**SULTAN**

**56189**

**BS/DS-5_1**

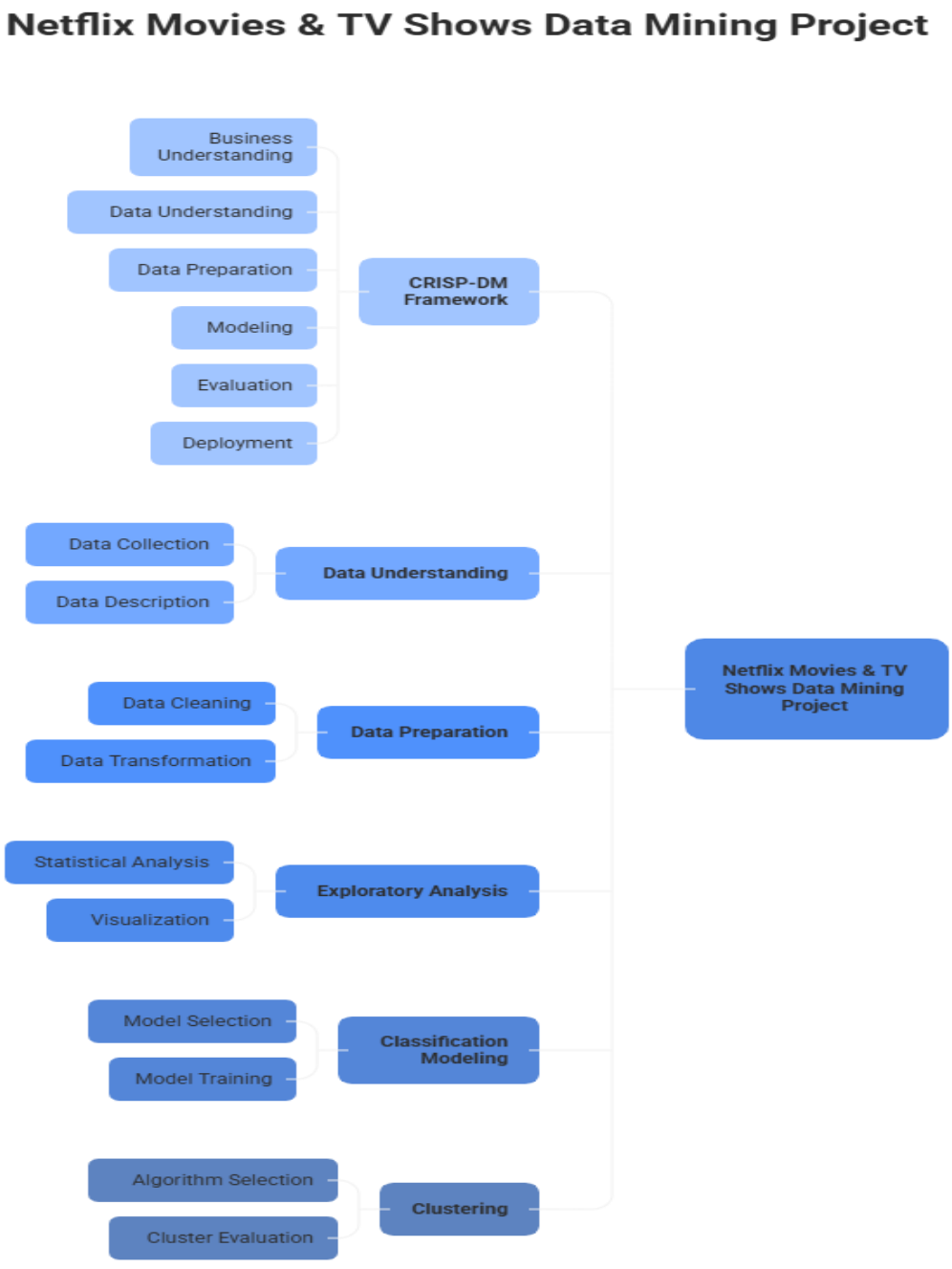
**Documentation**

**Netflix Movies & TV Shows**

**Data Mining Project**

## 1. Introduction

This document provides complete documentation for the Netflix Movies & TV Shows Data Mining Project. The project follows the CRISP-DM (Cross-Industry Standard Process for Data Mining) framework and includes data understanding, data preparation, exploratory analysis, classification modeling, clustering, and the development of a recommendation system. The objective is to extract insights from the Netflix dataset and build machine learning models that support better content discovery and personalization.



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**2. Dataset Overview**

The dataset used in this project is the **Netflix Movies & TV Shows dataset**, publicly available on Kaggle.
It contains metadata for Netflix titles, including:

- Type (Movie or TV Show)
- Title
- Director
- Cast
- Country of origin
- Date added
- Release year
- Rating
- Duration
- Genres (listed_in)
- Description

These attributes support multiple data mining tasks such as classification, clustering, trend analysis, and recommendation modeling.

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**3. CRISP-DM Workflow**

This project is structured according to the CRISP-DM methodology:

• **Business Understanding**

Identify goals such as classifying content type, grouping similar content, and providing recommendations.

• **Data Understanding**

Explore dataset structure, missing values, feature types, and initial visualization of distributions.

• **Data Preparation**

Includes:

- Handling missing values
- Cleaning and transforming duration
- Encoding categorical variables
- Converting textual descriptions using TF-IDF
- Splitting the dataset for training/testing

• **Modeling**

Three types of models were created:

1. **Classification Models**
   Predict whether a title is a Movie or TV Show using:
   - Logistic Regression
   - Random Forest Classifier
   - Gradient Boosting Classifier
2. **Clustering Model**
   K-Means clustering applied on TF-IDF vectors of descriptions to group similar content.
3. **Recommendation Model**
   A content-based recommender using cosine similarity.

• **Evaluation**

Metrics used for model evaluation:

- Accuracy
- Precision
- Recall
- F1-score
- Silhouette score (for clustering)

• **Deployment**

Trained models (TF-IDF vectorizer and KMeans model) were saved using joblib for future integration into applications.

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**4. Exploratory Data Analysis (EDA)**

The EDA phase focuses on understanding patterns and trends in the dataset.

**Key analyses performed:**

- **Distribution of content types (Movies vs TV Shows)**
  Count plots and pie charts show that Netflix has more Movies than TV Shows.
- **Top countries producing Netflix content**
  Using value_counts and bar plots to find leading countries.
- **Release year trends**
  A histogram of release years shows how content production changes over time.
- **Genre distribution**
  The "listed_in" column is split to analyze the most frequent genres.
- **Missing values analysis**
  Missing fields in director, cast, rating, and country were identified and handled.

EDA helps shape the preprocessing and modeling strategies.

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**5. Data Cleaning and Preparation**

Data preparation included:

**• Handling Missing Values**

Columns like director, cast, country, and rating contained missing entries.
These were filled using placeholder values or left as-is depending on relevance.

**• Duration Cleaning**

Movie durations (e.g., "120 min") were converted into integer minutes.
TV show seasons were handled separately if needed.

**• Encoding Target Variable**

type (Movie/TV Show) was converted into numerical form using LabelEncoder.

**• Feature Engineering**

Categorical columns were prepared for modeling using:

- OneHotEncoder (for nominal features)
- StandardScaler (for numerical features)

• **Train-Test Split**

The dataset was split into training and testing sets to train and evaluate classification models.

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**6. Classification Models**

Three classifiers were trained to predict whether a title is a **Movie or TV Show**:

**1. Logistic Regression**

Simple and interpretable linear model.

**2. Random Forest Classifier**

Ensemble of decision trees, robust and effective.

**3. Gradient Boosting Classifier**

Boosting-based model that often provides high accuracy.

**Evaluation Metrics**

Each model was evaluated using:

- Accuracy
- Precision
- Recall
- F1 Score
- Confusion Matrix
- Classification Report

The model with the highest **F1 score** was selected as the best model.

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**7. Clustering Analysis**

Clustering was performed using **K-Means** on TF-IDF vectors derived from textual descriptions.

**Steps:**

1. Convert descriptions into numerical vectors using **TF-IDF**.
2. Reduce dimensionality using **TruncatedSVD** for visualization.
3. Apply **K-Means** clustering.
4. Interpret clusters by analyzing top terms from each cluster.

**Evaluation**

Clustering was evaluated using **Silhouette Score**, which measures how well data points fit into clusters.

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**8. Recommendation System**

A **content-based recommendation system** was implemented.

**How it works:**

1. Convert descriptions into TF-IDF vectors.
2. Compute **cosine similarity** between all pairs of titles.
3. When a user inputs a title, return the top N most similar titles.

This allows Netflix-like personalized recommendations based solely on content similarity.

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**9. Model Saving (Deployment)**

To prepare for deployment, the following models were saved using joblib:

joblib.dump(tfidf_model, "tfidf.pkl")

joblib.dump(kmeans_model, "kmeans.pkl")

These files can later be loaded into:

- Web apps
- APIs
- Recommendation engines
- Dashboards

This step simulates the deployment phase of CRISP-DM.

**10. Conclusion**

This project demonstrates how data mining techniques can extract meaningful insights from entertainment data.
Using:

- EDA
- Classification
- Clustering
- Recommendation modeling

it becomes possible to enhance user experiences on platforms like Netflix by improving search, categorization, and personalized recommendations.

The project provides a complete end-to-end machine learning workflow and shows how modern data mining techniques support real-world applications.