Kidney failure prediction at an early stage usingMachine Learning: A Comparative Study

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Abstract:
Chronic kidney disease (CKD) is a medicalcomplication of a person due to which the kidney can't filter the blood due to which the body fills with extra water and waste products. It can lead to stroke, heart attack, heart failure,swelling of the feet and kidney failure, which can lead to death. The global health problemis growing rapidly as more and more people are being diagnosed with CKD. With advancing technology, as well as ongoing medical research, machine learning is being used in the healthcare sector to diagnose many diseases early. ML algorithms and decoding methods have been very useful in extracting, analyzing data and making predictions when a person is positive or negative about a disease based on the given data sets. ML algorithms and in-depth reading have been proven to be very true in detecting CKD early. Machine learning algorithms, Cat boost classifier, Support Vector Machine (SVM), Decision Tree (DT), Random Forest,KNN, ANN were studied and applied in this work to perform comparative analysis to shapea ML model which will accurately predict if a person is positive to CKD or not. This paper uses pre-data processing, including background and above-mentioned machine learning algorithms to build the most accurate model to accurately detect this disease CKD and perform a comparative research of variousML algorithms for prognosis of CKD.

Keywords: Machine Learning, Data Mining,ANN, KNN, Decision Trees, Logistic Regression, Support Vector Machine, Data Preprocessing, Feature extraction.

I. Introduction

When the blood filtering capability of the kidney is hindered, the disease is called Chronic Kidney disease. Chronic Diseases refers to diseases persisting for a long time. When the kidney fails to strain the waste products and blood, fluid starts building up in the body due to which excess fluids get deposited in the body and severalconsequences are seen, like swelling in feet, irritation, and high blood pressure due to whichthere is an increased risk of heart related diseases (Heart Attack, Heart Failure, Difficultyin breathing). These fluid buildup can cause deposition of some salts in the body which cancause cystic ovaries in women. Some complications of CKD are:

- High BP
- Low blood count
- Weaker bones and muscles
- Nerve damage
- Poor nutritional health
- Fluid retention
- Uremia

CKD is evaluated by measured glomerular filtration rate (GFR) and creatinine level which is calculated by blood test KFT. All such parameters like creatinine level, GFR valueare calculated using KFT (kidney function test).In severe cases, CKD may lead to kidney transplants or permanent dialysis. This paper is made to detect CKD at an early stage, as in later stages, the chances of survival and recovery is very low. We have used variousML algorithms like Cat boost Classifier, KNN, ANN, Decision Tree, SVM, and Random Forestand also indicate a more accurate prediction model by performing a comparative analysis on the basis of efficiency of predicted outcomes by different techniques.

I. Literature Survey:

Md. Rashed-Al-Mahfuz[1] introduces a reliable method of classifying CKD and selecting annotations with simplified enhancement and cost effectiveness. In this study the classifiers were constructed using different algorithms such as RandomForest, Gradient-boosting, and extreme gradient-boosting,logistic-regression, and support-vector machines. The outcome of this study showed that the key features recognized by SHAPE were congruous with present-day medical diagnosis. It was described that the RandomForest method provided maximumaccuracy with pathologically divided sets of attributes. Therefore the proposed RF separator and reduced diagnostic criteria can be used to reduce money and time.

Anusorn Charleonnan[2] presented a paper in which Machine learning strategies were used to predict CKD using clinical data. These speculative models are based on a databaseof CKD and the efficiency of these models is put together to select the best CKD forecast.

Gazi Mohammed Ifraz[3] presents a paper in which they have done a comparative analysis of different Machine Learning algorithms and When contradictory verification measures are used in the diagnosis of chronic kidneydisease, the LR method goes beyond other

procedures.

D.M. Perera[4] shows an approach to control the CKD using a proper diet plan by using the classification techniques on the test result obtained from the patient's medical records. In this research classifiers are constructed using different algorithms like Multiclass-Decision-Jungle, Multiclass-Decision-Forest, and Multiclass-Neural-Network and Multiclass-Logistic-Regression [3].

Akash Maurya[5] presents Machine Learningtechniques and suggests a proper diet plan forCKD patients using classification algorithmson medical test information. Dietary recommendations for patients will be given according to the potassium level calculated using potassium levels in the blood to delaythe progression of CKD.

H. Zhang.et al[6]]investigates the effectivenessof Artificial Neural Network (ANN) models while using the survival forecast for ChronicKidney Disease (CKD) patients.

T. G. Kaur.et al[7] predicted chronic kidneydisease applying several data miningtechniques in the Hadoop environment. MLmodels,KNN and SVM were used in the study.Creatinine-level, and GFR value in the blood isa significant factor used for the prognosis forthe disease. This model will help to reducecosts and increase the accuracy of results.

Jiong Ming Qin[8] proposed CKD diagnosticmethod based on data attribution and samplediagnostics .After a random drop in non-datavalues set by KNN compliance, the integratedmodel can achieve satisfactory accuracy.

Qin, J.[9] developed a classification model for anticipating transitional intervals of Kidney disease stages 3 to 5 and also used Decision Tree, K-nearest neighbor, NaïveBayes and Artificial neural networks to obtain information and create a classification model with a selected set of features.

S.Vijayarani.at.al [10] predicted kidney diseases by using Support Vector Machine and Artificial Neural Network. The analysis incorporates thebehavior of the two techniques above for accuracy and performance time.

S Krishnamurthy [12] In this paper, he established and assessed a series of models based on Artificial Intelligence taking into account small variables such as gender, age, comorbidities, and medications. These modelsanticipate patients' risk of developing CKD within six or twelve months. Among the several techniques tested. Highlights contain diabetes, age, gout, and the use of sulfonamides and angiotensin, all of which make sense according to CKD.

Qiong Bai[13] 5 ML techniques, incorporate Logistic Regression, Naïve Bayes, Random Forest, Decision Tree and K-nearest neighborshave been taught and examined using five-foldverification. The strength of each model is comparable to that of the Kidney Failure Risk Equation (KFRE) .The three ML models, whichinclude retreat, Naïve Bayes and the Random Forest, display similarity and susceptibility compared to KFRE. KFRE has high accuracy and precision. This analysis demonstrated the power of ML in evaluating CKD predictionsbased on readily available findings. Three ML algorithms with optimal performance and sensitive points propose potential use inpatient evaluation.

Marwa Almasoud[14] This paper aims to analyze the ability of machine learning methods for predicting CKD using a small set of features. Various mathematical analysis were performed on it to remove obsolete features such as ANOVA tests, Pearsonaffiliates, and Cramer's V tests. The more accurate results come from the Gradient Boosting classifier.

Arsh K. Jain[15] In this paper performed a structured evaluation of the impact of neutral-pH , low-GDP collate to standard-PD solutions. In this analysis, neutral pH, low GDPsolutions caused a large amount of urine over 6 months and better RRF retention during all treatment periods.

Giorgina Barbara Piccoli[16] This study aimed toidentify factors associated with the risk of adverse effects associated with pregnancy in females with CKD, with special significance of stage 1 CKD. We aim to work on whether the adverse pregnancy results in females with stage 1 CKD were due to high blood pressure,proteinuria, systemic disease, or other clinically unrelated CKD-related-factors.

Kunihiro Matshushita[17] In this, Two important steps for CKD, eGFR and albuminuria, enhance the prognosis of CVD risk in addition to the usual risk factors, especially CVD death diseases. For the same purpose, the purpose of this study was to predict various stages of CKD using machine-readable algorithms foundin the medical records of the affected people. Specifically, this study used Random Forestand J48 algorithms to obtain a stable and effective model for determining the various stages of CKD with complete medical accuracy. A relative study of the outcomeuncovered that J48 predicted CKD in all categories better than the random forest. Manal.

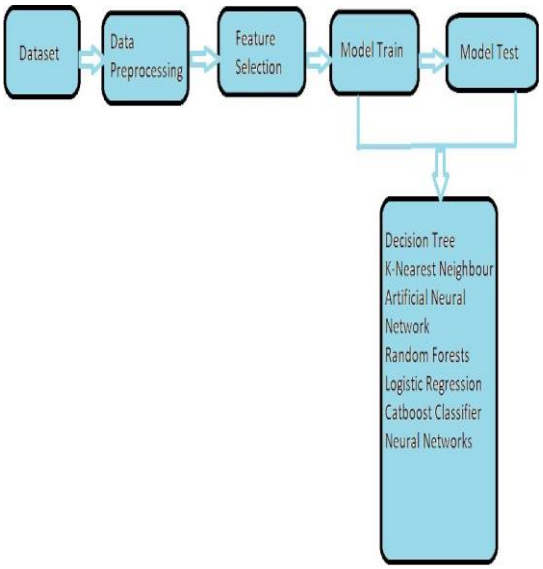
AAbdel-Fattah [19] this paper proposes a combination of machine learning strategies that include feature selection and how to classify a learning machine based on largedatasets used to diagnose CKD. Feature selection methods, i.e., Relief-F and Chi-squared, were used to select key features.Six distinctive methods were applied in this study: Decision Tree (DT), Logistic Regression (LR), Naive Bayes (NB), Random Forest (RF), vector support machine (SVM), and Gradient-Boosted Trees as integrated learning

algorithms. Or in each algorithm, the opposite confirmation results and test results are computer-based based on full features,Relief-F and selected chi-squared features. The outcome shows that SVM, DT, and GBT Classifiers with selected features obtained excellent performance and greater accuracy.

These CKD measures for predicting CVD, especially if the data are already limited toother clinical indicators. When the risk profile is to be continuously improved other biological symptoms may be helpful, and indicating the pathophysiological process of CVD such as coronary artery calcium and high-sensitivity troponin T heart appear specifically promising. Future clinical recommendations may need to be updated on how to include CKD values andother biological indicators into CVD predictors, relying on the results of an interesting CVD, target population, and the possibility of such measures and biomarkers.

Hamida Ilyas[18] prior identification and treatment of CKD is highly advisable as it can lead to the avoidance of undesirable side effects. A machine learning method is widely recommended for prior identification of symptoms and for the prognosis of several And heart failure. It seems valid to consider.

II. Methodology



1. Decision Tree

It is a form of supervised learning. By usingthis we can solve both retrieve and edit problems. This separator acts as a tree data structure, where internal nodes display attributes or datasets, branches showing decision rules and leaf nodes indicating the result. It includes two types of nodes, name Decision and Leaf. The decision tree is based on the CART (Classification and Regression Tree) algorithm. It simply asks the question and is based on the result and divides the tree into a few small trees.

Confusion Matrix:

	Predicted No	**Predicted Yes**
Actual No	26	2
Actual Yes	0	12

2. K-nearest neighbors (KNN):

Used for stage prediction problems. It is a typeof supervised learning strategy. It does notthink about the data provided, it is also knownas a non-parameter learning algorithm. It is also known the learning algorithm is lazy because it does not learn anything during training from the training set, instead itperforms a database function as required. It keeps data in training and separates data continuously when it receives new data.

3. Random Forest:

The informal forest forms manydecision-making trees and based on their results further advances the diversification andreversal of processes. A few decision trees aremade using random subset sets of trainingdatabases. Algorithm run time is faster and allows for missing data. Random Forest makes a random algorithm. Decision stage is the mode of classes produced by cutting trees.

	Predicted No	**Predicted Yes**
Actual No	26	2
Actual Yes	1	11

4. Support Vector Machine:

A model for partitioning and reversing a Vector-support machine (SVM) that can be used to solve specific and indirect problems. This data is divided using hyperplanes. In this case, each item of data is sorted as a point in the n-d space, the value of each item becomesthe sum of the object.

	Predicted No	**Predicted Yes**
Actual No	28	0
Actual Yes	12	0

5. Logistic Regression:

Indentation is a mathematical method ofpredicting a binary outcome, such as yes orno, based on a predetermined data set. The systematic regression model predicts the variance of the dependent data by analyzing the relationship between one or more independent variables present.

6. Neural Networks:

It is a series of algorithms that attempt to find basic relationships in a set of data through a process that mimics how the human brain works. In this sense, neural networks refer to neuron systems, which can be an organic or synthetic environment.

7. Artificial Neural Network:

ANN models are extremely flexible for human emotional systems. ANN incorporates computational units similar to those of neuronsof the biological nervous system known as synthetic neurons.

ANN is capable of learning and modeling indirect and complex relationships as most relationships between input and output are notinterconnected. After training, ANN is able to determine non-binding relationships from intangible data, and as a result is generally made.

	Predicted No	**Predicted Yes**
Actual No	27	1
Actual Yes	6	6

III. DATASET:

We did some research on a set of chronic kidney disease data downloaded from kaggel. This database contains 25 attributes (including 10 categories, 14 numbers and a classattribute). Specific 'category', possibly 'ckd' or 'not ckd' - ckd = chronic kidney disease. There are 400 lines. Data needs to be cleaned up: because it has NaNs and numerical features need to be forced to float. Basically, we were instructed to delete ALL LINES with Nans, without limitation - that is, any line with oneNN, is deleted.

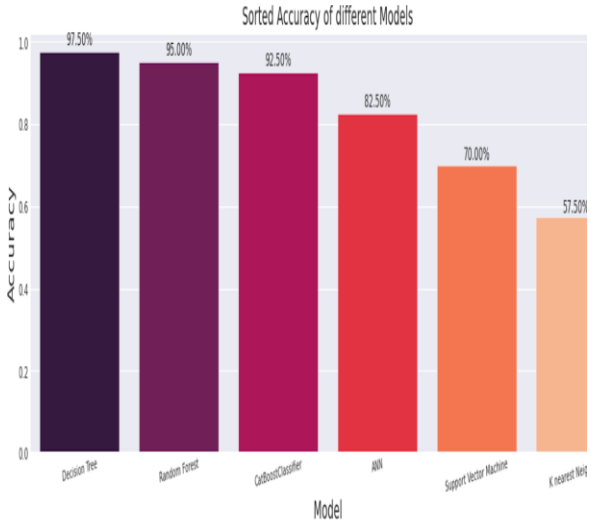
	age	bp	sg	al	su	rbc	pc	pcc	ba	bgr	...	pcv	wbcc	rbcc	htn	dm	cad	appet	
0	48.0	80.0	1.020	1.0	0.0	NaN	normal	notpresent	notpresent	121.0	...	44.0	7800.0	5.2	yes	yes	no	good	
1	7.0	50.0	1.020	4.0	0.0	NaN	normal	notpresent	notpresent	NaN	...	38.0	6000.0	NaN	no	no	no	good	
2	62.0	80.0	1.010	2.0	3.0	normal	normal	notpresent	notpresent	423.0	...	31.0	7500.0	NaN	no	yes	no	poor	
3	48.0	70.0	1.005	4.0	0.0	normal	abnormal	present	notpresent	117.0	...	32.0	6700.0	3.9	yes	no	no	poor	y
4	51.0	80.0	1.010	2.0	0.0	normal	normal	notpresent	notpresent	106.0	...	35.0	7300.0	4.6	no	no	no	good	

Chronic Kidney Disease Dataset Data Set Information:

We use the following presentations to collect data
years - years
bp - blood pressure
sg - certain gravitational force
albumin
su - sugar
rbc - red blood cells
pc - pus cell
pcc - pus cell clumps
bacteria
bgr - random blood sugar
blood urea
sc - serum creatinine
salt - sodium
pot - potassium
hemoglobin - hemoglobin
pcv - full cell volume
wc - the number of white blood cells
rc - the number of red blood cells
htn - high blood pressure
dm - diabetes
Cad - a disease of the coronary artery
hunger - appetite
pedal edema
anemia
class - class

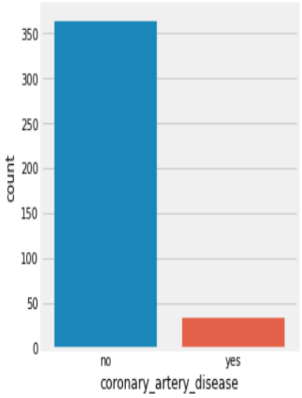
IV. Conclusion:

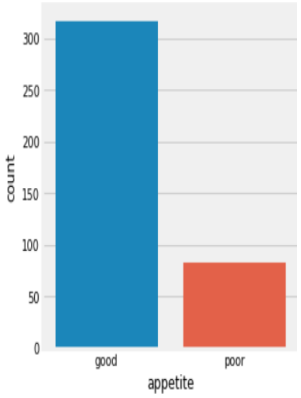
This paper presents a comparative analysis of predictive algorithms to determine the mosteffective predictive algorithm to detect chronickidney failure in advance. The database shows input parameters collected from symptomatic patients and models are trained and validated the input parameters provided. Decision Tree, Random Forests, KNN, ANN, Cat-boost classifiers, SV machine learning models are designed to test CKD. Model performance is assessed based on predictive accuracy by building up a confusion matrix for individual models. Research results have shown that the Cat boost Classifier model and the Decision tree classifier predict better CKD compared to artificial neural networks and Vector Support machines. Comparisons canalso be made based on the time of the study, the selection of the feature set as an improvement of this study.

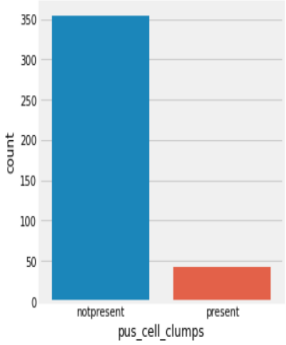


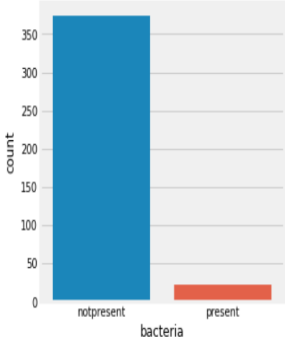
V. Results and Analysis:

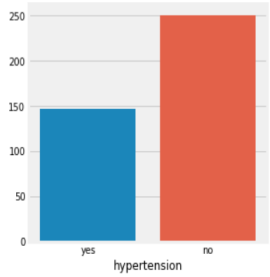
Comparative analysis of various attributes of dataset:

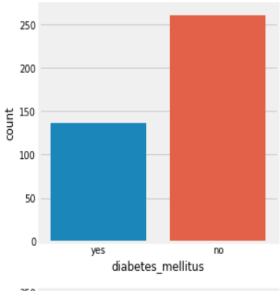


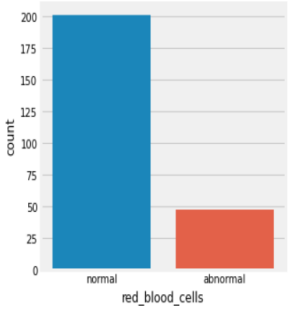


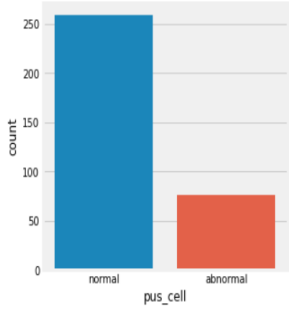






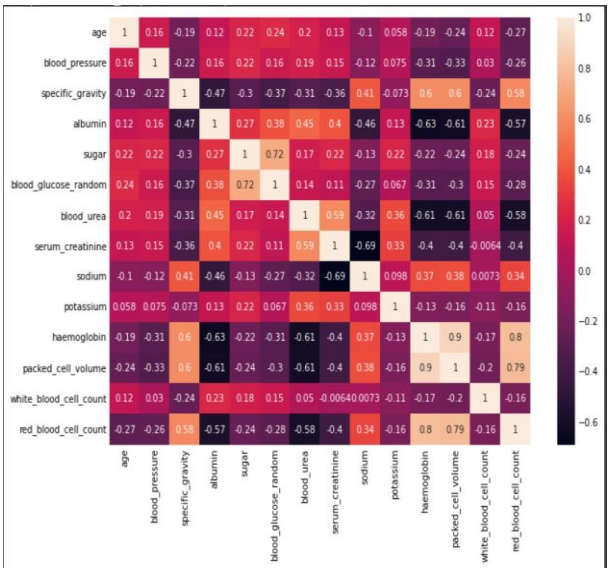






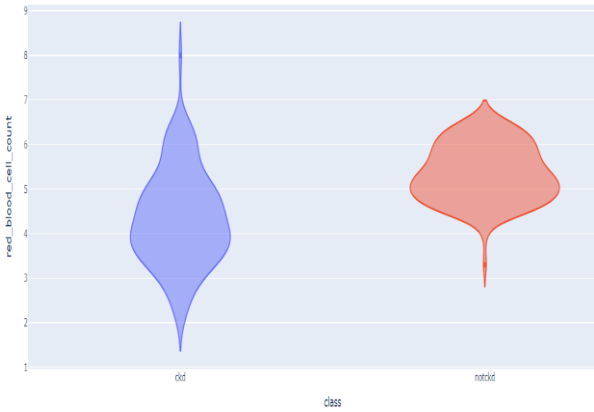
Heat map:

A Heat map is a way of showing a certain type of matrix structure. To use the heat map data must be in matrix form. By matrix we meanthat the index name and column name must be identical in some way for the data we fill with in the cells to be relevant.



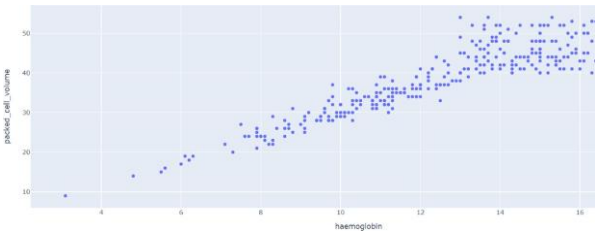
Violin plot of red blood cell:

The violin plot is a combination of box structure and kernel density plot, which reflects the height of the data. It is used to visualize the distribution of numerical data. Unlike the box structure that can only display summary statistics, the violin sections show summary statistics and the density of eachvariation.



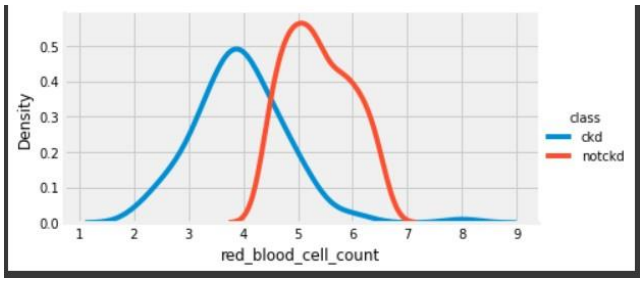
Scatter plot:

Scatter structure is a type of structure ordiagram using Cartesian links to display values usually in two dynamic data sets. When points are coded, one additional variation canbe displayed.

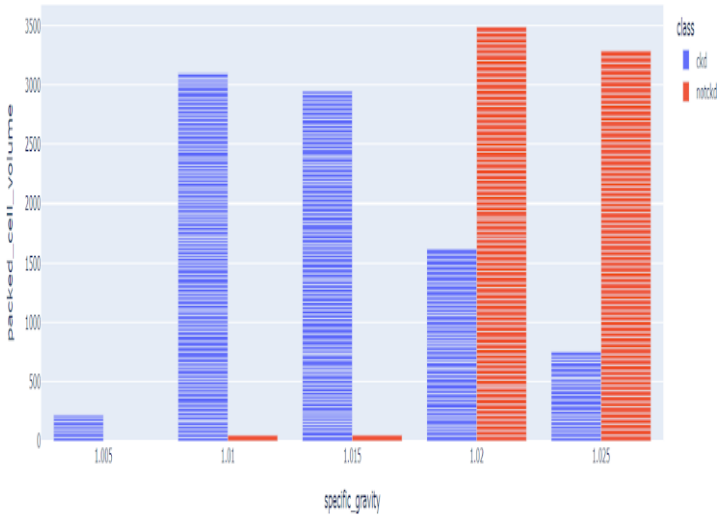


KDE plot:

The kernel density estimate (KDE) structure is a way of detecting the distribution of visuals in a database, analogous in a histogram. KDE stands for data using a continuous curve inone or more directions.



Bar graph:



Preprocessing:

When you create a machine learning project, itis not always a problem for us to meet clean and formatted data. And while any data processing is done, it is compulsory to clean it and format it in a format. So in this case, we are using a data processing function.

	age	blood_pressure	specific_gravity	albumin	sugar	red_blood_cells	pus_cell	pus
0	48.0	80.0	1.020	1.0	0.0	1	1	
1	7.0	50.0	1.020	4.0	0.0	1	1	
2	62.0	80.0	1.010	2.0	3.0	1	1	
3	48.0	70.0	1.005	4.0	0.0	1	0	
4	51.0	80.0	1.010	2.0	0.0	1	1	

pus_cell_clumps	bacteria	blood_glucose_random	blood_urea	serum_creatinine	sodiu
0	0	121.0	36.0	1.2	137.
0	0	352.0	18.0	0.8	137.
0	0	423.0	53.0	1.8	141.
1	0	117.0	56.0	3.8	111.
0	0	106.0	26.0	1.4	131.

Feature extraction:

Feature extract refers to the process of converting raw data into numerical featuresthat can be processed while retaining information in the original data set. It producesbetter results than using direct machine learning over raw data.

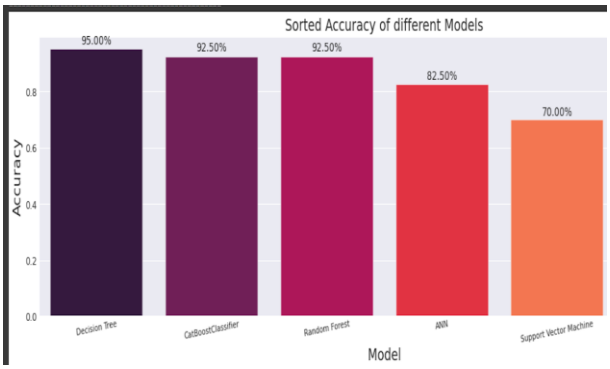
	white_blood_cell_count	blood_glucose_random	blood_urea
0	7800.0	121.0	36.0
1	6000.0	352.0	18.0
2	7500.0	423.0	53.0
3	6700.0	117.0	56.0
4	7300.0	106.0	26.0
...	...	...	...
395	6700.0	140.0	49.0
396	7800.0	75.0	31.0
397	6600.0	100.0	26.0
398	7200.0	114.0	50.0
399	6800.0	131.0	18.0

packed_cell_volume	albumin	haemoglobin	age	sugar	hypertension
44.0	1.0	15.4	48.0	0.0	1
38.0	4.0	11.3	7.0	0.0	0
31.0	2.0	9.6	62.0	3.0	0
32.0	4.0	11.2	48.0	0.0	1
35.0	2.0	11.6	51.0	0.0	0
...	...	...	...	...	...
47.0	0.0	15.7	55.0	0.0	0
54.0	0.0	16.5	42.0	0.0	0
49.0	0.0	15.8	12.0	0.0	0
51.0	0.0	14.2	17.0	0.0	0
53.0	0.0	15.8	58.0	0.0	0

Confusion Matrices of used algorithms:

```
Confusion matrix of  CatBoostClassifier
[[25  3]
 [ 0 12]]
Accuracy score is  0.925
==================================================
Confusion matrix of  Support Vector Machine
[[28  0]
 [12  0]]
Accuracy score is  0.7
==================================================
Confusion matrix of  Decision Tree
[[26  2]
 [ 0 12]]
Accuracy score is  0.95
==================================================
Confusion matrix of  ANN
[[27  1]
 [ 6  6]]
Accuracy score is  0.825
==================================================
Confusion matrix of  Random Forest
[[26  2]
 [ 1 11]]
Accuracy score is  0.925
```

Result:



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