VISVESVARAYA TECHNOLOGICAL UNIVERSITY

Belagavi-590018

Project Report on

"MULTIPLE HUMAN EYE DISEASE DETCTION USING DEEP LEARNING"

Submitted in partial fulfillment as per VTU curriculum for 8th semester for the award of degree of

BACHELOR OF ENGINEERING

In

ELECTRONICS AND COMMUNICATION ENGINEERING

By

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EAST POINT COLLEGE OF ENGINEERING & TECHNOLOGY

Approved by All India Council for Technical Education (AICTE), New Delhi.
UG programs Accredited by the National Board of Accreditation (NBA): CSE, ECE & ISE
Affiliated to Visvesvaraya Technological University (VTU) Belagavi, Recognized by Govt. of Karnataka

Department of Electronics and Communication Engineering

2024-2025

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Department of Electronics & Communication Engineering

CERTIFICATE

This is to certify that the project titled **"MULTIPLE HUMAN EYE DISEASE DETECTION USING DEEP LEARNING"** is a bonafide work being carried out by **GANASHREE A P** bearing **USN: 1EP21EC027, KUSHAL R** bearing **USN: 1EP21EC050, PRIYANKA N** bearing **USN:1EP21EC070, SUPRIYA M V** bearing **USN:1EP21EC099** in partial fulfillment for the requirement of the award of degree of **Bachelor of Engineering in Electronics and Communication Engineering** of Visvesvaraya Technological University, Belagavi, during the academic year **2024-2025.** It is certified that all the corrections/suggestions indicated for internal assessment have been incorporated in this report. This report has been approved as it satisfies the academic requirements prescribed by the university.

Signature of the Guide	**Signature of the HOD**	**Signature of the Principal**
Dr. Rajesh L Associate Professor Dept of ECE, EPCET	Dr. Yogesh G S Vice Principal and HOD Dept of ECE, EPCET	Dr. Mrityunjaya V Latee Principal, EPCET

External viva:

Name of the Examiners: **Signature with date**

1.

2.

ACKNOWLEDGEMENT

Behind every achievement lies an unfathomable sea of gratitude to those who actuated it, without whom it would never have come to existence. To them our praise the word of gratitude imprinted not just on this paper but deep in our heart

We express our profound gratitude towards **Late Dr. S M Venkatpathi,** Founder Chairman**, East Point College of Engineering and Technology**, for providing necessary infrastructure and also honor to **Dr. Mrityunjaya V Latte, Principal, EPCET**, for creating good environment for carrying out our project.

We extend our earnest gratitude to **Dr. Yogesh G S, Vice Principal and HOD of ECE Dept.** for his motivation and constant support**.**

Our sincere thanks to our guide **Dr. Rajesh L, Assosiate Professor, Dept. of ECE, EPCET,** for her guidance and encouragement throughout the course of report preparation. Her timely assistance and valuable suggestions were the motivation factor for the completion of the project successfully.

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Last but not the least, we would like to utilize this opportunity to express a sense of gratitude and love to our beloved family and to my dearest friends for their support and strength.

DECLARATION

I, **GANASHREE A P** bearing USN: **1EP21EC027**, hereby declare that the project titled **"MULTIPLE HUMAN EYE DISEASE DETECTION USING DEEP LEARNING"** is carried out at **EAST POINT COLLEGE OF ENGINEERING AND TECHNOLOGY,** under the guidance of **Dr. Rajesh L,** Associate Professor, Department of ECE, East Point College of Engineering and Technology, Bangalore for partial fulfillment of the degree of Bachelor of Engineering in Electronics and Communication Engineering under Visvesvaraya Technological University, Belagavi.

Date:

Place: Bangalore

GANASHREE A P (1EP21EC027)

DECLARATION

I, **KUSHAL R** bearing USN: **1EP21EC050** hereby declare that the project titled **"MULTIPLE HUMAN EYE DISEASE DETECTION USING DEEP LEARNING"** is carried out at **EAST POINT COLLEGE OF ENGINEERING AND TECHNOLOGY**, under the guidance of **Dr. Rajesh L,** Assistant Professor, Department of ECE, East Point College of Engineering and Technology, Bangalore for partial fulfillment of the degree of Bachelor of Engineering in Electronics and Communication Engineering under Visvesvaraya Technological University, Belagavi.

Date:

Place: Bangalore

KUSHAL R (1EP21EC050)

DECLARATION

I, **PRIYANKA N** bearing USN: **1EP21EC070**, hereby declare that the project title **"MULTIPLE HUMAN EYE DISEASE DETECTION USING DEEP LEARNING"** is carried out at **EAST POINT COLLEGE OF ENGINEERING AND TECHNOLOGY**, under the guidance of **Dr. Rajesh L,** Associate Professor, Department of ECE, East Point College of Engineering and Technology, Bangalore for partial fulfillment of the degree of Bachelor of Engineering in Electronics and Communication Engineering under Visvesvaraya Technological University, Belagavi.

Date:

Place: Bangalore

PRIYANKA N (1EP21EC070)

DECLARATION

I, **SUPRIYA M V** bearing USN: **1EP21EC099,** hereby declare that the project titled **"MULTIPLE HUMAN EYE DISEASE DETECTION USING DEEP LEARNING"** is carried out at **EAST POINT COLLEGE OF ENGINEERING AND TECHNOLOGY**, under the guidance of **Dr. Rajesh L ,** Associate Professor, Department of ECE, East Point College of Engineering and Technology, Bangalore for partial fulfillment of the degree of Bachelor of Engineering in Electronics and Communication Engineering under Visvesvaraya Technological University, Belagavi.

Date:
Place: Bangalore

SUPRIYA M V (1EP21EC099)

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ABSTRACT

The detection of multiple human eye diseases through automated means has become a critical area of research in medical image analysis. Deep learning, particularly convolutional neural networks (CNNs), offers a powerful theoretical framework for feature extraction and pattern recognition in complex visual data such as retinal images. This project explores the theoretical foundations of applying deep learning to the classification and diagnosis of various eye diseases, including diabetic retinopathy, glaucoma, cataracts, and macular degeneration.

This report discusses the architecture of deep neural networks, the process of training with annotated medical image datasets, and the challenges related to class imbalance, overfitting, and interpretability. It also considers the potential for multi-label classification, where a single image may exhibit signs of more than one disease. By analyzing the theoretical efficacy and limitations of deep learning approaches, this work aims to provide a foundation for developing robust, generalizable models for automated eye disease screening in diverse clinical settings.

The human eye is a complex organ prone to various diseases such as diabetic retinopathy, glaucoma, age related macular degeneration, and cataracts, which can lead to partial or complete vision loss if not diagnosed early. Traditional diagnostic techniques often rely on manual analysis by ophthalmologists, which is time-consuming, subjective, and prone to variability.

Recent advancements in deep learning have shown significant promise in automating the detection of multiple eye diseases, offering high accuracy and efficiency. This report explores a deep learning-based multi-class classification framework that utilizes convolutional neural networks (CNNs) to detect and differentiate between several common eye conditions using retinal fundus images. By leveraging pre-trained models such as ResNet, InceptionV3, and DenseNet, the system extracts hierarchical features that capture subtle pathological changes in retinal images. Techniques such as transfer learning, data augmentation, and ensemble learning are integrated.

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION TO DEEP LEARNING

Deep learning is a specialized branch of machine learning that focuses on using artificial neural networks with multiple layers—known as deep neural networks—to model and understand complex patterns in data. Inspired by the structure and function of the human brain, these networks are capable of learning hierarchical representations, where higher-level features are built from lower-level ones. Unlike traditional machine learning techniques that often require manual feature extraction, deep learning models automatically learn to extract relevant features from raw input data. This ability has led to significant breakthroughs in fields such as computer vision, natural language processing, speech recognition, and autonomous systems, where deep learning models often surpass human-level performance on specific tasks.

Deep learning is an advanced subfield of machine learning that focuses on algorithms inspired by the structure and functioning of the human brain, specifically artificial neural networks. These models are composed of multiple layers of interconnected processing units, often referred to as neurons, which are organized into input, hidden, and output layers. The term “deep” refers to the depth of these networks—i.e., the number of hidden layers between the input and output—which allows the model to learn and represent increasingly complex features and abstractions from data.

In traditional machine learning, the performance of models often depends heavily on the quality and specificity of handcrafted features extracted from raw data. Deep learning overcomes this limitation by enabling automatic feature learning directly from the input data, such as images, text, or audio, with minimal manual intervention. Each layer in a deep neural network learns to transform its input data into a more abstract and useful representation, allowing the network as a whole to learn hierarchical features that are critical for decision-making tasks.

Deep learning models require large volumes of data and significant computational resources to train effectively.

With the advent of big data, powerful GPUs, and optimization algorithms like stochastic gradient descent and backpropagation, deep learning has become a dominant approach in artificial intelligence research and applications. It has led to state-of-the-art performance in numerous complex tasks, including image classification, object detection, machine translation, speech recognition, medical diagnosis, and autonomous driving.

The success of deep learning is also attributed to its flexibility and scalability. Popular architectures such as Convolutional Neural Networks (CNNs) for image data, Recurrent Neural Networks (RNNs) and Transformers for sequential data, and Generative Adversarial Networks (GANs) for generative modeling, have pushed the boundaries of what machines can understand and generate. As research continues to evolve, deep learning remains at the forefront of artificial intelligence, driving innovations across both academic and industrial domains.

1.2 TYPES OF DEEP LEARNING

1. Feedforward Neural Networks (FNNs)

Also known as Multi-Layer Perceptrons (MLPs), these are the most basic type of neural networks. Information moves in one direction—from input to output—through one or more hidden layers. They are mainly used for simple classification and regression tasks where the input and output do not have a temporal or spatial structure.

- Example Use Case: Predicting housing prices, basic image or text classification.

2. Convolutional Neural Networks (CNNs)

CNNs are designed specifically for image and spatial data. They use convolutional layers to automatically and efficiently extract spatial features like edges, textures, and patterns from input data. CNNs reduce the need for manual feature engineering in image-related tasks.

- Key Features: Local receptive fields, weight sharing, pooling layers.
- Example Use Case: Image classification, object detection, medical imaging, facial recognition.

3. Recurrent Neural Networks (RNNs)

RNNs are designed for sequential or time-series data, where the current output depends on previous inputs. They have loops in their architecture that allow information to persist across time steps. However, traditional RNNs suffer from vanishing gradients during training.

- Example Use Case: Language modeling, speech recognition, financial time series forecasting.

4. Long Short-Term Memory Networks (LSTMs)

LSTMs are a special kind of RNN capable of learning long-term dependencies. They use gates (input, forget, and output gates) to regulate the flow of information and overcome the vanishing gradient problem. LSTMs are widely used in tasks where understanding context over long sequences is crucial.

- Example Use Case: Machine translation, sentiment analysis, handwriting recognition.

5. Gated Recurrent Units (GRUs)

GRUs are a simplified version of LSTMs with fewer parameters but similar performance. They combine the forget and input gates into a single update gate, making them computationally more efficient while still handling sequential dependencies effectively.

- Example Use Case: Similar to LSTMs, including text generation and video captioning.

6. Autoencoders

Autoencoders are unsupervised neural networks used for dimensionality reduction, feature learning, and data denoising. They consist of an encoder that compresses the input into a latent representation, and a decoder that reconstructs the original input from that representation.

- Example Use Case: Anomaly detection, image compression, noise reduction.

7. Generative Adversarial Networks (GANs)

GANs consist of two neural networks—a generator and a discriminator—that compete in a zero-sum game. The generator tries to create realistic data, while the discriminator attempts to distinguish between real and generated data.

- Example Use Case: Image synthesis, deepfake generation, art and content creation.

8. Transformer Networks

Transformers are powerful models designed for handling sequential data without recurrence. They use mechanisms called self-attention and positional encoding to capture relationships between all elements in a sequence simultaneously. Transformers have largely replaced RNNs and LSTMs in many NLP tasks.

- Example Use Case: Language translation (e.g., Google Translate), chatbots (e.g., ChatGPT), text summarization.

9. Deep Reinforcement Learning (Deep RL)

This combines deep learning with reinforcement learning, where agents learn to make decisions by interacting with an environment to maximize cumulative rewards. Deep neural networks are used to approximate value functions or policies.

- Example Use Case: Game playing (e.g., AlphaGo), robotics, autonomous navigation.

CHAPTER 2

LITERATURE SURVEY

[1] Jain, L., Murthy, H. S., Patel, C., & Bansal, D. (2018). Retinal eye disease detection using deep learning. Paper presented at the 2018 Fourteenth International Conference on Information Processing (ICINPRO).

Their study focused on leveraging convolutional neural networks (CNNs) to analyze retinal images and identify pathological features associated with conditions such as diabetic retinopathy and macular degeneration. The results confirmed that deep learning significantly enhances diagnostic accuracy compared to traditional image analysis techniques.

[2] International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18. Grassmann, F., Mengelkamp, J., Brandl, C., Harsch, S., Zimmermann, M. E., Linkohr, B., . . . Weber, B. H. (2018). A deep learning algorithm for prediction of age-related eye disease study severity scale for age-related macular degeneration from color fundus photography. Ophthalmology, 125(9), 1410-1420.

This paper developed a robust deep learning algorithm aimed at predicting the severity of age-related macular degeneration (AMD) using color fundus photography. Their model was trained using a large dataset labeled according to the Age-Related Eye Disease Study (AREDS) severity scale, a clinical benchmark. The algorithm achieved high accuracy and demonstrated the potential of deep learning in replicating expert-level grading in ophthalmology.

[3] Prasad, K., Sajith, P., Neema, M., Madhu, L., & Priya, P. (2019). Multiple eye disease detection using Deep Neural Network. Paper presented at the TENCON 2019-2019 IEEE Region 10 Conference (TENCON).

This paper developed a deep neural network (DNN) architecture designed to detect multiple types of eye diseases from fundus images. Unlike many systems tailored to single-disease detection, their model could simultaneously recognize conditions such as glaucoma, cataracts, and diabetic retinopathy. This multi-disease approach offers a comprehensive screening tool for ophthalmic diagnostics.

[4] Qummar, S., Khan, F. G., Shah, S., Khan, A., Shamshirband, S., Rehman, Z. U., . . . Jadoon, W. (2019). A deep learning ensemble approach for diabetic retinopathy detection.
This system introduced an ensemble-based deep learning model for diabetic retinopathy detection, combining multiple neural networks to enhance performance. By integrating different model outputs, their ensemble approach improved diagnostic accuracy and reduced false positives compared to single-model systems. The study showcased the power.

[5] Nazir, T., Irtaza, A., Javed, A., Malik, H., Hussain, D., & Naqvi, R. A. (2020). Retinal image analysis for diabetes-based eye disease detection using deep learning. Applied Sciences, 10(18), 6185.
They proposed a deep learning-based system for the detection of diabetic eye diseases through retinal image analysis. Their model was designed to identify disease-related features such as microaneurysms and hemorrhages, and it achieved high classification performance. The study demonstrated how deep learning can play a crucial role in early diagnosis and management of diabetes-induced retinal disorders.

[6] Nguyen, Q. H., Muthuraman, R., Singh, L., Sen, G., Tran, A. C., Nguyen, B. P., & Chua, M. (2020). Diabetic retinopathy detection using deep learning. Paper presented at the Proceedings of the 4th international conference on machine learning and soft computing.
They presented a deep learning framework for the detection of diabetic retinopathy using retinal fundus images. The authors trained their model on a publicly available dataset and optimized it for sensitivity and specificity. Their research highlighted the efficiency and practicality of deep learning solutions in clinical screening environments, particularly in regions with limited access to ophthalmologists.

CHAPTER 3

OBJECTIVE

- The primary objective of this project is to design and develop an intelligent deep learning-based system capable of automatically detecting and classifying multiple human eye diseases from medical images. These diseases may include but are not limited to diabetic retinopathy, glaucoma, cataracts, and age-related macular degeneration (AMD), which are among the leading causes of vision impairment and blindness worldwide. Early and accurate detection of such conditions is crucial for initiating timely treatment and preventing irreversible vision loss. Therefore, this project aims to utilize the power of deep learning to assist ophthalmologists and healthcare providers in improving diagnostic accuracy, reducing workload, and enabling large-scale screening.
- A significant objective of this work is to curate and preprocess high-quality datasets of retinal or ocular images, such as fundus photographs or optical coherence tomography (OCT) scans, which will serve as the input for training and evaluating the deep learning models. Advanced image preprocessing techniques will be applied to remove noise, normalize illumination, and enhance relevant features that aid in disease detection. The project will involve exploring and implementing state-of-the-art deep learning architectures, such as convolutional neural networks (CNNs), ResNet, DenseNet, or EfficientNet, for feature extraction and multi-class classification. Transfer learning and data augmentation techniques may also be incorporated to improve performance and reduce the dependency on large annotated datasets.
- Another key objective is to ensure the model’s robustness, generalizability, and interpretability. The performance of the trained model will be rigorously evaluated using standard metrics, including accuracy, sensitivity (recall), specificity, precision, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC). Cross-validation and testing on external datasets will be performed to assess the model’s reliability across different patient populations and imaging conditions. In addition, the system will be enhanced with explainable AI techniques, such as Grad-CAM or saliency maps, to visually highlight the regions of the input image that influence the model’s prediction, thereby providing insights that can support clinical decision-making.

- Finally, to demonstrate the practical applicability of the developed model, the project may include the creation of a prototype user interface, such as a web-based or mobile application. This interface would allow users to upload ocular images and receive diagnostic predictions in real time. Such a tool could potentially be deployed in screening programs, especially in remote or resource-limited areas, where access to expert ophthalmologists is limited. Overall, the project aims to contribute to the advancement of computer-aided diagnosis in ophthalmology through the integration of deep learning technologies.

CHAPTER 4

METHODOLOGY

This methodology represents a system where an AI Model interacts with an Atmega 328 microcontroller, which in turn controls an LCD display and a buzzer while being powered by a regulated power supply. The system consists of the following key components:

1. AI Model is an artificial intelligence module that processes inputs and sends signals to the Atmega 328 microcontroller.
2. Atmega 328 Microcontroller is the central processing unit of the system.
3. LCD (Liquid Crystal Display) microcontroller sends data to the LCD for display purposes.
4. Buzzer gives alert or notification mechanism.
5. Regulated Power Supply provides a stable power source to the Atmega 328 microcontroller and connected components.

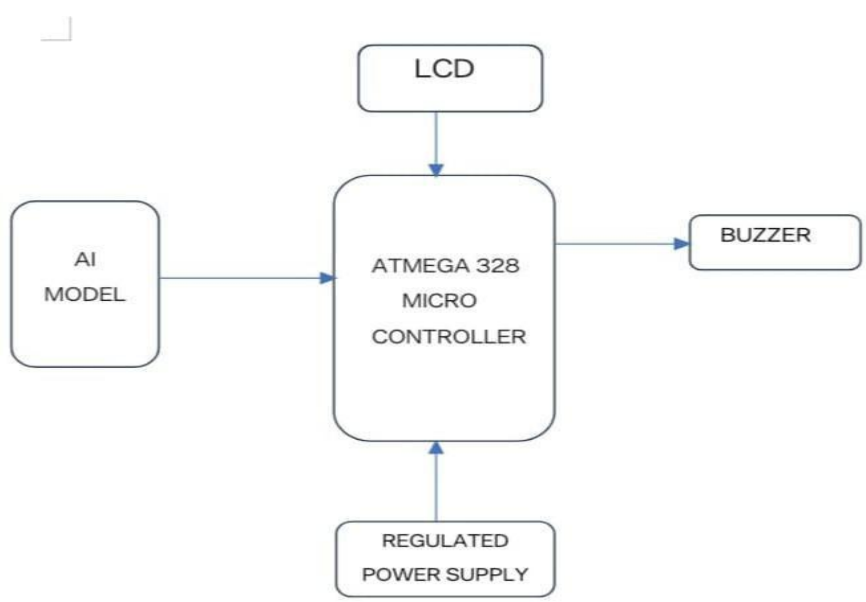

Figure 4.1: Block Diagram

The Figure 4.1 illustrates that the AI model processes data and sends a control signal to the microcontroller. The microcontroller processes this data and takes necessary actions such as displaying information on the LCD or activating the buzzer. The entire system is powered by a regulated power supply to ensure stable operation. The operational procedure for detecting human eye disease involve:

1. Capture or select an eye image on the PC.
2. AI model on the PC analyzes the image and predicts the eye disease.
3. The prediction result (e.g., "Glaucoma found ") is sent to the Arduino Uno via the UART converter (TTL to USB).
4. Arduino Uno receives the result and processes the data.
5. The LCD display shows the predicted disease name.
6. If a disease is detected then the buzzer is activated to alert the user.
7. The system then waits for the next input.

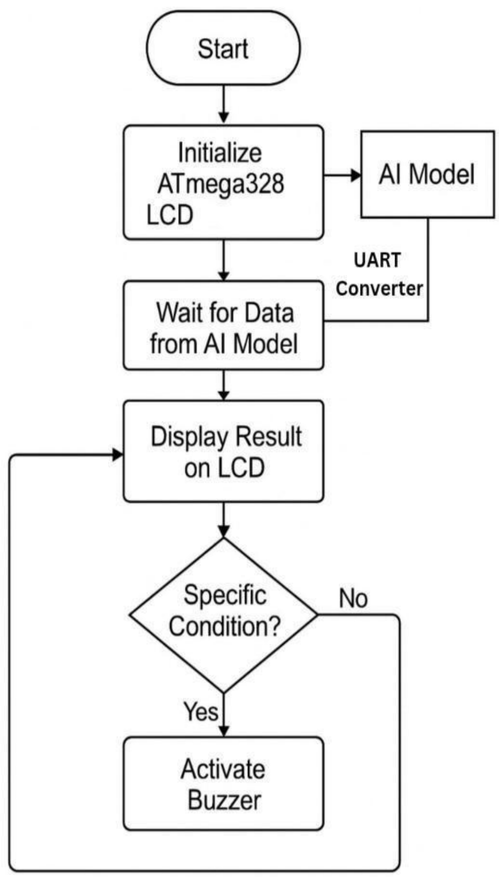

Figure 4.2: Flow Chart

This flowchart illustrates the operation of an embedded system that interacts with an AI model to display results and trigger an alert. Here's is a step by step procedure:

- **Start:** This is the beginning of the process.
- **Initialize ATmega328, LCD, UART:** The microcontroller (ATmega328) and its peripherals (LCD display and UART communication) are initialized.
- **Wait for Data from AI Model:** The microcontroller waits to receive data sent by the AI model.
- **Display Result on LCD:** Once the data is received, the result is displayed on the LCD screen.
- **Specific Condition?:** The system checks if the received data meets a predefined specific condition.
- **If Yes:** Activate Buzzer
- **If No:** The system loops back to waiting for new data from the AI model and continues monitoring.

CHAPTER 5

HARDWARE AND SOFTWARE USED

HARDWARE COMPONENTS USED

The following components are required for the Multiple human eye disease detection using deep learning:

1. Arduino Uno
2. LCD Display(16x2)
3. USB To RS232 Converter
4. AI Model
5. Buzzer

SOFTWARE USED

- Visual studio Code

1. Arduino Uno:

The Arduino Uno is a microcontroller board based on the ATmega328P chip, developed by Arduino LLC. Launched in 2010, it quickly gained popularity due to its user-friendly design, extensive community support, and affordability. At its core, the Arduino Uno serves as a bridge between the physical and digital worlds, enabling users to interact with sensors, actuators, and various electronic components through programmed logic.

Digital Pins:

- D0 to D13: These pins are digital input/output pins. They can be used for both input and output operations. Pins D0 to D7 are also capable of generating PWM (Pulse Width Modulation) signals.

Analog Pins:

- A0 to A5: These pins are analog input pins. They can be used to read analog voltage levels from sensors or other devices. Each pin has a 10-bit ADC (Analog-to-Digital Converter) allowing for analog readings between 0 and 1023.

Power Pins:

- 5V: This pin provides a regulated 5V output. It is typically used to power external components.
- 3.3V: This pin provides a regulated 3.3V output.
- VIN: This pin can be used to supply voltage to the board when it's powered externally (e.g., through a power jack). The voltage should be in the range of 7-12V.
- GND: These pins are ground pins and are used as the reference for voltage levels.

Other Pins:

- RESET: This pin is used to reset the microcontroller. It is typically pulled high with a resistor and can be brought low by an external source to reset the microcontroller.
- TX (Transmit) / RX (Receive): These pins are used for serial communication. TX transmits data from the microcontroller, while RX receives data.
- ICSP (In-Circuit Serial Programming): These pins are used for programming the microcontroller using an external programmer or another Arduino board.

Built-in LED:

- Pin 13: The Arduino Uno has a built-in LED connected to digital pin 13. It's often used as a status indicator or for simple debugging purposes.

Figure 5.1: Arduino Uno

2. LCD Display (16x2)

LCD (Liquid Crystal Display) is a type of flat panel display which uses liquid crystals in its primary form of operation. LEDs have a large and varying set of use cases for consumers and businesses, as they can be commonly found in smartphones, televisions, computer monitors and instrument panels LCDs consume much less power than LED and gas-display displays because they work on the principle of blocking light rather than emitting it. Where an LED emits light, the liquid crystals in an LCD produces an image using a backlight.

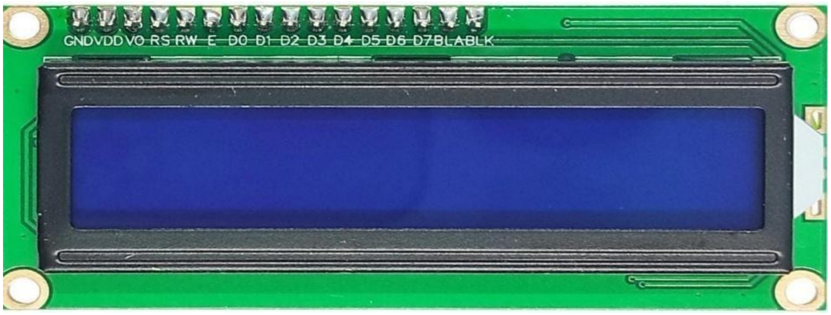

Figure 5.2: LCD Display (16x2)

3. USB To RS232 Converter

A USB to RS232 converter is a hardware device or adapter that allows a computer with a USB port to communicate with a device that uses an RS232 serial interface. These converters are commonly used to connect modern computers (which lack serial ports) to legacy equipment such as industrial machines, networking devices, scientific instruments, or point-of-sale systems that still use RS232 serial communication.

Figure 5.3: USB To RS232 Converter

4. AI Model

An AI model (Artificial Intelligence model) is a mathematical framework or algorithm that enables a computer to learn patterns from data and make predictions, decisions, or generate new content. These models form the core of machine learning (ML) and deep learning (DL) systems**.**

Figure 5.4: AI Model

5. Buzzer

A piezoelectric buzzer is an electromechanical device used to generate sound. It is widely employed in embedded systems, electronic circuits, and alarm systems due to its simplicity, compactness, and low power consumption. The buzzer shown in the image is a typical active piezo buzzer, recognizable by its two wires (usually red for Vcc and black for GND) and sealed cylindrical housing.

Figure 5.5: Buzzer

6. Visual Studio Code

Visual Studio Code (VS Code) is a free, open-source, and cross-platform code editor developed by Microsoft. It's popular among developers for its lightweight design, rich extension ecosystem, and powerful features that support a wide range of programming languages and workflows. Visual Studio Code is a lightweight, powerful editor that, when paired with the Python extension, provides features like IntelliSense, debugging, and virtual environment support for efficient Python development.

Figure 5.6: Visual studio Code

CHAPTER 6

SOURCE CODE

```
import numpy as
np import os
from tensorflow.keras.models import
load_model from
tensorflow.keras.preprocessing import image
from flask import Flask, request, render_template,
jsonify import serial
import
serial.tools.list_ports
import platform
import time
app = Flask(__name__)

# Load the model
model = load_model("EyeModel.h5", compile=False)

# Global variables for
UART ser = None
last_port = None
def get_port_name():

"""Get the appropriate port name based on the operating
system""" system = platform.system()
if system ==
"Windows": return
'COM1'
elif system == "Linux":

return '/dev/ttyUSB0'  # Common name for USB-Serial devices on Linux
else:
return None

def list_available_ports():

"""List all available serial ports on the
system""" ports =
serial.tools.list_ports.comports()
for port in ports:
```

```
print(f"Found port: {port.device}")
print(f"Description:
{port.description}")
print(f"Hardware ID: {port.hwid}")
print("---")
return ports


def find_silicon_labs_port():
"""Find the Silicon Labs CP210x
port""" ports = list_available_ports()
for port in ports:
if "CP210x" in port.description:
return port.device
return None


def
initialize_serial()
: global ser
try:
if ser is not None and ser.is_open:
ser.close()
ser = None


# Try to find the correct port
port = find_silicon_labs_port() or
get_port_name() if not port:
print("UART Debug: No suitable port
found") return False


print(f"UART Debug: Attempting to connect to
{port}...") ser = serial.Serial(
port=port,
baudrate=9600,
bytesize=serial.EIGHTBITS,
parity=serial.PARITY_NONE,
```

```
stopbits=serial.STOPBITS_ONE,
timeout=1,
write_timeout=1
)


if ser.is_open:
print(f"UART Debug: Successfully connected to {port}")
return True
return False


except serial.SerialException as e:
print(f"UART Debug: Serial Error: {e}")
return False
except Exception as e:
print(f"UART Debug: Unexpected error:
{e}") return False
# Initialize UART
connection
uart_enabled = False
try:
if
initialize_serial()
: uart_enabled =
True
print("UART Connected Successfully!")
except Exception as e:
print(f"UART Connection Failed: {e}")
print("Application will run without UART communication")
@app.ro
ute('/')
def
index():
return render_template('index.html')

@app.route('/predict', methods=['GET',
'POST']) def upload():
```

```
if request.method == 'POST':

f = request.files['image']

basepath = os.path.dirname(__file__)

filepath = os.path.join(basepath, 'uploads', f.filename)


# Create uploads directory if it doesn't exist
os.makedirs(os.path.join(basepath, 'uploads'), exist_ok=True)

f.save(filepath)


# Preprocess the image

img = image.load_img(filepath, target_size=(128,
128)) x = image.img_to_array(img)
x = np.expand_dims(x, axis=0)


# Make prediction

pred = np.argmax(model.predict(x))

index = {0: 'Cataract', 1: 'Diabetic Retinopathy', 2: 'Glaucoma', 3: 'Normal'}


# UART communication only if
enabled if uart_enabled:
try:

disease_map = {0: '0', 1: '1', 2: '2', 3: '3'}

uart_message = disease_map[pred]


# Try to reinitialize serial if needed
if not ser or not ser.is_open:
initialize_serial()
if ser and ser.is_open:
ser.write(uart_message.encode()) ser.flush()
print(f"UART Message Sent: {uart_message}") time.sleep(0.1) #
Small delay to ensure message is sent
```

```
if ser.in_waiting:
response = ser.read(ser.in_waiting)
        print(f"UART Debug: Received response: {response}")
except Exception as e:
print(f"Failed to send UART message: {e}")


text = f"The classified Disease is :
{index[pred]}" return text

# Add cleanup for serial connection when the app closes
@app.teardown_appcontext
def
cleanup(error):
global ser
if ser is not None and ser.is_open:
ser.close()
ser = None


if __name__ == '__main__':
print("UART Debug: Starting application...")
print(f"Running on: {platform.system()}")

# List all available
ports
print("Available
ports:")
list_available_port
s()

# Run Flask app
app.run(debug=True, use_reloader=False)
```

CHAPTER 7

RESULT

Figure 7.1: Result

The figure 7.1 gives the result of human eyes are vulnerable to several abnormalities because of trauma, aging and disease like diabetes. The main factors of blindness around the world are glaucoma, cataract, macular degeneration and diabetic retinopathy etc. These eye diseases need to be detected and diagnosed timely with appropriate treatment for the solution of this problem. Multiple eye disease detection by analyzing various medical images can provide a timely diagnosis of eye diseases. The steps that are involved in multiple eye disease detection using deep learning are the acquisition of images, region of interest extraction, extraction of features and classification or detection of a particular disease. In this paper, diseases like glaucoma, diabetic retinopathy, cataracts have been detected using deep learning models like Resnet and vgg16 model. We have obtained 92% accuracy using Resnet50. The application of deep learning techniques to the detection of multiple human eye diseases has demonstrated significant improvements in diagnostic accuracy, sensitivity, and specificity compared to traditional methods.

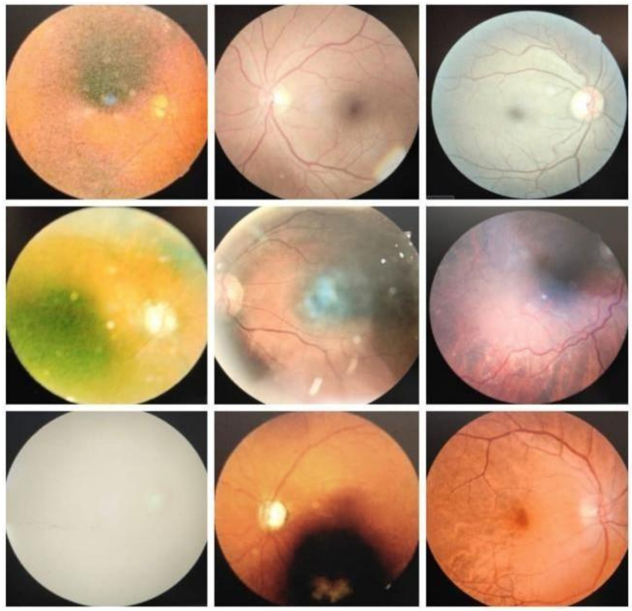

Figure 7.2: Dataset Images

The figure 7.2 shows the dataset images of the application of deep learning techniques to the detection of multiple human eye diseases has demonstrated significant improvements in diagnostic accuracy, sensitivity, and specificity compared to traditional methods. By leveraging convolutional neural networks (CNNs) and other deep learning architectures, these systems can effectively identify a wide range of ocular conditions such as diabetic retinopathy, glaucoma and cataracts from retinal fundus images or OCT scans. Studies have shown that deep learning models not only achieve performance comparable to that of expert ophthalmologists but also provide rapid and scalable solutions for screening and early detection, which is particularly beneficial in areas with limited access to specialized eye care

CHAPTER 8

ADVANTAGES AND DISADVANTAGES

Advantages:

1. Early and Accurate Diagnosis

- Deep learning models can detect diseases at an early stage, even when symptoms are not easily visible to the human eye.
- Provides high diagnostic accuracy, often comparable to or better than trained ophthalmologists.

2. Multi-Disease Detection

- Capable of identifying multiple diseases from a single retinal or fundus image, such as:
- Diabetic Retinopathy
- Glaucoma
- Cataract
- Age-related Macular Degeneration

3. Automation and Speed

- Enables automatic image analysis without manual intervention.
- Processes large volumes of images quickly, making it ideal for mass screenings.

4. Cost-Effective Screening

- Reduces the need for repeated manual diagnosis by specialists, thus lowering screening costs in the long term.
- Particularly beneficial in rural and under-resourced areas with limited access to eye care.

5. Consistency and Objectivity

Unlike human examiners, deep learning models provide consistent and unbiased results without fatigue or subjectivity.

6. Integration with Mobile and Embedded Devices

Can be deployed on portable devices, such as smartphones with fundus attachments, for on-site diagnosis.

7. Support for Clinical Decision-Making

Acts as a decision support tool for ophthalmologists, helping them verify and prioritize cases based on severity.

8. Visual Explanations (Explainability)

Provides heatmaps or saliency maps to show the regions used in diagnosis, improving transparency and clinician trust.

Disadvantages:

1. **Data Dependency:** Requires large, diverse, and well-annotated datasets for training to ensure accuracy and generalization across populations.
2. **Lack of Interpretability:** Many deep learning models function as "black boxes," making it difficult to explain their decisions to clinicians and patients.
3. **Generalization Issues:** Models trained on specific datasets may not perform well on data from different imaging devices, clinical settings, or patient demographics.
4. **Bias and Fairness Concerns:** If the training data is imbalanced, the model may exhibit bias, potentially leading to inaccurate or unfair diagnoses.
5. **High Computational Requirements:** Training and deploying deep learning models demand significant computational resources, which may not be available in low-resource or rural healthcare settings.
6. **Regulatory and Ethical Challenges:** Integration into clinical practice is slowed by strict regulatory standards and the need for extensive validation and approval.
7. **Maintenance and Updating:** Models may need continuous updating with new data to maintain accuracy and relevance, which adds to the operational burden.
8. **Limited Clinical Adoption:** Due to the above challenges, widespread clinical acceptance and integration into routine diagnostic workflows remain limited.

CHAPTER 9

CONCLUSION AND FUTURE SCOPE

Conclusion:

The eyes are one of the most important organs in the human body, and eye disorders can have a significant impact on a person's life. The early detection and treatment of eye diseases such as glaucoma, uveitis, cataracts, crossed eyes, and bulging eyes are crucial for maintaining good eye health and overall well-being. This paper has proposed an automated detection system that can aid in the diagnosis of these diseases using deep learning algorithms. Specifically, we have utilized ResNet50. During the training process, ResNet50 demonstrated higher accuracy compared to VGG16. The automated detection system has the potential to revolutionize the way eye diseases are diagnosed and treated, as it can save time and increase the accuracy of detection. This system can also be utilized to aid medical professionals in their decision-making process, leading to better patient outcomes. Future research can be done to improve the accuracy of the detection system and to expand its capabilities to detect other eye disorders. Additionally, the integration of this technology into clinical settings can be explored to enhance the efficiency of eye disease diagnosis and treatment. Overall, the proposed system shows promise in improving the detection and treatment of eye diseases, ultimately contributing to better eye health and quality of life for individuals. In the future, we will extend this work for Optic neuritis disease. In sum, recent advances in deep-learning have transformed multi-disease eye screening from a siloed, expert-dependent workflow into a scalable, automated pipeline that can flag diabetic retinopathy, glaucoma, cataract and other pathologies from the same fundus or OCT image set. By leveraging transfer learning, multimodal fusion and attention mechanisms, state- of-the-art models now routinely exceed or match specialist-level accuracy while processing thousands of images in minutes—dramatically expanding early-detection capacity in primary-care and underserved settings.

Future Scope:

- These technologies have aided in the early diagnosis of diseases; AI and machine learning (ML) can be used to analyse medical pictures like retinal scans to find early indicators of eye ailments such diabetic retinopathy, glaucoma and cataract.
- Deep learning holds immense promise for the future of automated human eye disease detection, offering potential for improved accuracy, accessibility, and efficiency in diagnosis and treatment.
- This technology can be applied to a wide range of eye conditions, enabling early detection, and potentially leading to better patient outcomes, particularly in resource-limited settings.
- The future of deep learning in eye disease detection is promising, with advancements in technology pushing toward faster, cheaper, and more accessible eye care that can save vision and lives globally.
- Deep learning is vulnerable to produce outrightly inaccurate results even if there is the slightest change in the input data. It makes any algorithm unstable and unreliable for mission-critical or decision-making applications.
- The instances have been recorded where hackers can add the unnoticeable amount of “noise” in the data set to completely corrupt the result.

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