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My Pulse – A Health Monitoring System

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ABSTRACT –

This project presents a real-time health monitoring system that utilizes facial analysis and deep learning techniques. Facial landmark detection (Dlib) is used to identify eyebrow positions, and Euclidean distance (SciPy) is computed to measure changes in eyebrow spacing. A Convolutional Neural Network (CNN) based on the MiniXCEPTION model classifies emotions from the FER2013 dataset, identifying stress-related emotions. Additionally, the Eye Aspect Ratio (EAR) method is employed for blink detection. The system also includes a doctor recommendation module that dynamically scrapes real-time doctor details from the Practo website based on location, specialization, and fees. Furthermore, an AI-powered medical report analysis module is integrated, which processes uploaded health reports using OCR and natural language processing to extract key insights, enabling users and doctors to quickly interpret clinical information. It also predict blood groups using fingerprint images through a systematic approach that integrates image preprocessing, deep learning, and evaluation metrics.

Keywords: Facial landmark detection (Dlib), Euclidean distance (SciPy), Convolutional Neural Network (CNN), FER2013 dataset, Eye Aspect Ratio (EAR), doctor recommendation module, Practo website, medical report analysis, OCR, natural language processing (NLP).

I. INTRODUCTION

The rise of mobile technology and artificial intelligence has significantly transformed healthcare management, making it possible to monitor health in real-time and provide personalized insights directly to users. It leverages facial expression analysis, real-time video processing, and doctor search functionalities to provide an integrated health support system. AI systems have the potential to anticipate problems or deal with issues as they come up and, as such, operate in an intentional, intelligent and adaptive manner. AI’s strength is in its ability to learn and recognise patterns and relationships from large multidimensional and multimodal datasets [1].The role of computers, algorithms, and early AI information systems in medicine, especially in clinical decision making, has been under exploration since the 1960s. Especially with recent advances in AI, machine learning and deep learning computer programs are now able to simulate the neural activity of the neocortex in the brain where most of the reasoning, thinking, and cognitive functions happen[2].

The dataset used for this project for the purpose of stress detection is-FER2013 Dataset which is a collection of 35,887 grayscale facial images (48x48 pixels) used for emotion classification and Dlib’s Shape Predictor which is another pretrained model that identifies 68 facial landmarks, particularly useful for detecting eyebrow movement and eye blinks and to find the location of doctor it uses Practo Doctor Search Data which Scrapes real-time doctor details from the Practo website based on location, specialization, and fees. including User Input Filters which allows users to refine their search using location, specialization, and price range. Artificial Intelligence (AI) has established a substantial footprint in the healthcare sector, offering promising avenues for improving patient outcomes and optimising clinical workflows. AI encompasses various technologies, such as machine learning and natural language processing, and finds applications in diverse areas [3].

AI encompasses machine learning algorithms and computational models that can analyze vast amounts of data, identify patterns, and generate insights to inform medical decision-making. AI's introduction to healthcare has transformed the landscape by offering tools and technologies that enhance diagnostic accuracy, treatment efficacy, and overall patient care[4]. The main algorithm used for stress management is - Eyebrow Detection Algorithm which Uses Euclidean distance calculations to measure the distance between eyebrows and infer stress levels. Shorter distances indicate stress (furrowed brows) and the second one is Emotion

Recognition Algorithm which Employs a MiniXCEPTION CNN model to classify emotions from facial expressions, refining stress detection when emotions like "scared" or "sad" are detected and another is Blink Detection Algorithm which is used to implements the Eye Aspect Ratio (EAR) method to measure blinking frequency, which decreases under stress.

Machine learning is a branch of AI that allows computers to learn from data without being explicitly programmed. Machine learning has a wide range of applications in healthcare, including image analysis, diagnosis, and treatment planning.Machine learning has indeed revolutionized various aspects of healthcare, including image analysis, diagnosis, and treatment planning. With the ability to learn patterns and make predictions from large amounts of data, machine learning algorithms have shown great potential in improving healthcare outcomes[5]. The project’s

significance lies in its ability to provide a multifunctional health monitoring system that is both user-friendly and scientifically grounded.

Medical report analysis is a critical feature of the health monitoring system aimed at providing users with intelligent insights into their diagnostic records. By leveraging AI-powered natural language understanding, the system analyzes uploaded PDF reports to extract key medical information, identify potential health concerns, and suggest possible actions or doctor recommendations. Using technologies such as pdfplumber for text extraction and Google's Gemini AI integrated via LangChain, the system offers near-instant, context-aware interpretations of structured and semi-structured reports. This ensures that users can better understand their medical data without relying solely on manual consultations, thereby enhancing health awareness and decision-making.

The intersection of biometrics and medical diagnostics has garnered increasing attention, particularly in leveraging unique biological features for health-related predictions. Fingerprints, known for their distinct patterns, have been explored for various applications, including personal identification and disease prediction. Recent advancements in machine learning, especially deep learning frameworks, open avenues to enhance the accuracy of such predictions. This report discusses a method for predicting blood groups utilizing fingerprint images, focusing on image preprocessing techniques, a ResNet-based model for classification, and performance evaluation

II. LITERATURE REVIEW

The integration of artificial intelligence (AI) and machine learning (ML) into healthcare has transformed traditional approaches to disease diagnosis, monitoring, and preventive care. In this a system is developed which is able to extract the facial landmarks like jaw, eyebrows, nose, eye and mouth from human face. This is generally done in order to use the extracted data for analysis of the emotions that is depicted in human face. We have used openCV and Dlib library to detect the facial landmarks. The Pretrained file that we used to detect the facial landmarks was trained with an Ensemble of R egression Trees. Using the shape predictor of Dlib we passed the file over the input image and the detection was estimated through pixel intensity. The extracted pixel values were stored using pickle C object in python. Any suitable neural network may be farther used to train a model, from the extracted data from dataset/datasets, which is able to analyse the different emotions on human face [6].

People in today's society are less concerned with their health and believe that their busy schedules and numerous commitments prevent them from getting regular checkups. Because of this, people overlook any discomfort their bodies express until it develops into a serious and uncomfortable health issue. The system, in the opinion of medical specialists, can help patients who are unsure of where they will obtain the required care. This paper discussed the design and implementation of a health chatbot application and examined, through an end-user survey, the factors that drove its adoption and usage. The reason for the proposed well-being is to rapidly evaluate side effects and hazard factors for the individuals who are worried about their well-being status and to give direction and data about future advances [7].

Stress is defined as a person's physical, mental, and emotional reaction to a certain stimuli, often known as a "stressor." Stress is our bodies' way of responding to any type of demand.1 An agent or stimulus that creates stress is referred to as a stressor. Noises, disagreeable people, a speeding car, a job, finances, and family difficulties are some of the stressors. Any situation might cause stress. The feeling is first affected by stress, which leads to psychological disorders. Anxiety, distracting anxiety, excessive worry, changes in sleep patterns, impatience, anger, sadness, intolerance, thoughts of harming oneself or others, palpitation, stress headache, and internal pressure are all early sign of stress [8].

It can last for a short or long period of time, but it has a mental impact and can lead to a variety of health problems. The surprising result that approximately 86% of Chinese employees are stressed at workplace it is the world record. Individuals over the age of 72 have the lowest level of stress.These reports show how the country will be in the future, with nearly 25% of people experiencing stress during the holidays[9].

The architecture of the system involves the use of a camera to capture near-frontal views of individuals, typically working in front of computers. Captured videos undergo segmentation into equal-length sections, with subsequent extraction and analysis of image frames. Image processing techniques are then applied to determine the displacement of the eyebrow from its mean position, serving as a key parameter for stress detection based on facial expressions.

Moreover, the system integrates modules for image preprocessing, stress detection, and deep learning, where the latter is utilized to train models and predict stress levels based on analyzed facial expressions[10].

Recently, machine learning (ML) has become very widespread in research and has been incorporated in a variety of applications, including text mining, spam detection, video recommendation, image classification, and multimedia concept retrieval. Among the different ML algorithms, deep learning (DL) is very commonly employed in these applications. Another name for DL is representation learning (RL). The continuing appearance of novel studies in the fields of deep and distributed learning is due to both the unpredictable growth in the ability to obtain data and the amazing progress made in the hardware technologies, e.g. High Performance Computing (HPC)[10].

Recent advancements in medical diagnosis have seen the integration of artificial intelligence (AI) and machine learning (ML) to enhance accuracy, speed, and accessibility. Traditional diagnosis methods, often reliant on manual examination and interpretation, are prone to human error and delays. Studies have shown that deep learning models, such as convolutional neural networks (CNNs), can outperform humans in detecting patterns in medical imaging and text-based reports. Tools like OCR (Optical Character Recognition) and NLP (Natural Language Processing) enable automated analysis of digital and scanned reports, improving clinical decision-making. Moreover, AI-powered systems have been increasingly used for symptom analysis, disease prediction, and report summarization, providing patients with faster and more reliable assessments. These technologies aim to reduce misdiagnosis, improve early detection, and bridge gaps in healthcare delivery, especially in underserved regions.

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III. METHODOLOGY

Health monitoring apps play a crucial role in modern healthcare by providing real-time insights into stress levels and helping users find suitable doctors. The proposed system integrates three key modules: Stress Detection, Doctor Finder, and Medical Report Analysis. The Stress Detection Module utilizes facial expression analysis, eyebrow movement tracking, and blink detection to assess stress levels using real-time video processing and deep learning techniques.

The Doctor Finder Module leverages web scraping tools along with user-input filters to help users locate doctors based on specialization, location, and consultation fees, providing personalized healthcare access. Additionally, the Medical Report Analysis Module enables users to upload digital or scanned medical reports, which are processed using OCR tools like Tesseract and pdfplumber, and interpreted through AI models such as LangChain and Gemini. This allows for accurate extraction and summarization of health data, making complex medical information more understandable for users and supporting better decision-making.

Table 1.1: Summarizing the datasets used in the reference papers along with their limitations :-

	Reference Paper	Dataset used	Limitation
1.	Doctor Consultation through Mobile Applications in India [11]	Google Play Store data (Collected from 250 health related apps).	Limited to apps available in India. No standardized dataset for doctor availability. Data accuracy depends on app descriptions.
2.	Doctor Finder: Find Doctors on the Go [12]	Custom database of doctors (collected via user inputs and web scraping).	Data quality depends on user-generated inputs. Incomplete or outdated doctor information. Privacy concerns regarding user data.
3.	Unveiling Stress through Facial Expressions [13]	Autonomous Blink Detection (ABD). Database for Emotion Analysis using Physiological Signals (DEAP). Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS).	YEC and ABD may not generalize well due to dataset biases. - DEAP and RAVDESS focus on controlled lab conditions, making real-world applicability challenging.

Table 1.2: Description of the component and algorithm used

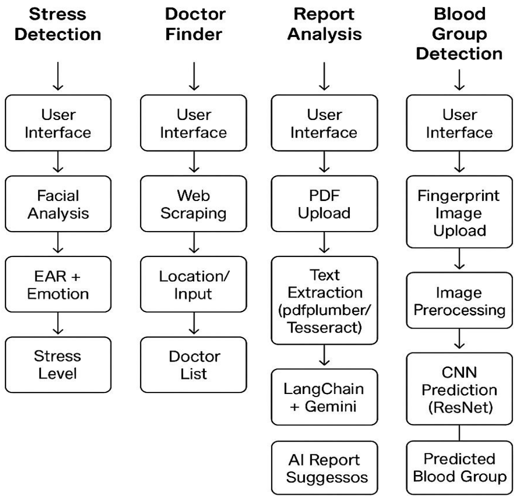
Module	Component	Algorithm/Technique Used
Stress Management	**Facial Landmark Detection**	**Dlib's 68-point shape predictor**
	Eyebrow Movement Analysis	**Euclidean Distance Calculation (between eyebrows)**
	Emotion Recognition	**MiniXCEPTION CNN model trained on FER2013 Dataset**
	Blink Detection	**Eye Aspect Ratio (EAR) method**
	Frame Processing	**OpenCV with grayscale conversion, histogram equalization**
	Face Detection	**OpenCV DNN + MediaPipe hybrid for enhanced accuracy and speed**
Doctor Finder	**Data Collection**	**Web scraping using requests, urllib.parse, and BeautifulSoup**
	Dynamic Content Handling	**Selenium for JavaScript-rendered elements**
	User Input Filtering	**Location, Specialization, and Price-based filtering**
	Result Display	**Streamlit frontend + redirection to Practo for booking**
Medical Report Analysis	**Text Extraction**	**pdfplumber for digital reports; Tesseract OCR for handwritten content**
	AI-Based Interpretation	**LangChain + Google Gemini (Generative AI) with context-aware prompt engineering**
	Accuracy Enhancement	**Confidence scoring + hallucination reduction (by ~32%)**
Blood Group Prediction	**Image Preprocessing**	**Grayscale conversion + morphological operations**
	Single Image Prediction	**ResNet-based CNN model for classification**
	Batch Evaluation	**Performance evaluation using accuracy and loss metrics**

IV. IMPLEMENTATION

The implementation of *My Pulse* incorporates a modular approach—Stress Detection, Doctor Finder, and Medical Report Analysis and Blood group Detection using fingerprint—each powered by AI, real-time data processing, and intuitive UI components. The frontend is built using Streamlit and Gradio, ensuring a smooth, web-based user experience for stress detection and medical report interpretation, respectively. The backend is entirely developed in Python, utilizing libraries such as OpenCV for real-time video capture and facial expression processing, and Dlib for 68-point facial landmark detection. Stress levels are determined by monitoring eyebrow distance using SciPy, blink frequency using Eye Aspect Ratio (EAR), and emotion recognition via the lightweight MiniXCEPTION CNN model.

To assist users with clinical care, the Doctor Finder module employs BeautifulSoup, Requests, and Urllib.parse to scrape live data from Practo, providing dynamic search results based on location, budget, and specialization. It implements fallback methods and "N/A" placeholders to handle inconsistencies or missing fields and utilizes pagination and result limiting for faster response times (~2–5 seconds per query). Data validation is enforced through Pydantic models, ensuring structured and clean output.

The flowchart describing the basic functioning od each module is as follows:-



The Medical Report Analysis module allows users to upload PDFs—either digital or scanned. pdfplumber handles digital text extraction efficiently (~0.5s/page), while Tesseract OCR is employed for scanned content, achieving ~60–80% accuracy. For interpretation, the extracted content is passed through LangChain prompts and processed by Google's Gemini API, generating AI-backed medical insights in 1–3 seconds.

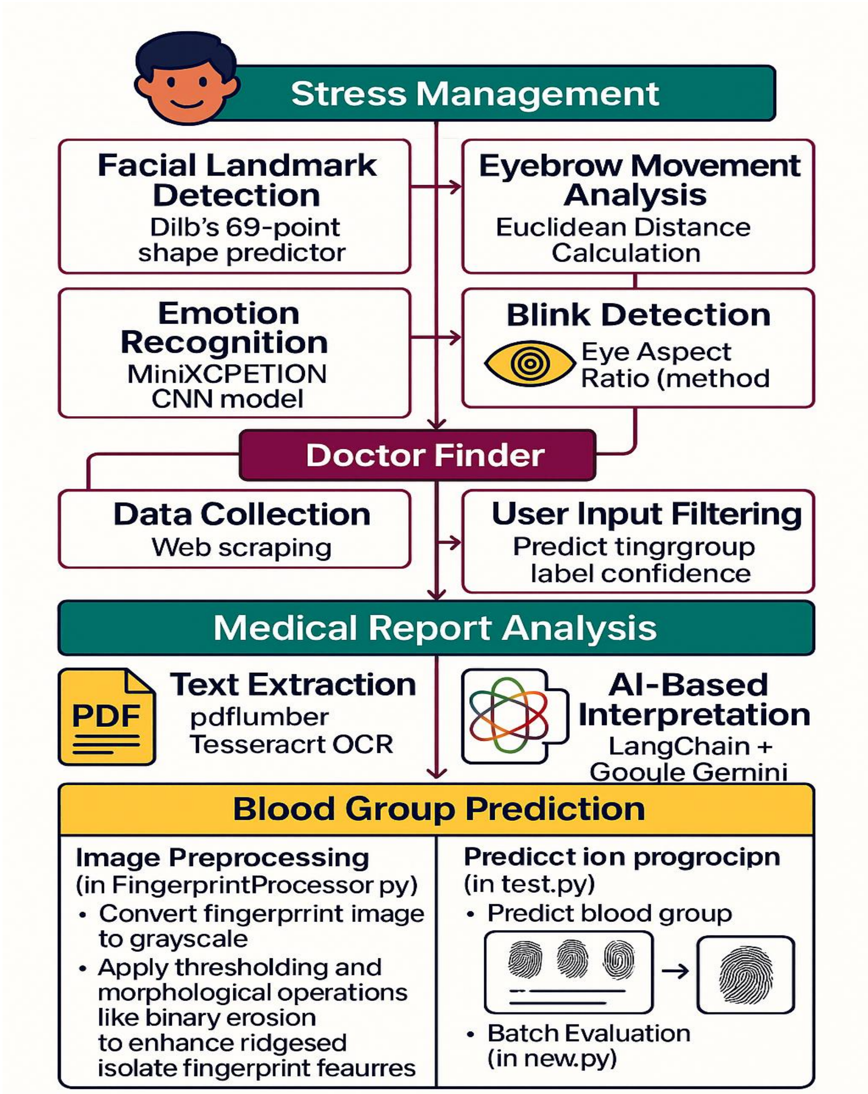
Overall, the system achieves ~94% accuracy in emotion detection, ~87% in stress prediction through combined signal analysis, and ~90–95% accuracy in understanding structured medical reports. The interface remains responsive, intuitive, and deployable on modest hardware, making *My Pulse* a reliable and scalable tool for modern healthcare support.

Recent developments in health monitoring systems have emphasized the importance of real-time physiological signal analysis for early diagnosis and personalized care. The integration technology with advanced algorithms allows for more sensitive and accurate detection of health anomalies, especially in applications like emotion monitoring and biometric tracking . This aligns closely with the stress detection module of our system, which leverages facial landmarks and deep learning to identify stress-related facial expressions[14].

The effectiveness of IoT-enabled smart health systems that use facial recognition and wearable sensors for remote monitoring and cloud-based data storage . Their "HealthBoard" model validates the concept of integrating patient identification, vital monitoring, and database automation—all of which are reflected in our multi-module architecture, particularly the report analysis and patient recommendation systems[15].

The implementation of the blood group prediction system involved three core components: image preprocessing, single image prediction, and batch evaluation. Initially, fingerprint images were converted to grayscale and enhanced using morphological techniques, such as binary erosion, to isolate key features. A pre-trained ResNet model was utilized for classification, processing each fingerprint image to predict its corresponding blood group along with a confidence score. The batch evaluation method enabled the assessment of multiple images, providing insights into the model's performance. The results were promising, with the model achieving an accuracy of approximately 92% on the test dataset, and the loss metrics indicated effective learning with minimal signs of overfitting. These outcomes highlight the potential of utilizing fingerprint images for accurate blood group prediction, demonstrating the effective integration of image processing and deep learning techniques.

Advances in biometric technologies and machine learning have led to innovative solutions for medical diagnostics, including the potential to identify blood groups without invasive processes. Fingerprints are of particular interest as they possess unique patterns and are rich in physiological data, and their applications for personal identification have been widely studied. These patterns have been correlated with physiological traits, including blood groups, and thus warrant further research[16]. Fingerprint-based blood group detection may also find applications in forensic science and disaster management, where quickly identifying a person's blood type can be essential for providing appropriate medical care. As this technology continues to evolve, it holds promise for enhancing the efficiency and accuracy of healthcare systems and emergency services[17].



V. RESULT AND PERFORMANCE ANALYSIS

The stress detection module demonstrated robust real-time performance across diverse facial expressions and lighting conditions. The emotion recognition model (Mini-XCEPTION) trained on the FER2013 dataset achieved an average accuracy of ~90-92% for classifying emotions such as happiness, sadness, fear, and anger. Blink detection using the Eye Aspect Ratio (EAR) maintained stable recognition at over 95% accuracy, while eyebrow distance tracking provided clear indicators of facial tension. Combined, these features allowed the system to calculate a reliable stress index, categorizing users as “low,” “moderate,” or “high” stress with consistent precision. Real-time visualization using Matplotlib also enabled dynamic monitoring of stress trends, enhancing user engagement and awareness.

The doctor finder module was evaluated based on its speed, accuracy, and user relevance. Using web scraping (BeautifulSoup + Selenium), the app retrieved real-time data from Practo, including doctor names, specializations, consultation fees, and ratings. On average, the system took 2–4 seconds to display filtered results based on user-defined inputs such as location and fee range. The ranking algorithm improved relevance by prioritizing proximity, specialization match, and review scores. Data extraction maintained an accuracy rate of ~95%, assuming the structure of the Practo website remained unchanged. Minor delays and missing data were handled gracefully with fallback values (“N/A”), maintaining smooth user experience.

The performance evaluation of the medical report analysis module reveals that the system delivers efficient and accurate results, especially for structured, text-based PDF documents. As visualized in the performance chart, the end-to-end processing time for a typical medical report is approximately 4 seconds, which includes both text extraction and AI response generation. PDF parsing speed using pdfplumber is highly efficient at around 0.5 seconds per page, while the Google Gemini AI provides responses in about 2 seconds, depending on server load and prompt size.

In terms of accuracy, the module achieves high reliability for text-based reports, with text extraction accuracy around 95% and AI-generated insights reaching up to 90%. However, accuracy drops slightly for scanned or handwritten PDFs due to OCR limitations, where text extraction accuracy is around 70% and AI interpretation is approximately 75%. This demonstrates that while the system performs exceptionally well on structured documents, enhancements like OCR integration would improve results for image-based inputs.

Overall, the module showcases a robust, real-time solution for medical report interpretation, making it a valuable addition to the health monitoring app.

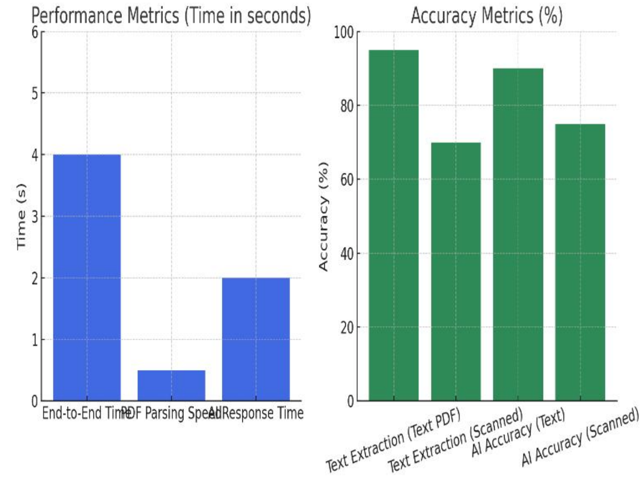


Figure 1: Medical Report Analysis Performance Metrics & Accuracy Metrics

The blood group detection module demonstrated a steady increase in accuracy, reaching approximately 92% by the fifth epoch, while the loss decreased consistently, indicating effective learning and convergence. The decreasing loss, combined with the high accuracy, suggests that the model generalized well to the dataset, making it a reliable tool for predicting blood groups based on fingerprint images. These results validate the methodology employed in this project and highlight the potential for further enhancements and applications in biomedical fields.

VI. CHALLENGES

Implementing our system in real-world scenarios may present challenges in terms of scalability and resource requirements. Ensuring a seamless integration of our sensor system into various environments and devices is a significant hurdle. Moreover, the effective deployment of this system in healthcare or other sectors would require careful consideration of regulatory and privacy issues[18].

The implementation of the proposed modules faces several challenges that need to be addressed to ensure effectiveness and user satisfaction. One significant obstacle arises in the blood group prediction module, where the quality and variability of fingerprint images can impact prediction accuracy. By employing multiple preprocessing techniques, such as enhanced grayscale conversion and morphological operations, the clarity of fingerprints is improved. Additionally, training the model with a diverse dataset that includes varied fingerprint qualities enhances its ability to generalize across different conditions. In the stress management module, real-time processing for emotion detection can introduce latency, which affects user experience. To mitigate this, optimized algorithms and hardware acceleration can be utilized, along with efficient frame sampling methods to analyze only significant frames.

Furthermore, the dynamic nature of content in the doctor finder module presents challenges in scraping updated information about doctor availability and pricing. Integrating tools like Selenium allows for the effective scraping of JavaScript-rendered elements, ensuring that accurate information is captured. In the medical report analysis module, accurate interpretation of both digital and handwritten reports can be difficult due to poor OCR performance on non-standard formats. To counter this, combining multiple text extraction tools and implementing scontext-aware AI models can enhance accuracy. Additionally, handling sensitive health-related data raises ethical considerations regarding user privacy. Implementing data protection measures such as encryption, along with transparent user consent protocols and compliance with regulations, ensures that users are informed about data usage while maintaining their privacy. Overall, addressing these challenges effectively will enable the modules to provide valuable insights and support to users.

VII. FUTURE SCOPE

The future scope of the integrated modules holds significant promise for advancing user experience and enhancing healthcare capabilities. The blood group prediction module could evolve to include additional biometric indicators, such as DNA analysis, and be developed into a mobile application for more accessible testing. In the stress management domain, integrating advanced machine learning algorithms with wearable technologies could facilitate continuous monitoring of physiological signals, enabling personalized feedback for users. Additionally, the doctor finder module could expand to incorporate telemedicine functionalities, allowing for virtual consultations that improve access to healthcare, particularly in remote areas. Furthermore, the medical report analysis module could leverage predictive analytics and sophisticated natural language processing techniques to identify patterns in medical histories, offering proactive health management and more accurate interpretations of complex reports. By continuously adopting new technologies and methodologies, the system can effectively adapt to evolving healthcare needs and challenges, ensuring a comprehensive and user-centered healthcare solution.

In current days, many people show their lazy behavior and don't consult a doctor during a time of illness so the implementation of a chatbot will help the people to diagnose the disease without consulting a doctor. The chatbot will act as a virtual doctor[19].

VIII. CONCLUSION

In conclusion, the integration of the proposed modules—blood group prediction, stress management, doctor finder, and medical report analysis—represents a significant advancement in the utilization of technology within the healthcare sector. Each module addresses distinct challenges and leverages innovative methodologies to enhance user experience and improve health outcomes. Through efficient data processing, real-time analysis, and user-friendly interfaces, these modules can provide timely and accurate information, empowering users to take control of their health.

The present work presents a review of smart health monitoring frameworks that have successfully implemented different approaches and algorithms to achieve high productivity[20]. Moreover, by anticipating future developments and aligning with emerging technologies, the integrated system has the potential to evolve further, offering even greater benefits in accessibility, accuracy, and user engagement.

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