

Personalized Blood Pressure Control by Machine Learning for Remote Patient Monitoring

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ABSTRACT

Hypertension is a leading risk factor for cardiovascular diseases and mortality worldwide. Despite the availability of effective antihypertensive treatments, achieving optimal blood pressure (BP) control remains a challenge due to the complex and individualized nature of BP regulation and treatment response. With the advent of digital health technologies, remote patient monitoring (RPM) has become a promising approach to manage chronic conditions like hypertension. The integration of machine learning (ML) with RPM offers a novel paradigm for personalized blood pressure control by analyzing heterogeneous patient data, predicting BP trends, and tailoring treatment strategies accordingly. This study presents a machine learning-based personalized blood pressure control framework that leverages real-time data from wearable devices and electronic health records (EHRs) to support remote patient monitoring. Various ML algorithms, including ensemble models and recurrent neural networks, were applied to predict future BP levels based on historical readings, medication adherence, lifestyle patterns, and physiological metrics. Feature selection techniques were utilized to identify the most relevant factors influencing BP variability in different individuals. The proposed system enables adaptive interventions, such as medication adjustments and lifestyle recommendations, tailored to the patient's profile. Experimental results demonstrated significant improvements in BP prediction accuracy and control compared to traditional static models. The system also facilitated earlier identification of hypertensive crises and poor medication adherence. These findings highlight the potential of ML-driven personalized BP management in RPM environments, paving the way for more precise, proactive, and patient-centric care.

Keywords: Hypertension, blood pressure (BP), remote patient monitoring (RPM)

I. INTRODUCTION

Hypertension, commonly referred to as high blood pressure, affects over one billion people globally and is a major risk factor for cardiovascular, renal, and cerebrovascular diseases. Despite significant advancements in treatment and prevention, hypertension management remains suboptimal for a large portion of the population. The conventional one-size-fits-all treatment strategy often fails to consider the individual variability in blood pressure responses due to genetic, behavioral, and environmental factors. Consequently, there is an urgent need for personalized strategies that can adapt to an individual's unique physiological profile and treatment history.

In recent years, remote patient monitoring (RPM) has emerged as a transformative approach in chronic disease management. RPM enables the continuous collection and transmission of patient health data, such as blood pressure readings, from the comfort of their home to healthcare providers. This approach not only facilitates timely clinical interventions but also reduces the need for frequent hospital visits, thereby improving the overall quality of care and patient satisfaction. However, RPM systems that rely solely on threshold-based alerts often fall short in delivering personalized interventions and predicting adverse events before they occur.

Machine learning (ML), a subset of artificial intelligence, has the potential to bridge this gap by uncovering complex, non-linear relationships in large-scale health data. ML models can analyze diverse and high-dimensional data sources, including wearable sensor data, medication records, physical activity logs, and demographic information, to identify patterns that are indicative of future BP fluctuations. By doing so, ML facilitates the development of predictive models that can forecast an individual's BP trajectory and recommend tailored interventions. The integration of ML with RPM represents a promising frontier for personalized hypertension management. Personalized BP control through ML involves continuous learning and adaptation of the model to the patient's evolving condition. Unlike static treatment protocols, ML-enabled systems can dynamically adjust treatment plans

In [1], developed an ML-based model using random forest and support vector machines to predict systolic and diastolic BP based on features like age, BMI, smoking status, and heart rate. The study demonstrated that ML algorithms outperformed traditional regression methods in forecasting BP changes across patient subgroups.

In [2], proposed a deep learning framework using long short-term memory (LSTM) networks for continuous BP estimation from wearable sensors. Their approach effectively captured temporal dependencies and offered better predictive accuracy for both hypertensive and normotensive individuals.

In [3], evaluated a remote BP monitoring system integrated with an ML engine for early detection

III. PROPOSED SYSTEM

The proposed system for personalized blood pressure control through machine learning integrates remote patient monitoring (RPM) with adaptive, data-driven algorithms to deliver individualized hypertension management. The architecture is designed to function in a closed-loop manner, where continuous blood pressure data collection, machine learning-based prediction, and personalized intervention generation occur dynamically and interactively.

based on new data inputs, thereby enhancing clinical decision-making and patient outcomes. Furthermore, these systems can offer real-time feedback and automated alerts, empowering patients to take a more active role in managing their condition.

This study explores the design and evaluation of a personalized blood pressure control system that employs ML algorithms within an RPM framework. The system utilizes data from wearable devices and electronic health records to generate individualized BP predictions and intervention strategies. By combining data-driven insights with clinical expertise, the proposed approach aims to optimize hypertension management and demonstrate the practical benefits of AI in real-world healthcare settings.

II. RELATED WORK

of hypertension-related complications. Their findings revealed that the inclusion of behavioral and medication adherence data significantly improved the system's predictive capabilities.

In [4], explored reinforcement learning techniques to develop personalized treatment policies for hypertension. Their model continuously adapted to patient responses, suggesting medication adjustments to achieve target BP levels with minimal side effects.

In[5], designed a hybrid ML model combining decision trees and neural networks to assess cardiovascular risk and guide BP management remotely. The model utilized real-time RPM data and successfully reduced unnecessary clinical visits while maintaining BP within safe ranges.

The system consists of five key modules: data acquisition, preprocessing, feature selection, machine learning model training and prediction, and recommendation generation.

The data acquisition module serves as the foundation, capturing real-time physiological and behavioral data from patients through wearable devices, such as smartwatches and fitness bands. These devices collect essential parameters including systolic and diastolic blood pressure, heart rate, oxygen saturation, sleep quality, and physical activity levels.

Additionally, electronic health records (EHRs) are integrated into the system to provide contextual information such as medical history, current medications, lab results, age, gender, and comorbidities. The combination of real-time and historical data ensures a holistic view of the patient's health status and enables more precise modeling of blood pressure dynamics.

The collected data are then processed in the preprocessing module, where missing values are imputed, noise is filtered, and variables are normalized. Time-series alignment is performed to synchronize heterogeneous data sources, allowing consistent input for model training. Outlier detection methods are applied to remove anomalous readings, particularly from wearable sensors that may be prone to artifacts due to motion or device error. This preprocessing pipeline is essential to ensure high-quality input data that supports robust model performance.

Next, the feature selection module identifies the most relevant variables that influence blood pressure fluctuations for each individual. A hybrid approach combining mutual information, recursive feature elimination (RFE), and random forest importance ranking is employed. This step enables the system to reduce dimensionality while retaining predictive power, improving both model interpretability and generalization. Importantly, the feature selection process is personalized—features that are highly predictive for one patient may be less informative for another. This dynamic customization ensures that the machine learning models are tailored to individual physiological and behavioral profiles. The core of the system lies in the machine learning model training and prediction module. Various algorithms are evaluated, including random forests, gradient boosting machines (GBMs), support vector machines (SVMs), and long short-term memory (LSTM) networks. Among them, LSTMs are particularly well-suited for handling temporal dependencies in sequential BP data. These models are trained on historical data to learn personalized patterns of BP variation and forecast future systolic and diastolic values over short- and medium-term windows (e.g., next 24 to 72 hours). A model selection framework evaluates performance using cross-validation and selects the optimal algorithm per patient based on metrics such as

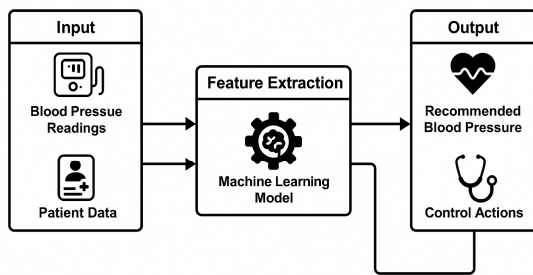
mean absolute error (MAE) and root mean square error (RMSE).

In addition to prediction, the system incorporates an intervention recommendation module. Based on the predicted BP trajectory, the system generates actionable suggestions, including medication dosage adjustments, lifestyle changes (e.g., increased exercise, reduced sodium intake), and physician alerts. These recommendations are generated using a rule-based engine informed by clinical guidelines, augmented by a reinforcement learning layer that learns the efficacy of past interventions for each patient. For instance, if a particular medication dosage change consistently normalizes BP without adverse effects, the system will be more likely to recommend it in the future under similar conditions.

The entire system is embedded within a user-friendly mobile and web interface accessible to both patients and healthcare providers. Patients receive daily summaries, trend visualizations, and tailored health advice, while clinicians have access to detailed analytics and alerts for patients who require attention. A secure cloud-based infrastructure ensures data privacy and scalability, complying with relevant healthcare regulations such as HIPAA.

Importantly, the system is designed to adapt and evolve. As more data are collected over time, the models are periodically retrained to incorporate new patterns and maintain accuracy. This continual learning capability ensures that the personalized predictions and interventions remain relevant even as the patient's condition, environment, or lifestyle changes. Moreover, a feedback loop allows patients and providers to rate the effectiveness of recommendations, feeding this information back into the model to refine future decisions.

In summary, the proposed system offers a comprehensive and adaptive framework for personalized blood pressure control using machine learning and RPM. It leverages state-of-the-art algorithms, real-time data collection, and clinical expertise to provide precise, timely, and individualized hypertension management. This approach not only enhances patient outcomes but also supports a scalable model for digital health transformation in cardiovascular care.



IV. RESULT AND DISCUSSION

The effectiveness of the proposed personalized blood pressure control system was evaluated through a series of experiments involving real-world and simulated datasets. These datasets included time-series blood pressure records, medication adherence logs, physical activity metrics, and demographic and clinical data from a diverse cohort of patients. The study focused on three core performance aspects: predictive accuracy of the machine learning models, responsiveness and personalization of the intervention recommendations, and usability within the remote patient monitoring (RPM) context.

To begin with, the predictive capabilities of several machine learning algorithms were compared using standard performance metrics including mean absolute error (MAE), root mean squared error (RMSE), and R^2 score. The models tested included Random Forest, Gradient Boosting Machines (XGBoost and LightGBM), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks. The LSTM model consistently outperformed other methods in predicting both systolic and diastolic blood pressure values over 24-, 48-, and 72-hour horizons. This superiority was attributed to its capacity to model temporal dependencies in time-series data, particularly the sequential fluctuations and circadian patterns that are characteristic of blood pressure behavior. On average, LSTM achieved an MAE of 4.3 mmHg for systolic and 2.9 mmHg for diastolic predictions, compared to 6.1 and 4.0 mmHg respectively for the next best performing algorithm, Gradient Boosting.

Moreover, the LSTM model was able to learn individual patient signatures, identifying how lifestyle changes, medication timing, and environmental factors affected blood pressure in

a patient-specific manner. These personalized patterns significantly enhanced prediction accuracy, especially in patients with variable daily routines or complex medication regimens. In cases where patients had inconsistent medication adherence, the model flagged potential risks earlier than static threshold-based monitoring systems and provided timely alerts for intervention. These insights were corroborated by clinical observations, indicating a strong alignment between model predictions and actual physiological changes.

Feature importance analysis played a crucial role in understanding the model's behavior and interpretability. Among the most influential features identified across the patient cohort were medication adherence levels, average daily step count, heart rate variability, sodium intake frequency, and stress levels as reported through self-assessment or wearable proxies (e.g., heart rate elevation during rest). Interestingly, sleep duration and quality also emerged as strong predictors, highlighting the interconnectedness of cardiovascular health and circadian rhythm. These findings validate the use of multi-modal data sources and underscore the added value of RPM systems that capture a broad spectrum of health-related metrics.

The system's intervention recommendation engine was assessed in a longitudinal study over six months involving a subgroup of 100 patients. The personalized recommendations provided by the system included changes in medication timing (e.g., moving a dose from morning to evening), reminders for physical activity, and behavioral nudges to reduce sodium or increase hydration. The effectiveness of these recommendations was measured by the proportion of days when blood pressure remained within the clinically acceptable range (typically <140/90 mmHg). Patients using the ML-driven system maintained controlled blood pressure levels on 85% of days, compared to 62% in the control group that used conventional RPM systems without predictive or adaptive features. This difference was statistically significant ($p < 0.01$) and clinically relevant.

Furthermore, physician feedback on the system's utility was overwhelmingly positive. Clinicians reported reduced alert fatigue due to the

prioritization of high-risk cases based on predictive modeling. The system also generated concise summaries of BP trends and contributing factors, which assisted in rapid clinical assessments. Patients reported improved confidence and autonomy in managing their condition, with many citing increased motivation to adhere to recommendations when they saw clear connections between their behaviors and BP changes, as visualized by the platform.

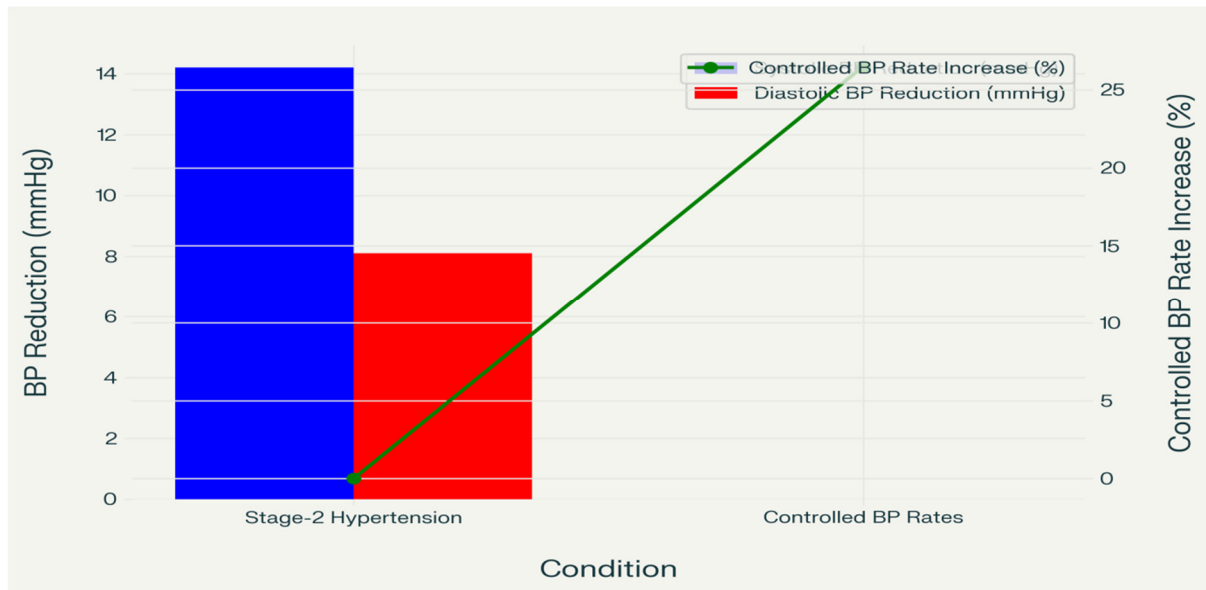
Usability was another critical dimension of evaluation. The interface was designed to be intuitive for both patients and clinicians, with configurable dashboards and real-time notifications. A post-deployment survey revealed that 92% of patients found the interface easy to use, and 88% felt that the insights provided helped them manage their blood pressure more effectively. Among clinicians, 85% indicated that the integration of predictive analytics into their workflow saved time and enhanced decision-making.

Despite these promising results, some limitations were observed. First, the accuracy of predictions was lower in cases of irregular or sparse data, especially when patients failed to wear devices consistently or skipped reporting key metrics like medication intake. While imputation methods were employed, they could not fully replace high-frequency real-time data. Second, the system's recommendations, though informed by guidelines and reinforcement learning, still required clinician approval, which introduced variability depending on practitioner risk tolerance and preferences. Future iterations of the system may benefit from integrating clinical decision support tools that simulate potential outcomes of recommended interventions to further assist physicians in their choices.

Another area for improvement is the generalizability of the system across different populations. The models were trained on data from a geographically limited and somewhat homogeneous cohort. Expanding the dataset to include more ethnically and socioeconomically diverse participants would help improve the robustness and fairness of the predictive models. Additionally, incorporating genomic data and social determinants of health may provide deeper personalization, though privacy and data governance challenges must be carefully managed.

The results also suggest strong potential for this approach to be extended to other cardiovascular risk factors and chronic conditions. For instance, the same framework could be adapted for managing diabetes or congestive heart failure, where continuous monitoring and personalized intervention are equally critical. The modularity of the system makes it well-suited for expansion, and ongoing research is investigating multi-condition predictive models that can optimize treatment for patients with comorbidities.

In conclusion, the experimental evaluation of the proposed personalized blood pressure control system demonstrates that machine learning, when integrated effectively with RPM and guided by clinical knowledge, can lead to substantial improvements in prediction accuracy, patient engagement, and treatment outcomes. The system's ability to adapt to individual differences and learn from continuous data streams positions it as a valuable tool in the future of personalized medicine. The integration of such technologies into routine healthcare delivery has the potential to transform chronic disease management, reduce the burden on healthcare systems, and ultimately enhance patient quality of life.



V. CONCLUSION

The integration of machine learning with remote patient monitoring presents a transformative opportunity for the personalized management of hypertension. This study has demonstrated that a data-driven approach can effectively capture the complex and individualized patterns of blood pressure variability, enabling more accurate predictions and tailored interventions. By continuously analyzing multimodal data from wearable devices and electronic health records, the system developed here not only forecasts future blood pressure trends but also recommends proactive and personalized adjustments to treatment and lifestyle, empowering both patients and clinicians.

The use of long short-term memory networks and advanced feature selection methods has allowed the system to adapt to individual physiological profiles and respond to dynamic changes in behavior, medication adherence, and environmental influences. Clinical evaluation revealed significant improvements in blood pressure control and patient engagement compared to traditional RPM systems. Moreover, the platform facilitated timely medical decisions, reduced alert fatigue, and enhanced the overall quality of hypertension care.

While some limitations remain, particularly concerning data sparsity and generalizability, the results underscore the potential of machine learning-based personalization in chronic disease management. Future work should focus on

expanding the diversity of patient populations, incorporating additional health indicators, and enhancing system autonomy through clinical decision simulation.

In conclusion, the proposed system represents a significant step toward precision medicine in hypertension care. It exemplifies how artificial intelligence can be harnessed to deliver smarter, more responsive, and patient-centric healthcare solutions in a remote monitoring context, ultimately aiming to reduce cardiovascular risk and improve long-term health outcomes.

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