Individual Algorithms Applied

In this section, we apply various algorithms to predict survival based on selected features from tl dataset.

Selected Features

The features used for model training are:

- **survived**: Indicates whether the passenger survived (1) or not (0) *(Target Variable)*
- **pclass**: Passenger class (1st, 2nd, 3rd)
- **sex**: Gender of the passenger
- **age**: Age of the passenger
- **sibsp**: Number of siblings or spouses aboard
- **parch**: Number of parents or children aboard
- **fare**: Ticket fare paid by the passenger
- **embarked**: Port of embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)
- **class**: Passenger class (1st, 2nd, 3rd)
- **who**: Gender group (man, woman, child)
- **adult_male**: Indicates if the passenger is an adult male (1 = Yes, 0 = No)
- **deck**: Deck where the cabin is located
- **embark_town**: Town of embarkation
- **alive**: Indicates whether the passenger is alive (1) or not (0)
- **alone**: Indicates whether the passenger is alone (1) or not (0)

Target Variable

- **survived**: This is the target variable we aim to predict using the selected features.

In [1]:
```
# !pip install catboost
```

In [2]:
```
# import libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from catboost import CatBoostClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, classificat
from sklearn.tree import DecisionTreeRegressor, DecisionTreeClassifier
```

In [3]:
```
# data import titanic
df = sns.load_dataset('titanic')
df.head()
```

Out[3]:

	survived	pclass	sex	age	sibsp	parch	fare	embarked	class	who	adult
0	0	3	male	22.0	1	0	7.2500	S	Third	man	
1	1	1	female	38.0	1	0	71.2833	C	First	woman	
2	1	3	female	26.0	0	0	7.9250	S	Third	woman	
3	1	1	female	35.0	1	0	53.1000	S	First	woman	
4	0	3	male	35.0	0	0	8.0500	S	Third	man	

pre-processing

In [ ]:

```
df.isnull().sum().sort_values(ascending=False)
```

Out[ ]:

```
deck           688
age            177
embarked         2
embark_town      2
survived         0
pclass           0
sex              0
sibsp            0
parch            0
fare             0
class            0
who              0
adult_male       0
alive            0
alone            0
dtype: int64
```

In [5]:

```
# impute missing values using knn imputers in age
from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors=5)
df['age'] = imputer.fit_transform(df[['age']])

# impute embarked missing values using pandas
df['embarked'] = df['embarked'].fillna(df['embarked'].mode()[0])
df['embark_town'] = df['embark_town'].fillna(df['embark_town'].mode()[0])
# drop deck column
df.drop('deck', axis=1, inplace=True)

# df missing values
df.isnull().sum().sort_values(ascending=False)
```

Out[5]:
```
survived       0
pclass         0
sex            0
age            0
sibsp          0
parch          0
fare           0
embarked       0
class          0
who            0
adult_male     0
embark_town    0
alive          0
alone          0
dtype: int64
```

In [6]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 14 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   survived     891 non-null    int64
 1   pclass       891 non-null    int64
 2   sex          891 non-null    object
 3   age          891 non-null    float64
 4   sibsp        891 non-null    int64
 5   parch        891 non-null    int64
 6   fare         891 non-null    float64
 7   embarked     891 non-null    object
 8   class        891 non-null    category
 9   who          891 non-null    object
 10  adult_male   891 non-null    bool
 11  embark_town  891 non-null    object
 12  alive        891 non-null    object
 13  alone        891 non-null    bool
dtypes: bool(2), category(1), float64(2), int64(4), object(5)
memory usage: 79.4+ KB
```

In [7]:
```python
# convert each category column to category
categorical_cols = df.select_dtypes(include=['object', 'category']).colum
# add this as a new column in the dataframe
df[categorical_cols] = df[categorical_cols].astype('category')
```

In [8]:
```python
df[categorical_cols].info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 6 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   sex          891 non-null    category
 1   embarked     891 non-null    category
 2   class        891 non-null    category
 3   who          891 non-null    category
 4   embark_town  891 non-null    category
 5   alive        891 non-null    category
dtypes: category(6)
memory usage: 6.1 KB
```

In [9]:
```python
# split data into X and y
X = df.drop('survived', axis=1)
y = df['survived']

# split data into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
```

Simple Decesion tree

In [10]:
```python
# One-hot encode categorical columns
X_train_encoded = pd.get_dummies(X_train, columns=categorical_cols)
X_test_encoded = pd.get_dummies(X_test, columns=categorical_cols)

# Ensure the same columns in train and test sets
X_train_encoded, X_test_encoded = X_train_encoded.align(X_test_encoded, j

# create the model
dt_model = DecisionTreeClassifier(random_state=42)

# train the model
dt_model.fit(X_train_encoded, y_train)

# predictions
y_pred_dt = dt_model.predict(X_test_encoded)

# evaluate the model
print(f'Accuracy Score: {accuracy_score(y_test, y_pred_dt)}')
print(f'Confusion Matrix: \n {confusion_matrix(y_test, y_pred_dt)}')
print(f'Classification Report: \n {classification_report(y_test, y_pred_d
```

```
Accuracy Score: 1.0
Confusion Matrix:
 [[105   0]
 [  0  74]]
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       105
           1       1.00      1.00      1.00        74

    accuracy                           1.00       179
   macro avg       1.00      1.00      1.00       179
weighted avg       1.00      1.00      1.00       179
```

Catboost classifier

In [11]:
```python
# run the catboost classifier
model = CatBoostClassifier(iterations=100,
                           learning_rate=0.1,
                           depth=3,
                           loss_function='Logloss',
                           eval_metric='Accuracy',
                           random_seed=42,
                           verbose=False)

# train the model
model.fit(X_train, y_train, cat_features=categorical_cols.tolist())
```

```
# predictions
y_pred = model.predict(X_test)

# evaluate the model
print(f'Accuracy Score: {accuracy_score(y_test, y_pred)}')
print(f'Confusion Matrix: \n {confusion_matrix(y_test, y_pred)}')
print(f'Classification Report: \n {classification_report(y_test, y_pred)}
```

```
Accuracy Score: 1.0
Confusion Matrix:
 [[105   0]
 [  0  74]]
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       105
           1       1.00      1.00      1.00        74

    accuracy                           1.00       179
   macro avg       1.00      1.00      1.00       179
weighted avg       1.00      1.00      1.00       179
```

RandomForestClassifier

In [12]:

```
from sklearn.ensemble import RandomForestClassifier

# create the model
rf_model = RandomForestClassifier(random_state=42)

# train the model
rf_model.fit(X_train_encoded, y_train)

# predictions
y_pred_rf = rf_model.predict(X_test_encoded)

# evaluate the model
print(f'Accuracy Score: {accuracy_score(y_test, y_pred_rf)}')
print(f'Confusion Matrix: \n {confusion_matrix(y_test, y_pred_rf)}')
print(f'Classification Report: \n {classification_report(y_test, y_pred_r
```

```
Accuracy Score: 1.0
Confusion Matrix:
 [[105   0]
 [  0  74]]
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       105
           1       1.00      1.00      1.00        74

    accuracy                           1.00       179
   macro avg       1.00      1.00      1.00       179
weighted avg       1.00      1.00      1.00       179
```

AdaBoostClassifier

In [13]:

```
from sklearn.ensemble import AdaBoostClassifier

# create the model
```

```
ada_model = AdaBoostClassifier(random_state=42)

# train the model
ada_model.fit(X_train_encoded, y_train)

# predictions
y_pred_ada = ada_model.predict(X_test_encoded)

# evaluate the model
print(f'Accuracy Score: {accuracy_score(y_test, y_pred_ada)}')
print(f'Confusion Matrix: \n {confusion_matrix(y_test, y_pred_ada)}')
print(f'Classification Report: \n {classification_report(y_test, y_pred_a
```

```
Accuracy Score: 1.0
Confusion Matrix: 
 [[105   0]
 [  0  74]]
Classification Report: 
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       105
           1       1.00      1.00      1.00        74

    accuracy                           1.00       179
   macro avg       1.00      1.00      1.00       179
weighted avg       1.00      1.00      1.00       179
```

```
c:\Users\Hp\miniconda3\envs\machine_learning\Lib\site-
packages\sklearn\ensemble\_weight_boosting.py:527: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMM
algorithm to circumvent this warning.
  warnings.warn(
```

xgb

In [14]:

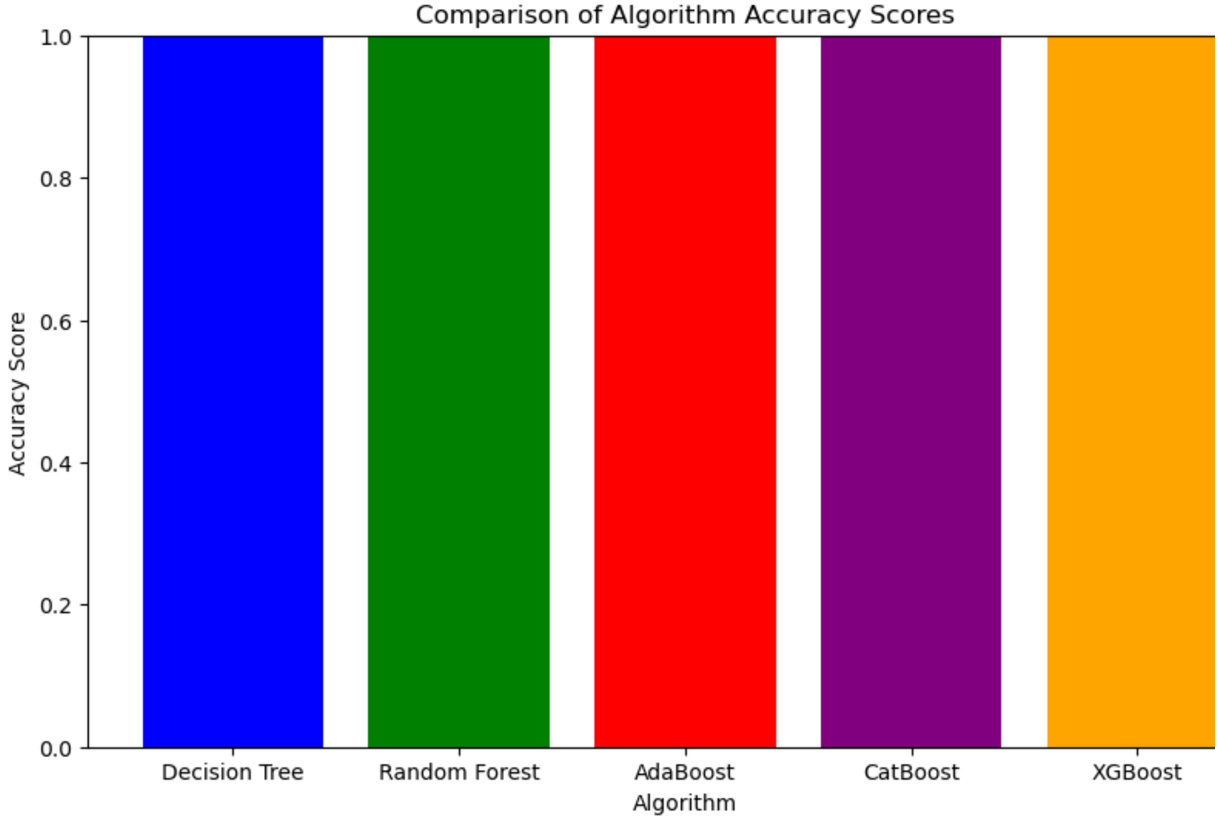
```
import xgboost as xgb

# !pip install xgboost


# create the model
xgb_model = xgb.XGBClassifier(random_state=42)

# train the model
xgb_model.fit(X_train_encoded, y_train)

# predictions
y_pred_xgb = xgb_model.predict(X_test_encoded)

# evaluate the model
print(f'Accuracy Score: {accuracy_score(y_test, y_pred_xgb)}')
print(f'Confusion Matrix: \n {confusion_matrix(y_test, y_pred_xgb)}')
print(f'Classification Report: \n {classification_report(y_test, y_pred_x
```

```
Accuracy Score: 1.0
Confusion Matrix:
 [[105   0]
 [  0  74]]
Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       105
           1       1.00      1.00      1.00        74

    accuracy                           1.00       179
   macro avg       1.00      1.00      1.00       179
weighted avg       1.00      1.00      1.00       179
```

Comparison

In [15]:

```python
# Accuracy scores of each model
accuracy_scores = {
    'Decision Tree': accuracy_score(y_test, y_pred_dt),
    'Random Forest': accuracy_score(y_test, y_pred_rf),
    'AdaBoost': accuracy_score(y_test, y_pred_ada),
    'CatBoost': accuracy_score(y_test, y_pred),
    'XGBoost': accuracy_score(y_test, y_pred_xgb)
}

# Plotting the accuracy scores
plt.figure(figsize=(10, 6))
plt.bar(accuracy_scores.keys(), accuracy_scores.values(), color=['blue',
plt.xlabel('Algorithm')
plt.ylabel('Accuracy Score')
plt.title('Comparison of Algorithm Accuracy Scores')
plt.ylim(0, 1)
plt.show()
```



All Algorithms

Select Features and Target

In this section, we define the features and the target variable for our model.

Features

The selected features from the dataset are:

- **pclass**: Passenger class (1st, 2nd, 3rd)
- **sex**: Gender of the passenger
- **age**: Age of the passenger
- **sibsp**: Number of siblings or spouses aboard
- **parch**: Number of parents or children aboard
- **fare**: Ticket fare paid by the passenger

Target Variable

The target variable is:

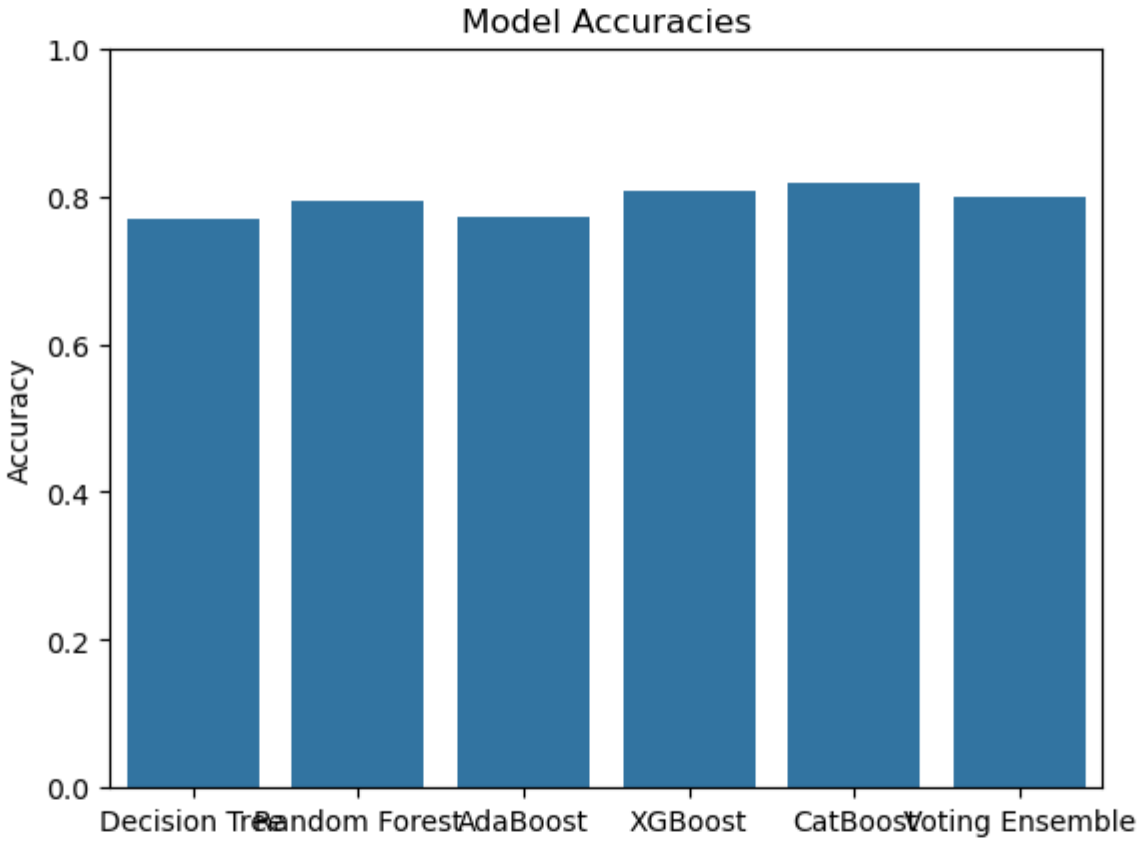
- **survived**: Indicates whether the passenger survived (1) or not (0)

In [16]:

```
import pandas as pd
import numpy as np
from datasets import load_dataset
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from catboost import CatBoostClassifier
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
import seaborn as sns

# Load the Titanic dataset
df = sns.load_dataset('titanic')

# Select features and target
X = df[['pclass', 'sex', 'age', 'sibsp', 'parch', 'fare']]
y = df['survived']

# Handle missing values (for simplicity, fill missing 'age' values with t
X['age'].fillna(X['age'].median(), inplace=True)

# Define categorical and numerical columns
categorical_cols = ['pclass', 'sex']
numerical_cols = ['age', 'sibsp', 'parch', 'fare']

# Create a preprocessing pipeline
```

```python
preprocessor = ColumnTransformer(
    transformers=[
        ('num', StandardScaler(), numerical_cols),
        ('cat', OneHotEncoder(), categorical_cols)
    ]
)

# Create models
models = {
    'Decision Tree': Pipeline(steps=[('preprocessor', preprocessor),
                                      ('classifier', DecisionTreeClassifi
    'Random Forest': Pipeline(steps=[('preprocessor', preprocessor),
                                      ('classifier', RandomForestClassifi
    'AdaBoost': Pipeline(steps=[('preprocessor', preprocessor),
                                 ('classifier', AdaBoostClassifier(estima
    'XGBoost': Pipeline(steps=[('preprocessor', preprocessor),
                                ('classifier', XGBClassifier(use_label_en
    'CatBoost': Pipeline(steps=[('preprocessor', preprocessor),
                                 ('classifier', CatBoostClassifier(silent
}

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,

# Fit models and evaluate accuracy
results = {}
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    results[name] = accuracy

# Create an ensemble model using VotingClassifier
voting_clf = VotingClassifier(estimators=[(name, model) for name, model i
voting_clf.fit(X_train, y_train)
y_pred_voting = voting_clf.predict(X_test)
voting_accuracy = accuracy_score(y_test, y_pred_voting)
results['Voting Ensemble'] = voting_accuracy

# Display the results
print("Model Accuracies:")
for model, accuracy in results.items():
    print(f"{model}: {accuracy:.2f}")

# Visualize the results
sns.barplot(x=list(results.keys()), y=list(results.values()))
plt.title('Model Accuracies')
plt.ylabel('Accuracy')
plt.ylim(0, 1)
plt.show();
```

```
C:\Users\Hp\AppData\Local\Temp\ipykernel_34288\3135495894.py:24: FutureWarning
value is trying to be set on a copy of a DataFrame or Series through chained
assignment using an inplace method.
The behavior will change in pandas 3.0. This inplace method will never work be
the intermediate object on which we are setting values always behaves as a cop

For example, when doing 'df[col].method(value, inplace=True)', try using
'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) ins
to perform the operation inplace on the original object.


  X['age'].fillna(X['age'].median(), inplace=True)
C:\Users\Hp\AppData\Local\Temp\ipykernel_34288\3135495894.py:24:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/st
user_guide/indexing.html#returning-a-view-versus-a-copy
  X['age'].fillna(X['age'].median(), inplace=True)
c:\Users\Hp\miniconda3\envs\machine_learning\Lib\site-
packages\sklearn\ensemble\_weight_boosting.py:527: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMM
algorithm to circumvent this warning.
  warnings.warn(
c:\Users\Hp\miniconda3\envs\machine_learning\Lib\site-packages\xgboost\core.py
UserWarning: [05:11:50] WARNING: C:\buildkite-agent\builds\buildkite-windows-c
autoscaling-group-i-0015a694724fa8361-1\xgboost\xgboost-ci-windows\src\learner
740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
c:\Users\Hp\miniconda3\envs\machine_learning\Lib\site-
packages\sklearn\ensemble\_weight_boosting.py:527: FutureWarning: The SAMME.R
algorithm (the default) is deprecated and will be removed in 1.6. Use the SAMM
algorithm to circumvent this warning.
  warnings.warn(
c:\Users\Hp\miniconda3\envs\machine_learning\Lib\site-packages\xgboost\core.py
UserWarning: [05:11:57] WARNING: C:\buildkite-agent\builds\buildkite-windows-c
autoscaling-group-i-0015a694724fa8361-1\xgboost\xgboost-ci-windows\src\learner
740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
Model Accuracies:
Decision Tree: 0.77
Random Forest: 0.79
AdaBoost: 0.77
XGBoost: 0.81
CatBoost: 0.82
Voting Ensemble: 0.80
```


Model Accuracies
1.0
0.8
0.6
0.4
0.2
0.0
Accuracy
Decision Tree
Random Forest
AdaBoost
XGBoost
CatBoost
Voting Ensemble

In [ ]:

In [ ]:

In [ ]: