In [40]:
```
import warnings
warnings.filterwarnings("ignore")
import matplotlib.pyplot as plt
import plotly.express as px
import pandas as pd
import numpy as np
import seaborn as sns
```

In [11]:
```
#importing data
df = pd.read_csv("B:\studio\workspace\datamining\out.csv",sep=",")
infos= df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 40 columns):
 #   Column                       Non-Null Count  Dtype  
---  ------                       --------------  -----  
 0   months_as_customer           1000 non-null   int64  
 1   age                          1000 non-null   int64  
 2   policy_number                1000 non-null   int64  
 3   policy_bind_date             1000 non-null   object 
 4   policy_state                 1000 non-null   object 
 5   policy_csl                   1000 non-null   object 
 6   policy_deductable            1000 non-null   int64  
 7   policy_annual_premium        1000 non-null   float64
 8   umbrella_limit               1000 non-null   int64  
 9   insured_zip                  1000 non-null   int64  
 10  insured_sex                  1000 non-null   object 
 11  insured_education_level      1000 non-null   object 
 12  insured_occupation           1000 non-null   object 
 13  insured_hobbies              1000 non-null   object 
 14  insured_relationship         1000 non-null   object 
 15  capital-gains                1000 non-null   int64  
 16  capital-loss                 1000 non-null   int64  
 17  incident_date                1000 non-null   object 
 18  incident_type                1000 non-null   object 
 19  collision_type               1000 non-null   object 
 20  incident_severity            1000 non-null   object 
 21  authorities_contacted        1000 non-null   object 
 22  incident_state               1000 non-null   object 
 23  incident_city                1000 non-null   object 
 24  incident_location            1000 non-null   object 
 25  incident_hour_of_the_day     1000 non-null   int64  
 26  number_of_vehicles_involved  1000 non-null   int64  
 27  property_damage              1000 non-null   int64  
 28  bodily_injuries              1000 non-null   int64  
 29  witnesses                    1000 non-null   int64  
 30  police_report_available      1000 non-null   int64  
 31  total_claim_amount           1000 non-null   int64  
 32  injury_claim                 1000 non-null   int64  
 33  property_claim               1000 non-null   int64  
 34  vehicle_claim                1000 non-null   int64  
 35  auto_make                    1000 non-null   object 
 36  auto_model                   1000 non-null   object 
 37  auto_year                    1000 non-null   int64  
 38  fraud_reported               1000 non-null   object 
 39  _c39                         1000 non-null   int64  
dtypes: float64(1), int64(20), object(19)
memory usage: 312.6+ KB
```

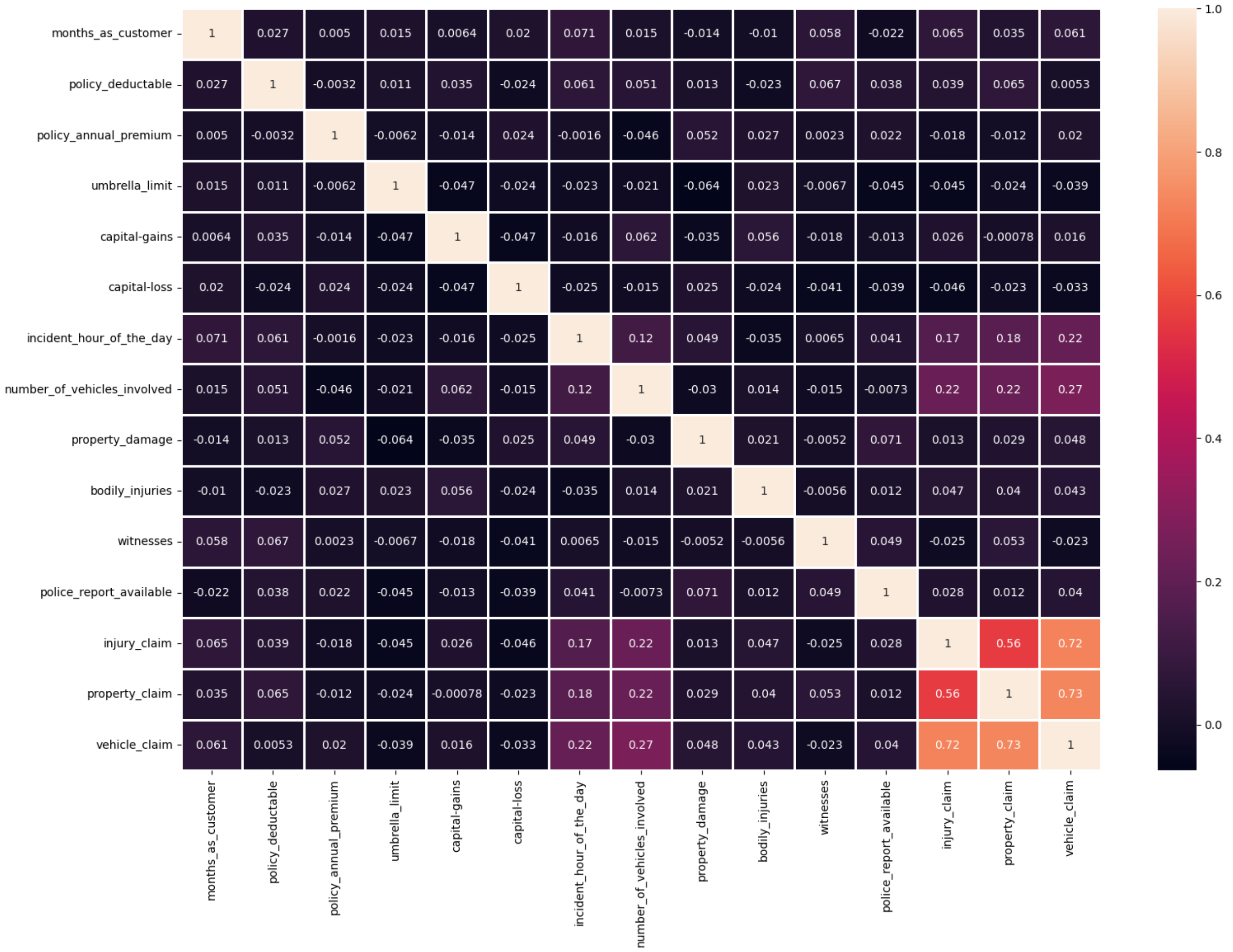
In [12]:
```
#Checking pour les valeurs nulls
df.isnull().sum()
```

Out[12]:

```
months_as_customer             0
age                            0
policy_number                  0
policy_bind_date               0
policy_state                   0
policy_csl                     0
policy_deductable              0
policy_annual_premium          0
umbrella_limit                 0
insured_zip                    0
insured_sex                    0
insured_education_level        0
insured_occupation             0
insured_hobbies                0
insured_relationship           0
capital-gains                  0
capital-loss                   0
incident_date                  0
incident_type                  0
collision_type                 0
incident_severity              0
authorities_contacted          0
incident_state                 0
incident_city                  0
incident_location              0
incident_hour_of_the_day       0
number_of_vehicles_involved    0
property_damage                0
bodily_injuries                0
witnesses                      0
police_report_available        0
total_claim_amount             0
injury_claim                   0
property_claim                 0
vehicle_claim                  0
auto_make                      0
auto_model                     0
auto_year                      0
fraud_reported                 0
_c39                           0
dtype: int64
```

In [49]:

```
#nous voyons que nous avons bien netoyyer notre dataset et on a aucune valeur null
#heatMap
plt.figure(figsize=(18,12))
corr=df.corr()
sns.heatmap(data = corr, annot = True, fmt = '.2g', linewidth = 1)
plt.show()
```



In [11]:
```python
#cheking pour les valeurs uniques
unique=df.nunique()
print(unique)
```

```
months_as_customer              391
age                              46
policy_number                  1000
policy_bind_date                951
policy_state                      3
policy_csl                        3
policy_deductable                 3
policy_annual_premium           991
umbrella_limit                   11
insured_zip                     995
insured_sex                       2
insured_education_level           7
insured_occupation               14
insured_hobbies                  20
insured_relationship              6
capital-gains                   338
capital-loss                    354
incident_date                    60
incident_type                     4
collision_type                    3
incident_severity                 4
authorities_contacted             5
incident_state                    7
incident_city                     7
incident_location              1000
incident_hour_of_the_day         24
number_of_vehicles_involved       4
property_damage                   2
bodily_injuries                   3
witnesses                         4
police_report_available           2
total_claim_amount              763
injury_claim                    638
property_claim                  626
vehicle_claim                   726
auto_make                        14
auto_model                       39
auto_year                        21
fraud_reported                    2
_c39                           1000
dtype: int64
```

In [14]:

```
#eliminons les colonnes qui ont beaucoups de valeurs uniques et qui ne peuvent pas nous aider
to_drop = ['policy_number','policy_bind_date','policy_state','insured_zip','incident_location
df.drop(to_drop, inplace = True, axis = 1)
df
```

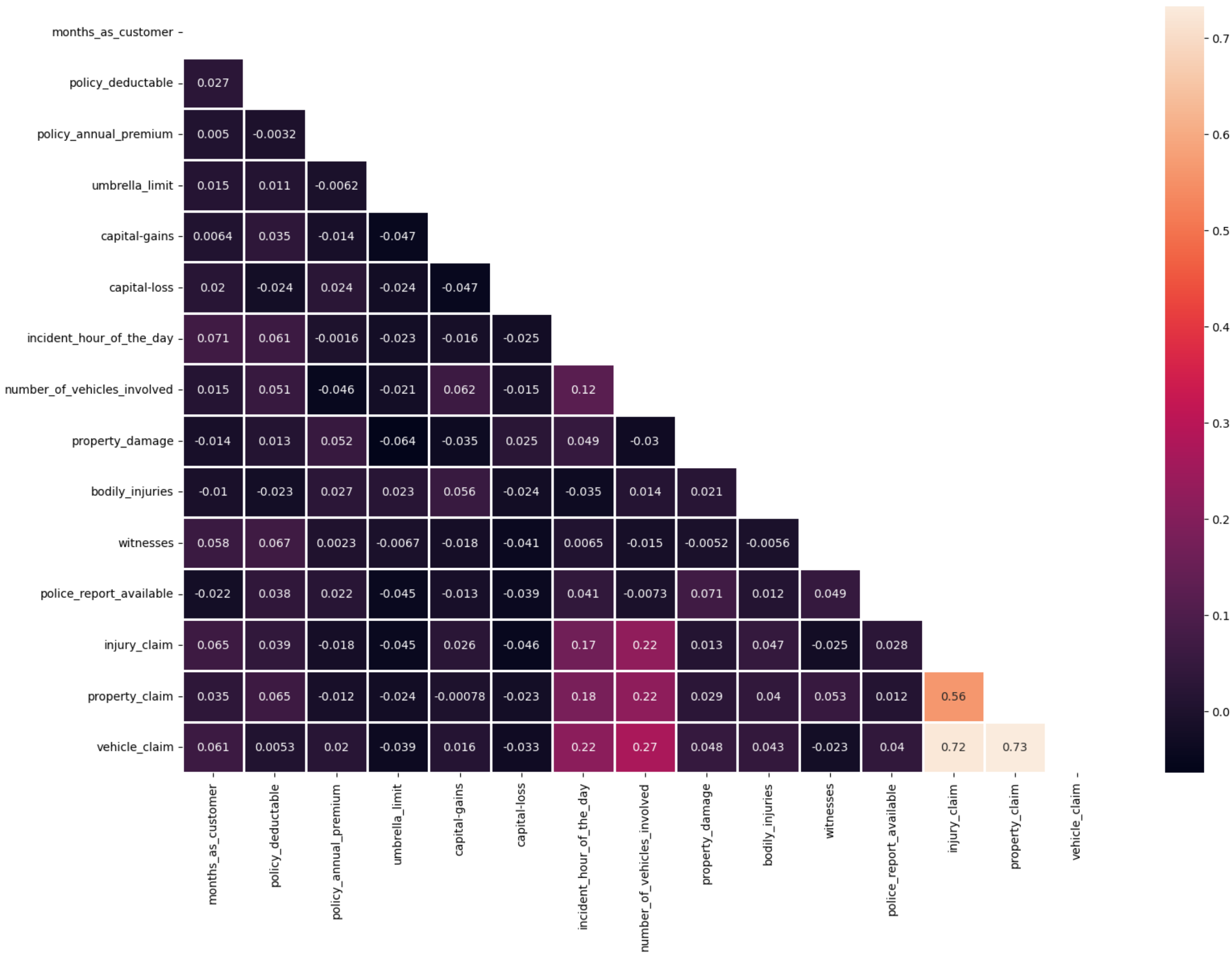
Out[14]:

	months_as_customer	age	policy_csl	policy_deductable	policy_annual_premium	umbrella_limit	insured_se
0	202	34	100/300	500	848.07	3000000	MAI
1	224	40	100/300	2000	1291.70	0	FEMAI
2	241	45	500/1000	2000	1104.50	0	FEMAI
3	64	25	250/500	1000	954.16	0	MAI
4	166	37	100/300	2000	1337.28	8000000	MAI
...	...	...	...	...	...	...	
995	95	32	500/1000	2000	1356.64	0	MAI
996	205	42	100/300	2000	1387.70	4000000	FEMAI
997	41	25	100/300	1000	1004.14	0	MAI
998	137	35	500/1000	500	1107.07	0	FEMAI
999	194	34	100/300	500	1429.96	0	FEMAI

1000 rows × 27 columns

In [41]:

```
# checking pou multicolinéarité  pour eviter  des conclusions erronées

plt.figure(figsize = (18, 12))

corr = df.corr()
mask = np.triu(np.ones_like(corr, dtype = bool))

sns.heatmap(data = corr, mask = mask, annot = True, fmt = '.2g', linewidth = 1)
plt.show()
```



In [16]:
```
"""
En observant le graphique ci-dessus, on constate une forte corrélation entre 'Age' et le 'mour
 Nous allons donc supprimer la colonne 'Age'.
 De même, il existe une forte corrélation entre 'total_claim_amount',
'injury_claim', 'property_claim', 'vehicle_claim' , 'total_claim'  est la somme
 de tous les autres. Nous allons donc supprimer la colonne 'total_claims'
"""
df.drop(columns = ['age', 'total_claim_amount'], inplace = True, axis = 1)
df
```

Out[16]:

	months_as_customer	policy_csl	policy_deductable	policy_annual_premium	umbrella_limit	insured_sex	in
0	202	100/300	500	848.07	3000000	MALE	
1	224	100/300	2000	1291.70	0	FEMALE	
2	241	500/1000	2000	1104.50	0	FEMALE	
3	64	250/500	1000	954.16	0	MALE	
4	166	100/300	2000	1337.28	8000000	MALE	
...	...	...	...	...	...	...	
995	95	500/1000	2000	1356.64	0	MALE	
996	205	100/300	2000	1387.70	4000000	FEMALE	
997	41	100/300	1000	1004.14	0	MALE	
998	137	500/1000	500	1107.07	0	FEMALE	
999	194	100/300	500	1429.96	0	FEMALE	

1000 rows × 25 columns

In [17]:
```
#separation du label du data-frame

X=df.drop('fraud_reported',axis=1)
y=df['fraud_reported']
```

In [18]:
```
#Encodage des colonnes categoriels
cat_df=X.select_dtypes(include=['object'])
```

In [19]:
```
# affichage des valeurs uniques de chaque colonne
for col in cat_df.columns:
    print(f"{col}: \n{cat_df[col].unique()}\n")

cat_df=pd.get_dummies(cat_df,drop_first=True)

cat_df
```

```
policy_csl:
['100/300' '500/1000' '250/500']

insured_sex:
['MALE' 'FEMALE']

insured_education_level:
['JD' 'PhD' 'Masters' 'Associate' 'High School' 'MD' 'College']

insured_occupation:
['exec-managerial' 'sales' 'machine-op-inspct' 'prof-specialty'
 'craft-repair' 'adm-clerical' 'farming-fishing' 'tech-support'
 'other-service' 'transport-moving' 'priv-house-serv' 'armed-forces'
 'protective-serv' 'handlers-cleaners']

insured_relationship:
['not-in-family' 'unmarried' 'husband' 'other-relative' 'wife' 'own-child']

incident_type:
['Vehicle Theft' 'Single Vehicle Collision' 'Multi-vehicle Collision'
 'Parked Car']

collision_type:
['Front Collision' 'Side Collision' 'Rear Collision']

incident_severity:
['Minor Damage' 'Major Damage' 'Total Loss' 'Trivial Damage']

authorities_contacted:
['None' 'Other' 'Police' 'Ambulance' 'Fire']
```

Out[19]:

	policy_csl_250/500	policy_csl_500/1000	insured_sex_MALE	insured_education_level_College	insured_educati
0	0	0	1	0	
1	0	0	0	0	
2	0	1	0	0	
3	1	0	1	0	
4	0	0	1	0	
...	...	...	...	...	
995	0	1	1	0	
996	0	0	0	0	
997	0	0	1	0	
998	0	1	0	0	
999	0	0	0	0	

1000 rows × 39 columns

In [20]:
```
# extraction des colonnes numeriques

num_df = X.select_dtypes(include = ['int64'])
num_df
```

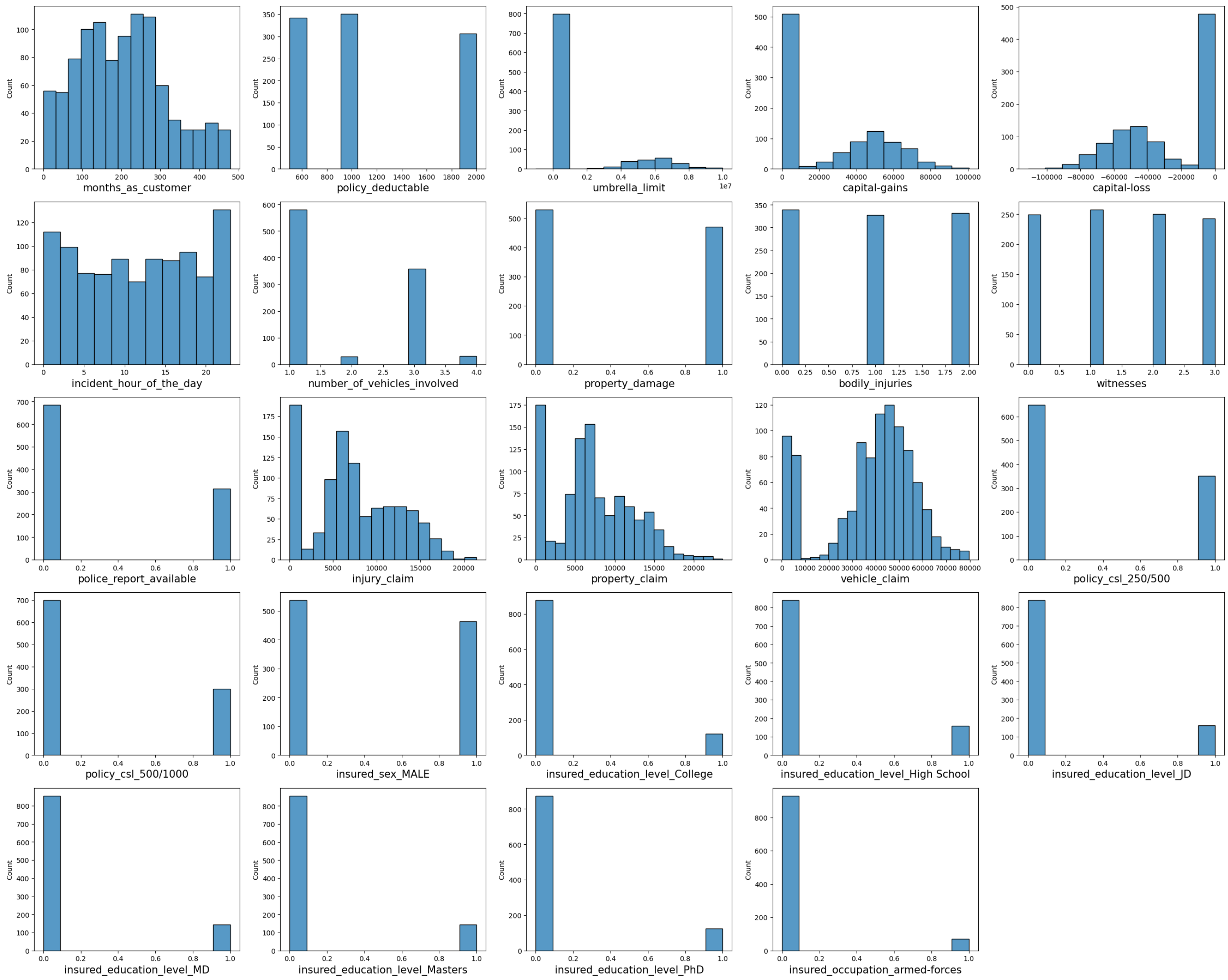
Out[20]:

	months_as_customer	policy_deductable	umbrella_limit	capital-gains	capital-loss	incident_hour_of_the_day	numb
0	202	500	3000000	31000	-30200	5	
1	224	2000	0	0	-55600	21	
2	241	2000	0	0	0	5	
3	64	1000	0	53200	0	22	
4	166	2000	8000000	27500	0	10	
...	...	...	...	...	...	...	
995	95	2000	0	67800	-48600	21	
996	205	2000	4000000	0	0	19	
997	41	1000	0	35400	0	13	
998	137	500	0	0	-45300	21	
999	194	500	0	67800	0	11	

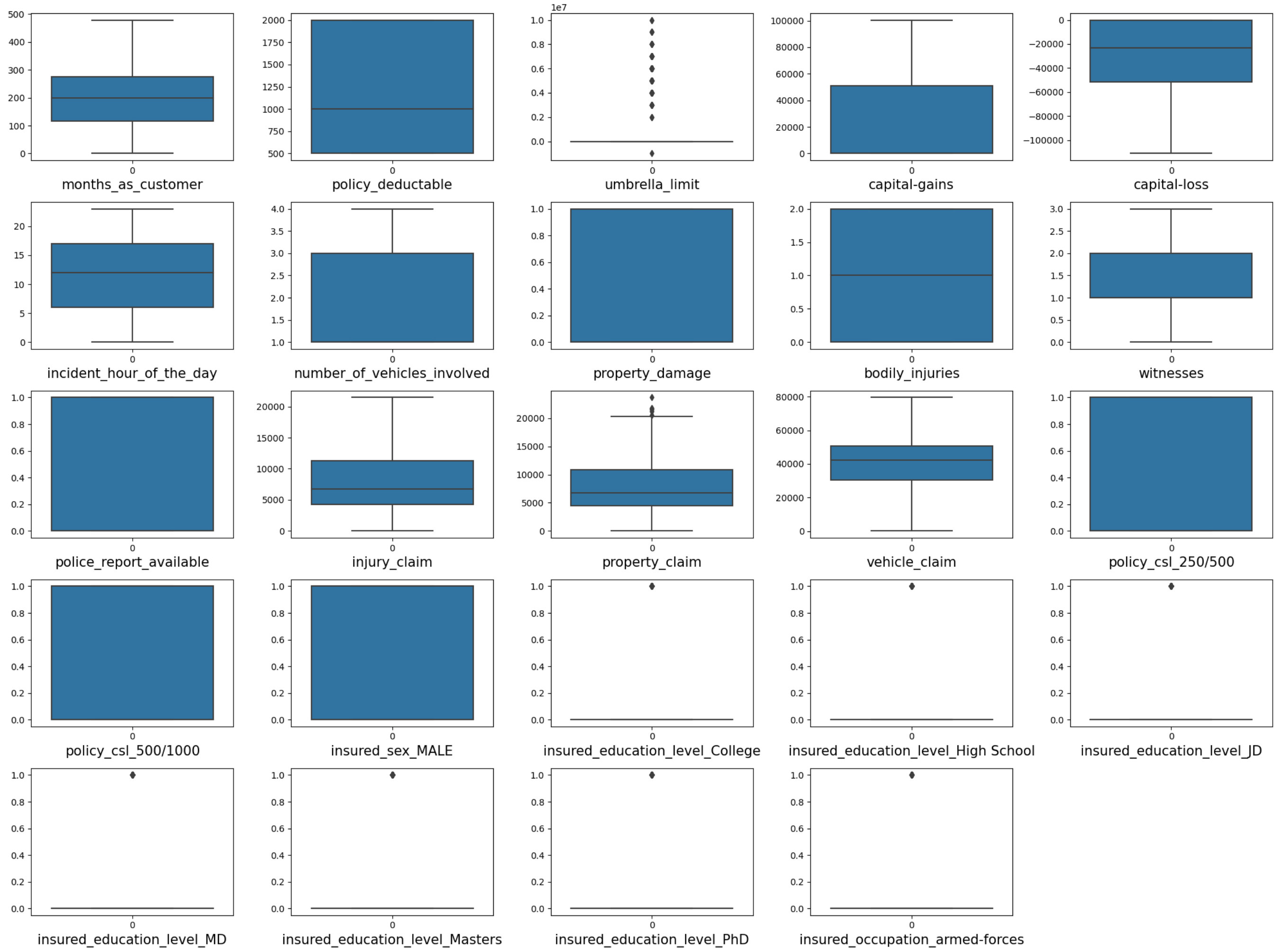
1000 rows × 14 columns

In [21]:

```
#comibinaison des colonnes numerique et categoriels pour avoir une seule dataset

X = pd.concat([num_df, cat_df], axis = 1)

plotnumber = 1
plt.figure(figsize = (25, 20))
for col in X.columns:
    if plotnumber <= 24:
        ax = plt.subplot(5, 5, plotnumber)
        sns.histplot(X[col])
        plt.xlabel(col, fontsize = 15)

    plotnumber += 1

plt.tight_layout()
plt.show()
```



In [22]:
```
#notre data est bien

#verifions notre data est ce qu'elle contient des valeurs abberantes "outliers"

plt.figure(figsize = (20, 15))
plotnumber = 1

for col in X.columns:
    if plotnumber <= 24:
        ax = plt.subplot(5, 5, plotnumber)
        sns.boxplot(X[col])
        plt.xlabel(col, fontsize = 15)

    plotnumber += 1
plt.tight_layout()
plt.show()
```



In [23]:

```
#Des valeurs aberrantes sont présentes dans certaines colonnes numériques.
#Nous mettrons à l'échelle les colonnes numériques ultérieurement.

"""splitting data"""

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25)

X_train.head()
X_test.head()
y_train.head()
y_test.head()

num_df = X_train[['months_as_customer', 'policy_deductable', 'umbrella_limit','capital-gains',
num_df
```

Out[23]:

	months_as_customer	policy_deductable	umbrella_limit	capital-gains	capital-loss	incident_hour_of_the_day	numbe
38	431	2000	0	65700	0	4	
377	7	1000	0	0	-45300	21	
328	162	1000	0	30700	0	7	
125	11	2000	0	56600	-45800	22	
217	298	500	0	47800	0	17	
...	...	...	...	...	...	...	
360	47	500	0	64800	-24300	23	
417	475	500	0	67400	-83200	20	
434	120	1000	0	77900	0	3	
522	78	500	0	0	0	20	
143	460	1000	4000000	0	0	20	

750 rows × 12 columns

In [24]:

```
# Scaling des valeurs numerique dans otre dataset

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
scaled_data = scaler.fit_transform(num_df)

scaled_num_df = pd.DataFrame(data = scaled_data, columns = num_df.columns, index = X_train.ind
scaled_num_df.head()

X_train.drop(columns = scaled_num_df.columns, inplace = True)

X_train = pd.concat([scaled_num_df, X_train], axis = 1)
X_train
```

Out[24]:

	months_as_customer	policy_deductable	umbrella_limit	capital-gains	capital-loss	incident_hour_of_the_day	nu
38	1.921330	1.459624	-0.471306	1.458923	0.958487	-1.118478	
377	-1.708106	-0.196530	-0.471306	-0.892070	-0.651741	1.338975	
328	-0.381308	-0.196530	-0.471306	0.206491	0.958487	-0.684810	
125	-1.673866	1.459624	-0.471306	1.133291	-0.669514	1.483531	
217	0.782851	-1.024607	-0.471306	0.818394	0.958487	0.760750	
...	...	...	...	...	...	...	
360	-1.365707	-1.024607	-0.471306	1.426718	0.094723	1.628087	
417	2.297969	-1.024607	-0.471306	1.519756	-1.998929	1.194419	
434	-0.740827	-0.196530	-0.471306	1.895485	0.958487	-1.263035	
522	-1.100347	-1.024607	-0.471306	-0.892070	0.958487	1.194419	
143	2.169570	-0.196530	1.287299	-0.892070	0.958487	1.194419	

750 rows × 53 columns

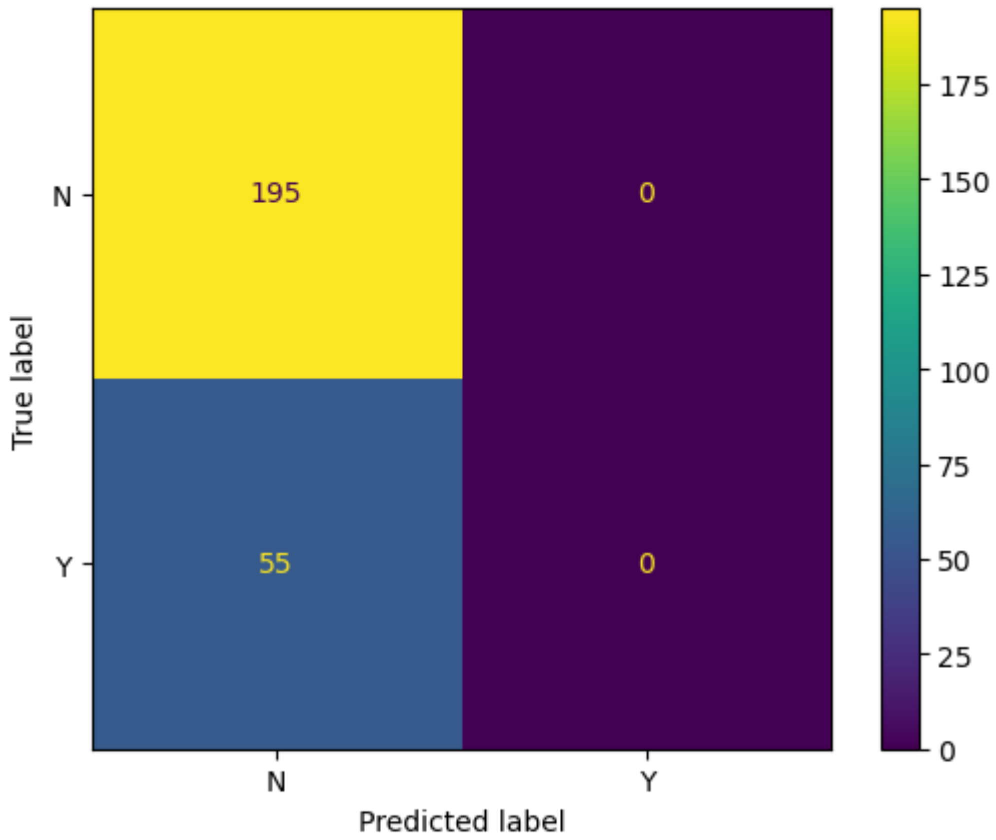
In [25]:

```
#passant maintenant au partie d'entrainement des modéles
#nous avons choisis SVM, KNN, DT, RF et SGB
```

In [42]:

```python
"""---------------Models---------------"""
"""SVM"""
from sklearn.svm import SVC

svc = SVC()

svc.fit(X_train, y_train)

y_pred = svc.predict(X_test)

# accuracy_score, confusion_matrix and classification_report

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

svc_train_acc = accuracy_score(y_train, svc.predict(X_train))
svc_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of Support Vector Classifier is : {svc_train_acc}")
print(f"Test accuracy of Support Vector Classifier is : {svc_test_acc}")

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))

#matrice de confusion
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_test, y_pred, labels=svc.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=svc.classes_)
disp.plot()
plt.show()
#nous voyons que le model SVM classifier (SVC) n'a pas pu de bien classier les fraudes il nous
```

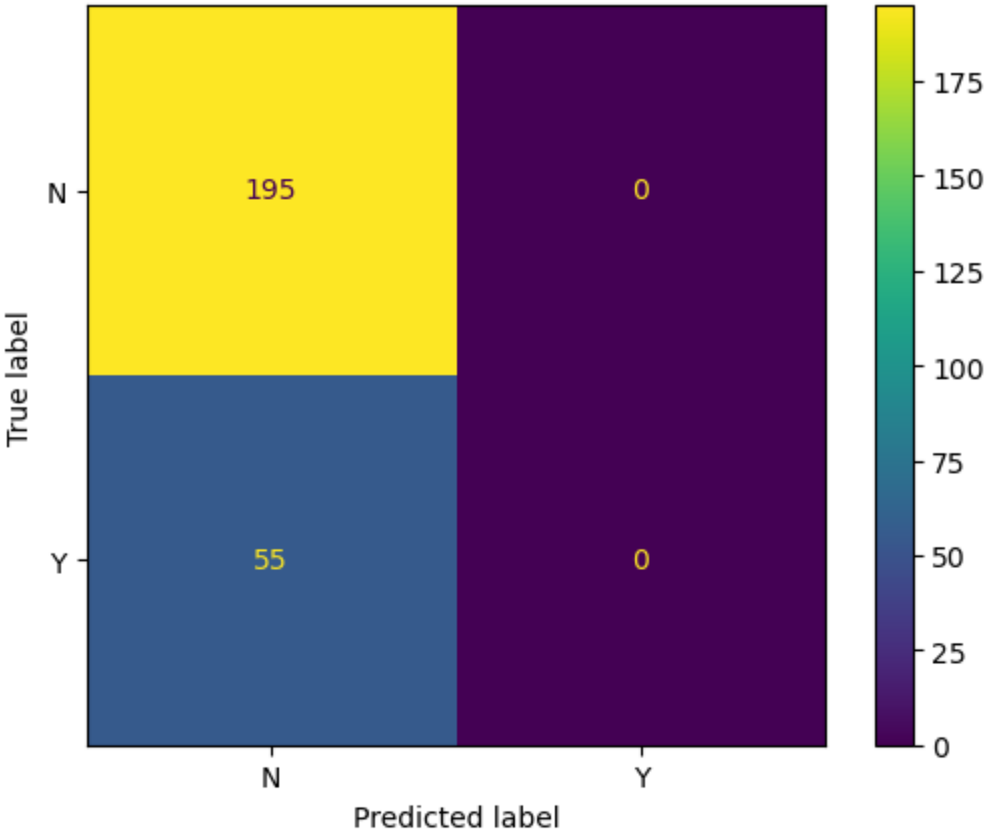
```
Training accuracy of Support Vector Classifier is : 0.84
Test accuracy of Support Vector Classifier is : 0.78
[[195   0]
 [ 55   0]]
              precision    recall  f1-score   support

           N       0.78      1.00      0.88       195
           Y       0.00      0.00      0.00        55

    accuracy                           0.78       250
   macro avg       0.39      0.50      0.44       250
weighted avg       0.61      0.78      0.68       250
```



In [27]:

In [43]:
```
"""KNN"""
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors = 30)
knn.fit(X_train, y_train)

y_pred = knn.predict(X_test)
# accuracy_score, confusion_matrix and classification_report
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
knn_train_acc = accuracy_score(y_train, knn.predict(X_train))
knn_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of KNN is : {knn_train_acc}")
print(f"Test accuracy of KNN is : {knn_test_acc}")

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))

#matrice de confusion
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_test, y_pred, labels=knn.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=knn.classes_)
disp.plot()
plt.show()
#nous voyons que le model KNN aussi  n'a pas pu de bien classier les fraudes il nous a classi
```

```
Training accuracy of KNN is : 0.7453333333333333
Test accuracy of KNN is : 0.78
[[195   0]
 [ 55   0]]
              precision    recall  f1-score   support

           N       0.78      1.00      0.88       195
           Y       0.00      0.00      0.00        55

    accuracy                           0.78       250
   macro avg       0.39      0.50      0.44       250
weighted avg       0.61      0.78      0.68       250
```

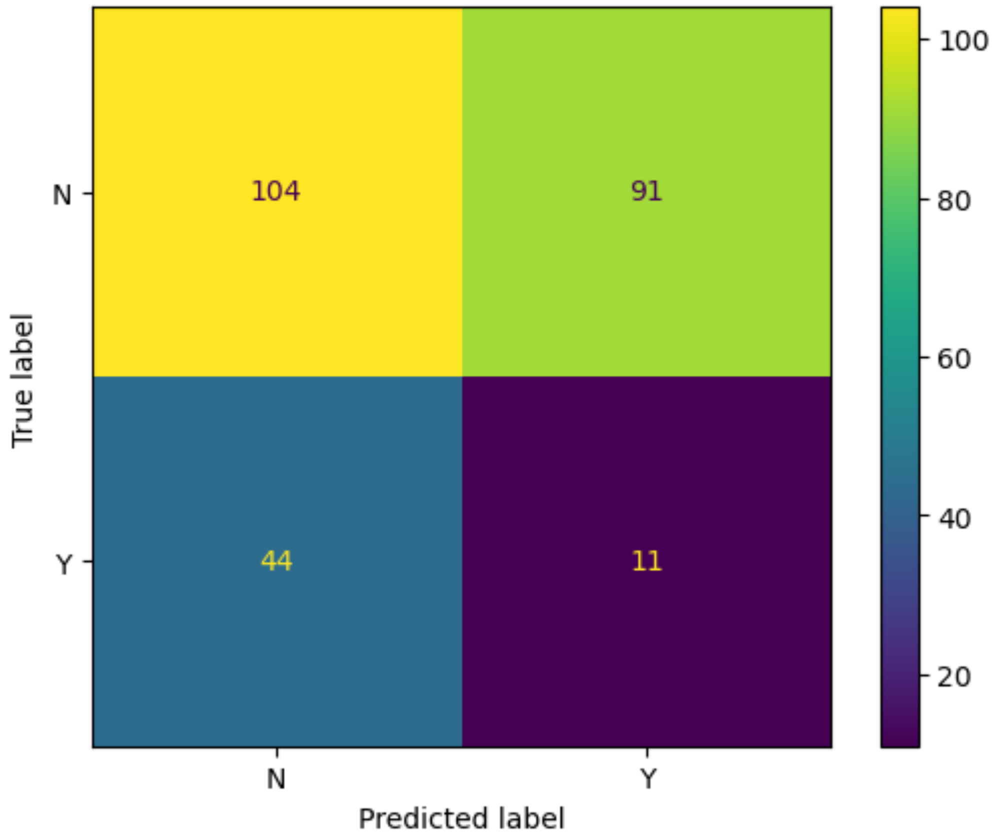


In [29]:

In [44]:

```
"""DT"""

from sklearn.tree import DecisionTreeClassifier
dtc = DecisionTreeClassifier()
dtc.fit(X_train, y_train)

y_pred = dtc.predict(X_test)


# accuracy_score, confusion_matrix and classification_report

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

dtc_train_acc = accuracy_score(y_train, dtc.predict(X_train))
dtc_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of Decision Tree is : {dtc_train_acc}")
print(f"Test accuracy of Decision Tree is : {dtc_test_acc}")

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
#matrice de confusion
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_test, y_pred, labels=dtc.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=dtc.classes_)
disp.plot()
plt.show()
#pour le model DT n'a pas pu de bien classier les fraudes il nous a classifé des non fraud con
```

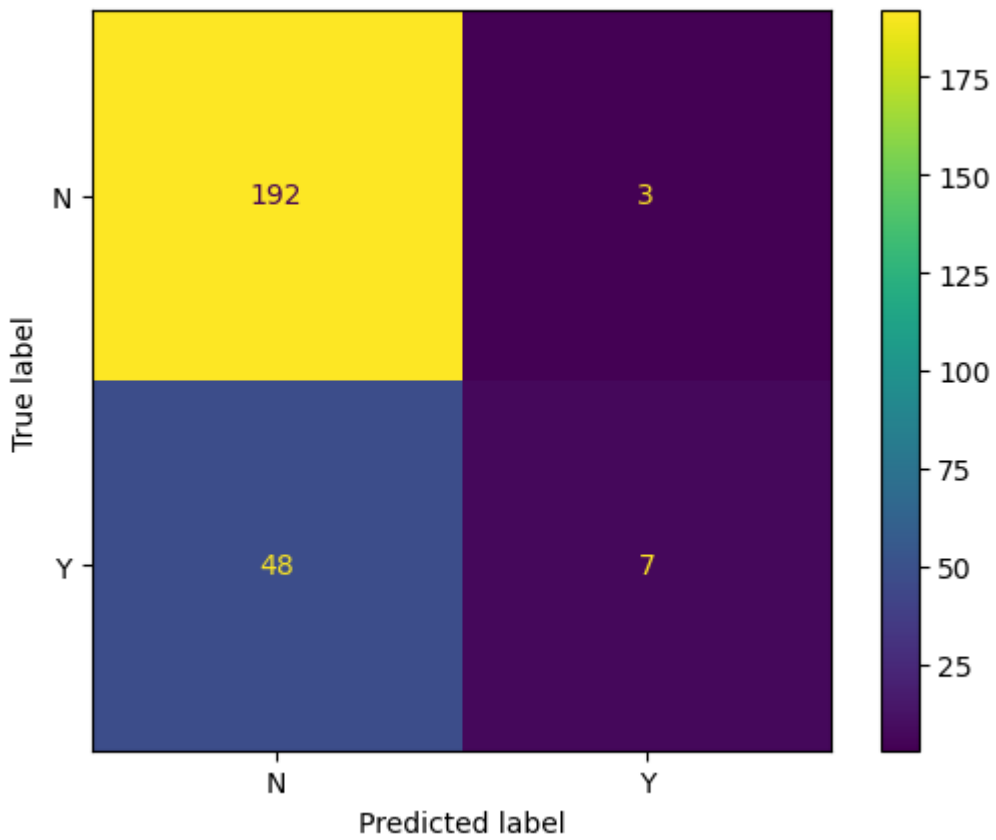
```
Training accuracy of Decision Tree is : 1.0
Test accuracy of Decision Tree is : 0.46
[[104  91]
 [ 44  11]]
              precision    recall  f1-score   support

           N       0.70      0.53      0.61       195
           Y       0.11      0.20      0.14        55

    accuracy                           0.46       250
   macro avg       0.41      0.37      0.37       250
weighted avg       0.57      0.46      0.50       250
```



In [31]:

In [45]:
```python
"""RF"""

from sklearn.ensemble import RandomForestClassifier
rand_clf = RandomForestClassifier(criterion= 'entropy', max_depth= 10, max_features= 'sqrt', r
rand_clf.fit(X_train, y_train)

y_pred = rand_clf.predict(X_test)

# accuracy_score, confusion_matrix and classification_report

from sklearn.metrics import accuracy_score, confusion_matrix, classification_report

rand_clf_train_acc = accuracy_score(y_train, rand_clf.predict(X_train))
rand_clf_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of Random Forest is : {rand_clf_train_acc}")
print(f"Test accuracy of Random Forest is : {rand_clf_test_acc}")

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
#matrice de confusion
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_test, y_pred, labels=rand_clf.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=rand_clf.classes_)
disp.plot()
plt.show()
#pour le model RF a été un peu de bien classier les fraudes il nous a classifé  bien le non fr
```

```
Training accuracy of Random Forest is : 0.976
Test accuracy of Random Forest is : 0.796
[[192   3]
 [ 48   7]]
              precision    recall  f1-score   support

           N       0.80      0.98      0.88       195
           Y       0.70      0.13      0.22        55

    accuracy                           0.80       250
   macro avg       0.75      0.56      0.55       250
weighted avg       0.78      0.80      0.74       250
```

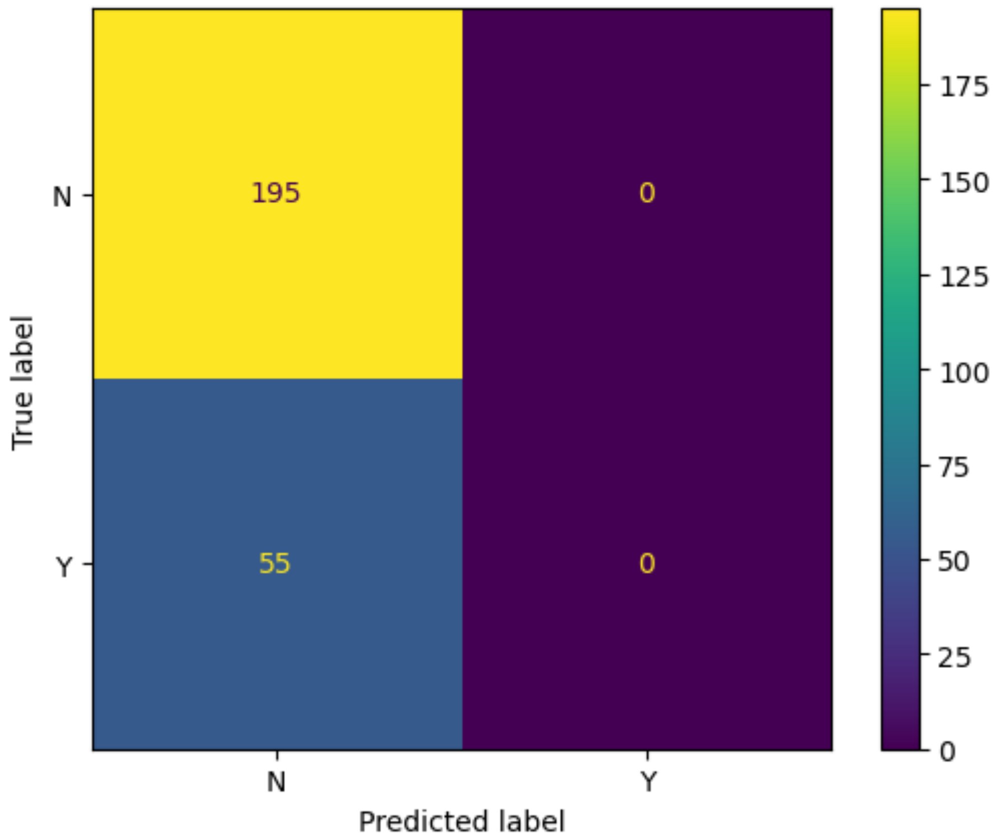


In [33]:

In [53]:

```
"""Stochastic Gradient Boosting (SGB)"""
from sklearn.ensemble import GradientBoostingClassifier
sgb = GradientBoostingClassifier(subsample = 0.90, max_features = 0.70)
sgb.fit(X_train, y_train)

# accuracy score, confusion matrix and classification report of stochastic gradient boosting c

sgb_acc = accuracy_score(y_test, sgb.predict(X_test))

print(f"Training Accuracy of Stochastic Gradient Boosting is {accuracy_score(y_train, sgb.pred
print(f"Test Accuracy of Stochastic Gradient Boosting is {sgb_acc} \n")

print(f"Confusion Matrix :- \n{confusion_matrix(y_test, sgb.predict(X_test))}\n")
print(f"Classification Report :- \n {classification_report(y_test, sgb.predict(X_test))}")
#matrice de confusion

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_test, y_pred, labels=sgb.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=sgb.classes_)
disp.plot()
plt.show()
#pour le model SGB il est come RF , il a été un peu de bien classier les fraudes il nous a cla
```

```
Training Accuracy of Stochastic Gradient Boosting is 0.924
Test Accuracy of Stochastic Gradient Boosting is 0.736

Confusion Matrix :-
[[172  23]
 [ 43  12]]

Classification Report :-
              precision    recall  f1-score   support

           N       0.80      0.88      0.84       195
           Y       0.34      0.22      0.27        55

    accuracy                           0.74       250
   macro avg       0.57      0.55      0.55       250
weighted avg       0.70      0.74      0.71       250
```



In [35]:

In [ ]:
```
#Voting Classifier

from sklearn.ensemble import VotingClassifier

classifiers = [('Support Vector Classifier', svc), ('KNN', knn),  ('Decision Tree', dtc), ('Ra
                 ('SGB', sgb),]

vc = VotingClassifier(estimators = classifiers)
vc.fit(X_train, y_train)

y_pred = vc.predict(X_test)
```

In [ ]:
```
# accuracy_score, confusion_matrix and classification_report

vc_train_acc = accuracy_score(y_train, vc.predict(X_train))
vc_test_acc = accuracy_score(y_test, y_pred)

print(f"Training accuracy of Voting Classifier is : {vc_train_acc}")
print(f"Test accuracy of Voting Classifier is : {vc_test_acc}")

print(confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
#matrice de confusion

from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
cm = confusion_matrix(y_test, y_pred, labels=vc.classes_)
disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=vc.classes_)
disp.plot()
plt.show()
```

In [58]:
```
#Comparaiso des modèles
models = pd.DataFrame({
    'Model' : ['SVC', 'KNN', 'Decision Tree', 'Random Forest', 'SGB', 'Voting Classifier'],
    'Score' : [svc_test_acc, knn_test_acc, dtc_test_acc, rand_clf_test_acc,  sgb_acc, vc_test_
})

models.sort_values(by = 'Score', ascending = False)
```

Out[58]:

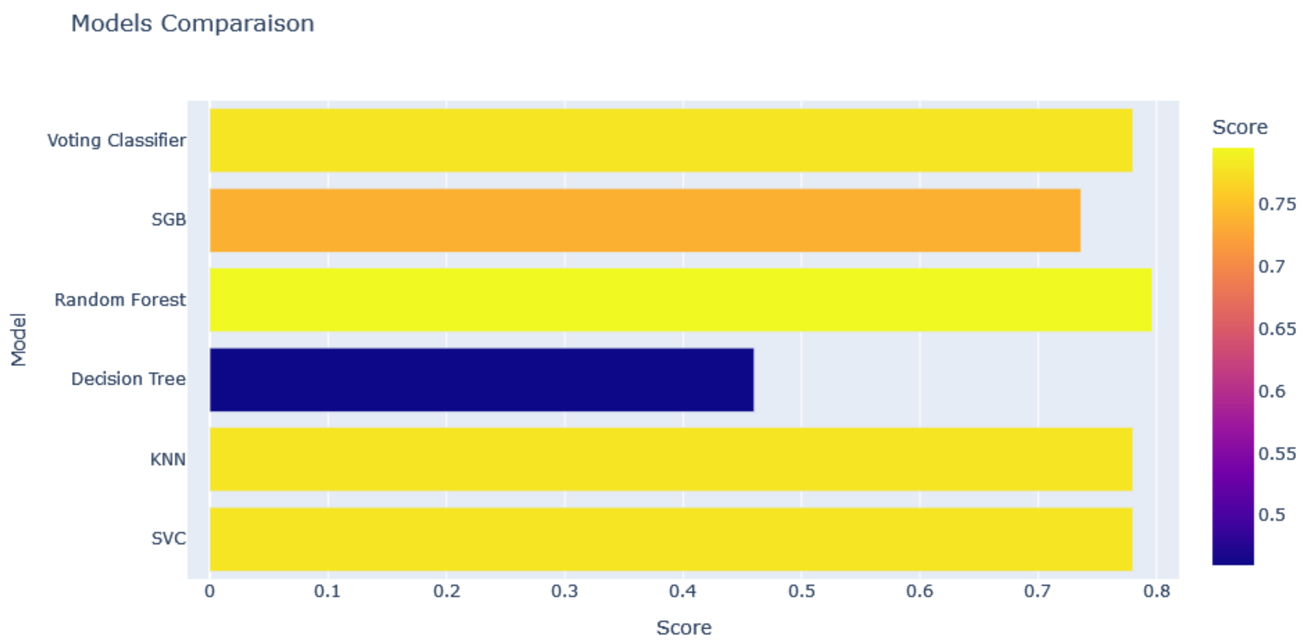
	Model	Score
3	Random Forest	0.796
0	SVC	0.780
1	KNN	0.780
5	Voting Classifier	0.780
4	SGB	0.736
2	Decision Tree	0.460

In [59]:

```
warnings.filterwarnings("ignore", category=DeprecationWarning)
import plotly.express as px
```

In [64]:

```
px.bar(data_frame = models, x = 'Score', y = 'Model', color = 'Score', template = 'plotly_whi
```



In [ ]: