

QS World Rankings 2025 Analysis

A CASE STUDY REPORT

Submitted by

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For the course

Data Science - 21CSS303T

*In partial fulfillment of the requirements for
the degree of BACHELOR OF TECHNOLOGY*



DEPARTMENT OF COMPUTING TECHNOLOGIES

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BONAFIDE CERTIFICATE

Certified that Computer Networks, A Case Study Report titled “**QS World Rankings 2025 Analysis**”, is the Bonafide work of **Diptayan Jash** (RA2211003010890), who carried out the case study under my supervision. Certified further, that to the best of my knowledge the work reported herein does not form any other work.

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Date:

Introduction

The QS World University Rankings are globally recognized for evaluating universities based on several academic and employer-related metrics. Predicting these rankings can help universities benchmark themselves and identify areas of improvement. In this project, we leverage structured historical data and apply advanced machine learning and deep learning techniques to predict the overall QS score for universities. Our goal is not only to achieve high prediction accuracy but also to interpret the contribution of different factors towards the rankings.

GitHub Link: <https://github.com/djdiptayan1/QS-World-Rankings-2025-Analysis-DS>

Objectives

- Predict the **Overall Score** for universities using multiple features.
- Understand feature importance and interpret model behaviour.
- Build and evaluate different ML/DL models to select the best performing one.
- Visualize data trends and model performance.
- Identify limitations and potential improvements.

Methodology

Data Collection and Initial Exploration

The dataset, QS World University Rankings contains global university ranking data compiled by QS for the year 2025. Each row represents a university, and the columns include various metrics that affect the university's performance in the global ranking system.

Key Features and Their Descriptions

Column Name	Description
RANK_2025	QS ranking of the university in 2025
RANK_2024	QS ranking of the university in 2024 (used to track improvement or drop)
Institution_Name	Full name of the university or institution
Location	Country in which the university is located
Region	Region or continent (e.g., Asia, Europe, North America)
SIZE	Classification of institution size (e.g., L, XL)
FOCUS	Whether the university is specialized or comprehensive
RES.	Research intensity category (e.g., Very High, High)
STATUS	Whether the university is Public or Private

Score-Based Metrics

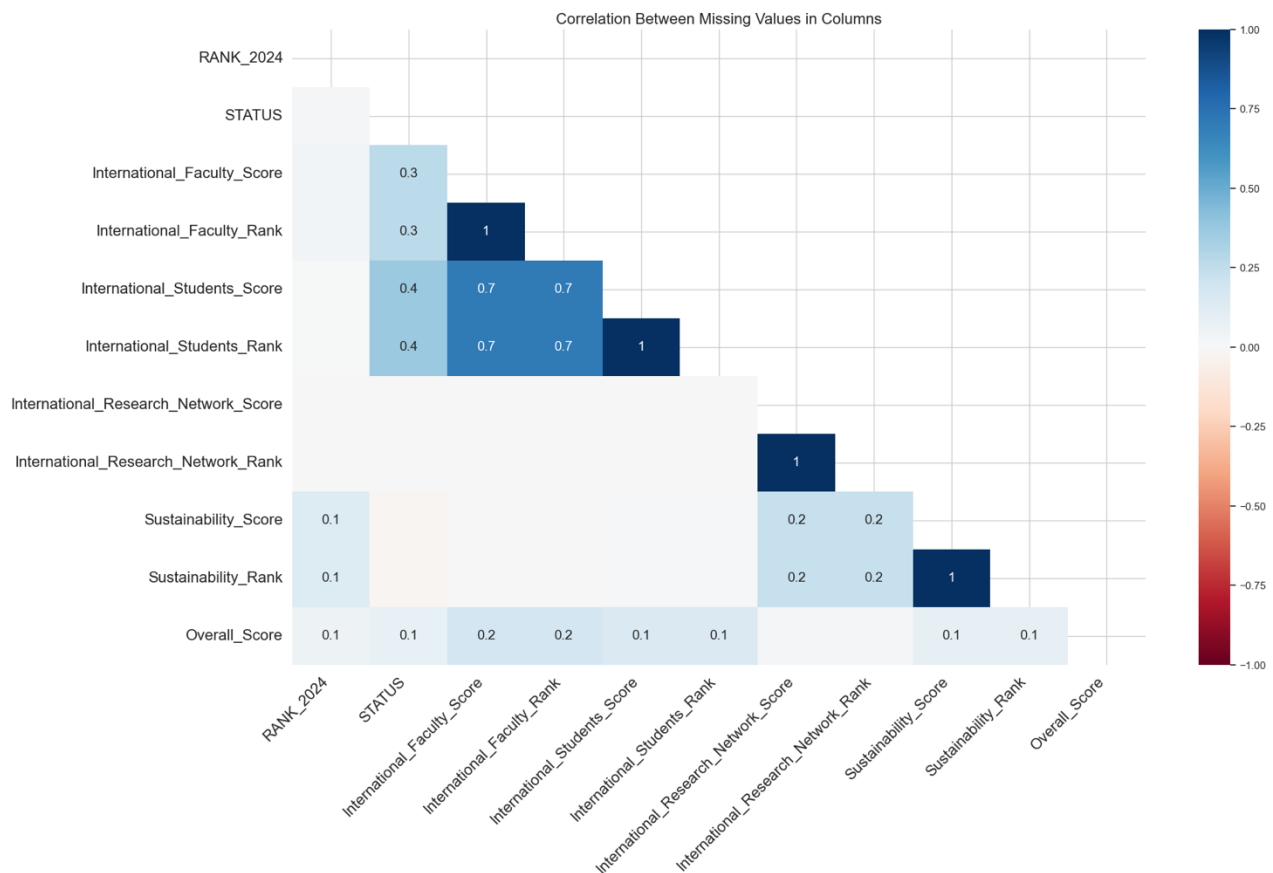
Metric	What it Measures
Academic_Reputation_Score	Score from global academic survey
Academic_Reputation_Rank	Rank position based on academic reputation
Employer_Reputation_Score	Score from employer survey on graduate quality
Employer_Reputation_Rank	Rank based on employer feedback
Faculty_Student_Score	Measures student-to-faculty ratio
Faculty_Student_Rank	Rank position for faculty/student ratio
Citations_per_Faculty_Score	Research impact based on citations per faculty member
Citations_per_Faculty_Rank	Ranking based on citation score
International_Faculty_Score	Percentage of international faculty members
International_Faculty_Rank	Rank based on international faculty
International_Students_Score	Percentage of international students
International_Students_Rank	Rank based on international student ratio
International_Research_Network_Score	Score reflecting international research collaboration
International_Research_Network_Rank	Rank based on global research partnerships
Employment_Outcomes_Score	Score for alumni employment success
Employment_Outcomes_Rank	Rank based on employment outcomes
Sustainability_Score	Measures how sustainable and eco-conscious the institution is
Sustainability_Rank	Ranking based on environmental & sustainability initiatives
Overall_Score	Final total score combining all weighted components

Data Cleaning and Preprocessing

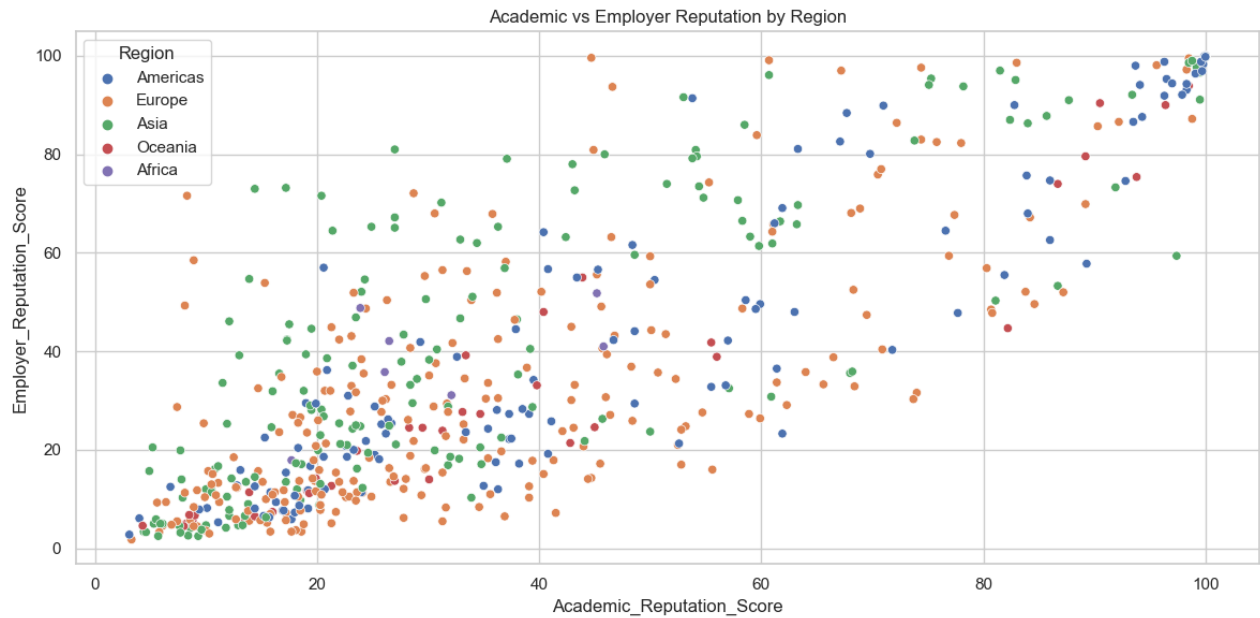
- Rank columns containing values like "601+", "127=" were converted to numerical format (e.g., 601, 127).
- Columns such as Overall_Score, RANK_2024, RANK_2025, and all *_Rank fields were converted to float64.
- Categorical columns like Region, Location, STATUS, etc., were encoded using LabelEncoder.
- Missing values were handled using:
 - Row removal for Overall_Score (target)
 - Mode imputation for categorical fields
 - Mean imputation for numerical scores
 - Dummy placeholder 999 for rank columns
- A final df.dropna() was applied to ensure a completely clean dataset.
- StandardScaler was used to normalize all numeric features.

Data Visualization and EDA

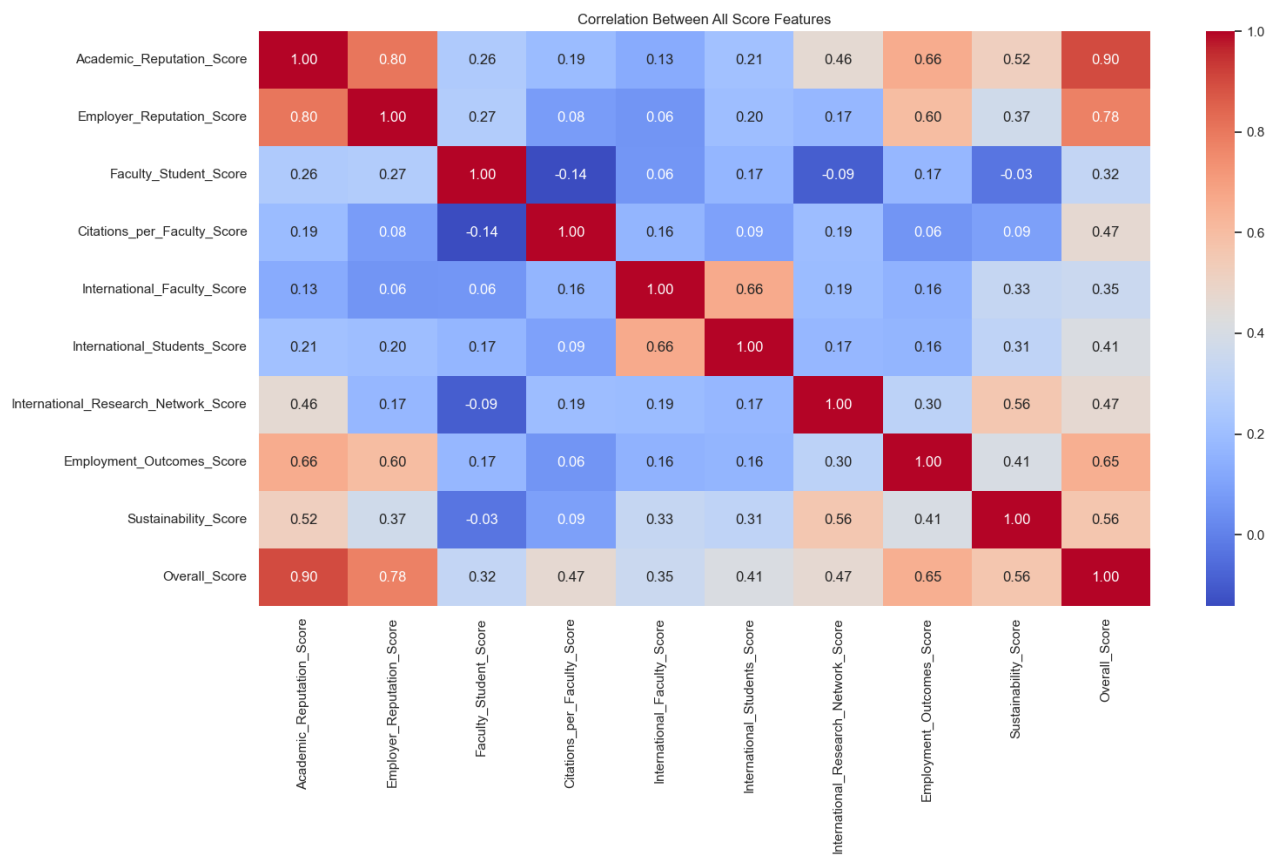
- **Correlation Matrix:** A heatmap was plotted to understand the correlation between features and the Overall Score.



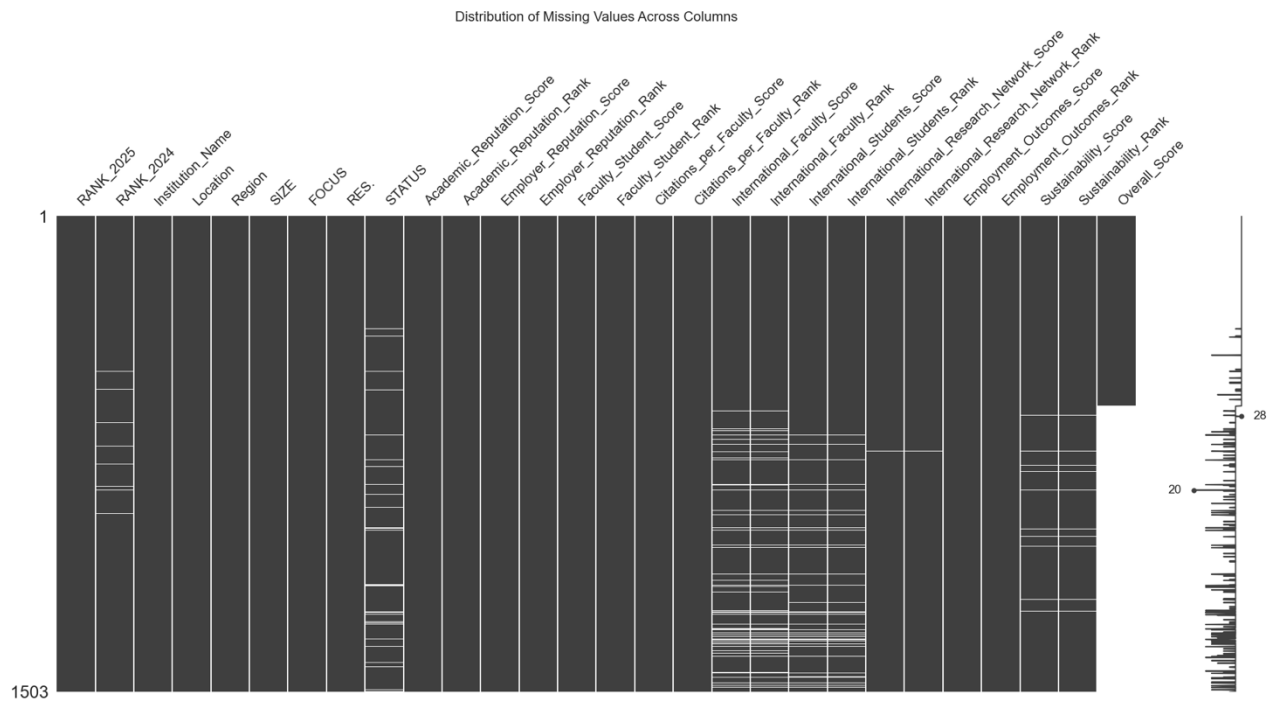
- **Distribution Plots:** Distribution of key features such as Academic Reputation and Employer Reputation was visualized.



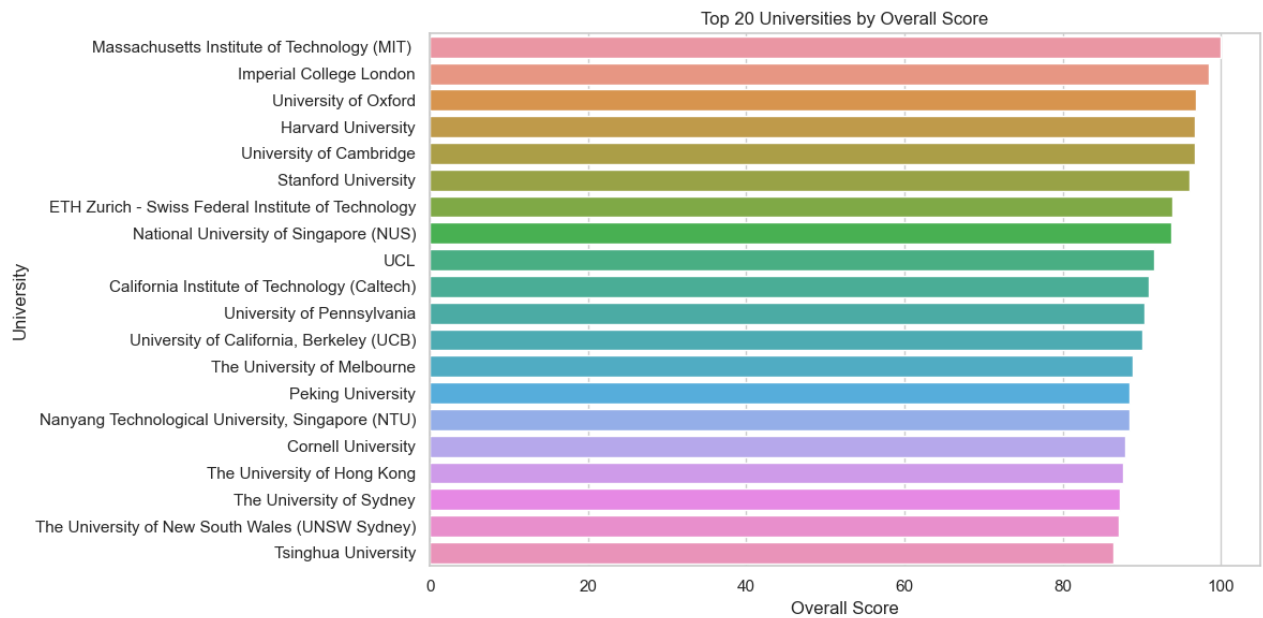
- **Outlier Detection:** Boxplots were used to check for extreme outliers.



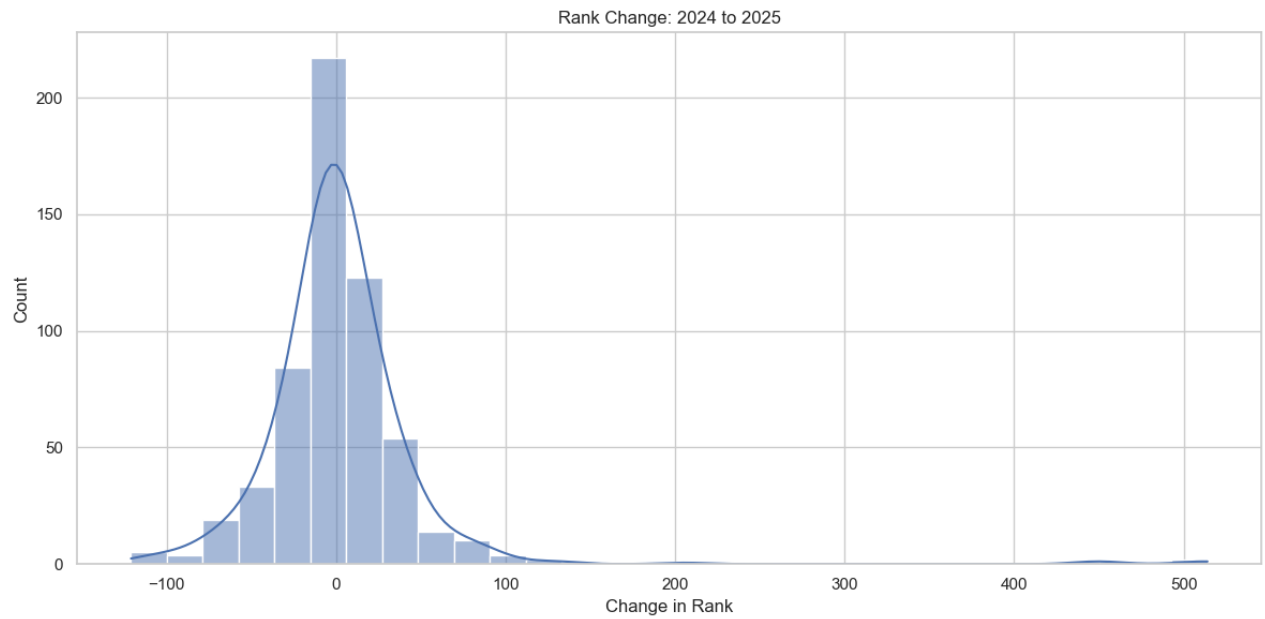
- Visualizing Missing Data Patterns



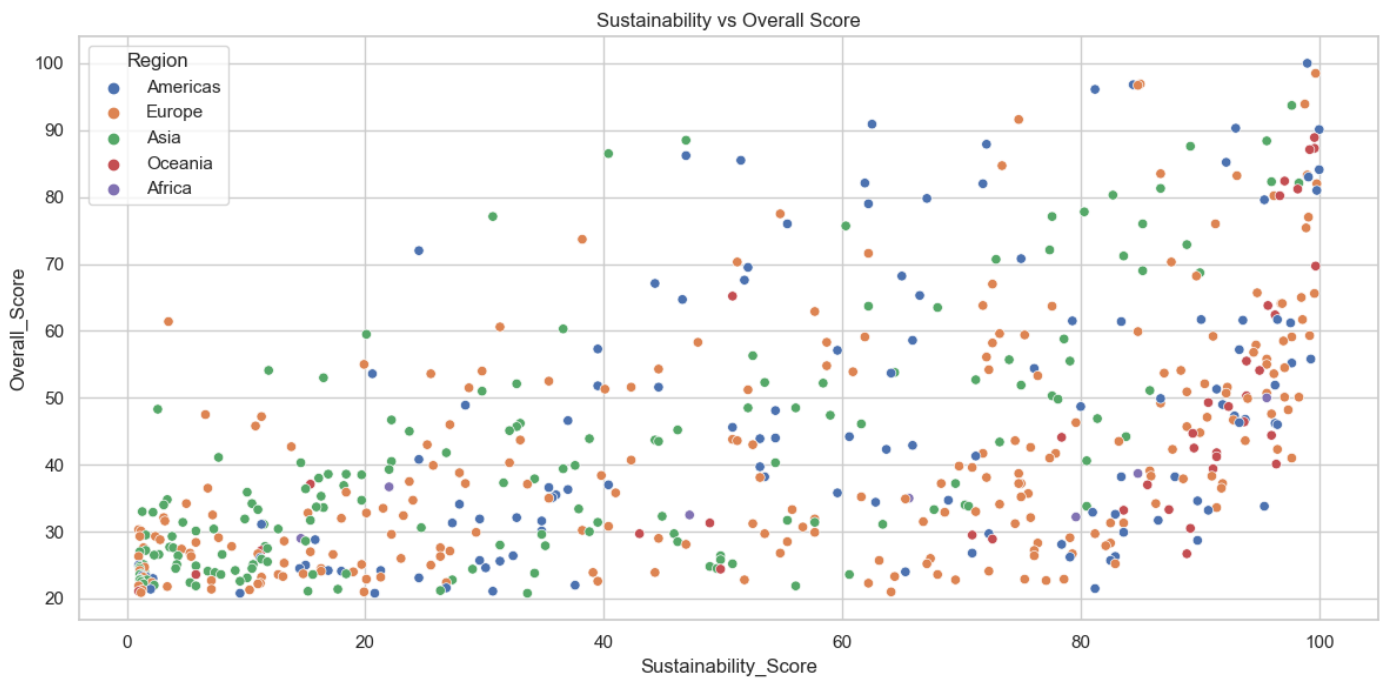
- Top 20 universities by Overall score



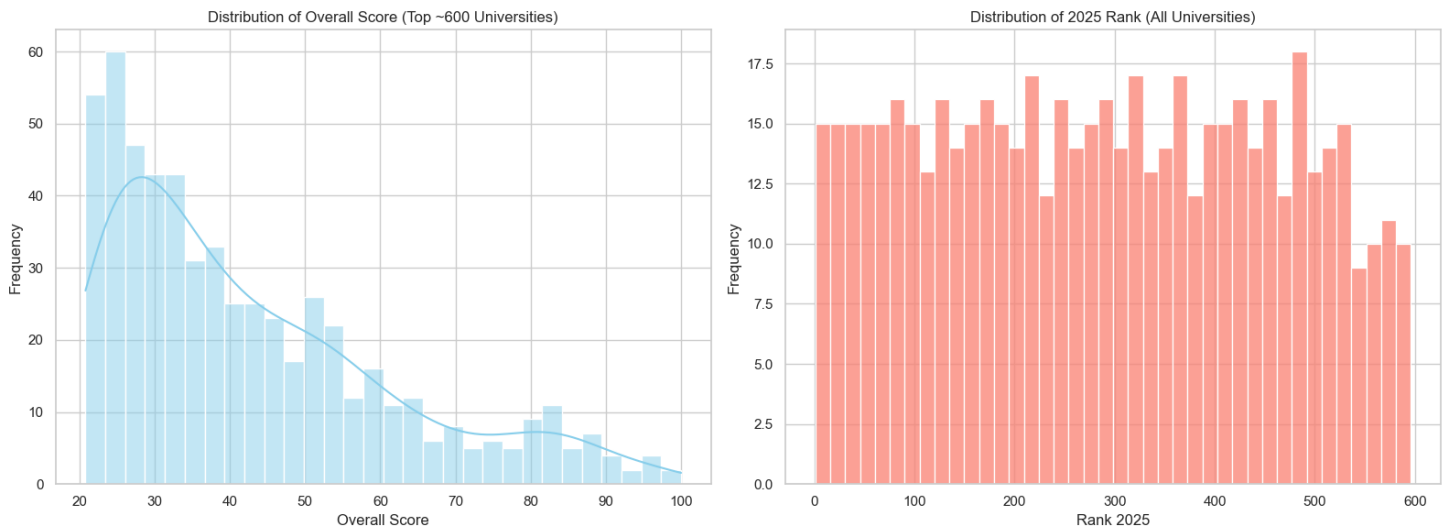
- **Rank Change in 2024 v/s 2025**



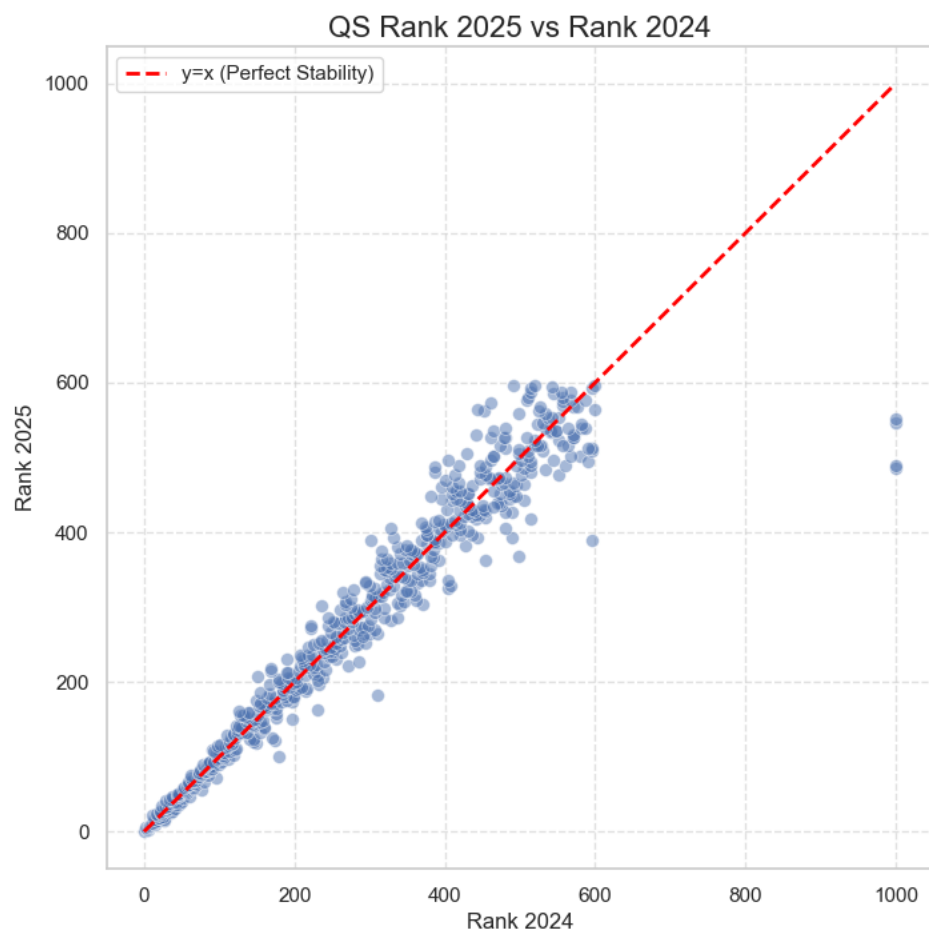
- **Sustainability v/s overall score**



- **Distribution of overall score and 2025 rankings**



- **Stability of 2024 and 2025 rankings**



Model Development

To accurately predict the **Overall Score** for universities, a wide range of **classical machine learning models** and **deep learning models** were developed, trained, and evaluated. Each model type was selected to explore different aspects of data patterns from simple linear trends to highly non-linear and complex relationships.

Classical Machine Learning Models

1. Linear Regression

Linear Regression was the **baseline model**, representing the simplest method to understand the relationship between the input features and the target score. It assumes a **linear relationship** between the independent variables and the dependent variable (Overall Score).

- **Objective:** Provide a straightforward and interpretable model.
- **Strength:** Very fast to train and easy to interpret.
- **Limitation:** Cannot capture non-linear relationships.

2. Ridge Regression

Ridge Regression introduces **L2 regularization** to the linear model. This means it **adds a penalty** equal to the square of the magnitude of the coefficients to the loss function, discouraging large coefficients and thus reducing the risk of overfitting.

- **Objective:** Improve generalization performance while maintaining linearity.
- **Strength:** Effective when many features are correlated.
- **Limitation:** Still assumes linearity; cannot model complex patterns.

3. Lasso Regression

Lasso Regression uses **L1 regularization**, which can **shrink some coefficients to zero**, effectively performing **feature selection**.

- **Objective:** Improve model performance and reduce complexity by ignoring irrelevant features.
- **Strength:** Useful when we suspect that only a subset of features are meaningful.
- **Limitation:** Can be unstable if many features are highly correlated.

4. K-Nearest Neighbors (KNN) Regressor

KNN Regressor is a **non-parametric model** that predicts the output based on the **average outcome of the k closest data points** in the training set.

- **Objective:** Capture local relationships in data without assuming a global functional form.
- **Strength:** Very flexible; no assumptions about data distribution.
- **Limitation:** Computationally expensive at prediction time; sensitive to the choice of 'k' and distance metric.

5. Support Vector Regression (SVR) with RBF Kernel

SVR with an RBF (Radial Basis Function) kernel allows modeling of **non-linear relationships** by mapping input features into a higher-dimensional space.

- **Objective:** Find a function that has at most ϵ deviation from the actual targets and is as flat as possible.
- **Strength:** Handles non-linear data efficiently.
- **Limitation:** Sensitive to hyperparameters (C, epsilon, kernel parameters).

6. Random Forest Regressor

Random Forest builds **an ensemble of decision trees** using bootstrap aggregation (bagging).

The final prediction is the average of the outputs of all trees.

- **Objective:** Reduce variance compared to individual decision trees and improve prediction accuracy.
- **Strength:** Robust to overfitting; handles non-linearities well.
- **Limitation:** Less interpretable compared to linear models.

7. Gradient Boosting Regressor

Gradient Boosting is a **sequential ensemble method** where each new tree tries to correct the errors made by the previous ones.

- **Objective:** Minimize prediction errors through a series of incremental improvements.
- **Strength:** Highly accurate and powerful.
- **Limitation:** Can overfit if not carefully tuned (learning rate, number of trees).

Deep Learning Models

Deep learning approaches were designed to **capture very complex, high-dimensional, and non-linear patterns** that traditional models might miss. All networks were built and trained using **TensorFlow/Keras**.

1. Simple Dense Model

- **Architecture:**
 - 2 hidden layers.
 - Each layer used **ReLU activation** functions to introduce non-linearity.
- **Objective:** Build a basic yet deep enough network capable of learning non-linear mappings between features and the Overall Score.
- **Strength:** Quick to train and simple to tune.
- **Limitation:** Can overfit if the dataset is small.

2. Deep Dense Model with Dropout

- **Architecture:**
 - Deeper network with **more neurons per layer**.
 - Added **Dropout layers** after dense layers to randomly deactivate a subset of neurons during training.
- **Objective:** Increase model capacity while controlling overfitting.
- **Strength:** Generalizes better than a simple dense model, especially on unseen data.
- **Limitation:** Requires careful tuning of the dropout rate.

3. Regularized Dense Network

- **Architecture:** Like Deep Dense but with **additional regularization techniques**:
 - **Lower learning rate.**
 - **Dropout regularization** after multiple layers.
- **Objective:** Ensure **slow and stable convergence** and **prevent overfitting**.
- **Strength:** Very stable during training; good generalization.
- **Limitation:** Training time is longer due to a lower learning rate.

Model Evaluation

Metrics used for evaluation:

- **R² Score:** Measures how well the model predicts variance in the data.
- **Mean Absolute Error (MAE)**
- **Root Mean Squared Error (RMSE)**

Performance Summary

Models	R2_Score	MSE	RMSE
LinearRegression	0.999996	0.001079	0.032843
Lasso	0.999992	0.002181	0.046705
Ridge	0.999651	0.090147	0.300245
RandomForest	0.938467	15.911768	3.988956
GradientBoosting	0.929891	18.129514	4.257877
SVR	0.917246	21.399282	4.625936
KNN	0.850719	38.602412	6.213084

Performance Summary DeepLearning

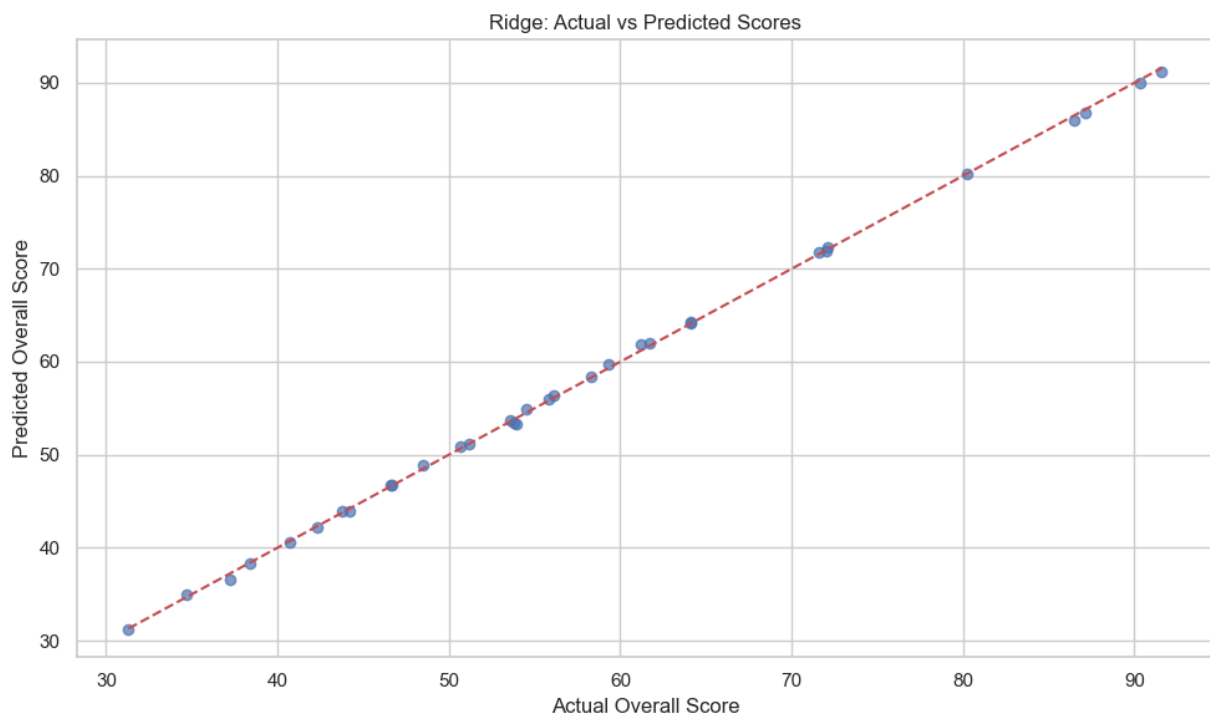
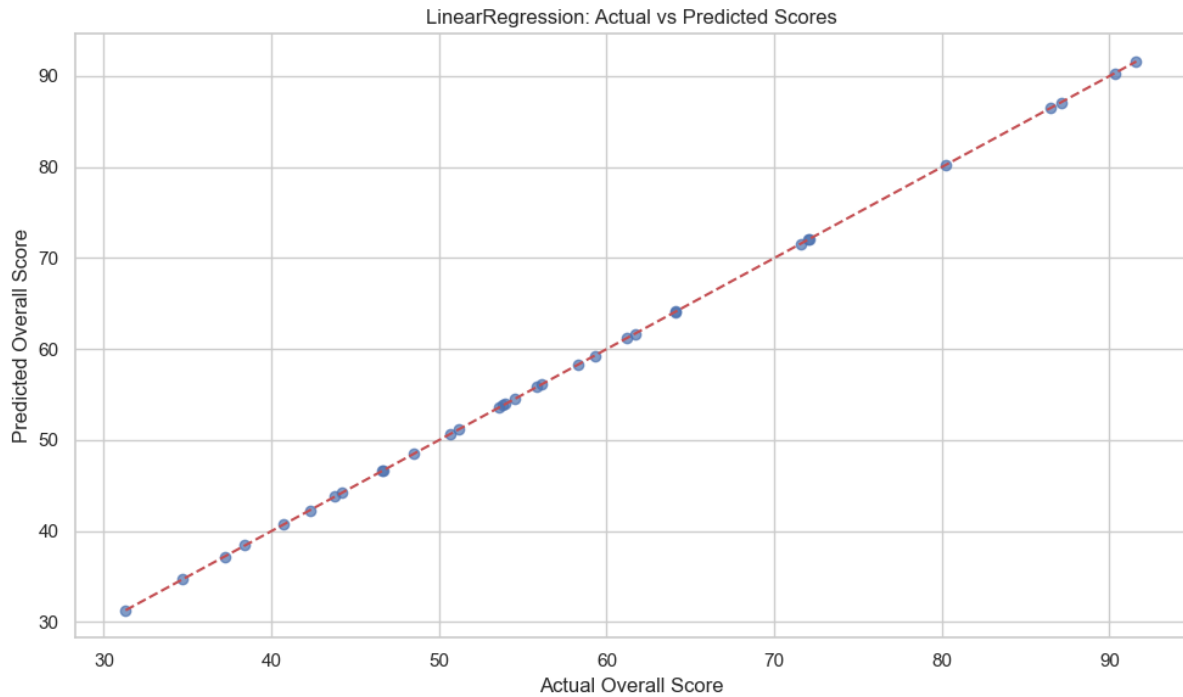
Models	Test_MAE
Deep_Dense	5.720979
Simple_Dense	6.851562
Regularized_Dense	8.381104

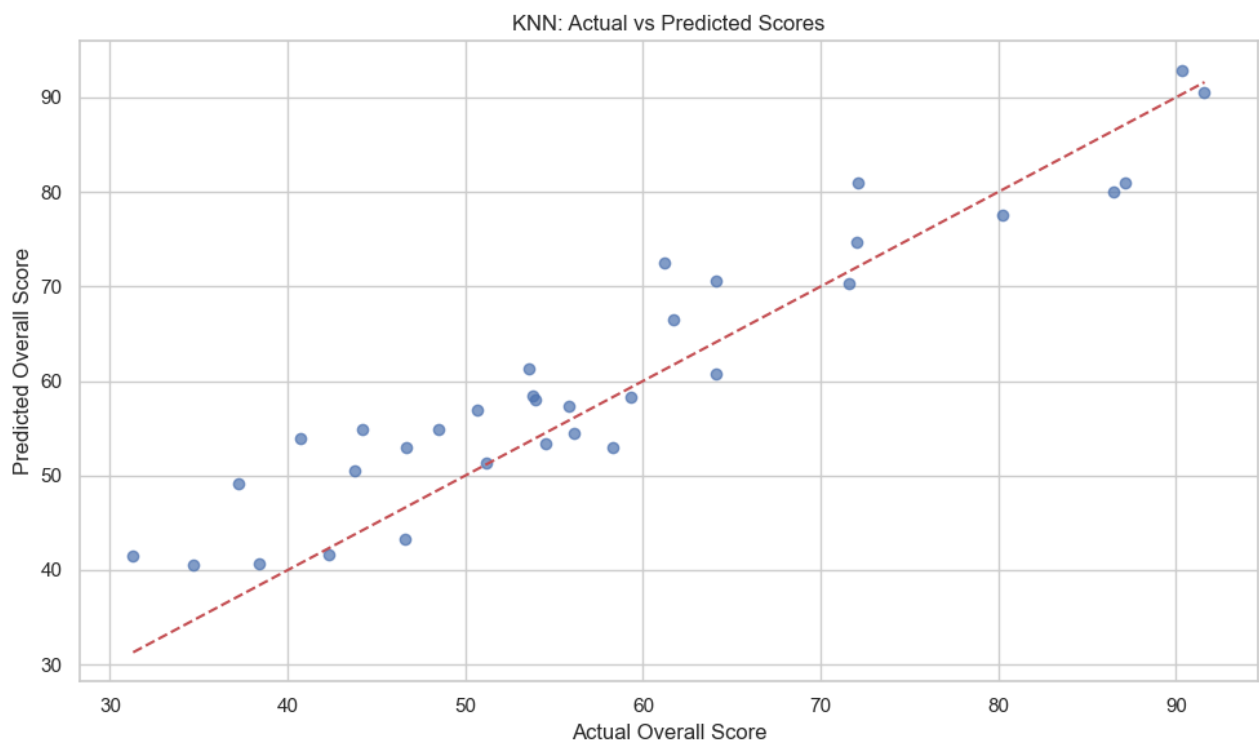
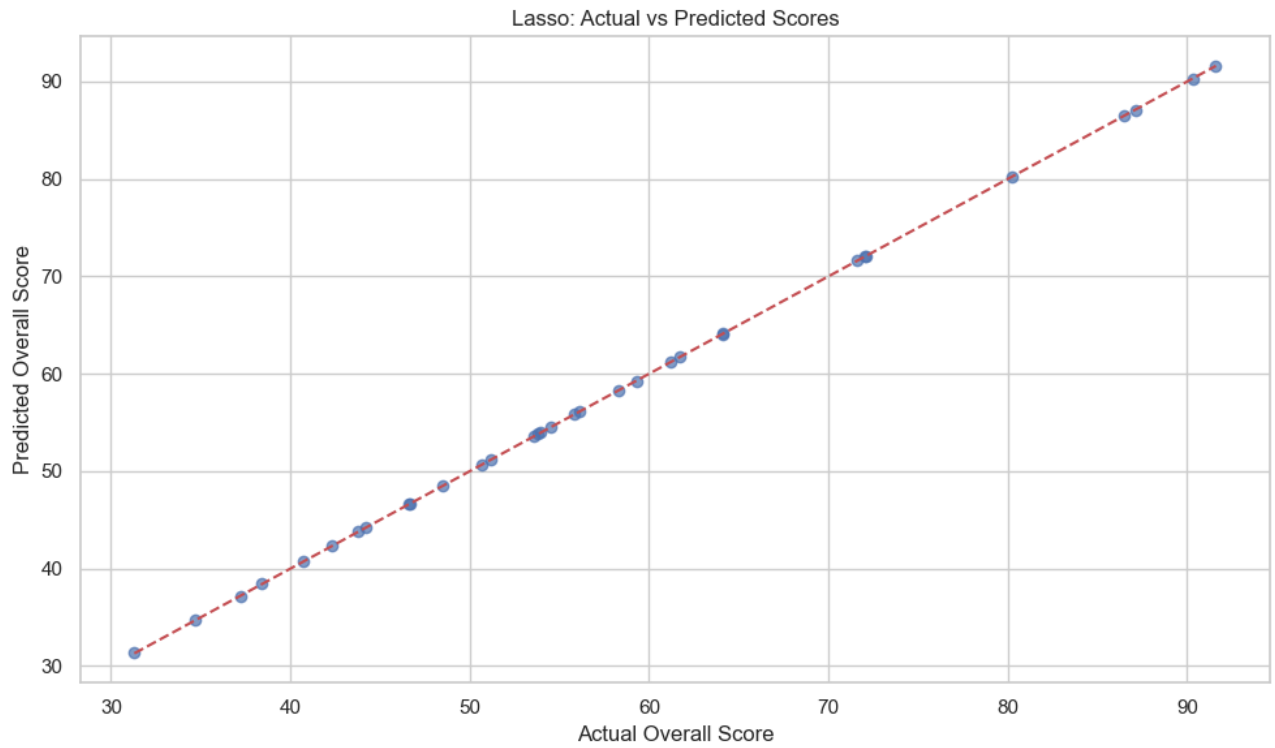
Interpretability

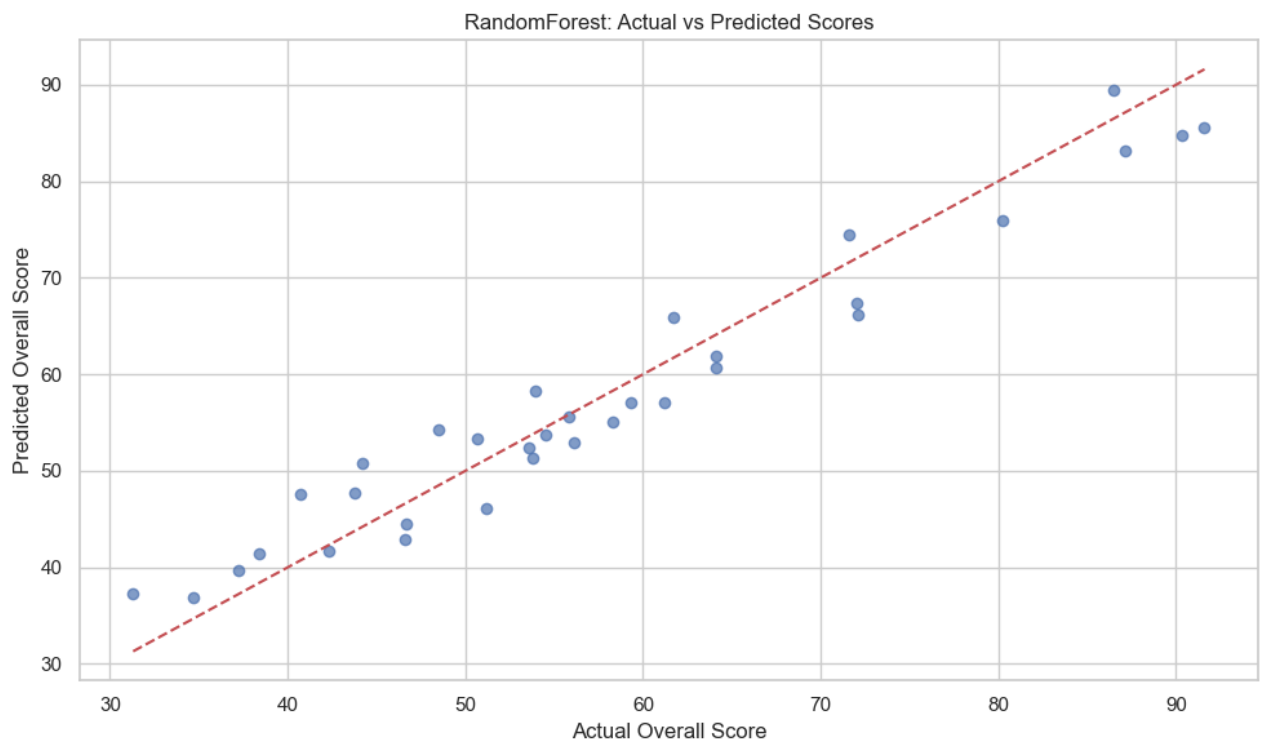
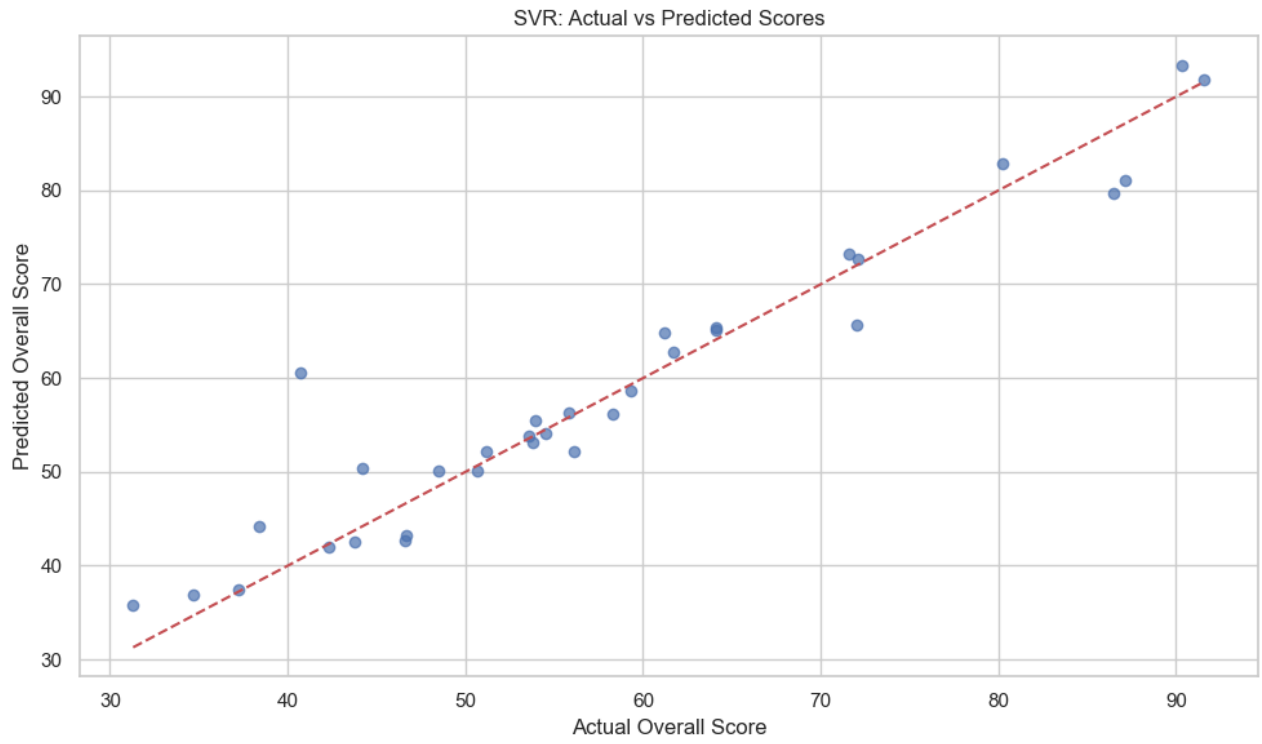
- **Tree-based models** showed that **Academic Reputation Score**, **Employer Reputation Score**, and **Citations per Faculty Score** were the top features.
- **SHAP values** were optionally used to explain feature contributions in tree models.

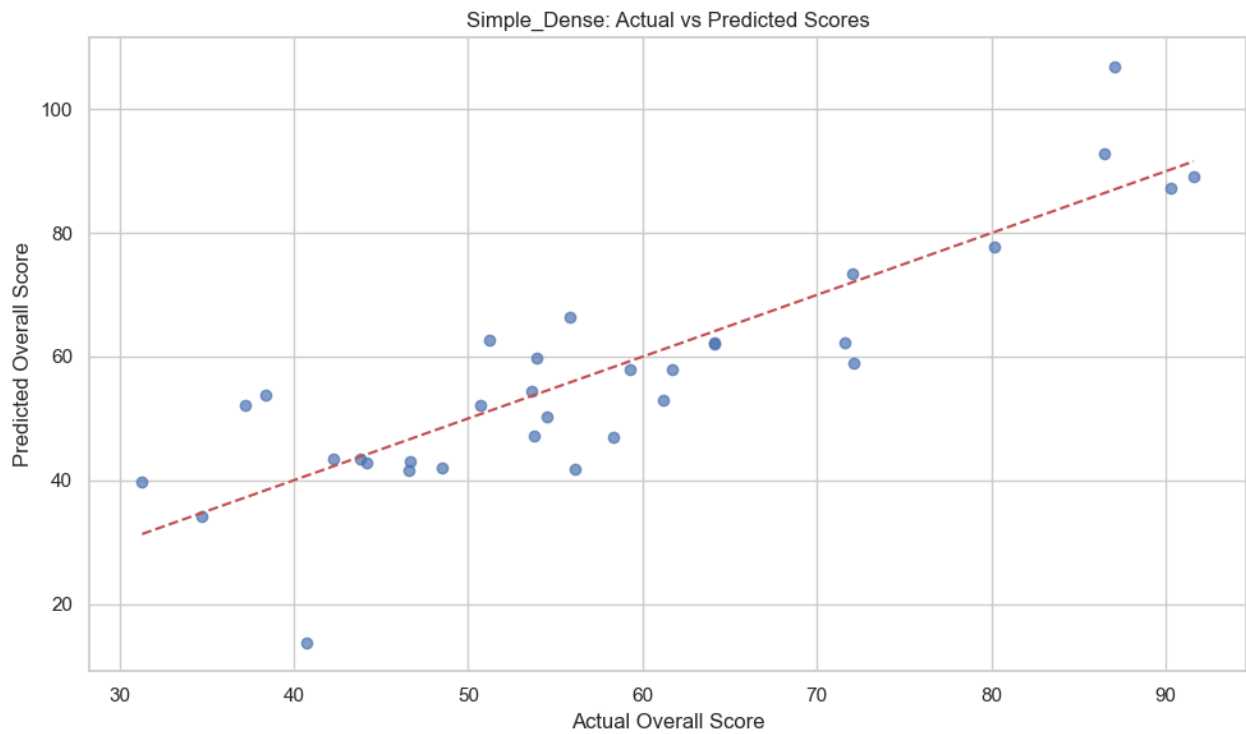
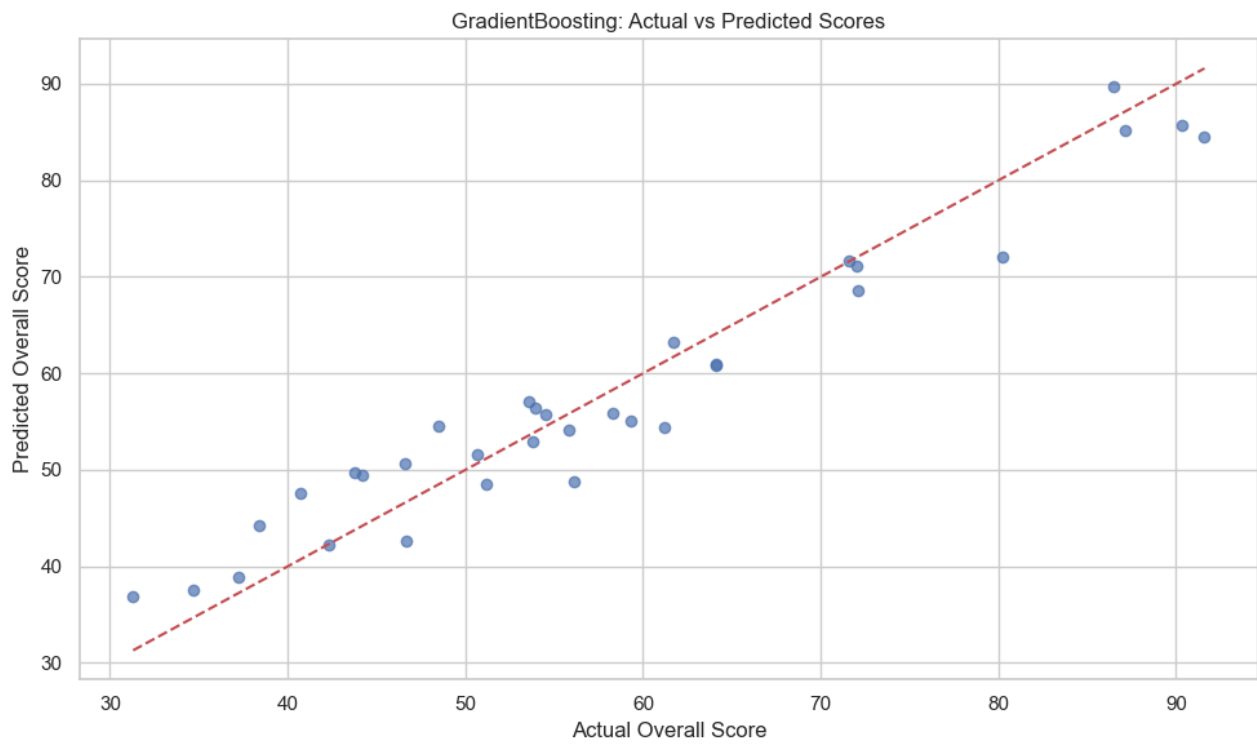
Prediction and Final Visualization

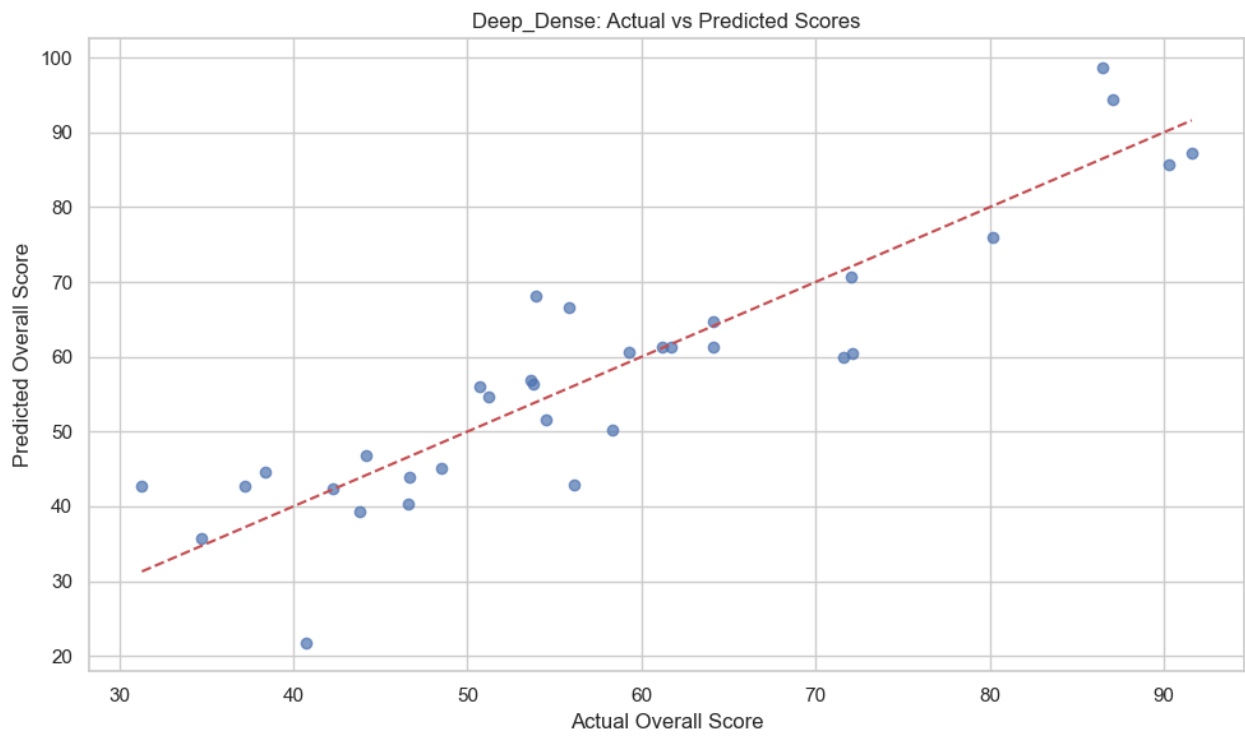
- Scatter plots between predicted vs. actual scores confirmed the high accuracy visually (points closely aligned to the $y=x$ line).
- Final predictions for test data were tabulated.
- Some universities were predicted to have higher/lower overall scores than their 2024 rankings suggested.





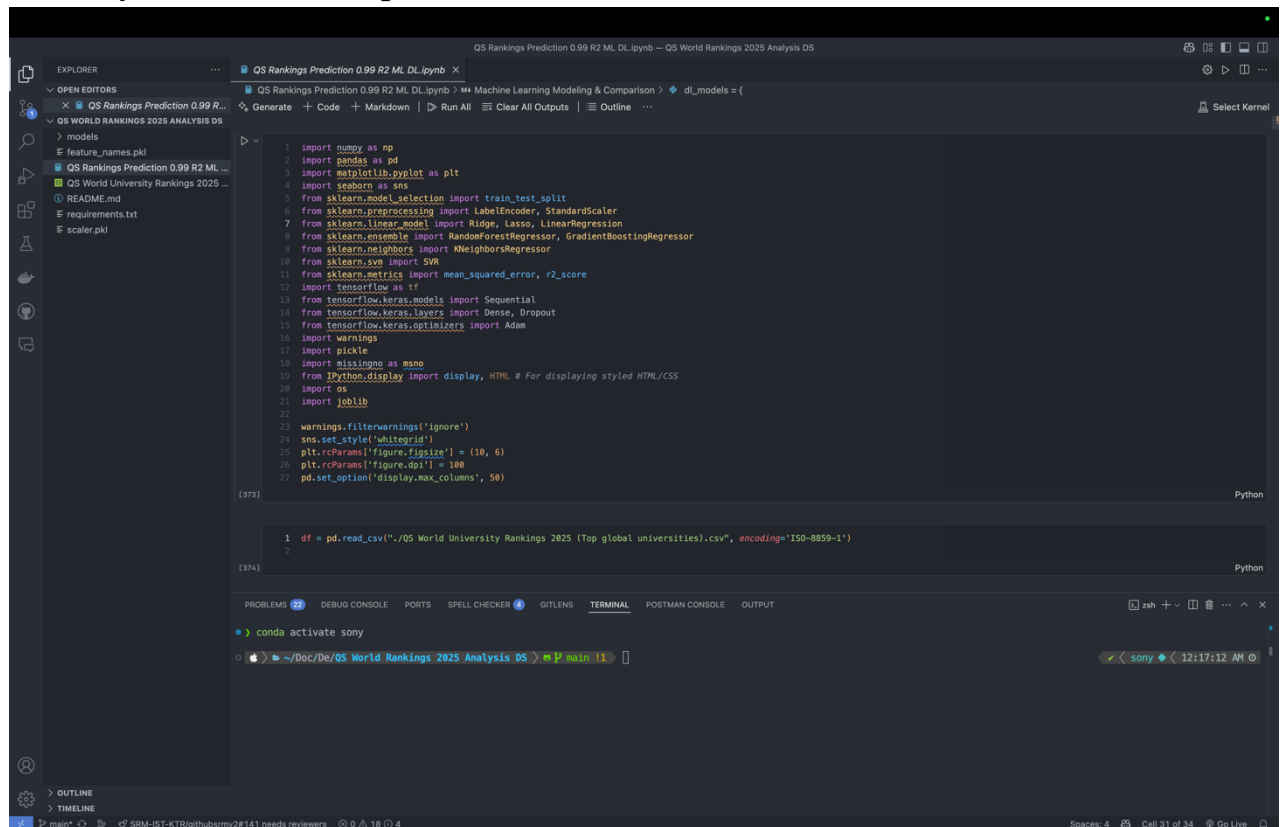






Screenshots:

Library and dataset import:



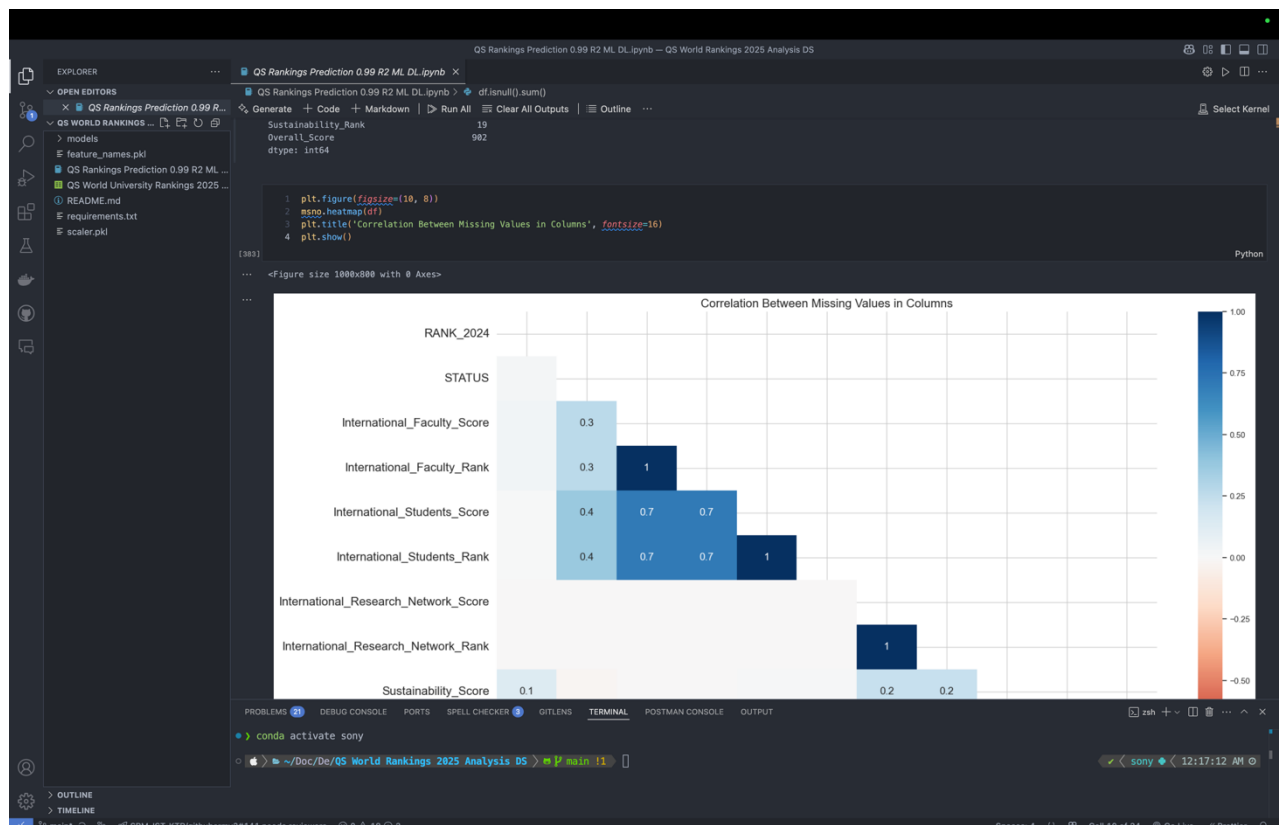
The screenshot shows a Jupyter Notebook interface with the following code in the first two cells:

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import seaborn as sns
5 from sklearn.model_selection import train_test_split
6 from sklearn.preprocessing import LabelEncoder, StandardScaler
7 from sklearn.linear_model import Ridge, Lasso, LinearRegression
8 from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
9 from sklearn.neighbors import KNeighborsRegressor
10 from sklearn.svm import SVR
11 from sklearn.metrics import mean_squared_error, r2_score
12 import tensorflow as tf
13 from tensorflow.keras.models import Sequential
14 from tensorflow.keras.layers import Dense, Dropout
15 from tensorflow.keras.optimizers import Adam
16 import warnings
17 import pickle
18 import missingno as msno
19 from IPython.display import display, HTML # For displaying styled HTML/CSS
20 import os
21 import joblib
22
23 warnings.filterwarnings('ignore')
24 sns.set_style('whitegrid')
25 plt.rcParams['figure.figsize'] = (10, 6)
26 plt.rcParams['figure.dpi'] = 100
27 pd.set_option('display.max_columns', 50)
```

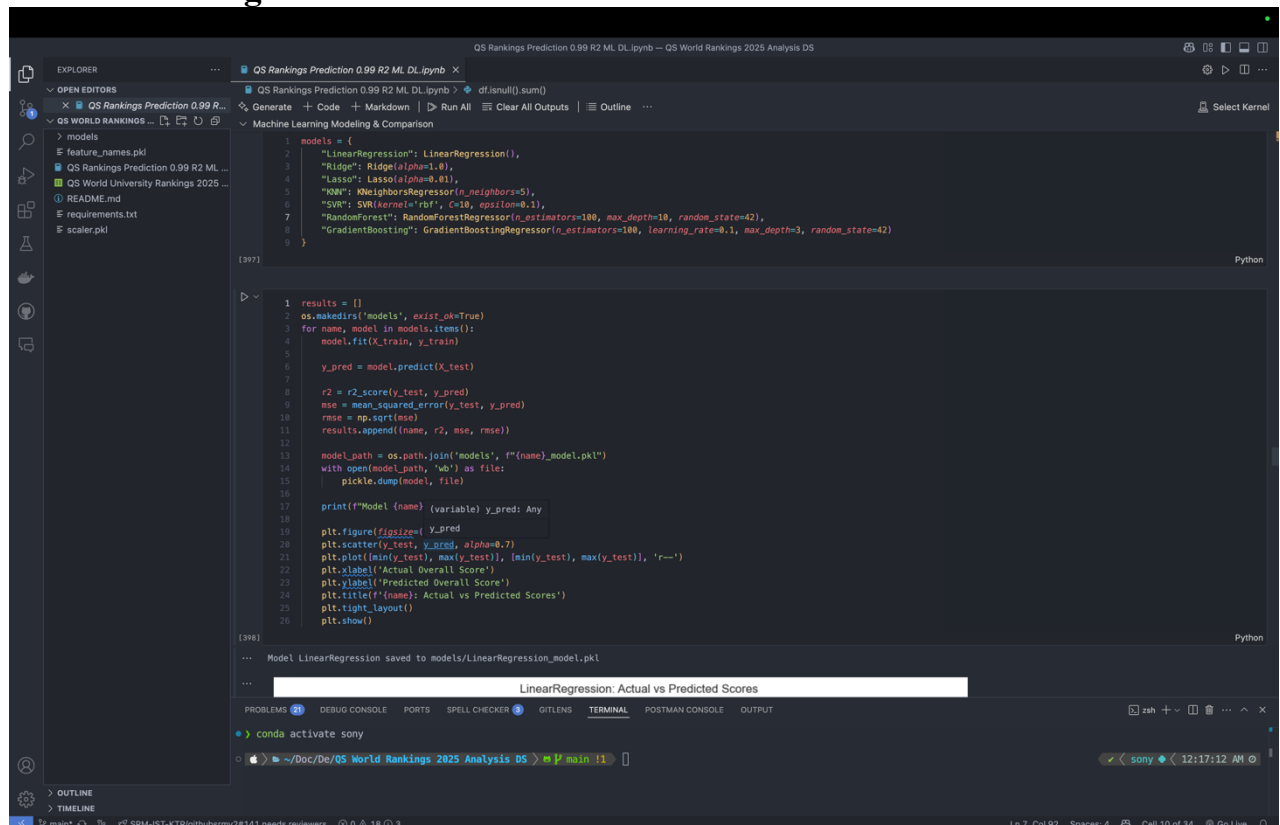
```
1 df = pd.read_csv("../QS World University Rankings 2025 (Top global universities).csv", encoding='ISO-8859-1')
2
```

The terminal at the bottom shows the command `conda activate sony` being executed.

Analyzing the data:



Model Training:



```
1 models = {
2     "LinearRegression": LinearRegression(),
3     "Ridge": Ridge(alpha=1.0),
4     "Lasso": Lasso(alpha=0.01),
5     "KNN": KNeighborsRegressor(n_neighbors=5),
6     "SVR": SVR(kernel="rbf", C=10, epsilon=0.1),
7     "RandomForest": RandomForestRegressor(n_estimators=100, max_depth=10, random_state=42),
8     "GradientBoosting": GradientBoostingRegressor(n_estimators=100, learning_rate=0.1, max_depth=3, random_state=42)
9 }

[397] Python

1 results = []
2 os.makedirs('models', exist_ok=True)
3 for name, model in models.items():
4     model.fit(X_train, y_train)
5
6     y_pred = model.predict(X_test)
7
8     r2 = r2_score(y_test, y_pred)
9     mse = mean_squared_error(y_test, y_pred)
10    rmse = np.sqrt(mse)
11    results.append((name, r2, mse, rmse))
12
13    model_path = os.path.join('models', f'{name}_model.pkl')
14    with open(model_path, 'wb') as file:
15        pickle.dump(model, file)
16
17    print(f"Model {name} (variable) y_pred: Any")
18
19    plt.figure(figsize=(10, 7))
20    plt.scatter(y_test, y_pred, alpha=0.7)
21    plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'r--')
22    plt.xlabel('Actual Overall Score')
23    plt.ylabel('Predicted Overall Score')
24    plt.title(f'{name}: Actual vs Predicted Scores')
25    plt.tight_layout()
26    plt.show()

[398] Python

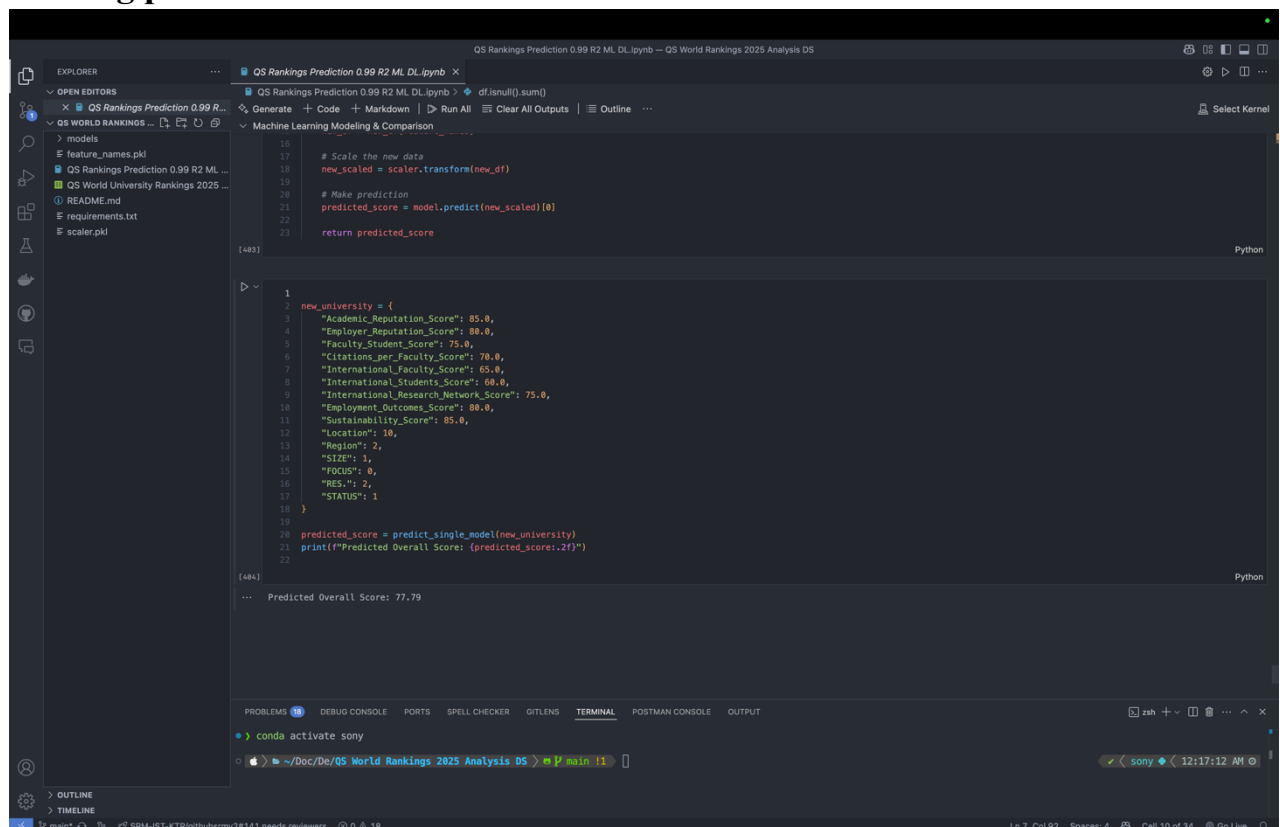
... Model LinearRegression saved to models/LinearRegression_model.pkl
...

LinearRegression: Actual vs Predicted Scores
```

conda activate sony

~/Doc/De/QS World Rankings 2025 Analysis DS > P main !1

Making prediction:



```
16 # Scale the new data
17 new_scaled = scaler.transform(new_df)
18
19 # Make prediction
20 predicted_score = model.predict(new_scaled)[0]
21
22 return predicted_score

[403] Python

1 new_university = {
2     "Academic_Reputation_Score": 85.0,
3     "Employer_Reputation_Score": 80.0,
4     "Faculty_Student_Score": 75.0,
5     "Citations_per_Faculty_Score": 70.0,
6     "International_Faculty_Score": 65.0,
7     "International_Students_Score": 50.0,
8     "International_Research_Network_Score": 75.0,
9     "Employment_Outcomes_Score": 80.0,
10    "Sustainability_Score": 85.0,
11    "Location": 10,
12    "Region": 2,
13    "SIZE": 1,
14    "FOCUS": 0,
15    "RES.": 2,
16    "STATUS": 1
17 }
18
19 predicted_score = predict_single_model(new_university)
20 print(f"Predicted Overall Score: {predicted_score:2f}")

[404] Python

... Predicted Overall Score: 77.79
```

conda activate sony

~/Doc/De/QS World Rankings 2025 Analysis DS > P main !1

Results

- Achieved **~0.99 R²** score with the deep learning model.
- Identified **Academic Reputation, Employer Reputation, and Citations per Faculty** as critical factors.
- Successfully predicted QS Overall Scores with minimal error.
- Visualizations validated that predictions were reliable and aligned well with actual scores.

Limitations

- **Data Quality:** Some columns like Overall_Score were missing for several rows, reducing training data size.
- **External Factors:** Rankings can also depend on political, funding, or administrative changes not captured in the dataset.
- **Bias:** Heavy reliance on a few metrics may bias model predictions toward certain regions or university types.
- **Deep Learning Overfitting:** Despite Dropout layers, slight overfitting was still a potential risk, especially with relatively small dataset size (~1500 samples).

Conclusion

This project successfully demonstrates how machine learning and deep learning techniques can predict university rankings with high precision. A thorough data science pipeline — from collection to presentation — ensured the reliability of the predictions. While the model showed excellent performance, future improvements could include expanding the dataset, incorporating real-time features (like latest research output, patents, student reviews), and using more complex architectures (e.g., ensemble models).

Overall, the project lays a strong foundation for intelligent prediction systems in educational rankings and analytics.