1. Overview

Based on the descriptive and exploratory analysis done in notebook 00_data_understanding, this Python Script will work on 2 models: logistic and decission tree classifier, we will chose the best model based on the one that has better evaluation metrics. We will then improve the chosen model with tuned hyperparameters.

2. Data Understanding

2.1 Data Description

This notebook will use the dataset: df_data_processed excel sheet created in the previous notebook: 01_data_preprocessing

2.2 Import Necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
from sklearn.exceptions import ConvergenceWarning


from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import roc_curve, auc, confusion_matrix
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer, roc_auc_score

import pickle
import warnings
warnings.filterwarnings('ignore', category=ConvergenceWarning)
```

3. Code

3.1 Import the database

In [2]:
```
df = pd.read_excel('df_data_processed.xlsx')
df.head()
```

Out[2]:

	amount_tsh	gps_height	population	basin	region	extraction_type_class	payment_type
0	-0.084999	2.053863	-0.041306	-0.540016	-0.633090	-0.521411	-0.897587
1	-0.100621	-0.965049	-0.379739	-0.540016	0.555492	-0.463637	0.771866
2	-0.100621	-0.965049	-0.379739	1.471270	0.131062	2.617222	0.771866
3	-0.100621	-0.965049	-0.379739	-1.053126	0.131062	-0.521411	-1.330306
4	-0.006889	0.511216	-0.125914	0.697368	0.135714	2.617222	-0.641415

5 rows × 36 columns

In [3]:
```
df.shape
```

Out[3]: (59400, 36)

3.2 Import the database

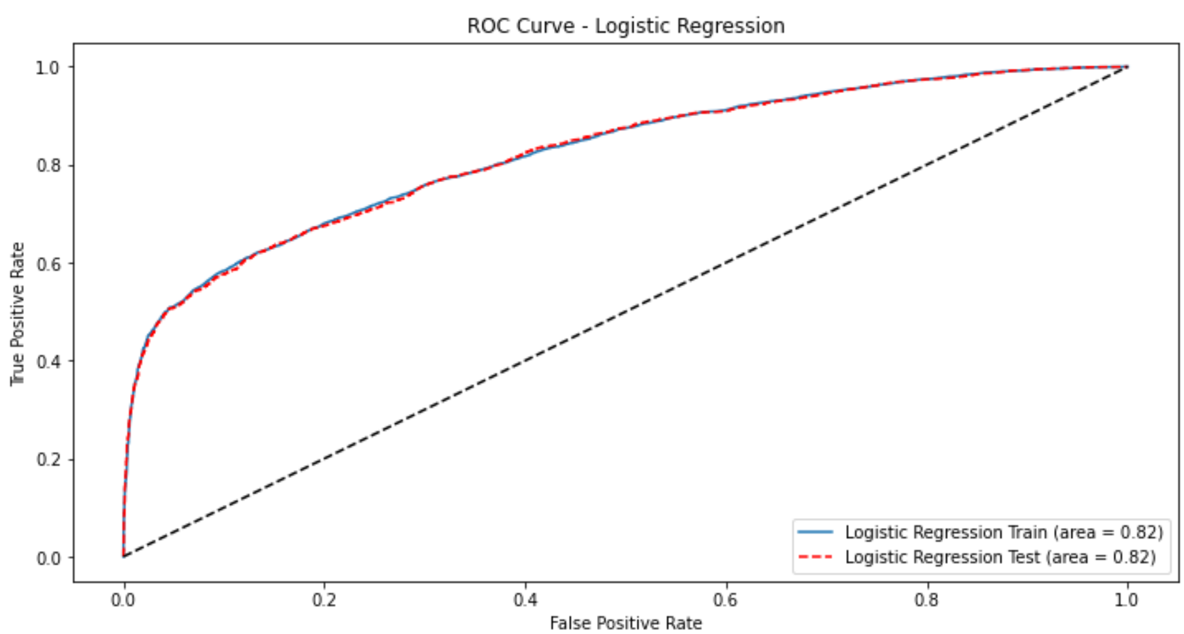
In [4]:
```
df_train = df[df['is_test']==0]
df_test = df[df['is_test']==1]
```

In [5]:
```
y_train = df_train['status_group']
X_train = df_train.drop(['status_group','is_test'], axis=1)

y_test = df_test['status_group']
X_test = df_test.drop(['status_group','is_test'], axis=1)
```

3.3 Baseline model creations

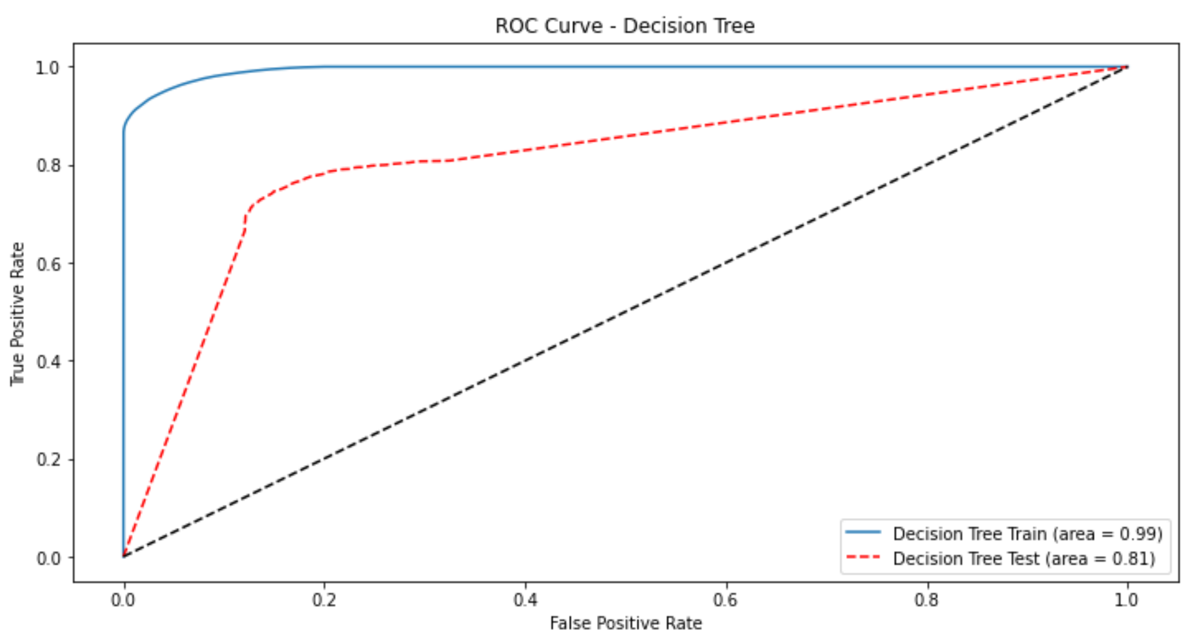
3.3.1 Logistic regression

In [6]:
```
# Initialize the Logistic Regression model
log_reg = LogisticRegression()

# Fit the model to the training data
log_reg.fit(X_train, y_train)

# Predict probabilities on the training and test set
y_pred_prob_log_reg_train = log_reg.predict_proba(X_train)[:, 1]  # Training p
y_pred_prob_log_reg_test = log_reg.predict_proba(X_test)[:, 1]  # Test probabi

# Compute ROC curve and AUC for training data
fpr_log_reg_train, tpr_log_reg_train, _ = roc_curve(y_train, y_pred_prob_log_r
auc_log_reg_train = auc(fpr_log_reg_train, tpr_log_reg_train)

# Compute ROC curve and AUC for test data
fpr_log_reg_test, tpr_log_reg_test, _ = roc_curve(y_test, y_pred_prob_log_reg_
auc_log_reg_test = auc(fpr_log_reg_test, tpr_log_reg_test)

# Plotting ROC Curves
plt.figure(figsize=(12, 6))
plt.plot(fpr_log_reg_train, tpr_log_reg_train, label='Logistic Regression Trai
plt.plot(fpr_log_reg_test, tpr_log_reg_test, color='red', linestyle='--', labe
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Logistic Regression')
plt.legend(loc="lower right")
plt.show()
```



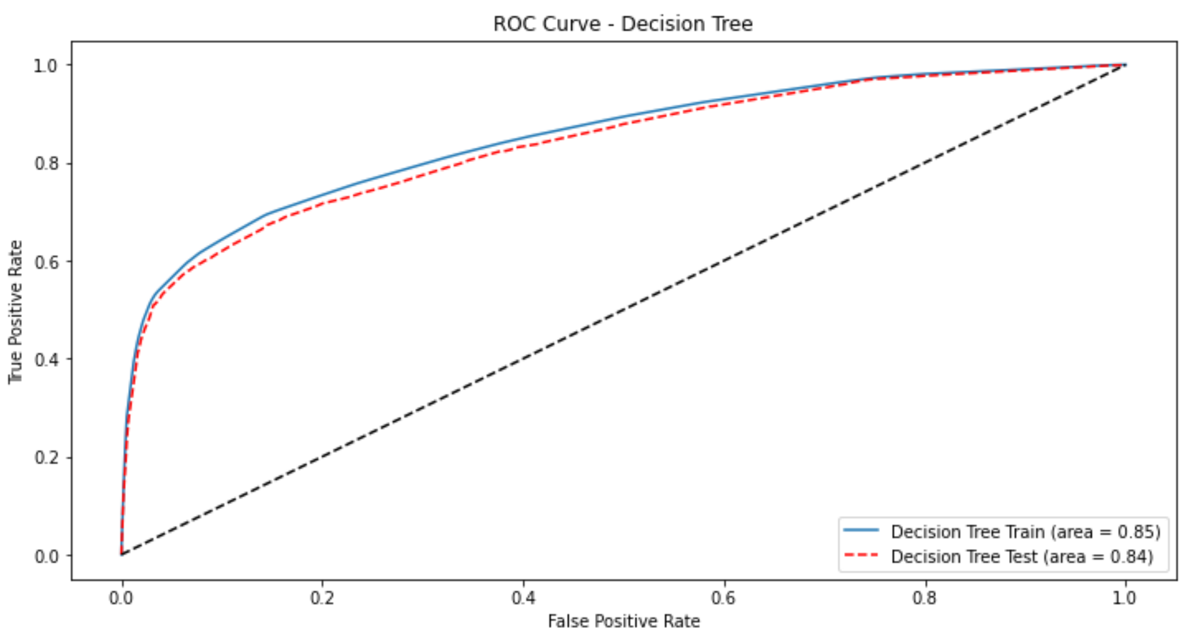
3.3.2 Decision Tree

In [7]:
```
# Initialize the Decision Tree model
decision_tree = DecisionTreeClassifier()

# Fit the model to the training data
decision_tree.fit(X_train, y_train)

# Predict probabilities on the training and test set
y_pred_prob_tree_train = decision_tree.predict_proba(X_train)[:, 1]  # Trainin
y_pred_prob_tree_test = decision_tree.predict_proba(X_test)[:, 1]  # Test prob

# Compute ROC curve and AUC for training data
fpr_tree_train, tpr_tree_train, _ = roc_curve(y_train, y_pred_prob_tree_train)
auc_tree_train = auc(fpr_tree_train, tpr_tree_train)

# Compute ROC curve and AUC for test data
fpr_tree_test, tpr_tree_test, _ = roc_curve(y_test, y_pred_prob_tree_test)
auc_tree_test = auc(fpr_tree_test, tpr_tree_test)

# Plotting ROC Curves
plt.figure(figsize=(12, 6))
plt.plot(fpr_tree_train, tpr_tree_train, label='Decision Tree Train (area = {:
plt.plot(fpr_tree_test, tpr_tree_test, color='red', linestyle='--', label='Dec
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Decision Tree')
plt.legend(loc="lower right")
plt.show()
```



checking max_depth to mitigate overfitting

In [8]:
```
# Initialize the Decision Tree model
decision_tree = DecisionTreeClassifier(max_depth=7)

# Fit the model to the training data
decision_tree.fit(X_train, y_train)

# Predict probabilities on the training and test set
y_pred_prob_tree_train = decision_tree.predict_proba(X_train)[:, 1]  # Trainin
y_pred_prob_tree_test = decision_tree.predict_proba(X_test)[:, 1]  # Test prob

# Compute ROC curve and AUC for training data
fpr_tree_train, tpr_tree_train, _ = roc_curve(y_train, y_pred_prob_tree_train)
auc_tree_train = auc(fpr_tree_train, tpr_tree_train)

# Compute ROC curve and AUC for test data
fpr_tree_test, tpr_tree_test, _ = roc_curve(y_test, y_pred_prob_tree_test)
auc_tree_test = auc(fpr_tree_test, tpr_tree_test)

# Plotting ROC Curves
plt.figure(figsize=(12, 6))
plt.plot(fpr_tree_train, tpr_tree_train, label='Decision Tree Train (area = {:
plt.plot(fpr_tree_test, tpr_tree_test, color='red', linestyle='--', label='Dec
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve - Decision Tree')
plt.legend(loc="lower right")
plt.show()
```



3.4 Hyper tuning

3.4.1 Decision Tree Classifier

We are going to do hyper parameter tuning with Decision Tree classifier and the Logistic regression and we will keep the model that gives the best results

The code below is commented as it takes an approximated time of 20 minutes for it to run. However, in the following cell you can see that the best_tree is saved in a pickle

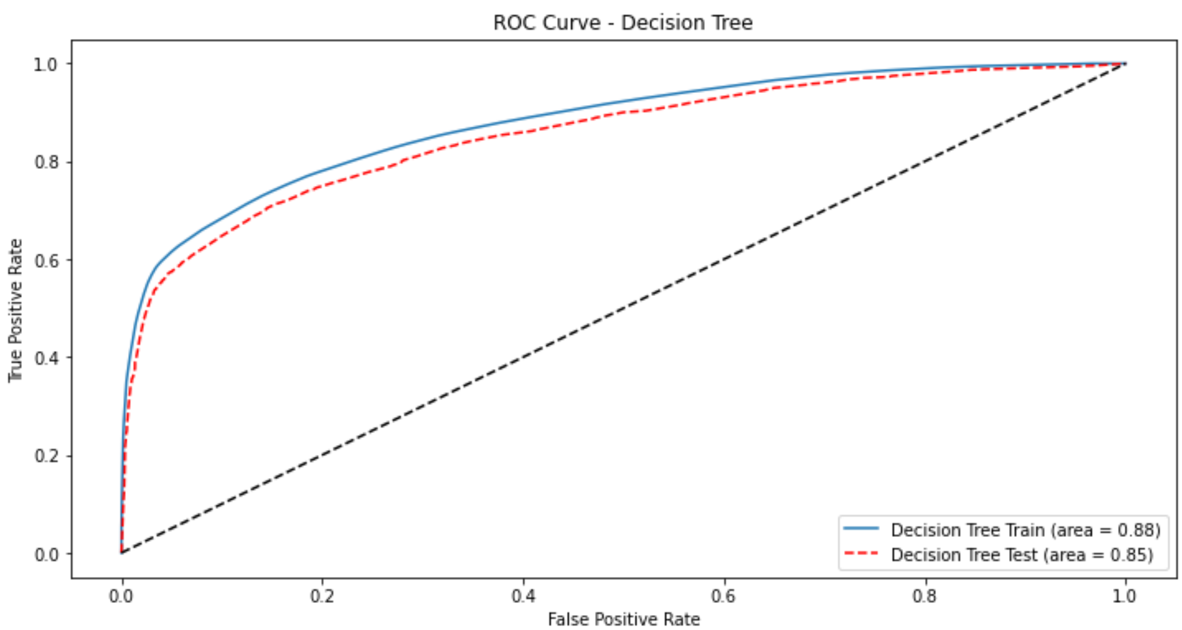
In [9]:
```
# # Initialize the Decision Tree model
# decision_tree = DecisionTreeClassifier()

# # Define the parameter grid to search
# param_grid = {
#     'max_depth': range(5, 10),  # Explore depths from 1 to 20
#     'min_samples_split': range(5, 15, 2),  # Minimum number of samples requi
#     'min_samples_leaf': range(5, 10),  # Minimum number of samples required
#     'max_features': ['auto', 'log2', None]  # Number of features to consider
# }

# # Define the scoring function using AUC
# scorer = make_scorer(roc_auc_score, needs_proba=True)

# # Setup the grid search with cross-validation
# grid_search = GridSearchCV(estimator=decision_tree, param_grid=param_grid, s

# # Fit grid search on the training data
# grid_search.fit(X_train, y_train)

# # Find the best model
# best_tree = grid_search.best_estimator_

# # Output the best parameter combination and the corresponding score
# print("Best parameters found:", grid_search.best_params_)
# print("Best AUC achieved:", grid_search.best_score_)

# # Optional: Evaluate the best model on the test set
# y_pred_proba_best_tree = best_tree.predict_proba(X_test)[:, 1]
# test_auc = roc_auc_score(y_test, y_pred_proba_best_tree)
# print("Test AUC of best model:", test_auc)
```

```
Best parameters found: {'max_depth': 9, 'max_features': None, 'min_samples_le
af': 8, 'min_samples_split': 5}
Best AUC achieved: 0.8536670908679319
Test AUC of best model: 0.8547149697762877
```

In [ ]:
```
# Save the best_tree in a pickle
pickle.dump(best_tree, open(f"model_objects/best_tree.pickle", 'wb'))
```

Let's do the curve ROC and see the values AUC with the values for this Decision TreeClassifier

In [10]:
```
# # Predict probabilities on the training and test set
# y_pred_prob_tree_train = best_tree.predict_proba(X_train)[:, 1]  # Training 
# y_pred_prob_tree_test = best_tree.predict_proba(X_test)[:, 1]  # Test probab

# # Compute ROC curve and AUC for training data
# fpr_tree_train, tpr_tree_train, _ = roc_curve(y_train, y_pred_prob_tree_trai
# auc_tree_train = auc(fpr_tree_train, tpr_tree_train)

# # Compute ROC curve and AUC for test data
# fpr_tree_test, tpr_tree_test, _ = roc_curve(y_test, y_pred_prob_tree_test)
# auc_tree_test = auc(fpr_tree_test, tpr_tree_test)

# # Plotting ROC Curves
# plt.figure(figsize=(12, 6))
# plt.plot(fpr_tree_train, tpr_tree_train, label='Decision Tree Train (area = 
# plt.plot(fpr_tree_test, tpr_tree_test, color='red', linestyle='--', label='D
# plt.plot([0, 1], [0, 1], 'k--')
# plt.xlabel('False Positive Rate')
# plt.ylabel('True Positive Rate')
# plt.title('ROC Curve - Decision Tree')
# plt.legend(loc="lower right")
# plt.show()
```



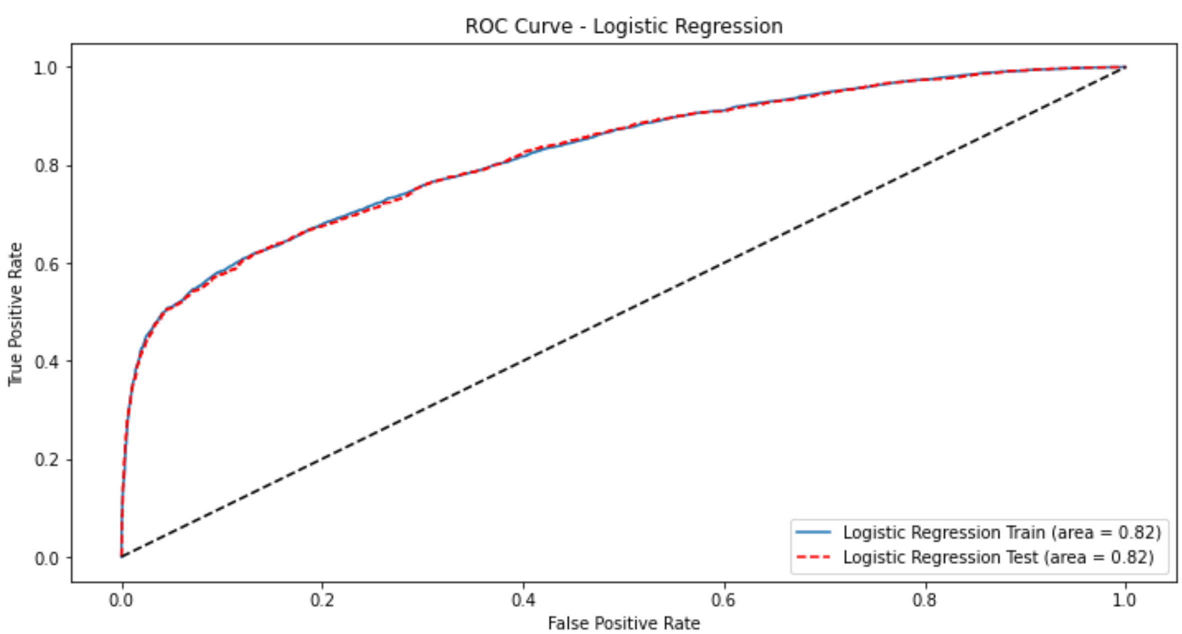
3.4.2 logistic regression

We are going to comment the cell below as it takes an approximate time of 20 minutes for it to run.

In [ ]:
```
# # Initialize the Logistic Regression model
# logistic_regression = LogisticRegression()

# # Define the parameter grid to search
# param_grid = {
#     'C': [0.001, 0.01, 0.1, 1, 10, 100],  # Inverse of regularization streng
#     'solver': ['newton-cg', 'lbfgs', 'liblinear', 'sag', 'saga'],  # Algorit
#     'max_iter': [100, 200, 300],  # Maximum number of iterations taken for t
# }

# # Define the scoring function using AUC
# scorer = make_scorer(roc_auc_score, needs_proba=True)

# # Setup the grid search with cross-validation
# grid_search = GridSearchCV(estimator=logistic_regression, param_grid=param_g

# # Fit grid search on the training data
# grid_search.fit(X_train, y_train)

# # Find the best model
# best_log_reg = grid_search.best_estimator_

# # Output the best parameter combination and the corresponding score
# print("Best parameters found:", grid_search.best_params_)
# print("Best AUC achieved:", grid_search.best_score_)

# # Optional: Evaluate the best model on the test set
# y_pred_proba_best_log_reg = best_log_reg.predict_proba(X_test)[:, 1]
# test_auc = roc_auc_score(y_test, y_pred_proba_best_log_reg)
# print("Test AUC of best model:", test_auc)
```

Let's do the curve ROC and see the values AUC with the values for this Logistic Regressor

In [12]:
```
# # Predict probabilities on the training and test set using the Logistic Regr
# y_pred_prob_log_reg_train = best_log_reg.predict_proba(X_train)[:, 1]  # Tra
# y_pred_prob_log_reg_test = best_log_reg.predict_proba(X_test)[:, 1]  # Test 

# # Compute ROC curve and AUC for training data
# fpr_log_reg_train, tpr_log_reg_train, _ = roc_curve(y_train, y_pred_prob_log
# auc_log_reg_train = auc(fpr_log_reg_train, tpr_log_reg_train)

# # Compute ROC curve and AUC for test data
# fpr_log_reg_test, tpr_log_reg_test, _ = roc_curve(y_test, y_pred_prob_log_re
# auc_log_reg_test = auc(fpr_log_reg_test, tpr_log_reg_test)

# # Plotting ROC Curves
# plt.figure(figsize=(12, 6))
# plt.plot(fpr_log_reg_train, tpr_log_reg_train, label='Logistic Regression Tr
# plt.plot(fpr_log_reg_test, tpr_log_reg_test, color='red', linestyle='--', la
# plt.plot([0, 1], [0, 1], 'k--')
# plt.xlabel('False Positive Rate')
# plt.ylabel('True Positive Rate')
# plt.title('ROC Curve - Logistic Regression')
# plt.legend(loc="lower right")
# plt.show()
```

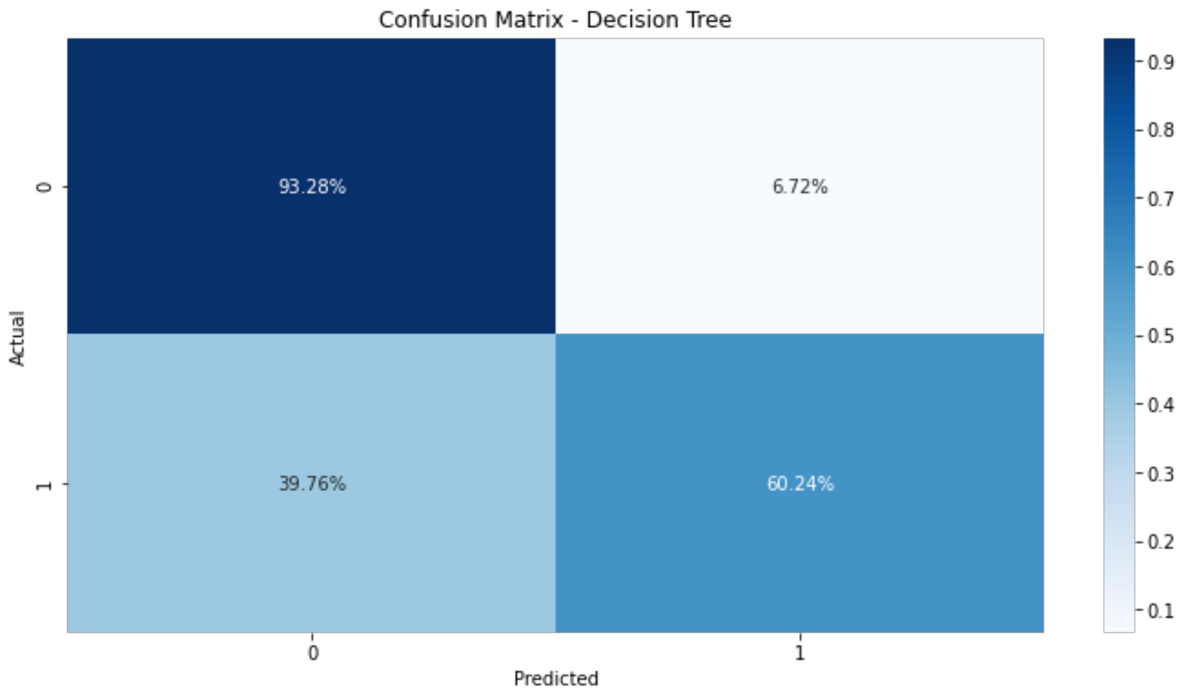


3.5 Confusion matrix

3.5.1 Decision Tree Classifier

In [34]:
```
# Let's apply a threshold to the probabilities of y_pred_prob_log_reg_test to
y_pred_tree = np.where(y_pred_prob_tree_test >= 0.5, 1, 0)

# Confusion Matrix for Decision Tree
cm_tree = confusion_matrix(y_test, y_pred_tree)
```

In [35]:
```
# Normalize the confusion matrix by row (actual class)
cm_tree_normalized = cm_tree.astype('float') / cm_tree.sum(axis=1)[:, np.newax

# Plotting the Confusion Matrix for Decision Tree
plt.figure(figsize=(12, 6))
sns.heatmap(cm_tree_normalized, annot=True, fmt='.2%', cmap='Blues', xticklabe
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Decision Tree')
plt.show()
```



False Negatives (FN): 39.76%

- Impact: A high rate of false negatives means that a significant proportion of the positive class (e.g., non-functional pumps) is being misclassified as negative (e.g., functional pumps). This could lead to serious issues in the business context, as non-functional pumps that are not identified will not receive the necessary maintenance or repairs, leading to prolonged downtimes and possibly affecting the service quality and user satisfaction.
- Business Problem Impact: This could result in increased downtime for the pumps, higher maintenance costs over time, and a negative impact on customer satisfaction due to unreliable water supply.

False Positives (FP): 6.72%

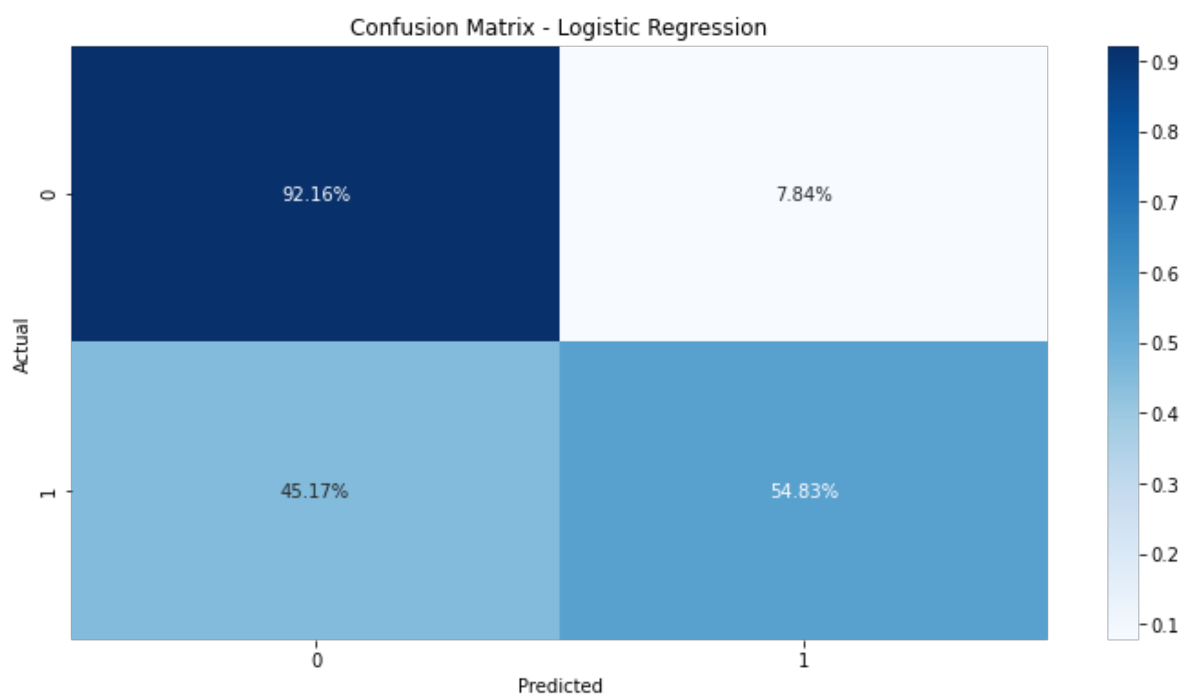
- Impact: A relatively low rate of false positives indicates that only a small proportion of the negative class (e.g., functional pumps) is being misclassified as positive (e.g., non-functional pumps). While this is less severe compared to false negatives, it still leads to unnecessary maintenance actions being taken on functional pumps.

- Business Problem Impact: This could lead to inefficient allocation of resources, where time and effort are spent on checking or repairing pumps that are actually functional. This can increase operational costs and divert attention from genuinely non-functional pumps that need repairs.

3.5.2 Logistic Regression

In [26]:
```
# Let's apply a threshold to the probabilities of y_pred_prob_log_reg_test to
y_pred_log_reg = np.where(y_pred_prob_log_reg_test >= 0.5, 1, 0)

# Confusion Matrix for Logistic Regression
cm_log_reg = confusion_matrix(y_test, y_pred_log_reg)
```

In [31]:
```
# Normalize the confusion matrix by row (actual class)
cm_log_reg_normalized = cm_log_reg.astype('float') / cm_log_reg.sum(axis=1)[:,

# Plotting the Confusion Matrix for Logistic Regression
plt.figure(figsize=(12, 6))
sns.heatmap(cm_log_reg_normalized, annot=True, fmt='.2%', cmap='Blues', xtickl
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Logistic Regression')
plt.show()
```

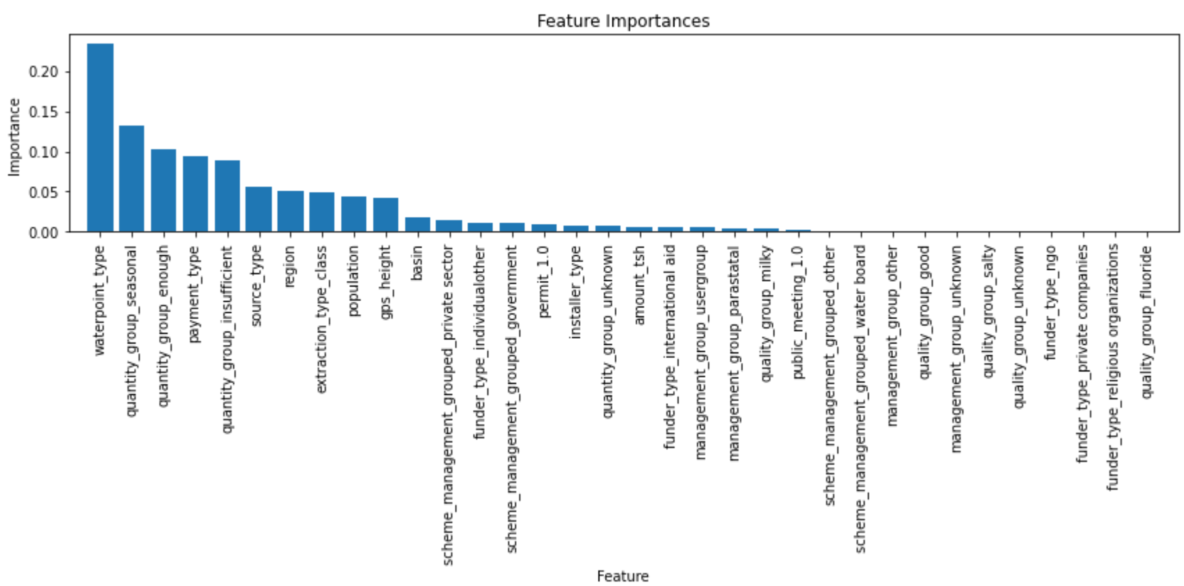


The conclusion that we arrive to with the confusion matrix of the logistic regression is the same as the one from the Decision Tree Classifier although, it is worth noting that this one has higher proportions in false negatives (45.17%) and false positives (7.84%).

4. Feature importance

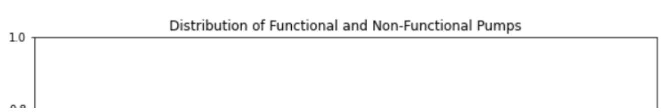
We are now going to execute a feature importance code to be able to see the level of importance of all variables when doing the predictions

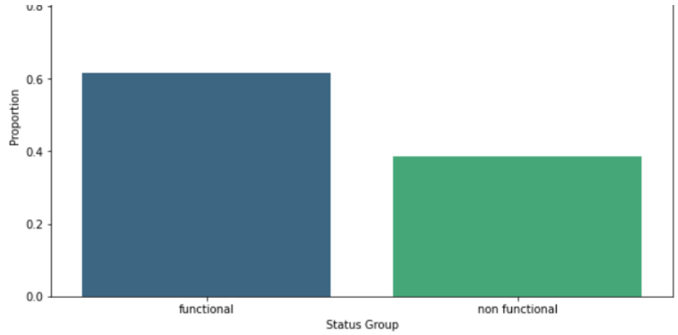
In [36]:
```
# Obtain the most important features affecting the status of a pump
importances = best_tree.feature_importances_

# Obtener los nombres de las características
feature_names = X_train.columns

# Create a bar graph for the importance of the characteristics
indexes = np.argsort(importances)[::-1]  # Order importances in descending ord

plt.figure(figsize=(12, 6))
plt.title("Feature Importances")
plt.bar(range(X_train.shape[1]), importances[indexes], align="center")
plt.xticks(range(X_train.shape[1]), feature_names[indexes], rotation=90)
plt.xlim([-1, X_train.shape[1]])
plt.xlabel("Feature")
plt.ylabel("Importance")
plt.tight_layout()
plt.show()
```



5. Conclusion

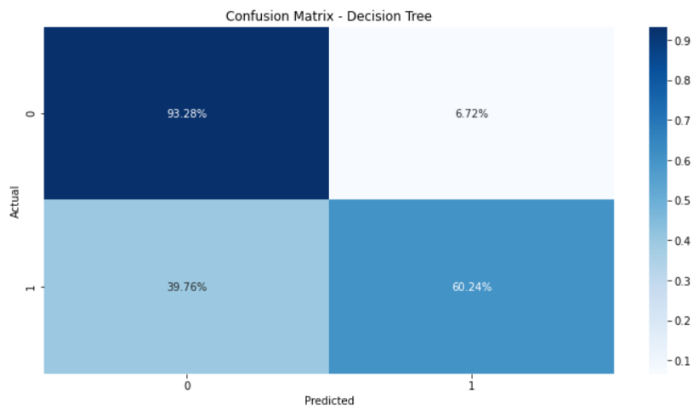
Considering the distribution of the dependent variable





As we can see there is not an imbalance problem even though the majority of pumps are functional.

Diving into the model results, let's begin by looking into the confusion matrix



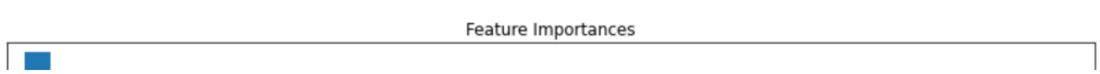
The confusion matrix indicates that the model has a high rate of false negatives (39.76%), which can significantly impact the business by failing to identify non-functional pumps that need repairs. This can lead to prolonged downtimes and negatively affect customer satisfaction. The false positive rate (6.72%) is relatively low, meaning fewer resources will be wasted on unnecessary maintenance. However, the primary concern should be reducing the false negative rate to ensure that non-functional pumps are correctly identified and repaired promptly.

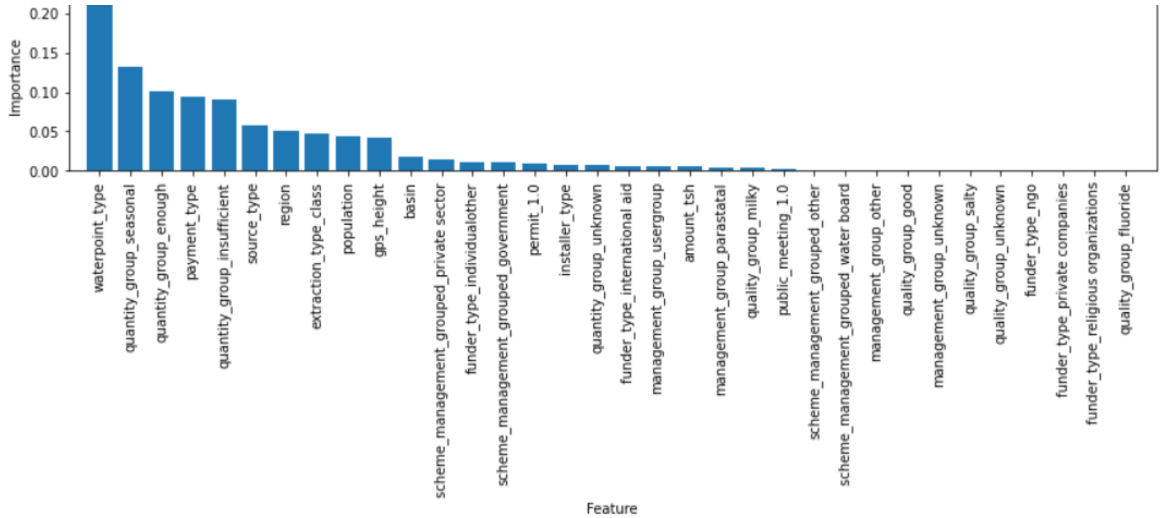
Based on the metrics, the best AUC and confusion matrix is obtained with a Decision Tree Classifier. As is observable, the AUC is of 0.85 for the test. In the case of the Logistic Regression model, an AUC of 0.82 is obtained for the test.

The variables that are most important and that permit us to best descriminate are:

1. waterpoint_type
2. quantity_group_seasonal
3. quantity_group_enough
4. payment_type
5. quantity_group_insufficient

We are interested in these 5 variables because they are the ones that have the most influence when determining whether a pump is functional or non-functional.





Considering that we used a one-hot encoder and that the categories for each variable were treated as independent variables, the three variables that contribute the most to the model are:

1. waterpoint_type
2. quantity_group
3. payment_type

Here we will show the contingency tables for each variable divided into functional, functional with repairs, and non functional pumps:

```
Table for payment_type:
```

payment_type	annually	monthly	never pay	on failure	other	per bucket	unknown
status_group							
functional	8.49	16.99	35.27	7.53	1.89	18.88	10.94
functional needs repair	5.72	21.47	44.17	6.42	2.73	9.47	10.01
non functional	2.87	8.29	52.85	5.29	1.42	10.89	18.39

```
Table for quantity_group:
```

quantity_group	dry	enough	insufficient	seasonal	unknown
status_group					
functional	0.49	67.11	24.54	7.21	0.66
functional needs repair	0.86	55.59	33.59	9.64	0.32
non functional	26.52	40.04	25.25	5.74	2.46

```
Table for waterpoint_type:
```

waterpoint_type	cattle trough	communal standpipe	communal standpipe multiple	dam	hand pump	improved spring	other
status_group							
functional	0.26	54.95	6.93	0.02	33.49	1.75	2.60
functional needs repair	0.05	52.35	15.01	0.00	23.84	1.97	6.79
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

non functional	0.13	37.40	14.11	0.00	24.77	0.60	22.99

6. Recommendations

1. Considering that most of the functional pumps have monthly payment plans or a per bucket, the Tanzanian government can consider modifying the existing payment plans of those pumps where the payments are different from those payment types, so that the chance of the pump being functional can be increased.

2. Considering that almost none of the functional pumps are dry, it is possible to verify which pumps are dry as a proxy variable to know if they are functional or not and thus focus efforts on repairing them.

3. We recommend investing in communal standpipe multiple access points as they best detect pump functionality.