LifeBot : AI health companion for everyone

Capstone Project Proposal

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Mentor Consent Form

I hereby agree to be the mentor of the following Capstone Project Team

Project Title: LifeBot : AI health companion for everyone

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Project Overview

LifeBot is an AI-driven healthcare system designed for real-time health monitoring and efficient medical data management. It simplifies complex health information, making it accessible and understandable for users, while providing continuous tracking of vital signs. The proprietary wearable, non-invasive device measures SpO_2, respiration rate, stress levels, blood pressure, body temperature, air quality index (AQI), pulse rate, arrhythmia detection, and glucose levels through Continuous Glucose Monitoring (CGM).

The system features multilingual output to cater to users with limited literacy, delivering health information in their preferred language. Integrated with the LifeBot mobile app, it generates detailed health reports, allowing users to upload medical records through scanning, PDF uploads, or direct device linking. AI algorithms organize and analyze health data, enabling users to track multiple reports in one place while automatically detecting health risks and recommending timely medical consultations.

LifeBot bridges the gap between traditional health monitoring and AI-driven insights by offering personalized guidance on diet and lifestyle adjustments based on individual health conditions. Its user-friendly design ensures accessibility for all, promoting proactive health management, early risk detection, and improved healthcare outcomes.

Problem Statement:

LifeBot: AI Health Companion for Everyone addresses the gap in personalized healthcare by integrating AI-driven non-invasive health monitoring, automated medical data management, and real-time risk detection, enabling proactive health management and timely medical interventions.

Need Analysis

"As a healthcare professional, I observe that managing health effectively is a struggle for countless patients. I strongly believe Life Bot is not just a technological advancement but a much-needed step toward a healthier future for society."

Dr. Harinder Jit Singh Gill (Fortis Hospital)

Vital signs are often not monitored regularly, and timely medical consultations are not accessed, leading to preventable complications. Continuous monitoring is required for chronic conditions like diabetes, hypertension, and cardiovascular diseases, but frequent hospital visits are not always feasible.

Life Bot offers an innovative AI-powered solution for non-invasive health monitoring, real-time risk detection, and seamless medical report management. It empowers users to track vital signs, receive early health warnings, and get personalized lifestyle recommendations. With a doctor recommendation feature, it ensures timely medical guidance, improving patient outcomes and reducing treatment delays. By integrating AI, real-time data, and digital health tools, Life Bot makes healthcare more accessible, proactive, and efficient, revolutionizing preventive care and easing the burden on hospitals.

Key Societal Needs & Solutions:

1. **Rising Chronic Diseases**: Conditions like hypertension, diabetes, and cardiovascular diseases require regular monitoring. LifeBot's glucose, blood pressure, and stress level tracking ensures proactive health management.
2. **Limited Healthcare Access**: People in remote areas lack specialized medical care. LifeBot's AI-based doctor recommendation system connects users with the right specialists based on detected risks.
3. **Medical Report Management**: Managing multiple reports is tedious and often leads to delayed diagnosis. OCR-based scanning and AI-driven organization help users track their health efficiently.
4. **Real-Time Health Alerts & Personalized Guidance**: LifeBot's real-time monitoring instantly notifies users of critical health changes, while its AI-driven recommendation engine provides personalized diet and lifestyle suggestions tailored to individual health data, ensuring timely action and effective management of medical conditions.

Literature Survey

Literature Review

The purpose of this review is to explore AI-based healthcare technologies, their applications, and limitations, positioning this study within digital health communication. It evaluates AI-powered health monitoring systems in proactive healthcare management and patient communication. The review covers Theoretical Orientation, Selection of Literature, Existing Systems and Technologies, Parameter Measurement, and Modern-Day Analysis, concluding with research hypotheses.

Theoretical Orientation

AI-powered healthcare integrates machine learning, biomedical engineering, and digital communication. Computational health informatics underpins AI-driven healthcare, enhancing accessibility, efficiency, and personalization. AI supports professional communication through real-time monitoring, risk prediction, and automated recommendations. The study follows human-AI collaboration theories, where AI assists rather than replaces human expertise, and incorporates user-centered design to enhance usability. AI-driven healthcare systems are evolving to enhance decision support and patient care. The integration of deep learning models in diagnostics and wearable health devices further demonstrates AI's potential in healthcare applications.

Selection of Literature Studies were selected based on:

- Topics Covered: AI-based health monitoring, non-invasive sensing, AI-driven risk detection, and medical data management.
- Search Strategy**:** Keywords such as "AI health monitoring," "wearable health devices," and "digital healthcare communication" in IEEE Xplore, PubMed, and Google Scholar.
- Inclusion Criteria**:** Peer-reviewed articles, conference papers, and reports (2020–2024) focusing on AI in healthcare.

A systematic review methodology was employed to ensure relevant and high-quality sources. Studies discussing sensor fusion techniques and AI-augmented medical imaging were also considered to provide a holistic understanding of modern advancements in digital health.

Existing Systems and Technologies

- AI-Powered Health Monitoring: Apple Watch, Fitbit (heart rate, SpO_2, stress), Biofourmis (biosensors, remote monitoring).
- Minimally Invasive Glucose Monitoring: Know Labs Bio-RFID (RF waves), SugarBEAT (skin-adhered CGM).
- AI-Based Health Report Management: Google Health AI (EHR analysis), IBM Watson Health (disease prediction, treatment planning).
- AI-Driven Risk Detection & Doctor Recommendation: Ada Health, Babylon Health (AI symptom analysis), QardioCore (arrhythmia detection).
- Personalized Diet & Lifestyle Guidance: MyFitnessPal, HealthifyMe (nutrition tracking), Lumen (breath analysis).

The landscape of AI-driven healthcare technologies continues to expand, with companies exploring the integration of real-time patient monitoring and predictive analytics to enhance personalized treatment plans. The emergence of federated learning for secure AI-based health data analysis also marks a significant shift in the way medical insights are derived and shared across platforms.

Parameter Measurement

- SpO_2: Transmissive pulse oximetry is more accurate than reflective methods.
- Stress: AI models improve real-time stress detection but require personalization.
- Blood Pressure: Cuff-based methods remain standard; cuffless validation is ongoing.
- Pulse/Arrhythmia: Image recognition enables low-cost hypertension screening.
- Respiration: FFT or Bandpass Filtering (0.1–0.5 Hz) extract frequency from ECG.
- Air Quality Index (AQI): Sensors detect CO_2, NH_3, NOx, PM2.5, PM10 for health risk assessment.
- Temperature: Infrared sensors measure body temperature via radiation.
- Glucose: CGM offers a minimally invasive alternative to traditional methods.

The integration of AI in biosensor technology has enabled real-time multi-parameter health monitoring, providing continuous data streams for improved predictive analytics. AI algorithms now enhance parameter measurement accuracy by compensating for external influences such as motion artifacts and environmental conditions, making health tracking more robust and efficient.

Modern-Day Analysis

- **Non-Invasive Stress Monitoring**: HRV and GSR-based models evolved into multimodal AI systems (2022–2024), with real-time edge computing enhancing detection but requiring personalization [14], [24].
- **Blood Pressure Monitoring**: Cuffless BP monitoring via rPPG and AI showed promise (2022–2024) but faced challenges in accuracy and validation [9], [16], [17].
- **Heart Rate & SpO_2**: Smartphone-based monitoring advanced (2023–2024), but wearable SpO_2 devices had high failure rates, limiting medical use [5], [6], [18]–[20], [22].
- **Air Quality Prediction**: AI/IoT-based monitoring improved with CNN-LSTM (2022–2024), but sensor accuracy and regional calibration remain challenges [1], [2], [15], [21].

Recent advancements in AI-driven wearable technologies have led to improved accuracy and reliability in health monitoring. However, challenges remain in the validation and regulatory approval of these AI systems, particularly for clinical applications. AI-based diagnostic tools are increasingly being adopted in clinical settings, but concerns regarding data privacy, standardization, and AI bias continue to be critical discussion points.

Research Hypotheses

H1: AI-powered multimodal stress monitoring surpasses traditional HRV-based methods.

H2: Cuffless BP monitoring achieves clinical accuracy with personalized calibration.

H3: AI-integrated SpO_2 monitoring enhances remote healthcare but is unsuitable for critical care.

H4: AI-driven AQI models improve health risk assessment but require region-specific calibration.

Objectives

1. To develop a non-invasive AI-powered health monitoring system that tracks key health parameters using advanced sensing techniques.
2. To utilize AI-driven analytics for real-time risk detection and automated health report management, enhancing medical decision-making.
3. To design a personalized health and lifestyle recommendation engine that tailors diet and wellness plans based on individual medical conditions.
4. To compare the efficacy and accuracy of the proposed system with existing healthcare technologies.
5. To ensure secure and scalable data management, integrating cloud storage and a user-friendly mobile interface for continuous monitoring and accessibility.

Methodology

Health Monitoring System Methodology:

1. Data Collection: Users input health data via monitoring devices using ESP32 micro-controller or scan medical reports using the app's camera-based scanner (React Native/Kotlin).
2. Data Handling & Storage: The backend (Node.js/Django/Flask) processes data, storing reports securely in PostgreSQL/MySQL on AWS S3/Google Cloud.
3. AI & Machine Learning: ML models (TensorFlow/PyTorch) detect health risks.
    - OCR (Google Vision/Tesseract) extracts text from medical reports.
    - NLP (spaCy/NLTK) analyzes scanned documents for insights.
4. Data Preprocessing & Standardization: Before analysis, raw medical data is cleaned, normalized, and converted into structured formats. This step ensures consistency in scanned reports and health readings, improving AI model accuracy.
5. Health Trend Analysis & Visualization: The system generates personalized health trends based on historical data, showing users insights like blood pressure fluctuations, glucose level variations, and fitness improvements through interactive charts.
6. Risk Detection & Doctor's Recommendation: The system detects health risks and alerts users via Firebase Auth/JWT. Doctor's Alerts recommend specialists based on detected conditions (e.g., cardiologist for heart issues).
7. Structured Data & Reports: A microservices-based admin dashboard provides structured insights for doctors.
8. Dietary Recommendations: AI suggests foods to avoid based on health conditions.
9. User Notifications: Users receive alerts on critical health risks and appointments.

Flowchart:

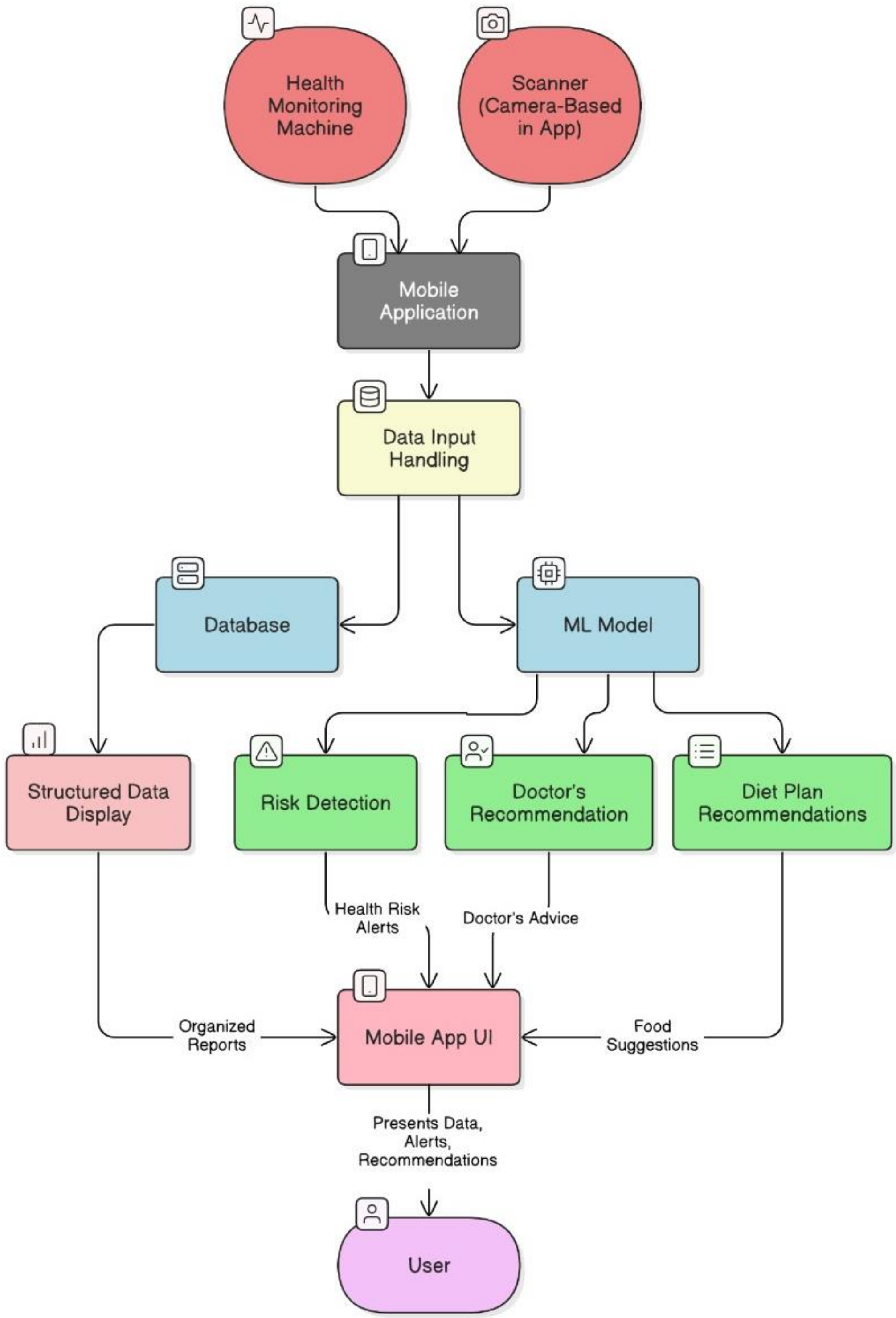

Fig1: System architecture flowchart detailing data acquisition, processing, risk detection, and user interface for the Health Monitoring Machine.

Work Plan

Sr. No.	Activity	Month	March				April				May				June				July				August				September				October				November			
		Week	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36
	Hardware																																					
1	Component Selection & Procurement	Plan	■																																			
		Actual																																				
2	Sensor Testing	Plan		■																																		
		Actual																																				
3	Caliberation	Plan			■																																	
		Actual																																				
4	Circuit Design & Simulation	Plan			■	■																																
		Actual																																				
5	PCB Design	Plan					■																															
		Actual																																				
6	Fabrication	Plan						■	■																													
		Actual																																				
7	Hardware Prototyping & Integration	Plan							■	■																												
		Actual																																				
8	Final Hardware Assembly & Enclosure Design (CAD Design)	Plan								■																												
		Actual																																				
	Software Architecture & Microservices Planning																																					
9	Define Microservices Components and Responsibilities	Plan									■																											
		Actual																																				
10	Architecture Design & Tech Stack Finalization	Plan										■																										
		Actual																																				
11	Database & Storage Design	Plan											■	■																								
		Actual																																				
	Frontend (Mobile App) Development																																					
12	UI/UX Design	Plan													■																							
		Actual																																				
13	App Development	Plan														■	■	■																				
		Actual																																				
14	Testing & Iteration	Plan																	■	■																		
		Actual																																				
	Backend & Microservices Development																																					
15	Microservices Implementation	Plan																			■	■																
		Actual																																				
16	API Gateway & Service Communication	Plan																					■	■														
		Actual																																				
17	Database Integration	Plan																							■	■												
		Actual																																				
	Machine Learning & AI Integration																																					
18	Data Collection & Preprocessing	Plan																									■											
		Actual																																				
19	Model Development	Plan																										■										
		Actual																																				
20	Model Deployment & Integration	Plan																											■									
		Actual																																				
21	Testing & Validation	Plan																												■								
		Actual																																				
	Integration, Testing																																					
22	Hardware-Software Integration	Plan																													■	■						
		Actual																																				
23	End-to-End Testing	Plan																															■					
		Actual																																				
24	User Acceptance Testing (UAT)	Plan																																■				
		Actual																																				
	Deployment & Maintenance																																					
25	Deployment	Plan																																	■			
		Actual																																				
26	Documentation & Training	Plan																																		■		
		Actual																																				
27	Documentation & Reporting	Plan																																			■	■
		Actual																																				

Fig 2: Project timeline outlining hardware, software, machine learning integration, and deployment phases.

1. The project timeline begins in March with hardware development, starting with Component Selection and Procurement in the first two weeks. This is followed by Sensor Testing in week 3 and Calibration in week 4. Circuit Design and Simulation take place in weeks 5 and 6, leading into PCB Design in week 7. Fabrication is scheduled for weeks 8 and 9, followed by Hardware Prototyping and Integration in weeks 10 and 11. The hardware phase wraps up with Final Hardware Assembly and Enclosure Design (CAD) in week 12.
2. In May, the focus shifts to Software Architecture and Microservices Planning. This begins with defining Microservices Components and Responsibilities in week 13, followed by Architecture Design and Tech Stack Finalization in week 14. Database and Storage Design is planned for weeks 15 and 16.

3. From June to mid-July, the team will work on Frontend (Mobile App) Development. This phase starts with UI/UX Design in week 17, leading into App Development from weeks 18 to 20. The phase concludes with Testing and Iteration in week 21.
4. The project continues with Backend and Microservices Development from late July to August. Microservices Implementation is scheduled for weeks 22 and 23, followed by API Gateway and Service Communication in week 24. Database Integration will take place in week 25.
5. In September, the focus shifts to Machine Learning and AI Integration. Data Collection and Preprocessing occur in week 26, followed by Model Development in weeks 27 and 28. Model Deployment and Integration is planned for week 29, and the phase concludes with Testing and Validation in week 30.
6. October is dedicated to Integration and Testing, starting with Hardware-Software Integration in week 31. This is followed by End-to-End Testing in week 32 and User Acceptance Testing (UAT) in week 33.
7. Finally, in November, the project moves into Deployment and Maintenance. Deployment is scheduled for week 34, followed by Documentation and Training in week 35. The project wraps up with Documentation and Reporting in week 36.

Project Outcomes & Individual Roles

Table 1: Team Member Roles and Responsibilities (Individual Roles)

Team Member	Responsibilities
Kartik	- Sensor Testing
	- Calibration
	- Circuit Design & Simulation
	- PCB Design
	- Fabrication
	- Hardware-Software Integration
	- Deployment
Aditya	- Hardware Prototyping & Integration
	- Component Selection & Procurement
	- Final Hardware Assembly & Enclosure Design (CAD Design)
	- Database & Storage Design
	- Database Integration
	- Model Development
Harnoor	- Define Microservices Components and Responsibilities
	- User Acceptance Testing (UAT)
	- API Gateway & Service Communication
	- UI/UX Design
Dharam	- Architecture Design & Tech Stack Finalization
	- End-to-end-Testing
	- Microservices Implementation
	- Data Collection & Preprocessing
	- Model Deployment & Integration
	- Testing & Validation
Shwet	- App Development
	- Testing & Iteration
	- Documentation & Training
	- Documentation & Reporting

Project Outcomes:

1. Fully functional AI-powered health monitoring device.
2. Mobile application (iOS & Android) for user interaction and data access.
3. AI-driven backend system for health data analysis and report management.
4. Cloud-based health record storage and management system.
5. Documentation and research findings on system performance, usability, and future scalability.

Course Subjects

1. UEC001 Electronics Engineering
2. UNC504 Artificial Intelligence
3. UEC716 Database Management Systems
4. UEC612 Digital System Design
5. UEE612 Machine Learning Techniques

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