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AI-Powered Patient Health Monitoring System Using Flask

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Abstract: *This paper presents an efficient approach to the AI-Powered Patient Health Monitoring System. It is a web-based application built with Flask that tracks and analyzes patient vitals while providing AI-driven health insights. It supports user authentication, real-time monitoring, and data management in JSON format. Patients can log in to update vitals like temperature, heart rate, and oxygen levels. Integrated with the Bard API, it generates detailed health reports and predicts diseases such as pneumonia and asthma using a vitals-based model. The modular system includes a Flask backend, data processing scripts, and REST APIs for real-time assessments. Future upgrades may include database integration, advanced diagnostics, and wearable device compatibility, offering a scalable, intelligent solution for digital healthcare.*

Keywords: AI-Powered Health Monitoring. Flask Web Framework, Patient Vitals Tracking, Disease Prediction Model, Bard API Integration, Real-Time Monitoring

I. INTRODUCTION

In today's digital healthcare ecosystem, preventive care and real-time health tracking have become essential for timely interventions and improved public health outcomes. The AI Powered Patient Health Monitoring System Using Flask is a web-based application that enables individuals to input, update, and monitor their vital health parameters through an intuitive interface. Built using the lightweight and scalable Flask web framework, the system provides a secure backend for user authentication, structured data management, and real-time health monitoring. Patients can track critical metrics such as body temperature, blood pressure, heart rate, respiratory rate, glucose levels, and oxygen saturation. The use of JSON-based data storage ensures efficient record keeping, fast processing, and smooth integration with external APIs, healthcare applications, and cloud platforms. Flask sessions and encrypted API calls reinforce security and privacy, restricting access to authorized users only and protecting sensitive health data against breaches. The system is optimized for accessibility and user-friendliness, allowing individuals from all age groups and technical backgrounds to monitor their health with ease.

What sets this system apart is its integration with the Bard API, enabling real-time AI-powered analysis of patient vitals. Leveraging machine learning algorithms, the system interprets health trends, detects abnormalities, and predicts potential risks such as hypertension, diabetes, and respiratory disorders like COPD and asthma. Personalized health reports and actionable recommendations are generated instantly, alerting users to seek medical attention when necessary and suggesting lifestyle changes or diagnostic tests. This proactive approach bridges the gap between expensive in-person consultations and timely disease detection.

II. LITERATURE SURVEY

A. Esteva, B. Kuprel, R. A. Novoa, et al.	2017	Dermatologist-Level Classification of Skin Cancer with Deep Neural Networks	Nature
S. Ioffe and C. Szegedy	2015	Batch Normalization: Accelerating	Proc. ICML

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		Deep Network Training by Reducing Internal Covariate Shift	
A. G. Howard et al.	2017	Mobile Nets: Efficient Convolutional Neural Networks for Mobile Vision Applications	arXiv
P. Rajpurkar, J. Irvin, K. Zhu, et al.	2018	Deep Learning for Chest Radiograph Diagnosis	IEEE Trans. Med. Imaging
G. Hinton, L. Deng, D. Yu, et al.	2012	Deep Neural Networks for Acoustic Modeling in Speech Recognition	IEEE Signal Processing Magazine
D. P. Kingma and J. Ba	2014	Adam: A Method for Stochastic Optimization	arXiv
A. Vaswani, N. Shazeer, N. Parmar, et al.	2017	Attention is All You Need	Proc. NeurIPS
K. Simonyan and A. Zisserman	2014	Very Deep Convolutional Networks for Large-Scale Image Recognition	arXiv
C. Szegedy, W. Liu, Y. Jia, et al.	2015	Going Deeper with Convolutions	Proc. CVPR
J. Devlin, M. Chang, K. Lee, and K. Toutanova	2018	BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding	arXiv
T. Brown et al.	2020	Language Models are Few-Shot Learners	NeurIPS
F. Pedregosa et al.	2011	Scikit-learn: Machine Learning in Python	J. Mach. Learn. Res.
Y. LeCun, Y. Bengio, and G. Hinton	2015	Deep Learning	Nature

III. METHODOLGY

The Vital Data Collection and Storage module forms the foundation of the system's health monitoring process. Users begin by inputting essential health vitals such as body temperature, blood pressure, heart rate, respiratory rate, blood glucose levels, and blood oxygen saturation. The system is designed to validate this input to ensure data accuracy and consistency with medically accepted ranges. Once validated, all patient vitals are securely stored in a structured JSON format, enabling lightweight, fast, and scalable data management essential for real-time applications. In the AI-Powered Health Assessment stage, the system intelligently interprets the vitals entered by the user. If the values fall within healthy thresholds, they are simply displayed on the user's dashboard for tracking and reference. However, if the input shows signs of abnormality, the system triggers an advanced AI analysis by sending the collected vitals to the Bard Bot API. This AI engine processes the data based on clinical standards and returns a comprehensive evaluation, supporting faster identification of potential health issues. The returned report contains Comprehensive Health Reports and Risk Analysis, broken down into three key components: health summaries, risk assessments, and personalized recommended actions. These insights allow users to understand their overall health status and any potential dangers associated with their current vitals.

This flow diagram illustrates the core operational workflow of the AI-Powered Patient Health Monitoring System. The process begins when a user registers or logs in and gains access to the dashboard to enter or update their vital signs. After validating the input, if the vitals are within normal range, the system stores the data and displays it on the dashboard. If abnormalities are detected, the system triggers AI analysis using the Bard API, which generates a personalized health report. The AI report is assessed for potential health risks. If no risk is found, the system notifies the user that their health is normal. If risks are detected, the system predicts possible diseases, alerts the user, and provides tailored medical advice. The user can then take action such as consulting a doctor or making lifestyle changes.

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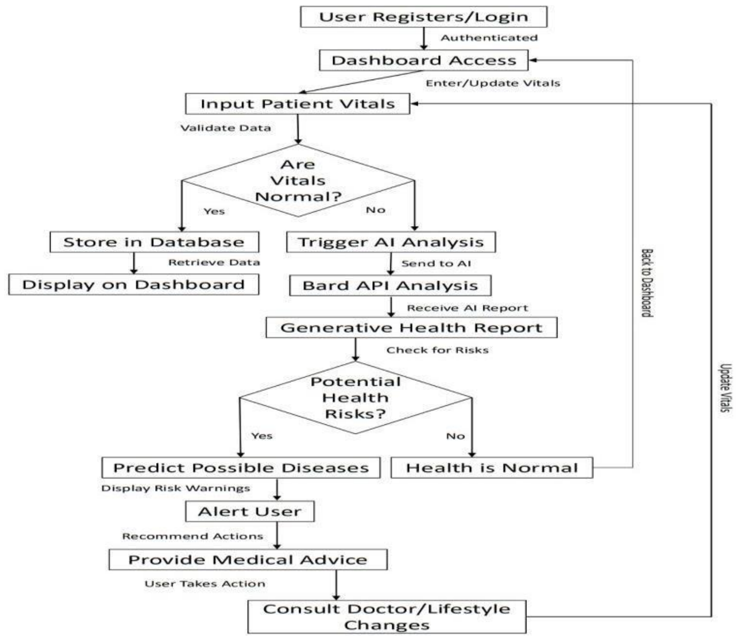

IV. RESULTS

The AI-Powered Patient Health Monitoring System effectively tracked vital signs over a 10day period and identified meaningful patterns that contribute to proactive healthcare. Among all monitored vitals, blood pressure showed the highest abnormal frequency, occurring five times. This persistent elevation in both systolic and diastolic readings is an early indicator of potential hypertension. Additionally, blood glucose levels crossed the normal threshold twice, signaling possible metabolic instability and a heightened risk of diabetes. No irregularities were recorded for other vitals such as heart rate, oxygen saturation, respiratory rate, and body temperature, suggesting general stability in cardiovascular and respiratory functions during the observation period. Through machine learning algorithms and the Bard API, the system predicted disease risks and distributed them based on abnormality frequency and severity. The resulting predictions emphasized hypertension (71.4%) as the most probable health condition, followed by diabetes (28.6%). These predictions align closely with the data collected, reaffirming the AI's reliability in trend detection and health risk assessment. The system provided actionable insights and lifestyle recommendations to address these conditions, demonstrating the value of AI-assisted diagnostics in promoting early intervention, reducing clinical visits, and empowering users to take charge of their well-being.

The Fig 2: Abnormal Vital Count Over 10 Days offers a visual summary of how often each monitored vital sign deviated from medically accepted ranges. It clearly illustrates that blood pressure experienced the highest frequency of abnormal readings (5 times), followed by blood glucose (2 times), while all other vitals maintained a count of zero. This visualization helps prioritize health interventions, showing that efforts should be concentrated on managing blood pressure through diet, stress control, and possible medication. The clear height difference in bars emphasizes which vital signs demand immediate attention. The Fig 3: Predicted Disease Risk Distribution, breaks down the AI-generated health predictions into proportional risks. According to the analysis, 71.4% of the predicted health threats were related to hypertension, while 28.6% were linked to diabetes. This segmentation helps users and healthcare professionals understand the dominant health concerns based on recent vitals. The circular layout is particularly effective for showing the weight of each condition in the overall diagnosis, reaffirming that blood pressure management should be the highest priority. It also reflects the accuracy of AI in converting raw vital sign data into understandable, risk-based insights.

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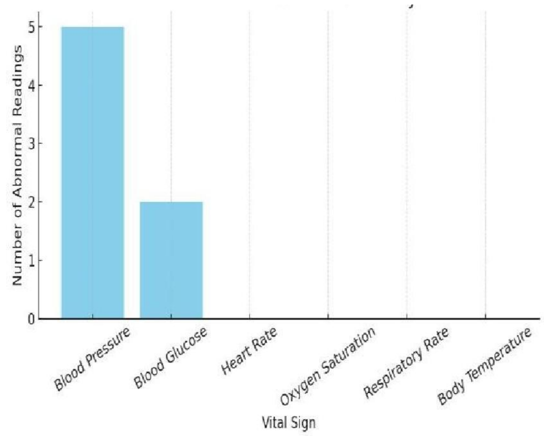

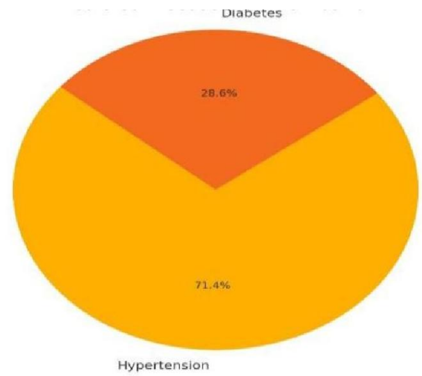

V. CONCLUSION

The AI-Powered Patient Health Monitoring System is an advanced healthcare solution that uses a Flask-based backend, AI analysis via the Bard Bot API, and real-time vital tracking to enable continuous monitoring and early disease detection. With a secure, user-friendly interface, patients can log in, input vitals, and receive AI-generated assessments and personalized recommendations. Leveraging machine learning, the system detects abnormal health trends and predicts risks such as hypertension, diabetes, cardiovascular, and respiratory issues. Graphical and statistical analyses highlight key risk patterns—71.4% hypertension and 28.6% diabetes—helping users and providers prioritize care. The system supports integration with IoT devices, EHRs, and remote monitoring, delivering real-time alerts and personalized health insights. This proactive, data-driven approach empowers users to manage their health effectively, promoting early intervention, better outcomes, and improved quality of life.

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