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Innovative machine learning approaches for prediction of hypoglycemia in patients with type 2 diabetes

Sachin Ramnath Gaikwad[1], Seeta Devi[2], Sameer Shekhar[3], Dipali Dumbre[4]
[1]Department of Artificial Intelligence and Machine Learning, Symbiosis Institute of Technology, Symbiosis International Deemed University, Pune, India
[2]Department of Obstetrics and Gynaecological Nursing, Symbiosis College of Nursing, Symbiosis International Deemed University, Pune, India
[3]Department of Computer Science and Engineering, Symbiosis Institute of Technology, Symbiosis International Deemed University, Pune, India
[4]Department of Medical and Surgical Nursing, Symbiosis College of Nursing, Symbiosis International Deemed University, Pune, India

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ABSTRACT

Medical data science advances using machine learning, which predicts glucose levels. A supervised machine learning technique is employed in which regression and classification methods are used to check the prediction performance. The unsupervised machine learning technique makes clusters based on variables' similarities. Furthermore, the prediction accuracy of conventional machine learning techniques is improved by proposing a transfer learning technique. Based on a median value of 67 mg/dL, the data set is divided into two groups: group 1 (BSL 57 mg/dL to 67 mg/dL) has 50.67% of the samples, and group 2 (with BSL 68 mg/dL to 79 mg/dL) has 49.33% of the samples. In regression analysis, 5-fold cross-validation is performed. The decision tree (DT) and gradient boosting (GB) individually provide a prediction accuracy of 18.2%. Regarding classification analysis, a 10-fold cross-validation configuration is used for training and testing the model. AdaBoost, GB, random forest, and neural network achieve an accuracy rate of 66.3% and an area under curve (AUC) score of 0.731. In unsupervised learning, the datasets are divided into three clusters. The clustering result is used in regression and classification models using transfer learning. The accuracy and precision of the AdaBoost and GB are as follows: 69.6%, 0.696 with f1 0.661 and 69.6%, 0.708 with f1 0.708, respectively.

Corresponding Author:

Seeta Devi
Symbiosis College of Nursing, Symbiosis International Deemed University
Pune 412115, India
Email: drseetadevi1981@gmail.com

1. INTRODUCTION

Diabetes mellitus (DM) is a long-term medical disorder that involves high blood glucose (BG) levels caused by an inability to make or use insulin properly. Keeping normal blood sugar levels can help prevent diabetic complications affecting both minor and large blood vessels [1]–[4]. Tight management of blood sugar levels elevates the chances of experiencing hypoglycemic episodes but concurrently diminutions the likelihood of enduring chronic complications [5]. Hypoglycaemia is commonly detected as a blood sugar level of less than 70 mg/dL, which causes two physiological responses: a counterregulatory reaction and decreased cognitive ability [6]–[8]. Hypoglycemia can cause significant cardiovascular events and results in fear of low blood sugar, melancholy, and abnormal muscular movements, in addition to depression and deviation in physical well-being [9]–[13].

Clinically, hypoglycemia is categorized as moderate (MH) or severe (SH) based on whether the patient requires medical assistance during episodes of low blood sugar or if there is a loss of consciousness [14]. It has been estimated that patients with type 1 diabetes (T1D) had around 1.6 episodes of mild hypoglycemia and 0.029 episodes of severe hypoglycemia every week [15]. Furthermore, among people with T2 diabetes receiving treatment, the frequency of severe hypoglycemia was around 0.44 episodes per person per year [16]. Furthermore, hypoglycemia is more common in hospitalized diabetic patients [17], [18]. Severe hypoglycemia is a significant risk, especially for people on insulin for a long time [5]. The body's counter-regulatory response is critical in preventing moderate hypoglycemia (MH) from becoming severe. However, for people with recurring episodes of low blood sugar, the frequency of hypoglycemia warning indicators eventually decreases, leading to diminished awareness of hypoglycemia and the appearance of symptomless hypoglycemia [19], [20]. In turn, it surges the likelihood of SH resulting in a vicious cycle [15], [21].

Hypoglycaemia during a hospital stay has been linked to an increased risk of mortality, longer hospital stays, more problems, and higher costs [22], [23]. Although there are hospital-based glycaemic management software solutions available, such as Glucommander, EndoTool, and Glucotab, they are expensive, less precise for the prediction of hypoglycemia, lack of assessment for patients who are critically ill, are incapable of predicting glucose levels for several hours in advance, and are not widely used [24]–[26]. In clinical settings, predicting hypoglycemia is critical. Several studies have emerged in the last ten years, applying traditional methodologies based on physiological and clinical parameters to predict hypoglycemia occurrences. Typically, these techniques were trained using historical data from electronic health records, including demographic information, lab test results, diabetic medicines, and other pertinent indicators connected with hypoglycemia.

For forecasting hypoglycemia, three methods have been proposed: one based on physiological predictions, another on data analysis, and a hybrid that combines both techniques [27], [28]. Numerous data-centric models have arisen within these methodologies, exploiting continuous glucose monitoring (CGM) data in combination with variables such as dietary intake, physical activity, use of insulin, and other factors [27]. Numerous research projects [29]–[31] primarily focus on developing time series models capable of forecasting BG levels. Gallo [29] used a first-order autoregressive (AR) model and a first-order polynomial model for predicting BG levels, focusing on prediction intervals of 30 or 45 minutes. A new technique was recently proposed that combines an autoregressive integrated moving-average (ARIMA) technique with a programmable algorithm [30]. When used to forecast hypoglycemia within a 30-minute, this novel model displayed faster detection times and fewer false alarms than conventional techniques including an adaptive univariate model and a classic ARIMA technique. Nevertheless, it is essential to note that this approach necessitates significant processing resources and presents issues for real-time implementation. Significant advances in medical data science have been made via machine learning techniques, including their application in predicting glucose levels and hypoglycemia [32]. In one of the research studies, an artificial neural network (ANN) was used which included five consecutive CGM observations as well as the measurement time [33]. While the ANN outperformed time series models such as the AR model in predicting accuracy [29], it struggled to detect abrupt variations in BG levels induced by events such as meals or insulin injections. Despite this increased complexity, this issue may be overcome by adding additional data, including nutritional intake [34]–[36] and insulin [36].

Pappada *et al.* [37] presented an alternative feed-forward neural network model; however, training this model required extensive inputs, including insulin doses, dietary details, lifestyle elements, emotional factors, and consecutive CGM data points. Aside from the neural network approach, numerous attempts to forecast hypoglycemia [24] have been attempted, including the use of decision-tree techniques [38], [39] and machine learning techniques employing self-monitoring BG data [40]. Nonetheless, many of these previous efforts essential various manual inputs to improve the precision of hypoglycemia prediction. Although multiple research papers have shown successful methods for forecasting overnight hypoglycemia, predicting post-meal hypoglycemia remains difficult due to the large glucose variations during meal hours. The main objective of unsupervised learning is to find useful and hidden patterns from the unknown data. It has much more resemblance to artificial intelligence (AI). Also, this type of learning uses real-time data analysis and helps pre-processing.

Supervised learning is used to train the data and predict output, whereas labeled data is used to train these learning algorithms. Accurate results are produced using supervised learning algorithms. Supervised learning does not closely resemble AI. So, we have also proposed an unsupervised learning methodology where unlabeled data is used to train unsupervised learning algorithms. The main objective of unsupervised learning is to find useful and hidden patterns from the unknown data. It has much more resemblance to AI. Also, this type of learning uses real-time data analysis and helps in pre-processing. Transfer learning method is a machine learning technique in which an existing model developed for one task is repurposed as the foundation for another activity. This method is commonly used in deep learning, where pre-built models are the foundation for computer vision and natural language processing tasks. This is especially advantageous given the large computational resources and effort required to create neural network models for such issues and the huge performance improvements they provide in related domains.

The authors evaluated relevant research papers from several databases under the requirements provided in the literature section criteria (LSC). The present research reviewed different databases, comprising of SCOPUS, PubMed, and IEEE Xplore. Articles of previous research findings associated with the current study. The survey period under consideration for inclusion extended from 2015 to August 2023 to gain a more in-depth knowledge of past study findings. Bakar *et al.* [41] reported that hypoglycemia can result in patients' deaths and neurological abnormalities. Around 66.7% of diabetes patients who attended casualty had hypoglycemia. In order to regulate the frequency of hypoglycemia in diabetic patients, this study examined the effects of characteristics, including occupation, education, knowledge, gender, and age. The outcome revealed a considerable impact on the likelihood of hypoglycemia. Sex, job profile, age, education, and knowledge are defining factors in hypoglycemia incidence. Another study by Alkhaldi *et al.* [42] reported that 29% of patients (or more than half) reported having more than four hypoglycaemic episodes among type 1 diabetic patients. Numerous risk variables were found, including young age, type-1 diabetes, long-term diabetes, and use of insulin.

In addition, Kalra *et al.* [43] reported that the risk of hypoglycemia typically increased after strong glycaemic control attempts. Diabetes mortality is six times higher in people with severe hypoglycemia than those without it. Frequent hypoglycemia episodes can impair the counter-regulatory system. It was concluded that key strategies for maintaining good sugar control, decreasing the event of hypoglycemia, and preventing long-term complications include early identification of risk factors and regular checking of sugar levels. Fonseka *et al.* [44]. stated that hypoglycemia became a significant issue globally, particularly while managing diabetic patients’ antidiabetic medications. Most patients experienced hypoglycaemic episodes with common signs of unconsciousness, which are most frequently observed in patients receiving injection insulin. The study found that patients taking insulin and oral medications should be informed of frequent hypoglycaemic symptoms to enable early detection and treatment to prevent neuroglycopenia. The most prevalent cause of hypoglycemia was skipping meals while taking insulin.

Yang *et al.* [45] mentioned that hypoglycemia is a frequent adverse reaction to diabetes medication. Authors used the validated machine learning techniques for the prediction of hypoglycemia among the type 2 diabetic patients. The embedding machine learning model (XGBoost3) performed the best of all the models examined in this study. For XGBoost, the accuracy is 0.82, and for the area under the curve (AUC), the accuracy is 0.93. This study reported that XGBoost technique was improved by vector-distributed memory techniques that could precisely forecast hypoglycemia among diabetic patients. Seo *et al.* [32] attempted to predict hypoglycemia alarm by thirty minute prediction window; the random forest (RF) techniques depicted the better results. It had an AUC of 0.966, a sensitivity of 0.896, and a specificity of 0.913%. The previous findings were reaffirmed in a more recent review. Various machine learning algorithms, neural networks, and supervised learning approaches were shown to accurately predict the risk factors associated with hypoglycemia early, assisting in avoiding complications in diabetic patients [46].

This work uses a mixture of feature miscellany strategies to solve the problem of dealing with unbalanced datasets. It evaluates the efficacy of various supervised and unsupervised learning models. It investigates the value of transfer learning approaches such as k-means regression and classification in predicting type 2 diabetic hypoglycemia. On the other hand, previous research studies focused mostly on dividing balanced datasets, and some studies focussed on developing effective classification or regression models of machine learning methods for predicting hypoglycemia.

2. METHOD

This work proposed an innovative methodology for hypoglycemia prediction in type 2 diabetes deploying machine learning techniques. Firstly, researchers used supervised machine learning methods in which regression and classification techniques were used. Secondly, an unsupervised learning method using k-mean clustering was used for data analysis. Figure 1 depicts the steps that were used in the proposed methodology for predicting hypoglycemia in type 2 diabetes.

2.1. Data collection and data pre-processing

The data used in the proposed model is real-time data collected from participants by personal interviews with the patients admitted to the hospital. Mainly, these questionnaires included risk factors that directly impact causing hypoglycemia. These data of risk factors for the prediction of hypoglycemia. The data was normalized using a label encoding technique, under which data was converted into numbers, and each factor was scored with 0 or 1 for every true and false value. Due to this data normalization, the current model could perform accurate predictions without overfeeding and overfitting data.

None of the columns had a large influence during predictions. The real-data set contained 303 samples and 18 columns with no missing values, of which 16 had categorical values. This data easily fit the regression model, while the classification model needed a categorical target variable. The data was grouped into two categories based on the median of the below sugar level (BSL) value. The categories of groups were 0 and 1, making these groups a categorical target variable and skipping the BSL value. After this, data was fit for the classification model prediction.

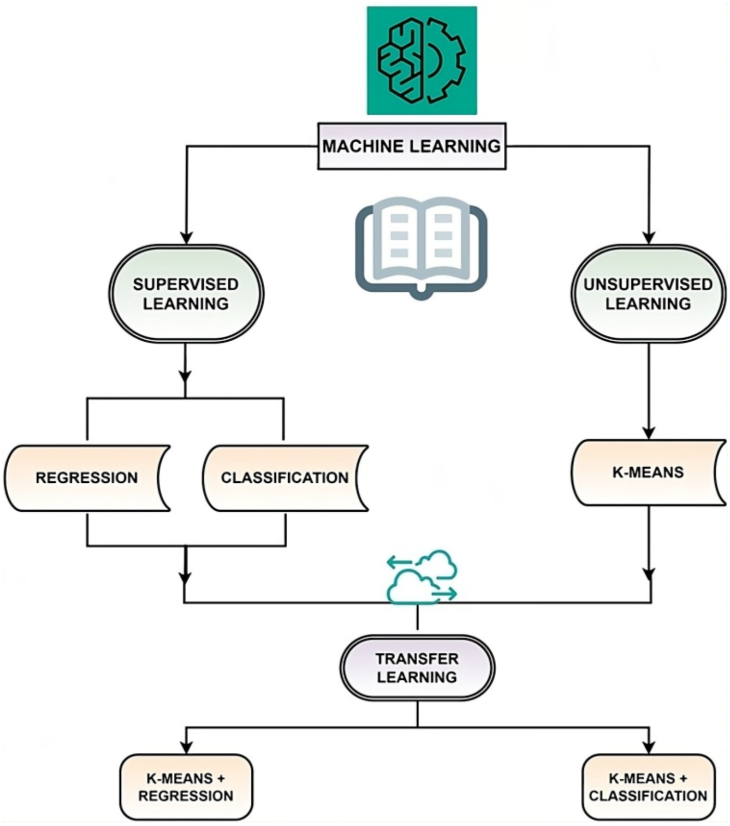


Figure 1. Methodology used in current study for prediction of hypoglycemia in type-2 diabetes

2.2. Supervised and unsupervised machine learning techniques for prediction of hypoglycemia

Regression is a supervised machine learning technique for prediction of a continuous numerical output or target variable based on one or more inputs. In the current study, the target variable was the numerical value of BSL. Thus, the prediction technique was compatible with model development, training, and predictions. Classification is also a supervised machine learning technique used to predict categorical data. The data was organized and pre-processed into categorical targets and then used for further training and predictions. The k-mean clustering unsupervised machine learning method was used for data analysis and to find the patterns in data.

2.2.1. Supervised learning using regression and classification

In supervised learning using regression model, seven statistical algorithms for prediction and results have been used. Figure 2 shows the proposed workflow for predicting hypoglycemia type-2 diabetes using Orange data mining tool. In Supervised learning using classification model, the data was categorized into two groups as this real-time dataset had the problem of unbalanced data. In trials, the first difficulty was categorizing the data in a balanced manner. The class imbalance was the major concern during the model development. It has been addressed by exercising various trials, including features, clustering, and descriptive statistics. After many trials and errors, investigators found the solution of categorizing the data based on the median of the BSL values, which was 67 mg/dl. The data was distributed in two balanced classes: group 1 consisted of 50.67% samples, and group 2 had 49.33%. With this grouping, investigators had applied different statistical algorithms, which was not possible in our main data due to the numeric target variable. Thus, group 1 had a BSL range of 57 mg/dl to 67 mg/dl, and group 2 had a 68 mg/dl range of 79 mg/dl.

We removed the BSL value variable from our data set and added another variable named group, which is selected as the target variable. Under this classification prediction, ten statistical algorithms have been used. Figure 3 shows the algorithms used: AdaBoost, gradient boosting (GB), logistic regression (LR), naïve Bayes (NB), k-nearest neighbours (kNN), RF, neural network, CN2 rule induction, decision tree (DT), and schohastic gradient descent (SGD). We trained the data and came up with a prediction model.

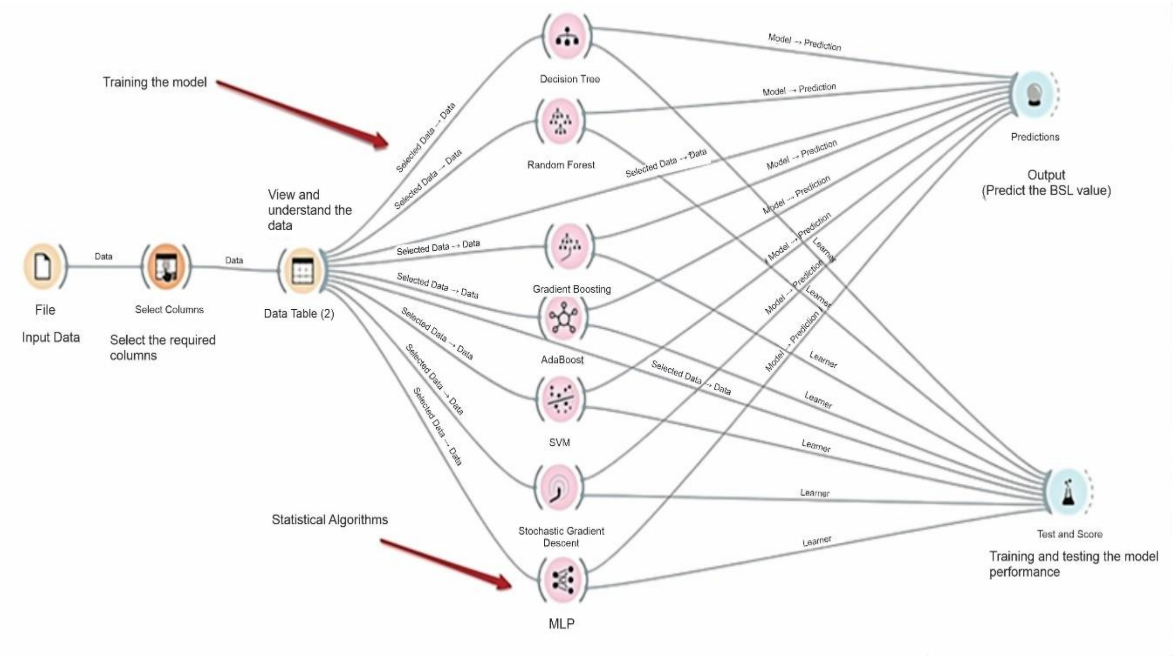


Figure 2. Workflow diagram for regression prediction of hypoglycemia in type-2 diabetes

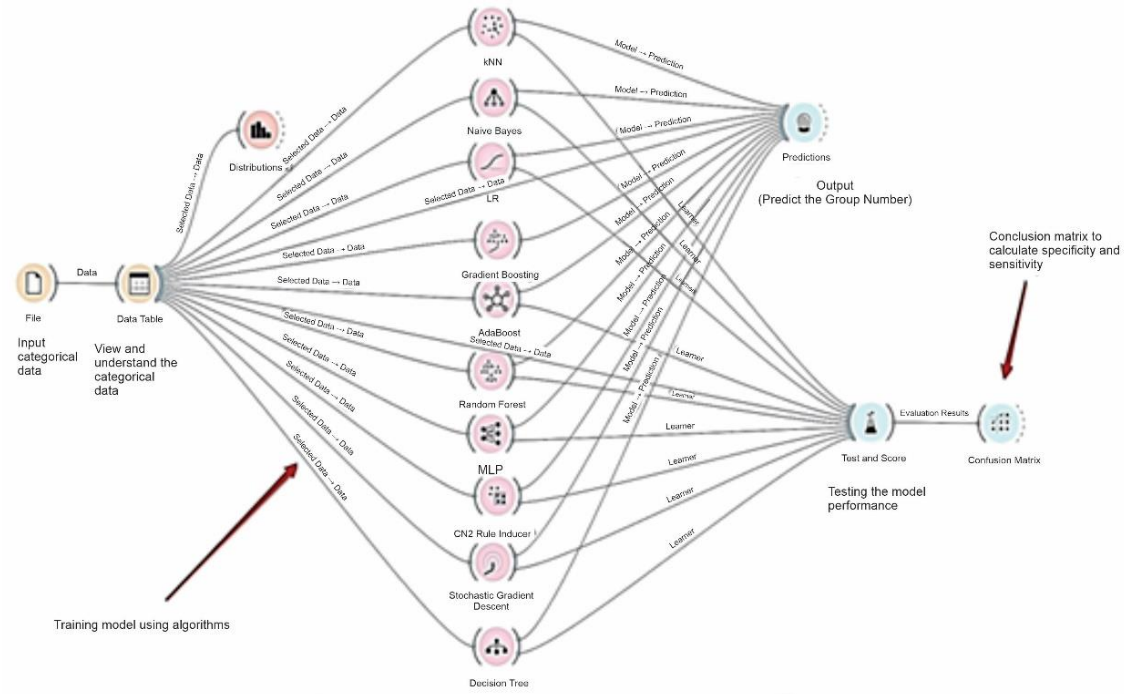


Figure 3. Workflow diagram for classification prediction of hypoglycemia in type-2 diabetes

2.2.2. Unsupervised learning using k-means

K-means clutering model is commonly used when the data to be grouped with similar characteristics. This model cluster the dataset into K distinct, non-overlapping subgroups or clusters in a simple and efficient manner. The centroid of each cluster is derived as the average of all the data points within that cluster. Nonetheless, K-means has some limitations, including as its sensitivity to outliers and its assumption that clusters are essentially spherical and of equal sizes, which may not necessarily correspond to the complexities of real-world data. Below is the diagram showing the clusters formed on the data used. K-mean clustering categorizes the data into 3 clusters as shown in Figure 4. The distribution of samples in C1, C2, and C3 are 73, 103, and 127, respectively. All the clusters are distributed according to similar patterns in the data for easy analysis. The clusters used in this study were the same size because they used some similarities and correlations in the data set. Investigators tried to form more clusters. However, three clusters only formed as it was giving better results. When these clusters are provided to the prediction model, good accuracy was obtained as researchers reduced the machine's effort and made the data pre-ready for the prediction tool so that the machine focuses more on getting results rather than sorting and then predicting. This clustering method also helped analyze the data because it could make bunches of data with some similarities and correlations, making it easy to interpret. Due to this clustering, we could easily identify the significant columns and find some correlations, which was very helpful in understanding the data.

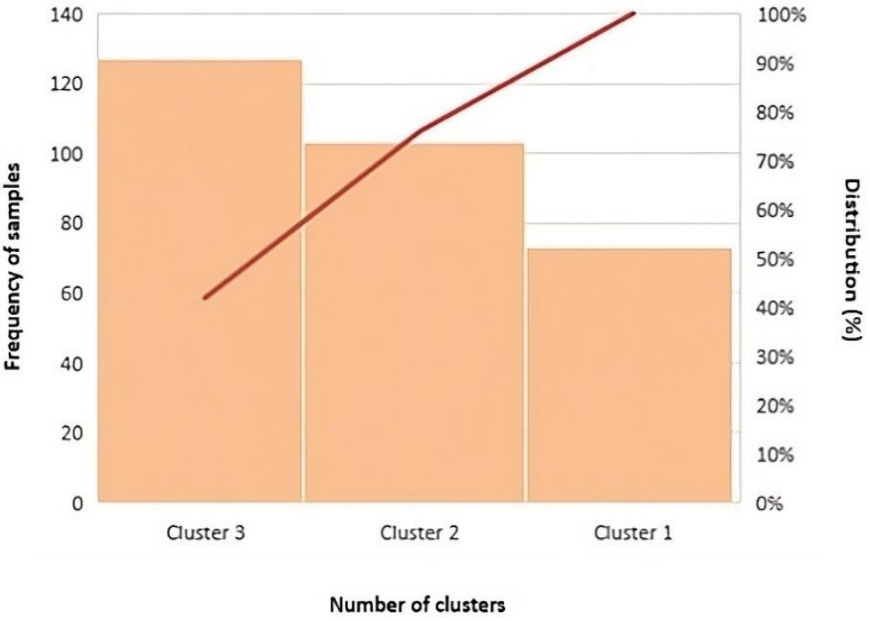


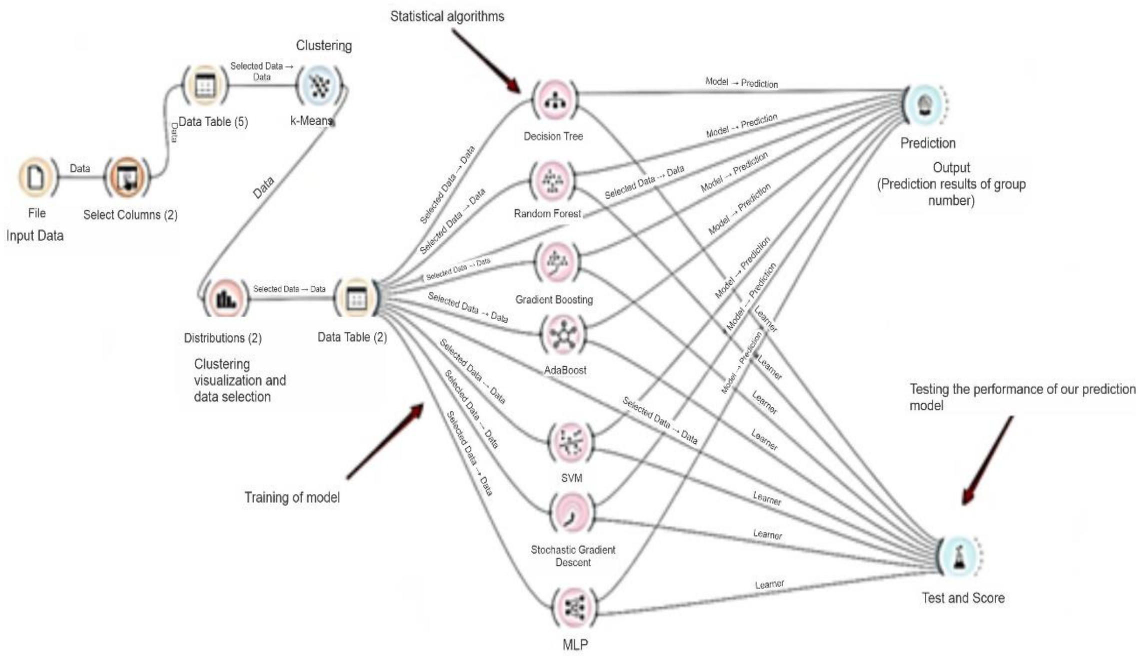
Figure 4. Data understanding using k-means clustering

2.3. Proposed transfer learning method for improving prediction accuracy

In this work, researchers found the prediction accuracy issues and improvement on real-world data. These issues were resolved by applying the transfer learning method, as shown in Figure 5. Transfer learning was beneficial for a small dataset, so it was suitable for prediction models and data evaluation. Both the prediction models-regression and classification were used in this technique. The data was transferred to predictors within each cluster in the regression model. Whereas, in the classification technique, the data was classified within each cluster as stated in the classification technique.

2.3.1. Regression using transfer learning method

Transfer learning is an machine learning model in which a model is trained on one task and fine-tuned for a related task. Instead of training from scratch, the researchers pre-trained the model that has already learned useful features, and the hyperparameters of all the algorithms used are also finely tuned. The proposed regression technique was used and passed on to all three clusters (C1, C2, and C3) separately and evaluated prediction results. All the algorithms were trained, and then the below workflow was used for the prediction model, as shown in Figure 5.


Statistical algorithms

Clustering

Input Data

Clustering visualization and data selection

Training of model

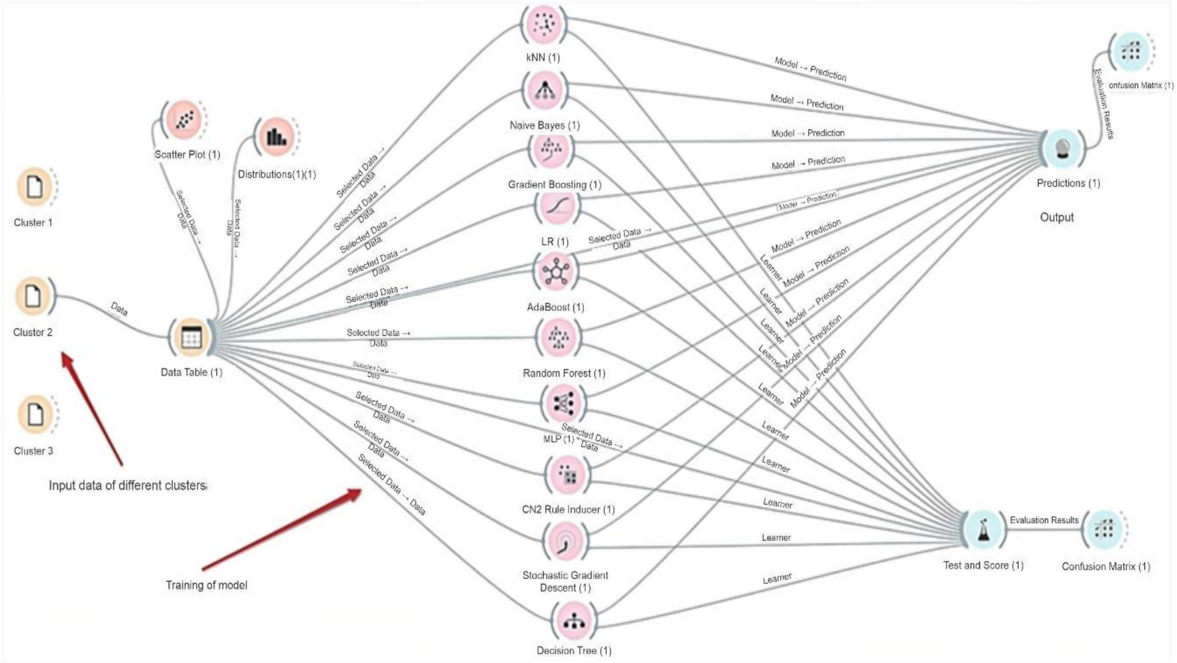
Output
(Prediction results of group number)

Testing the performance of our prediction model

Figure 5. Workflow for regression using transfer learning

2.3.2. Classification using transfer learning

Classification of data was performed in each of the clusters formed using k-means. The samples in the data are grouped into 1 and 2 and then transferred to machine learning algorithm. Figure 6 illustrates the workflow for classification using transfer learning. Cluster 1, cluster 2, and cluster 3 are provided separately generated using k-mean. Each cluster was then transferred to the classification prediction model and then trained, with prediction results evaluated.


Input data of different clusters

Training of model

Output

Figure 6. Workflow for classification using transfer learning

3. RESULTS

The BSL value in mg/dl in numeric data was considered the target variable. All 300 samples were used to train the machine learning model, and statistical algorithms were finely tuned and used for this purpose. The prediction model was evaluated using 5-fold cross-validation for precise model training. We obtain maximum performance of our model in 5 folds of testing, and then this model was used for predictions.

3.1. Input data

There were a total of 18 features included in the dataset. There are three features based on the role: input, output, and skipped. The sample feature was skipped; BSL is the target, and the remaining features are the input, as presented in Table 1. Figure 7 shows the data imbalance. The maximum frequency of participants was in the range of BSL 68 mg/dl to 70 mg/dl. This imbalanced data distribution affects the prediction results as more numbers are between 68 and 70. As a result of this, the maximum accuracy obtained is 18%. A classification technique was proposed to resolve this issue and obtain better prediction results. Figure 8 dipict the data distribution for BSL in a more discrete and informative form. Most participants are 66≤ BSL ≤72, 62.67%, and the remaining is 37.30%. Further, we try to understand the causes behind hypoglycemia type 2 diabetes. The major cause includes use of insulin (66%), poor diet intake (66%), gastric problems (58%), and increased exercise (64%). Other causes are advancing age (50%), skipping meals (44%), unusual weight loss (36%), diabetes over a longtime (36%), antidiabetic medicines (34%), consumption of alcohol (34%), use of same injection site frequently (36%), some of them had impaired liver/kidney (18%) and pregnant (17%).

Table 1. List of variables used in data

Sr. No.	List of Variables	Type of data	Features
1	Using insulin, using antidiabetic medicine, impaired liver/kidney, diabetes longtime, increased exercise, lack of knowledge about hypoglycemia, consumption of alcohol, poor dietary intake, skipping meals, advancing age, unusual weight loss, taking betablockers usage, use of same injection site frequently, thyroid problems, gastric problems and pregnancy	Categorical	Input
2	Sample	Numeric	Skipped
3	BSL value(mg/dl)	Numeric	Target

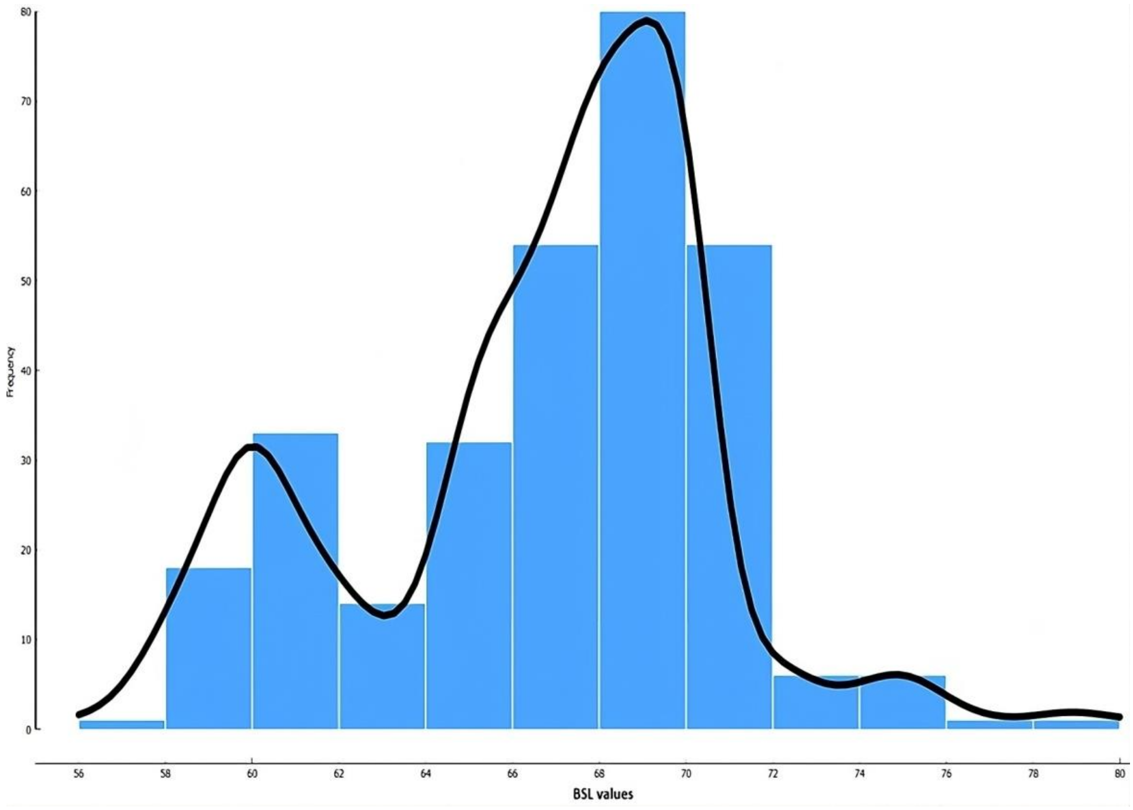


Figure 7. The distribution graph for BSL value

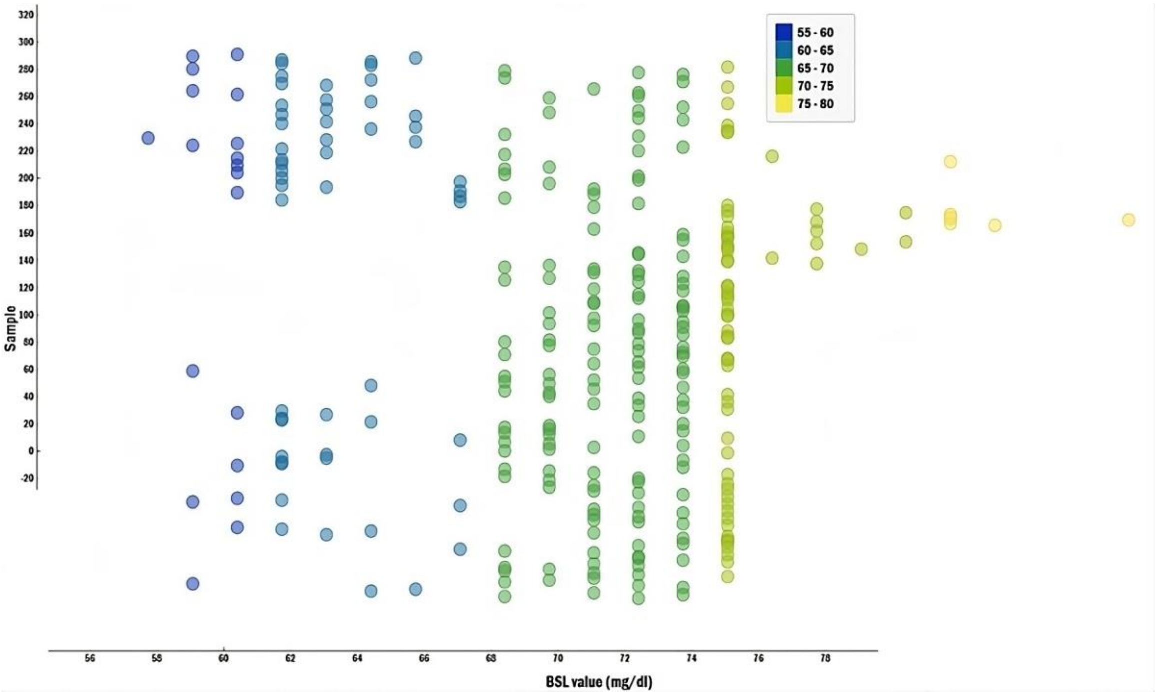


Figure 8. Scatter plot for the BSL value vs frequency of samples

3.2. Regression models

The regression model for prediction was developed using various statistical algorithms under section 2.2.1. Cross validation method was deployed to train and test the performance of prediction model. Different K-folds were tried and tested under cross validation. Better prediction results were obtained with 5-folds of training and testing for the input data. Figure 9 shows that the prediction model is evaluated in 5-fold cross-validation, each fold containing 20% samples. Further, the fold-wise distribution of the samples was analyzed. It is observed that the majority of the participants belong to 68≤ BSL ≤70 except fold-3. Fold-1 consists of 23.33% of participants, fold-2 consists of 31.67% of participants, fold-4 consists of 21.67% samples, and fold-5 consists of 35%. Whereas fold three consists of 23.33% in the 66 mg/d to 68 mg/dl range. All fine-tuned hyperparameters for the regression model are presented in Table 2. DT and GB showed better prediction output, 18.2%, than the remaining predictors.

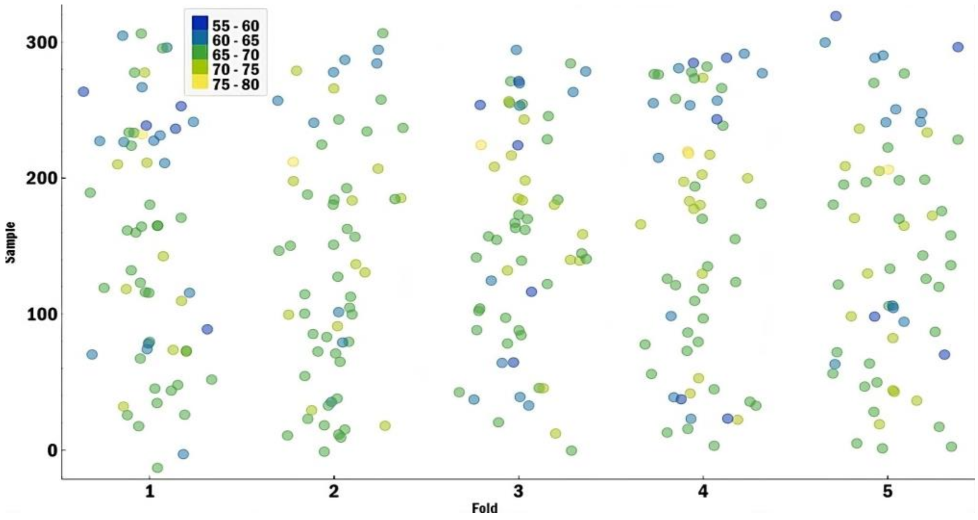


Figure 9. Scatter plot for the 5-folds cross validation for regression

Table 2. List models and fine-tuned hyperparameters used in regression

Algorithm	Hyperparameter	Value
DT	Minimum number of data points within leaf nodes	1
	Do not divide subsets that are less than a	5
	Limit the maximum depth of the tree to a specific value.	100
	Stop when the significant threshold is achieved [%]	95
	Trees number	38
RF	The count of features deliberated at every split	5
	Avoid splitting subsets if smaller than	5
	Technique	Extreme GB
	Trees number	75
	Rate of learning	0.3
	Replicable training	yes
GB	regularization	Lambda:0.0001
	Compel the depth of individual trees	7
	Quantity of training examples	1
	Quantity of attributes utilized in each tree	1
	Quantity of attributes included at each level.	1
	Quantity of attributes used at each division	1
	Base estimator	Tree
	Estimator quantity	33
AdaBoost	Rate of learning	0.1
	Fixed seed- random generator	50
	Regression loss function	Linear
	Cost (C)	3
	Regression cost epsilon (ε)	0.5
SVM	Kernel function	RBF
	Numerical tolerance	0.2
	Iteration limit	150
	Classification	Squared ε insensitive
	ε	0.14
	Regression	ε sensitive
	ε	0.8
	Regularization	Lasso (L1)
	Strength (α)	0.00011
SGD	Learning rate	Constant
	Initial learning rate	0.0012
	Number of iterations	5000
	Tolerance	0.001
	Shuffle data after each iteration	Yes
	Fixed seed for random shuffling	15
MLP	Neurons within concealed layers	100;50;25;10
	Initiation	Rel.u
	Solution	Adam
	Regularization (α)	0
	The maximum allowable count of iterations	500
	Training that can be replicable	Yes

The evaluation parameters mean square error (MSE), root mean square error (RMSE), mean absolute error (MAE), and coefficient of determination (R2) are considered for prediction as shown in Table 3. DT and GB have better accuracy than other algorithms. The DT and GB predicted values remained between 66 ≤ and DT GB < 68, 46%. The major influencing features under this range are gastric problems 65.2%, using insulins 78.2%, poor dietary intake 65.2%, and lack of knowledge about hypoglycemia 60.8%. These features played an important role in making the prediction. The maximum error for the predicted values under DT and GB is ±10 mg/dl. From these samples, DT and GB predicted about 44.93% accurately. The remaining samples had some minor prediction errors.

Table 3. Regression model evalaution

Model	MSE	RMSE	MAE	R^2
DT	12.77	3.574	2.877	0.182
RF	12.862	3.586	2.876	0.176
GB	12.770	3.574	2.877	0.182
AdaBoost	12.919	3.594	2.940	0.173
SVM	14.331	3.786	3.171	0.082
SGD	14.977	3.870	2.979	0.04
Neural Network	12.840	3.583	2.900	0.178

3.3. Classification technique

In this proposed prediction model, all the algorithms' hyperparameters were finely tuned. The model was tested and trained in 10-fold cross-validation, then predictions were made. GB Adaboost and multi-layer perceptron (MLP) obtained the most accurate prediction accuracy, specificity, and sensitivity values of all statistical algorithms used by the confusion matrix. All the hyperparameters for classification model are shown in Table 4. Figure 10 shows the fold-wise distribution of the data. Each fold contains 10% of the total sample, and then training was done. Due to the categorical data, the prediction factors differed from the regression tables. The maximum accuracy was obtained through this method. This method was the best-suited method for real data set.

Table 4. List models and fine-tuned hyperparameters used in classification

Algorithm	Hyperparameter	Value
DT	Minimum number of data points within leaf nodes	2
	Do not divide subsets that are less than a	5
	Limit the maximum depth of the tree to a specific value	100
	Stop when the significant threshold is achieved [%]	95
RF	Trees number	21
	The count of features deliberated at every split	5
	Avoid splitting subsets if smaller than	5
GB	Technique	catboost
	Trees number	98
	Rate of learning	0.288
	Replicable training	yes
	Regularization	Lambda: 0.05
	Compel the depth of individual trees	10
	Quantity of training examples	1
AdaBoost	Base estimator	Tree
	Number of estimators	500
	Learning rate	0.5
	Regression loss function	Linear
SGD	Classification	Squared Hinge
	Regression	ε sensitive
	Regularization	Elastic Net
	Mixing	0.15
	Strength (α)	0.00001
	Learning rate	Constant
	Initial learning rate	0.001
	Number of iterations	50
	Tolerance	0.001
	Shuffle data after each iteration	yes
	Fixed seed for random shuffling	15
MLP	Neurons within concealed layers	60;50;15;10
	Initiation	Rel.u
	Solution	Adam
	Regularization (α)	0
	The maximum allowable count of iterations	500
	Training that can be replicable	Yes
kNN	Number of neighbors	10
	Metric	Euclidean
	Weight	Uniform
CN2 rule inducer	Rule ordering	Ordered
	Covering algorithm	Exclusive
	Evaluation measure	Entropy
	Beam Width	5
	Minimum rule coverage	17
	Maximum rule length	5

Table 5 shows that the descent value of specificity and sensitivity determines the model's performance. Moreover, accuracy, AUC, and the other predictions were also better. Also, this solution categorizes data based on the median of the BSL value, balanced data, and their major columns. Figure 10 is one example of the data representation after classification. A confusion matrix, also known as an error matrix, is a structured table format designed to provide a visual depiction of how well an algorithm, which is frequently used in supervised learning, is performing. In this matrix, each row represents examples allocated to an actual class, while each column represents instances assigned to a predicted class, or vice versa. In the context of describing the properties of a screening test, sensitivity and specificity are used to guarantee that the anticipated values are appropriate and useful. These metrics can be used to make screening judgements about individuals, and it's crucial to remember that projected values don't always have to be high; they can be altered to optimise specificity and sensitivity as needed.

$$\text{specificity}=\frac{True\ negative}{True\ negative+False\ positive} \tag{1}$$

$$\text{sensitivity}=\frac{True\ positive}{True\ positive+False\ nagative} \tag{2}$$

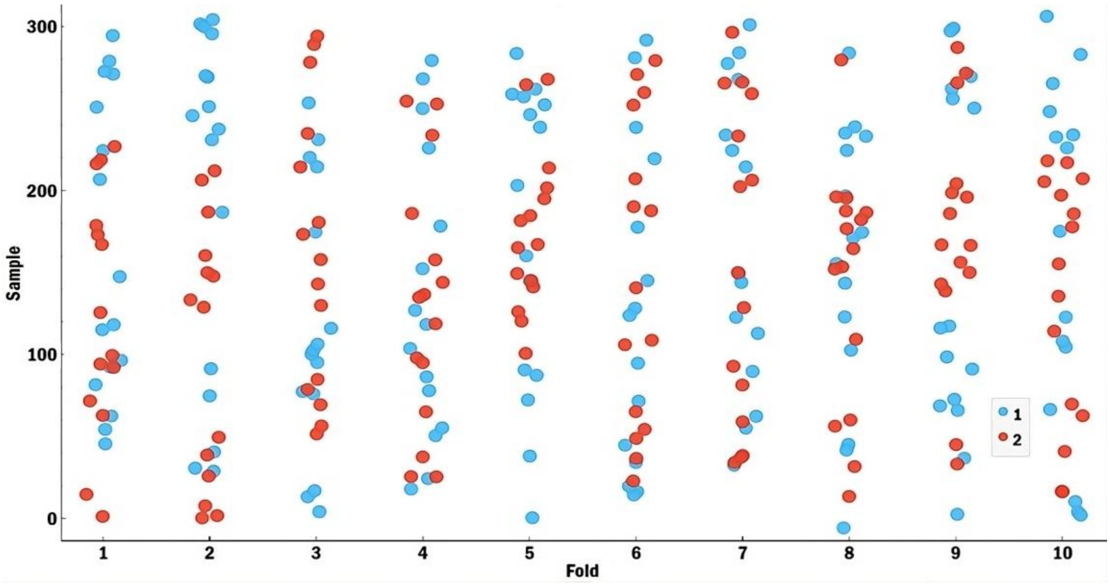


Figure 10. Scatter plot for the 10-folds cross validation for classification

Table 5. Prediction output for classification technique

Model	AUC	MCC	F1	Prec	Recall	Accuracy	Specificity	Sensitivity
Ada boost	0.731	0.327	0.663	0.664	0.663	0.663	0.688	0.645
GB	0.731	0.664	0.665	0.663	0.329	0.663	0.657	0.668
LR	0.634	0.186	0.593	0.593	0.593	0.593	0.590	0.596
NB	0.607	0.162	0.579	0.581	0.580	0.580	0.567	0.594
RF	0.730	0.327	0.663	0.663	0.663	0.663	0.651	0.675
Neural network	0.731	0.327	0.663	0.663	0.663	0.663	0.657	0.668
CN2 Rule inducer	0.690	0.306	0.653	0.653	0.653	0.653	0.652	0.653
SGD	0.574	0.149	0.572	0.575	0.573	0.573	0.533	0.546
KNN	0.680	0.221	0.575	0.625	0.600	0.600	0.681	0.559
DT	0.728	0.326	0.655	0.668	0.660	0.660	0.701	0.634

Due to data categorization, this model was developed in a balanced manner, and machine learning is more accurate. Moreover, our real dataset mostly distributed all the variables and causes equally. One of the major problems regarding data imbalance was thus resolved by dividing the data into categories and equally distributing the target variable based on the median of the target data. Figure 11 exemplifies how the data was balanced within the classes. It was one of the reasons this study could get better accuracy. Training and testing the data was easy for present model due to balanced data in every major and influencing variable.

Figure 12 shows the ROC curve analysis of group 1. A steeper curve indicates better discriminatory power i.e. the algorithm achieves a higher true positive rate and lower false positive rate. From the above curve, neural network and RF achieve a higher true positive value. Moreover, all the algorithms lying above the diagonal line, show better discriminatory power than random guessing. Also, the AUC shows the discriminatory power of the algorithms, using which we can compare their performance. Figure 13 shows the ROC analysis for patients lying in group 2. From this curve, neural network, RF and ada boost has a steeper curve and all the algorithms are lying above the diagonal line showing higher discriminatory power than random guessing.

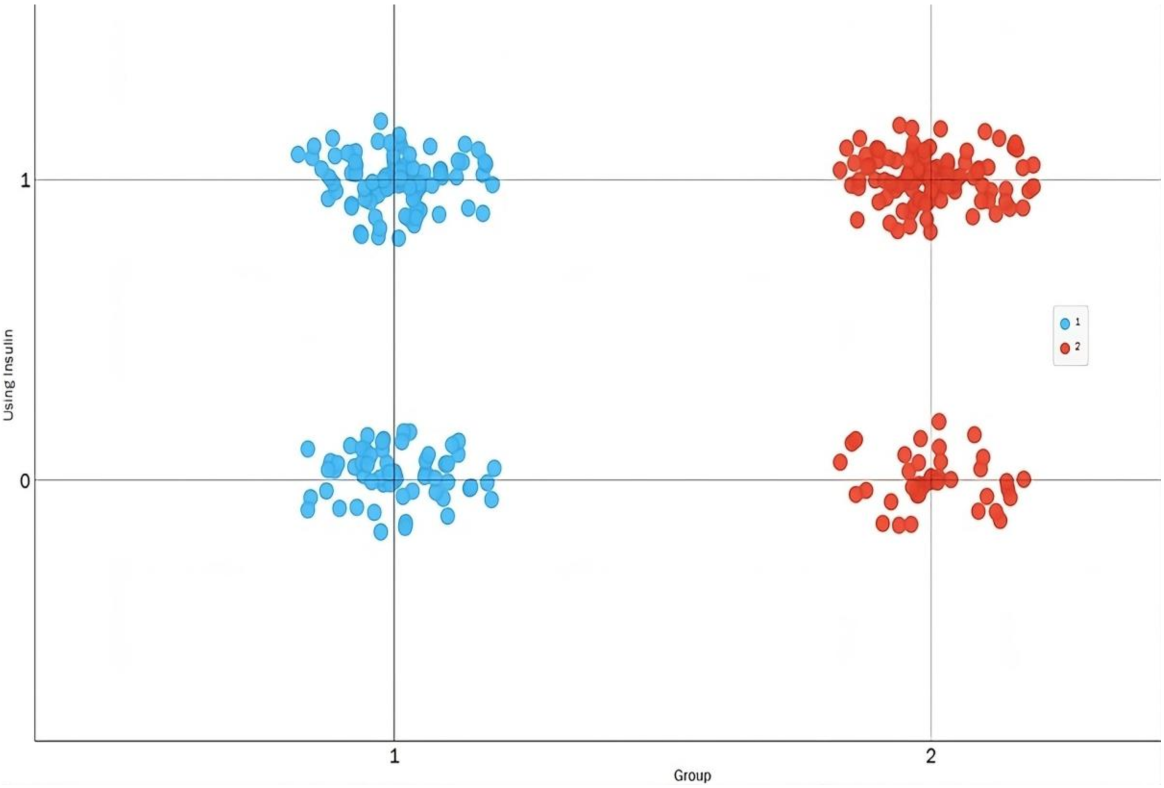


Figure 11. The distribution of group vs using insulins

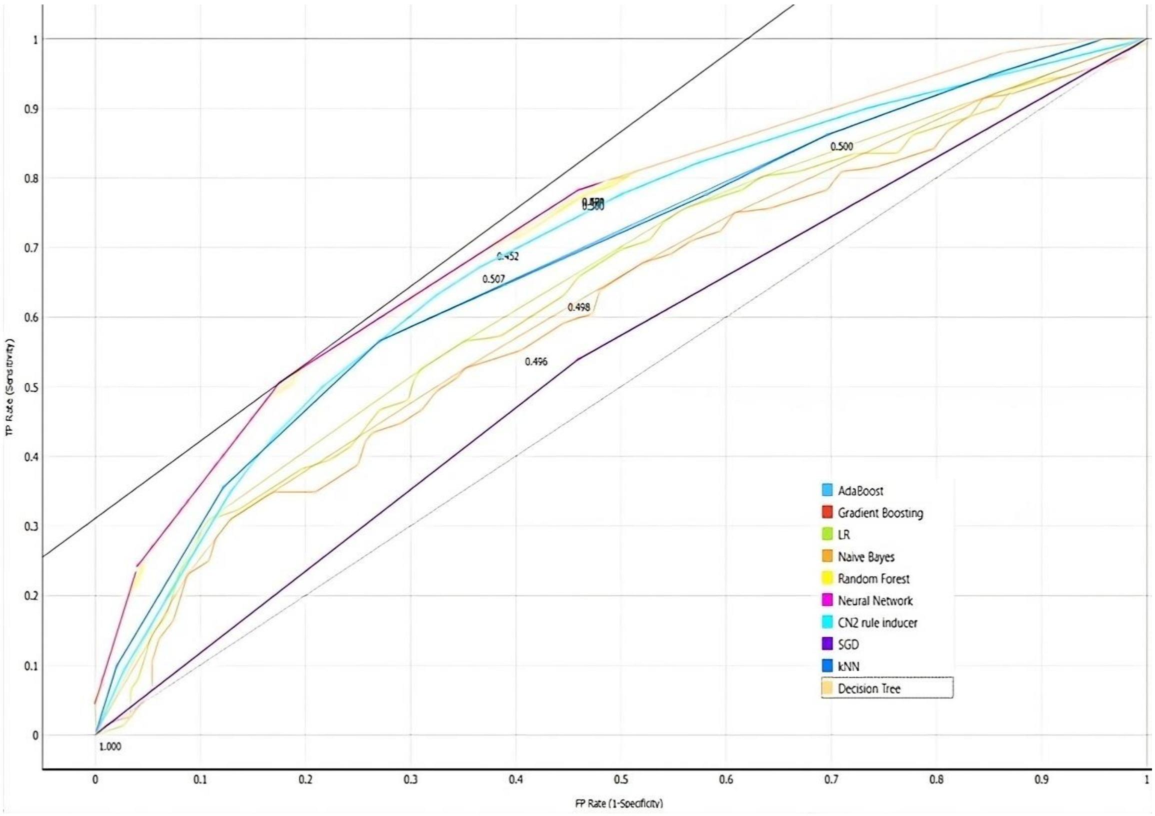


Figure 12. ROC analysis curve of group 1

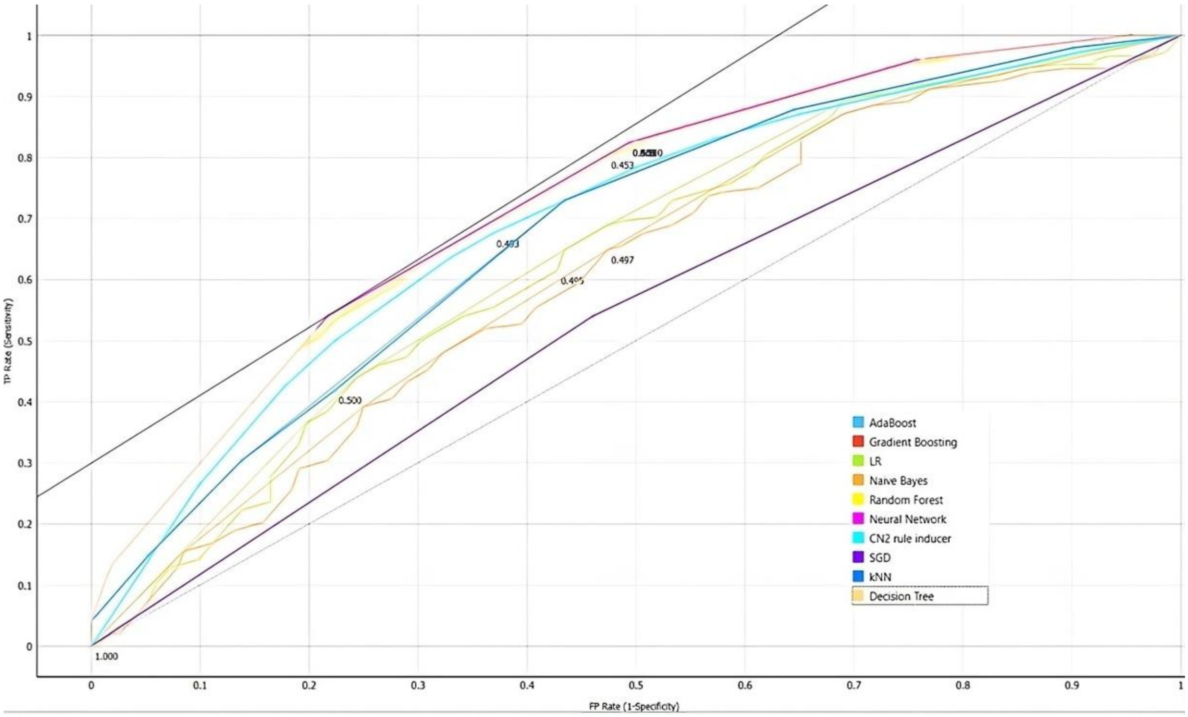


Figure13. ROC analysis curve for group 2

3.4. Transfer learning using regression model

In the previous sections, two methods were applied to get better prediction results. The transfer learning model was considered to obtain better outputs and compare and extract the best method suited for the input data. In the previous methods, input data was directly passed to the prediction model, but in this method, unsupervised and supervised learning techniques were used simultaneously. The model developed for our predictions of supervised learning has finely tuned algorithms, and we are also using K-mean clustering for unsupervised learning and data analysis. The hyperparameters were tuned as that of the regression model. So, in this method, researchers used the results obtained in clustering and passing over the clustered data to the model. This method improved the prediction accuracy because the data had passed was already sorted and reduced machine effort. This method achieves better prediction accuracy, as shown in Table 6. We used two methods for transfer learning- we have used both regression and classification models and have passed the clustering results.

The transfer learning was used in this model with two different techniques. Firstly, the regression model, passed on the data with numeric target BSL value, and evaluated the predictions separately for each cluster. The attached figures are the output of this method. As shown in Tables 6 to 8, all three clusters have different results. Cluster 1 has the better results than others. The data quality of cluster 1 is better and more organized as it would have been easy for the predictors to understand and predict. However, the prediction accuracy was very poor for cluster 2; possibly, the data was not that good, and the samples in this cluster are responsible for the low accuracy of the overall prediction. Cluster 3 had better results than cluster 2, so it can be concluded that the samples in clusters 1 and 3 are boosting our overall prediction scores using regression, whereas the sample data of cluster 2 is affecting the accuracy.

Table 6. Prediction output for cluster 1

Model	MSE	RMSE	MAE	R^2
DT	13.670	3.697	3.180	0.225
RF	13.756	3.709	3.196	0.220
GB	13.67	3.697	3.180	0.225
AdaBoost	13.765	3.710	3.208	0.220
SVM	15.618	3.952	3.054	0.115
SGD	15.911	3.989	3.242	0.098
Neural network	80.517	8.973	7.740	-3.565

Table 7. Prediction output for cluster 2

Model	MSE	RMSE	MAE	R^2
DT	13.720	3.704	2.736	0.044
RF	13.786	3.713	2.724	0.039
GB	13.720	3.704	2.736	0.044
AdaBoost	14.001	3.742	2.831	0.024
SVM	14.692	3.833	2.688	-0.024
SGD	13.894	3.727	2.743	0.032
Neural network	78.476	8.859	7.783	-4.468

Table 8. Prediction output for cluster 3

Model	MSE	RMSE	MAE	R^2
DT	11.499	3.391	2.712	0.158
RF	11.678	3.417	2.752	0.145
GB	11.499	3.391	2.712	0.158
AdaBoost	11.687	3.419	2.776	0.144
SVM	12.771	3.574	2.573	0.064
SGD	12.992	3.604	2.745	0.048
Neural network	86.175	9.283	8.170	-5.313

3.5. Transfer learning using classification model

The classification model's output results fetched better than the regression model. Thus, in this work, transfer learning is being used with the classification model to get better prediction outputs and to compare and analyze the prediction results of different cluster. We have used the classification prediction model and separately evaluated the results for each cluster. So, cluster 1 has 61 samples in group 1 and 41 in group 2. Similarly, cluster 2 has 29 in group 1 and 43 in group 2, and cluster 3 has 60 in group 1 and 66 in group 2. The grouping on this real data set was almost balanced, thus, this study obtained good accuracy after the prediction. The attached Tables 9 to 11 show the prediction accuracy obtained using transfer learning. After classifying the clusters, we obtained better accuracy, which was different from the case of classification using regression. So, according to this data nature, classification results are fetching good prediction accuracy.

It was observed that there was a slight variation in the prediction accuracy after tuning the hyperparameters. Thus, the hyperparameters are kept the same as the classification models. This method saved time and model complexity. After comparing the results before and after transfer learning, it is observed that better results were obtained in the case of transfer learning for the input data. The increase in the value of prediction accuracy is considerable. After using this method in the current classification model, prediction accuracy increased from 66% to 70%. For the regression model, prediction accuracy increased from 18% to 22.5%.

Table 9. Prediction results for cluster 1

Model	AUC	Accuracy	F1	Prec	Recall	MCC	Specificity	Sensitivity
AdaBoost	0.766	0.696	0.661	0.718	0.696	0.355	0.777	0.678
GB	0.766	0.696	0.692	0.692	0.696	0.357	0.708	0.692
LR	0.685	0.676	0.665	0.670	0.676	0.305	0.633	0.694
Naïve Bayes	0.664	0.676	0.654	0.674	0.676	0.299	0.666	0.679
RF	0.766	0.696	0.692	0.692	0.696	0.357	0.666	0.708
Neural network	0.767	0.696	0.697	0.697	0.696	0.370	0.619	0.750
CN2 rule inducer	0.703	0.676	0.639	0.689	0.676	0.302	0.722	0.666
SGD	0.531	0.559	0.553	0.550	0.559	0.064	0.504	0.621
kNN	0.637	0.676	0.639	0.689	0.676	0.302	0.750	0.644
DT	0.766	0.696	0.661	0.718	0.696	0.355	0.777	0.678

Table 10. Prediction results for cluster 2

Model	AUC	Accuracy	F1	Prec	Recall	MCC	Specificity	Sensitivity
AdaBoost	0.766	0.696	0.661	0.718	0.696	0.355	0.687	0.583
GB	0.766	0.696	0.675	0.699	0.696	0.347	0.687	0.583
LR	0.685	0.676	0.665	0.670	0.676	0.305	0.687	0.583
Naïve Bayes	0.664	0.676	0.654	0.674	0.676	0.299	0.645	0.500
RF	0.764	0.696	0.692	0.692	0.696	0.357	0.714	0.566
Neural network	0.767	0.696	0.697	0.697	0.696	0.370	0.650	0.666
CN2 rule inducer	0.703	0.676	0.639	0.689	0.676	0.302	0.750	0.555
SGD	0.531	0.559	0.553	0.550	0.559	0.064	0.616	0.500
kNN	0.723	0.657	0.596	0.687	0.657	0.259	0.833	0.481
DT	0.766	0.696	0.661	0.718	0.696	0.355	0.750	0.555

Table 11. Prediction results for cluster 3

Model	AUC	Accuracy	F1	Prec	Recall	MCC	Specificity	Sensitivity
AdaBoost	0.710	0.659	0.658	0.658	0.659	0.314	0.661	0.654
GB	0.710	0.659	0.658	0.658	0.659	0.314	0.661	0.654
LR	0.672	0.619	0.619	0.619	0.619	0.236	0.636	0.600
Naïve Bayes	0.649	0.603	0.601	0.602	0.603	0.202	0.611	0.592
RF	0.708	0.659	0.658	0.658	0.659	0.314	0.649	0.673
Neural network	0.71	0.659	0.655	0.661	0.659	0.315	0.649	0.673
CN2 rule inducer	0.682	0.651	0.649	0.651	0.651	0.298	0.652	0.648
SGD	0.567	0.563	0.562	0.569	0.563	0.134	0.600	0.535
kNN	0.655	0.548	0.503	0.601	0.548	0.156	0.680	0.514
DT	0.71	0.659	0.659	0.663	0.659	0.321	0.694	0.626

4. DISCUSSION

The researchers primarily collected data from hospitalized patients to construct hypoglycemia predicting models. The study found that the most common causes of hypoglycemia in people with type 2 diabetes were insulin usage (66%), insufficient nutritional intake (66%), gastrointestinal difficulties (58%), increased physical activity (64%), advanced age (50%), and meal skipping (44%). Similar findings were found in other research studies with statistical significance at P.001 [47]–[49]. The most prevalent causes of hypoglycemia are incorrect insulin administration, sulfonylurea, or glinide at an inappropriate time concerning meals or administering excessive amounts. In addition, hypoglycemia can be caused by an inadequate intake of exogenous glucose and a lack of insulin synthesis in circumstances such as liver failure, renal failure, and extreme physical activity [50]. The most common causes of hypoglycemia are the incorrect timing or high doses of insulin, sulfonylureas, or glinides, inadequate amounts of exogenous glucose, and a lack of insulin production in conditions such as liver failure, renal failure, and excessive physical exertion [50]. Interestingly, research has shown that those with a lower BMI have less insulin resistance, which can lead to more frequent bouts of hypoglycemia [51]. Thus, obese people are less likely to experience hypoglycemia, a condition known as the "obesity paradox" [52].

This study used both causative factors and machine learning approaches to predict hypoglycemia occurrences in patients with type 2 diabetes. Firstly, we used a supervised machine-learning strategy with regression and classification approaches. In addition, an unsupervised learning strategy was used for data processing, including k-means clustering. Our suggested model's dataset was based on real-time acquired information using a combination of personal interviews of patients admitted to the hospital. Our regression model easily handled this dataset. However, a categorical target variable was applied to the classification model. The dataset was split into two groups based on the median of the BSL value. We labeled these groups 0 and 1, our categorical target variable. Following this modification, the data was ready for prediction using the categorization model.

Various techniques were employed to address the imbalanced (how many times more) data, such as considering features, clustering, and descriptive statistics. After multiple efforts and experiments, the data could be classified using the median BSL value of 67mg/dl. This split produced two well-balanced classes, with group 1 accounting for 50.67% of the samples and group 2 accounting for 49.33%. In this study, ten different statistical techniques were employed in the categorization prediction phase. AdaBoost, GB, LR, NB, kNN, RF, neural network, CN2 rule induction, DT, and SGD are among the techniques used. Under the regression model, seven statistical algorithms were used for prediction. K-means clustering is a frequently used unsupervised machine learning approach to group or cluster data points based on similarity.

In this study, regarding regression models, DT and GB showed better results than other commonly used machine learning techniques. The anticipated values of DT and GB are 66 to 68, yielding a 46% accuracy rate. We got the maximum prediction accuracy by applying classification models such as GB, Adaboost, RF, and neural network, each with an accuracy score of 0.663. The categorization model produces better results than the regression model. As a result, in this work, transfer learning was used alongside the classification model to improve prediction results and contrast and analyze predictions across different clusters.

In the classification prediction model, each cluster was evaluated separately. Cluster 1 comprised 61 samples from group 1 and 41 from group 2. Similarly, cluster 2 has 29 samples from group 1 and 43 from group 2, while cluster 3 has 60 from group 1 and 66 from group 2. There was an increase in prediction accuracy from 66% to 70% after including this strategy in our classification model. The regression model's prediction accuracy increased from 18% to 22.5%. Yang *et al.* [30] developed XGBoost to build a prediction model for hypoglycemia risk, including paragraph vector-distributed memory (PV-DM) administered to people with type 2 diabetes. According to their findings, XGBoost 3 had the greatest accuracy and the biggest AUC for hypoglycemia prediction. Notably, with a p-value of less than 0.001, there was a statistically significant difference between this model and others [30]. In situations like this, machine learning techniques are quite useful. Transfer learning considerably improved the overall performance of the models after using regression and classification models, as well as k-means clustering, to measure their performance.

5. IMPLICATIONS OF THE STUDY

The study's findings have important significance for healthcare, since they provide unique machine learning methodologies for detecting hypoglycemia in type 2 diabetic patients. These strategies might improve early intervention, patient outcomes, and individualized treatment regimens, enhancing the overall management of diabetes-related problems. These criteria can be used by front-line workers in community health settings to protect diabetes patients from serious consequences.

6. CONCLUSION

We used machine learning approaches to develop hypoglycaemic prediction models. When applied to small, initial datasets, these models demonstrated sufficient sensitivity and specificity. Among all classification and regression models, classification models exceeded others in anticipating hypoglycemia. Regarding predicting hypoglycemia, AdaBoost, GB, RF, and neural networks showed improved accuracy and AUC values. Based on our findings, we discovered that improving accuracy, sensitivity, and precision requires a large dataset, which may effectively reduce false positive predictions. Future evaluations should be conducted to evaluate the viability of implementing these models in real-time circumstances. Furthermore, these models might possibly be developed to predict hypoglycemia and begin intervention procedures, lowering the occurrence of this serious complication in diabetes even further.

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BIOGRAPHIES OF AUTHORS

Sachin Ramnath Gaikwad is currently working as an Assistant Professor in the Department of Artificial Intelligence and Machine Learning, Symbiosis Institute of Technology, Pune Campus, Symbiosis International Deemed University, Pune, Maharashtra, India. He received the bachelor's degree from Savitribai Phule Pune University (SPPU), Maharashtra, India, and Master's degree in Electronics and Telecommunication Engineering from Dr. Babasaheb Ambedkar Marathwada University (BAMU), Maharashtra, India. He has completed Ph.D. degree in the Faculty of Engineering at Symbiosis International Deemed University, Pune, India. He is also a member of IEEE. His main research interests include energy, smart grid, healthcare, data analytics, socio-technical systems, decision-making methods, socio-inspired optimization, and artificial intelligence. He has 10 years of academic and reaserch experience in the field of engineering. He can be contacted at email: sachin.r.gaikwad@outlook.com.

Seeta Devi is currently working as an Associate Professor in the Department of Obstetrics and Gynaecological Nursing, Symbiosis College of Nursing (SCON), Symbiosis International Deemed University, Pune, Maharashtra, India. Her main research interest includes, preventive care required for an antenatal, intranatal and post-natal women in view to prevent the complications. She received her Bachelor's degree from Govt College of Nursing, NTR University of Health Sciences, Master's degree in the speciality Obstetrics and Gynaecological Nursing, Sri Venkateswara Institute of Medical Sciences, Tirupati and Ph.D. degree in Nursing (prevention of cervical cancer), MGM Institute of Health Sciences, Mumbai, Maharashtra, India. She has 15 years of teaching, clinical, administrative, and research experience in the field of nursing. She can be contacted at email: drseetadevi1981@gmail.com.

Sameer Shekhar is currently pursuing his bachelor's degree in Computer Science and Engineering from Symbiosis Institute of Technology, Symbiosis International Deemed University, Pune, Maharashtra. His main research interests include data analytics, artificial intelligence, and machine learning. He can be contacted at email: sameer.shekhar.btech2023@sitpune.edu.in.

Dipali Dumbre is currently working as an Assistant Professor in the Department of Medical and Surgical Nursing, Symbiosis College of Nursing, Symbiosis International Deemed University (SIU), Pune, Maharashtra, India. Her main research interest includes critical care nursing, and medical and surgical problems in men and women in view to prevent complications. She received her Bachelor's degree from St. Andrews College of Nursing, Maharashtra University of Health Sciences, her Master's degree in the specialty Medical and Surgical Nursing, Tehmi Grant Institute of Nursing Education, Maharashtra University of Health Sciences, and Ph.D. degree in Nursing (Development of Hypoglycemia Management Kit), JJTU, India. She has 16 years of teaching, clinical, administrative, and research experience in nursing. She can be contacted at email: dipalidumbre@scon.edu.in.