In [1]:
```
import pandas as pd
import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
dataset=pd.read_csv("income.csv")
```

In [3]:
```
dataset
```

Out[3]:

	age	workclass	fnlwgt	education	educational-number	civil-status	occupation	relationship	rac
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Blac
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	Whit
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	Whit
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Blac
4	18	?	103497	Some-college	10	Never-married	?	Own-child	Whit
...	...	...	...	...	...	...	...	...	.
48837	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	Whit
48838	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	Whit
48839	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	Whit
48840	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	Whit
48841	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	Whit

48842 rows × 15 columns

Inorder to convert the above categroical columns like educational_num into the numerical/ encode, we use one hot encoding

In [4]:
```
dataset.education.value_counts()
```

Out[4]:
```
education
HS-grad         15784
Some-college    10878
Bachelors        8025
Masters          2657
Assoc-voc        2061
11th             1812
Assoc-acdm       1601
10th             1389
7th-8th           955
Prof-school       834
9th               756
12th              657
Doctorate         594
5th-6th           509
1st-4th           247
Preschool          83
Name: count, dtype: int64
```

In [5]:
```
print(dataset.workclass.value_counts())
```

```
workclass
Private             33906
Self-emp-not-inc     3862
Local-gov            3136
?                    2799
State-gov            1981
Self-emp-inc         1695
Federal-gov          1432
Without-pay            21
Never-worked           10
Name: count, dtype: int64
```

In [6]:
```
print(dataset.occupation.value_counts())
```

```
occupation
Prof-specialty       6172
Craft-repair         6112
Exec-managerial      6086
Adm-clerical         5611
Sales                5504
Other-service        4923
Machine-op-inspct    3022
?                    2809
Transport-moving     2355
Handlers-cleaners    2072
Farming-fishing      1490
Tech-support         1446
Protective-serv       983
Priv-house-serv       242
Armed-Forces           15
Name: count, dtype: int64
```

In [7]:
```
dataset
```

Out[7]:

	age	workclass	fnlwgt	education	educational-number	civil-status	occupation	relationship	rac
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Blac
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	Whit
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	Whit
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Blac
4	18	?	103497	Some-college	10	Never-married	?	Own-child	Whit
...	...	...	...	...	...	...	...	...	.
48837	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	Whit
48838	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	Whit
48839	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	Whit
48840	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	Whit
48841	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	Whit

48842 rows × 15 columns

In [8]:
```
import pandas as pd
from sklearn.preprocessing import OneHotEncoder


# Specify the categorical columns you want to encode
categorical_columns = ['race', 'relationship','occupation', 'workclass', 'civi

# Create a copy of the dataset to avoid modifying the original
dataset_encoded = dataset.copy()

# Apply OneHotEncoder to all categorical columns at once
encoder = OneHotEncoder(sparse=False, drop='first')  # Set drop='first' to han

# Extract the categorical columns from the dataset
categorical_data = dataset[categorical_columns]

# Apply OneHotEncoder and create a DataFrame with the encoded values
encoded_data = encoder.fit_transform(categorical_data)
encoded_df = pd.DataFrame(encoded_data, columns=encoder.get_feature_names_out(

# Concatenate the new DataFrame with the original DataFrame
dataset_encoded = pd.concat([dataset_encoded, encoded_df], axis=1)

# Drop the original categorical columns if needed
dataset_encoded = dataset_encoded.drop(categorical_columns, axis=1)

# Now, 'dataset_encoded' contains the original data with the one-hot encoded c
(dataset_encoded)
```

2	28	336951	Assoc-acdm	12	Male	0	0	40	>50K
3	44	160323	Some-college	10	Male	7688	0	40	>50K
4	18	103497	Some-college	10	Female	0	0	30	<=50K
...	...	...	...	...	...	...	...	...	...
48837	27	257302	Assoc-acdm	12	Female	0	0	38	<=50K
48838	40	154374	HS-grad	9	Male	0	0	40	>50K
48839	58	151910	HS-grad	9	Female	0	0	40	<=50K
48840	22	201490	HS-grad	9	Male	0	0	20	<=50K
48841	52	287927	HS-grad	9	Female	15024	0	40	>50K

48842 rows × 87 columns

This Python method does one-hot encoding on designated categorical columns in a DataFrame ('dataset') using the scikit-learn `OneHotEncoder. It concatenates the original data with the one-hot encoded values to generate a new DataFrame ('dataset_encoded'). Dropping the first encoded category for each feature is how multicollinearity is handled when the 'drop' option is set to 'first'.

In [9]:
```
dataset_encoded.columns.values
```

Out[9]:
```
array(['age', 'fnlwgt', 'education', 'educational-number', 'gender',
       'capital gain', 'capital loss', 'duration(hrs)', 'income',
       'race_Asian-Pac-Islander', 'race_Black', 'race_Other',
       'race_White', 'relationship_Not-in-family',
       'relationship_Other-relative', 'relationship_Own-child',
       'relationship_Unmarried', 'relationship_Wife',
       'occupation_Adm-clerical', 'occupation_Armed-Forces',
       'occupation_Craft-repair', 'occupation_Exec-managerial',
       'occupation_Farming-fishing', 'occupation_Handlers-cleaners',
       'occupation_Machine-op-inspct', 'occupation_Other-service',
       'occupation_Priv-house-serv', 'occupation_Prof-specialty',
       'occupation_Protective-serv', 'occupation_Sales',
       'occupation_Tech-support', 'occupation_Transport-moving',
       'workclass_Federal-gov', 'workclass_Local-gov',
       'workclass_Never-worked', 'workclass_Private',
       'workclass_Self-emp-inc', 'workclass_Self-emp-not-inc',
       'workclass_State-gov', 'workclass_Without-pay',
       'civil-status_Married-AF-spouse',
       'civil-status_Married-civ-spouse',
       'civil-status_Married-spouse-absent', 'civil-status_Never-married',
       'civil-status_Separated', 'civil-status_Widowed',
       'country-born_Cambodia', 'country-born_Canada',
       'country-born_China', 'country-born_Columbia', 'country-born_Cuba',
       'country-born_Dominican-Republic', 'country-born_Ecuador',
       'country-born_El-Salvador', 'country-born_England',
       'country-born_France', 'country-born_Germany',
       'country-born_Greece', 'country-born_Guatemala',
       'country-born_Haiti', 'country-born_Holand-Netherlands',
       'country-born_Honduras', 'country-born_Hong',
       'country-born_Hungary', 'country-born_India', 'country-born_Iran',
       'country-born_Ireland', 'country-born_Italy',
       'country-born_Jamaica', 'country-born_Japan', 'country-born_Laos',
       'country-born_Mexico', 'country-born_Nicaragua',
       'country-born_Outlying-US(Guam-USVI-etc)', 'country-born_Peru',
       'country-born_Philippines', 'country-born_Poland',
       'country-born_Portugal', 'country-born_Puerto-Rico',
       'country-born_Scotland', 'country-born_South',
       'country-born_Taiwan', 'country-born_Thailand',
       'country-born_Trinadad&Tobago', 'country-born_United-States',
       'country-born_Vietnam', 'country-born_Yugoslavia'], dtype=object)
```

In [10]:
```
dataset_encoded=dataset_encoded.drop("education",axis=1)
```

In [11]:
```
df=dataset_encoded.copy()
```

In [12]:
```
dataset_encoded.columns.values
```

Out[12]:
```
array(['age', 'fnlwgt', 'educational-number', 'gender', 'capital gain',
       'capital loss', 'duration(hrs)', 'income',
       'race_Asian-Pac-Islander', 'race_Black', 'race_Other',
       'race_White', 'relationship_Not-in-family',
       'relationship_Other-relative', 'relationship_Own-child',
       'relationship_Unmarried', 'relationship_Wife',
       'occupation_Adm-clerical', 'occupation_Armed-Forces',
       'occupation_Craft-repair', 'occupation_Exec-managerial',
       'occupation_Farming-fishing', 'occupation_Handlers-cleaners',
       'occupation_Machine-op-inspct', 'occupation_Other-service',
       'occupation_Priv-house-serv', 'occupation_Prof-specialty',
       'occupation_Protective-serv', 'occupation_Sales',
       'occupation_Tech-support', 'occupation_Transport-moving',
       'workclass_Federal-gov', 'workclass_Local-gov',
       'workclass_Never-worked', 'workclass_Private',
       'workclass_Self-emp-inc', 'workclass_Self-emp-not-inc',
       'workclass_State-gov', 'workclass_Without-pay',
       'civil-status_Married-AF-spouse',
       'civil-status_Married-civ-spouse',
       'civil-status_Married-spouse-absent', 'civil-status_Never-married',
       'civil-status_Separated', 'civil-status_Widowed',
       'country-born_Cambodia', 'country-born_Canada',
       'country-born_China', 'country-born_Columbia', 'country-born_Cuba',
       'country-born_Dominican-Republic', 'country-born_Ecuador',
       'country-born_El-Salvador', 'country-born_England',
       'country-born_France', 'country-born_Germany',
       'country-born_Greece', 'country-born_Guatemala',
       'country-born_Haiti', 'country-born_Holand-Netherlands',
       'country-born_Honduras', 'country-born_Hong',
       'country-born_Hungary', 'country-born_India', 'country-born_Iran',
       'country-born_Ireland', 'country-born_Italy',
       'country-born_Jamaica', 'country-born_Japan', 'country-born_Laos',
       'country-born_Mexico', 'country-born_Nicaragua',
       'country-born_Outlying-US(Guam-USVI-etc)', 'country-born_Peru',
       'country-born_Philippines', 'country-born_Poland',
       'country-born_Portugal', 'country-born_Puerto-Rico',
       'country-born_Scotland', 'country-born_South',
       'country-born_Taiwan', 'country-born_Thailand',
       'country-born_Trinadad&Tobago', 'country-born_United-States',
       'country-born_Vietnam', 'country-born_Yugoslavia'], dtype=object)
```

In [13]:
```
df['gender'] = df['gender'].map({'Male': 1, 'Female': 0})
df['income'] = df['income'].map({'>50K': 1, '<=50K': 0})
```

In [14]:
```
df=df.drop("fnlwgt",axis=1) #dropping unnnecesssary columns
```

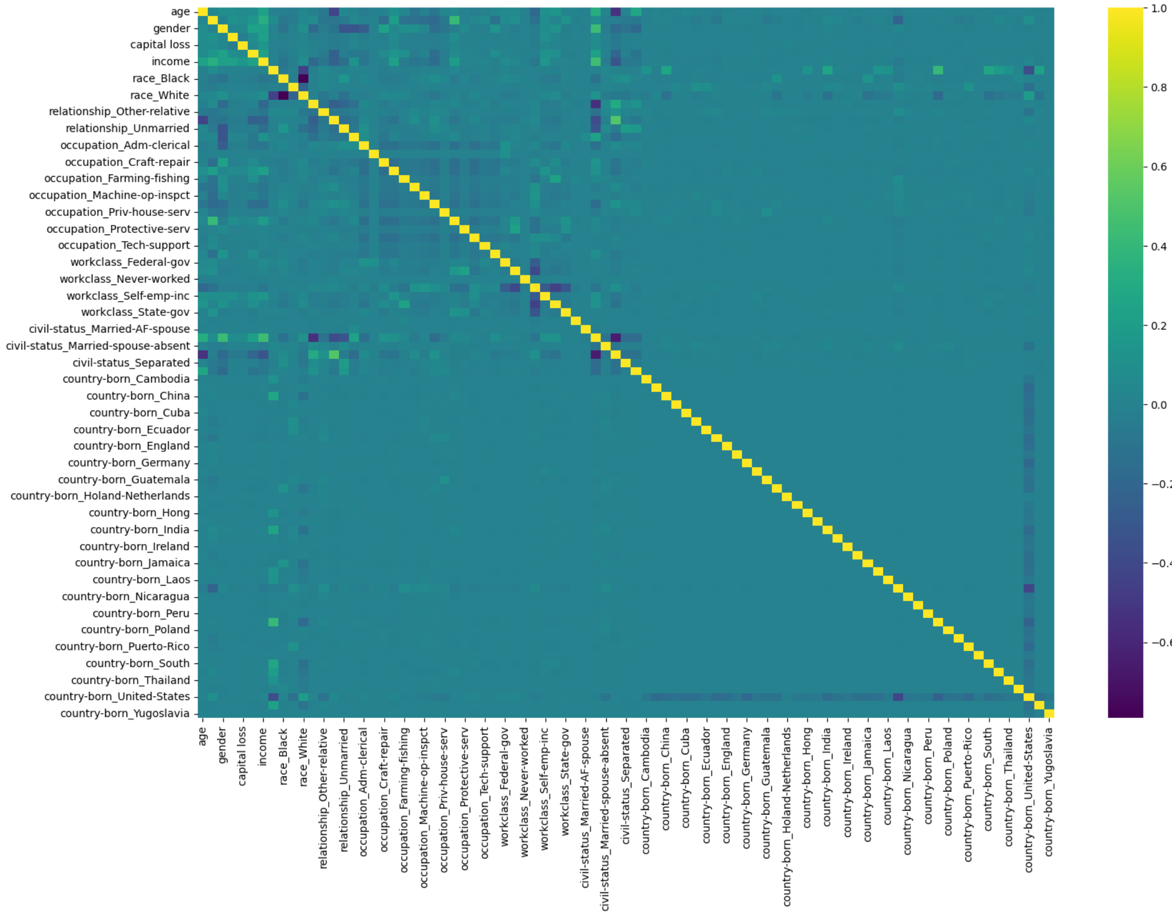
In [15]:
```
df
```

Out[15]:

	age	educational-number	gender	capital gain	capital loss	duration(hrs)	income	race_Asian-Pac-Islander	race_Black
0	25	7	1	0	0	40	0	0.0	1.(
1	38	9	1	0	0	50	0	0.0	0.(
2	28	12	1	0	0	40	1	0.0	0.(
3	44	10	1	7688	0	40	1	0.0	1.(
4	18	10	0	0	0	30	0	0.0	0.(
...	...	...	...	...	...	...	...	...	..
48837	27	12	0	0	0	38	0	0.0	0.(
48838	40	9	1	0	0	40	1	0.0	0.(
48839	58	9	0	0	0	40	0	0.0	0.(
48840	22	9	1	0	0	20	0	0.0	0.(
48841	52	9	0	15024	0	40	1	0.0	0.(

48842 rows × 85 columns

In [16]:
```
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(18, 12))
sns.heatmap(df.corr(), annot=False, cmap='viridis')
plt.show()
```



In [17]:
```
df.corr()
```

Out[17]:

	age	educational-number	gender	capital gain	capital loss	duration(hrs)	i
age	1.000000	0.030940	0.088120	0.077229	0.056944	0.071558	0.
educational-number	0.030940	1.000000	0.009328	0.125146	0.080972	0.143689	0.
gender	0.088120	0.009328	1.000000	0.047094	0.045480	0.228560	0.
capital gain	0.077229	0.125146	0.047094	1.000000	-0.031441	0.082157	0.
capital loss	0.056944	0.080972	0.045480	-0.031441	1.000000	0.054467	0.
...	...	...	...	...	...	...	
country-born_Thailand	-0.001766	0.007283	-0.007117	-0.002781	-0.002338	0.008558	-0.
country-born_Trinadad&Tobago	0.001056	-0.010201	-0.009342	-0.003039	0.004028	-0.002911	-0.
country-born_United-States	0.011888	0.104210	-0.011167	0.004191	0.009449	0.004390	0.
country-born_Vietnam	-0.012337	-0.007544	-0.001545	-0.002673	-0.000118	-0.008289	-0.
country-born_Yugoslavia	0.002905	-0.005798	0.005262	-0.000474	-0.004713	-0.000359	0.

85 rows × 85 columns

The above code snippet is used to find the correlation between each column with other columns.

In [18]:
```
corr_income=df.corr()['income'].abs()
sorted_corr=corr_income.sort_values()
no_columns_to_drop=int(0.8*len(df.columns))
cols_to_drop=sorted_corr.iloc[:no_columns_to_drop].index
df_dropped=df.drop(cols_to_drop,axis=1)
```

Here we are trying to drop the less related column and saving them in df_dropped

In [19]:
```
df_dropped
```

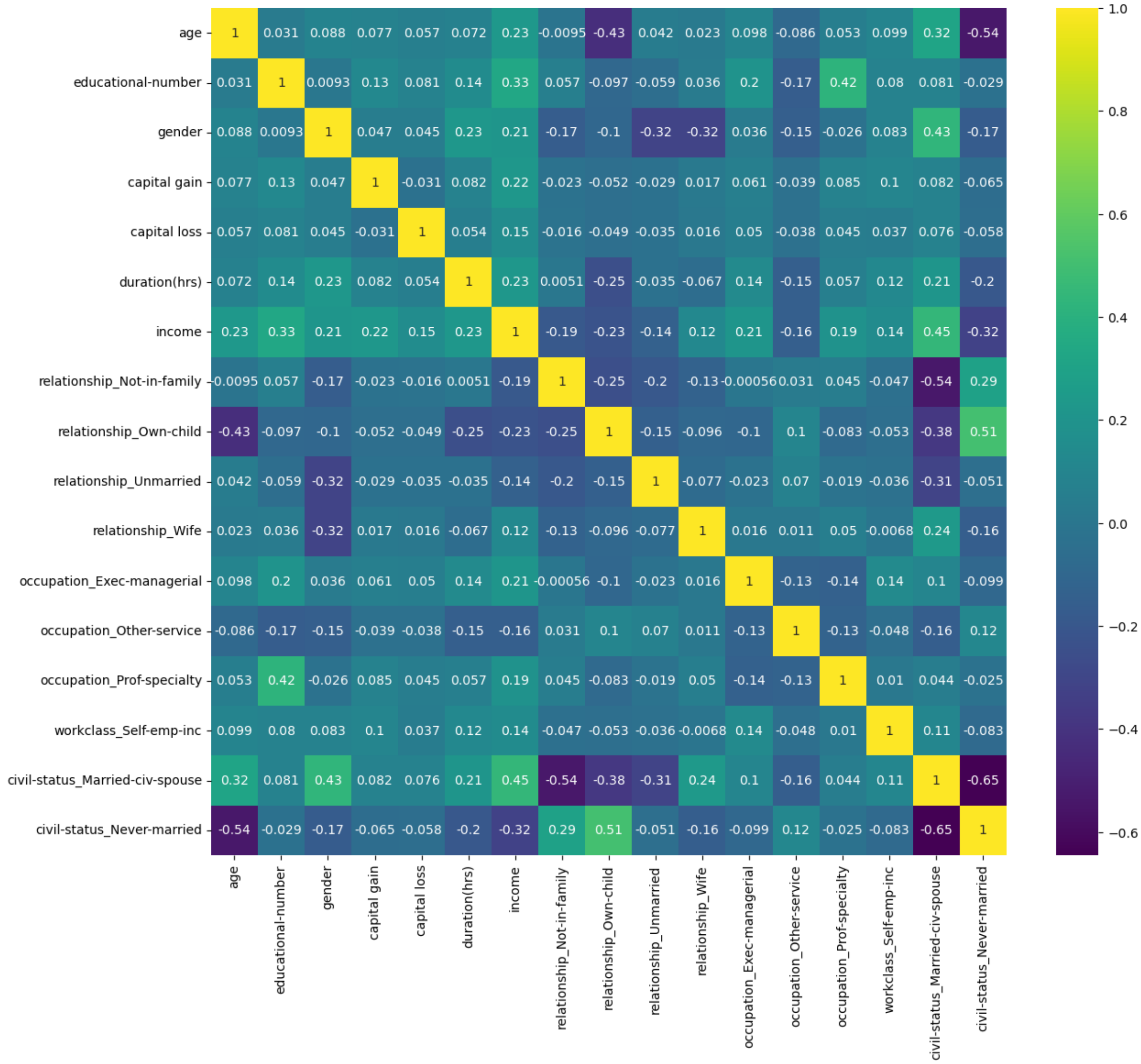
Out[19]:

	age	educational-number	gender	capital gain	capital loss	duration(hrs)	income	relationship_Not-in-family	relati
0	25	7	1	0	0	40	0	0.0	
1	38	9	1	0	0	50	0	0.0	
2	28	12	1	0	0	40	1	0.0	
3	44	10	1	7688	0	40	1	0.0	
4	18	10	0	0	0	30	0	0.0	
...	...	...	...	...	...	...	...	...	
48837	27	12	0	0	0	38	0	0.0	
48838	40	9	1	0	0	40	1	0.0	
48839	58	9	0	0	0	40	0	0.0	
48840	22	9	1	0	0	20	0	0.0	
48841	52	9	0	15024	0	40	1	0.0	

48842 rows × 17 columns

In [20]:
```python
plt.figure(figsize=(14,12))
sns.heatmap(df_dropped.corr(),annot=True, cmap='viridis')
```

Out[20]: <Axes: >



as we have more numerial datatype/yes or no in the columns we are going to use the random forest method which is decision tree

In [21]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split

train_df, test_df=train_test_split(df, test_size=0.2)
```

In [22]:
```
train_df
```

Out[22]:

	age	educational-number	gender	capital gain	capital loss	duration(hrs)	income	race_Asian-Pac-Islander	race_Black
26513	21	9	0	0	0	35	0	0.0	0.(
7800	23	3	1	0	0	35	0	0.0	0.(
10462	62	9	1	0	0	42	0	0.0	0.(
32138	68	10	1	0	0	40	1	0.0	0.(
39085	48	13	0	0	0	44	0	0.0	0.(
...	...	...	...	...	...	...	...	...	..
21609	27	13	1	0	0	40	0	0.0	0.(
11379	42	12	1	0	0	40	0	0.0	0.(
8037	40	10	1	0	0	40	0	0.0	0.(
41211	33	10	1	0	0	40	0	0.0	0.(
11884	41	9	1	0	0	40	0	0.0	0.(

39073 rows × 85 columns

In [23]:
```
test_df
```

Out[23]:

	age	educational-number	gender	capital gain	capital loss	duration(hrs)	income	race_Asian-Pac-Islander	race_Black
28426	64	9	1	0	0	5	0	0.0	0.(
29965	42	11	1	0	0	40	0	0.0	0.(
41204	68	14	1	0	0	18	0	0.0	0.(
37567	20	10	0	0	0	6	0	0.0	0.(
43112	30	7	1	0	0	40	0	0.0	0.(
...	...	...	...	...	...	...	...	...	..
7853	38	15	1	0	0	50	0	0.0	0.(
21665	19	9	0	0	0	40	0	0.0	1.(
20332	29	13	1	0	0	40	0	0.0	1.(
8240	17	8	1	0	0	35	0	0.0	0.(
40361	40	10	0	0	0	40	0	0.0	1.(

9769 rows × 85 columns

In [24]:
```
train_x=train_df.drop('income',axis=1)
train_y=train_df['income']

test_x=test_df.drop('income',axis=1)
test_y=test_df['income']
```

In [25]:
```
forest = RandomForestClassifier()
forest.fit(train_x, train_y)
```

Out[25]:
```
▾ RandomForestClassifier

RandomForestClassifier()
```

In [26]:
```
forest.score(test_x,test_y)
```

Out[26]:
```
0.8505476507319071
```

In [27]:
```
forest.feature_importances_
```

Out[27]:
```
array([2.27769187e-01, 1.32549511e-01, 1.94962520e-02, 1.20766128e-01,
       3.85553201e-02, 1.13351173e-01, 3.13161764e-03, 5.26329542e-03,
       9.60938430e-04, 6.86892328e-03, 1.69377746e-02, 2.34644009e-03,
       8.81705069e-03, 9.49130399e-03, 8.61244594e-03, 5.28785297e-03,
       8.57449484e-05, 6.02148930e-03, 1.84264238e-02, 4.11401096e-03,
       3.18202007e-03, 3.94465484e-03, 7.70832377e-03, 2.05486374e-04,
       1.68797117e-02, 3.02834328e-03, 6.41384693e-03, 4.49040705e-03,
       4.02835194e-03, 4.91328893e-03, 5.74632136e-03, 5.34432132e-06,
       9.94273365e-03, 6.69596335e-03, 7.67993656e-03, 4.45043324e-03,
       1.55690056e-04, 3.47603520e-04, 8.47004723e-02, 1.47546430e-03,
       4.38940742e-02, 2.62198852e-03, 2.28019458e-03, 2.72084178e-04,
       1.52620512e-03, 6.80279441e-04, 3.75341928e-04, 7.19587878e-04,
       2.29805497e-04, 1.95363225e-04, 3.31984250e-04, 9.43590100e-04,
       4.16976235e-04, 9.48820953e-04, 4.33986087e-04, 1.03925576e-04,
       1.90707818e-04, 5.33227149e-07, 1.05490152e-05, 1.88919263e-04,
       1.54928945e-04, 9.05327017e-04, 5.35747369e-04, 5.39205177e-04,
       7.85839332e-04, 4.56411021e-04, 6.98335687e-04, 1.27867759e-04,
       2.20602876e-03, 1.84947382e-04, 5.02310006e-05, 1.96974082e-04,
       1.02233464e-03, 5.02271903e-04, 5.37051873e-04, 4.90178635e-04,
       1.13379810e-04, 6.23193231e-04, 3.79266307e-04, 1.07830742e-04,
       1.21957390e-04, 7.31556926e-03, 3.75981603e-04, 3.56943284e-04])
```

In [28]:
```
forest.feature_names_in_
```

Out[28]:
```
array(['age', 'educational-number', 'gender', 'capital gain',
       'capital loss', 'duration(hrs)', 'race_Asian-Pac-Islander',
       'race_Black', 'race_Other', 'race_White',
       'relationship_Not-in-family', 'relationship_Other-relative',
       'relationship_Own-child', 'relationship_Unmarried',
       'relationship_Wife', 'occupation_Adm-clerical',
       'occupation_Armed-Forces', 'occupation_Craft-repair',
       'occupation_Exec-managerial', 'occupation_Farming-fishing',
       'occupation_Handlers-cleaners', 'occupation_Machine-op-inspct',
       'occupation_Other-service', 'occupation_Priv-house-serv',
       'occupation_Prof-specialty', 'occupation_Protective-serv',
       'occupation_Sales', 'occupation_Tech-support',
       'occupation_Transport-moving', 'workclass_Federal-gov',
       'workclass_Local-gov', 'workclass_Never-worked',
       'workclass_Private', 'workclass_Self-emp-inc',
       'workclass_Self-emp-not-inc', 'workclass_State-gov',
       'workclass_Without-pay', 'civil-status_Married-AF-spouse',
       'civil-status_Married-civ-spouse',
       'civil-status_Married-spouse-absent', 'civil-status_Never-married',
       'civil-status_Separated', 'civil-status_Widowed',
       'country-born_Cambodia', 'country-born_Canada',
       'country-born_China', 'country-born_Columbia', 'country-born_Cuba',
       'country-born_Dominican-Republic', 'country-born_Ecuador',
       'country-born_El-Salvador', 'country-born_England',
       'country-born_France', 'country-born_Germany',
       'country-born_Greece', 'country-born_Guatemala',
       'country-born_Haiti', 'country-born_Holand-Netherlands',
       'country-born_Honduras', 'country-born_Hong',
       'country-born_Hungary', 'country-born_India', 'country-born_Iran',
       'country-born_Ireland', 'country-born_Italy',
       'country-born_Jamaica', 'country-born_Japan', 'country-born_Laos',
       'country-born_Mexico', 'country-born_Nicaragua',
       'country-born_Outlying-US(Guam-USVI-etc)', 'country-born_Peru',
       'country-born_Philippines', 'country-born_Poland',
       'country-born_Portugal', 'country-born_Puerto-Rico',
       'country-born_Scotland', 'country-born_South',
       'country-born_Taiwan', 'country-born_Thailand',
       'country-born_Trinadad&Tobago', 'country-born_United-States',
       'country-born_Vietnam', 'country-born_Yugoslavia'], dtype=object)
```

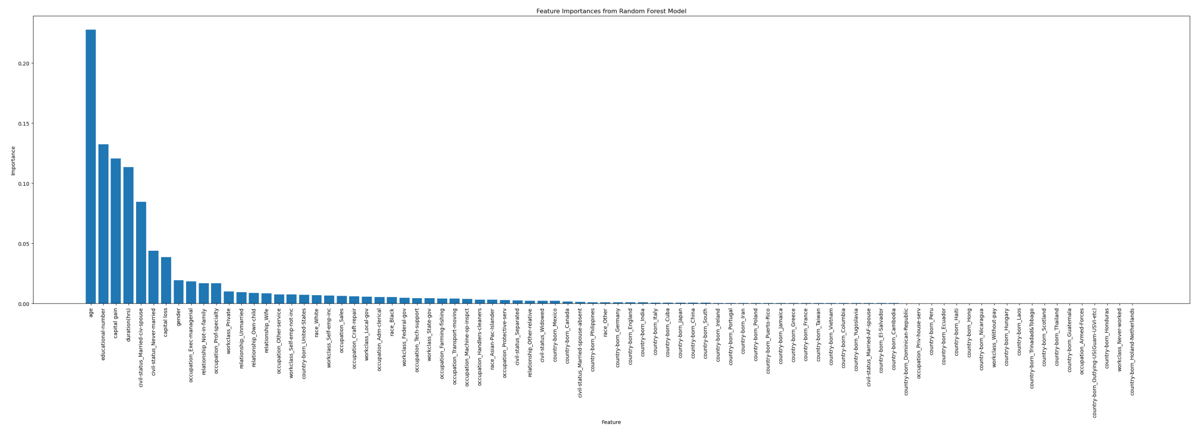
In [29]:
```
imp=dict(zip(forest.feature_names_in_,forest.feature_importances_,))
imp={k: v for k, v in sorted(imp.items(), key=lambda x: x[1], reverse=True)}
```

In [30]:
```
imp
```

Out[30]:
```
{'age': 0.22776918709972518,
 'educational-number': 0.1325495114732838,
 'capital gain': 0.12076612762577107,
 'duration(hrs)': 0.1133511727603843,
 'civil-status_Married-civ-spouse': 0.08470047231004649,
 'civil-status_Never-married': 0.04389407424222472,
 'capital loss': 0.03855532013033901,
 'gender': 0.019496252023684466,
 'occupation_Exec-managerial': 0.0184264237679468,
 'relationship_Not-in-family': 0.016937774585223664,
 'occupation_Prof-specialty': 0.016879711691908075,
 'workclass_Private': 0.009942733649112925,
 'relationship_Unmarried': 0.009491303988847457,
 'relationship_Own-child': 0.008817050691493228,
 'relationship_Wife': 0.008612445941775983,
 'occupation_Other-service': 0.007708323767159022,
 'workclass_Self-emp-not-inc': 0.007679936557383493,
 'country-born_United-States': 0.007315569256063832,
 'race_White': 0.006868923278094223,
 'workclass_Self-emp-inc': 0.006695963348043074 5,
 'occupation_Sales': 0.006413846928555106,
 'occupation_Craft-repair': 0.006021489303260678,
 'workclass_Local-gov': 0.005746321355834166,
 'occupation_Adm-clerical': 0.005287852969939939,
 'race_Black': 0.005263295421059831,
 'workclass_Federal-gov': 0.004913288925558095,
 'occupation_Tech-support': 0.004490407054585688,
 'workclass_State-gov': 0.004450433235321947,
 'occupation_Farming-fishing': 0.0041140109590015956,
 'occupation_Transport-moving': 0.004028351936422438,
 'occupation_Machine-op-inspct': 0.003944654837288792,
 'occupation_Handlers-cleaners': 0.003182020074742668,
 'race_Asian-Pac-Islander': 0.0031316176434774377,
 'occupation_Protective-serv': 0.003028343277590052,
 'civil-status_Separated': 0.0026219885241580646,
 'relationship_Other-relative': 0.002346440087683207,
 'civil-status_Widowed': 0.0022801945786933924,
 'country-born_Mexico': 0.002206028758016 4205,
 'country-born_Canada': 0.0015262051242539972,
 'civil-status_Married-spouse-absent': 0.0014754643008921863,
 'country-born_Philippines': 0.0010223346438747642,
 'race_Other': 0.0009609384300818054,
 'country-born_Germany': 0.0009488209533962511,
 'country-born_England': 0.0009435901001642391,
 'country-born_India': 0.0009053270169666037,
 'country-born_Italy': 0.0007858393316571668,
 'country-born_Cuba': 0.0007195878779281718,
 'country-born_Japan': 0.0006983356871999575,
 'country-born_China': 0.0006802794410833693,
 'country-born_South': 0.0006231932308214903,
 'country-born_Ireland': 0.0005392051767827252,
 'country-born_Portugal': 0.0005370518729750397,
 'country-born_Iran': 0.000535747368768037,
 'country-born_Poland': 0.0005022719026297704,
 'country-born_Puerto-Rico': 0.0004901786353448259,
 'country-born_Jamaica': 0.0004564110214898057 5,
 'country-born_Greece': 0.00043398608665183 33,
```

```
 'country-born_France': 0.00041697623547276954,
 'country-born_Taiwan': 0.0003792663073236689,
 'country-born_Vietnam': 0.00037598160310334136,
 'country-born_Columbia': 0.0003753419281918573,
 'country-born_Yugoslavia': 0.0003569432836144122,
 'civil-status_Married-AF-spouse': 0.00034760352040741306,
 'country-born_El-Salvador': 0.00033198424958012443,
 'country-born_Cambodia': 0.0002720841782824448,
 'country-born_Dominican-Republic': 0.00022980549667237396,
 'occupation_Priv-house-serv': 0.00020548637351793422,
 'country-born_Peru': 0.00019697408161068394,
 'country-born_Ecuador': 0.00019536322502935343,
 'country-born_Haiti': 0.0001907078183771404,
 'country-born_Hong': 0.00018891926328735132,
 'country-born_Nicaragua': 0.0001849473820948587,
 'workclass_Without-pay': 0.00015569005554100706,
 'country-born_Hungary': 0.00015492894518113174,
 'country-born_Laos': 0.0001278677587571243,
 'country-born_Trinadad&Tobago': 0.00012195739030432964,
 'country-born_Scotland': 0.00011337980986344161,
 'country-born_Thailand': 0.00010783074186528634,
 'country-born_Guatemala': 0.0001039255764973182,
 'occupation_Armed-Forces': 8.574494844167987e-05,
 'country-born_Outlying-US(Guam-USVI-etc)': 5.023100061304543e-05,
 'country-born_Honduras': 1.0549015238740057e-05,
 'workclass_Never-worked': 5.344321319963961e-06,
 'country-born_Holand-Netherlands': 5.332271488065066e-07}
```

In [31]:
```python
import matplotlib.pyplot as plt


# Plotting the feature importances
features = list(imp.keys())
importances = list(imp.values())

plt.figure(figsize=(40,10))
bar_width=0.6
plt.bar(range(len(features)), importances, align="center")
plt.xticks(range(len(features)), features, rotation=90)
plt.xlabel("Feature")
plt.ylabel("Importance")
plt.title("Feature Importances from Random Forest Model")
plt.show()
```



In [32]:
```python
from sklearn.model_selection import GridSearchCV
from sklearn.ensemble import RandomForestClassifier

param_grid = {
    'n_estimators': [50, 100, 250],
    'max_depth': [5, 10, 25, None],
    'min_samples_split': [2, 4],

    'max_features': [ 'sqrt', 'log2'],

}

grid_search = GridSearchCV(estimator=RandomForestClassifier(), param_grid=para
```

In [33]:
```
grid_search.fit(train_x, train_y)
```

```
n_estimators=100;, score=0.853 total time=   5.3s
[CV 3/5; 23/48] START max_depth=10, max_features=log2, min_samples_split=
4, n_estimators=100
[CV 3/5; 23/48] END max_depth=10, max_features=log2, min_samples_split=4,
n_estimators=100;, score=0.855 total time=   5.1s
[CV 4/5; 23/48] START max_depth=10, max_features=log2, min_samples_split=
4, n_estimators=100
[CV 4/5; 23/48] END max_depth=10, max_features=log2, min_samples_split=4,
n_estimators=100;, score=0.858 total time=   5.3s
[CV 5/5; 23/48] START max_depth=10, max_features=log2, min_samples_split=
4, n_estimators=100
[CV 5/5; 23/48] END max_depth=10, max_features=log2, min_samples_split=4,
n_estimators=100;, score=0.852 total time=   5.2s
[CV 1/5; 24/48] START max_depth=10, max_features=log2, min_samples_split=
4, n_estimators=250

[CV 1/5; 24/48] END max_depth=10, max_features=log2, min_samples_split=4,
n_estimators=250;, score=0.855 total time=  13.0s
[CV 2/5; 24/48] START max_depth=10, max_features=log2, min_samples_split=
4, n_estimators=250
```

In [34]:
```
grid_search.best_estimator_
```

Out[34]:
```
RandomForestClassifier
RandomForestClassifier(max_depth=25, min_samples_split=4, n_estimators=250)
```

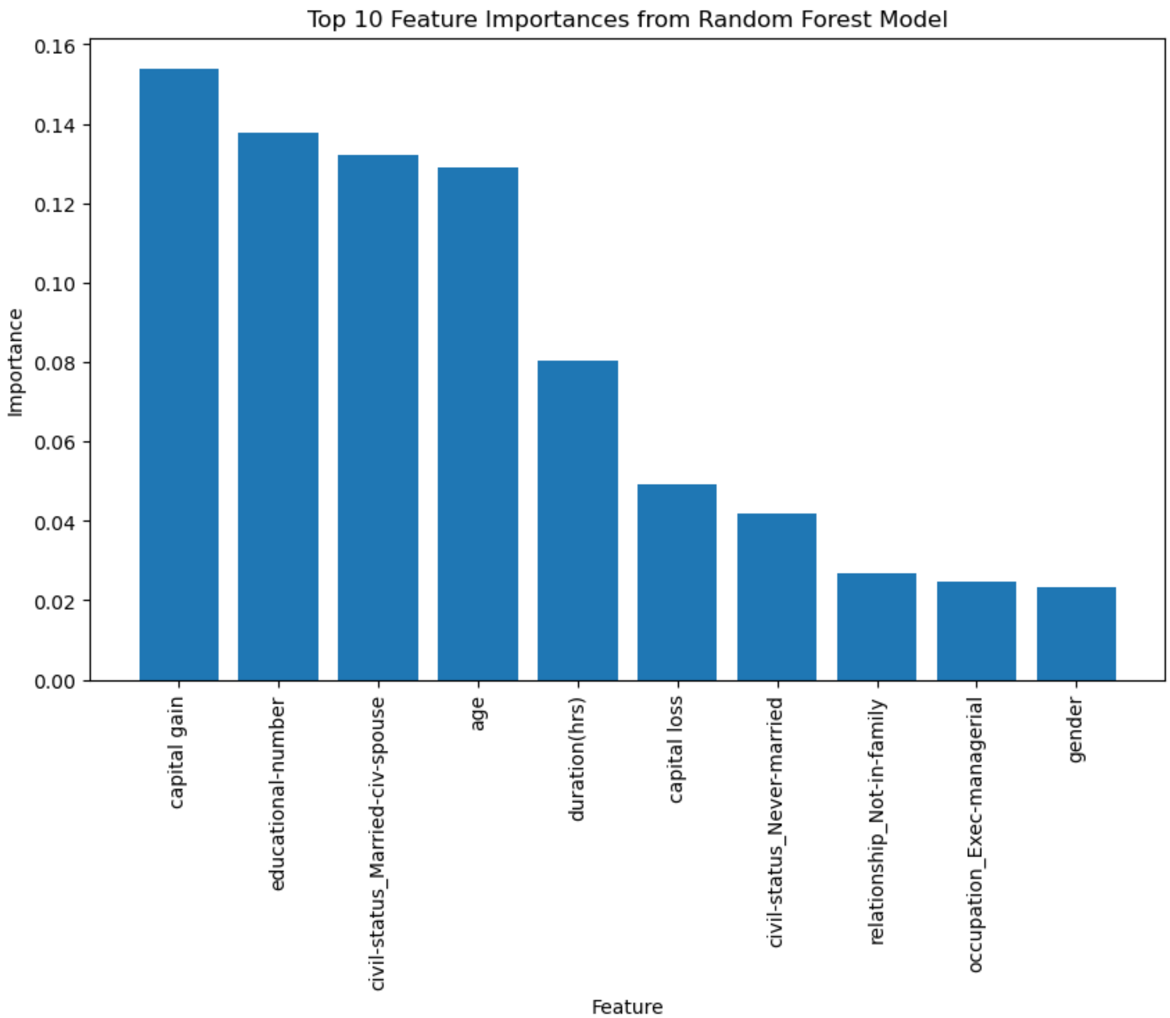
In [35]:
```
forest=grid_search.best_estimator_
forest.score(test_x,test_y)
```

Out[35]:
```
0.8657999795270754
```

In [36]:
```
imp=dict(zip(forest.feature_names_in_,forest.feature_importances_,))
imp={k: v for k, v in sorted(imp.items(), key=lambda x: x[1], reverse=True)}
```

In [37]:
```
top_10_features = list(imp.keys())[:10]
top_10_importances = [imp[feature] for feature in top_10_features]
```

In [38]:
```
plt.figure(figsize=(10, 6))
bar_width = 0.6
plt.bar(range(len(top_10_features)), top_10_importances, align="center")
plt.xticks(range(len(top_10_features)), top_10_features, rotation=90)
plt.xlabel("Feature")
plt.ylabel("Importance")
plt.title("Top 10 Feature Importances from Random Forest Model")
plt.show()
```



In [39]:
```
import numpy as np
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score, confusion_matrix, classification_r
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import RandomForestClassifier
```

In [40]:
```
# Define hyperparameters for each model
logreg_hyperparams = {'C': np.arange(0.1, 1.1, 0.3), 'multi_class': ['auto', '
rf_hyperparams = {'n_estimators': [50, 100, 250], 'max_depth': [5, 10, 25, Non
knn_hyperparams = {'n_neighbors': range(3, 8), 'weights': ['uniform', 'distanc
sgd_hyperparams = {'loss': ['hinge', 'log', 'modified_huber']}
```

These dictionaries define hyperparameters for machine learning models. For logistic regression, key parameters are the solver technique (solver), multi-class strategy (multi_class), and regularization strength (C). Random Forest hyperparameters include the number of trees (n_estimators), maximum depth (max_depth), minimum split samples (min_samples_split), and maximum features (max_features). k-Nearest Neighbors has parameters for the weight function (weights) and number of neighbors (n_neighbors). Stochastic Gradient Descent has a hyperparameter for the loss function (loss).

In [41]:
```
# Create a dictionary of models with their corresponding hyperparameters
models = {
    'Logistic Regression': {'model': LogisticRegression(), 'hyperparams': logr
    'KNN': {'model': KNeighborsClassifier(), 'hyperparams': knn_hyperparams},
    'SGD': {'model': SGDClassifier(), 'hyperparams': sgd_hyperparams},
    'Random Forest': {'model': RandomForestClassifier(), 'hyperparams': rf_hyp
}
```

There are four machine learning models in the "models" dictionary, each with corresponding hyperparameters. Stochastic Gradient Descent (SGD), Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression are among the models.

In [42]:
```
# Dictionary to store accuracy results
accuracy_results = {}

# Function to train and evaluate a model
def train_and_evaluate_model(name, model, params, train_x, train_y, test_x, te
    print(f'\nTraining {name}...')

    # Find the best hyperparameters
    best_params = find_best_hyperparameters(model, params, train_x, train_y)

    # Set the model with the best hyperparameters
    model.set_params(**best_params)

    # Train the model
    model.fit(train_x, train_y)

    # Evaluate the model
    evaluate_model(name, model, test_x, test_y)
```

The code defines a function train_and_evaluate_model that takes a model name, the model itself, its hyperparameters, training and testing data, and trains the model. It uses a function find_best_hyperparameters to determine the best hyperparameters and then evaluates the

In [43]:
```
# Function to find the best hyperparameters using GridSearchCV
def find_best_hyperparameters(model, params, train_x, train_y):
    grid_search = GridSearchCV(model, params, cv=5, n_jobs=-1)
    grid_search.fit(train_x, train_y)
    best_params = grid_search.best_params_
    print(f'Best Hyperparameters: {best_params}')
    return best_params
```

There are four machine learning models in the "models" dictionary, each with corresponding hyperparameters. Stochastic Gradient Descent (SGD), Random Forest, K-Nearest Neighbors (KNN), and Logistic Regression are among the models.

In [44]:
```
# Function to evaluate the model and print results
def evaluate_model(name, model, test_x, test_y):
    y_pred = model.predict(test_x)
    accuracy = accuracy_score(test_y, y_pred)
    accuracy_results[name] = accuracy

    print(f'Test Accuracy for {name}: {accuracy:.12f}')
    print(f'Confusion Matrix for {name}:\n{confusion_matrix(test_y, y_pred)}')
    print(f'Classification Report for {name}:\n{classification_report(test_y,
    print('-' * 50)
```

Using the model on the test data, the evaluate_model function predicts the labels and determines the accuracy. It prints the model's accuracy, confusion matrix, and classification report after updating the accuracy_results dictionary.

In [45]:
```
# Train and evaluate each model
for name, model_info in models.items():
    model = model_info['model']
    params = model_info['hyperparams']
    train_and_evaluate_model(name, model, params, train_x, train_y, test_x, te
```

```
Training Logistic Regression...
Best Hyperparameters: {'C': 1.0000000000000002, 'multi_class': 'auto', 'solve
r': 'newton-cg'}
Test Accuracy for Logistic Regression: 0.851366567714
Confusion Matrix for Logistic Regression:
[[6923  481]
 [ 971 1394]]
Classification Report for Logistic Regression:
              precision    recall  f1-score   support

           0       0.88      0.94      0.91      7404
           1       0.74      0.59      0.66      2365

    accuracy                           0.85      9769
   macro avg       0.81      0.76      0.78      9769
weighted avg       0.84      0.85      0.85      9769

--------------------------------------------------

Training KNN...
Best Hyperparameters: {'n_neighbors': 6, 'weights': 'distance'}
Test Accuracy for KNN: 0.843586856382
Confusion Matrix for KNN:
[[6768  636]
 [ 892 1473]]
Classification Report for KNN:
              precision    recall  f1-score   support

           0       0.88      0.91      0.90      7404
           1       0.70      0.62      0.66      2365

    accuracy                           0.84      9769
   macro avg       0.79      0.77      0.78      9769
weighted avg       0.84      0.84      0.84      9769

--------------------------------------------------

Training SGD...
Best Hyperparameters: {'loss': 'modified_huber'}
Test Accuracy for SGD: 0.811649094073
Confusion Matrix for SGD:
[[6560  844]
 [ 996 1369]]
Classification Report for SGD:
              precision    recall  f1-score   support

           0       0.87      0.89      0.88      7404
           1       0.62      0.58      0.60      2365

    accuracy                           0.81      9769
   macro avg       0.74      0.73      0.74      9769
weighted avg       0.81      0.81      0.81      9769

--------------------------------------------------

Training Random Forest...
```

```
Best Hyperparameters: {'max_depth': 25, 'max_features': 'sqrt', 'min_samples_
split': 4, 'n_estimators': 250}
Test Accuracy for Random Forest: 0.864059780940
Confusion Matrix for Random Forest:
[[7026  378]
 [ 950 1415]]
Classification Report for Random Forest:
              precision    recall  f1-score   support

           0       0.88      0.95      0.91      7404
           1       0.79      0.60      0.68      2365

    accuracy                           0.86      9769
   macro avg       0.84      0.77      0.80      9769
weighted avg       0.86      0.86      0.86      9769

--------------------------------------------------
```

The train_and_evaluate_model function is called to train, adjust hyperparameters, and assess each model on test data. This loop iterates through each model in the models dictionary, retrieves the corresponding model and hyperparameters, and then calls the function.

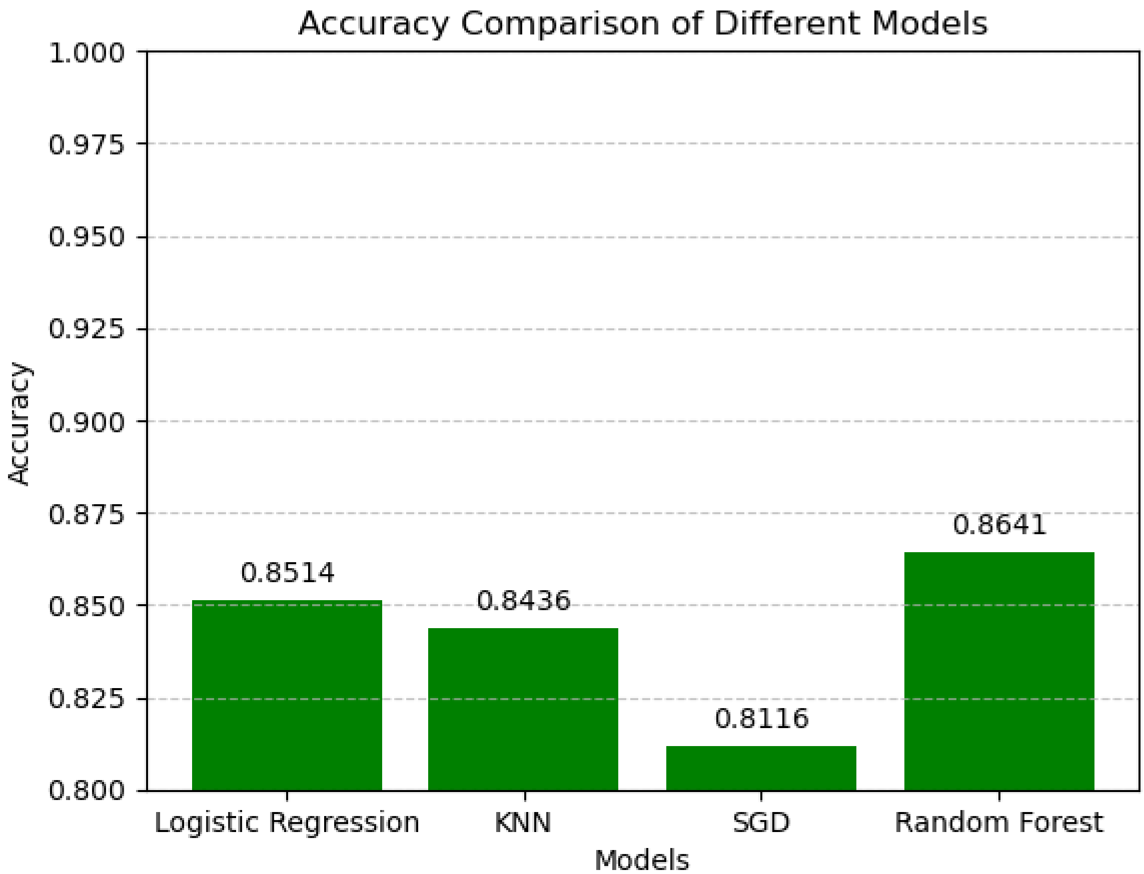
In [46]:

```
# Print final accuracy results
print('\nFinal Accuracy Results:')
for model_name, accuracy in accuracy_results.items():
    print(f'Accuracy for best {model_name}: {accuracy:.15f}')
```

```
Final Accuracy Results:
Accuracy for best Logistic Regression: 0.851366567714198
Accuracy for best KNN: 0.843586856382434
Accuracy for best SGD: 0.811649094073088
Accuracy for best Random Forest: 0.864059780939707
```

By iterating through the accuracy_results dictionary and displaying the accuracy for each model along with its name, the code prints the final accuracy results for each model.

In [47]:
```
import matplotlib.pyplot as plt

# TO Extract model names and accuracies for plotting
model_names = []
accuracies = []

# TO Populate model_names and accuracies from the Loop
for model_name, accuracy in accuracy_results.items():
    model_names.append(model_name)
    accuracies.append(accuracy)

# TO Create a bar graph
fig, ax = plt.subplots()
bars = ax.bar(model_names, accuracies, color='green')

# TO Display the accuracy values on top of each bar
for bar, accuracy in zip(bars, accuracies):
    plt.text(bar.get_x() + bar.get_width() / 2, bar.get_height() + 0.005, f'{a

# Customize the plot
plt.title('Accuracy Comparison of Different Models')
plt.xlabel('Models')
plt.ylabel('Accuracy')
plt.ylim(0.8, 1.0)  # Adjust the y-axis limits if needed
plt.grid(axis='y', linestyle='--', alpha=0.7)

# TO Show the plot
plt.show()
```


Accuracy Comparison of Different Models
Accuracy
1.000
0.975
0.950
0.925
0.900
0.875
0.850
0.825
0.800
0.8514
0.8436
0.8116
0.8641
Logistic Regression
KNN
SGD
Random Forest
Models