Innovation in Healthcare through Technology and Artificial Intelligence – Case Study: VitalView Blood Pressure Monitoring System

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Abstract

The rising prevalence of chronic diseases and the advancement of artificial intelligence and machine learning are driving significant shifts in the healthcare industry. Chronic diseases pose an urgent threat to the world's healthcare systems due to the rising number of fatalities, making the demand for innovative approaches imperative. Applying VitalView, a blood pressure monitoring system, as a case study, this thesis explores the intersection of these fields. The system's main goal is to employ AI and machine learning to offer personalized treatment for chronic diseases, especially blood pressure. To accomplish this, the study commences by examining the challenges faced by Albania's healthcare system, in particular issues connected to access, costs, and service quality. The study then digs into the development of VitalView, an innovative solution that meets the needs of patients and healthcare professionals. The creation of an algorithm for data analysis and communication is at the core of this work. Autoregressive Integrated Moving Average (ARIMA), among other machine learning models, improves the platform's ability to forecast blood pressure trends and simplify doctor-patient communication. The system also provides advice and recommendations for the patient's general state of health. The case study methodology is employed with the objective of putting this system's applications into action in real-life situations. Its findings show the potential of AI and machine learning to boost communication, improve the management of chronic blood pressure diseases, and *boost patient outcomes. This thesis demonstrates how innovative technologies could cope with pressing concerns of our time and contributes to the discussion on artificial intelligence in the healthcare industry. The VitalView system serves as an example of how innovation, data analysis, and user-centered design function together. It highlights how AI and machine learning have the potential to improve healthcare.*

Keywords: *artificial intelligence, machine learning, chronic diseases, blood pressure monitoring, personalized treatment, healthcare challenges, case study, VitalView, data analysis, communication.*

Introduction

In today's complex healthcare landscape, the emergence of modern technology and the assistance of artificial intelligence offer hope for medical innovation. The urgent need to solve healthcare issues and reduce expenses served as the motivation driving this study. Implementing technology and artificial intelligence is essential for improving patient care and healthcare efficiency in a time of growing healthcare demands and limited resources.

The aim of this study is to develop novel methods and strategies that not only improve the quality of healthcare services but also offer practical, economical responses to today's pressing healthcare issues. Additionally, the study aims to develop a model for healthcare innovation that is scalable and flexible, able to change in sync with new technological advancements and changing patient demands. It envisions a future where healthcare is not only more effective but also more cost-effective, empowering people to take control of their health and fostering healthier communities by fusing the power of cutting-edge technologies like Artificial Intelligence and data analytics with a patient-centered ethos.

The study addresses two key research questions:

Research Question 1: What impact can artificial intelligence and machine learning have, through personalized treatment of patients, in the management of chronic diseases?

Through this question, the thesis explores the ways personalized care for chronic diseases could be improved by machine learning and artificial intelligence. This investigation seeks to enhance individual patient treatment through user-centered design innovations.

Research Question 2: How can artificial intelligence and machine learning algorithms be used to reduce blood pressure fluctuations?

By analyzing this question, the study dives into the potential of AI and machine learning algorithms to decrease variations in blood pressure. The aim is to examine how modern technologies could ensure more consistent and controlled blood pressure levels.

This paper is guided by a clear hypothesis and objectives. The hypothesis posits that by applying artificial intelligence and machine learning in healthcare innovation would result in significant advancements. By facilitating quick communication with healthcare providers, personalized health tips and advice, and forecasting trends in systolic and diastolic blood pressure values, ultimately would lead to balanced blood pressure values, reduced medical costs and equitable high-quality healthcare services.

Hypothesis: Health innovation activities are improved significantly when the potential of artificial intelligence and machine learning is used.

By using the new technologies, blood pressure readings can be monitored and kept under control, medical costs can be reduced, and a comparable standard of care can be guaranteed through rapid interaction with the doctor, personalized advice, and analysis of coherent and recent information.

In pursuit of this hypothesis, the study outlines several key objectives:

1. To identify and analyze health problems in Albania.
2. To create an innovative solution to address these problems by developing a blood pressure monitoring system.
3. To create an algorithm that analyzes real data, identifies trends and realizes communication between the patient and the doctor.
4. To provide personalized recommendations and advice based on patients' personal data to improve the management of this chronic disease.

Together, these objectives form the foundation for an impactful research endeavor.

Literature Review

Artificial Intelligence in Healthcare

At the relationship of computer science and healthcare, artificial intelligence (AI) has emerged as an influential force in the area of healthcare. AI has the amazing ability to evaluate complex and multifaceted medical data, leading to quick and significant changes in the medical field. The conventional paradigms of disease management, therapy, and diagnosis have all undergone major shifts as a result of its application. It is amazing how flexible AI is in healthcare. For instance, AI enhances surgeons' ability in the field of surgery by detecting high-risk or difficult areas that need to be treated, improving the accuracy and safety of surgical treatments. AI speeds up the search for novel therapeutic compounds in drug discovery and development, saving time and resources for pharmaceutical companies. Additionally, AI finds a promising application in telemedicine and health monitoring systems, enabling remote patient monitoring and enabling thorough health data analysis, ultimately improving the overall effectiveness of healthcare delivery. (Ramesh, Kambhampati, Monson, & Drew, 2004)

Telemedicine

In the present digital world, telemedicine has made impressive strides, resulting in a variety of uses that closely resemble the study's goals. To aid in the systematic documentation of medical data and the preservation of important healthcare information, including diagnoses, medications, and appointment information, such applications carefully use electronic formats that are always accessible. With the introduction of virtual contacts between patients and healthcare professionals and the facilitation of treatment delivery, telemedicine has advanced beyond geographic limits and successfully managed the flow of information. But it's important to remember that there are different levels of AI technology integration acceptance among medical professionals. (Nittari, et al., 2020)

Machine Learning

The use of machine learning algorithms is naturally prompted by the different levels of complexity, sophisticated human-machine interactions, and decision-making phases that these systems exhibit. In the context of radiotherapy, where the majority of cancer patients get ionizing radiation therapy, especially in advanced stages of the disease, machine learning has emerged as a vital asset. Radiotherapy is a broad term that refers to a variety of procedures that not only speed up the process of going from consultation to treatment but also guarantee accurate delivery of the required dose of ionizing radiation and customize the course of action for every patient. (Naqa & Murphy, 2015)

Predictive Analytics

The medical industry is being rapidly transformed by predictive analytics, which encourages innovation and improves patient outcomes. Predictive analytics sorts through historical and real-time data using complex statistical algorithms, machine learning models, and data analytics tools to estimate upcoming medical events. This enables those who supply healthcare services to take well-informed decisions, improve patient care, and even forecast problematics. Predictive algorithms, for instance, have been created to identify high-risk patients who would need a hospital readmission, allowing healthcare institutions to put preventive measures into place. Predictive analytics also significantly influenced resource allocation during the COVID-19 epidemic, helping hospitals effectively manage the availability of beds, ventilators, and medical personnel. (Kankanhalli, Hahn, Tan, & Gao, 2016)

Augmented Dickey-Fuller Test

In this context, the Augmented Dickey-Fuller test (ADF test) is a statistical method used to identify the presence of unit roots in a time series. Non-stationary, in the majority of the cases, denotes the presence of a trend that makes analysis more difficult, whereas stationary denotes the absence of a discernible pattern that significantly changes the series' values over time. The ADF test begins by presenting the null hypothesis that the time series is non-stationary. This indicates that the autoregressive model has a unit root. If the time series has a unit root, this means that it has a stochastic trend. (Mushtaq, 2011). The starting point is the stochastic process:

$$\Delta y_t = \alpha y_{t-1} + \epsilon_t$$

where:

- Δy_t is the difference between y_t and y_{t-1}
- α is the tested parameter for the unit root
- ϵ_t is a white noise error term

If $\alpha=0$, then the series has a root of unity and is non-stationary. If $\alpha<0$, then the series is stationary. If the computed absolute value of the tau statistic exceeds the absolute DF or MacKinnon critical tau values, we reject the hypothesis that $\alpha=0$, in which case the time series is stationary. On the other hand, if the computed absolute value of the tau statistic does not exceed the absolute critical tau value, we do not reject the null hypothesis, in which case the time series is nonstationary.

ARIMA model

ARIMA(p,d,q) (Autoregressive Integrated Moving Average) is one of the most widely used methods for time series forecasting. The components of ARIMA are:

- AR part (Autoregressive) explains the relationship between an observation and its previous observations (lags). An AR term is commonly used to model the trend component of a time series. The parameter p is the order of the AR model, indicating the number of lags to be used as predictors. In mathematical form, the AR part is defined as:

$$\boldsymbol{\varphi_1 y_{t-1} + \varphi_2 y_{t-2} + \cdots + \varphi_p y_{t-p}}$$

- I (Integrated) is the order of differentiation applied to the time series data to make it stationary. A non-stationary series is one that has time-varying properties. The parameter d is the number of times that the time series has to be differenced before it becomes stationary.
- MA (Moving Average), this component models the relationship between an observation and the errors from previous observations. It helps to capture unexpected shocks or transient effects that cannot be modeled by trend and seasonality components. The parameter q is the order of the MA model, indicating the number of lagged forecast errors in the forecast equation. In mathematical form, MA is described as:

$$\boldsymbol{\theta_1 e_{t-1} + \theta_2 e_{t-2} + \cdots + \theta_q y_{t-q}}$$

(Fattah, Ezzine, Aman, Moussami, & Lachhab, 2018)

Differencing

The method of differencing is a common method used to make a non-stationary time series stationary. Basically, differentiation calculates the difference between consecutive observations. The more differentiation stages are completed, the more accurate the prediction is. In first-order differentiation, each value in the series is replaced by the difference between it and the previous value: $\Delta y_t = y_t - y_{t-1}$, where Δy_t is the difference between the value at time t, and the value at time t-1, y_{t-1}. Sometimes, first-order differentiation is not sufficient to make the series stationary. In these cases, it may be necessary to apply second-order differentiation, which is simply the first-order differentiation of data that has already been differentiated.

After differentiation, it is common to use statistical tests such as the Dickey-Fuller (ADF) test to confirm whether the series has become stationary. Stationarity is essential because many statistical modeling techniques assume or require the time series to be stationary to make reliable and valid inferences. (Abraham, Poole, & Poole, 1999)

VitalView – Blood Pressure Monitoring System

VitalView: this innovative blood pressure monitoring system, designed as part of this study, serves as a solution to address the needs of individuals suffering from chronic blood pressure issues. VitalView is a platform created to be used by both patients and healthcare providers.

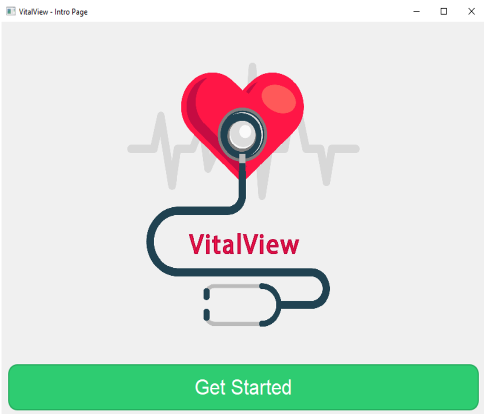


FIGURE 1 VitalView Blood Pressure Monitoring System

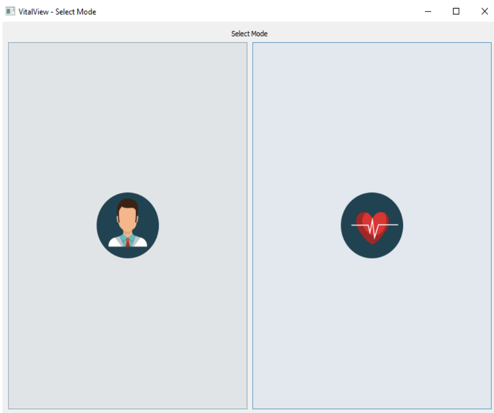


FIGURE 2 Doctor/Patient Portal Mode

It serves as a personalized health companion, providing support for people with chronic blood pressure issues. This method can be easily incorporated by patients into their everyday routines, becoming an essential element of their healthcare regimen. Patients may easily check their profile, add manually or watch their systolic and diastolic values, get important health information, and stay up to date with the help of this system. They may quickly visualize their data, including lowest, maximum, and average blood pressure measurements, providing a thorough insight of their progress, using graphical representations.

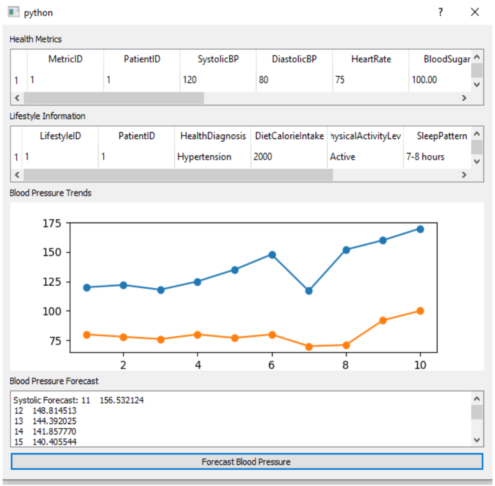


FIGURE 3 Doctor Portal - Patient Information &

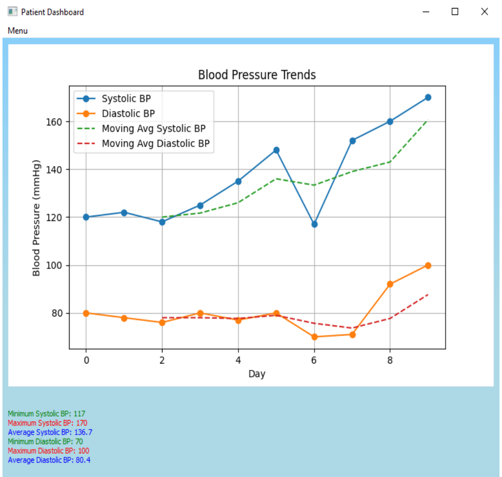
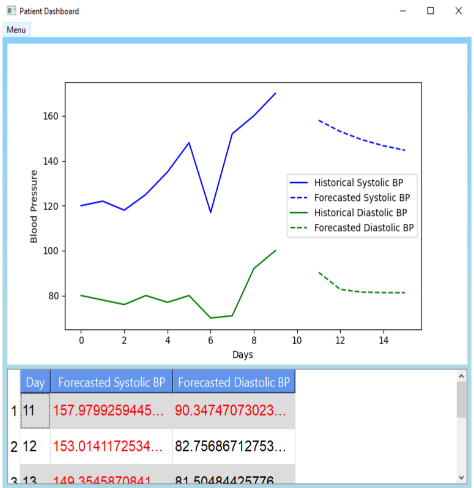


FIGURE 4 Patient Portal - Information Vizualization & Calculations

To improve health outcomes, VitalView collects real-time data in a cost-effective way, performs deep analysis by using machine learning algorithms (ADF test, differencing & ARIMA model), and can forecast trends in 5 upcoming days. By using this method, the system aims to actively involve patients and healthcare providers in the journey of this chronic disease. The technology updates end-users on the health trends in real-time and notifies all parties in case of emergency. Additionally, VitalView encourages better interaction and consultation between patients and their doctors, provides faster access to health services and reduces costs for patients. If offers a convenient, cost-free and efficient method for exchanging crucial health information by offering a channel of communication, as well as it empowers medical experts with all the information necessary to make informed decisions on the best course of action and modify treatment regimens. Doctors may rely on VitalView's real-time data to deliver accurate medical reccomendations and actions.



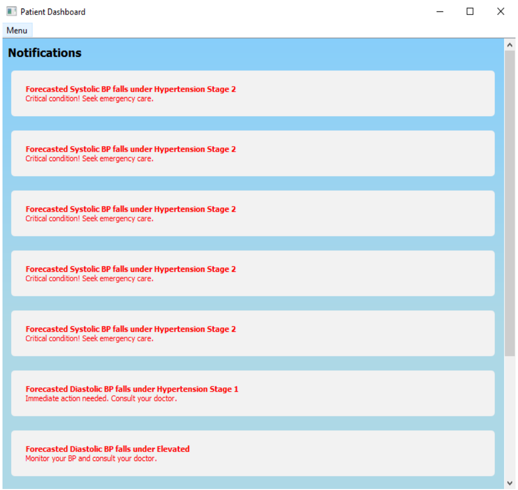


FIGURE 5 Patient's Forecasted Trend

FIGURE 6 Patient's Emergency Notifications

The process for predicting future systolic and diastolic blood pressure values involves several steps. The initial step is to conduct an analysis using the forecasting capabilities of the ARIMA model. The Augmented Dickey-Fuller (ADF) test and first-order differences calculations are used to determine the stationarity of the time series data. If the data is determined to be stationary, the ARIMA analysis can use it right away. If not, a differencing procedure must be used until the data become stationary. The ADF test indicates the parameter that is not stationary, indicating that it fluctuates with time. On the other hand, the ADF test defines the stationary values, which means the readings are more constant and show a trend. For non-stationary values, differencing is performed until the data meets the criteria of stationarity after reapplying the ADF test. Once the stationarity requirement is met for the new values, an ARIMA forecasting model is used. The model needs the p, d, and q parameters to be determined, which often entails examining various lags or delays. Modern tools can, however, automatically determine these parameters, such as the auto ARIMA function. The ARIMA prediction function is used to calculate future systolic and diastolic blood pressure values for the following five days after determining the model's parameters.

Furthermore, this novel system raises the bar for healthcare by making food suggestions, improving sleep quality, sending reminders to stay hydrated, providing stress-reduction techniques, and encouraging physical exercise based on user data. In addition to being software, VitalView is a thoughtful partner who is concerned about the welfare of its end users. This system is a potent illustration of the potential for making well-informed judgements about an individual's well-being that innovation and artificial intelligence create. Healthcare should no longer be difficult; rather, it should be an enjoyable journey towards a healthier and better life.

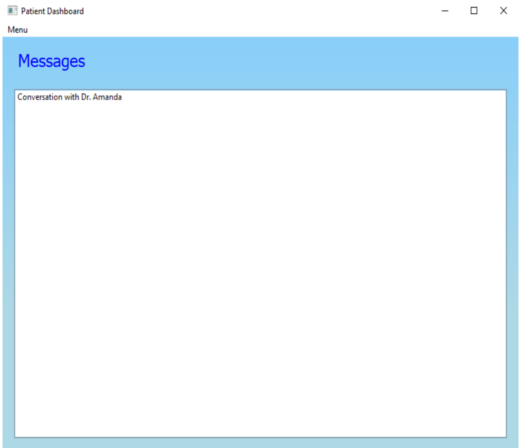


FIGURE 7 Doctor - Patient Communication

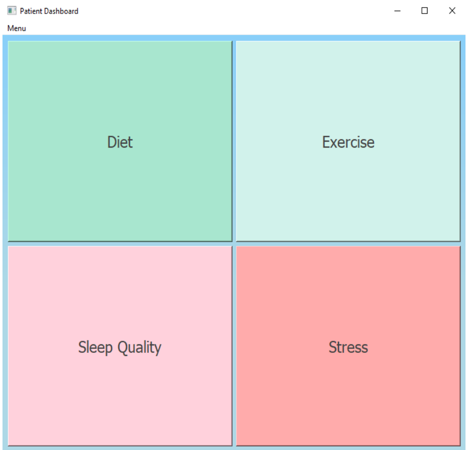


FIGURE 8 Patient General Healthcare Tips

VitalView plans to improve its technology in the future for improved healthcare. Predictions could be more accurate by considering lifestyle parameters like exercise, sleep patterns, stress and diet information. By integrating with health monitoring equipment, faster data collection and ongoing tracking could be made available, helping doctors make better decisions. An AI chatbot might provide support outside of business hours. It is also essential to create a network of specialists and healthcare workers for collaboration and patient support groups. Data security will be a top priority, with strict access controls, audits, encryption and privacy protection. Finally, VitalView would have the full capacity to deliver precise, customized, and cohesive healthcare advice.

Results & Conclusions

The study's findings suggest that the VitalView blood pressure monitoring system was successfully created, highlighting its potential to revolutionize healthcare in Albania. The system successfully tackles the issues of access, affordability, and service quality that present in the Albanian healthcare system by taking a user-centric approach. The VitalView prototype uses machine learning and AI algorithms to analyze patient data in real-time, spot trends in blood pressure, and promptly alert patients and medical professionals to any alarming numbers.