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Integrated HealthAI: Revolutionizing Healthcare through Advanced Diagnostic Systems

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Abstract

The incidence of skin cancer has increased dramatically and the need for early detection, management of the disease, and effective public health campaigns are therefore paramount. Here, we introduce an AI-powered health application, encompassing novel features for skin cancer detection, heart rate estimation, and a health-related chatbot, providing new opportunities for accessible healthcare solutions. With the chosen Skin Cancer Classification data set and the YOLOv8 model, the system successfully classifies skin cancers including actinic keratosis, basal cell carcinoma, dermatofibroma, and vascular lesions. It allows users to upload images of skin conditions and get instant data clinical insights, while for heart rate monitoring, it uses video analysis of the user's uploaded facial videos. The chatbot also gives individual health recommendations so that users can better make health-related decisions. The performance metrics (accuracy, precision, recall, and F1 score) present the effectiveness of the application for dermatology and health monitoring. Such tool is promising of better access to healthcare, encouraging screening and preventive care leading to better public health.

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1 Introduction

Human health is crucial for any society to move forward, and the rapid development of personal health care technologies allows individuals to deal with health related problems at home, instead of visiting doctors frequently [[1], [2]]. In the field of healthcare, artificial intelligence (AI) and machine learning (ML) have been showing up in many areas, and it is transforming diagnostics and patient care by providing an automated, personalized approach. AI skin cancer detection and heart rate sensors play an important role in increasing early diagnosis and accessibility to both technologies, especially in emergency departments, where healthcare professionals often experience a shortage.

To bridge this gap in accessibility to healthcare we present an AI powered health application which includes image based skin cancer detection, face based heart rate monitoring and a health related chatbot in this paper. This application implements YOLOv8 for skin cancer classification, Remote photoplethysmography (rPPG) for calculate the heart rate and use of natural language chatbot enable to provide reliable information about health which jointly reveal this application as a complete tool of self-care process solution for early diagnosis.

Objectives and Novelty Statement

The novel contributions of this research are as follows:

- To implement an algorithm for accurate skin cancer detection through image analysis.
- To implement facial recognition technology for heart health monitoring.
- To incorporate interactive AI Chatbot to enable seamless and fast information on a broad scope of health issues other than skin diseases.
- To develop the user friendly interface whereby we incorporate these components into one single Healthcare System.

Such a novelty in this work is that these functions are consolidated in a single and easily accessible tool, which alleviates the barriers to accessing healthcare, and promotes health self-management through diagnostic services directly to the user.

2 Literature Review

Machine Learning (ML) and Artificial Intelligence (AI), in turn, have greatly advanced the sphere of healthcare usage, especially in diagnostics and patient care. AI is essential in the field of skin cancer diagnosis, monitoring heart conditions, and chatbot-based healthcare assistance in the current study.

Dildar et al. [3] examined the problem of deep learning-based detection with an emphasis on VGG, ResNet, and Inception along with issues regarding the data diversity and augmentation. Likewise, Vidya and Karki have noted that preprocessing techniques are significant in the classification of skin cancer using ML and have used such models as Naive Bayes, ANNs, and SVMs to improve their accuracy [4]. AlSadhan et al. (2024) [5] used an integrated deep convolutional neural network, which showed great success in the classification of skin cancer types based on object detection processes. Musthafa et al. [6] suggested an optimized CNN architecture, with checkpoints and data augmentation, and received 97.78% validation accuracy and improved the performance of several previously developed dermatological lesion classification approaches.

Video-based methods have also been developed to monitor the health of the heart. Shao et al.[7] proposed a new hyperbolic embedding steered spatiotemporal graph convolutional network (HESGCN) to estimate remote heart rate, which reduces artifacts of motion and noise interference. A second study [8] used convolutional neural networks (CNNs) to recover photoplethysmographic (PPG) signals out of facial videos which allowed real-time monitoring of the heart rate considering the effects of light conditions and skin tones. Also, Pagano et al. [9] looked at the application of Support Vector Machines (SVMs) convolutional neural networks (CNNs) to estimate heart rate through facial videos, where preprocessor tools, including noise reduction and stabilization, are of great significance.

AI-powered chatbots are also integrated into healthcare, thus making it more accessible and real-time patient support. The authors of the study [10] created a disease prediction and treatment chatbot, which is based on NLP and ML and can process medical questions and give solutions. To ensure proper recommendations, Ayanouz et al. that suggested a smart chatbot architecture, which integrates NLP, modular processing, and machine learning-based symptom analysis with a medical database [11]. To test the reliability of an AI-based healthcare chatbot, Athota et al. constructed an intuitive user interface and used it in an iterative testing process [12]. Khadija et al.

created an NLP chatbot which can analyze symptoms and learn constantly [13]. In a similar manner, Divya et al. [14]the study created by a self-diagnostic chatbot based on decision trees and a formal medical knowledge base. Oyeleye et al. [15] contributed by curating a heart rate dataset and demonstrating the efficacy of Random Forest models for real-time health monitoring.

Improving the above AI-based approaches, this study will bring together skin cancer detection, heart health tracking, and chatbot-guided healthcare under one and easy-to-use system. This solution would increase accuracy in diagnosis and seal gaps in access to remote healthcare availability and provide its users with a tool to monitor their health constantly.

3 Materials and Methods

This study introduces a complex AI-based healthcare system, named Integrated **Integrated HealthAI**, which consists of three major components: **skin cancer detection, heart rate monitoring, and health chatbot**. To have reliable and accessible health-related insights, each module has been created with the help of appropriate datasets, tools, and algorithms. Application is of modular architecture where every component has its own functions but it is part of the complete health monitoring system.

3.1 Research Methodology Diagram

The research methodology is a step-by-step visualization of the steps that take place in the detection of skin cancer, heart rate monitoring, and the AI health chatbot. The first part illustrates the skin cancer detection model workflow, the initial stage of which is collecting the data (Roboflow), preprocessing, training, and accuracy evaluation (Roboflow), precision evaluation (Roboflow), recall evaluation (Roboflow), and F1 score evaluation (Roboflow). The second part describes the estimation process of the heart rate with the help of remote photoplethysmography (rPPG) when the facial video frame is handled, and the green intensity values are extracted with the help of this algorithm, and the heart rate is determined. The last part demonstrates the design of the AI-powered chatbot, talking about how user-executed queries are received in the frontend, interpreted by the backend on an API, and answered with an AI model (OpenAI GPT-4). These three modules combined offer a holistic, AI-based healthcare system, which can improve diagnostic abilities and accessibility.

The module was created to detect skin cancer with the help of YOLOv8 (You Only Look Once version 8), a real-time object detector created by Ultralytics. YOLOv8 is a good choice since it is state-of-the-art with regard to accuracy and speed, so it can be used in medical image detection, e.g. in skin lesion classification.

Datasets

Three datasets were first studied in the classification of skin cancer though Skin Cancer Classification Dataset was taken as final model training because it was more successful.

- Skin Cancer Recognizer Dataset
- Malignant or Benign Computer Vision Project Dataset
- Skin Cancer Classification Dataset

Other datasets evaluated:

- Skin Cancer Recognizer Dataset
  - 9 classes, 2,494 images
  - Example classes: BCC, AKIEC, DF, VASC, Melanoma, Nevus
  - Split: 70% train, 20% validation, 10% test
- Malignant or Benign Computer Vision Project Dataset

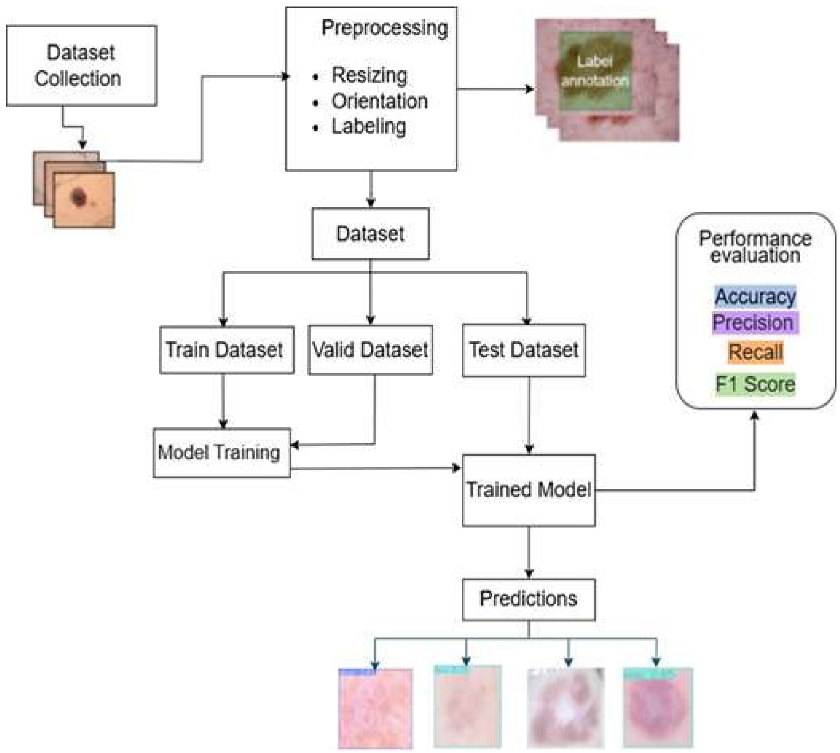

Figure 1. Flowchart of skin cancer detection module

- 2 classes, 527 images (Benign, Malignant)
- Split: 80% train, 12% validation, 8% test

- Skin Cancer Classification Dataset
  - 4 classes, 2,660 images (AKIEC, BCC, DF, VASC)
  - Split:
    - Train: 88% (2,343 images)
    - Validation: 8% (224 images)
    - Test: 4% (93 images)

Training was performed on Google Colab with GPU acceleration, leveraging the Ultralytics framework for smooth integration and monitoring.

Evaluation Metrics

To measure the model's diagnostic effectiveness, we evaluated it using key performance metrics:

- mAP@0.5 (Mean Average Precision)
- Precision
- Recall
- F1 Score
- Confusion Matrix Visualization

These metrics calculations have been done on the validation and test sets to give a wide perspective of the strengths and weaknesses of the model.

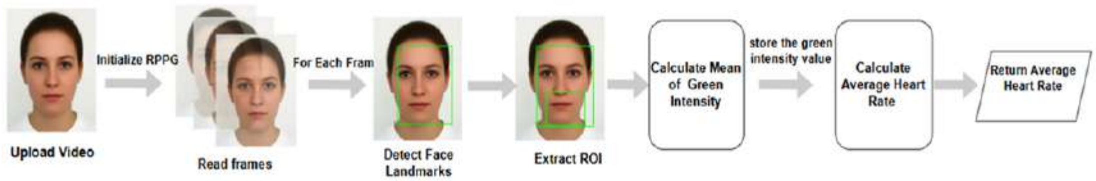

Figure 2. Flowchart of HR Monitoring

The second component of the system provides the possibility of detecting the heart rate with face video through a non-contact technique known as remote photoplethysmography (rPPG). This method involves slight variations in the color of the skin as a result of the blood flow to measure the rate of the heart.

Input Requirements

The users are requested to record a face video of 10-15 seconds and in a stable lighting environment with no fast movements. There should be a full view of the face, a frontal pose in the video.

Face Detection and ROI Selection

MediaPipe Face Mesh is used to detect the face in every video frame and extract Regions of Interest (ROIs) including forehead and cheeks. The areas are selected because of their high vascularity and the ability to be seen in normal lighting.

Signal Extraction and Filtering

Out of every ROI, the green channel is taken out of all the frames, because it has the strongest signal of the plethysmographic. The time-dependent change of intensities constitutes a raw signal, and it is subjected to:

- Detrending function
- Bandpass filter (0.7 Hz to 4 Hz) to isolate heart-rate frequencies

Implementation and Integration

The entire signal processing chain was created in Python and used openCV, NumPy, SciPy, and Matplotlib libraries. The output of the heart rate is sent back to the user via the Flask based REST API which is incorporated in the main application frontend.

The last module will offer the users a chatbot which is a conversational chat to help with general health related questions. It is a chatbot based on the integration of the OpenAI GPT-4 model via APIs.

API Integration

The chatbot is also hard-coded into the Express.js backend of the application using the OpenAI API. Whenever a user enters a query, it is sent to the backend to the GPT-4 model together with a system prompt to outline its purpose.

Response Handling

The frontend receives the response of GPT-4 in real-time through socket or fetch API. The chatbot interface guarantees a user-friendly and comfortable experience.

3.2 Investigation Site and Data Acquisition

In this health application project, the research problem is the creation of a system that can detect skin cancer, check the heart rate, and offer a chat-bot related to health. The training and testing dataset on the skin cancer

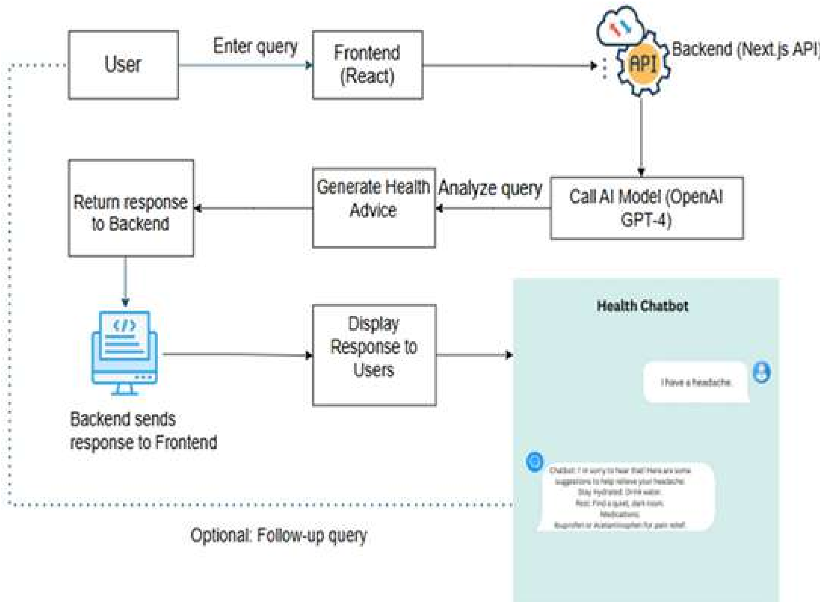

Figure 3. Flowchart of Chatbot

detection feature were downloaded into Roboflow, making it quality and reliable in terms of image data sets. Table 1: The descriptive statistics of the dataset are as follows:

Disease/Class	Total	Train	Valid	Test
Akiec	791	696	66	29
Bcc	1228	1071	111	46
Df	301	279	17	5
Vasc	340	297	30	13
Total	2660	2343	224	93

3.3 Heart Rate Monitoring Data Acquisition

In the case of the heart rate monitoring, the system receives face videos that are uploaded by the user and the videos are processed individually to produce the individual heart rate in response to video. The method takes advantage of real-time processing model, where one can record and post a face video directly. The system subsequently implements remote photoplethysmography (rPPG) technologies, mainly on the green channel to track pulse variations and be able to determine the heart rate.

3.4 Health Chatbot Data Source and Reliability

The chatbot about health works with Open AI GPT-4 model through an API key. Using this model, the chatbot will incorporate health tips and respond to user-related queries depending on localized circumstances.

In general, the approaches used in the three modules are equal to a powerful, effective, and user-friendly healthcare solution. Introducing AI-based solutions alongside trusted information gathering and processing

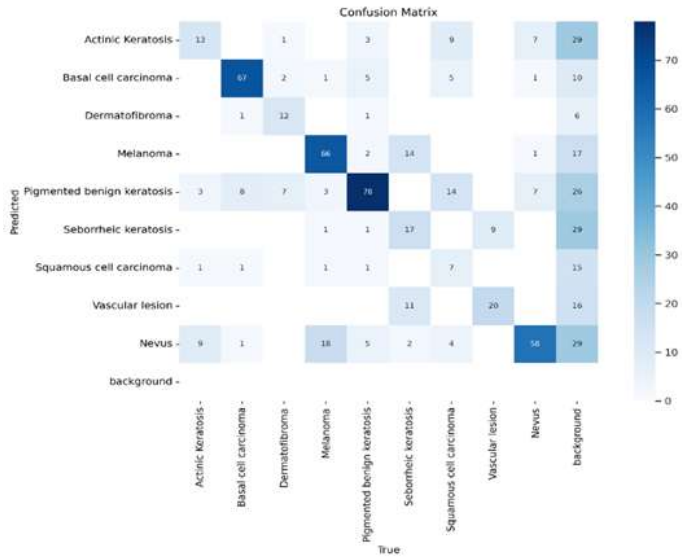

Figure 4. Confusion matrix of Dataset1 named as (Skin Cancer Recognizer)

pipelines, the Integrated HealthAI preconditions the creation of available and smart digital health services.

4 Results and Discussion

In this section, the performance of the three fundamental elements in the Integrated HealthAI system, which include Skin Cancer Detection, Heart Rate Monitoring, and the Health Chatbot, will be evaluated and interpreted. Different performance metrics, training trends, and confusion matrices and UI implementations are presented to have a broad overview of the effectiveness of the system and practical applicability.

4.1 Skin Cancer Detection

An object detection algorithm, which operates on the YOLO algorithm, is used in the skin cancer detection module. In order to test this module, three datasets are used, since they are unique in their own ways. The respective results get of all datasets are as follows.

4.1.1 Dataset 1: Skin Cancer Recognizer

This data set had 2.494 pictures and 9 different categories i.e. AKIEC, BCC, DF, MEL, PBK, SEK, SCC, VASC, and Nevus. The performance of the model was compared with the conventional metrics of classification (accuracy, precision, recall, and F1-score) in this dataset. These measures were used to determine the extent of differentiation of the possible types of skin lesions in the model.

Figure 4 indicates that the confusion matrix brings about the performance of all classes and indicates a significant imbalance in classes and numerous misclassifications. This illustrates the inherent difficulty of achieving high performance when classes have overlapping features or imbalanced sample sizes.

Figure 4 illustrates the classification performance of the model for skin cancer detection across nine classes (AKIEC, BCC, DF, MEL, PBK, SEK, SCC, VASC, Nevus).

Training Graphs

The training graphs indicating the performance of the model (in loss and accuracy).

Figure 5 illustrate the training and validation losses (box, classification, and DFL losses) and the evaluation metrics (precision, recall, mAP@50, and mAP@50-95) across epochs, showing consistent improvement over time.

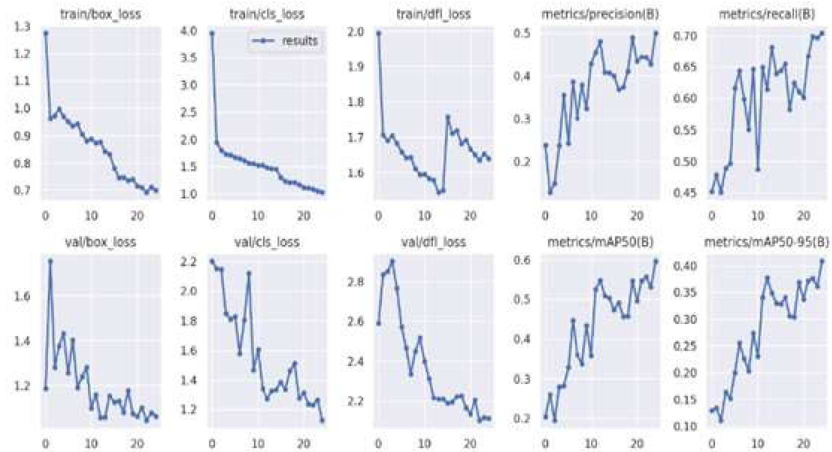

Figure 5. Training Graphs of Dataset1 named as (Skin Cancer Recognizer)

However, despite promising training behavior, the model's generalization ability was limited. Due to uneven class distribution and the relatively small number of samples in several categories, the model struggled to maintain high accuracy when tested on unseen data. These constraints have highlighted the significance of having balanced and representative datasets in medical imaging undertakings where mislabeling may result into grave misdiagnosis.

Overall, even though the Dataset 1 was a useful starting point, with its class balance, visual overlap between the lesions, and lack of data concerning some categories, it eventually restricted the ability of the dataset to be used once the final model is deployed.

4.1.2 Dataset 2: Malignant or Benign Computer Vision Project

This was a dataset of 527 images but the number of categories was only two benign and malignant. This task on binary classification was simple which enabled the model to score quite good performance in terms of the precision, recall and the F1-score which is evidenced by the confusion matrix illustrated in Figure 6. The majority of predictions were located in the diagonal signifying high rate of correct classification of benign and malignant samples.

Figure 6 illustrates the classification performance of the model for skin cancer detection across two classes (benign and malignant).

Training Graphs

The training graphs showing how well the model did (in terms of loss and accuracy).

The essential performance graphs are provided in Figure 7 in the form of training and validation losses (box loss, classification loss, and distribution focal loss) and precision, recall, and mean Average Precision (mAP50 and mAP50-95). The declining loss curves show efficient learning of the model, whereas the growing precision and recall show better detection performance as the training runs.

Besides, the model has a limitation in clinical applicability since the dataset is binary by nature. In actual dermatologic diagnosis, one has to differentiate between various types of skin lesions, most of which are similar in appearance. A two options policy, although useful in simple screening, cannot offer the precision of medical decision-making.

Altogether, despite the fact that Dataset 2 allowed rapid prototyping and showed high performance in a simplified environment, it is not capable of supporting the development of a strong diagnostic model because of its

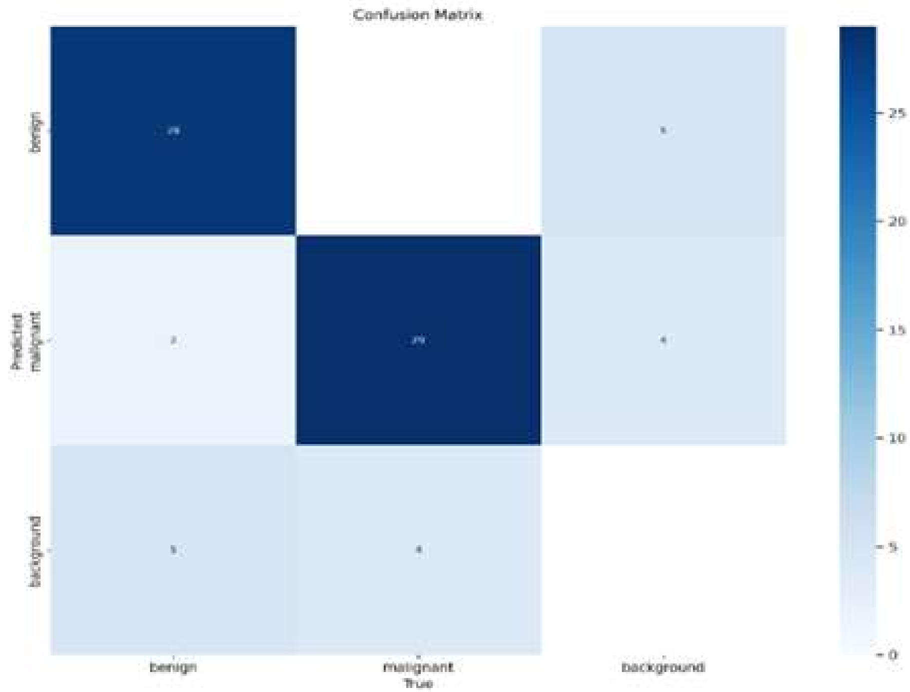

Figure 6. Confusion matrix of Dataset2 named as (Malignant or Benign Computer Vision Project)

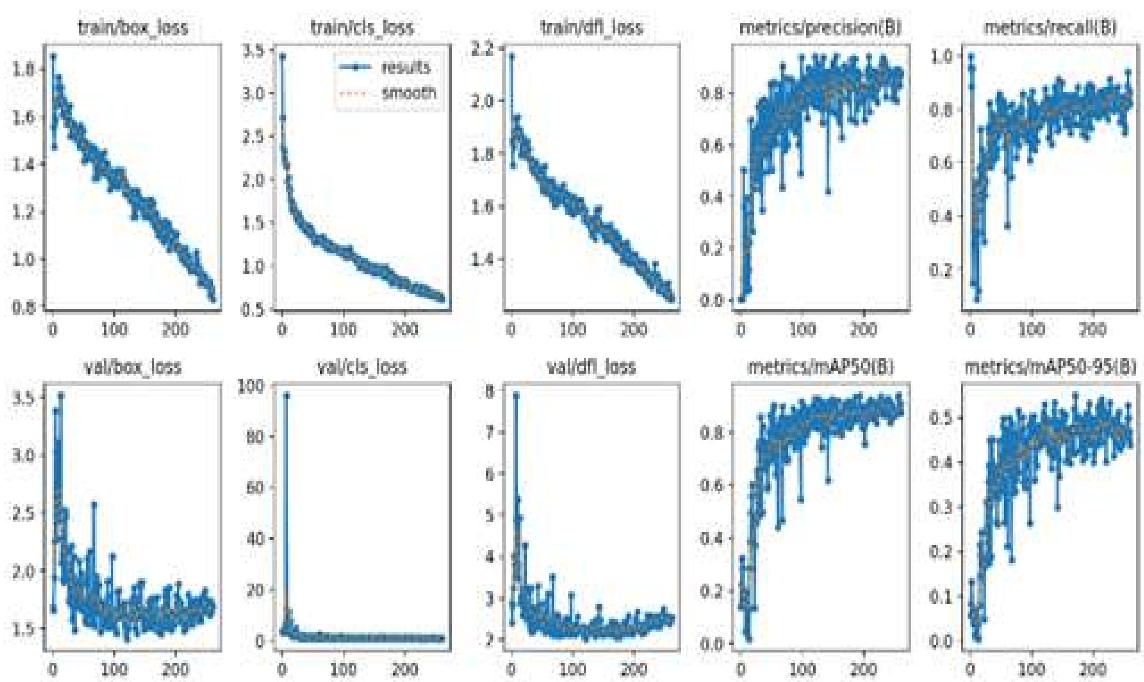

Figure 7. Training Graphs of Dataset2 named as (Malignant or Benign Computer Vision Project)

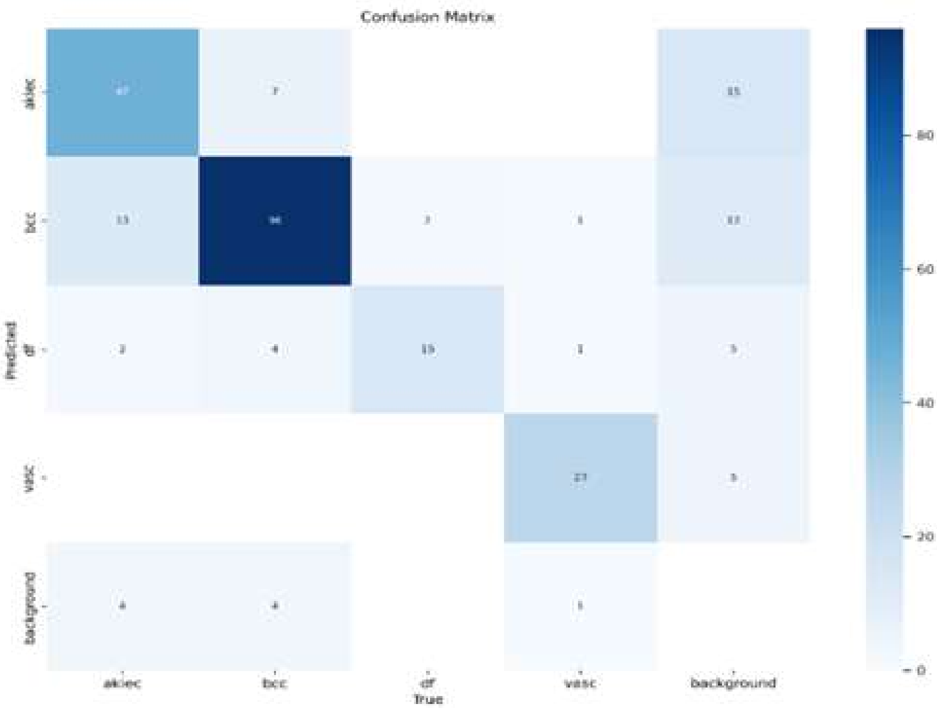

Figure 8. Confusion matrix of Dataset3 named as (Skin Cancer Classification)

small size, low diversity, and inability to distinguish between different classes. For clinically meaningful results, more complex and comprehensive datasets are necessary.

4.1.3 Dataset 3: Skin Cancer Classification

This dataset comprised 2,660 images spread evenly across four classes: AKIEC, BCC, DF, and VASC. Unlike previous datasets, this collection featured balanced class distribution, which played a crucial role in improving the model's predictive accuracy and reducing bias.

Figure 8 illustrates the classification performance of the model for skin cancer detection across four classes (AKIEC, BCC, DF,VASC).

Training Graphs

Figure 9 displays training loss decreases over time, indicating the model is improving its localization accuracy. The classification loss, which also decreases steadily, shows the model is getting better at predicting object classes.

Interpretation

Although the Skin Cancer Recognizer and Malignant or Benign Computer Vision Project datasets were available first for prototyping of the model, both have significant limitations that rendered them as unfit continent final modelling.

Skin Cancer Recognizer Dataset

This dataset is a bit larger with nine skin cancer categories and 2,494 images. It includes a wide variety of lesion types but is plagued with class imbalance and lacks the amount of samples for each class to achieve high accuracy. The model struggled to generalize due to it being very class dependent (View substantive Class Pairs). It also

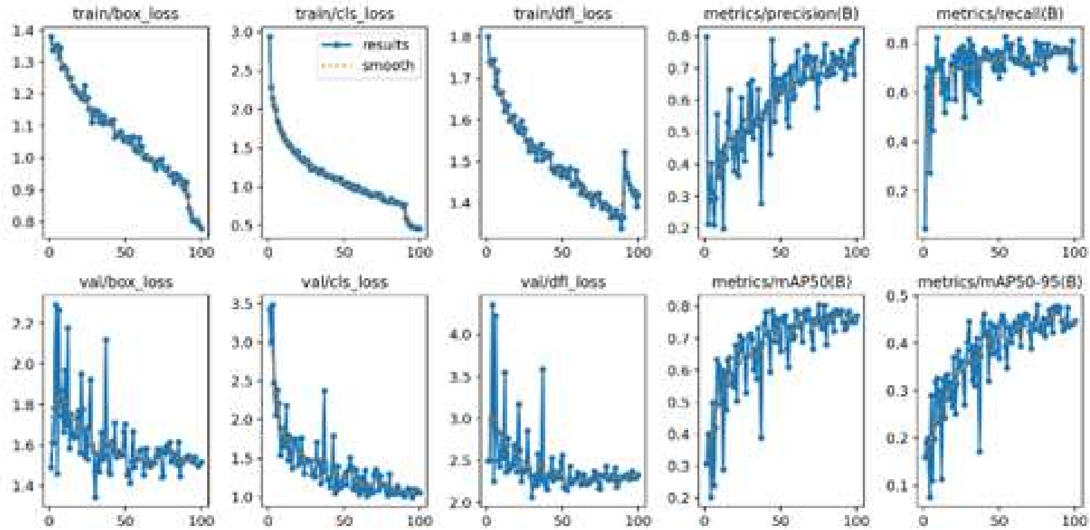

Figure 9. Training Graphs of Dataset3 named as (Skin Cancer Classification)

Figure 10. Interface of the AI Health Application

contained lesions sharing features, which might have been classified into the wrong category. For these reasons, it was not deemed accurate enough for final model training.

Malignant or Benign Computer Vision Project Dataset

This Dataset is Contains only 527 Images Into two classes: Benign and Malignant. Although it is a much simpler binary classification task, its small scale with simple patterns, the model was unable to generalize these complex patterns to make accurate predictions of skin cancer. Another problem that is related to the size of the dataset was that it can lead to overfitting since model may learn extremely detailed features which would not generalize well on other unseen skin lesions. The aim was to train a model that could generalize to different types of lesions, and as such this dataset alone could not be used.

In contrast, the Skin Cancer Classification Dataset was selected to develop final models because this set is larger, contains a wide variety of images and has better class distribution balance allowing for a more stable and strong model.

Figure 10 showcases the interface of the AI Health Application, featuring three key functionalities: Health Chat, Skin Cancer Detector, and Heart Beat Analyser.

The Skin Cancer Detector feature processes an uploaded image (akiectest0.jpg) and predicts the class as AKIEC. Similarly, it identifies BCC, VASC, or DF when corresponding images are uploaded.

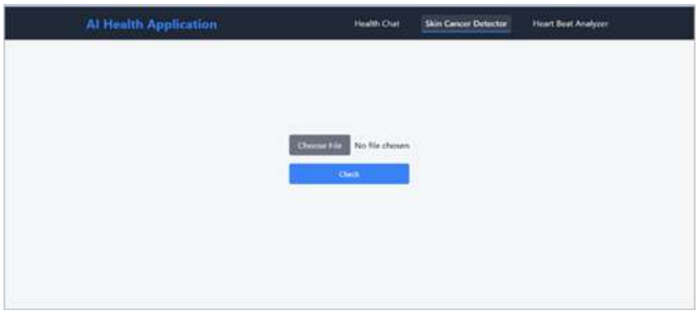

Figure 11. Skin Cancer Detection Module Interface

Figure 12. Detection outcome of Skin cancer Detector Module

4.2 Heart Rate Monitoring

The Heart Rate Monitoring module uses contactless rPPG techniques to estimate heart rate from facial video input. The system accurately detected facial ROIs and extracted green channel intensity changes to estimate pulse.

Figures 13 and 14 illustrate how users interact with the module and receive results in real time.

The Heartbeat Analyzer feature processes an uploaded video file (test.mp4) and calculates the heart rate. Similarly, it can process other video files to provide real-time heart rate analysis.

The Heart Rate Monitoring module, shown in Figure 13, allows users to upload a face video via the "Choose File" button and analyse their heart rate using "Check Heartbeat." As depicted in Figure 14, the system processes the video and displays the heart rate, offering a reliable, non-invasive health monitoring solution.

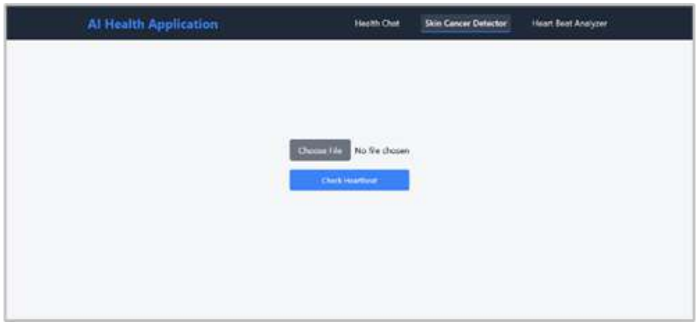

Figure 13. HR Monitoring Module Interface

Figure 14. Outcome of Heartbeat Analyser feature

Interpretation

The contactless heart rate monitoring module showed reliable performance for everyday wellness tracking. Though not a replacement for medical devices, it offers a convenient, non-invasive option for basic health monitoring.

4.3 Health Chatbot

The health chatbot, powered by OpenAI GPT-4, was integrated to handle real-time user queries on general health topics. As shown in Figures 15 and 16, the chatbot interface supports smooth interaction, offering users a seamless experience.

It provided informative responses on general health queries and common symptoms. To ensure responsible usage, the chatbot was deliberately limited from issuing medical diagnoses or emergency-related advice, and included clear disclaimers.

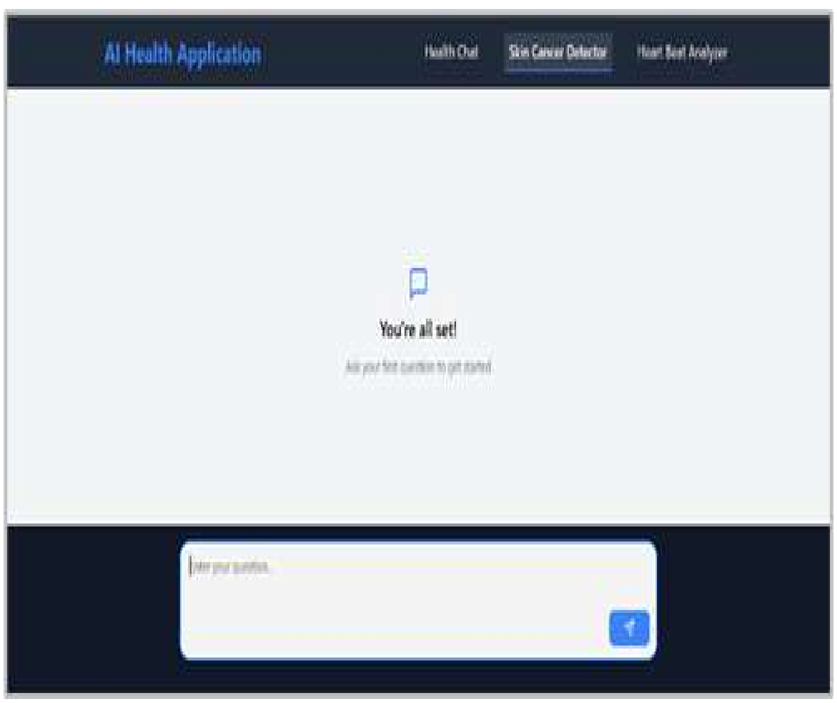

Figure 15. Health-related Chatbot Interface

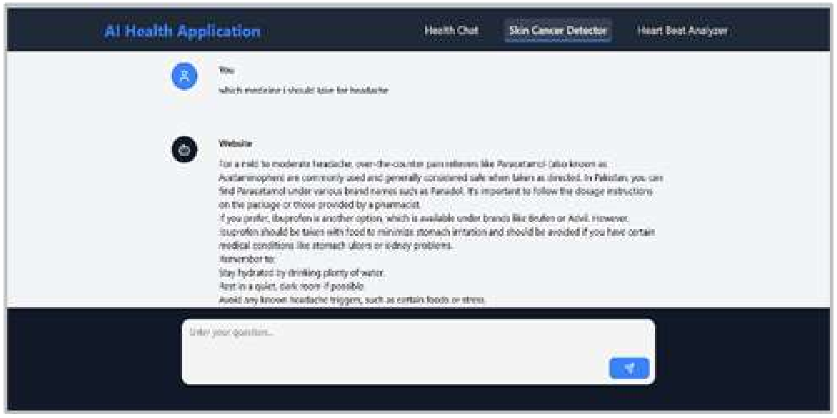

Figure 16. The Health Chat feature of the AI Health Application

The Health Chatbot Interface, as depicted in Figure 15, facilitates seamless interaction by allowing users to input health-related questions. Upon submission, the chatbot promptly analyses the query and provides a general response, as shown in Figure 16, ensuring a user-friendly and informative experience for individuals seeking instant health advice.

Interpretation

The chatbot adds significant value by offering users immediate access to general health information, especially in situations where healthcare professionals may not be readily accessible. While not a replacement for expert medical consultation, it serves as a supportive tool for health awareness and user engagement.

Overall, the results validate the practical potential of the Integrated HealthAI system. The skin cancer detection module demonstrated high diagnostic capability when trained on a balanced dataset. The heart rate monitoring system offered reliable contactless measurement, and the health chatbot provided responsive, informative support. Together, these modules contribute toward a user-friendly, AI-enhanced digital health platform aimed at early detection and general health assistance.

5 Conclusion

This research proposed the development of an AI-powered health application, having three key functionalities, such as skin cancer detection, heart rate monitoring, and chatbot to ask health-related queries. This project has shown the complete use of machine learning (YOLOv8) and NLP to improve diagnostic accuracy and accessibility in the health sector. The skin cancer detection module was able to accurately detect various conditions including actinic keratosis, basal cell carcinoma, vascular lesions, and dermatofibroma. However, heart rate monitoring system produced its output based on environmental factors, whereas chatbot was efficient in answering health related general questions.

Despite its successes, the project has a narrow dataset, a lack of awareness of the environment, and its chatbot responses are not personalized. Filling these gaps is a way forward for future work, and could include diverse dataset integration, expanded functionalities, and real-world clinical trials. This study highlights how AI can reshape healthcare systems by alleviating diagnostic burden on conventional clinicians and providing immediate and cost-effective solutions.

Author Contributions

Nimarta Davi: Conceptualization and supervision. **Bakhtawar:** Skin cancer model implementation. **Muhammad Tehmas Taj:** Heart rate module development. **zartasha Baloch:**Manuscript writing. **Bhavesh Kumar:** Health chatbot.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants.

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