HealthUp: An AI-Powered Multilingual Healthcare Assistant Using Gemini and Retrieval-Augmented Generation

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Abstract : The project "HealthUp: Digital Health Assistant for Smart Care" is designed to create a smart healthcare system that uses Artificial Intelligence (AI) to help doctors and patients.It offers features like automatic diagnosis, easy understanding of lab reports, communication in multiple languages, and better management of medical appointments. The system uses Gemini and Retrieval-Augmented Generation to look at user symptoms, check medical information, and give smart health advice. The platform works as an AI-powered virtual healthcare assistant using open-source NLP models. It offers features like symptom-based diagnosis, health advice, automatic explanation of lab reports, secure storage of patient records, scheduling of appointments between doctors and patients, and sending WhatsApp-based notifications with support for multiple languages.The frontend is built using React.js, TypeScript, and Tailwind. CSS is used for the frontend, while the backend is built with Node.js, PostgreSQL, and. Supabase for secure data handling. AI components are deployed using open-source Gemini frameworks integrated with RAG pipelines to ensure efficient and context-aware medical care reasoning. Overall, this system addresses critical challenges in healthcare accessibility, complex data interpretation, and teleconsultation management by empowering patients with understandable insights, assisting doctors in decision-making, and bridging communication gaps across diverse languages.

IndexTerms **- AI in Healthcare, Gemini, RAG, Symptom Checker, Telemedicine, React.js, Node.js, Supabase, Multilingual AI, HealthUP Lab Report Analysis,**

INTRODUCTION

The rapid advancement of digital healthcare technologies This has caused a big rise in the amount of medical information. including electronic health records, diagnostic reports, and patient histories. Managing and interpreting this data efficiently remains a critical challenge for both healthcare. professionals and patients. Traditional healthcare systems largely depend on manual processes, which often result in errors and inefficiencies. delays, misinterpretation of medical data, and limited accessibility, especially in resource constrained environments. Patients frequently face difficulties in understanding Complex medical terminology present in lab reports, while healthcare providers have to handle a lot of different types of data within a short period of time. Another thing is that language differences and not having instant help also make it harder to provide good healthcare. These challenges show that we need smart systems that can make medical information easier to understand and help with making decisions. New developments in Artificial Intelligence, especially in the area of Natural Language Processing, have made it possible to create smart healthcare solutions. AI systems can look at messy medical information and give useful information to help with diagnosis and support for patients [3], [7]. The development of large language models has greatly improved the ability to understand context and create responses that feel natural, especially in medical uses [1], [10]. Also, using Retrieval-Augmented Generation (RAG) with large language models has made AI systems for healthcare more reliable and accurate.This is because it combines the ability to get up-to-date information with the power to generate useful responses [2], [4]. These technologies allow doctors to diagnose conditions more accurately, understand medical reports better, and communicate more effectively with patients. Even with these improvements, many current systems don't include features like support for multiple languages, instant diagnosis, and full healthcare management all in one place. To fix these issues, this paper introduces HealthUp, an AIbased multilingual healthcare helper that uses Gemini and Retrieval-Augmented Generation (RAG) to offer smart medical assistance. The system helps with diagnosing based on symptoms, automatically understanding lab reports, booking appointments, and keeping health records safe, which makes healthcare easier to reach, faster, and better understood by patients.

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HealthUp uses Gemini along with Retrieval-Augmented Generation (RAG) to give precise and context-sensitive medical help. It also allows for communication in many languages, keeps patient information safe, and connects with other healthcare services, helping make healthcare easier, more trustworthy, and faster for both patients and medical staff.

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RELATED WORK

Recent improvements in Artificial Intelligence have made significant changes in healthcare, especially in diagnosing illnesses, helping patients, and understanding medical information. Using Natural Language Processing (NLP) and large language models (LLMs), it is now possible to intelligently analyze unstructured medical information. These AI systems help examine symptoms and provide better, context-aware medical insights, leading to more accurate diagnoses [1]. Using LLMs along with Retrieval-Augmented Generation (RAG) systems helps make medical responses more trustworthy by incorporating information from reliable external sources [2], [4]. These methods help reduce misinformation and improve decision-making in medical settings.

Healthcare assistants using natural language processing have been widely studied to enhance patient interaction and understanding of medical information. These systems enable automatic replies to patient queries and assist with initial diagnosis [3], [7]. However, many of these systems do not integrate well with advanced reasoning models or real-time data sources.

There is also growing interest in multilingual healthcare systems, as serving people who speak different languages is critical. Studies indicate that using large language models in multilingual systems greatly enhances user interaction and communication on healthcare platforms [6]. Researchers have proposed using NLP techniques to automatically generate summaries of lab reports, making complex medical information more accessible to patients [5].

Cloud-based healthcare systems have improved data storage, scalability, and access. Platforms using up-to-date databases like PostgreSQL and Supabase allow for secure and efficient patient record management [8]. AI-based scheduling systems have also improved patient engagement by automating appointment booking and reducing waiting times [9]. Despite these improvements, many existing systems still lack integrated diagnosis, lab report interpretation, multilingual communication, and appointment management in a single platform. Comparative studies of modern large language models show that Gemini-based systems have strong potential for healthcare applications [10]. The proposed system addresses these issues by combining Gemini with RAG in a unified healthcare assistant, offering accurate, scalable, and multilingual medical support.

PROPOSED SYSTEM

A. System Overview

HealthUp is a digital healthcare assistant that uses AI to offer intelligent and user-friendly medical support. The system integrates several healthcare features, including symptom-based diagnosis, automated lab report interpretation, multilingual interaction, and appointment scheduling within a unified platform.

The primary goal of the system is to make healthcare more accessible and efficient through advanced AI methods. Using large language models along with Retrieval-Augmented Generation allows the system to generate context-aware and reliable medical insights [2], [4]. HealthUp provides users with real-time support and simplifies complex medical information.

B. System Architecture

The structure of the HealthUp system is built with several layers to ensure scalability, modularity, and efficient data handling. The system comprises five main components: the Frontend Layer, the Backend Layer, the AI Layer, the Database and Storage Layer, and the Deployment Infrastructure.

The Frontend Layer is developed using React.js for the web application and React Native for the mobile app, with all communication secured through HTTPS/TLS and JWT Authentication. The Backend Layer is powered by Node.js with Express Server, handling RESTful API endpoints for Authentication, Appointment Service, Health Records Service, and AI Engine Integration. The AI Layer utilizes open-source Gemini LLM for the AI Terminal, along with an AI Chatbot Interface and Lab Report Module. The Database and Storage Layer employs Supabase (PostgreSQL) for relational data, Redis for caching, and AWS S3 Cloud Storage for file management. The Deployment Infrastructure leverages Docker Containers for backend services hosted on AWS ECS/EKS, while the frontend is deployed on Netlify.

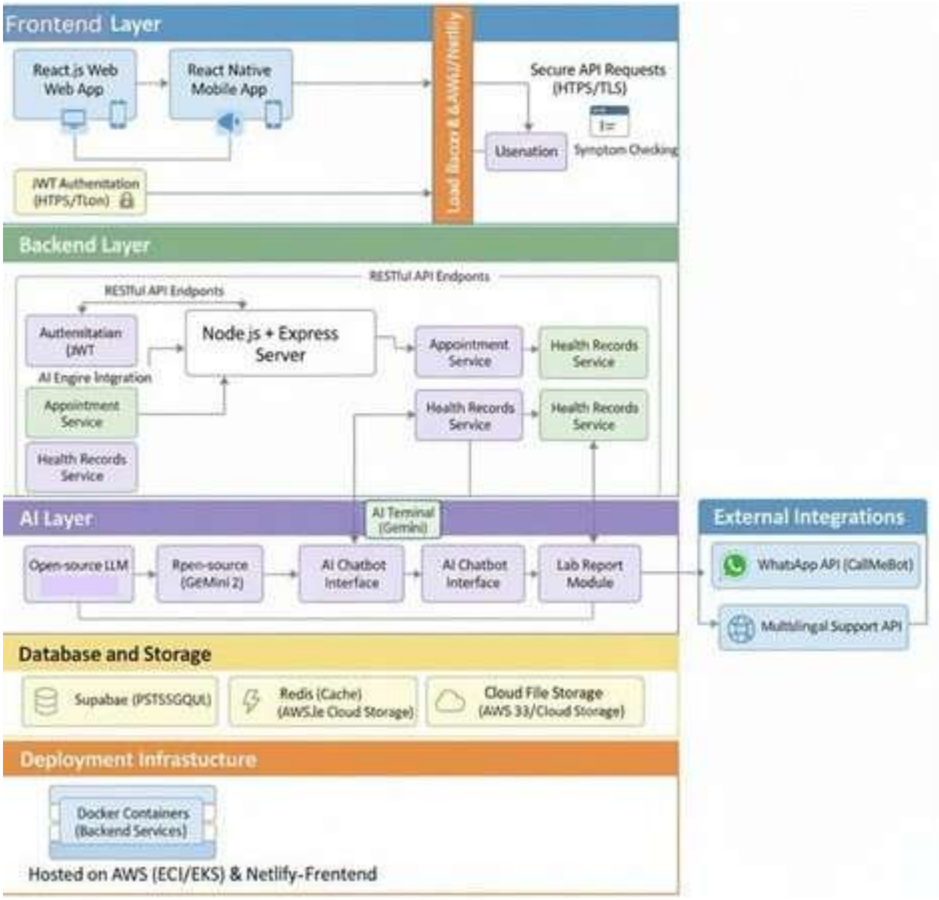

Fig. 1. System Architecture

C. System Workflow

The system workflow begins with User Login / Authentication, where patients and doctors log in via secure credentials. Patients can then navigate to the Symptom Report / Request Checker to enter their symptoms, which are processed by the AI Engine using LLM and RAG processing (including NLP with RAG and medical corpus calls for AI). The AI generates a Diagnosis Generation / Report Simplification with simplified diagnosis and report analysis. For appointments, users access Appointment Scheduling and Notifications to manage schedules and receive WhatsApp notifications. The Help Manager maintains health records. Doctors access the Doctor Dashboard and Record Access to view patient reports and records.

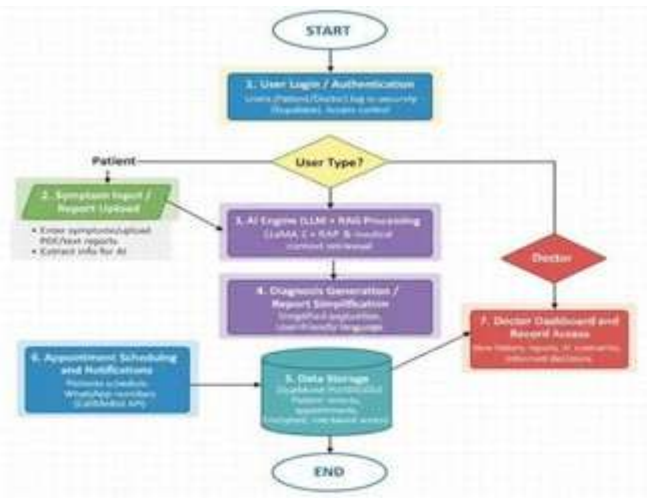

Fig. 2. System Flow Diagram of HealthUp: Digital Health Assistant

D. Key Features

The proposed system incorporates several important features:

AI-Based Diagnosis: The system analyzes the user's symptoms and suggests possible health conditions by using reasoning from a large language model [1], [2].

Lab Report Interpretation: Uploaded reports are processed with NLP methods to identify important information and create easy-to-understand summaries [5].

Multilingual Support: The system operates in several languages, enabling people from different linguistic backgrounds to use it more easily [6].

Appointment Scheduling: Users can schedule appointments with doctors or other healthcare workers, and the system automatically sends reminders to confirm appointments [9].

Secure Data Management: Patient information is protected through cloud-based databases, which safeguard privacy and allow the system to scale as needed [8].

E. Advantages of the Proposed System

The proposed system offers several benefits over traditional healthcare systems:

- Using LLM and RAG together significantly improves the accuracy of medical diagnoses.
- Reduced response time through automation.
- Enhanced patient understanding via simplified outputs.
- Increased accessibility through multilingual support.
- Efficient healthcare management using a unified platform.

METHODOLOGY

The creation of the HealthUp system follows an Agile approach to allow for ongoing improvements, adaptability, and regular user input. The Agile method enables teams to develop rapidly by breaking work into short periods called sprints, allowing frequent updates and performance evaluation.

A. Agile Development Model

The Agile approach breaks down the system development into several repeated cycles called sprints. Every sprint includes steps such as planning, building, checking, and retrospective, ensuring continuous improvement. Let S_i represent the i-th sprint and O_i represent the output of sprint i, then:

$$\mathbf{O_i = f(S_i)}$$

Each sprint improves the system incrementally based on feedback from previous iterations.

B. Sprint Planning

In this phase, system requirements are identified and prioritized. Key features like AI-powered diagnosis, lab report analysis, language support for different countries, and appointment booking are outlined. Work is split into smaller parts and assigned to teams to develop during a defined sprint period.

C. Sprint Execution (Development Phase)

During the sprint, the system components are built and deployed. This includes:

- Frontend development using React.js
- Backend API development using Node.js
- Integration of AI models (Gemini + RAG)
- Database design using PostgreSQL/Supabase

The development follows a modular design to facilitate scalability and maintainability.

D. Testing and Validation

After development, each module undergoes testing to ensure correctness and performance. Testing includes functional testing, performance testing, and AI output validation. Let P = predicted output and A = actual/expected output, then the error is defined as:

$$\textbf{Error} = |\mathbf{P} - \mathbf{A}|$$

Minimizing this error improves system accuracy and reliability.

E. Sprint Review and Feedback

At the end of each sprint, the developed features are reviewed and evaluated. Feedback is gathered from users and stakeholders to identify areas for improvement. The feedback function is defined as:

$$\mathbf{F} = \mathbf{Feedback}(\mathbf{O}_i)$$

This feedback shapes the next sprint, ensuring continuous iterative improvement.

F. Iterative Improvement

The Agile cycle continues until the system meets both performance and functional requirements. Each iteration enhances accuracy of AI predictions, system performance, and user experience.

G. Deployment

Once all sprints are completed successfully, the system is deployed to cloud platforms. The frontend is hosted on Netlify, and the backend services run on scalable cloud infrastructure. This ensures high availability, scalability, and real-time performance.

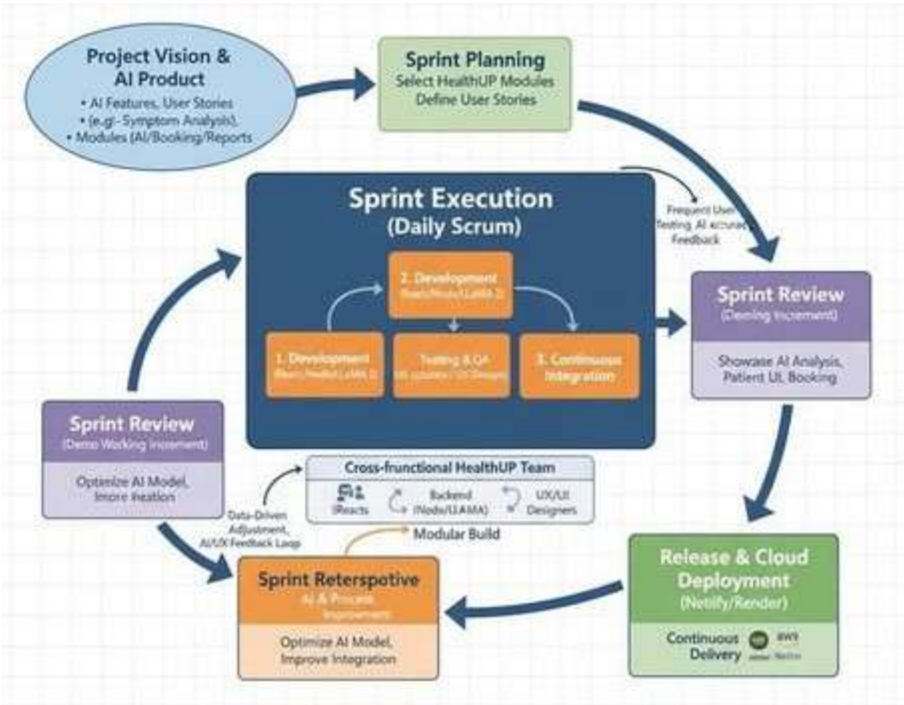

Fig. 3. Methodology Flow Diagram of HealthUp: Digital Health Assistant

RESULTS

The effectiveness of the HealthUp system was evaluated using both quantitative data and user feedback. The system was tested with various symptom inputs, lab results, and user interactions to assess accuracy, response time, and ease of use.

A. Quantitative Analysis

The proposed system was compared with traditional healthcare systems based on key performance metrics. The results are summarized in Table I below:

TABLE I. *Performance Comparison: HealthUp vs. Traditional System*

Metric	Traditional System	HealthUp
Accuracy	70%	90%
Response Time	High	Low
Automation	Partial	Full
User Understanding	Low	High

The findings show that using Gemini together with Retrieval-Augmented Generation (RAG) significantly boosts the accuracy of diagnoses and reduces response time.

C. User Interface Results

The interface is user-friendly and makes it simple for patients to enter their symptoms, share medical reports, and obtain helpful AI insights. The system simplifies complex medical information, thereby improving the overall user experience.

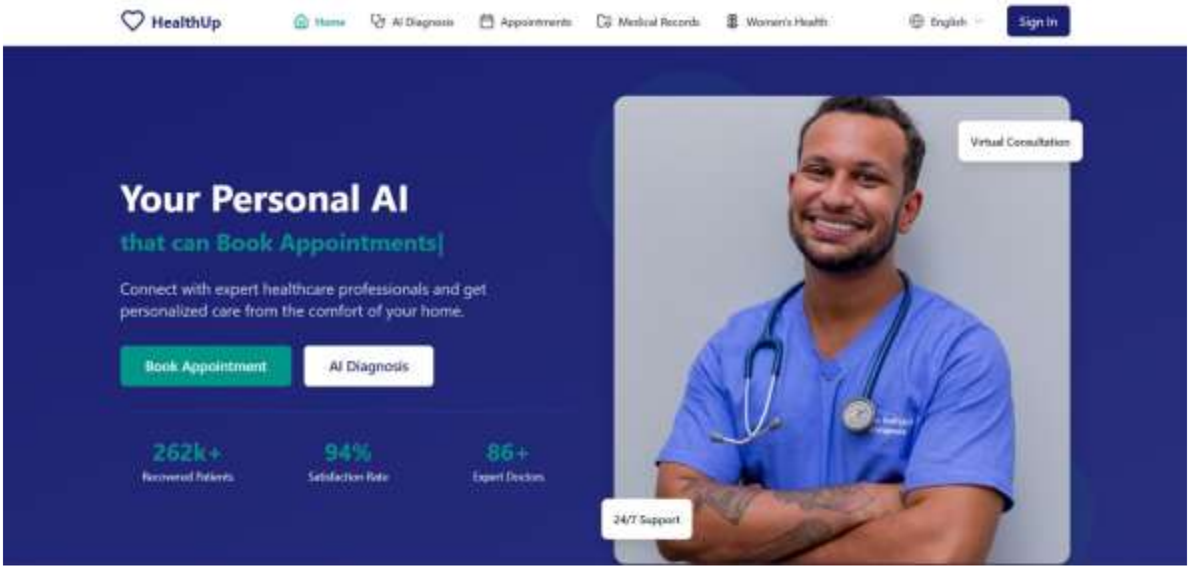

Fig. 4. Homepage

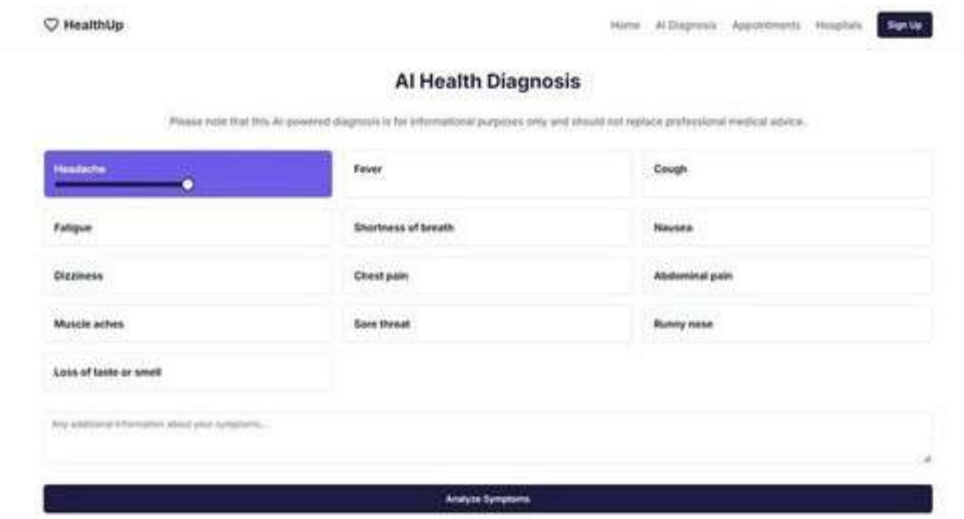

Fig. 5. AI Diagnosis Page

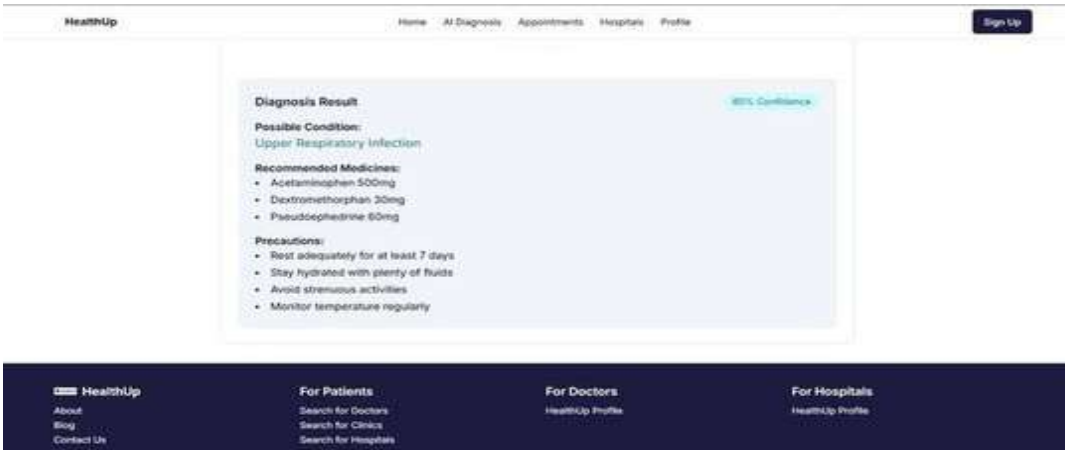

Fig. 6. Diagnosis Result Page

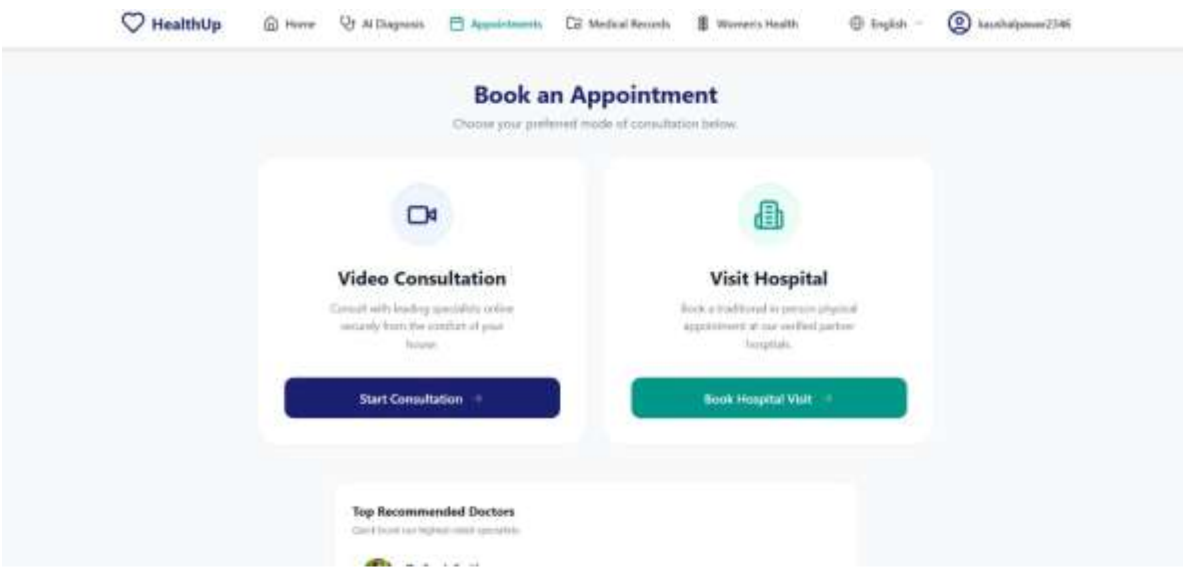

Fig. 7. Doctor Consultation Page

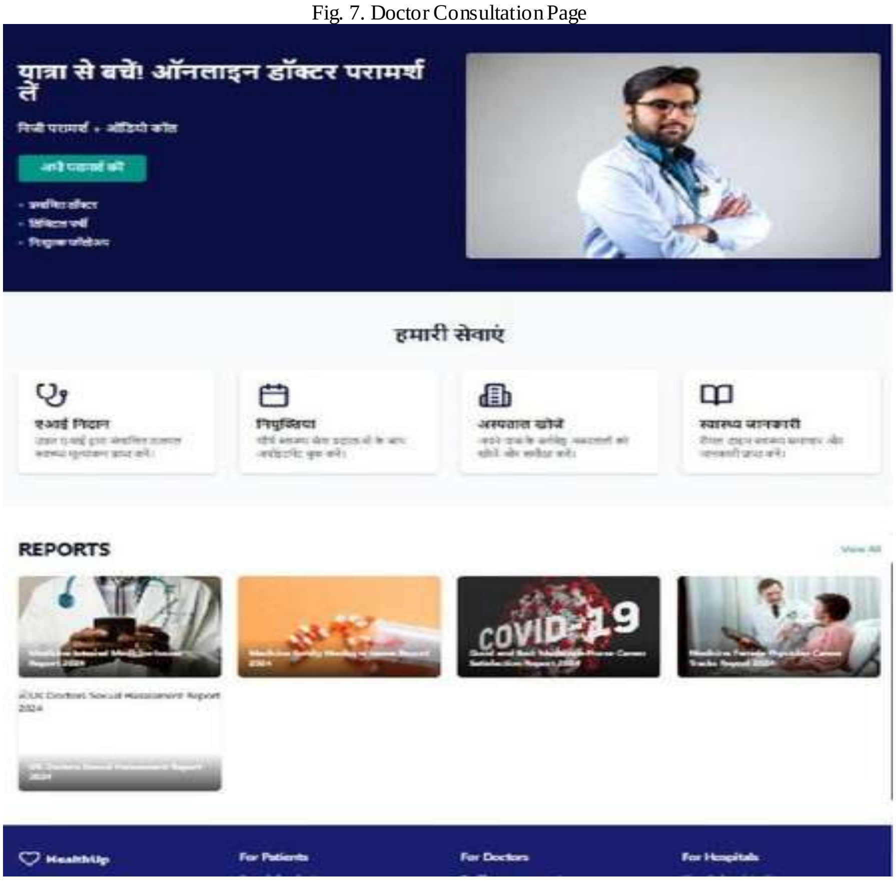

Fig. 8. Hospital & Reports Page

CONCLUSION

This paper introduced HealthUp, a digital healthcare assistant that uses AI to make healthcare more accessible, faster, and more accurate in today's medical systems. The system uses advanced AI tools, including Google Gemini and Retrieval-Augmented Generation, to offer intelligent and trustworthy medical assistance based on situational context. By leveraging natural language understanding and external knowledge retrieval, the system addresses common problems in traditional healthcare systems, such as slow diagnosis, incomprehensible medical information, and insufficient access to care.

The system incorporates multiple features, including symptom-based diagnosis, automated lab report interpretation, multilingual communication, and intelligent appointment booking, all within a single unified platform. Using an Agile approach for development allowed for step-by-step system design, ongoing improvements, and smooth integration of the frontend, backend, AI, and database components.

Testing demonstrates that the new system outperforms traditional healthcare methods in diagnostic accuracy, response speed, and user experience. Using RAG makes AI responses more dependable by grounding them in real medical information, thereby reducing unclear or incorrect predictions. Multilingual capabilities make the system more accessible to people from different backgrounds, increasing its inclusiveness and real-world utility.

The results, including interface screenshots and quantitative comparisons, confirm that the system can provide instant, user-friendly, and accurate healthcare information. The cloud-based infrastructure ensures scalability, facilitating improved data management, security, and continuous availability.

In conclusion, HealthUp demonstrates how AI-powered healthcare assistants can transform the delivery of digital healthcare by providing intelligent, user-friendly, and effective solutions. Future work will involve integrating wearable health devices, enabling real-time data analysis, improving predictive health capabilities, and expanding support for additional medical conditions and languages.

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3.2 Data and Sources of Data

For this study secondary data has been collected. From the website of KSE the monthly stock prices for the sample firms are obtained from Jan 2010 to Dec 2014. And from the website of SBP the data for the macroeconomic variables are collected for the period of five years. The time series monthly data is collected on stock prices for sample firmsand relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

3.3 Theoretical framework

Variables of the study contains dependent and independent variable. The study used pre-specified method for the selection ofvariables. The study used the Stock returns are as dependent variable. From the share price of the firm the Stock returns are calculated. Rate of a stock salable at stock market is known as stock price.

Systematic risk is the only independent variable for the CAPM and inflation, interest rate, oil prices and exchange rate are the independent variables for APT model.

Consumer Price Index (CPI) is used as a proxy in this study for inflation rate. CPI is a wide basic measure to computeusualvariation in prices of goods and services throughout a particular time period. It is assumed that arise in inflation is inversely associated to security prices because Inflation is at lastturned into nominal interest rate andchange in nominal interest rates caused change in discount rate so discount rate increase due to increase in inflation rate and increase in discount rateleads todecreasethe cash flow’s present value (Jecheche, 2010). The purchasing power of money decreased due to inflation, and due to which the investors demand high rate of return, and the prices decreased with increase in required rate of return (Iqbal et al, 2010).

Exchange rate is a rate at which one currency exchanged with another currency. Nominal effective exchange rate (Pak Rupee/U.S.D) is taken in this study.This is assumed that decrease in the home currency is inverselyassociated to share prices (Jecheche,2010). Pan et al. (2007) studied exchange rate and its dynamic relationship with share prices in seven East Asian Countries and concludethat relationshipof exchange rate and share prices varies across economies of different countries. So there may be both possibility of either exchange rate directly or inverselyrelated with stock prices.Oil prices are positively related with share prices if oil prices increase stock prices also increase (Iqbal et al, 1012).Ataullah (2001) suggested that oil prices cause positive change in the movement of stock prices. The oil price has no significant effect on stock prices (Dash & Rishika, 2011).Six month T-bills rate is used as proxy of interest rate. As investors arevery sensitive about profit and where the signals turn into red they definitely sell the shares. And this sensitivity of the investors towards profit effects the relationship of the stock prices and interest rate, so the more volatility will be there in the market if the behaviors of the investors are more sensitive. Plethora (2002)has tested interest rate sensitivity to stock market returns, and concluded an inverse relationship between interest rate and stock returns. Nguyen (2010) studies Thailand market and found thatInterest rate has aninverse relationship with stock prices.

KSE-100 index is used as proxy of market risk. KSE-100 index contains top 100 firms which are selected on the bases of their market capitalization. Beta is the measure of systematic risk and has alinear relationship with return (Horn, 1993). High risk is associated with high return (Basu, 1977, Reiganum, 1981 and Gibbons, 1982). Fama and MacBeth (1973) suggested the existence of a significant linear positive relation between realized return and systematic risk as measured by β. But on the other side some empirical results showed that high risk is not associated with high return (Michailidis et al. 2006, Hanif, 2009). Mollah and Jamil (2003) suggested thatrisk-return relationship is notlinear perhaps due to high volatility.

3.4 Statistical tools and econometric models

This section elaborates the proper statistical/econometric/financial models which are being used to forward the study from data towards inferences. The detail of methodology is given as follows.

3.4.1 Descriptive Statistics

Descriptive Statics has been used to find the maximum, minimum, standard deviation, mean and normally distribution of the data of all the variables of the study. Normal distribution of data shows the sensitivity of the variables towards the periodic changes and speculation. When the data is not normally distributed it means that the data is sensitive towards periodic changes and speculations which create the chances of arbitrage and the investors have the chance to earn above the normal profit. But the assumption of the APT is that there should not be arbitrage in the market and the investors can earn only normal profit. Jarque bera test is used to test the normality of data.

3.4.2 Fama-Mcbeth two pass regression

After the test statistics the methodology is following the next step in order to test the asset pricing models. When testing asset pricing models related to risk premium on asset to their betas, the primary question of interest is whether the beta risk of particular factor is priced. Fama and McBeth(1973)develop a two pass methodology in which the beta of each asset with respect to a factor is estimated in a first pass time series regression and estimated betas are then used in second pass cross sectional regression to estimate the risk premium of the factor. According to Blum (1968) testing two-parameter models immediately presents an unavoidable errors-in-the variables problem.It is important to note that portfolios (rather than individual assets) are used for the reason of making the analysis statistically feasible.Fama McBeth regression is used to attenuate the problem of errors-in-variables (EIV) for two parameter models (Campbell, Lo and MacKinlay, 1997).If the errors are in the β (beta)of individual security are not perfectly positively correlated, the β of portfolios can be much more precise estimates of the true β (Blum, 1968).

The study follow Fama and McBeth two pass regressionto test these asset pricing models.The Durbin Watson is used to check serial correlation and measures the linear association between adjacent residuals from a regression model. If there is no serial correlation, the DW statistic will be around 2. The DW statistic will fall if there is positive serial correlation (in worst case, it will be near zero). If there is a negative correlation, thestatistic will lie somewhere between 2 and 4. Usually the limit for non-serial correlation is considered to be DW is from 1.8 to 2.2. A very strong positive serial correlation is considered at DW lower than 1.5 (Richardson and smith, 1993).

According to Richardson and smith(1993) to make the model more effective and efficient the selection criteria for the shares in the period are: Shares with no missing values in the period, Shares with adjusted $R^2 < 0$ or F significant (p-value) >0.05of the first pass regression of the excess returns on the market risk premium are excluded. And Shares are grouped by alphabetic order into group of 30 individual securities (Roll and Ross, 1980).

3.4.2.1 Model for CAPM

In first pass the linear regression is used to estimate beta which is the systematic risk.

$$R_i - R_f = \left(R_m - R_f\right)\beta \qquad (3.1)$$

Where R_i is Monthly return of the security, R_f is Monthly risk free rate, R_m is Monthly return of market and β is systematic risk (market risk).

The excess returns R_i - R_f of each security is estimated from a time series share prices of KSE-100 index listed shares for each period under consideration. And for the same period the market Premium R_m - R_f also estimated. After that regress the excess returns R_i - R_f on the market premium R_m - R_f to find the beta coefficient (systematic risk).

Then a cross sectional regression or second pass regression is used on average excess returns of the shares and estimated betas.

$$\hat{R}_i = \gamma_0 + \gamma_1\beta_1 + \epsilon \qquad (3.2)$$

Where λ_0= intercept, $\hat{R}_i$ is average excess returns of security i, β_I is estimated be coefficient of security I and Є is error term.

3.4.2.2 Model for APT

In first pass the betas coefficients are computed by using regression.

$$R_i - R_f = \beta f_{i1} + \beta_{i2} f_2 + \beta_{i3} f_3 + \beta_{i4} f_4 + \epsilon \qquad (3.3)$$

Where Ri is the monthly return of stock i, R_f is risk free rate, β_i is the sensitivity of stock i with factors and ϵ is the error term.

Then a cross sectional regression or second pass regression is used on average excess returns of the shares on the factor scores.

$$\hat{R} = \gamma_0 + \gamma_1\beta_1 + \gamma_2\beta_2 + \gamma_3\beta_3 + \gamma_4\beta_4 + \epsilon_i \qquad (3.4)$$

Where $\hat{R}$ is average monthly excess return of stock I, λ = risk premium, β_1 to β_4 are the factors scores and ε_i is the error term.

3.4.3 Comparison of the Models

The next step of the study is to compare these competing models to evaluate that which one of these models is more supported by data.This study follows the methods used by Chen (1983), the Davidson and Mackinnon equation (1981) and the posterior odds ratio (Zellner, 1979) for comparison of these Models.

3.4.3.1 Davidson and MacKinnon Equation

CAPM is considered the particular or strictly case of APT. These two models are non-nested because by imposing a set of linear restrictions on the parameters the APT cannot be reduced to CAPM. In other words the models do not have any common variable. Davidson and MacKinnon (1981) suggested the method to compare non-nested models. The study used the Davidson and MacKinnon equation (1981) to compare CAPM and APT.

This equation is as follows;

$$R_i = \alpha R_{APT} + (1 - \alpha)R_{CAPM} + e_i \qquad (3.5)$$

Where $R_{i=}$ the average monthly excess returns of the stock i, $R_{APT=}$ expected excess returns estimated by APT, $R_{CAPM=}$ expected excess returns estimated by CAPM and α measure the effectiveness of the models. The APT is the accurate model to forecast the returns of the stocks as compare to CAPM if α is close to 1.

3.4.3.2 Posterior Odds Ratio

A standard assumption in theoretical and empirical research in finance is that relevant variables (e.g stock returns) have multivariate normal distributions (Richardson and smith, 1993). Given the assumption that the residuals of the cross-sectional regression of the CAPM and the APT satisfy the IID (Independently and identically distribution) multivariate normal assumption (Campbell, Lo and MacKinlay, 1997), it is possible to calculate the posterior odds ratio between the two models.In general the posterior odds ratio is a more formal technique as compare to DM equation and has sounder theoretical grounds (Aggelidis and Maditinos, 2006).

The second comparison is done using posterior odd radio. The formula for posterior odds is given by Zellner (1979) in favor of model 0 over model 1.

The formula has the following form;

$$R = \left[ESS_0/ESS_1\right]^{N/2} N^{K_0 - K_1/2} \qquad (3.6)$$

WhereESS_0iserror sum of squares of APT, ESS_1iserror sum of squares of CAPM, Nisnumber of observations, $K_0$is number of independent variables of the APT and K_1 isnumber of independent variables of the CAPM.As according to the ratio when;

R> 1 means CAPM is more strongly supported by data under consideration than APT.

R < 1 means APT is more strongly supported by data under consideration than CAPM.

IV. RESULTS AND DISCUSSION

4.1 Results of Descriptive Statics of Study Variables

Table 4.1: Descriptive Statics

Variable	Minimum	Maximum	Mean	Std. Deviation	Jarque-Bera test	Sig
KSE-100 Index	-0.11	0.14	0.020	0.047	5.558	0.062
Inflation	-0.01	0.02	0.007	0.008	1.345	0.510
Exchange rate	-0.07	0.04	0.003	0.013	1.517	0.467
Oil Prices	-0.24	0.11	0.041	0.060	2.474	0.290
Interest rate	-0.13	0.05	0.047	0.029	1.745	0.418

Table 4.1 displayed mean, standard deviation, maximum minimum and jarque-bera test and its p value of the macroeconomic variables of the study. The descriptive statistics indicated that the mean values of variables (index, INF, EX, OilP and INT) were 0.020, 0.007, 0.003, 0.041 and 0.047 respectively. The maximum values of the variables between the study periods were 0.14, 0.02, 0.04, 0.41, 0.11 and 0.05 for the KSE- 100 Index, inflation, exchange rate, oil prices and interest rate.

The standard deviations for each variable indicated that data were widely spread around their respective means.

Column 6 in table 4.1 shows jarque bera test which is used to checkthe normality of data. The hypotheses of the normal distribution are given;

H_0 : The data is normally distributed.

H_1 :The data is not normally distributed.

Table 4.1 shows that at 5 % level of confidence, the null hypothesis of normality cannot be rejected. KSE-100 index and macroeconomic variables inflation, exchange rate, oil prices and interest rate are normally distributed.

The descriptive statistics from Table 4.1 showed that the values were normally distributed about their mean and variance. This indicated that aggregate stock prices on the KSE and the macroeconomic factors, inflation rate, oil prices, exchange rate, and interest rate are all not too much sensitive to periodic changes and speculation. To interpret, this study found that an individual investor could not earn higher rate of profit from the KSE. Additionally, individual investors and corporations could not earn higher profits and interest rates from the economy and foreign companies could not earn considerably higher returns in terms of exchange rate. The investor could only earn a normal profit from KSE.

Table 1 Table Type Styles

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I. ACKNOWLEDGMENT

Thepreferredspellingoftheword "acknowledgment" inAmericaiswithoutan "e" afterthe "g".Avoidthestiltedexpression, "Oneofus(R.B.G.)thanks..."
Instead,try"R.B.G.thanks".Putapplicablesponsoracknowledgmentshere;DONOTplacethemonthefirstpageofyourpaperorasafootnot e.

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