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Predictive Modeling for Hypertension Detection: A Machine Learning Approach

Anirban Mondal
Student
Department of Information Technology
JIS College of Engineering, Kalyani, India

Kankana Hazra,
Student
Department of Computer Science & Engineering
Meghnad Saha Institute of Technology, Kolkata, India

Abstract : Millions of people worldwide suffer from hypertension,often known as high blood pressure, which can have serious consequences for their cardiovascular system if left undiagnosed and untreated. Effective preventative measures and therapy for hypertension depend on early and precise recognition of the condition. This project aims to create a machine learning-based system for detecting hypertension, offering a scalable and affordable means of quickly identifying those at risk. The suggested system uses cutting-edge machine learning algorithms, such as Random Forest, Logistic Regression, Support Vector Machine, and Decision Tree methods, to evaluate pertinent medical data and make precise predictions about the state of hypertension. The main input data sources are physiological indicators like blood pressure readings, heartrate, and demographic data. The model also considers medical history and lifestyle factors, providing a thorough method for detecting hypertension.

***IndexTerms* - Hypertension, Random Forest, Logistic Regression, Support Vector Machine, Decision Tree.**

I. Introduction

INTRODUCTION

Hypertension, commonly known as high blood pressure, is a prevalent and chronic medical condition characterized by elevated blood pressure levels in the arteries. It poses a significant health risk globally, contributing to various cardiovascular diseases, including heart attack, stroke, and kidney failure. Despite being a manageable condition, hypertension often goes undiagnosed or untreated, leading to severe complications and premature death. Therefore, a comprehensive understanding of hypertension, its causes, risk factors, diagnosis, treatment, and prevention strategies is essential for public health awareness and effective management.

Hypertension can be categorized into two main types: primary (essential) hypertension and secondary hypertension. Primary hypertension, accounting for the majority of cases, develops gradually over time and has no identifiable cause. It is often linked to lifestyle factors, including poor diet, lack of physical activity, obesity, and stress. On the other hand, secondary hypertension results from an underlying medical condition, such as kidney disease, hormonal disorders, or medication side effects.

Various risk factors contribute to the development of hypertension, including age, family history, ethnicity, obesity, excessive alcohol consumption, tobacco use, high salt intake, and chronic stress. Additionally, certain medical conditions, such as diabetes, sleep apnea, and high cholesterol, increase the likelihood of developing hypertension.

Diagnosing hypertension involves measuring blood pressure levels using a sphygmomanometer, which provides two readings: systolic pressure (the pressure when the heart beats) and diastolic pressure (the pressure when the heart rests between beats). Blood pressure is typically expressed as systolic over diastolic pressure (e.g., 120/80 mmHg), with normal blood pressure considered below 120/80 mmHg.

Hypertension is diagnosed when blood pressure consistently exceeds 130/80 mmHg on multiple occasions. Classification of hypertension severity is based on blood pressure readings, ranging from stage 1 hypertension (130-139/80-89 mmHg) to stage 2 hypertension (≥140/≥90 mmHg). Additionally, ambulatory blood pressure monitoring and home blood pressure monitoring may be recommended for accurate diagnosis and assessment of blood pressure variability. Hypertension affects 1 in 3 adults worldwide. This common, deadly condition leads to stroke, heart attack, heart failure, kidney damage and many other health problems.

The number of people living with hypertension (blood pressure of 140/90 mmHg or higher or taking medication for hypertension) doubled between 1990 and 2019, from 650 million to 1.3 billion. Nearly half of people with hypertension globally are currently unaware of their condition. More than three-quarters of adults with hypertension live in low- and middle-income countries.

Older age and genetics can increase the risk of having high blood pressure, but modifiable risk factors such as eating high-salt diet, not being physically active and drinking too much alcohol can also increase the risk of hypertension. Lifestyle changes like eating a healthier diet, quitting tobacco and being more active can help lower blood pressure. Some people may need medicines that can control hypertension effectively and prevent related complications. The prevention, early detection and effective management of hypertension are among the most cost-effective interventions in health care and should be prioritized by countries as part of their national health benefit package offered at a primary care level. The economic benefits of improved hypertension treat-ment programmers outweigh the costs by about 18 to 1. “Hypertension can be controlled effectively with simple, low-cost medication regimens, and yet only about one in five people with hypertension have controlled it.” Said Dr. Tedros Adhanom Ghebreyesus, WHO Director-General. “Hypertension control programmers remain neglected, under-prioritized and vastly underfunded. Strengthening hypertension control must be part of every country’s journey towards universal health coverage, based on well-functioning, equitable and resilient health systems, built on a foundation of primary health care.” The report is being launched during the 78th Session of the United Nations General Assembly which addresses progress for the Sustainable Development Goals including health goals on pandemic preparedness and response, ending tuberculosis and attaining Universal Health Coverage. Better prevention and control of hypertension will be essential to progress in all of these. An increase in the number of patients effectively treated for hypertension to levels observed in high-performing countries could prevent 76 million deaths, 120 million strokes, 79 million heart attacks, and 17 million cases of heart failure between now and 2050. “Most heart attacks and strokes in the world today can be prevented with affordable, safe, accessible medicines and other interventions, such as sodium reduction,” said Michael R. Bloomberg, WHO Global Ambassador for Noncommunicable Diseases and Injuries. “Treating hypertension through primary health care will save lives, while also saving billions of dollars a year.”

Globally, the most significant modifiable risk factor for cardiovascular disease is still arterial hypertension. The global incidence and prevalence of hypertension and associated cardiovascular consequences remain increased despite extensive knowledge about prevention and treatment strategies [1,2]. This is mostly because to inadequate measures for identification, prevention, and control of the condition. The identification of hypertension remains difficult due to the significant degree of variability in blood pressure (BP) readings and the absence of distinct symptoms.

Through yearly screening programs, the World Hypertension League has spearheaded a global campaign to increase public awareness of the significance of hypertension since 2005. Of the 502079 individuals in the 2018 study with hypertension, only 59.5% knew they had the condition [3]. This data demonstrates that the National Health Services' screening methods are still unable to accurately identify hypertension. Given that identifying risk factors for hypertension may facilitate earlier interventions, aimed at preventing future development of hypertension, early detection of its appearance, and reducing the incidence of its long-term consequences, it is imperative to find new strategies to improve hypertension detection at a population level.

Artificial intelligence (AI) is the umbrella term for any computer system that can carry out tasks that would typically need human intelligence. AI has been effectively applied to the healthcare industry in recent years, demonstrating its applicability as a tool for controlling a variety of clinical diseases [4, 5]. Every year, the Italian Society of Hypertension (SIIA) launches a nationwide campaign to raise awareness of the significance of detecting excessive blood pressure. Numerous hypertension-related questionnaires have been distributed over the years, creating a sizable dataset. Specifically, from 2015 to 2019, 37110 people took part in the World Hypertension Day campaigns. After excluding individuals with high blood pressure who had previously been diagnosed, 20206 subjects were left from the original dataset; of these, 4192 patients (20.75%) had recently been diagnosed with hypertension. Three measures of systolic and diastolic blood pressure as well as heart rate are included in the data, along with questions regarding general knowledge about hypertension and demographics and risk factors. The objective was to use supervised machine learning (ML) techniques on such a big dataset to identify a model that can distinguish between unknown hypertension and evaluate its performance in comparison to the screening protocols in use today. A training set of 14144 records and a validation set of 6062 samples were created from the data. We trained a 10-fold cross-validation process on the initial training set for four machine learning models: logistic regression, decision tree, random forest and support vector machine. We can investigate the use of machine learning techniques in the identification and prognosis of hypertension in this paper. By doing this, we can identify hypertension in its early stages and assist individuals in adopting the appropriate preventative measures to shield themselves from more serious conditions. Large datasets of physiological and clinical parameters can be used, and machine learning models can be trained to identify individuals at risk or already afflicted with hypertension by analyzing patterns and correlations. We can detect hypertension at an early stage because of the great potential that the integration of machine learning algorithms with healthcare systems holds for revolutionizing the early detection and management of hypertension. Given that it's now essential to predict hypertension risk early on, we can employ machine learning to achieve this. We can examine a dataset that includes medical records from a varied population of men and women using machine learning algorithms. The dataset contains crucial parameters that can be used to forecast hypertension in its early stages. We will examine various factors among these parameters, including age, gender, type of chest pain (CP), cholesterol, fasting blood sugar (FBS), resting electrocardiogram (restecg), maximal heart rate attained during exercise (thalach), and more. We have chosen several algorithms to use for the identification of hypertension in this dataset, each with specific advantages and disadvantages. These algorithms yield nearly identical prediction values, ranging from 80% to 100%, which is why we are using them. As a component of artificial intelligence, machine learning is receiving a lot of interest in the management of chronic illnesses. It is thought to be a more accurate option for predicting diseases like hypertension than conventional methods. Thus, we must establish a predictive model for high blood pressure susceptibility. This work aims to create a machine learning prediction model for individuals. It matters because our goal is to develop a predictive model that will aid in the diagnosis of hypertension. Detecting hypertension through a variety of techniques can benefit communities and medical professionals alike. We will discuss our relevant research, our suggested work (data sets and data sources used in our study along with the models and methods employed), all our experimental findings, and the survey results in the remaining sections of the paper.

NEED OF THE STUDY.

AI has been successfully used in healthcare in recent years as auseful medical tool in a variety of clinical situations [3, 4]. In specifically, machine learning (ML) is intended to make highlyaccurate predictions about an individual's outcome based on patterns learned from collected data rather than explicit programming. In the realm of hypertension, many machine learning methods have been used with extremely varied results.

In [5], the study proposed a deep learning-based method for detecting hypertension from electrocardiogram (ECG) signals.They trained convolutional neural networks (CNNs) on a largedataset of ECG recordings and achieved promising results in hypertension detection. In [6] Y. Wang, et al. focused onpredicting hypertension risk using demographic data such as age, gender, BMI, and lifestyle factors. They employed variousmachine learning algorithms including support vector machines (SVM) and decision trees, demonstrating the feasibility ofusing demographic information for hypertension prediction.

In [7], a study proposed a smartphone-based approach forautomated hypertension detection using photoplethysmography (PPG) signals. They developed a machine learning algorithm toanalyze PPG signals collected through smartphone cameras and achieved accurate hypertension detection. Alghamdi et al. investigated the use of wearable sensors combined with recurrent neural networks (RNNs) for continuous monitoring and detection of hypertension in [8]. They collected physiological data from wearable devices and developed RNNmodels to detect hypertensive episodes with high accuracy.

S. Mokeddem et al. proposed a feature selection approach usinggenetic algorithms to identify the most relevant features for hypertension detection. They applied machine learningtechniques on the selected features and achieved improvedperformance compared to using the entire feature set [9].Martinez-Ríos et al.'s review [10] offers a thoroughexamination of the relevant literature. The study's conclusionwas that, despite disagreements on which algorithms perform best, what metrics should be used to assess the model, and mostimportantly, what kinds of data and features should becollected, machine learning has shown to be effective inidentifying hypertensive individuals.

RESEARCH METHODOLOGY

The methodology section outlines the plan and method that how the study is conducted. This includes Universe of the study, sample of the study, Data and Sources of Data, study's variables and analytical framework. The details are as follows.

3.1 Data Source and Data Set

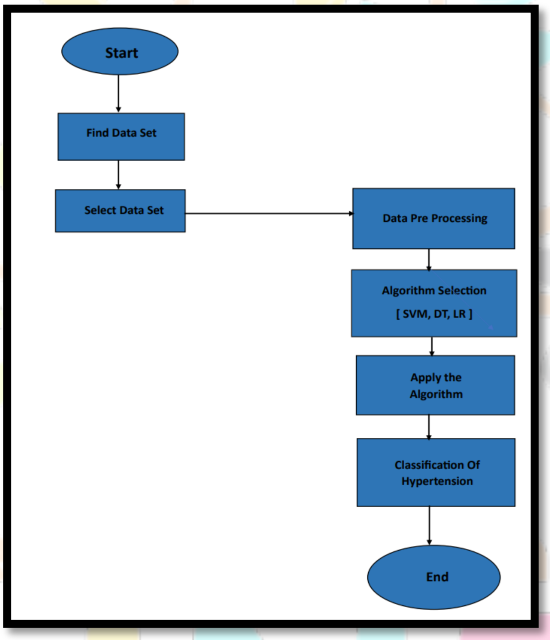


Figure 1: Flow chart of the proposed methodology

3.2 Methodology

The proposed methodology is described in Figure 1. Using dataon a person's health, demographics, and physiological factors, machine learning can be used to detect hypertension by creating prediction models. Here's a project comprises of following steps:

3.2.1 Data Collection:

Collect pertinent datasets with data on people's medical histories, blood pressure readings, age, sex, and ethnicity, medical history, lifestyle factors (exercise, nutrition), and any other pertinent characteristics. When handling sensitive health information, make sure that data privacy and legal requirementslike the Health Insurance Portability and Accountability Act arefollowed.

3.2.2 Data Preprocessing:

Eliminate mistakes, outliers, and missing values from the data. To make sure that machine learning algorithms work with categorical variables, encrypt them and normalize numerical features. To properly assess the performance of the model, divide the data into test, validation, and training sets.

3.2.3 Model Selection and Training:

Select the right machine learning algorithms based on performance, scalability, and interpretability for categorizationjobs. Here we are using **Random Forest, Logistic Regression,Decision Tree** and Support Vector machine models to train our dataset.

3.2.3.1 **Decision Tree (DT):** DT offer a transparent and interpretable framework for decision making by partitioning the feature space into a set of hierarchicalrules. Decision trees are particularly well-suited for capturing non-linear relationships between featuresand outcomes.

3.2.3.2 **Logistic Regression (LR):** It is a classic statistical method. Logistic regression models the probability ofan event occurring based on one or more independentvariables, making it well-suited for identifying the likelihood of hypertension based on a combination ofclinical features. Despite its simplicity logistic regression can provide valuable insights into the relationship between predictor variables and hypertension risk.

3.2.3.3 **Random Forest (RF):** It is an ensemble learningtechnique in which it harnesses the power of multipledecision trees to improve prediction accuracy androbustness. By constructing a multitude of decision trees and aggregating their outputs, random forest canmitigate overfitting and enhance generalization performance Random forest's ability to handle high- dimensional feature spaces and nonlinear relationships makes it a versatile tool in the quest for accurate hypertension prediction.

3.2.3.4 **Support Vector Machine (SVM):** It excels in separating classes by finding the optimal hyperplane that maximizes the margin between data points of different classes. SVMs are particularly effective in cases where the boundary between classes is nonlinearand complex, making them well-suited for hypertension detection tasks.

3.2.4 *Model Evaluation:*

Examine the way trained models perform on the test set to make sure they are resilient and generalizable. Analyze the performance of several models and, using predetermined assessment criteria, choose the model that performs the best.

The Algorithm of proposed methodology

3.2.4.1 Read Data:

- Read the data from a CSV file named "ht_data.csv"into a Pandas Data Frame.

3.2.4.2 Data Preprocessing:

- Display the first 5 rows of the Data Frame.
- Check for missing values in the Data Frame.
- Drop columns with any missing values.
- Get descriptive statistics of the Data Frame.
- Extract feature variables (x) and target variable (y)from the Data Frame.

3.2.4.3 Feature Scaling:

- Standardize the feature variables using StandardScaler from sklearn.preprocessing.

3.2.4.4 Split Data:

- Split the data into training and testing sets usingtrain_test_split from sklearn. model_selection.
- Set the test size to 40% of the total dataset.

3.2.4.5 Model Training:

- Initialize the classifier model from sklearn.tree with'gini' criterion and maximum depth of 5.
- Train the model using the training data (xtrain, ytrain).

3.2.4.6 Model Evaluation:

- Make predictions on the test set (xtest) using thetrained model.
- Calculate the confusion matrix and accuracy score of the model using confusion matrix and accuracy_score from sklearn.metrics.

3.2.4.7 Output:

- Print the confusion matrix and accuracy score obtained from the model evaluation.

3.2.5 *Results and Analysis:*

We divide the whole dataset into train and test dataset which isin 60:40 ratio. After that train the dataset with all the selected algorithms, we get the different accuracy in different algorithmlike:

- Logistic regression Algorithm Accuracy is: 86.05%
- Decision Tree Algorithm Accuracy is: 92.3%
- Support Vector Machine Accuracy is: 85.34%

IV. RESULTS AND DISCUSSION

To detect the Hypertension, we use three classifiers which are SVM, DT and Logistic Regression. The performance of hypertension detection is assessed using some Performance Matrix: Sensitivity, Specificity, F1 Score, Accuracy, and precision. Here, accuracy refers to a specific Hypertension model's overall accuracy. For true positive target values (output value), the ratios are Recall (Pos) and Precision (Pos). For true negative target values, the ratios are Recall (Neg) and Precision (Neg). In an ideal world, Table 1 would be used to measure each experimental result.

4.1 Here are some little details about the methods.

4.1.1 Accuracy:

Accuracy measures the proportion of correct predictions out of the total predictions made.

Equation No. 01

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

4.1.2 Sensitivity (Recall):

Sensitivity measures the proportion of actual positive cases that were correctly identified by the model.

Equation No. 02

$$\text{Sensitivity} = \frac{TP}{TP+FN}$$

4.1.3 Specificity:

Specificity measures the proportion of actual negative cases that were correctly identified by the model.

Equation No. 03

$$\text{Specificity} = \frac{TN}{TN+FP}$$

4.1.4 F1 Score:

F1 Score is the harmonic mean of precision and recall, providing a balance between the two metrics.

Equation No. 04

$$\text{F1 Score} = \frac{2*(Precision * Recall)}{Precision * Recall}$$

4.1.5 Precision:

Precision measures the proportion of true positive predictions out of all positive predictions made by the model.

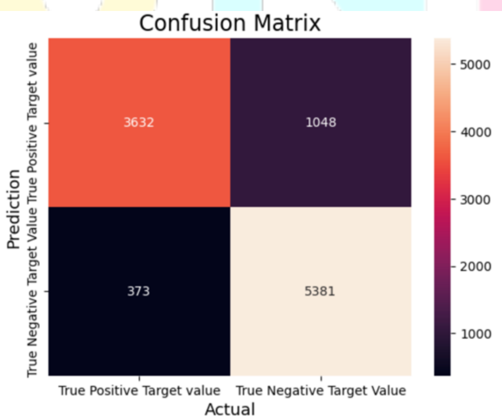
Equation No. 05

$$\text{Precision} = \frac{TP}{TP+FP}$$

4.2 Observation applying Supporting Vector Machine

Applying Supporting Vector Machine, the values have been getting as following that based on Sensitivity it is 90.67%, based on sspecificity it is 83.66%, based on Accuracy it is 86.40% and based on F1 Score it is 83.66%. Below is the figure of Supporting Vector Machine or SVM.

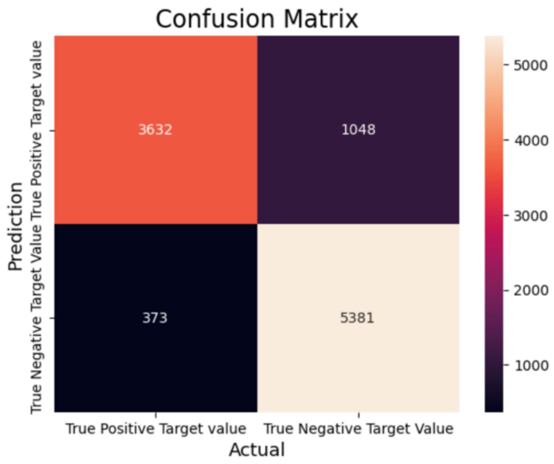
Figure -2: A confusion Table for Supporting Vector Machine



4.3 Observation applying Logistic Regression

Applying Supporting Vector Machine, the values have been getting as following that based on Sensitivity it is 90.67%, based on sspecificity it is83.66%, based on Accuracy it is 86.40% and based on F1 Score it is 83.66%.
Below is the figure of Logistic Regression.

Figure -3: A confusion Table for Logistic Regression

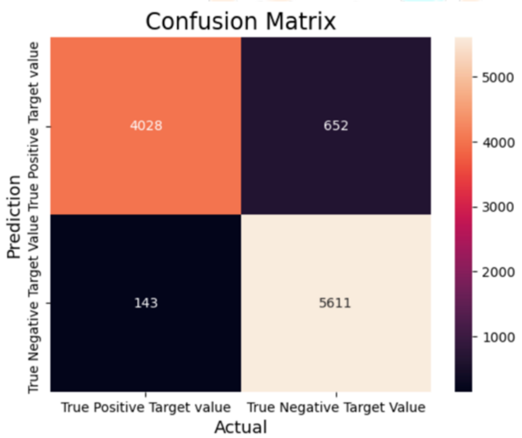


4.4 Observation applying Decision Tree

Applying Supporting Vector Machine, the values have been getting as following that based on Sensitivity it is 96.66%, based on sspecificity it is89.63%, based on Accuracy it is 94.77% and based on F1 Score it is 91.06%.

Below is the figure of Confusion Table for Decision Tr

Figure -4: A confusion Table for Decision Tree



4.5 Summarized Result

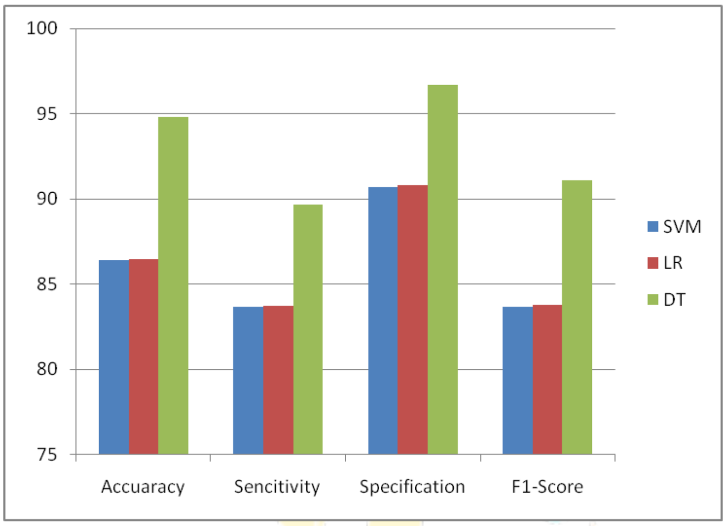
Based On the three classifiers which are SVM, DT and Logistic Regression. and Performance Matrixes such that Sensitivity, Specificity, F1 Score, Accuracy, and precision here it the summarized result in table format.

Table 01

Performance Matrix	Classifier		
	SVM	**LR**	DT
Accuracy	**90.67**	**90.67**	90.66
Sensitivity	**83.66**	**83.66**	89.63
Specificity	**86.4**	**86.4**	94.77
F1- Score	83.66	83.66	91.06

4.5.1 Bar Graph Based on The Summarized Result

Figure -5: BAR Graph



4.5.1 Competitive Analysis

Feature	Project A (OWN Project)	Project B	Project C	Project D
Author	Anirban Mondal, Kankana Hazra, ANNWESHA BANERJEE	Patnaik et al. [1]	López-Martínez et al. [2]	Asmin Sakka, Dina Qarashai, Ahmad Altarawneh [3]
Data Source	Kaggle	Korean National Health Insurance Corporation (NHIC) data	National Centre for Health Statistics.	NSL-KDD & N-BaIoT
ML Algorithm	SVM RF DT	SVM	LR	SVM RF DT
Accuracy	SVM– 84.85% LR – 85.50% DT – 92.58%	SVM - 80.23%	LR – 82.5%	SVM – 77.51% RF - 81.50% DT – 82.7%

I. CONCLUSION

V. Conclusion

The Hypertension Detection System (HDS) project represents a ground-breaking initiative aimed at revolutionizing the early detection and management of hypertension using cutting-edge artificial intelligence (AI) technology. Hypertension, commonly known as high blood pressure, is a prevalent and often asymptomatic condition that significantly increases the risk of cardiovascular diseases, stroke, and other serious health complications. Through the integration of AI algorithms, machine learning models, and advanced data analytics, the HDS project seeks to enhance the accuracy, efficiency, and accessibility of hypertension screening and diagnosis, ultimately improving patient outcomes and reducing the burden of hypertension-related morbidity and mortality.
At the core of the HDS project is the development of sophisticated AI algorithms capable of analyzing diverse datasets, including electronic health records, medical imaging, genetic profiles, wearable sensor data, and lifestyle factors. By leveraging the power of machine learning, these algorithms can extract valuable insights from large-scale, heterogeneous datasets to identify individuals at risk of developing hypertension, predict disease progression, and tailor personalized treatment plans. Additionally, AI-powered decision support systems enable healthcare providers to stratify patients based on their individual risk profiles, prioritize interventions, and optimize resource allocation for maximum impact. Using a large dataset gathered from Kaggle, supervised machine learning algorithms were able to identify hypertension with a moderate degree of accuracy and a subpar level of sensitivity. If further refined and tested in various cohorts, this approach could aid in the screening process for hypertension and could be a more affordable option than having patients evaluated by doctors. Future studies should consider the application of machine learning techniques to create a clinical model that, in practice, combines the need to save costs, especially in environments with limited resources, with the accuracy of diagnosing hypertension.

VI. Acknowledgment

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