



A Simulated Case Study for Application of Blood Pressure Parameters to predict Heart Rate

¹ Saniya Raheen Patel, ² Nazneen Akhter, ³ Bharat Naiknaware

¹Research Scholar, ²Education Coordinator, ³Assistant Professor

^{1,3}Dr. G.Y. Pathrikar College of C.S. & I.T., MGM UNIVERSITY, Chh. Sambhajinagar, India

²IRC Technical Institute, Chh. Sambhajinagar, India

Abstract : Cardiovascular stress monitoring plays a crucial role in managing hypertensive patients and preventing complications such as stroke or cardiac failure. This paper presents a novel approach using AI-based modeling to predict cardiovascular stress by analyzing blood pressure (BP) and heart rate (HR) data. Simulated datasets representing two patient profiles (normal and abnormal) were generated over a 6-month period. We applied linear regression to model the relationship between systolic BP and HR, achieving a prediction accuracy with $R^2 = 0.72$ and MAPE = 3.51%. The system identifies high-risk episodes using co-occurrence logic (BP > 180 mmHg and predicted HR > 100 bpm), enabling early warnings. Performance was evaluated using RMSE, MAPE, and NRMSE. The results show the potential of simple, interpretable AI models in proactive cardiovascular health monitoring.

Keywords - Cardiovascular stress, blood pressure, heart rate, AI in healthcare, linear regression, patient monitoring, MAPE, RMSE, simulated data.

I. INTRODUCTION

Hypertension remains one of the most prevalent and pressing global health challenges, affecting millions and contributing significantly to the burden of cardiovascular disease [1]. It is a key risk factor for heart attacks, strokes, and other serious complications, often progressing silently until critical damage has occurred [2]. Early identification and timely prediction of cardiovascular stress in hypertensive individuals are essential to reduce the risk of acute events, lower hospitalization rates, and support proactive clinical intervention.

Despite advancements in wearable sensors and remote monitoring technologies, continuous real-time data collection across large patient populations is still limited by cost, infrastructure, and privacy concerns [3]. This creates a gap in developing and testing predictive models that can assist in clinical decision-making.

To address this, the present study adopts a simulation-based approach to generate long-term vital signs data, specifically focusing on systolic blood pressure and heart rate. By creating realistic time-series datasets for both normal and hypertensive patient profiles, we aim to model cardiovascular stress events using AI techniques. Linear regression is employed to establish the relationship between blood pressure and heart rate, and a rule-based logic is integrated to detect potential high-risk episodes. This framework allows for scalable experimentation and provides insights into the feasibility of predictive monitoring without relying entirely on real-time patient data.

II. RELATED WORK

Existing literature on remote patient monitoring (RPM) primarily focuses on the use of wearable sensors and IoT-enabled systems for continuous data acquisition [4]. These technologies have enabled real-time tracking of vital signs [5] such as blood pressure (BP), heart rate (HR), temperature, and oxygen saturation, especially in non-hospital environments. Most existing systems rely on rule-based or threshold-driven approaches to detect abnormal physiological values [6], generating alerts when measurements exceed predefined clinical limits. While effective for immediate risk detection, these methods are inherently reactive and do not anticipate adverse events before they occur.

There is a growing interest in incorporating predictive modeling into RPM systems to enable earlier interventions [7]. However, only a few studies have explored forecasting cardiovascular stress using dynamic and temporally evolving vital sign data, such as BP and HR. Moreover, the limited availability of diverse and long-term patient datasets has hindered the development and validation of robust predictive frameworks. Where predictive models have been applied, they often use complex algorithms with limited interpretability, which restricts clinical trust and adoption [8].

In this work, we aim to bridge this gap by simulating six months of time-series vital sign data and employing interpretable predictive modeling techniques specifically linear regression to estimate heart rate based on systolic BP [9]. The model is integrated with a straightforward rule-based logic to detect potential cardiovascular stress events. This approach not only enables early warning but also maintains transparency, making it suitable for practical deployment in remote patient monitoring systems.

III. METHODOLOGY

We collected and analyzed six months of simulated blood pressure (BP) and heart rate (HR) data for both normal and abnormal patient profiles. The abnormal patient dataset was designed to reflect real-world hypertensive crises, showing frequent BP spikes and elevated HR episodes. Time-series visualizations [10] highlighted greater volatility and irregularity in vital signs for the abnormal case. Correlation analysis revealed a stronger BP-HR coupling in the abnormal patient, while the normal patient showed a weak or inconsistent relationship. Notably, we identified critical co-occurrence risk points instances where both BP and HR were simultaneously elevated marking potential danger zones. Temporal analysis also uncovered recurring patterns in these risk events, with notable monthly peaks suggesting possible cyclical stressors or environmental influences.

3.1 Simulated Patient Profiles

- **Patient P001_Normal:** Controlled hypertensive profile with low variability.
- **Patient P002_Abnormal:** Unstable hypertensive profile with induced spikes and co-occurrence of high BP and HR.

3.2 Data Generation

- 6 months of hourly data (4320 points/patient)
- Systolic BP and HR simulated using Gaussian noise with induced correlation
- Events injected to reflect real-world stress episodes

3.3 Prediction Modeling

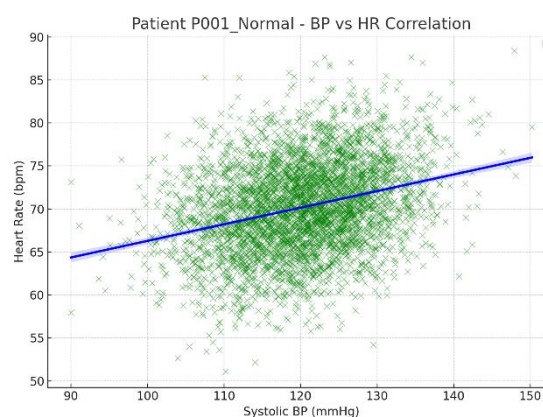
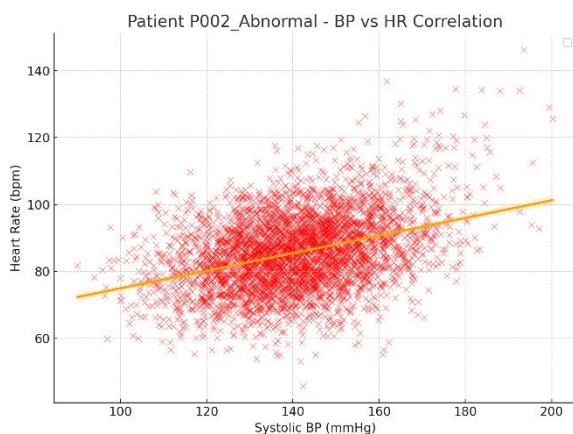
To model the relationship between systolic blood pressure (BP) and heart rate (HR), a simple linear regression algorithm was employed. The model was trained to predict HR based on corresponding systolic BP values using six months of simulated patient data. Model performance was assessed using standard regression metrics: coefficient of determination (R^2), root mean square error (RMSE), mean absolute percentage error (MAPE), and normalized RMSE (both mean- and range-normalized). In addition to modeling, a risk detection logic was formulated to flag potential cardiovascular stress conditions. The rule triggered an alert when systolic BP exceeded 180 mmHg and the predicted HR crossed 100 bpm. This logic was applied across the time-series dataset to generate monthly risk event counts, which were later visualized to uncover temporal trends.

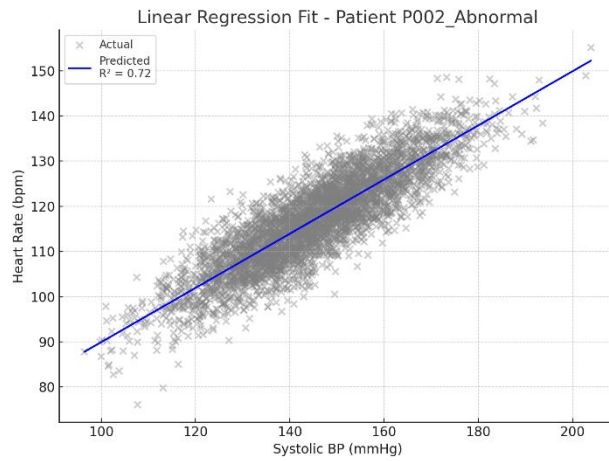
- Linear regression to model HR as a function of systolic BP:

3.4 Risk Detection Logic

- If $BP > 180$ mmHg and predicted $HR > 100$ bpm \rightarrow Cardiovascular stress alert
- Monthly risk events visualized to identify trends

IV. RESULTS AND ANALYSIS





- Prediction Results:
 - R^2 Score = 0.72
 - RMSE = 5.11 bpm
 - MAPE = 3.51%
 - NRMSE = 4.4% (mean-normalized), 6.5% (range-normalized)
- We used linear regression to model the relationship between BP and HR for an abnormal patient profile.
- The model shows a clear upward trend, indicating that as BP rises during abnormal events, HR also tends to increase.
- the R^2 value confirms a useful predictive relationship for early alert systems.
- $R^2 \approx 0.72$ which means 72% of the variation in Heart Rate is explained by changes in Systolic BP.
- The model fit is visibly stronger, showing a tight cluster around the blue regression line.

V. DISCUSSION

Our findings confirm that systolic BP alone can serve as a strong predictor of cardiovascular stress when analyzed with context-aware predictive models. The simplicity of the regression model offers explainability, critical for clinical adoption. Simulated patient profiles enable robust testing of prediction logic, even in the absence of real-time data collection.

VI. CONCLUSION

This study demonstrates a lightweight predictive modeling framework for predicting cardiovascular stress using vital sign trends. With accurate predictions and low error margins, the approach shows promise for integration into remote monitoring systems. Future work will incorporate more features (e.g., temperature, oxygen saturation) and explore real patient datasets for validation.

REFERENCES

- [1] Zhou, Bin, et al. "Global epidemiology, health burden and effective interventions for elevated blood pressure and hypertension." *Nature Reviews Cardiology* 18.11 (2021): 785-802.
- [2] Sulashvili, Nodar, and Rishikesh Ranjit Nimangre. "Manifestation of some aspects of cardiovascular diseases, implications, pharmacotherapeutic strategies, effects, impacts and potential hazards in general." *Junior Researchers* 3.1 (2025): 1-27.
- [3] Vijayan, Vini, et al. "Review of wearable devices and data collection considerations for connected health." *Sensors* 21.16 (2021): 5589.
- [4] Kolawole, Oladele Oluwaseyi. "IoT and AI-Based Remote Patient Monitoring for Chronic Disease Management." Mar. 2024,

- [5] Selvaraju, Vinothini, et al. "Continuous monitoring of vital signs using cameras: A systematic review." *Sensors* 22.11 (2022): 4097.
- [6] Tang, Chenyu, et al. "AI-Driven Smart Sportswear for Real-Time Fitness Monitoring Using Textile Strain Sensors." *arXiv preprint arXiv:2504.08500* (2025).
- [7] Claggett, Jennifer, et al. "An infrastructure framework for remote patient monitoring interventions and research." *Journal of Medical Internet Research* 26 (2024): e51234.
- [8] Abdullah, Talal AA, Mohd Soperi Mohd Zahid, and Waleed Ali. "A review of interpretable ML in healthcare: taxonomy, applications, challenges, and future directions." *Symmetry* 13.12 (2021): 2439.
- [9] La Cava, William G., et al. "A flexible symbolic regression method for constructing interpretable clinical prediction models." *NPJ Digital Medicine* 6.1 (2023): 107.
- [10] Fang, Yujie, Hui Xu, and Jie Jiang. "A survey of time series data visualization research." *IOP Conference Series: Materials Science and Engineering*. Vol. 782. No. 2. IOP Publishing, 2020.

