International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 3, 2025

Recognition Of Depression By Non-Psychiatric Physician

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ABSTRACT

Depression is a widespread mental health disorder that often goes unrecognized, especially in primary care settings where patients commonly consult non-psychiatric physicians. These physicians may focus primarily on physical symptoms, potentially overlooking subtle psychological signs of depression. As a result, many individuals with depression do not receive timely or appropriate mental health care, which can worsen their condition and impact overall well-being.

This project aims to assist non-psychiatric physicians in identifying early signs of depression through facial emotion recognition using machine learning. A Convolutional Neural Network (CNN) model is employed to analyze facial expressions captured during patient interactions. The model is trained on a dataset of emotional images to detect specific emotions such as sadness, anger, or lack of expression that may indicate depressive tendencies. This provides physicians with an additional, objective tool for evaluating a patient's emotional state.

The system serves as a supportive diagnostic aid rather than a replacement for clinical judgment. By integrating facial emotion analysis into routine check-ups, non-psychiatric physicians can be alerted to possible depressive symptoms and refer patients for specialized psychological evaluation. This approach promotes early detection, reduces the chances of misdiagnosis, and helps ensure that patients receive the mental health support they need in a timely manner.

Keywords: Facial Emotion Recognition, Convolutional Neural Network, Depression Diagnosis, Mental Health, Machine Learning.

1-INTRODUCTION

Depression is a common mental health disorder that often remains undiagnosed, especially when patients visit non-psychiatric physicians for physical ailments [2], [5]. Many individuals are unaware of their mental health condition or hesitate to express emotional concerns, making early detection challenging [4], [6]. Non-psychiatric doctors may not always have the expertise or time to identify subtle psychological symptoms [5], [7]. To address this issue, our project proposes an AI-based system that uses facial emotion recognition to detect signs of depression [1], [9]. A Convolutional Neural Network (CNN) model analyzes patient facial expressions to identify emotions such as sadness or lack of affect [2], [9]. This system acts as a supportive tool to assist physicians in recognizing depression during routine consultations [3], [8]. It helps in flagging potentially depressed individuals for further psychological evaluation [3], [6]. The model enhances clinical decision-making without replacing professional judgment. Ultimately, this approach aims to promote early diagnosis and better mental health care access

Existing System:

The existing system for detecting depression largely depends on patient self-reporting and clinical questionnaires. Non-psychiatric physicians often focus on physical symptoms, overlooking mental health issues. Diagnosis typically requires referral to a mental health specialist. There is minimal use of technology to detect non-verbal emotional cues. As a result, many depression cases remain undiagnosed or are identified too late.

Proposed System:

The proposed system uses facial emotion recognition to help non-psychiatric physicians detect signs of depression. It employs a Convolutional Neural Network (CNN) to analyze patient facial expressions during consultations. Emotions such as sadness or lack of expression are flagged as potential indicators of depression. This system acts as a supportive diagnostic tool without replacing the doctor's judgment. It enables early identification and timely referral for mental health evaluation.

2.RELATED WORK

Depression is a growing concern worldwide, and many cases go undetected, especially when patients visit non-psychiatric physicians for physical health issues. Traditional detection methods like the PHQ-9 and BDI rely on self-reporting, which may not always be accurate due to stigma, denial, or lack of awareness. To overcome these limitations, recent studies have explored the use of artificial intelligence (AI) for more objective analysis. Facial emotion recognition has gained attention as a promising approach, as facial expressions often reveal emotional states subconsciously. Researchers have applied machine learning techniques, especially Convolutional Neural Networks (CNNs), to classify emotions like sadness, anger, or joy with high accuracy. Mollahosseini et al. and others demonstrated the power of CNNs in facial emotion classification tasks. Some systems, like Affectiva and Emotient, have been used to assess emotional states by analyzing facial micro-expressions. These systems have shown potential for detecting depression and other mood disorders. Furthermore, integrating multimodal data such as speech tone, facial features, and body language has been found to improve recognition accuracy, though it adds complexity. While psychiatrists have started using such tools, non-psychiatric physicians still lack access to practical and efficient solutions for mental health detection. The need for lightweight, real-time tools that can assist general practitioners in detecting depression is clear. Our project addresses this gap by offering a CNN-based facial emotion recognition system tailored for non-psychiatric use. It provides real-time emotional analysis during regular consultations, helping doctors identify early signs of depression without requiring specialized psychiatric training. Such tools can enhance diagnostic support, encourage early intervention, and ultimately improve mental health outcomes in general healthcare settings.

3.REQUIREMENT ANALYSIS

3.1Functional Requirements:

These are the requirements that the end user specifically demands as basic facilities that the system should offer. All these functionalities need to be necessarily incorporated into the system as a partof the contract.

Functional requirements for Recognition Of Depression By Non-Psychiatric Physicians using technology and machine learning include:

- **User Authentication and Access Control**

Users (such as physicians or researchers) must log in securely to access the system. The system should allow new user registration and existing user login/logout.

- **Image Input and Acquisition**

The system must support uploading facial images or capturing live photos using a webcam. It should ensure that the image is of sufficient quality for analysis (e.g., proper lighting, face visibility).

- **Facial Expression Recognition**

The system must detect and analyze facial features using techniques like OpenCV and CNN. It must classify facial emotions such as sadness, anger, neutrality, etc.

Non-Functional Requirements:

These are basically the quality constraints that the system must satisfy according to the project contract. The priority or extent to which these factors are implemented varies from one project to other. They are also called non-behavioral requirements.

Software Requirements:

Blockchain Platform : Ethereum , Hyperledger Fabric

Front-End : HTML, CSS , JavaScript

Backend : Python 3.6.0 ,MySQL,Web3.py

Development Tools : Truffle and Ganache, MySQL Workbench, Postman, Visual Studio Code

Hardware Requirements:

Processor : I5 Core

Ram : 8GB

Hard Disk : 1TB

Operating System : Windows 10, Linux

4.DESIGN

System Architecture:

The system architecture is designed as a modular, layered framework that efficiently processes facial images to detect emotional states and assess the risk of depression. It combines front-end interaction, backend processing, and machine learning intelligence into a cohesive workflow. Each component has a defined role in ensuring smooth operation, from user authentication to emotion analysis and depression prediction.

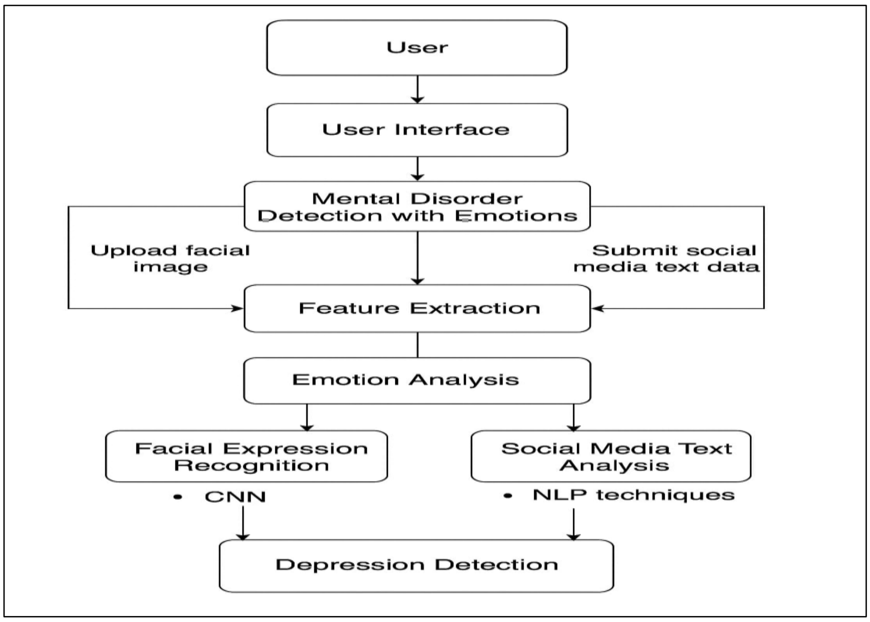
At the front-end, a user interface is built using HTML, CSS, and JavaScript, which allows users (e.g., physicians or assistants) to upload images or access live camera feeds. This UI interacts with the user-friendly system built on the PyQt5 framework, providing an intuitive experience even for non-technical users. It offers features like login/signup (via Supabase), image preview, and displaying real-time emotion and depression results in textual or graphical format.

The backend layer is developed using Python, which handles core functionalities such as image preprocessing, emotion recognition using CNN models, and depression risk classification using algorithms like Logistic Regression, K-NN, and Decision Trees. This layer also manages data communication between the user interface and database, stores predictions, and controls access based on user roles. Libraries such as OpenCV, NumPy, Pandas, and TensorFlow play crucial roles in processing and classifying the images.

The system is further supported by database and cloud services. Supabase is used for real-time authentication, user session management, and secure storage of metadata and analysis results. The backend may optionally connect to MySQL for storing image paths, emotion scores, and user logs. The architecture is scalable and can be deployed across web servers or integrated with telemedicine platforms for broader use. It ensures privacy,

International Journal of
Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 3, 2025

security, and reliability by adhering to good software practices and cloud standards.



4.1.2 Technical Architecture:

The The technical architecture of the system is built using a combination of machine learning frameworks, front-end technologies, and cloud-based services to enable real-time analysis of emotional states from facial images. The core processing logic is written in Python 3.6, leveraging libraries such as TensorFlow, NumPy, OpenCV, and scikit-learn for deep learning, emotion recognition, and model training. The models used include Convolutional Neural Networks (CNNs) for facial emotion recognition and Logistic Regression, K-NN, and Decision Trees for classification of depression risk. Feature extraction is performed on facial landmarks to quantify emotional states, which are then used to predict potential mental health conditions.

The frontend is developed using HTML, CSS, and JavaScript, offering an interactive dashboard where users can upload images or use a webcam for live input. The system utilizes Supabase for user authentication, database storage, and backend integration. Supabase serves as a cloud-based alternative to Firebase, providing features like REST APIs and PostgreSQL support. It manages user data, login sessions, and analysis records securely. The communication between the frontend and backend is facilitated via API calls or JavaScript-based functions, ensuring smooth data flow and responsive updates. Additionally, WebRTC APIs and browser capabilities are used to capture images from a user's camera for instant processing.

The system is designed with scalability and portability in mind. Development tools like Visual Studio Code, Truffle, Ganache, and Postman are used for writing, testing, and managing smart contracts and API requests, although blockchain integration (Ethereum/Hyperledger) is optional and can be extended in future versions. The technical stack ensures that the software runs efficiently on Windows or Linux, requiring only a standard machine with an Intel i5 processor, 8 GB RAM, and 1 TB HDD. This modular technical architecture enables fast deployment, easy debugging, and future extensibility—allowing additional modules like voice analysis or real-time video emotion tracking to be integrated with minimal changes to the existing framework.

In terms of model training and dataset management, the system uses the FER-2013 (Facial Expression Recognition 2013) dataset for training the CNN-based emotion recognition model. The training process involves preprocessing grayscale images, resizing them, normalizing pixel values, and labeling emotions using LabelEncoder. Model performance is optimized using callbacks like EarlyStopping, ReduceLROnPlateau, and ModelCheckpoint to prevent overfitting and ensure high validation accuracy. The final trained model is saved in .h5 format, and predictions are made in real-time when a new image is provided by the user. This deep learning model is at the heart of the system, enabling high-accuracy emotional detection even from subtle facial cues.

The architecture also includes a camera integration and analysis module that uses JavaScript and Colab APIs to take photos or capture live video. The photo capture is encoded using base64 and passed to the backend model for emotion classification. The results include the primary emotion, confidence score, a breakdown of all emotions, and a calculated depression risk score. These outputs are visualized using Python's plotting libraries or displayed dynamically in the web interface. This real-time interaction between browser-based tools and Python's backend makes the architecture both innovative and highly practical for on-the-go depression screening, especially in general clinical settings without specialized psychiatric equipment.

To enhance user experience, the system uses visual cues like charts and status indicators (e.g., "Low Risk", "High Risk") to present results clearly. The front end is also designed to be responsive, ensuring compatibility across devices such as laptops, desktops, and tablets. For deployment, the system can be hosted locally or integrated into web platforms using lightweight Python web servers or frameworks like Flask.

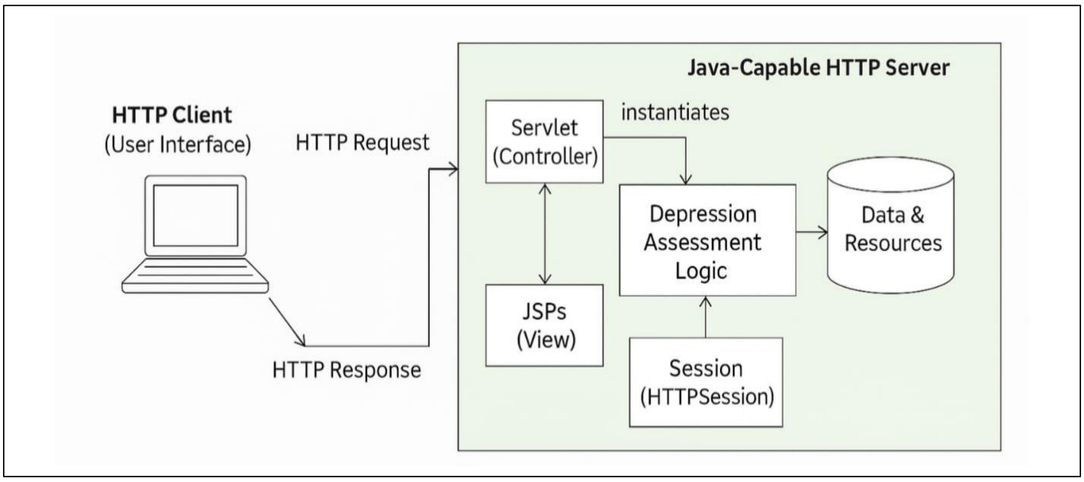


Fig. 4.1.2.1 Technical Architecture

5. IMPLEMENTATION

Pandas:

Pandas are a popular Python library for data analysis. It is not directly related to Machine Learning. As we know that the dataset must be prepared before training. In this case, Pandas comes handy as it was developed specifically for data extraction and preparation. It provides high-level data structures and wide variety tools for data analysis. It provides many inbuilt methods for groping, combining and filtering data.

Numpy:

NumPy is a very popular python library for large multi-dimensional array and matrix processing, with the help of a large collection of high-level mathematical functions. It is very useful for fundamental scientific computations in Machine Learning. It is particularly useful for linear algebra, Fourier transform, and random number capabilities. High-end libraries like TensorFlow uses NumPy internally for manipulation of Tensors.

Matplotlib:

Matplotlib is a very popular Python library for data visualization. Like Pandas, it is not directly related to Machine Learning. It particularly comes in handy when a programmer wants to visualize the patterns in the data. It is a 2D plotting library used for creating 2D graphs and plots. A module named pyplot makes it easy for programmers for plotting as it provides features to control line styles, font properties, formatting axes, etc. It provides various kinds of graphs and plots for data visualization, viz., histogram, error charts, bar chats, etc,

Seaborn:

Seaborn is a Python data visualization library that is based on Matplotlib and closely integrated with the NumPy and pandas data structures. Seaborn has various dataset- oriented plotting functions that operate on data frames and arrays that have whole datasets within them. Then it internally performs the necessary statistical aggregation and mapping functions to create informative plots that the user desires. It is a high-level interface for creating beautiful and informative statistical graphics that are integral to exploring and understanding data.

Pickle module:

Pickle module is used for serializing and de-serializing a Python object structure. Any object in Python can be pickled so that it can be saved on disk. What pickle does is that it "serializes" the object first before writing it to file. Pickling is a way to convert a python object (list, dict, etc.) into a character stream. The idea is that this character stream contains all the information necessary to reconstruct the object in another python script.

Jupyter Notebook:

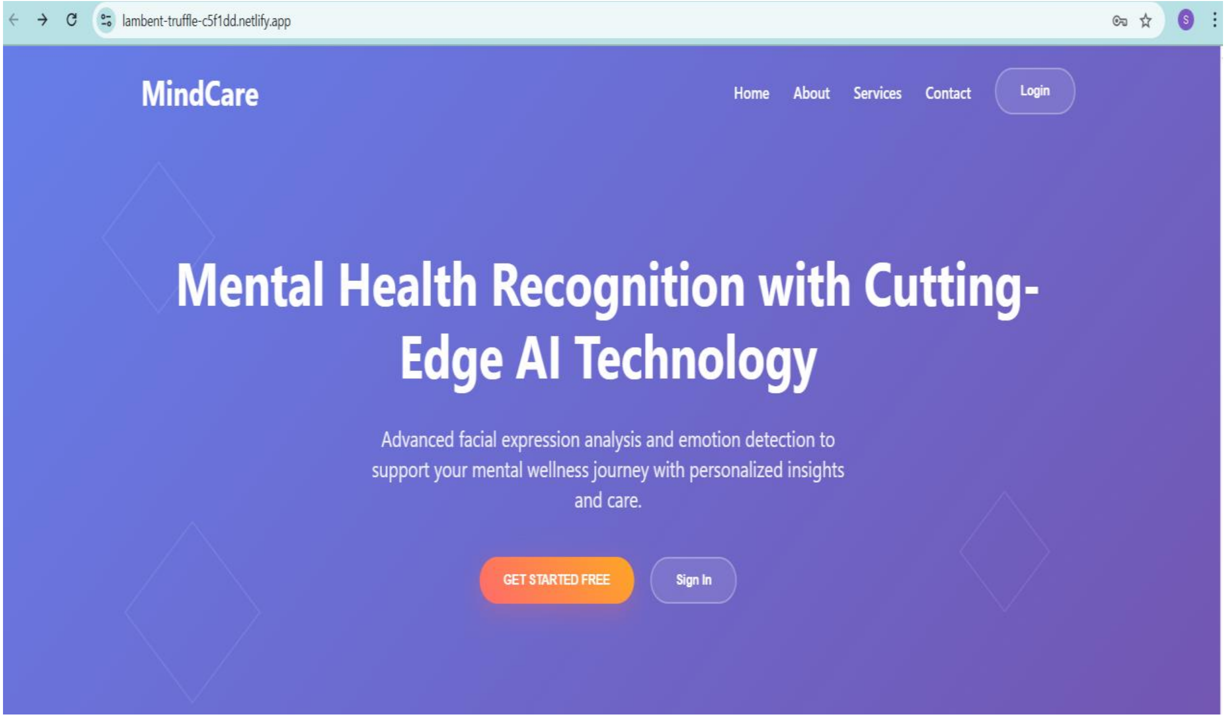
The Jupyter Notebook is an open source web application that you can use to create and share documents that contain live code, equations, visualizations, and text. Jupyter Notebook is maintained by the people at Project Jupyter.

Jupyter Notebooks are a spin-off project from the IPython project, which used to have an IPython Notebook project itself. The name, Jupyter, comes

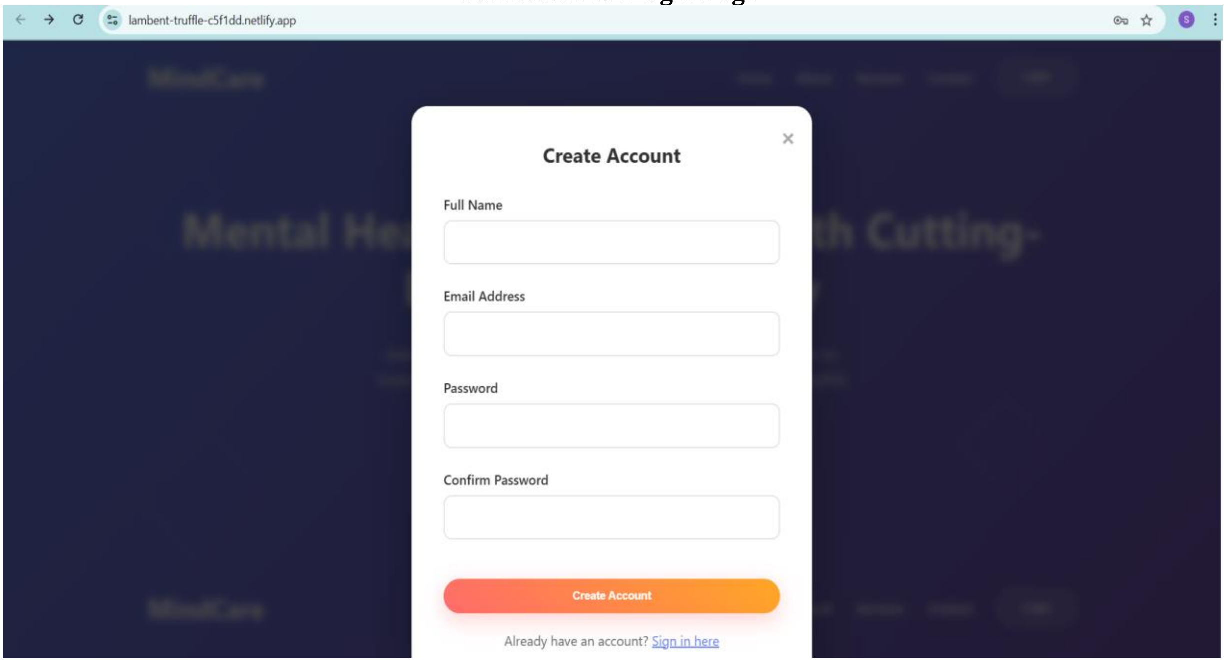
International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 3, 2025

from the core supported programming languages that it supports: Julia, Python, and R. Jupyter ships with the IPython kernel, which allows you to write your programs in Python, but there are currently over 100 other kernels that you can also use.

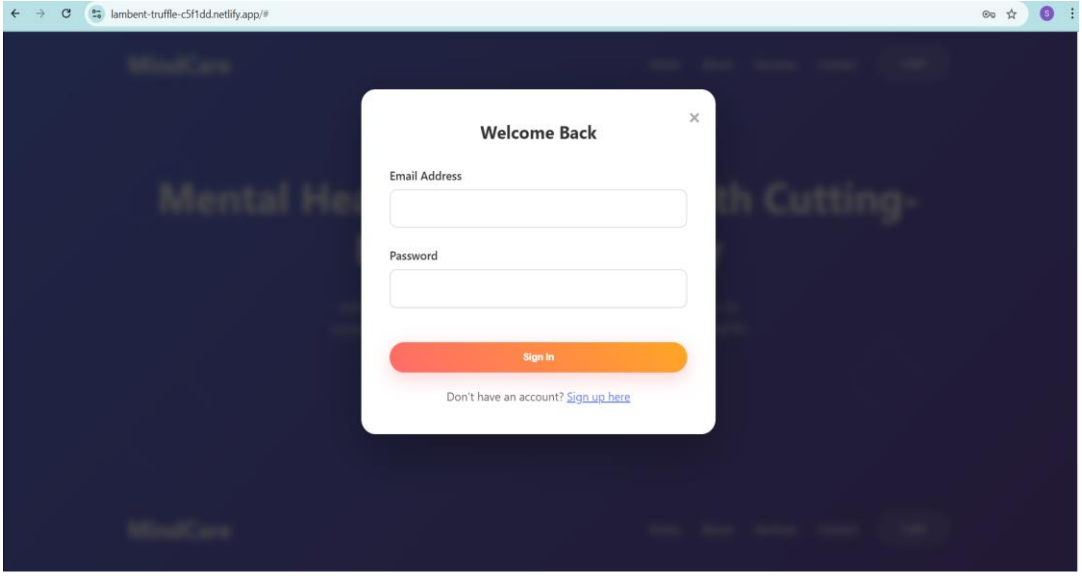
6.SCREENSHOTS



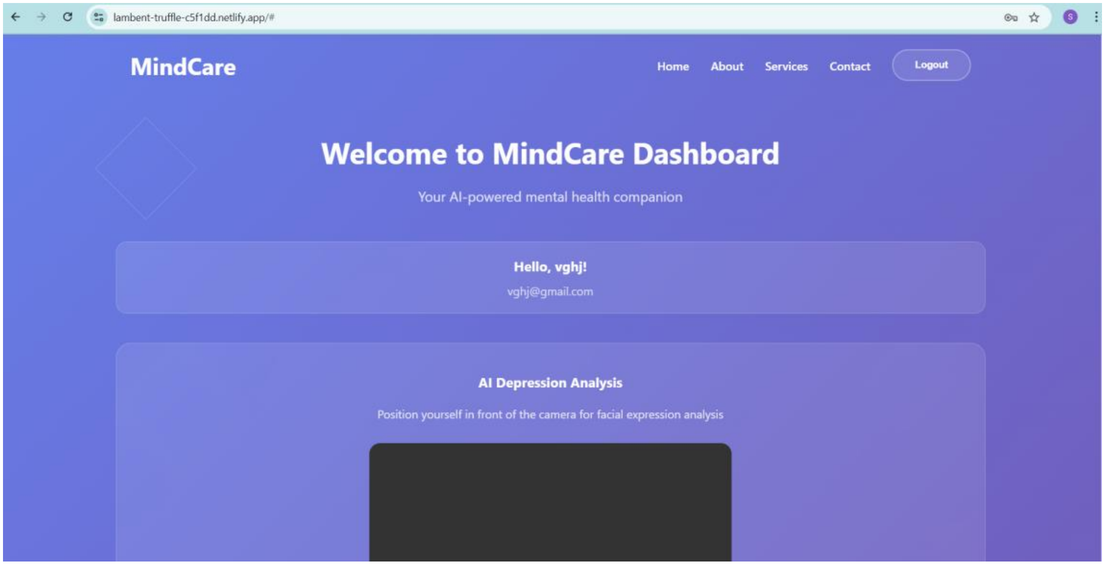
Screenshot 6.1 Login Page



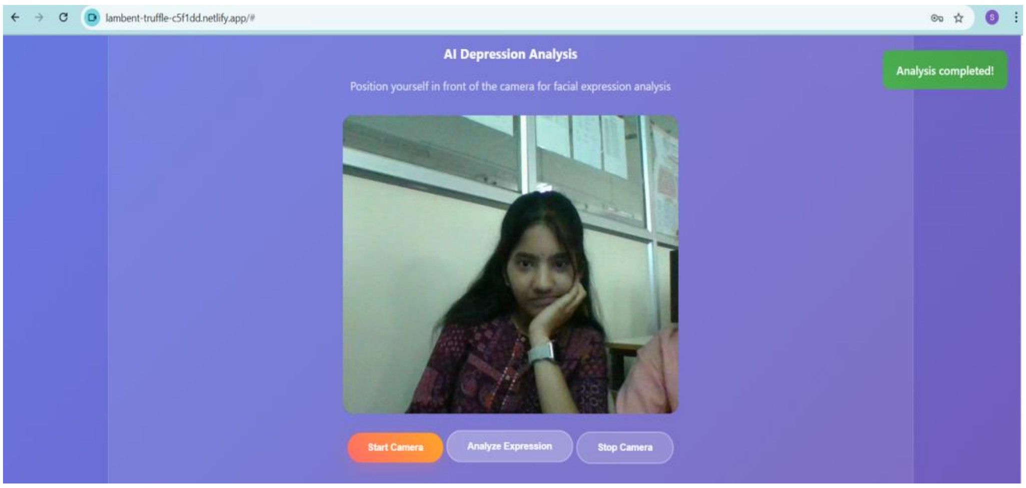
Screenshot 6.2 Create Account Page



Screenshot 6.3 Sign In Page



Screenshot 6.4 Dashboard Page



Screenshot 6.5

International Journal of
Information Technology & Computer Engineering
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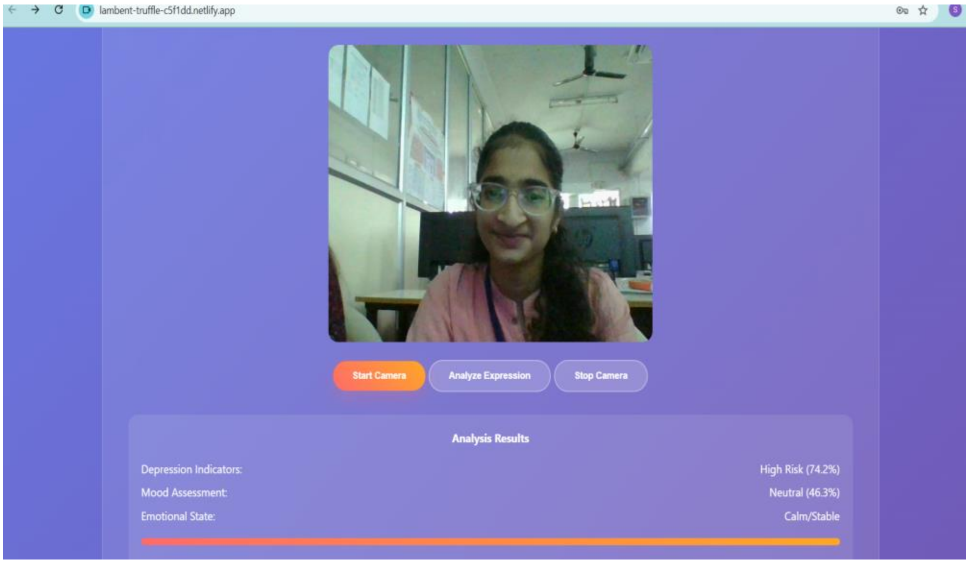
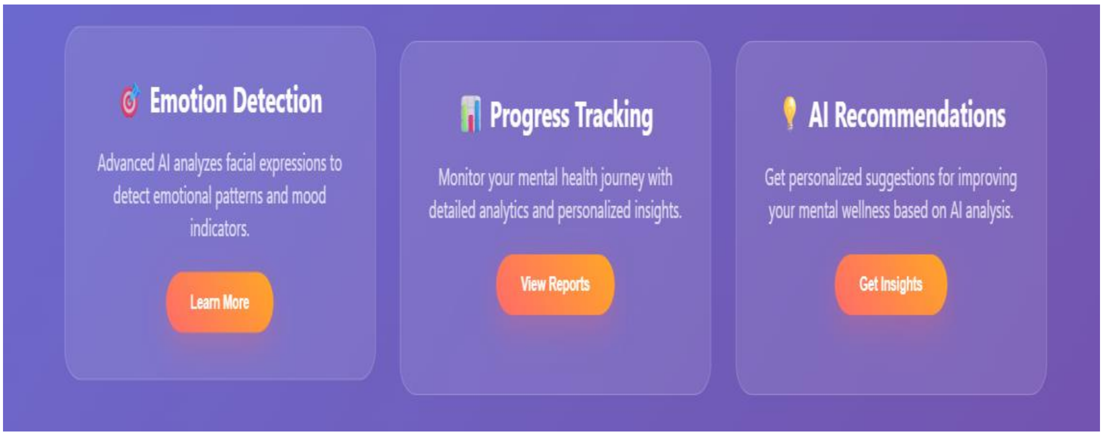
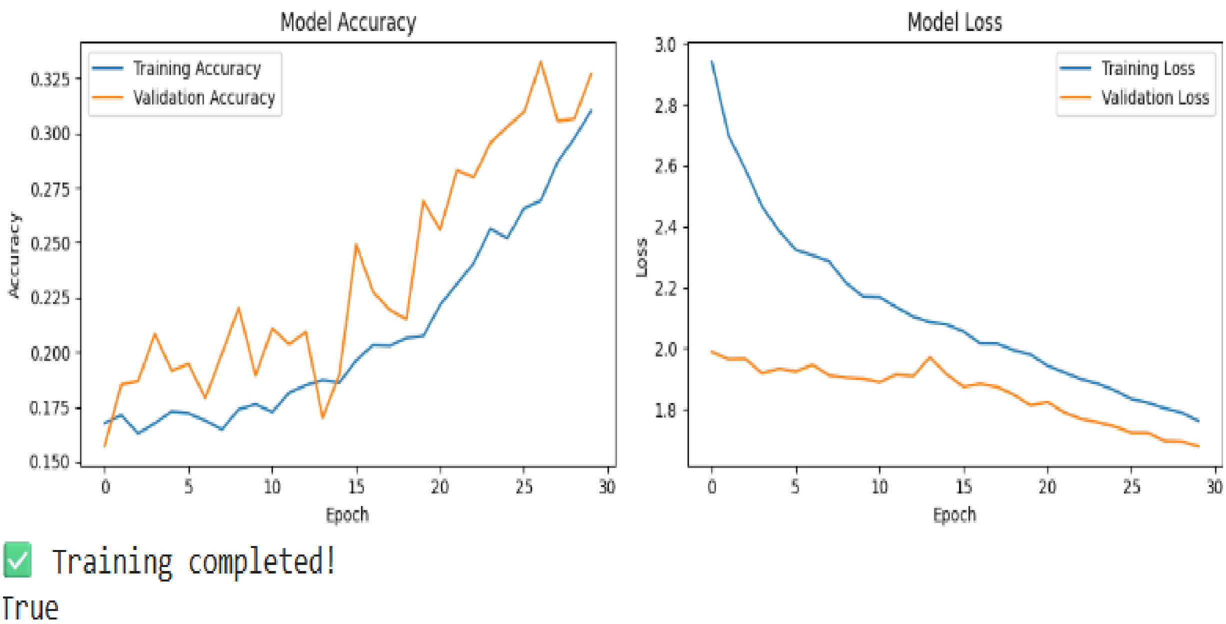


Screenshot 6.6



Screenshot 6.7



Screenshot 6.8

7. CONCLUSION

This project demonstrates the potential of machine learning to assist non-psychiatric physicians in the early detection of depression by analyzing facial emotions from patient images. Using deep learning models trained on datasets like FER-2013, the system can recognize emotional expressions such as sadness, anger, etc which are often linked to depressive states. This approach provides a quick, and cost-effective screening tool that can be used in general clinical settings. It helps bridge the gap where psychiatric expertise is not immediately available, allowing for timely mental health referrals. While the system does not replace clinical diagnosis, it acts as a supportive aid to raise early alerts.

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