## Machine Learning - Classification (Assignment)

#### **Problem Statement or Requirement:**

The client wants to develop a machine learning-based application that can accurately **predict the presence of Chronic Kidney Disease (CKD)** in patients based on multiple clinical and demographic parameters. Early detection of CKD is critical to enabling timely medical intervention and improving patient outcomes.

#### 1. Problem Statement

Domain Selection - Machine Learning

Learning Selection - Supervised Learning

It is a Classification

## 2. Basic information of the Dataset

Rows = 399

Columns = 25

#### 3. Preprocessing

This dataset contains 11 categorical columns which is Nominal so I used One-Hot-Encoder to convert Categorical columns to Numerical Columns

We have also standardised the dataset using StandardScaler function to ensure there is defined range between data

4. Working out with different Algorithms to find the best model

**Support Vector Machine** 

## **Hyper tuning Parameters grid:**

	mean_fit_tim e	std_fit_tim	mean_score_time	std_score_time	param_C	param_gamma	param_kerne I	params	split0_test_sco re	split1_test_sco re	split2_test_sco re	split3_test_sco re	split4_test_sco re	mean_test_sco	std_test_score	rank_test_scor
0	0.018402	0.009238	0.019347	0.00577	10	auto	linear	{'C': 10, 'gamma': 'auto', 'kernel': 'linear'}	0.984445	0.984436	0.984436	0.96875	0.984195	0.981252	0.006252	23
1	0.025279	0.010769	0.017068	0.003894	10	auto	rbf	{'C': 10, 'gamma':	0.96901	1	0.984305	0.984305	1	0.987524	0.011617	9
2	0.057689	0.003059	0.01468	0.002015	10	auto	poly	{'C': 10, 'gamma': 'auto', 'kernel': 'poly'}	1	0.984305	0.96875	0.984305	1	0.987472	0.0117	11
3	0.035888	0.010634	0.014354	0.002494	10	auto	sigmoid	{'C': 10, 'gamma': 'auto', 'kernel': 'sigmoid'}	0.984445	1	0.984305	0.96875	0.968508	0.981202	0.011745	33
4	0.020226	0.002409	0.01296	0.001076	10	scale	linear	{'C': 10, 'gamma': 'scale', 'kernel': 'linear'}	0.984445	0.984436	0.984436	0.96875	0.984195	0.981252	0.006252	23
5	0.020775	0.005514	0.014392	0.003578	10	scale	rbf	{'C': 10, 'gamma': 'scale', 'kernel': 'rbf'}	0.96901	1	0.984305	0.984305	1	0.987524	0.011617	9
6	0.022446	0.00298	0.013446	0.001496	10	scale	poly	{'C': 10, 'gamma': 'scale', 'kernel': 'poly'}	1	0.984305	0.96875	0.984305	1	0.987472	0.0117	11
7	0.014683	0.007503	0.012745	0.001339	10	scale	sigmoid	{'C': 10, 'gamma': 'scale', 'kernel': 'sigmoid'}	0.96901	1	0.984305	0.953307	0.968508	0.975026	0.015876	40
8	0.016037	0.003813	0.012252	0.001482	100	auto	linear	('C': 100, 'gamma': 'auto', 'kernel': 'linear')	0.984445	0.984436	0.984436	0.96875	0.984195	0.981252	0.006252	23
9	0.014451	0.003811	0.011855	0.001183	100	auto	rbf	{'C': 100, 'gamma': 'auto', 'kernel': 'rbf}	0.984445	1	0.984305	0.984305	1	0.990611	0.007666	1
10	0.02201	0.002584	0.011118	0.001158	100	auto	poly	('C': 100, 'gamma': 'auto', 'kernel': 'poly')	0.984445	1	0.984305	0.984305	0.984195	0.98745	0.006275	13
11	0.014559	0.00456	0.011994	0.000427	100	auto	sigmoid	'gamma': 'auto', 'kernel':	1	0.984436	0.984436	0.96875	0.984195	0.984363	0.009883	15
امه		ا ممممما	0.044070	0.000.47	400			'gamma': 'scale',	0.004445	0.004400		0.00075				
12	0.014761	0.003989	0.011073	0.000947	100	scale	linear	'gamma': 'scale', 'kernel': 'linear'} {'C': 100, 'gamma': 'scale',	0.984445 0.984445	0.984436	0.984436 0.984305	0.96875	0.984195	0.981252		23
			0.012184			scale		'kernel': 'rbf'} {'C': 100,		1			1			13
14		0.001937		0.001217	100	scale	poly	'gamma': 'scale', 'kernel': 'poly') 'gamma': 'scale',	0.984445	1	0.984305	0.984305	0.984195	0.98745		
15	0.01291	0.002514	0.01272	0.00132	100	scale	sigmoid	'kernel':  ciamoid!\ {'C': 1000,	1	0.984436			0.984195	0.984363		15
16		0.004872	0.013129	0.001025	1000	auto	linear	'gamma': 'auto', 'kernel': 'linear'} {'C': 1000,	0.984445	0.984436		0.96875	0.984195	0.981252		23
17	0.013355	0.002317	0.013419	0.000791	1000	auto	rbf	'gamma': 'auto', 'kernel': 'rbf'} {'C': 1000,	0.984445	1	0.984305	0.984305	1	0.990611		1
18		0.003433	0.012653	0.000756	1000	auto	poly	'gamma': 'auto', 'kernel': 'poly') 'G: 1000; 'gamma': 'auto',	0.95367	1	0.984305	0.984436	0.984195	0.981321		
19	0.015098	0.00537	0.011679	0.001144	1000	auto	sigmoid	'kernel': (C': 1000,	0.984445	0.984436	0.984436	0.96875	0.968508	0.978115		
20	0.012184	0.003327	0.011391	0.000546	1000	scale	linear	'gamma': 'scale', 'kernel': 'linear'} {'C': 1000,	0.984445	0.984436	0.984436	0.96875	0.984195	0.981252		23
21		0.001488	0.01199	0.000796	1000	scale	rbf	'gamma': 'scale', 'kernel': 'rbf'} {'C': 1000,	0.984445	1	0.984305		1	0.990611		
22	0.019491	0.002713	0.0121	0.000796	1000	scale	poly	'gamma': 'scale', 'kernel': 'poly'} {'C': 1000,	0.95367	1	0.984305	0.984436	0.984195	0.981321		
23	0.010982	0.003055	0.010868	0.00039	1000	scale	sigmoid	'gamma': 'scale', 'kernel': 'sigmo {'C': 2000,	0.984445	0.984436	0.984436	0.96875	0.968508	0.978115	0.007745	34
24	0.010862	0.002234	0.010965	0.000689	2000	auto	linear	'gamma': 'auto', 'kernel': 'linear')	0.984445	0.984436	0.984436	0.96875	0.984195	0.981252	0.006252	23
25	0.011962	0.004353	0.011827	0.001039	2000	auto	rb	{'C': 2000, f 'gamma': 'auto'	0.984445		0.984305	0.984305	1	0.99061	1 0.007666	1
26	0.018879	0.001119	0.012498	0.001083	2000	auto	poly	'kernel': 'rbf'] {'C': 2000, ' 'gamma': 'auto',	0.95367		0.984305	0.984436	0.984195	0.98132	1 0.015102	2 17
27	0.010446		0.011782	0.000902		auto		'kernel': 'poly']	0.984445	0.984436						
28	0.010135	0.000757	0.011908	0.001148	2000	scale		('C': 2000,	0.984445	0.984436	0.984436	0.96875	0.984195	0.98125	2 0.006252	
29	0.011051	0.000822	0.01201	0.000425	2000	scale		'kernel': 'linear'] {'C': 2000, f 'gamma': 'scale',	0.984445	1	0.984305	0.984305	1	0.99061	1 0.007666	
30	0.018907	0.000229	0.01315	0.000598	2000	scale	poly		0.95367	1	0.984305	0.984436	0.984195	0.98132	1 0.015102	2 17
31	0.01151	0.002163	0.012616	0.000813	2000	scale	sigmoid	'kernel': 'poly') {'C': 2000, 'gamma': 'scale',	0.984445	0.984436	0.984436	0.96875	0.968508	0.97811	5 0.007745	34
32	0.01047	0.00164	0.011488	0.000938	3000	auto	linea	'kernel': 'sigmo {'C': 3000, r 'gamma': 'auto',	0.984445	0.984436	0.984436	0.96875	0.984195	0.98125	2 0.006252	23
33	0.010629	0.000204	0.012834	0.000878	3000	auto	rb		0.984445	1	0.984305	0.984305	1	0.99061	1 0.007666	5 1
34	0.019506	0.000832	0.01207	0.00111	3000	auto	poly	'kernel': 'rbf') {'C': 3000, / 'gamma': 'auto',	0.95367	,	0.984305	0.984436	0.984195	0.98132	1 0.015102	2 17
35	0.010803	0.000742	0.012751	0.001019	3000	auto	sigmoid	'kernel': 'poly') 'gamma': 'auto', 'kernel':	0.984445	0.984436	0.984436	0.96875	0.968508	0.97811	5 0.007745	34
36	0.009097	0.001311	0.012787	0.000776	3000	scale	linea	{'C': 3000, 'gamma': 'scale',	0.984445	0.984436	0.984436	0.96875	0.984195	0.98125	2 0.006252	23
37	0.010238	0.002137	0.011927	0.000491	3000	scale	rb	'kernel': 'linear') {'C': 3000, f 'gamma': 'scale',	0.984445	1	0.984305	0.984305	1	0.99061	1 0.007666	5 1
38	0.018455	0.00131	0.009421	0.000915	3000	scale		{ G. SUUU,	0.95367		0.984305	0.984436	0.984195	0.981321	0.015102	17
39	0.018455	0.00131	0.009421	0.000915	3000		poly	'kernel': 'poly'} {'C': 3000,	0.95367	0.984436		0.984436	0.964195	0.981321		
39	0.009926	0.000801	0.010727	0.000398	3000	scale	sigmoid	'gamma': 'scale', 'kernel': 'sigmo	0.984445	0.984436	0.984436	0.96875	0.968508	0.978115	0.007745	34

## **Evaluation Metrics Report:**

	precision	recall	f1-score	support
0	0.97	1.00	0.98	32
1	1.00	0.98	0.99	48
accuracy			0.99	80
macro avg	0.98	0.99	0.99	80
weighted avg	0.99	0.99	0.99	80

## ROC AUC Score:

# **Decision Tree**

## **Hyper tuning Parameters grid:**

```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,grid.predict_proba(x_test)[:,1])
```

0.99934895833333334

#### <u>grid:</u>

	mean_fit_time	std_fit_time	mean_score_ti	std_score_tim	param_criterio	param_splitter	params	split0_test_sco	split1_test_sco	split2_test_sco	split3_test_sco	split4_test_sco	mean_test_sco	std_test_score	rank_test_scor
0	0.003235	0.00086		0.001125	gini	random	{'criterion': 'gini', 'splitter': 'random'}	0.96875		0.907658		0.984195			2
1	0.004018	0.001713	0.010908	0.001261	gini	best	{'criterion': 'gini', 'splitter': 'best'}	0.95367	0.890137	0.922956	0.95241	0.968254	0.937485	0.027873	5
2	0.004414	0.000813	0.008617	0.000626	entropy	random	('criterion': 'entropy', 'splitter': 'random')	0.95367	0.968452	0.984436	0.96875	0.968508	0.968763	0.009732	1
3	0.004293	0.00047	0.0106	0.000448	entropy	best	{'criterion': 'entropy', 'splitter': 'best'}	0.96901	0.891049	0.937949	0.920683	0.968254	0.937389	0.029595	6
4	0.003563	0.001407	0.010228	0.002093	log_loss	random	{'criterion': 'log_loss', 'splitter': 'random'}	0.96901	0.953307	0.922956	0.9375	0.952586	0.947072	0.015645	3
5	0.00371	0.000608	0.008687	0.001288	log_loss	best	{'criterion': 'log_loss', 'splitter': 'best'}	0.96901	0.90625	0.953591	0.936147	0.968254	0.94665	0.023483	4

#### **Evaluation Metrics Report:**

	precision	recall	f1-score	support
0	1.00	0.97	0.98	32
1	0.98	1.00	0.99	48
accuracy			0.99	80
macro avg	0.99	0.98	0.99	80
weighted avg	0.99	0.99	0.99	80

#### **ROC AUC Score:**

```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,grid.predict_proba(x_test)[:,1])
0.984375
```

# **Random Forest**

#### **Hyper tuning Parameters grid:**

	mean fit time	std fit time	mean_score_ti	std_score_tim	param_criterio	params	split0_test_sc	split1_test_sc	split2_test_sc	split3_test_sc	split4_test_sc	mean_test_sc	std_test_scor	rank_test_sco
	mean_in_unio	stu_iit_tiiie	me	e	n	parame	ore	ore	ore	ore	ore	ore	e	re
0	0.236706	0.009368	0.018948	0.001431	gini	{'criterion': 'gini'}	0.984445	0.952916	0.984436	0.984305	1	0.98122	0.015389	2
1	0.242593	0.009106	0.018219	0.001255	entropy	{'criterion': 'entropy'}	0.984445	0.952916	0.984436	0.984305	0.984049	0.97803	0.012558	3
2	0.225827	0.020249	0.019445	0.002277	log_loss	{'criterion': 'log loss'}	0.984445	0.984305	0.968974	0.96875	1	0.981295	0.011645	1

#### **Evaluation Metrics Report:**

	precision	recall	f1-score	support
0	1.00	0.97	0.98	32
1	0.98	1.00	0.99	48
accuracy			0.99	80
macro avg	0.99	0.98	0.99	80
weighted avg	0.99	0.99	0.99	80

#### **ROC\_AUC Score:**

```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,grid.predict_proba(x_test)[:,1])
1.0
```

# **Logistic Regression**

## **Hyper tuning Parameters grid:**

mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_muiti_cias 8	param_penalty	param_solver	params	split0_test_score	split1_test_score	split2_test_score	split3_test_score	split4_test_score	mean_test_score	std_test_score	rank_test_score
0.001306	0.000401	0	0	auto	I1	lbfgs	{'multi_class': 'auto', 'penalty': 11', 'solv	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22
0.008803	0.001386	0.00937	0.002663	auto	11	liblinear	{'multi_class': 'auto', 'penalty': '11', 'solv	0.95367	1	0.968974	0.96875	0.968508	0.971981	0.015178	17
0.001702	0.0004	0	0	auto	I1	newton-cg	{'multi_class': 'auto', 'penalty': 11', 'solv	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22
0.001302	0.000597	0	0	auto	11	newton-cholesky	{'multi_class': 'auto', 'penalty': 11', 'solv	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22
0.000702	0.000399	0	0	auto	II	sag	{'multi_class': 'auto', 'penalty': 11', 'solv	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22
0.000603	0.000492	0	0	multinomial	None	liblinear	{'multi_class': 'multinomial', 'penalty': 'Non	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22
0.0004	0.000489	0	0	multinomial	None	newton-cg	{'multi_class': 'multinomial', 'penalty': 'Non	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22
0.000504	0.000451	0	0	multinomial	None	newton-cholesky	{'multi_class': 'multinomial', 'penalty': 'Non	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22
0.000826	0.000415	0	0	multinomial	None	sag	{'multi_class': 'multinomial', 'penalty': 'Non	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22
0.000202	0.000404	0	0	multinomial	None	saga	{'multi_class': 'multinomial', 'penalty': 'Non	NaN	NaN	NaN	NaN	NaN	NaN	NaN	22

## **Evaluation Metrics Report:**

	precision	recall	f1-score	support
0	0.97	1.00	0.98	32
1	1.00	0.98	0.99	48
accuracy			0.99	80
macro avg	0.98	0.99	0.99	80
weighted avg	0.99	0.99	0.99	80

#### **ROC AUC Score:**

```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,grid.predict_proba(x_test)[:,1])
```

1.0

# **K-Nearest Neighbor**

## **Hyper tuning Parameters grid:**

	mean_fit_time	std_fit_time	mean_score_ti		param_algorith m	param_weights	params	split0_test_scor	split1_test_scor	split2_test_scor	split3_test_scor	split4_test_sco	mean_test_scor	std_test_score	rank_test_score
0	0.005845	0.002815	0.188478	0.011524	auto	uniform	{'algorithm': 'auto', 'weights': 'uniform'}	0.923168	0.968974	0.938259	0.968974	0.968508	0.953577	0.019269	1
1	0.00446	0.000542	0.191545	0.016062	auto	distance	'distance'}	0.923168	0.968974	0.938259	0.968974	0.968508	0.953577	0.019269	1
2	0.005321	0.001406	0.013454	0.001234	ball_tree	uniform	{'algorithm': 'ball_tree', 'weights': 'uniform'}	0.923168	0.968974	0.938259	0.968974	0.968508	0.953577	0.019269	1
3	0.003346	0.000546	0.008332	0.000522	ball_tree	distance	{'algorithm': 'ball_tree', 'weights': 'distance'}	0.923168	0.968974	0.938259	0.968974	0.968508	0.953577	0.019269	1
4	0.003623	0.000794	0.01229	0.0016	kd_tree	uniform	{'algorithm' 'kd_tree', 'weights' 'uniform'}	0.923168	0.968974	0.938259	0.968974	0.968508	0.953577	0.019269	1
5	0.003247	0.000232	0.009234	0.001232	kd_tree	distance	('algorithm': 'kd_tree'; 'weights': 'distance'}	0.923168	0.968974	0.938259	0.968974	0.968508	0.953577	0.019269	1
6	0.002103	0.000665	0.214797	0.004446	brute	uniform	{'algorithm': 'brute', 'weights': 'uniform'}	0.923168	0.968974	0.938259	0.968974	0.968508	0.953577	0.019269	1
7	0.003453	0.000468	0.051256	0.081017	brute	distance	{'algorithm': 'brute', 'weights': 'distance'}	0.923168	0.968974	0.938259	0.968974	0.968508	0.953577	0.019269	1

## **Evaluation Metrics Report:**

	precision	recall	f1-score	support
0	0.97	1.00	0.98	32
1	1.00	0.98	0.99	48
accupacy			0.00	90
accuracy macro avg	0.98	0.99	0.99 0.99	80 80
weighted avg	0.99	0.99	0.99	80

## **ROC\_AUC Score:**

0.99934895833333334

```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,grid.predict_proba(x_test)[:,1])
```

# **Naïve Bayes**

## **Evaluation Metrics Report:**

	precision	recall	f1-score	support
0	0.67	1.00	0.80	32
1	1.00	0.67	0.80	48
accuracy			0.80	80
macro avg	0.83	0.83	0.80	80
weighted avg	0.87	0.80	0.80	80

## ROC AUC Score:

```
from sklearn.metrics import roc_auc_score
roc_auc_score(y_test,classifier.predict_proba(x_test)[:,1])
```

0.8776041666666666

## 5. Best Model

The Best Model I have selected is "Random Forest" algorithm

#### Reason

The classification model has demonstrated excellent performance across all evaluation metrics. Notably, the ROC-AUC score is 1.0, which indicates a perfect separation between the positive and negative classes. This suggests that the model has learned the patterns in the data extremely well and is highly effective at predicting Chronic Kidney Disease (CKD) outcomes.

All other metrics such as accuracy, precision, recall, and F1-score are also consistently high, reinforcing the fact that this is a well-generalized and robust model suitable for deployment or further validation.