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Clinical Feature-Based Validation And Calibration For Diagnosing Hypertension And Cardiovascular Diseases

Dr. Saud Alharbi
Department of Family and Community Medicine, Faculty of Medicine, Universty of Tabuk ,KSA
Salrehily@ut.edu.sa

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Abstract:

The measurement of a patient's blood pressure reading is a vital biomarker that is utilized in the diagnosis of hypertension in addition to other cardiovascular diseases. Historically, it was measured with irregular and frequently extremely painful technology that was based on a cuff, such as a sphygmomanometer. This equipment was used to monitor blood pressure. In any case, it requires the collection of a number of distinct sensors; hence, this strategy is not only expensive but also inconvenient and time-consuming. The inclusion of an advanced technique that is pioneered on machine learning is incorporated as section of the remit of this study. This compendium of research's findings lead to the development of a model that is capable of correctly predicting systolic blood pressure (SBP). Clinical and lifestyle aspects were included when assessing the model. A extensive range of alternatives are available for application in training algorithms in addition to the numerous machine learning techniques that may be employed. In mandate to determine how to increase the model's accuracy, the findings of its testing and validation were examined. In mandate to accomplish the aim of precisely identifying the SBP, research was done on all three classes of hypertension utilizing the methodology that was described.

Keywords: *Clinical Feature Extraction, Systolic blood pressure, Cadiovascular disease, Hypertension, Calibration framework, Machine learning, Training.*

1. Introduction

These days, one of the biggest risk factors for cardiovascular and cerebrovascular diseases is hypertension, also known as high blood pressure (BP), which accounts for about 31% of deaths worldwide [1]. High blood pressure is also one of the most significant risk factors for stroke. According to the World Health Organization (WHO), hypertension was the leading cause of death worldwide in 2014, accounting for the deaths of 9.4 million individuals [2]. Hypertension is the risk factor that is regarded to be the second most significant after diabetes for developing cardiovascular disease [3]. Diabetes is the risk factor that is considered to be the first most significant. Because a sizeable portion of those who have hypertension either do not experience any symptoms as a result of it or fail to take any action to bring it down, it is sometimes referred to as the "silent killer." This moniker was given to hypertension as a result of these two facts. The blood pressure, or BP, of a patient is one of the most important periodic factors that can help medical experts diagnose cardiovascular illnesses in patients. BP is also known as the patient's blood pressure.

A lower reading for the diastolic blood pressure, also known as the DBP, is an indication of a lower reading for the blood pressure overall. The most reliable measurement that can be taken of a patient's blood pressure is the systolic blood pressure (also known as SBP). The phrase "mean arterial pressure" (MAP) refers to the average blood pressure that takes place throughout the course of a single cardiac cycle [4]. When either the systolic or diastolic blood pressure (BP/DBP) is greater than 140/90 mm Hg, hypertension is diagnosed [5]. Hypertension is a condition that can cause harm to internal organs. One of the potential complications of having hypertension is organ failure. The typical range of results for mean arterial pressure (MAP) is between 70 and 110 mm Hg [6]. This range of values is regarded to be healthy. Patients diagnosed with hypertension are strongly encouraged to perform regular blood pressure checks on themselves. Because there are so many things that might affect blood pressure, such as nutrition, the use of cigarettes, stress, and others, it is possible that blood pressure measurements will be inaccurate. In order to arrive at an accurate diagnosis, continuous monitoring of the patient's blood pressure is required. Continuous monitoring of blood pressure also helps physicians provide more effective therapy by enabling them to more accurately deliver medication, which is one of the ways in which this monitoring assists them [7].

The use of a cuff and a certain amount of intrusion into the body is required for the most popular and accurate techniques of measuring a person's blood pressure [8, 9]. However, you will only find technology of this kind in medical facilities such as hospitals and other such establishments. The auscultatory and oscillometric methods that are utilized to determine SBP and DBP measurements do not pose any health risks or cause any discomfort to the patient. These techniques are used as the foundation for the vast majority of today's blood pressure monitors. The readings that these devices provide, on the other hand, are not continuous and are instead depending on the cuff.

To diagnose hypertension, doctors look at a patient's blood pressure readings from an arterial blood pressure monitor called a sphygmomanometer [10]. This device is the gold standard for measuring blood pressure and consists of an inflating cuff, a mechanism of inflation that can be handled manually or automatically, and a mercury manometer.

Medical studies show that hypertension can be halted in its tracks and its consequences mitigated through early diagnosis, behavioral modification, and tight control. However, hypertension is often called a "silent killer" because the majority of persons with the ailment show no indications or symptoms of having the condition [10]. Some people with hypertension also report other symptoms, such as nausea, chest pain, headaches, difficulty breathing, nosebleeds, and palpitations. These symptoms are not specific to this disease, and they usually don't show up until the patient's hypertension is rather severe [11]. As a result, hypertension identification and monitoring continue to be areas of active study, especially in low-income countries with less comprehensive and preventative medical services.

Machine learning (ML) techniques can now detect and monitor numerous medical diseases, including hypertension [12], thanks to the abundance of clinical data made available in electronic health records (EHRs). Machine learning is used in many different ways in the medical profession, from simple techniques like logistic and linear regression to complex methods like artificial neural networks (ANN), which can have a wide range of architectural configurations and properties. Machine learning (ML) models are created to provide physicians with a resource that will aid them in their decision-making [13]. Recently, new measuring approaches that are

based on machine learning have been created in an effort to provide faster methods for the calibration process [14]. These methods exert the signals made by the ECG and PPG. To determine an individual's blood pressure, a variety of characteristics and attributes are derived from their PPG and ECG data via machine learning. In mandate to use the PPG and ECG together, this is done. Because of the simplicity of our proposed estimating scheme, utilizing a single PPG signal is a viable substitute. This approach may be utilized to continuously generate estimated BP [15]. This article presents a novel machine learning-based SBP prediction method that incorporates a wide range of variables in addition to SBP values.

2. The Components and Procedures

This paper proposes a recent modeling technique to predict the estimate of SBP for discussion. Machine learning was used to gather the clinical characteristics and lifestyle factors required for the proposed approach, which was then used to build the approach. This makes it possible to arrive at the most precise findings that are practical. The procedure of the proposed SBP predicted method is depicted in Figure 1, which may be found here. The steps involved in this procedure are broken down into their component parts further on in this section.

In total, there were 501 features, with the SBP functioning as the primary feature for achieving the aim. In addition, there were 14 clinical features that were scrutinized during this research. Nevertheless, when the model was being evaluated, some of the features were left unselected so that the accuracy of the model's performance may be improved.

In order to determine which method of machine learning will prove to be the most effective for the model, a number of different machine learning approaches [16, 17] have been computed. These machine learning approaches include linear regression (LR), support vector machine (SVM), decision tree regression (DTR), Gaussian process regression (GPR), and artificial neural network (ANN). According to the findings, the ANN method had the highest level of precision when compared to the other approaches. It had been decided to examine several distinct combinations of percentages for the training, validation, and testing processes.

The various amounts of neurons that were hidden had been modified [18]. Later, feature extraction had to be carried out once more, with one of the traits being chosen before each testing and validation session. This was done so that the results could be validated based on a range of criteria. The validation process took place as follows. According to the findings, each of the 14 distinguishing characteristics was a good match for the model. After the review of the final model, the conclusion was predictable, and the number of errors that could have occurred was kept to a minimum.

2.1 The use of datasets

In this research, the online dataset has been used [19]. The dataset contains information from 270 patients and 14 independent predictive variables. As a result of the fact that the classification and calculation of feature variables is used for training, testing, and estimating. These 14 variables with 270 samples that were included in the model after it was built with the data from the datasets as shown in Table 1. A comparison of algorithms was developed in order to determine which one might provide the most reliable estimates of SBP. In order to get the most optimal result, various algorithms [20, 21], including LR, SVM, GPR, and ANN, had been put through their paces.

Feature Name	***Description***
Age	*The age of the patient*
Sex	*The gender of the patient*
Chest pain type	*The type of chest pain experienced by the patient*
BP	*The blood pressure level of the patient*
Cholesterol	*The cholesterol level of the patient*
FBS over 120	*The fasting blood sugar test results over* 120 *mg/dl*
EKG results	*The electrocardiogram results of the patient*
Max HR	*The maximum heart rate levels achieved during exercise testing*
Exercise angina	*The angina experienced during exercise testing*
ST depression	*The ST depression on an Electrocardiogram*
Slope of ST	*The slope of ST segment electrocardiogram readings*
Number of vessels fluro	*The amount vessels seen in Fluoroscopy images*
Thallium	*The Thallium Stress test findings*
Heart Disease	*Whether or not the patient has been diagnosed with Heart Disease*

2.2 Pseudocode for the Proposed Method

2.2.1 Input

• A set of clinical characteristics for a patient group with established hypertension and cardiovascular disease.

• A group of candidate clinical characteristics that will be utilized for the purposes of validation and calibration.

2.2.2 Output

• A hypertension and cardiovascular disease diagnostic model that has been verified and calibrated, utilizing the candidate clinical features as inputs.

2.2.3 Steps

1. Create two distinct groups from the dataset: the training group and the validation group.

2. Train a model on the training set using the candidate clinical features using the candidate clinical features.

3. Conduct an analysis of the model using the validation set.

4. Adjust the parameters of the model based on the validation set.

5. Send back the model that has been checked and adjusted.

2.2.3.1 Splitting the dataset

In mandate to guarantee equal levels of cases of cardiovascular disease and hypertension in the training and validation sets, the dataset was stratified. For this, standard machine learning techniques like class label-based stratification and arbitrary splitting were used.

2.2.3.2 Training the model

The model can be trained with a variety number of machine learning algorithms, Including logistic regression, support vector machines, or random forests, amongst others. The particular clinical features that are being utilized and the performance measures that are wanted will both play a role in the selection of the algorithm.

2.2.3.3 Validating the model

The model should be assessed on the validation set according to numerous criteria, including accuracy and others. "Calibrating" a model is the procedure of adjusting its predictions so that they fit more closely with the real labels. Isotonic regression and platt scaling are just two of the various methods that can be utilized to achieve this objective. The selection of the appropriate approach will depend on the specific model being used as well as the desired performance metrics.

2.2.3.4 Calibrating the model

The model might then be returned to the user once it has been trained, assessed, and calibrated. Before the model can be viewed as validated and calibrated, this step is required. The model can then be used to predict the possibility that newly detected individuals would experience cardiovascular disease or hypertension. The subsequent pseudocode illustrates how to train, assess, and fine-tune a logistic regression model for the diagnosis of cardiovascular disorders and hypertension:

 # Split the dataset into training and validation sets.

training_set, validation_set = split_dataset(dataset)

 # Train a logistic regression model on the training set.

model = LogisticRegression()

model.fit(training_set.X, training_set.y)

 # Evaluate the model on the validation set.

predictions = model.predict(validation_set.X)

accuracy = accuracy_score(validation_set.y, predictions)

precision = precision_score(validation_set.y, predictions)

recall = recall_score(validation_set.y, predictions)

f1_score = f1_score(validation_set.y, predictions)

 # Calibrate the model using the validation set.

model = PlattScaling().fit(validation_set.X, validation_set.y)

 # Return the validated and calibrated model.

return model

3. The Machine Learning Algorithms

Following the computation of five different machine learning methods (LR, SVM, DTR, GPR, ANN) [20, 21], the ANN method was found to have the best performance. Table 2 shows a comparison among all these five ML methods. The mean average error (MAE) [22, 23] for this method was approximately 10.78mmHg, which was lower than other methods. As a result, the ANN was the major tool [24] that utilized in this research to make predictions on the SBP. The Support Vector Machine (SVM), is a form of non-linear model that is commonly applied for classification-related endeavors. Although it is more complex to train and comprehend, it outperforms LR in terms of precision when used to intricate datasets. Decision Tree Regression (DTR), a tree-based model, is a versatile tool that can be used for both regression and classification tasks. It is not impacted by data noise and is simple to comprehend. On the other hand, it has the capacity to overfit on small datasets. The non-linear model known as Gaussian Process Regression (GPR) is adaptable enough to do tasks comprising regression as well as classification. On more complicated datasets, it produces more accurate results than DTR, despite being more challenging to learn and understand. The Artificial Neural Network, or ANN, is a sophisticated non-linear model that can do both classification and regression tasks. It is the machine learning model that produces the most accurate results when applied to complicated datasets; nevertheless, it is also the model that is the most challenging to train and analyze.

Table 2: Comparison on various machine learning models

Feature	**LR**	**SVM**	**DTR**	**GPR**	**ANN**
Linearity	Linear	Non-linear	Non-linear	Non-linear	Non-linear
Model type	Generative	Discriminative	Generative	Generative	Discriminative
Interpretability	High	Medium	Low	Low	Low
Robustness	High	High	Medium	Medium	Low
Scalability	High	High	Medium	Medium	Low
Training time	Fast	Slow	Medium	Medium	Slow
Inference time	Fast	Fast	Fast	Fast	Fast
Common use cases	Classification	Classification	Regression, classification	Regression	Classification, regression

In order to locate the most effective training algorithm, start with a configuration of 10 hidden neurons, used 80% of the data for training, 10% for validation, and 10% for testing, respectively, and then continued on from there. Table 3 presents the results between number of hidden neurons and overall performance. Table 4 presents the cumulative error percentage for the different ratios of training, testing and validation. Table 5 presents comparison of performance on different grades of blood pressure. Table 6 presents an overall comparison of performance on results. Table 7 presents performance results based on percentage of training, testing and validation. Table 8 presents comparison among various training algorithms

According to the results presented, training appears to have the highest accuracy when compared to the other approaches. Following that, the proportion of training data is readjusted and the outcomes are compared.

The most accurate result was accomplished by allocating 90% of the time to training, 5% of the time to validation, and 5% of the time to testing, respectively.

One method that was used to evaluate the effectiveness of the training was changing the total number of neurons that were concealed on the hidden layer. The original blueprint asked for ten hidden neurons, but as training progressed, numerous different hidden neuron counts were tested to see which network configuration performed the best.

4. Discussion

In theory, the system may make a great deal more errors than it actually does at the moment. In an effort to get rid of these unclear characteristics, a number of studies had already been carried out to assess how effective the relative efficacy had been. It is ensured that the model contained no superfluous characteristics and that it passed all of the validation tests with flying colors. The actions that need to be taken in order to validate the results are outlined in the following paragraphs.

The ANN was trained, validated, and tested on all twelve of the characteristics specified above, with the SBP feature serving as the goal feature. In order to guarantee that the findings were reliable throughout all sessions and trained without selecting any features at any point.

After training with 14 characteristics, the error percentage for errors of less than 5 mmHg, 10 mmHg, 15 mmHg and 20mmHg. In order to receive the greatest potential results from the training process, then make sure that none of the 14 characteristics are left untrained.

A 20-bin error histogram is displayed in Figure 2-4 for different ratios of training testing and validation, with zero being represented by the orange line, training errors being represented by the blue bar, and test errors being represented by the red bar. As can be seen in the illustration, errors have a tendency to congregate around the orange line, which indicates an error value of zero, and diminish as the error value grows.

For the assessment of SBP, our model was able to meet the benchmark set by the British Hypertension Society (BHS) [25], indicating that its performance is on par with an A. The British Hypertension Society's previous standard was consulted in mandate to make this determination.

The MAE and STD error margins should both be 8 mmHg, whereas the error margin for the approach that

estimates blood pressure without invasive procedures should be less than 5 mmHg. Both our mean absolute error (MAE) of 3.03 mmHg and our standard deviation (STD) of 6.11 mmHg fall within the permissible range defined by the AAMI [26].

5. Conclusion

In this research, a new model for calculating SBP based on a machine learning algorithm has been developed. The model was composed of three distinct phases: input, calibration, and output. The various parts of the process inspired the stage names. The approach began with the selection and retrieval of datasets associated with clinical and lifestyle characteristics. This was done so that could better grasp the connection between the two. Thirteen different attributes' values, including SPB values, were chosen to serve as training data. Five different types of machine learning have been compared so far; these include LR, SVM, DTR, GPR, and ANN. The results show that ANN is capable of the highest level of accuracy.

In the second part of the process, the actual calibration was done. After looking at the MAE and STD results, it was determined that BRA was the most effective method of PE. Next, the various percentages of data that had been used for training, validation, and testing are compared. There were no complications with this surgery. The most precise result was attained by initially training with 90% of the data, then validating with 5% of the data, and finally testing with 5% of the data. It is presumed that the ANN had a single hidden layer, and that initially, this layer included 10 hidden neurons. Multiple types of hidden neurons were tested, however it was discovered that the optimal number of hidden neurons for the ANN to give correct results was 15. This held true regardless of the diversity of hidden neuron types used.

In the third phase of development, changes were made to the entered data and characteristics to ensure the model was accurate. In order to ensure the accuracy of the findings, avoid making value selections for model variables where there was a high degree of ambiguity. The studied model receives an A for its SBP estimation accuracy according to both the BHS standard and the AAMI standard. The model qualifies since it satisfies both of these criteria. Because of this, the model of prediction that theorized and built turned out to be very accurate. However, if the data associated with the features were more reliable, the model's performance might theoretically be improved even further.

Table 3: Number of hidden neurons and overall performance

	Number of hidden neurons	*MAE (mmHg)*	*STD (mmHg)*	*Accuracy (%)*
	2 *hidden neurons*	10.26	12.87	81.63
	4 *hidden neurons*	10.19	12.97	80.00
	5 *hidden neurons*	10.07	12.81	84.08
	6 *hidden neurons*	7.59	9.85	87.14
	7 *hidden neurons*	5.27	7.82	86.02
	10 *hidden neurons*	5.07	7.79	88.47

	11 *hidden neurons*	3.09	6.23	91.43
	15 *hidden neurons*	7.00	9.24	90.71
	16 *hidden neurons*	7.58	10.55	92.04
	20 *hidden neurons*	9.30	12.31	91.02

Table 4: Cumulative error percentage

Features	1	2	3	4	5	6	7	8	9	10	11	12	13	14
70% *training*, 15% *validation*, 15% *testing*														
$Error\ (mmHg) < 5$	37	56	25	31	39	43	40	30	28	28	50	39	39	52
$Error\ (mmHg) < 10$	67	83	57	57	71	71	69	59	57	61	78	67	54	55
$Error\ (mmHg) < 15$	87	93	76	76	87	86	86	76	76	77	91	84	66	76
$Error\ (mmHg) < 20$	88	92	75	75	87	83	89	80	80	76	90	83	65	78
80% *training*, 10% *validation*, 10% *testing*														
$Error\ (mmHg) < 5$	37	56	25	31	39	43	40	30	28	28	50	39	55	60
$Error\ (mmHg) < 10$	67	83	57	57	71	71	69	59	57	61	78	67	64	76
$Error\ (mmHg) < 15$	87	93	76	76	87	86	86	76	76	77	91	84	75	57
$Error\ (mmHg) < 20$	88	90	76	72	83	83	83	74	74	78	90	85	76	59
90% *training*, 5% *validation*, 5% *testing*														
$Error\ (mmHg) < 5$	37	56	25	31	39	43	40	30	28	28	50	39	40	50

$Error\ (mmHg) < 10$	67	83	57	57	71	71	69	59	57	61	78	67	76	57
$Error\ (mmHg) < 15$	87	93	76	76	87	86	86	76	76	77	91	84	68	66
$Error\ (mmHg) < 20$	88	95	78	78	88	89	89	79	79	79	90	86	70	69

Table 5: Comparison of performance on different grades of blood pressure

$70\%\ training, 15\%\ validation, 15\%\ testing$		$Error < 5\ mmHg$	$Error < 10\ mmHg$	$Error < 15\ mmHg$	$Error < 20 mmHg$
$Results$		66	87	95	96
	$Grade\ A$	59	83	93	92
BHS	$Grade\ B$	49	74	88	87
	$Grade\ C$	39	64	83	82
$80\%\ training, 10\%\ validation, 10\%\ testing$					
$Results$		66	87	95	92
	$Grade\ A$	59	83	93	91
BHS	$Grade\ B$	49	74	88	89
	$Grade\ C$	39	64	83	82
$90\%\ training, 5\%\ validation, 5\%\ testing$					
$Results$		66	87	95	94
	$Grade\ A$	59	83	93	92
BHS	$Grade\ B$	49	74	88	89
	$Grade\ C$	39	64	83	85

Table 6: Comparison of performance on results.

	$MAE\ (mmHg)$	$STD\ (mmHg)$
$Results\ \ from\ proposed\ method$	3.13	6.25
$Advancement\ of\ Medical\ Instrumentation\ (AAMI)$	5.12	8.19

Table 7: Performance results based on percentage of training , testing and validation

$Percentage\ of\ data\ training, validation, and\ testing$	$MAE\ (mmHg)$	$STD\ (mmHg)$	$Accuracy\ (\%)$
$70\%\ training, 15\%\ validation, 15\%\ testing$	6.13	10.26	90.60
$80\%\ training, 10\%\ validation, 10\%\ testing$	5.71	8.57	93.63
$90\%\ training, 5\%\ validation, 5\%\ testing$	5.04	7.48	92.89

Table 8: Comparison among various training algorithms

$70\%\ training,\ 15\%\ validation,\ 15\%\ testing$	$MAE\ (mmHg)$	$STD\ (mmHg)$	$Accuracy\ (\%)$
LR	9.415	11.649	66.085
SVM	5.313	8.891	69.455
DTR	8.045	10.422	71.983
GPR	8.823	14.153	71.058
ANN	7.199	7.038	73.082
$80\%\ training,\ 10\%\ validation,\ 10\%\ testing$			
LR	11.40	14.10	78.12

SVM	6.43	10.76	82.10
DTR	9.74	12.62	85.09
GPR	11.40	14.10	84.00
ANN	6.43	10.76	86.39
90% *training*, 5% *validation*, 5% *testing*			
LR	11.67	14.44	81.93
SVM	6.59	11.02	86.10
DTR	9.97	12.92	89.24
GPR	10.94	17.54	88.09
ANN	8.92	8.73	90.60

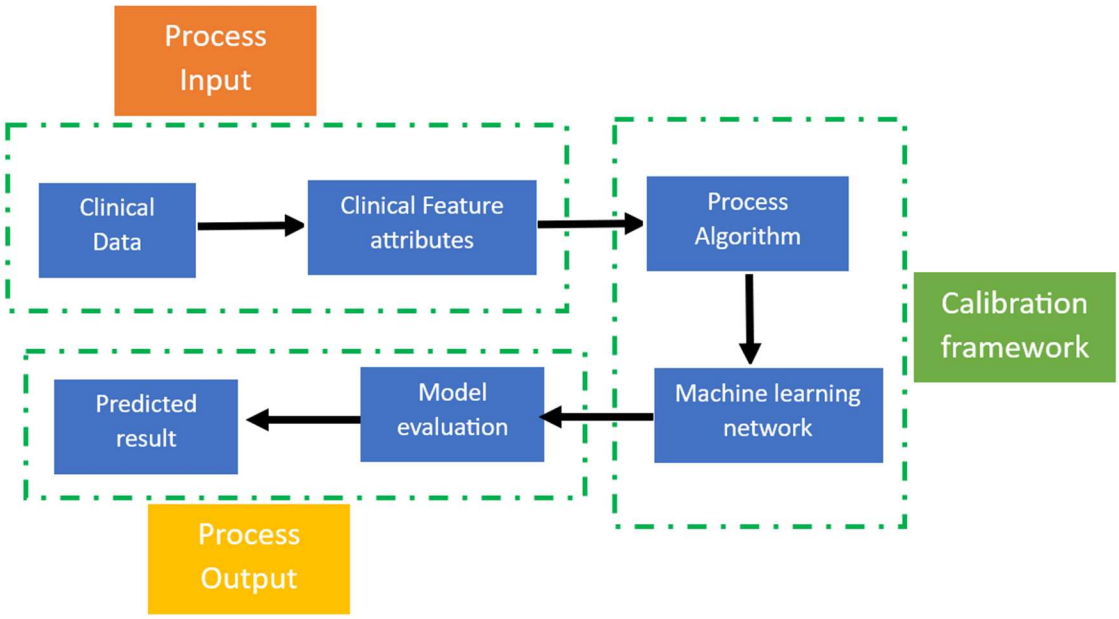

Figure 1: Block diagram of the proposed model

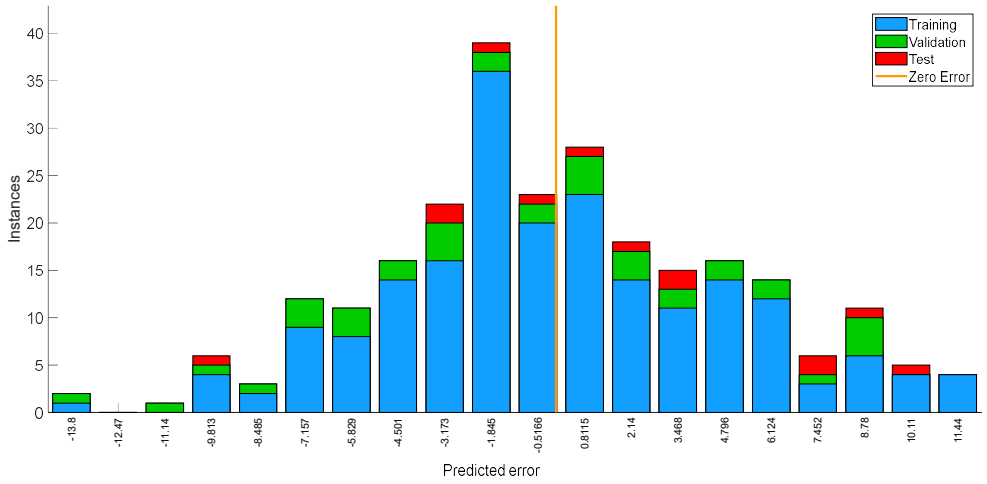

Figure 2: Predicted error (mmHg) for the case 70% training,15% validation,15% testing

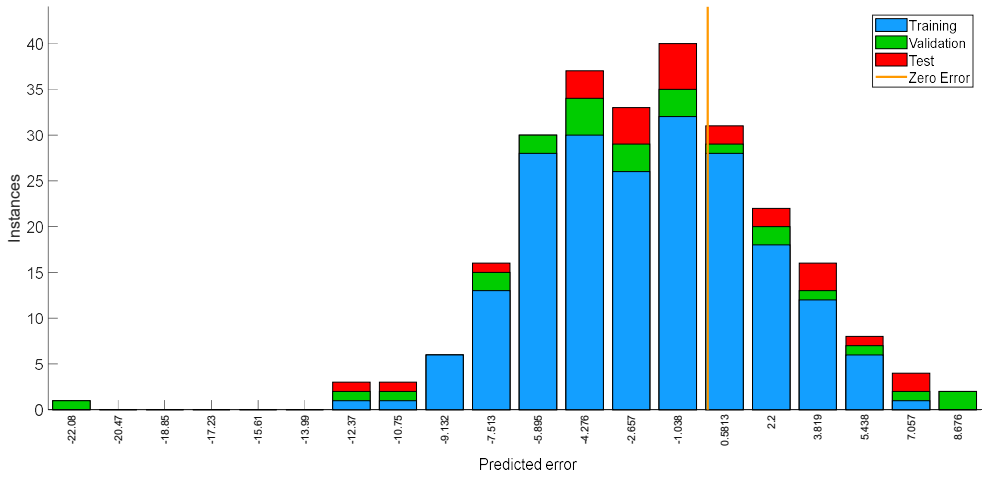

Figure 3: Predicted error (mmHg) for the case 80% training,10% validation,10% testing

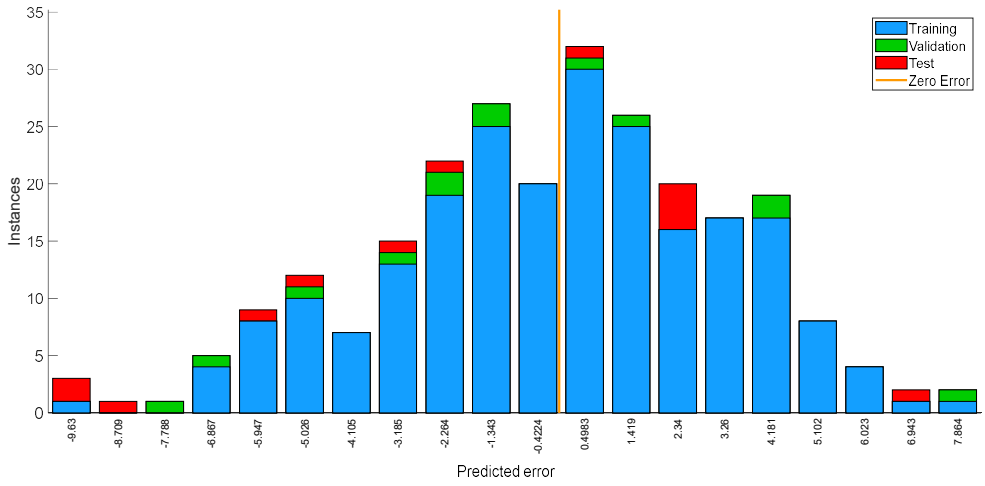

Figure 4: Predicted error (mmHg) for the case 90% training,5% validation,5% testing

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