An Evaluation and Selection of Machine Learning Models for Blood Pressure Prediction

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ABSTRACT

Blood pressure (BP) prediction using machine learning (ML) algorithms has emerged as a critical area of research in the field of healthcare. ML methods provide particular advantages by using the power of large datasets. Firstly, they enable the creation of tailored predictive models that can take into account a wide range of individual characteristics such as medical history and lifestyle. When carefully trained and validated, these models have the ability to detect high blood (BP) pressure at an early stage, allowing for preventive interventions and customized healthcare regimens. Furthermore, the use of ML in BP prediction can help to reduce healthcare costs by optimizing resource allocation and also offers a viable route for improving the precision of healthcare interventions. This study used an ML model to predict future fluctuations of an individual's BP using their future calendar events. The study was done in Uasin-Gishu County, Kenya. Design science method was employed for the study. The data was collected using a smartwatch, which collected the BP and heart rate, and a smartphone application which collected the individuals' moods, activities, and calendar events. The algorithms that were selected and evaluated for the predictive ML models are; Lasso Regression, Linear Regression, ElasticNet, K-Nearest Neighbors (KNN), Decision Tree Regressor, and Gradient Boosting Regressor (GBR). The Holdout method's test data set, R-Squared (R2) and Mean Squared Error (MSE) were used to evaluate the models. The GBR predictive model was the best performing out of the selected models and was implemented using the Iterative and Incremental Development Model. The GBR model gave a MSE score of 0.182 and R^2 score of 0. 992. A two sample T-test was also conducted giving a T-statistic of 0.047 and a P-value of 0.963. These scores depict the GBRs' good performance in predicting an individual's BP using future planned activities.

Keywords: *Artificial Intelligence, Blood Pressure, Gradient Boosting Regression, Machine Learning, Prediction*

I. INTRODUCTION

The prediction of blood pressure using machine learning entails integrating data from different sources to construct models that can estimate an individual's blood pressure levels, assisting in early detection and individualized healthcare interventions. This technology has the potential to significantly improve hypertension management and health outcomes. In the medical field, prediction and early diagnosis are critical for avoiding health complications. The growing interest in hypertension risk prediction stems from the need for early identification of people at risk of this condition, which these preventive interventions could assist. Predicting the risk of developing high blood pressure can help to pinpoint important risk factors that contribute to hypertension, provide sensible estimates of future hypertension risk, and identify high-risk individuals who can be targeted for healthy behavioral changes and medical treatment to prevent hypertension (Chowdhury et al., 2022). This research therefore sought to determine the best machine learning model for the prediction of BP given the data collected.

There are many algorithms that have been used for regression or classification of BP or hypertension. The type of algorithm used depends on the specific prediction target; whether continuous reading of BP or whether the person is susceptible to hypertension or not. Furthermore, the nature of the input data is an important consideration, as it determines whether a regression or classification solution is warranted. Some of the examples of studies that have used machine learning (ML) models for prediction are: Liu et al. (2018) did a study on Identification of Hypertension by Mining Class Association Rules from Multi-Dimensional Features in 2018. Their objective was a class association rules-based method to identify hypertension. This was to utilize the relationship existing in multi-dimensional features to characterize hypertension pattern more effectively, in order to improve the identification performance. Class association rules-based classifier (CAR-Classifier), overlapping sliding window algorithm, LibSVM, Decision Tree, and Naive Bayes used as baseline methods. 128 subjects were recruited, 67 of them were healthy (35 males, 32 females, 53.2±9.2 years), and the rest were hypertension patients (33 males, 28 females, 55.6±7.9 years) which were diagnosed by an experienced physician. Ballistocardiogram (BCG) signal, and Heart Rate Variation (HRV) were used. The researchers found that the relationship among extracted features could be fully exploited, based on which the proposed method identified hypertension with higher performance. CARs were of high consistency, high helpfulness and high usability, which means that the mined CARs could be used as a reference for analyzing hypertension condition in-depth (Liu et al., 2018).

In 2018, a study was done by Patnaik et al. (2018) to predict the occurrence of essential hypertension using annual health records. The main objective was to predict if an individual will have hypertension in the next year. Data was collected from Korean National Health Insurance Corporation (NHIC) data, containing Electronic medical records. Classifiers; Naive Bayes classifier, Support vector machine (SVM), Logistic regression, Random Forest, Multi-layer Perceptron were used for the study. The results showed that the accuracy range was 66% to 81%, SVM being the most accurate model (Patnaik et al., 2018). Zhang et al. (2019) used the gradient boosting decision tree (GBDT) to predict blood pressure rates based on human physiological data collected by the EIMO device in this study. The study participants were healthy individuals ages between 20 to 30 years. ECG and PPG are examples of EIMO equipment-specific signal collection. The optimal parameters were chosen using the cross-validation method to prevent over-fitting. As a result, this approach outperformed methods such as ridge regression, lasso regression, and KNN algorithm in terms of accuracy and performance in calculating the mean absolute error (MSE) evaluation index. When predicting the BP of an individual, calculating the SBP has an accuracy rate of more than 70% and calculating the DBP has an accuracy rate of more than 64%. To conclude, using the GBDT was the best method for predicting numerous individuals' BP; furthermore, the inclusion of data such as age, body fat, ratio, and height, increased the accuracy of the algorithm, indicating that the addition of new attributes aids in prediction performance (Zhang et al., 2019). Studies, such as the one done by Liu et al. (2018), underscore the progress achieved by predictive machine learning algorithms in the context of hypertension prediction. They identified hypertension in individuals by the use of ML among other results.

The models that were identified were Lasso, Linear Regression, ElasticNet, K-Nearest Neighbors, Decision Tree Regressor and Gradient Boosting Regressor.

Multiple Linear Regression is a statistical technique for predicting a variable's outcome based on the values of two or more variables. It is an extension of linear regression and is also referred to as multiple regression (Etemadi & Khashei, 2021). The difference between the equation for Linear Regression and the equation for Multiple Regression is that the latter requires the ability to handle many inputs, whereas Linear Regression requires just one. In Scikit-learn there is no alternative library to implement Multiple Linear Regression it only has Linear Regression, which works for both Linear Regression and Multiple Regression like in this particular case.

For Linear Regression models, Lasso regression analysis is a shrinkage and variable selection method, it shrinks the regression coefficients towards zero (Ranstam & Cook, 2018). The purpose of lasso regression is to find the subset of predictors that produces the least amount of prediction error for a quantitative response variable. Lasso accomplishes this by imposing a constraint on the model parameters that leads some regression coefficients to decrease toward zero.

Elastic Net is a regression approach that simultaneously does variable selection and regularization. The basic principle underlying the Elastic Net is regularization; it is a series of strategies that can assist minimize overfitting in neural networks, enhancing the accuracy of deep learning models when they are fed new data from the issue domain (Giglio & Brown, 2018). The K-Nearest Neighbors (KNN) algorithm predicts the values of new data points based on 'feature similarity.' This means that a value is assigned to the new point based on how similar it is to the points in the training set (Triguero et al., 2019). Scikit-learn’s Kneighbors.

A decision tree constructs regression or classification models (in this case, a regression model) in the form of a tree structure. It incrementally cuts down a dataset into smaller and smaller sections while also developing an associated decision tree (Fiskin et al., 2021). A tree with decision nodes and leaf nodes is the end result. Gradient boosting is a type of ensemble method in which generates numerous weak models and combines them to improve overall performance, it is a type of machine learning boosting. It is based on the assumption that when the best potential next model is coupled with prior models, the overall prediction error is minimized (Cai et al., 2020). Other algorithms such as Random Forest and deep learning models were considered. These algorithms were not selected because of interpretability, computational efficiency, and the dimensionality of the dataset.

The primary goal of this study is to identify, train and evaluate a machine learning solution that can predict an individual's future blood pressure (BP) levels by using their historical BP readings, their moods and activity data.

II. METHODOLOGY

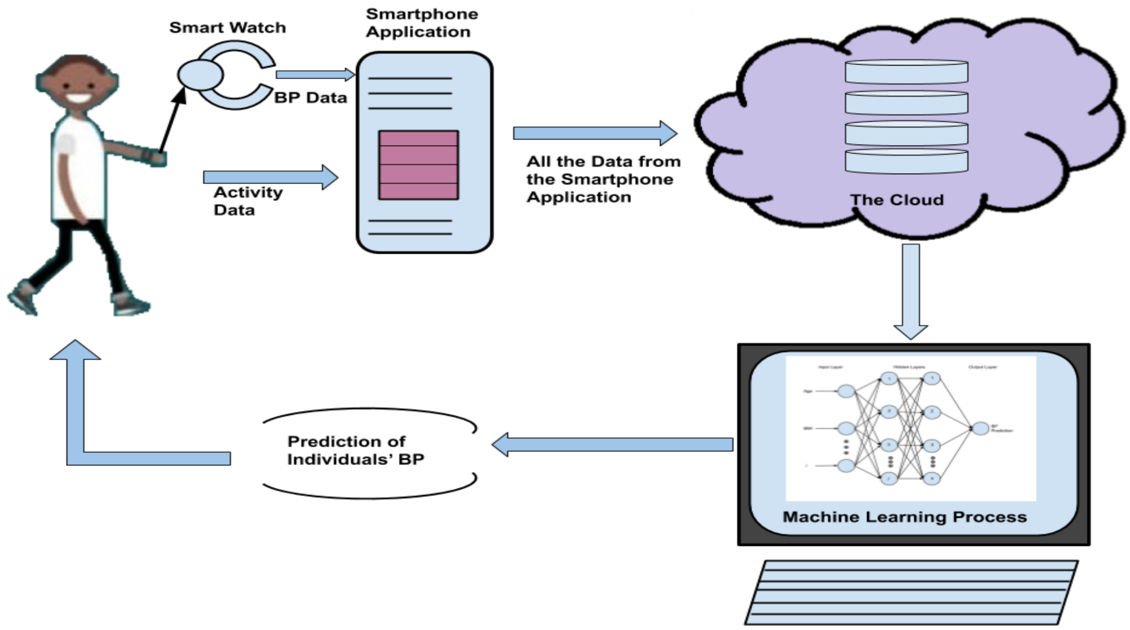
The principal objective of this research was to ascertain the optimal ML model for predicting an individual's blood pressure based on the dataset gathered. The study aimed to discern which specific ML model exhibits the highest performance and predictive accuracy in the context of BP estimation, thereby contributing to the advancement of predictive healthcare solutions. The study predicted an individual's future short term blood pressure, whether high, normal or low, using their previous BP data, their activities and future calendar events. The predictions, in turn, could be used to warn individuals of future blood pressure fluctuations so that they would take appropriate measurements to prevent the fluctuations.

The methodology that was used for the study is design science. Design science involves the creation and evaluation of Information Technology artefacts that are intended "to solve observed problems, to make research contributions, to evaluate the designs, and to communicate the results to appropriate audiences." (Peffers et al., 2007). The study was done in Uasin-Gishu County, Kenya. Rapid Application Development was used in order to design the smartphone application that captured the data from the individuals. The data for the study was collected using a smartwatch, which collected the BP (which entailed the systolic blood pressure and diastolic blood pressure) and heartrate. A smartphone application was used, which collected the mood, activities and future calendar events of the individuals. The other features collected during the data collection process include; gender, age, height and weight (for calculation the Body Mass Index (BMI)), their exercise level, smoking status, alcohol level, sleep level, and their medication. These were collected using the smartphone application as well.

The study's population consisted of individuals without a diagnosed hypertension condition. Therefore, the focus group comprised those whose high blood pressure status was undisclosed due to the condition's asymptomatic nature, often referred to as the "silent killer." Inclusion criteria encompassed individuals aged 35 and above, aligning with the World Health Organization's findings that approximately 1.28 billion adults aged 30 to 79 worldwide have hypertension (World Health Organization, 2023). Exclusion criteria pertained to individuals with known hypertension who were currently under medication. A total of 45 individuals were involved in the study.

As depicted in figure 1, the data for this study was collected through the smartwatches and the smartphone application provided to the individuals. The BP was measured via the smartwatch and sent to the smartphone application. The users provided the future calendar events using the phone application, and the participant manually entered data such as the activities done during the day. The data collected was then sent to the cloud and used to train the predictive ML algorithm.

Figure 1:
System Architecture for the Collection of Data and Prediction of an Individual's BP



Comparative Analysis and Selection of ML Models for Predictive Blood Pressure Estimation

A thorough and comprehensive methodology was used to determine the most appropriate machine learning models for blood pressure prediction. The study began with the development of specific research objectives and criteria, highlighting the necessity of both prediction accuracy and interpretability in the context of healthcare. A group of potential algorithms, including Lasso regression, Linear Regression, ElasticNet among others were rigorously selected for the comparison in order to analyze the models. These models were tested using cross-validation techniques, which reduced the impact of random data splits and offered reliable estimates of their performance.

Validation of a model is the process of evaluating a model on test data. It is used to confirm that the model can predict an outcome given certain conditions. This process provides the general ability of the trained model. Mean Square Error (MSE) and Coefficient of Determination or R-Squared (R^2) were used to validate the predictive models.

MSE is the average of the squared difference between the actual value and the predicted value (Chicco et al., 2021). It is the standard way of calculating the cost function for gradient boosting regressor. The values here lie between 0 to infinity, the smaller the MSE the better the model.

$$MSE = \frac{1}{n}\sum_{i-1}^{n}(y_i - \hat{y}_i)^2$$

Where:

MSE; mean squared error
n; number of data points.

y; observed values.
$\hat{y}$; predicted values.

R^2 score is one of the metrics used to evaluate the performance of a regression machine learning model. It measures the amount of variance in prediction compared to the actual values. The values of R^2 fall between 1 and 0; 1 means that the model is perfect, while 0 means that the model will perform poorly on unseen data (Chicco et al., 2021).

$$R^2 = 1 - \frac{SSr}{SSm}$$

Where:

SSr; squared sum error of regression line.
SSm; squared sum error of mean line.

Cross-validation was also done; since it is difficult to know the best values for hyper-parameters, it is important to tune the hyper-parameters several times in order to achieve a model that is accurate. GridSearchCV which comes in Scikit-learn's model selection package, has been used to automate the process of hyper-parameter tuning.

The six models selected were; Lasso Regression, Linear Regression, ElasticNet, K-Nearest Neighbors (KNN), Decision Tree Regressor, and Gradient Boosting Regressor. These models were evaluated for their efficacy in predicting an individual's blood pressure based on the collected dataset, forming a comprehensive range of machine learning techniques for the research investigation.

Ethical Considerations

A researcher should maintain moral standards while conducting their study. Therefore, the researcher ensured that the participants of the study had prior adequate information from which they could choose to participate or not. A letter from the institute of Post Graduate and Research Studies of Kabarak University as well as a permit from National Commission for Science Technology and Innovation (NACOSTI) vetted, to make sure that the ethical considerations were ensured (NACOSTI Ref No: 153713). The privacy and confidentiality of the respondents' information were protected by strict ethical standards. All research participant data were handled with strict privacy protocols, including encryption, limited access, and anonymization, ensuring that personal information remains confidential and securely protected throughout the research process. The researcher also assured the respondents that the research is only for academic purposes.

III. RESULTS

Findings for the Identification and Training of a Machine Learning Algorithm

The first objective was to identify and train a machine learning algorithm to learn and predict future blood pressure readings. The researcher used Anaconda, which is a Python distribution platform for scientific computing, and Jupyter Notebook which is a web application that allows for creation of code, for coding purposes. The following steps were involved:

Step 1: Using the tools mentioned, the data was cleaned and analyzed. This involved removing errors and inconsistencies, handling missing values, and encoding categorical variables.

Data analysis comprises statistical exploration, visualization, and feature engineering to prepare it for an ML model.

Step 2: Pre-processing was then done so the models would take in the given data. This included cleaning, normalization, feature scaling, and splitting the data into training and testing sets, ensuring that it was suitable for ML model input.

Step 3: Using ML libraries like Scikit-learn, the researcher identified and tested several models to find one that works well with the data collected. The anonymized data collected from the participants was used to train the models. These are the steps that were taken:

i. Data Preparation: Clean and preprocess the data.
ii. Models Selection: Choose multiple machine learning models.
iii. Split Data: Divide data into training and testing sets.
iv. Model Training: Train each model using the training data.
v. Evaluation: Assess model performance with testing data using metrics.
vi. Select Best Model: Pick the model with the best performance.
vii. Hyperparameter Tuning: Fine-tune the chosen mode.
viii. Final Model: Use the optimized model for predictions.

Results of the Identified and Trained Models

Out of all the identified models, Decision Tree Regressor and Gradient Boosting Regression performed the best as shown in Table 1. An R^2 value of 0.99 signifies that the model features can elucidate 99% of the target variance, whereas a value of 0.3 indicates that the model features can only elucidate 30% of the variance (Allwright, 2022). The R^2 score of both models was 0.992. Although the R^2 scores of all models were above 90%, their MSE scores varied greatly. The MSE scores for the two models were 0.219 and 0.182 respectively. The MSE and the R^2 score methods have been used to predict blood pressure as they give accurate results. An example is a study done by Honglv et al. (2023). They predicted the SBP and DBP of college students using Decision Trees which revealed a high prevalence of hypertension in Yunnan college students, with gender, BMI, only child status, and red wine consumption as significant predictors (Honglv et al., 2023).

Gradient boosting is a form of boosting in ML. It returns a prediction model in the shape of an ensemble of weak prediction models, usually decision trees to improve predictive accuracy and reduce overfitting (Hoare, 2017). The concept is based on the assumption that the best next model, when combined with prior models, minimizes the overall prediction error. This algorithm is gaining popularity due to its prediction speed and accuracy, particularly with big and complex datasets (Hoare, 2017). It was used for the regression model because of its lower MSE compared to the Decision Tree Regressor. Other variants of the Gradient Boosting algorithm like the AdaBoost, Extreme Gradient Boosting Machine (XGBM), LightGBM and CatBoost were considered. The Gradient Boosting algorithm was considered out of the rest because of the size and type of the dataset acquired.

Table 1:
Results of Each Identified Model

Model Name	MSE score	R^2 score
Multiple Linear Regression	0.975	0.966
Lasso Regression	1.157	0.957
Elastic Net	0.927	0.961
K-Nearest Neighbours	0.773	0.971
Decision Tree Regressor	0.219	0.992
Gradient Boosting Regressor	0.182	0.992

Note. The table shows the MSE and R^2 scores of each model.

Fitting the Gradient Booting Regression Model for Blood Pressure Prediction

This outlines the methodical process through which the Gradient Boosting Regressor (GBR) model was defined and fitted for the purpose of predicting the individuals' blood pressure levels:

Step 1: Import libraries. The imported libraries access pre-built tools, functions, and algorithms that streamline the development and implementation of the ML models. A few examples have been give below.

```
import numpy as np
import pandas as pd
import scipy
```

Step 2: Read the data. The imported data is used as a foundation for training, validating, and testing the model, allowing it to learn and make predictions based on patterns within the data.

```
df = pd.read_csv('Data.csv')
```

Step 3: Feature engineering. This is done to enhance the predictive power of the model by selecting, creating, or transforming relevant input features, making the model more effective at capturing underlying patterns in the data.

```
# convert to datetime
df['Hour'] = pd.to_datetime(df['Time'])
```

Step 3: Encoding the data. This is essential to represent categorical variables as numerical values, enabling the model to process and learn from this data, as most machine learning algorithms require numerical input.

```
# Using Labelencoder to convert categorical to numerical
le = LabelEncoder()
df['Gender'] = le.fit_transform(df['Gender'])
```

Step 4: Picking out the relevant attributes for regression modelling.

```
correlation = df.corr(method='pearson')
columns = correlation.nlargest(10, 'Sbp').index
columns
```

Step 5: Assigning variables. This is necessary to store, manipulate, and represent data.

```
X = df[columns]
y = X['Sbp']. values
X = X.drop('Sbp', axis = 1).values
```

Step 6: Split the data into training and testing sets. This creates separate datasets for training, validation, and testing, allowing for model development, assessment, and evaluation.

```
X_train, X_test, y_train, y_test = train_test_split (X, y, test_size = 0.30, random_state=42)
```

Step 7: Define the model. This is to specify the architecture, algorithms, and parameters, providing a framework for learning patterns from data and making predictions.

model = GradientBoostingRegressor()

Step 8: Fit the model on the training dataset. The model is fitted in order to train it on the provided data, enabling it to learn patterns and relationships within the data for making predictions.

model.fit(X_train, y_train)

All these steps are crucial in machine learning to ensure that models are trained effectively, perform well, and make accurate predictions.

Performance of the ML Model on Predicting Future Blood Pressure Based on Past Readings and Activity Data

Using this evaluation matrix, the Gradient Boosting Regressor Model had a MSE score of 0.182 and a R^2 score of 0.992. These results show that the created model using GBR is accurate, it can predict both the SBP and the DBP of an individual at a future point in time given the independent variables that were used.

Figure 2:
This Image Shows the SBP Prediction, the Test Data and Their Difference.

Out[34]:

	Prediction	Test Data	Difference
0	118.186517	118	-0.186517
1	114.195993	114	-0.195993
2	115.098294	115	-0.098294
3	119.853309	120	0.146691
4	116.238001	116	-0.238001
5	124.926891	125	0.073109
6	114.347829	115	0.652171
7	110.343997	110	-0.343997
8	137.079042	137	-0.079042
9	119.895421	119	-0.895421

This analysis pertains to the prediction of Systolic Blood Pressure (SBP). As illustrated in Figure 2, the disparities observed between the predicted and test data are notably small. In order to assess the statistical significance of these discrepancies, a two-sample T-test was conducted, yielding the following outcomes:

T-statistic: 0.047
P-value: 0.963

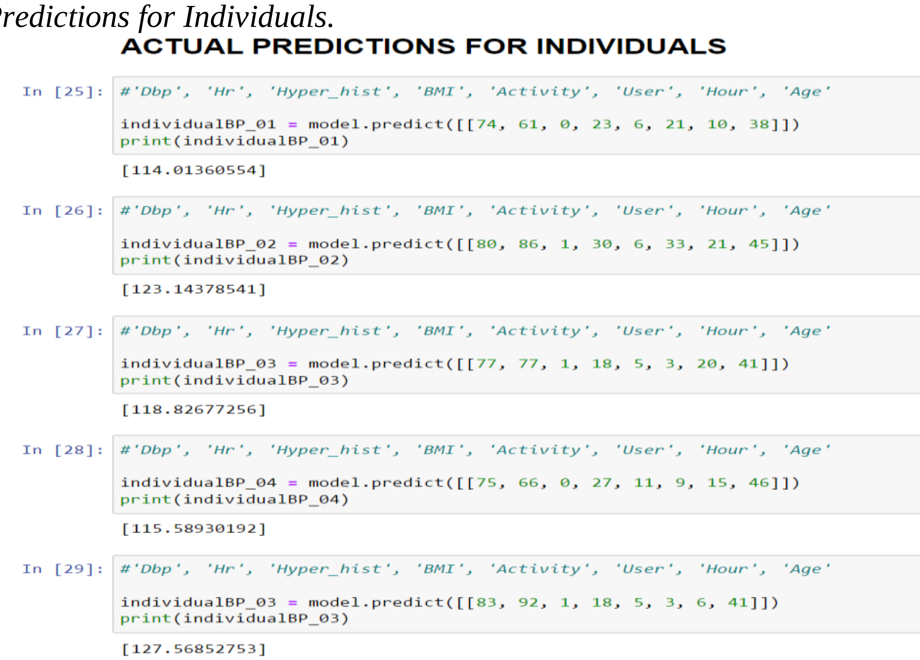
The results of the T-test indicate that there is no statistically significant difference between the means of the prediction and test data. Consequently, this underscores the accuracy of the model.

The Actual Predictions

To enhance the validation process of the Gradient Boosting Regression model especially in relation to the R^2 score, the researcher got additional data and subsequently employed the model to forecast the values of the independent variables. The researcher used the section on the Smart Health application called Calendar Events to predict the BP of some individuals. The Calendar Events had no Mood section, this is because one cannot predict their moods at a future date, while it is somewhat easier to predict one's future activities. Therefore, these predictions were done without using the Mood feature. The results showed accurate readings in predicting the short term blood pressure for the individuals.

The results in figure 3 shows the variables the researcher used to predict an individual's BP. These variables include the diastolic BP, systolic BP, the participant's hypertension history, their BMI, the activity, mood, the hour the BP was taken and their age. The print statement displays the individuals predicted BP which the square brackets below each print statement can show. The findings demonstrate that the prediction of systolic BP using the input variables exhibited a high degree of accuracy. A comparative analysis of these results against the actual predictions revealed a remarkable level of similarity.

Figure 3:
The Actual Predictions for Individuals.



ACTUAL PREDICTIONS FOR INDIVIDUALS

```
In [25]: #'Dbp', 'Hr', 'Hyper_hist', 'BMI', 'Activity', 'User', 'Hour', 'Age'

         individualBP_01 = model.predict([[74, 61, 0, 23, 6, 21, 10, 38]])
         print(individualBP_01)

         [114.01360554]

In [26]: #'Dbp', 'Hr', 'Hyper_hist', 'BMI', 'Activity', 'User', 'Hour', 'Age'

         individualBP_02 = model.predict([[80, 86, 1, 30, 6, 33, 21, 45]])
         print(individualBP_02)

         [123.14378541]

In [27]: #'Dbp', 'Hr', 'Hyper_hist', 'BMI', 'Activity', 'User', 'Hour', 'Age'

         individualBP_03 = model.predict([[77, 77, 1, 18, 5, 3, 20, 41]])
         print(individualBP_03)

         [118.82677256]

In [28]: #'Dbp', 'Hr', 'Hyper_hist', 'BMI', 'Activity', 'User', 'Hour', 'Age'

         individualBP_04 = model.predict([[75, 66, 0, 27, 11, 9, 15, 46]])
         print(individualBP_04)

         [115.58930192]

In [29]: #'Dbp', 'Hr', 'Hyper_hist', 'BMI', 'Activity', 'User', 'Hour', 'Age'

         individualBP_03 = model.predict([[83, 92, 1, 18, 5, 3, 6, 41]])
         print(individualBP_03)

         [127.56852753]
```

Table 2:
Actual BP Measurement of the individuals compared to the predicted value

Actual Measurement	Predicted Measurement	Difference
114	114.014	0.014
123	123.144	0.144
119	118.827	0.173
115	115.589	0.589
128	127.569	0.431

Note. The table shows the difference between the measured BP and the predicted BP.

Two models did well when the models were fitted, Decision Tree Regressor and Gradient Boosting Regression. The GBR model was used because it performed best out of the two. It was also chosen because it is often better than Decision Tree Regressor as it combines multiple decision trees to reduce overfitting, capture complex relationships, and improve predictive accuracy (Hoare, 2017).

IV. DISCUSSION

The principal aim of this investigation was to systematically assess and choose an optimal ML model for the predictive modeling of blood pressure, undertaken amidst a varied selection of prospective models. Within the models examined, the Gradient Boosting Regressor (GBR) and Decision Tree Regressor demonstrated good performance, with the GBR model exhibiting superior efficacy. Its precision, reliability, and adaptability were discerned through rigorous validation procedures. Corroborating findings align with a study conducted by Zhang et al. (2019), wherein the Gradient Boosting Decision Tree (GBDT) was employed for blood pressure rate prediction based on physiological data acquired through the EIMO device, reflecting analogous noteworthy outcomes. Notably, this method surpassed alternative approaches such as ridge regression, lasso regression, and the KNN algorithm in terms of accuracy and mean absolute error (MSE) evaluation.

In the context of clinical implications for blood pressure forecasting, the Gradient Boosting Regressor (GBR) model emerges as an ideal choice for detailed customization and refinement. Its accuracy makes it a very good tool for predicting clinical trial outcomes. These outcomes underscore the exceptional predictive capacity of the GBR model, positioning it as an invaluable tool for forecasting an individual's future blood pressure and facilitating early intervention to mitigate hypertension risks.

V. CONCLUSION

The primary objective of this study was to evaluate and select an appropriate machine learning model for the purpose of blood pressure prediction, from a diverse array of potential models. Different ML models were tested to determine which would perform the best given the dataset presented to the models. The models tested in this study were; Multiple Linear Regression, Lasso Regression, Elastic Net, The K-Nearest Neighbors, Decision Tree Regressor, and Gradient Boosting Regressor. Of the six algorithms tested, Decision Tree Regressor and Gradient Boosting Regressor performed well, the best of them all being Gradient Boosting Regressor model, which had an MSE score of 0.182 and R^2 score of 0. 992.

Compared to many models, the GBR model is one of the best for prediction because it offers unparalleled predictive accuracy. It also offers a lot of flexibility and uses excellent technique for minimizing over-fitting. The GBR model is also adoptable as it can capture complex non-linear relationships in the data. Its ensemble nature leads to more stable and reliable predictions compared to individual models. It's robustness also enables it to be less sensitive to outliers compared to some other algorithms and it also handles missing data well by default (Saini, 2021). In conclusion, the Gradient Boosting Regression model was able to achieve the goal of predicting an individual's future BP and with exceptional validation scores.

VI. RECOMMENDATIONS

This study revealed that Gradient Boosting Regression is the most suitable model when it comes to prediction; in this case, blood pressure prediction. Based on this premise, prospective research endeavors should explore the application of the Gradient Boosting algorithm for addressing intricate datasets in the area of blood pressure prediction. This is justified by its aptitude for identifying complex data patterns, mitigating overfitting concerns, and enhancing predictive precision via the principles of ensemble learning.

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