced system language technology which includes Faster R-CNN, wherein DFU datasets are used to categorize the foot images. foot images are collected from a health center and a number of the foot images are captured via 3 digital cameras with different pixels. The DFU datasets consist of 4,000 pictures, with 2,000 used for the training set and 2,000 used for the testing set. An extra two hundred images had been used for sanity checking; images that DFUC 2020 individuals could use to carry out preliminary experiments on their models earlier than the release of the testing set. The training set includes DFU pictures only, and the testing set is made out of images of DFU, different foot/skin situations, and images of healthy feet. The dataset is heterogeneous, with factors that include distance, angle, orientation, lighting, awareness, and the presence of background items all various among photographs. We recollect this detail of the dataset to be important, for the reason that future models will want to account for numerous environmental elements in a system being utilized in non-clinical settings. Thus, the result shows the percentage of ulcers formed and the comparative performance of different neural networks from the proposed method.

- Zhengnan Yuan, *et al*. (2018) In this paper, a brand-new smart health embedded device that could notify patients of the status of an open wound to guarantee accurate cicatrization in actual time for ulcer foot in diabetes prevention has been designed. Specifically, this system monitors the recovery system via the saturation of exudate in the absorbent dressing and the pathogen of contamination by estimating the top gas of the wound primarily based totally on the numerous bacteria's metabolites. The accumulated data has been transmitted on transportable gadgets in real-time to tell the affected person the current situation of the wound and provide advice. Finally, the algorithm of the diabetes wound recovery system is explored in this work, which also can be carried out for associated clinical studies in diabetes prevention. The measurement outcomes have a mistake of 0.9% and 2.3%, respectively for temperature and humidity in the detection of cicatrization. In the assessment of pathogen of wound contamination, the mistake of predicting the attention of various gases turned into the most effective 2.8%.

- Anqi Mao, *et al.* (2019) This work describes a wearable device that detects pressure and heat in a compressive orthotic and generates an alarm when the values exceed the standard margin of safety. Foot ulcers in diabetic people should be treated and prevented in this way. The microcontroller, Arduino Nano, is applied to control two force sensors FSR402 and four temperature sensors LM35DZ, that are used to locate pressure and heat at different spots inside the compressive orthotic. The temperature sensor has a 0.25°C precision. To communicate data to the computer, a pair of Bluetooth HC-06 are employed. The pressure and temperature difference thresholds are 3.38 N and 2.2 °C, respectively. At the user interface, an alarm and caution LED will be activated.

- Carvalho. A*, et al.* (2019) Infrared thermal (IRT) imaging has been used as a research method for early detection of DFU because an increase in skin temperature is a sign of inflammation and a decrease is a sign of poor vascularization. There are two types of DFU: neuro-ischemic and ischemic. A database with dynamic IRT plantar foot examination images of 39 active DFU patients was created, and the images were analyzed by measuring the mean temperature of regions of interest (ROI), which correspond to the most frequently documented locations of DFU. Statistics revealed that, with the exception of the ROI located at the medial forefoot, there was no considerable degree of differences between thermal asymmetry values and thermal recovering distinctions in all ROI. The ROIs in both feet were calculated, as well as the thermal value. Three included studies classified thermal images into regions of Interest (ROI) and ulcer areas. used an SVM classifier. used a 5-class k-nearest neighbor (k-NN) algorithm.

- Acharya U. R, *et al.* (2018) This paper summarizes that diabetes reduces blood circulation to the foot, the temperature in the plantar foot decreases. Thermography is a non-invasive imaging technique that uses an infrared (IR) camera to observe thermal patterns. It enables qualitative and visual documentation of temperature fluctuation in vascular tissues. However, manually diagnosing these temperature changes is difficult. Thus, a computer-assisted diagnosis (CAD) system may aid in accurately detecting diabetic feet to avoid traumatic outcomes such as ulcerations and lower extremity complications. Plantar foot thermograms are taken from 33 healthy people and 33 people with type 2 diabetes for this study. Discrete wavelet transforms (DWT) and higher-order spectral (HOS) techniques are used to decompose these foot images. The texture and entropy features of the image are extracted. the maximum accuracy of 89.39%, the sensitivity of 81.81%, and specificity of 96.97% using only five features.

- Achar. A, *et al.* (2017) This paper describes a novel method for demarcating and estimating ulcer boundaries using optical images captured with a hand-held digital camera. The proposed method employs a gray-based fuzzy similarity measure based on an image's spatial knowledge. The fuzzy measure is employed in the construction of the similarity matrix. By calculating the mean contrast for 26 different color channels from 14 different color spaces, the best color channel was determined. It was discovered that the Db color channel has the highest mean contrast and thus provides the best segmentation results when compared to other color channels. To effectively delineate the wound region, the fuzzy spectral clustering (FSC) method was applied to the Db color channel. Various morphological operations were used to effectively post-process the segmented wound regions. The proposed segmentation technique's performance was validated by ground-truth images labeled. 91.5% segmentation accuracy, 86.7%, performance evaluation shows the robustness of the proposed method of wound area segmentation.

- Adel Salh, *et al.* (2017), A thermal camera is connected to a Samsung smartphone, which is used to acquire thermal images, in the proposed system. This thermal imaging system has a simulated temperature gradient higher than 2.2 °C, which corresponds to the temperature difference that can indicate the development of ulcers (according to the literature). Basic image processing techniques are used to process and segment the acquired images. Two techniques are used in the analysis and interpretation: the Otsu thresholding technique and the Point-to-Point mean difference technique. Thermal images were analyzed and interpreted using the proposed system, which was implemented on the MATLAB Mobile platform. the system was successful in identifying the location of the increase in temperature.

- André Britto de Carvalho*, et al.* (2021) Machine learning-based solutions to this challenge have recently been offered. Deep learning techniques are being used to aid in the treatment of DFUs, specifically the diagnosis of ulcers. by taking photographs of the patient's feet, we propose a revision to the original Faster R-CNN algorithm. modifying parameter settings and applying data augmentation approaches We utilized a 2000-item training dataset. Specialists have annotated photographs of DFUs. The Monte Carlo cross-validation method was used to validate the training. technique. Our proposal had a comparable performance of 91.4 percent, an F1 score of 94.8 percent, and an average accuracy of 91.4 percent. The detector had a detection speed of 332ms, which was faster than standard detectors.

- Manu Goyal*, et al.* (2019) This paper summarizes the proposed model, we gathered a large collection of 1775 images to create a strong deep learning model. DFU images by tracing the region of interest in this data set's ground truths. Annotator software was used to record the results of DFU. Overall, faster R-CNN with the InceptionV2 model using five-fold cross-validation using two-tier transfer learning, a mean average was attained. For inferencing, a number with a precision of 91.8 percent and a speed of 48 ms, with a model size of 57.2 MB and a single image We tested the performance of the models to illustrate the resilience and feasibility of our technique for real-time prediction. Using a smartphone app and an NVIDIA Jetson TX2. This is an excellent article that shows how deep learning can be used in real-time. DFU localization can be improved even more using more data sets.

- Goyal.M and Hassanpour.S, (2020) The detection of DFU in the DFUC2020 challenge dataset, which contains 4,500 DFU images, is proposed in this work utilizing deep learning approaches, EfficientDet Architectures. To avoid inaccurate negative and positive predictions, we modified the EfficientDet architecture further. We used the Shades of Gray method to pre-process the dataset in order to increase the algorithms' performance. We employed data augmentation techniques effectively to discover the complex characteristics of DFUs of varied sizes and grades. Using a scoring cutoff and deleting overlapping bounding boxes, we improved the inference of the original efficientDet algorithm. Multiple results were submitted.

CHAPTER 3

AIM AND SCOPE

3.1 AIM

- The project aims to study the foot temperature of diabetic patients and to classify the ulcer stages using machine learning techniques.
- Thus, allowing the diabetic patient to review their foot conditions and avoid the future complication of foot amputations.

3.2 SCOPE

- The project involves the detection of ulcer stages and temperature calculation to study different diabetic patients. The diabetic foot ulcer can be detected by usingR-CNN Algorithms based on image processing techniques.
- The diabetic foot temperature data can be monitored by using LM35 sensors and an android application is developed to view the diabetic foot temperature data and stored it in thetext file for future analysis.
- The developed Smart applications for diabetic foot ulcers represent a cost-effective, remote, and convenient healthcare solution.
- The use of MATLAB provides flexible, two-way integration with many programming languages,including Python.
- Our proposed system combines both temperature calculation and image processing machine language techniques to predict foot ulcer formation and hopes to reduce the rate of foot amputations.

CHAPTER 4

MATERIALS AND METHODS

4.1 HARDWARE SYSTEM

The connections between the sensors and the microcontroller, as well as the transfer of collected data to an android application through Bluetooth, are depicted in Figure 4.1. It includes the core components of LCD, voltage regulator, input power supply, Arduino mega Board 2560, lm35 sensor 10, HC-O5 device. Input power supply connected to the regulator, for voltage regulating12v to 5v and then regulated voltage is given to Arduino mega board 2560.LCDdata pins are connected to Arduino mega board 2560 digital pins. VDD connected to 5V supply and GND pin will be connected to GND.HC-05 device has 4 pins, VCC pin is connected to 5v, GND pin is connected to ground, TX and RX pins are connected to controller RX and TX pins respectively. LM35 sensor connected to Arduino mega board 2560. It has three pins. 1 pin connected to positive and 3 pins connected to negative. Output 2 pin connectedto the controller of an analog pin. Same connections for the remaining 9 LM35 sensors. The sensors are then connected to the insoles. Each insole has five sensors at the contralateral foot (left and right foot).

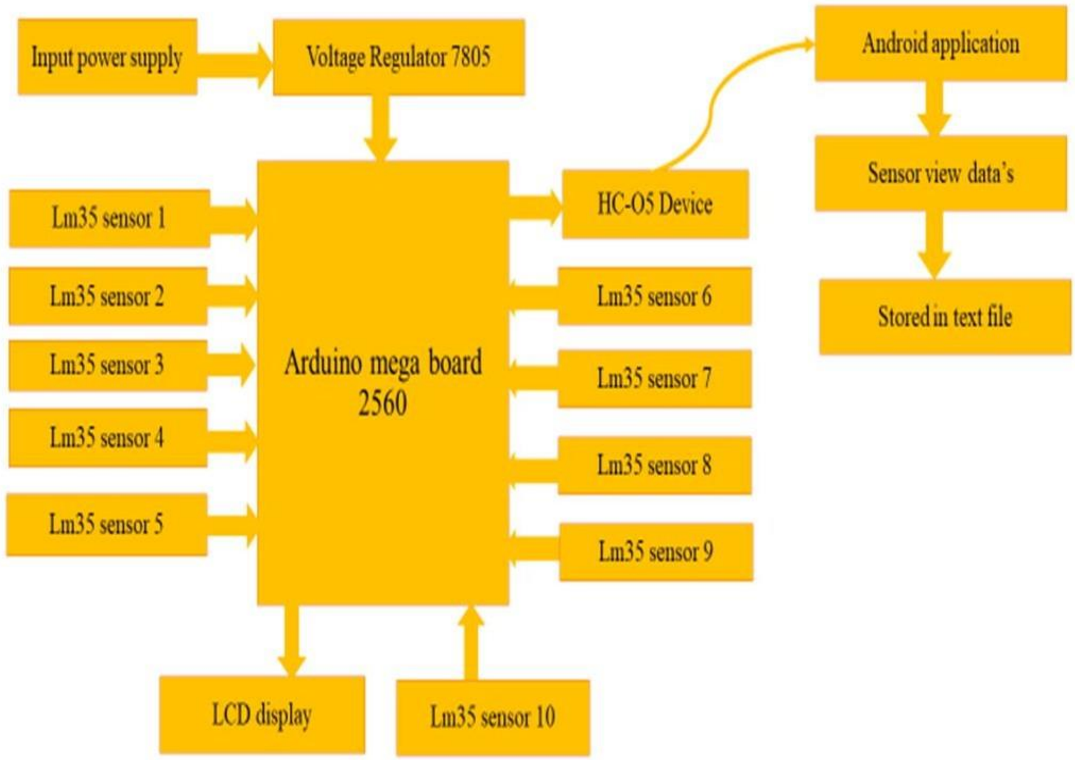

Fig:4.1 Hardware Block Diagram for the proposed system

4.2 HARDWARE COMPONENTS

4.2.1 POWER SUPPLY:

A power supply of a 12V DC device needs a 12V DC adapter. We use direct current because it allows a constant flow of current to a device.

4.2.2 VOLTAGE REGULATOR 7805:

An LM7805 Voltage Regulator that maintains the outputs at +5 volts. The voltage regulator IC maintains the output voltage at a constant value. There are Three-pin IC: Input Pin: The Input pin is the pin that accepts the incoming DC voltage, which the voltage regulator will eventually regulate down to 5 volts. Ground: The ground pin establishes the ground for the regulator. Output Pin: The Output pin is the regulated 5 volts DC.

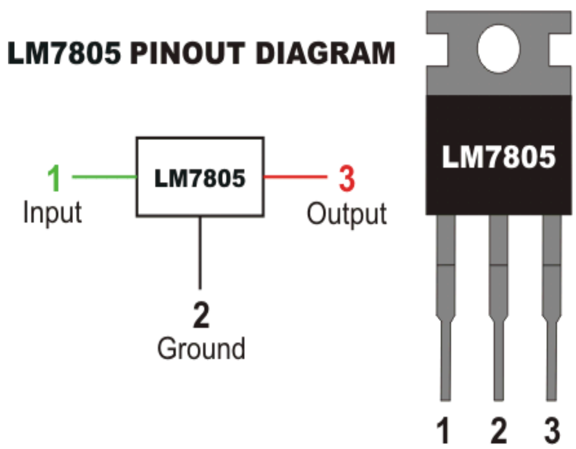

Fig:4.2 voltage regulator 7805

4.2.3 ARDUINO MEGA 2560:

Arduino Mega 2560 is a Microcontroller board primarily based totally on Atmega2560. It comes with a greater memory area and I/O pins compared to different boards. There are fifty-four digital I/O pins and sixteen analog pins included on the board. Arduino software program known as Arduino IDE is used to the software the board that's a common software program used all forums belonging to the Arduino family. Designing a task, the usage of Arduino Mega offers you the power of operating with a greater memory area and processing power that permits you to work with numerous sensors at once.

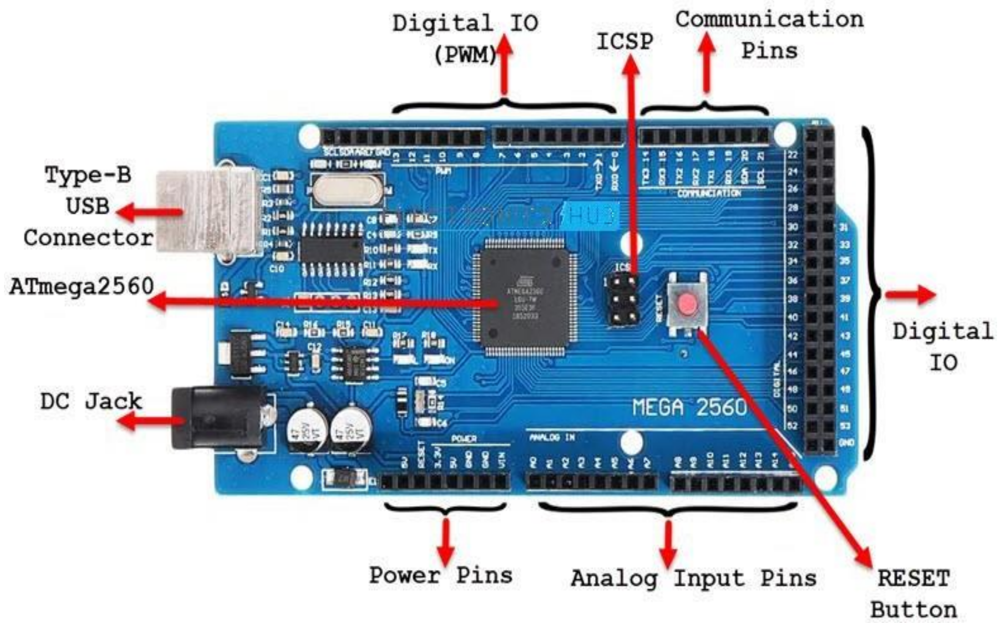

Fig:4.3 Arduino Mega Board 2560

4.2.4 LM 35 SENSORS:

The LM 35 is an analog temperature sensor that measures degrees Celsius. It can be used to measure temperature more precisely than a thermistor. We employed ten sensors on the contralateral foot to assess foot temperature in our experiment.

Features:

• Directly calibrated at Degrees Celsius (Centigrade)

• Guaranteed 0.5°C accuracy (at +25°C)

• Temperature range: 55°C to +150°C

• Suitable for use in distant locations

• Low cost since wafers are trimmed at the wafer level

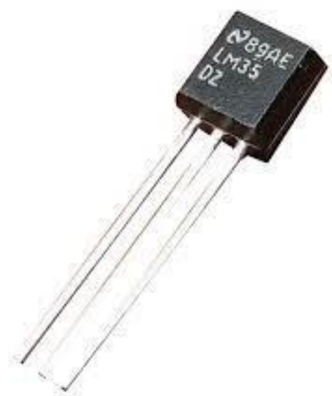

Fig:4.4 LM35 sensor

4.2.5 HC-05 device:

The HC-05 Bluetooth Module is a simple Bluetooth SPP (Serial Port Protocol) module that allows you to set up a transparent wireless serial connection. It communicates with the controller or PC via serial communication, which makes it simple to use. There are six pins on it.

1. Key/EN: If the Key/EN pin is set to high, then this module will work in commandmode. Otherwise, by default, it is in data mode.
2. HC-05 module has two modes,

   1. Data mode: Data transfer between devices.

   2. Command mode: To send these commands to the module serial (USART)port is used.

3**. VCC:** Connect 5 V or 3.3 V to this Pin.

4. **GND:** Ground pin of the module.

5. **TXD:** Transmit Serial data (wirelessly received data by Bluetooth module transmitted out serially on TXD pin)

6. **RDX:** Receive data serially (received data will be transmitted wirelessly by Bluetooth module).

7. **State:** It tells the module is connected or not.

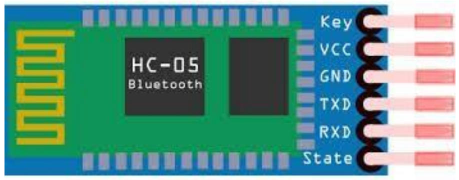

Fig:4.5 pin configuration

Fig: 4.6 HC-05 device

4.2.6 LCD DISPLAY:

Liquid Crystal Display is a term that refers to a display that is made up of liquid crystals. There are a total of 14 pins with numbers on them. The version described here is the most commonly used in practice because of its low charge and high-quality opportunities. It is entirely based on the HD44780 microcontroller (Hitachi). Each trace on the LCD display panel has sixteen characters. A 5x7 dot matrix is included with each character. The LCD is mechanically cleared once the power supply is turned on. This procedure lasts roughly 15 milliseconds. Following that, the display is ready to use.

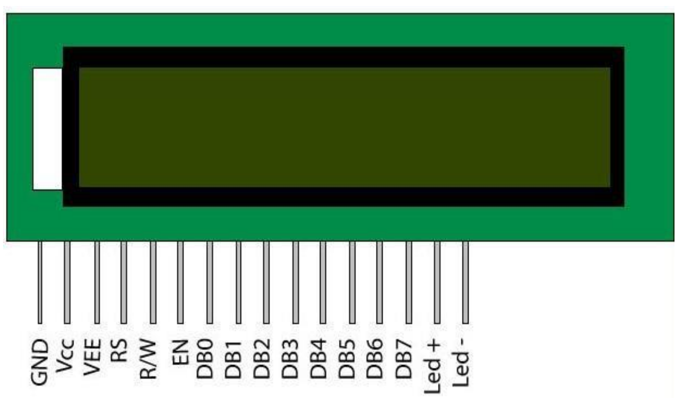

Fig:4.7 Pin Diagram of LCD Display

4.3 Pair HC-05 and smartphone:

1. Search for a new Bluetooth device from your phone. You will find a Bluetoothdevice with the “HC-05” name.
2. Click on connect/pair device option; the default pin for HC-05 is 1234 or 0000.

After pairing the two Bluetooth devices, open the terminal software on the PC and choose the port where the USB to the serial module is connected. Open the Bluetooth terminal application on your smartphone and connect to the associated device HC-05. It's simple to communicate; all we have to do is input it into the smartphone's Bluetooth terminal application. The characters will be transferred wirelessly to the HC-05 Bluetooth module. It will send it serially to the smartphone, which will display it on the terminal.

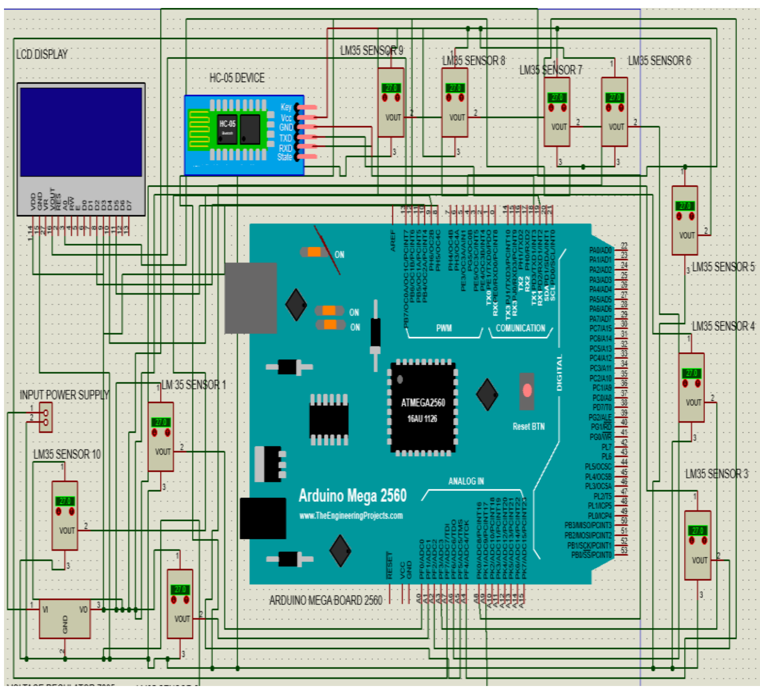

Fig 4.8 Circuit Diagram of The Hardware Model

The hardware system's circuit diagram is shown in Fig. 4.8. The wire connections between the microcontroller and the LM35 sensors, LCD, and Bluetooth device are described in detail.

4.4 ANDROID APPLICATION

Android application is advanced in an android-centered IDE referred to as Android studio. Android applications are advanced with the use of the Java language. Android Studio includes all of the Android SDK (software improvement kit) tools to design, test, debug and profile your app, it relies upon the IntelliJ Idea IDE (integrated development environment), which has proved itself to be an outstanding IDE and has been in use via way of means of many Androids users. A diabetic foot ulcer application is created to track foot temperature measurements, which are saved in a text file and accessed by the physician for future reference. Filling out the userID and password credentials is the initial step in any application. The device must then be paired with a smartphone through Bluetooth. The userID and password must be entered on the home page, as shown in Fig. 4.9. The temperature data are displayed on the data page, which is depicted in fig 4.10.

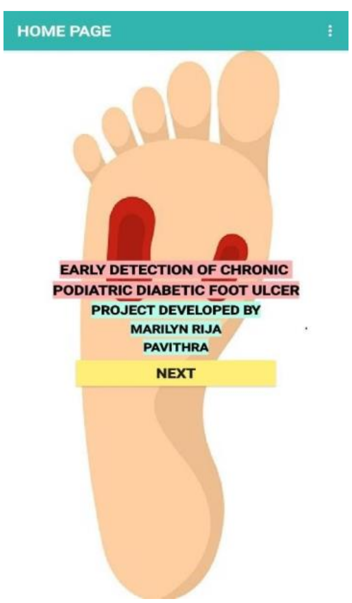

Fig: 4.9 Application Home Page

Fig:4.10 Application Data page

4.5 METHODOLOGY

An overall of 20 participants underwent the temperature measurement Amongst 20, n=4 had been non-diabetic. Their temperature values had been much like dermal temperature. Each area of contralateral feet becomes different by 2.2℃. The temperature of non-diabetic applicants was taken as standard temperature, and we compared it with the values of diabetic sufferers with preliminary foot complications with intermediate foot complications. There had been n=9 patients with preliminary foot complications or no complications had been measured and their mean foot temperature and standard deviation of left and right foot had been taken in comparison. The mean difference between the left and right foot was calculated. When the value of the mean difference is greater than 1.45, then it indicates abnormal temperature and predicts the future ulcer formation in the patients. The location of temperature sensors is depicted in figure 4.11. The areas were chosen based on the likelihood of ulcer formation in the majority of patients. Right/left toe, 1st metatarsal head, 4th metatarsal head, mid arch, and plantar foot of contralateral feet are the locations that are characterized.

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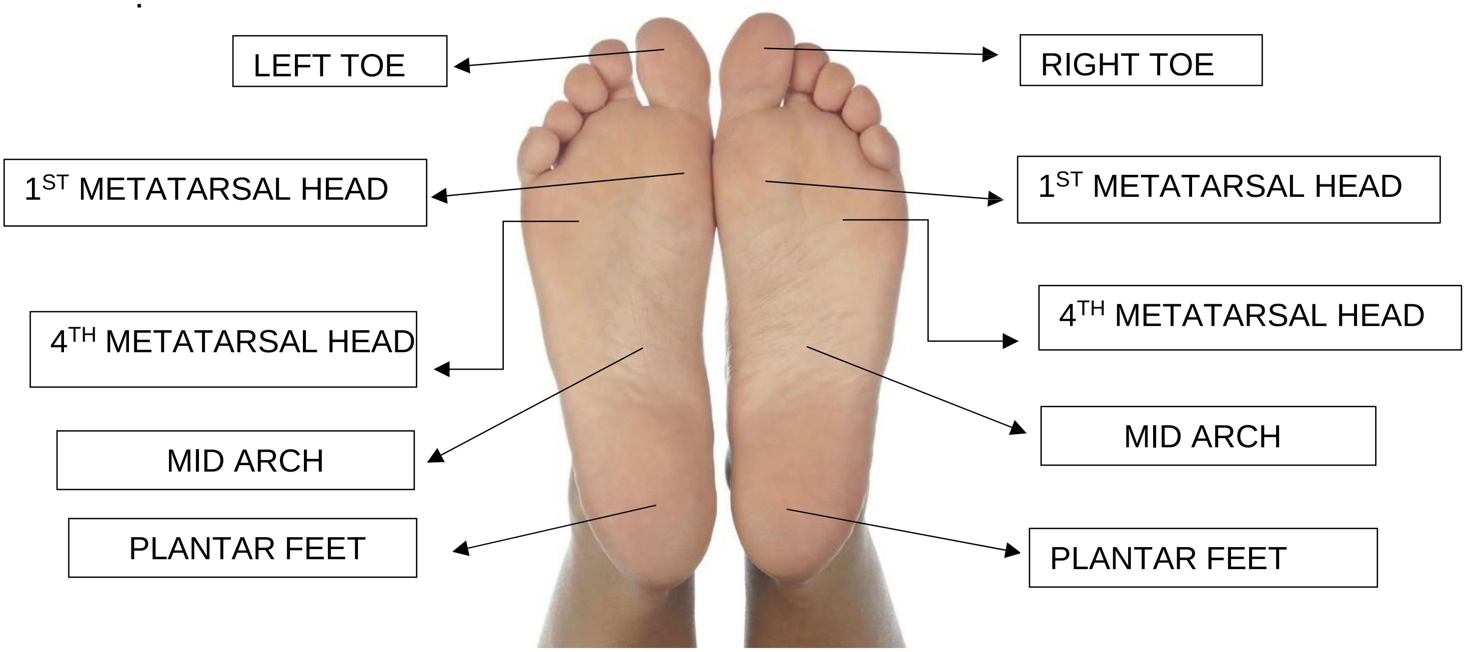


Fig:4.11 sensor placement

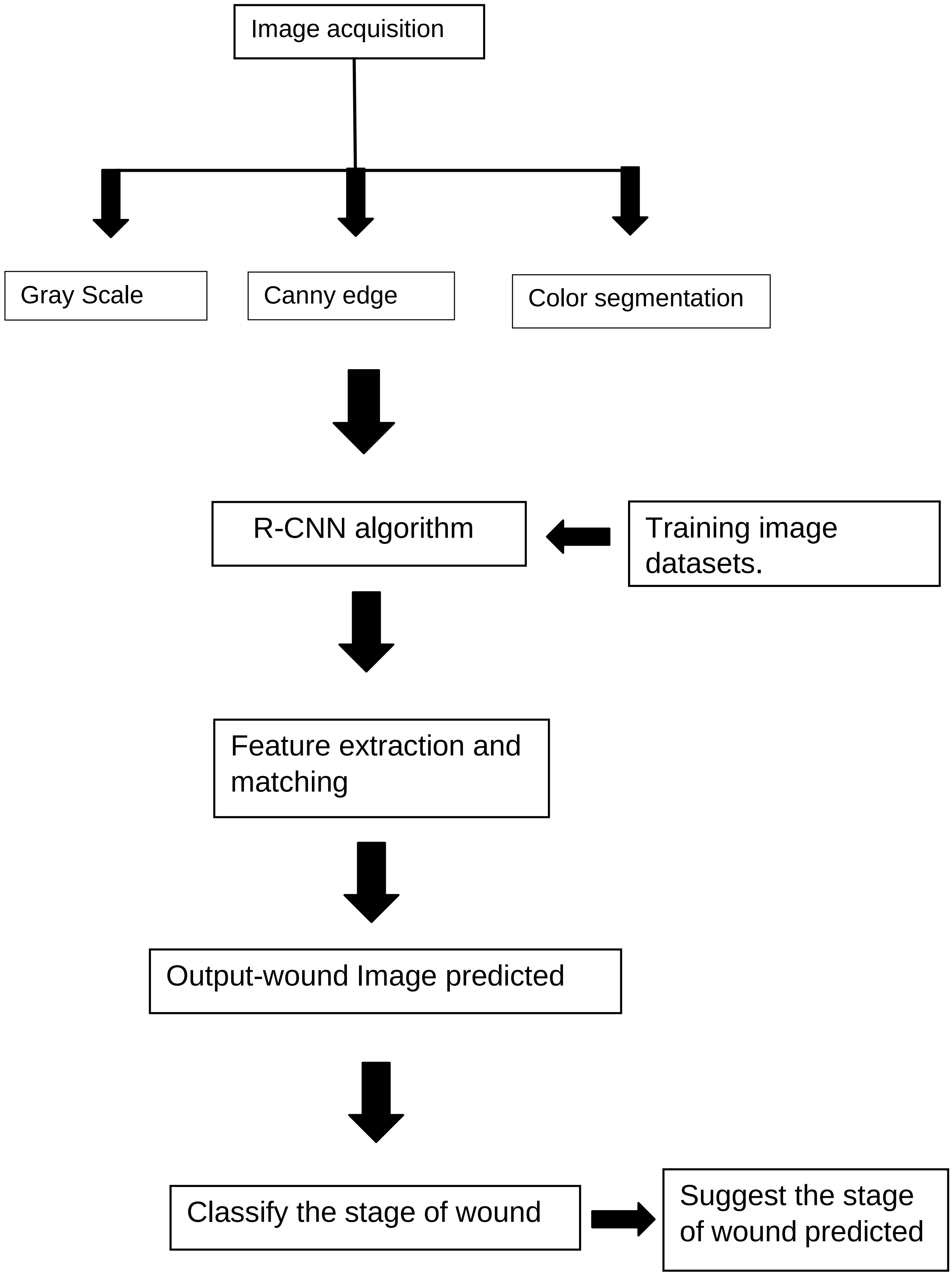
4.6 SOFTWARE SYSTEM

The image processing of the diabetic foot ulcer is carried out on MATLAB software by the use of python language. It is viable to write down Python in an Integrated Development Environment, which includes Thonny, PyCharm, NetBeans, or Eclipse which might be especially beneficial while handling large collections of Python files. In this project, Python can be written in Thonny Software. The block diagram, explains the algorithm of image processing. The image is fed from the open-source and is processed into three stages in MATLAB, they're grayscale, canny edge detection, and color segmentation. After, the processed image is compared with the R-CNN algorithm. The R-CNN algorithm identifies the area of interest and localizes the wound within the picture.

Steps in image processing

1. Image acquisition
2. Grayscale
3. Canny-edge detector
4. Color segmentation

4.6.1 SOFTWARE ALGORITHM



4.6.2 STEPS IN IMAGE PROCESSING

Image Acquisition:

In image processing, image acquisition is the action of retrieving the image from an external source for further processing. The unprocessed diabetic images are taken from the internet and some of the images are gathered from the diabetic center and are processed.

Grayscale:

A grayscale (or gray level) image is simply one in which the only colors areshades of gray, from white to black. In a binary image, a pixel can only take on either the value 0 or the value 255. In contrast, in a greyscale or color image, a pixel can take on any value between 0 and 255. The main reason why grayscale representations are often used for extracting descriptors instead of operating on color images directly is thatgrayscale simplifies the algorithm and reduces computational requirements. The raw images of a diabetic foot ulcer are converted to grayscale images, and the resultant matrix of the imread statement comprises 256×256 or 65,536 elements. The first statement takes the grey values of all the pixels in the grayscale image and put them into a matrix (256×256 elements), which is now a MATLAB variable on which various matrix operations may be performed.

Fig 4.12 GRAYSCALE

Canny Edge Detector:

Canny edge detection is a method to extract beneficial structural data from distinctive vision objects and dramatically reduce the quantity of information to be processed. It has been broadly carried out in diverse computer vision systems. It is used to locate the edges in a photograph. It accepts a grayscale image as input and makes use of a multi-level algorithm. Fig 4.13 shows the canny edge conversion using the grayscale image.

Steps accompanied in canny edge detection:

1. Noise Reduction - Removal of noise in input image using a Gaussian filter.
2. Gradient Calculation - Computing the by-product of the Gaussian filter to calculate the gradient of image pixels to achieve magnitude along x and y dimensions.
3. Non-Maximum Suppression - we use the Non-Maximum Suppression technique. neglect the one's edge points which don't make a contribution greater in the direction of characteristic visibility.
4. Hysteresis Thresholding - Lastly, use the Hysteresis Thresholding approach to maintain the pixels better than the gradient magnitude and neglect those lower than the low threshold value.

Fig 4.13 CANNY EDGE DETECTION

Color Segmentation:

Color segmentation is used to determine the wound region after the procedure of canny edge detection. To locate little things, count them, differentiate them by color, acquire an image and do image analysis. RGB color vectors are commonly used in color image processing to achieve segmentation results. Pixel values in RGB images now consist of a list of three values, indicating the red, green, and blue color components of the current pixel. Matrix 'G' is a three-dimensional matrix 256x256x3.To classify each RGB pixel in a given image as having a color in the specified range or not, it is necessary to have a measure of similarity. Here in our project, we have given values of RGB as for color1= (255,255,50), color2= (255,191,0), color3 = (255,51,51) compared with the skin tone of average (255,224,189). thus, the wound regions are differentiated with segment thresholding. Fig 4.14 shows the result of color segmentation of the foot image. The outcome of color segmentation of the foot picture is shown in Figure 4.14.

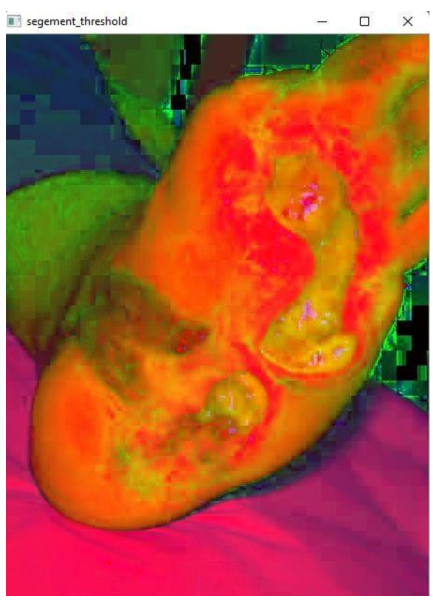


Fig 4.14 color segmentation

4.7 R-CNN ALGORITHM

The system makes use of Python programming language with Google's Tensorflow Machine Learning Library to construct and set up the CNN. Separate duties for object detection are categorization and localization. R-CNN is an abbreviation for region-based fully convolutional neural network The overall performance is analyzed based on real-world situations examined in the neural network. The datasets of about 100 pictures are collected and processed and the wound features are extracted and developed for matching. The network structure makes use of nine convolutional and max-pooling layers, accompanied by two fully connected layers. Four regions shape an object with varying scales, colors, textures, and enclosure. The selective search identifies those patterns in the image and based on that, proposes numerous areas.

4.7.1 Steps in R-CNN

- We first take a pre-trained convolutional neural network.
- Then, this model is retrained. We train the last layer of the network based onthe number of classes that need to be detected.
- The third step is to get the Region of Interest for each image. We then reshapeall these regions so that they can match the CNN input size.
- Finally, we train a linear regression model to generate tighter bounding boxesfor each identified object in the image.

4.7.2 FEATURE MATCHING

ORB (Oriented Fast BRIEF) is a fast, robust local feature detector that we use in our CNN architecture to extract wound image information. A fast key point detector is used in this method. The Brute-Force matcher is a feature matcher that uses some distance calculation to match the descriptor of one feature in the first set with all other features in the second set. And the one that is the closest is returned. To make the BF matcher, we must first construct the BFMatcher object with cv.BFMatcher (). It accepts two parameters that are optional. The first is known as the norm Type. It indicates the measurement of the distance to be used.

BFMatcher.match() and BFMatcher.knnMatch are two crucial methods to use once it's been constructed (). The best match is returned by the first. The second function produces k best matches, with k being a user-specified number. If k=2, two match lines will be drawn for each key point. If we wish to draw it selectively, we'll need to pass a mask.

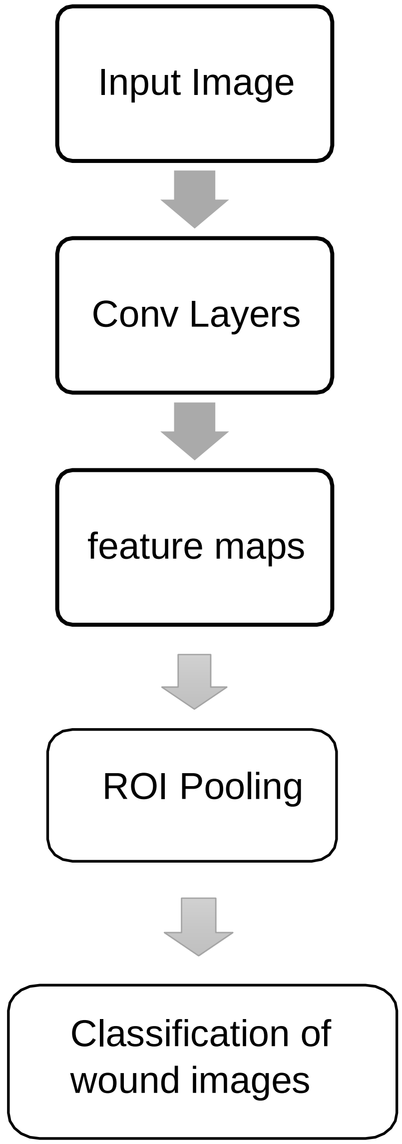
ORB Descriptors with Brute-Force Matching:

Brute-Force Matching with ORB Descriptors is used to feature match all of the datasets and train images. The features are matched using ORB descriptors, and the search for descriptors begins. After that, we make a BFMatcher object that measures distance. Then, with trained images, we utilize the Matcher.match() method to get the best matches. The matches = bf.match(des1,des2) line produces a list of DMatch objects.

4.7.3 Algorithm for Feature Detection and Matching

- Find a set of distinctive key points
- Define a region around each key point
- Extract and normalize the region content
- Compute a local descriptor from the normalized region

4.7.4 R-CNN ARCHITECTURE



The input image is gathered from a variety of open-source sources;100 images are obtained and preprocessed. There are nine convolutional layers and max-pooling layers in the R-CNN network structure. Following that, the wound picture features are retrieved in 3 stages. The feature maps are used to extract important structures or features from wound pictures. The datasets and trained images are then features matched using ORB Descriptors and Brute-Force Matching. A suggested neural network based on regions is effective at separating various items based on the region of interest. Different-sized images cover the region of interest. It has two fully connected layers with set sizes after ROI pooling. It combines the data from the preceding layer to produce a final output that categorizes the wound phases. The stages are, initial stage-1, stage 2 with dermis loss, and stage 3 with a severe loss with exposed tendons.

CHAPTER 5

RESULT

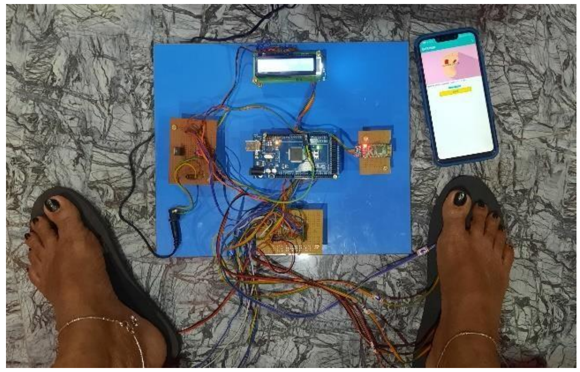


Fig: 5.1 Hardware prototype

The temperature is measured when the feet are positioned on the insoles where the temperature sensors are attached, as shown in Fig. 5.1. The values are displayed on an LCD and are also connected through Bluetooth, and the values are also presented on the application.

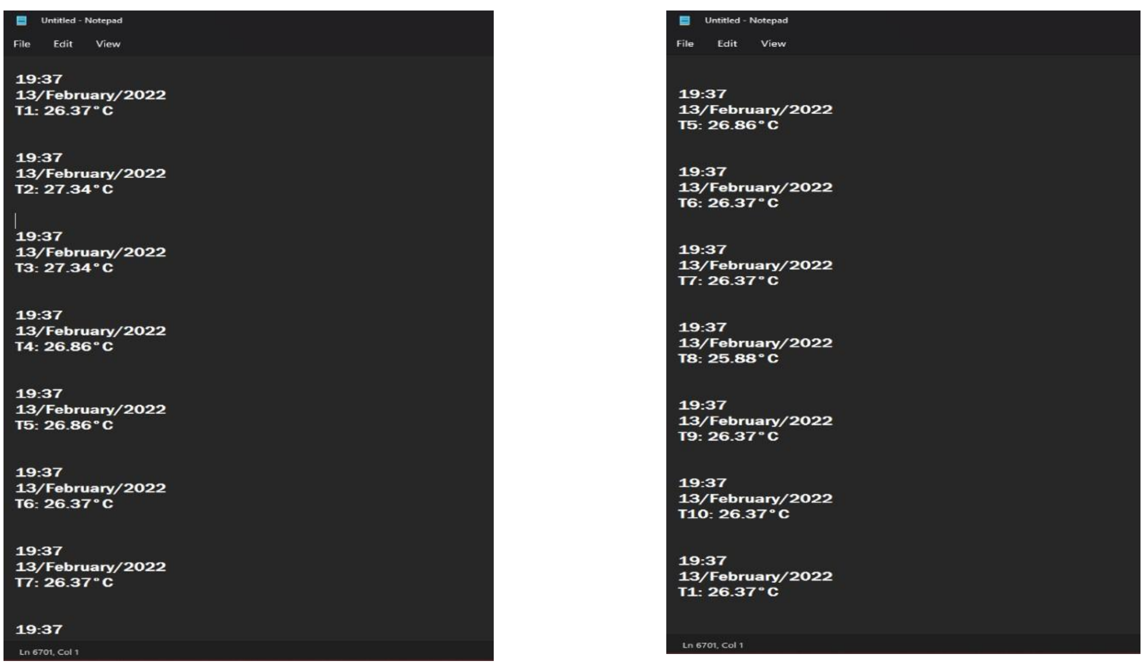


Fig 5.2: Temperature values stored as Txt file

The outcome of the temperature readings contained in the text file is shown in Fig 5.2. The document includes the values of ten sensors as well as the date and time. The physician can utilize this to investigate temperature fluctuations and keep track of them on a regular basis.

TABLE:5.1 CHARACTERISTICS OF THE PATIENT

	Group 1 Non-diabetic n=4	*Group 2 Diabetic complication initial n=9*	*Group 3 Diabetic Complication intermediate n=7*
Gender (male: Female)	2:2	4:5	2:5
Age (mean ± SD)	49 ±3.7	60 ± 6.7	58 ± 6.4
Temperature ℃ Left foot Mean ± SD Range	27.83 ± 1.5 25.5 - 31℃	32.81 ± 2.4 29.7 – 34.6℃	33.34 ± 2.4 29.7 – 34.6℃
Right foot *Mean ± SD Range*	28.32 ± 2.4 25.7 - 31℃	31.64 ± 2.1 29.5 – 33.0℃	30.83 ± 3.2 30.5 – 35.7℃
Mean difference	1.15	1.45	2.51
Area most affected	NA	1st metatarsal head 4th metatarsal head toe	Toe 4th metatarsal head Mid arch

NA- not applicable; mean difference >2.51 – abnormal

The assessment of temperature fluctuations among 20 members who are at an early stage with a complicated stage, as shown in table:5.1, is compared to the temperatures of normal members. As a result, the mean difference is larger than 1.45, indicating that the temperature is abnormal.

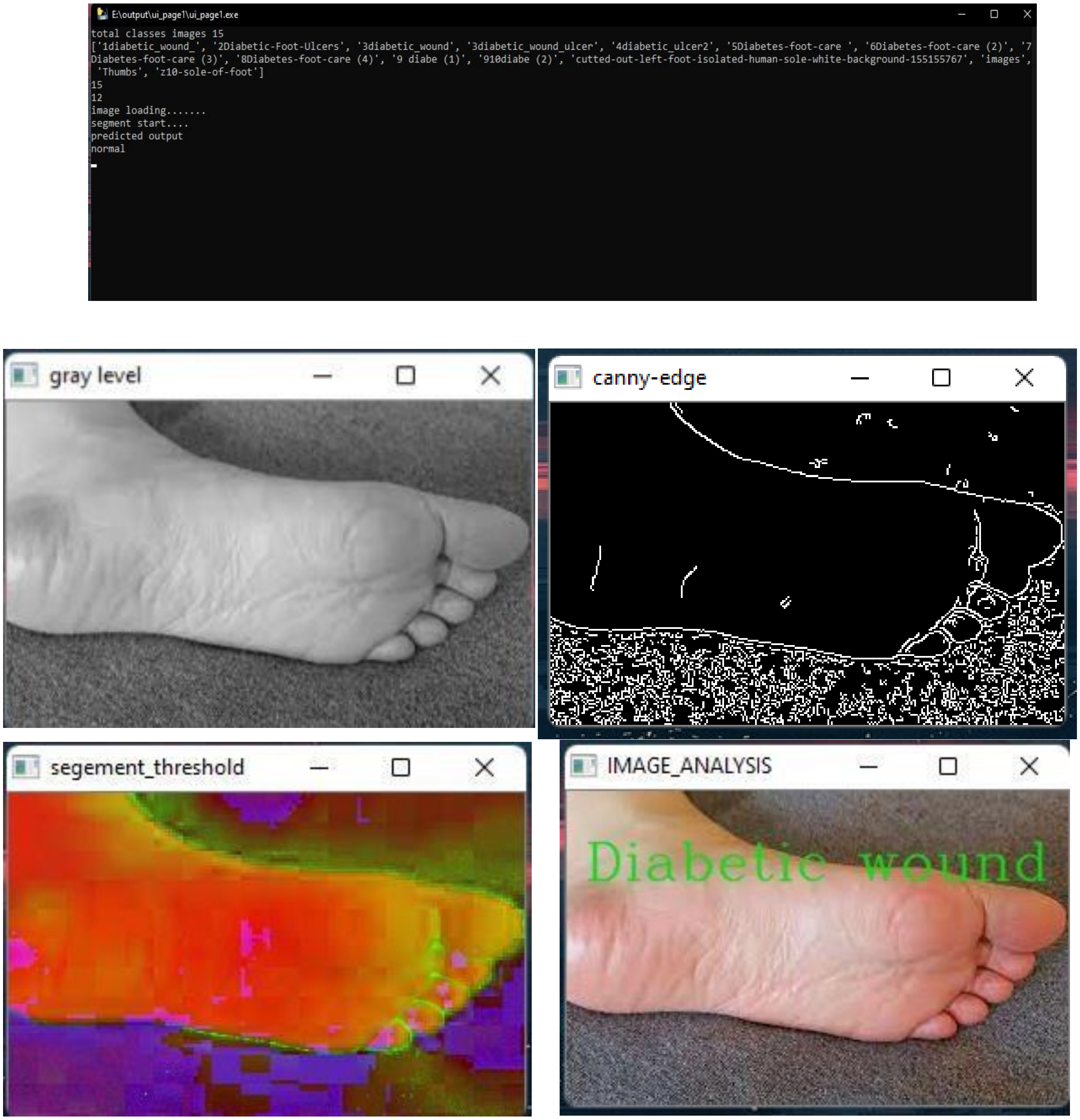


Fig 5.3: result of normal foot

Figure 5.3 depicts the outcome of a normal foot, in which the R-CNN architecture predicts the output of the foot picture and recommends a therapy.

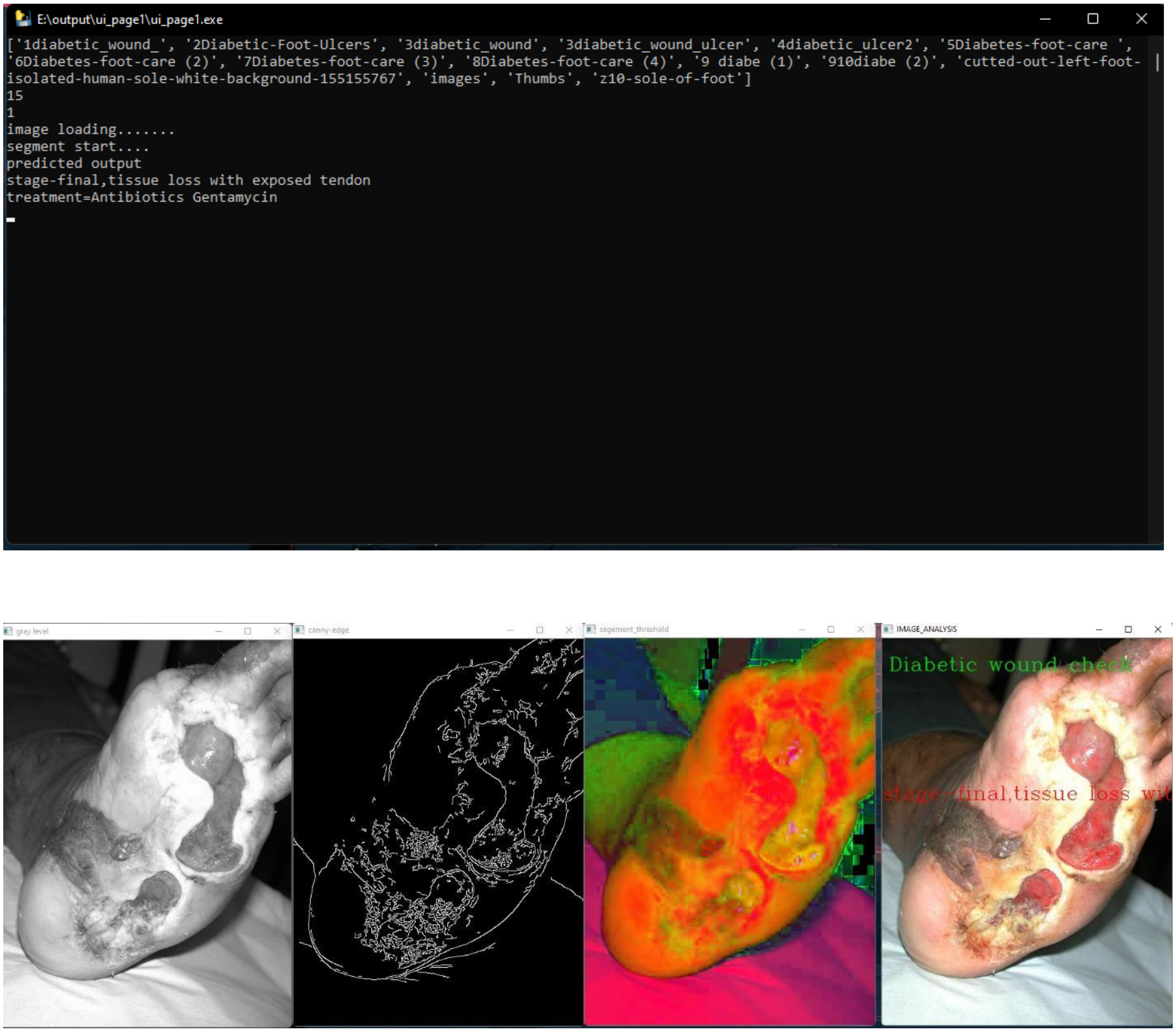


Fig 5.4: result shows the final stage of the wound

Figure 5.4 depicts the outcome of feet in the final stages of a foot ulcer and recommends therapeutic approaches. The anticipated output of a normal and abnormal foot is divided into three stages: preliminary, intermediate, and final. The algorithm's accuracy is 100 percent. Because the datasets are smaller, the prediction time is faster. It gives the model an edge in terms of being generally applicable for diagnosis.

CHAPTER 6
CONCLUSION

The proposed system offers the framework for foot ulcer tracking and predicting the stages of the wound. This system is an indicative tool, the very last prognosis is carried out by the physician. we developed an image processing method to train various algorithms which can be the R-CNN algorithm that can automatically discover and phase the diabetic foot ulcer and classify the stage of the wound. we made an observation on foot temperature in applicants with diabetes and non-diabetic participants with our developed hardware prototype, that's constructed with temperature sensors in specific places in the contralateral foot. thus, the proposed technique offers diabetic sufferers a chance to study their feet for possible ulcers.

CHAPTER 7
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