

A Comprehensive Review of Machine Learning Techniques for Non-Invasive Blood Pressure Prediction and Hypertension Detection

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Abstract: Blood pressure prediction has become a major research focus due to the growing need for early hypertension detection and continuous health monitoring. Traditional cuff-based measurements are often inconvenient, intermittent, and unsuitable for real-time analysis. Recent advancements in machine learning provide powerful alternatives for non-invasive and continuous blood pressure estimation using physiological signals such as photoplethysmography (PPG), electrocardiography (ECG), and demographic attributes. This review paper presents a detailed analysis of machine learning and deep learning models applied to blood pressure prediction, including regression methods, ensemble classifiers, and advanced architectures like CNN and LSTM. It explores feature extraction techniques, dataset characteristics, evaluation metrics, and current challenges. The study highlights recent developments, research gaps, and future opportunities for improving accuracy, reliability, and real-time clinical applicability.

Keywords—*Blood Pressure Prediction, Machine Learning, Hypertension Detection, Photoplethysmography (PPG), Deep Learning, Non-Invasive Monitoring, Health Analytics*

I. INTRODUCTION

Introduction

Blood pressure (BP) is one of the most critical physiological parameters for assessing cardiovascular health. Hypertension, characterized by consistently high blood pressure, is a major risk factor for heart disease, stroke, kidney failure, and other serious health conditions. According to the World Health Organization, hypertension affects over one billion people worldwide, contributing significantly to global morbidity and mortality. Early detection and continuous monitoring of blood pressure are essential for timely interventions and improved patient outcomes. Traditional methods for measuring blood pressure, such as the sphygmomanometer or cuff-based devices, are widely used but have limitations. These methods are intermittent, require manual operation, and can be uncomfortable for patients, making them unsuitable for continuous or real-time monitoring. Moreover, the accuracy of cuff-based measurements can be influenced by external factors such as body position, movement, or operator errors.

Recent advancements in machine learning (ML) and artificial intelligence have enabled the development of innovative approaches for non-invasive and continuous blood pressure monitoring. By leveraging physiological signals such as photoplethysmography (PPG), electrocardiography (ECG), and demographic information, machine learning models can predict systolic and diastolic blood pressure with promising accuracy. Regression models, ensemble learning techniques, and deep learning architectures such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks have been applied to extract meaningful features from signals and capture complex non-

linear relationships. Numerous datasets, including MIMIC, PPG-BP, and UCI Blood Pressure datasets, have facilitated research in this domain by providing annotated physiological signals for model training and evaluation. Various studies have focused on feature engineering, signal pre-processing, handling imbalanced datasets, and optimizing model performance for accurate BP prediction. Despite significant progress, challenges remain, such as the variability of signals across individuals, noise in sensor data, model generalization, and real-time deployment constraints [2]. This review paper aims to provide a comprehensive analysis of recent machine learning techniques used for blood pressure estimation and hypertension detection. It explores methodologies, datasets, feature extraction strategies, evaluation metrics, and recent advancements in deep learning models. Additionally, it identifies research gaps and highlights future directions for improving accuracy, reliability, and clinical applicability, ultimately contributing to the development of robust, non-invasive, and continuous blood pressure monitoring systems [1].

II. LITRETURE REVIEW

The literature survey reviews major advancements in blood pressure prediction and hypertension detection, with a focus on traditional machine learning techniques. Earlier research largely employed conventional algorithms and manually extracted features to estimate blood pressure values and classify hypertensive conditions. Despite achieving reasonable accuracy, these approaches suffer from limited robustness and scalability. This section provides a concise overview of such methods and discusses their shortcomings, which have led to the exploration of more sophisticated learning models..

Blood Pressure Prediction and hypertension Detection:

Blood pressure prediction and hypertension detection play a vital role in the early diagnosis and management of cardiovascular diseases. Traditional methods primarily rely on cuff-based measurements and clinical assessments, which may be inconvenient for continuous monitoring. Recent advancements in machine learning and data-driven techniques have enabled the development of automated systems capable of predicting blood pressure levels using physiological signals, demographic data, and lifestyle factors. These approaches aim to improve accuracy, efficiency, and accessibility of hypertension screening. Early detection through intelligent prediction models can assist healthcare professionals in timely intervention, reduce the risk of severe complications, and support personalized healthcare solutions. Continuous research in this domain contributes to the development of reliable, non-invasive, and cost-effective monitoring systems.

Authors [1] Hypertension remains a major global public health challenge due to its strong association with severe complications such as stroke, renal failure, and cardiovascular diseases. Early and accurate detection is widely recognized as a crucial preventive measure for reducing mortality and enabling timely clinical intervention. Several studies have investigated the potential of machine learning techniques to improve hypertension detection by enhancing diagnostic accuracy and reliability. Recent research reports the development of novel ML-based frameworks that outperform conventional approaches, achieving accuracy levels higher than previously documented benchmarks. These findings highlight the effectiveness and robustness of data-driven models in supporting early diagnosis, facilitating timely treatment, and improving patients' overall quality of life.

Authors [3] High blood pressure monitoring is essential for the early detection and prevention of cardiovascular diseases. Recent studies have explored photoplethysmography (PPG) as a promising non-invasive technique for continuous blood pressure estimation. A deep learning-based approach utilizing AlexNet in the time-frequency domain has been proposed for classifying blood pressure levels using PPG signals from a publicly available dataset. After preprocessing and data balancing, the model demonstrated high classification performance, achieving an accuracy of 98.89% and superior specificity. The proposed approach outperformed other well-known deep learning architectures, highlighting the effectiveness of AlexNet and the potential of PPG-based deep learning models for accurate, non-invasive blood pressure monitoring.

This work [4] evaluates machine learning models for hypertension risk prediction using large-scale health data from Indonesia. Models incorporating patient history achieved higher accuracy; however, models excluding personal history also demonstrated reliable predictive performance. Gradient boosting algorithms, particularly LightGBM, showed

superior results. Key predictors included age, body weight, and family history. The findings indicate that effective hypertension risk screening is feasible even in low-resource settings where patient history data may be limited.

This research [5] developed an explainable machine learning model to predict high intraoperative blood pressure variability (IBPV) using preoperative clinical features. A retrospective dataset of noncardiac surgeries was analyzed using the XGBoost algorithm. The proposed model demonstrated good predictive performance, achieving high accuracy and specificity. Explainability analysis identified age, ASA classification, and preoperative plasma albumin levels as key predictors of high IBPV. The findings highlight the potential of explainable ML models to support intraoperative circulatory management and improve surgical outcomes, while emphasizing the need for external validation across diverse clinical settings.

III. FINDINGS OF THE SURVEY

This survey systematically reviewed recent research on blood pressure prediction and hypertension detection using machine learning and deep learning techniques. The findings indicate a clear shift from traditional statistical and rule-based approaches toward data-driven models that leverage large-scale physiological, clinical, and demographic data. Conventional methods, although simple and interpretable, often suffer from limited accuracy, poor generalization, and dependence on handcrafted features. In contrast, machine learning models such as Random Forest, Support Vector Machines, XGBoost, and LightGBM have demonstrated improved predictive performance by effectively capturing nonlinear relationships among risk factors.

A key finding of the survey is the growing importance of non-invasive sensing technologies, particularly photoplethysmography (PPG), for continuous blood pressure monitoring. Several studies reported that combining PPG signals with deep learning architectures such as CNNs, AlexNet, and ResNet significantly enhances classification accuracy for hypertension stages. Transforming one-dimensional physiological signals into time–frequency representations or images further improves feature extraction and model robustness. These approaches show strong potential for real-time and wearable healthcare applications. Another major observation is the role of large-scale healthcare datasets in improving model reliability. Studies utilizing millions of patient records achieved more stable and generalizable results compared to small clinical datasets. However, data imbalance, missing values, and noise remain critical challenges. The use of data preprocessing, balancing techniques, and feature selection methods was found to be essential for achieving optimal performance. Explainable AI techniques, particularly SHAP-based analysis, have increasingly been adopted to identify key predictors such as age, body weight, family history, and biochemical parameters, thereby enhancing model transparency and clinical trust. The survey also reveals that incorporating patient history generally improves prediction accuracy; however, models excluding historical data can still perform effectively using accessible demographic and lifestyle features. This is particularly important for low-resource settings where complete patient records may not be available. Despite notable performance gains, many studies lack external validation, limiting their clinical applicability. Overall, the findings confirm that machine learning–based frameworks significantly advance hypertension detection and blood pressure prediction, while highlighting the need for standardized datasets, explainable models, and real-world validation to support large-scale clinical deployment.

CONCLUSION

This survey highlights the significant progress achieved in blood pressure prediction and hypertension detection through machine learning and deep learning techniques. The reviewed studies demonstrate that data-driven models outperform traditional methods by effectively capturing complex and nonlinear relationships among physiological, clinical, and demographic features. Non-invasive sensing approaches, particularly those based on photoplethysmography signals, combined with advanced deep learning architectures, have shown strong potential for

continuous and real-time monitoring. The adoption of explainable artificial intelligence methods further improves model transparency and clinical trust by identifying key risk factors influencing predictions. However, challenges such as data imbalance, limited external validation, and variability in datasets remain unresolved. Future research should focus on developing standardized evaluation protocols, improving model generalizability, and validating these systems across diverse populations and clinical environments. Overall, machine learning-based frameworks represent a promising and effective direction for early hypertension detection, personalized healthcare, and improved cardiovascular disease management.

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