Predicting Athletic Performance: A Machine Learning Analysis of Powerlifting

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Abstract

This research project investigates the powerlifting dataset through comprehensive machine learning analysis, focusing on two main objectives: predicting total competition weight (TotalKg) and classifying drug testing status (Tested). The study employs multiple supervised learning algorithms, including Decision Trees, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and Neural Networks, complemented by clustering analysis using K-means and DBSCAN.

For regression analysis, the model predicts TotalKg using variables including Best3DeadliftKg, BodyweightKg, Age, Sex, Equipment, and Federation membership. Feature engineering, particularly the creation of a derived Strength metric, significantly improved model performance. The classification analysis predicts testing status using features such as Sex_encoded, Age, Strength, and Federation tiers.

The results demonstrate that Decision Trees achieved the best classification performance with an AUC of 0.938 and high precision (0.985). Clustering analysis revealed two distinct DBSCAN clusters and eight K-means clusters, providing insights into athlete groupings based on performance patterns and competition characteristics. The study's findings contribute to understanding performance factors in powerlifting and the relationship between competition levels and testing protocols.

This project highlights the effectiveness of machine learning techniques in sports analytics, specifically in predicting performance metrics and understanding testing patterns in powerlifting

competitions. The results provide valuable insights for competition organizers, coaches, and athletes in understanding performance determinants and testing protocols in the sport.

Introduction

Overview of Powerlifting as a Sport

Powerlifting is a strength sport that tests athletes' maximal strength through three fundamental lifts: the squat, bench press, and deadlift. Unlike Olympic weightlifting, which focuses on explosive movements, powerlifting emphasizes pure strength in these three compound movements. Athletes compete in weight classes and are categorized by age, gender, and equipment usage (raw/classic or equipped).

Key Components:

1. Competition Lifts:
    - Squat: Barbell lifted from a rack, lowered to below parallel, and returned to standing
    - Bench Press: Barbell lowered to chest and pressed to full arm extension
    - Deadlift: Barbell lifted from floor to hip level with locked knees and shoulders

2. Competition Rules:
    - Three attempts allowed for each lift
    - Best successful attempt in each lift contributes to total
    - Strict technical requirements and commands from referees
    - Equipment categories: Raw/Classic (minimal support gear) vs. Equipped (supportive suits/shirts)

Project Objectives and Methodology

This Final Term Project (FTP) aims to apply machine learning techniques to analyze powerlifting competition data through several phases:

Phase I: Data Preprocessing and Feature Engineering
- Dataset cleaning and standardization

- Feature creation and transformation
- Handling missing values and outliers
- Implementation of SMOTE for class balancing

Phase II: Regression Analysis

- Prediction of total competition weight (TotalKg)
- Feature selection and engineering
- Model development and evaluation
- Performance optimization techniques

Phase III: Classification Analysis

- Prediction of drug testing status
- Implementation of multiple classifiers:
    - Decision Trees with pruning optimization
    - Support Vector Machines with various kernels
    - K-Nearest Neighbors
    - Neural Networks
    - Logistic Regression
    - Naive Bayes

Phase IV: Clustering Analysis

- Implementation of K-means clustering
- DBSCAN algorithm application
- Association rule mining using Apriori algorithm

The analysis utilizes a comprehensive dataset containing competition results, athlete information, and performance metrics, providing insights into patterns and relationships within the sport of powerlifting.This project aims to contribute to the understanding of performance factors in powerlifting and provide valuable insights for athletes, coaches, and competition organizers through data-driven analysis.

Description of the Dataset

The Open Powerlifting dataset is a comprehensive collection of powerlifting competition results from international competitions across various federations. This dataset tracks athlete performances in the sport of powerlifting, which consists of three main lifts: squat, bench press, and deadlift. For each of these three lifts, an athlete is given three attempts. The attempts must follow a progressive pattern where each subsequent attempt must be heavier than the previous one. If an athlete fails to complete a lift successfully, they cannot decrease the weight for their next attempt in that lift. The best successful attempt from each lift is then combined to calculate the athlete's total score for the competition

Dataset Characteristics

1. The dataset includes both raw and equipped lifting results
2. Records span multiple federations, countries, and weight classes
3. Contains both male and female competitors
4. Tracks various age groups and competition divisions

Justification

1. This extensive dataset comprises over 1.6 million observations, making it a rich source of data for analysis
2. The dataset contains both numerical features, such as "Squat Kg," "Bench Kg," "Deadlift Kg," and categorical features, including "Sex," "Event," and “Country." etc.
3. Since the Open Powerlifting dataset is publicly available, it ensures transparency and reproducibility in our analysis.

Industry Relevance

1. The dataset functions as a crucial tool for competition planning and performance optimization. Athletes and coaches can use historical data to set realistic goals, select appropriate weight classes, and develop effective attempt strategies. The inclusion of data from multiple

federations allows competitors to identify organizations that best match their competitive aspirations.

2. This comprehensive database enables coaches and athletes to develop evidence-based training programs by analyzing successful lifting patterns and understanding the relationship between body weight and strength. The detailed recording of equipment usage and performance outcomes provides essential insights for training methodology and competition strategy.

Variable Selection and Analysis Report

1. Regression Analysis (Total Weight Prediction)

Dependent Variable

- TotalKg: Total weight lifted in competition

Independent Variables

1. Performance Metrics:
    - Best3DeadliftKg: Best deadlift performance
    - BodyweightKg: Athlete's body weight
2. Demographic Features:
    - Age: Athlete's age
    - Sex: Gender of athlete
3. Competition Factors:
    - Equipment: Type of equipment used
    - Federation: Competition organizing body
    - Tested: Drug testing status

2. Classification Analysis (Testing Status Prediction)

Dependent Variable

- Tested: Binary variable indicating drug testing status (0: Not Tested, 1: Tested)

Independent Variables

1. Athlete Characteristics:
    - Sex
    - Age

- Strength (derived feature)

2. Competition Level Indicators:
    - Fed_ELITE
    - Fed_MAJOR
    - Fed_REGIONAL

Phase1: Feature Engineering and Exploratory Data Analysis

Target Variable and Model Design

In competitive powerlifting, total lifted weight (**TotalKg**) serves as the primary performance metric. Our regression analysis adopts a two-step approach to predict this value effectively:

Step 1: Strength Prediction We first predict a normalized strength metric that accounts for variations in body mass and equipment usage. This intermediate step helps isolate fundamental strength patterns by reducing the impact of body size variations.

Step 2: Total Weight Conversion The predicted strength values are then converted to competition totals (TotalKg) by accounting for the athlete's body weight. This transformation provides results in the standard metric used in powerlifting competitions.

Variable Summary:

1. *TotalKg:* The final competition total in kilograms, serving as the primary target variable for regression tasks.
2. *Strength:* A normalized strength metric calculated as TotalKg divided by Bodyweight. This variable accounts for variations in body mass and will be used as an intermediate target variable in regression tasks.
3. *Sex:* Biological sex of the athlete, a fundamental factor influencing strength potential due to physiological differences. This categorical variable will be used for classification and clustering.
4. *Equipment:* The type of competition equipment used (Raw, Single-ply, Multi-ply, Wraps), which significantly affects lifting performance. This categorical variable will be utilized in classification and clustering tasks.
5. *Bodyweight:* The athlete's body mass, a crucial predictor of performance due to its influence on muscle cross-sectional area and leverages. This continuous variable will be used in regression, classification, and clustering tasks.

6. *Tested:* A binary indicator of drug testing status at competitions, potentially capturing systematic performance differences. This categorical variable will be used in classification and clustering tasks. We have identified data imbalance in this variable and have used SMOTE technique to balance the training data for classification
7. *Best3SquatKg:* The best squat performance, serving as a strong indicator of overall strength potential. This continuous variable will be utilized in regression tasks.
8. *Age:* The age of the athlete, capturing age-related performance patterns and physiological factors. This continuous variable will be used in regression, classification, and clustering tasks.

EDA Findings:

1. *Distribution analysis:* Explore the distribution of each variable, identifying potential outliers, skewness, and kurtosis. Visualize the distributions using histograms, box plots, and probability plots.
2. *Relationship analysis:* Investigate the relationships between variables using scatter plots, correlation matrices, and pair plots. Identify potential linear or non-linear relationships between variables.
3. *Group comparisons:* Compare the distribution and statistical measures of variables across different groups (e.g., sex, equipment type, tested status) using box plots, violin plots, and summary statistics.
4. *Missing data analysis:* Assess the presence and patterns of missing data in the dataset. Determine appropriate strategies for handling missing values (e.g., imputation, deletion).
5. *Feature engineering:* Create new features based on domain knowledge or observed patterns in the data. For example, creating interaction terms between variables or transforming variables to capture non-linear relationships.

Next Steps:

Based on the EDA findings, the following steps will be taken for classification, regression, and clustering tasks:

1. *Data preprocessing:* Handle missing data, encode categorical variables, and scale continuous variables as needed.
2. *Data cleaning:* Check for and remove any duplicate data points in the dataset. Our initial analysis did not find any duplicates, but it's important to ensure data integrity before proceeding with modeling tasks.
3. *Feature selection:* Select the most informative features for each task based on their relevance and potential impact on the target variable.
4. *Model selection:* Choose appropriate models for each task (e.g., logistic regression for classification, linear regression for regression, k-means for clustering) based on the nature of the variables and the relationships observed in the EDA.
5. *Model evaluation:* Assess the performance of the selected models using appropriate evaluation metrics and validation techniques (e.g., cross-validation, holdout validation).

By leveraging the insights gained from this EDA, we aim to build robust and informative models for classification, regression, and clustering tasks in the powerlifting dataset.

Features Excluded from Analysis

Several variables were intentionally excluded from our model based on various methodological and practical considerations:

Competition-Specific Data:

Individual Attempt Records (Squat1-4Kg, Bench1-4Kg, Deadlift1-4Kg): While the first squat attempt could provide valuable insights for coaches in weight selection strategy for subsequent lifts, including these attempts would effectively leak information about the final total. These attempts directly sum to the competition total, making their inclusion circular in nature.

Performance Scoring Systems:

Wilks, McCulloch, Glossbrenner, IPFPoints: These standardized scoring systems are calculated using the total of all three lifts (squat, bench, deadlift) along with bodyweight and other factors. Including them would introduce data leakage as they contain information about our target

variable (total). Their inclusion would artificially inflate model accuracy without adding genuine predictive value.

Categorical Variables with High Cardinality:

1. *Name:* Individual athlete identifiers
2. *MeetName, MeetState, Country:* Competition location data
3. *Division:* Competition categories
4. *WeightClassKg, AgeClass:* Redundant with actual bodyweight and age measurements These variables either have too many unique values or provide information already captured in our selected features.

Competition Outcome:

- *Place:* Competition ranking is an outcome variable rather than a predictor
- *Event:* All selected data pertains to full powerlifting competitions

This feature selection strategy maintains model integrity by avoiding both data leakage and redundancy while focusing on genuinely predictive variables.

Data Cleaning Methodology

Our data cleaning process involved several systematic steps to ensure data quality and reliability for subsequent analysis:

1. Missing Value Treatment

Testing Status Standardization

- Converted 'Tested' column to binary format (1 for 'Yes', 0 for untested)
- This standardization enables numerical analysis while maintaining interpretability

Age Data Imputation

- Identified significant missing age values in the dataset
- Implemented a division-based imputation strategy:
  - Calculated mean ages for each competition division
  - Applied these averages to missing values within the same division
  - Maintained data integrity by marking unmatched cases as NaN
- This approach preserves the age-division relationship while handling missing data

2. Data Validation and Filtering

Lift Data Validation

- Removed invalid lift records through logical constraints:
  - Eliminated zero or negative values in squat, bench, and deadlift records
  - Ensured total weight exceeded individual lift components
  - These criteria eliminate physically impossible scenarios

Comprehensive Record Completion

- Applied complete case analysis for critical variables:
  - Total weight (TotalKg)
  - Individual lift performances (Best3SquatKg, Best3BenchKg, Best3DeadliftKg)
  - Body weight (BodyweightKg)
  - Age

Analysis of Strength Distribution Across Equipment Types

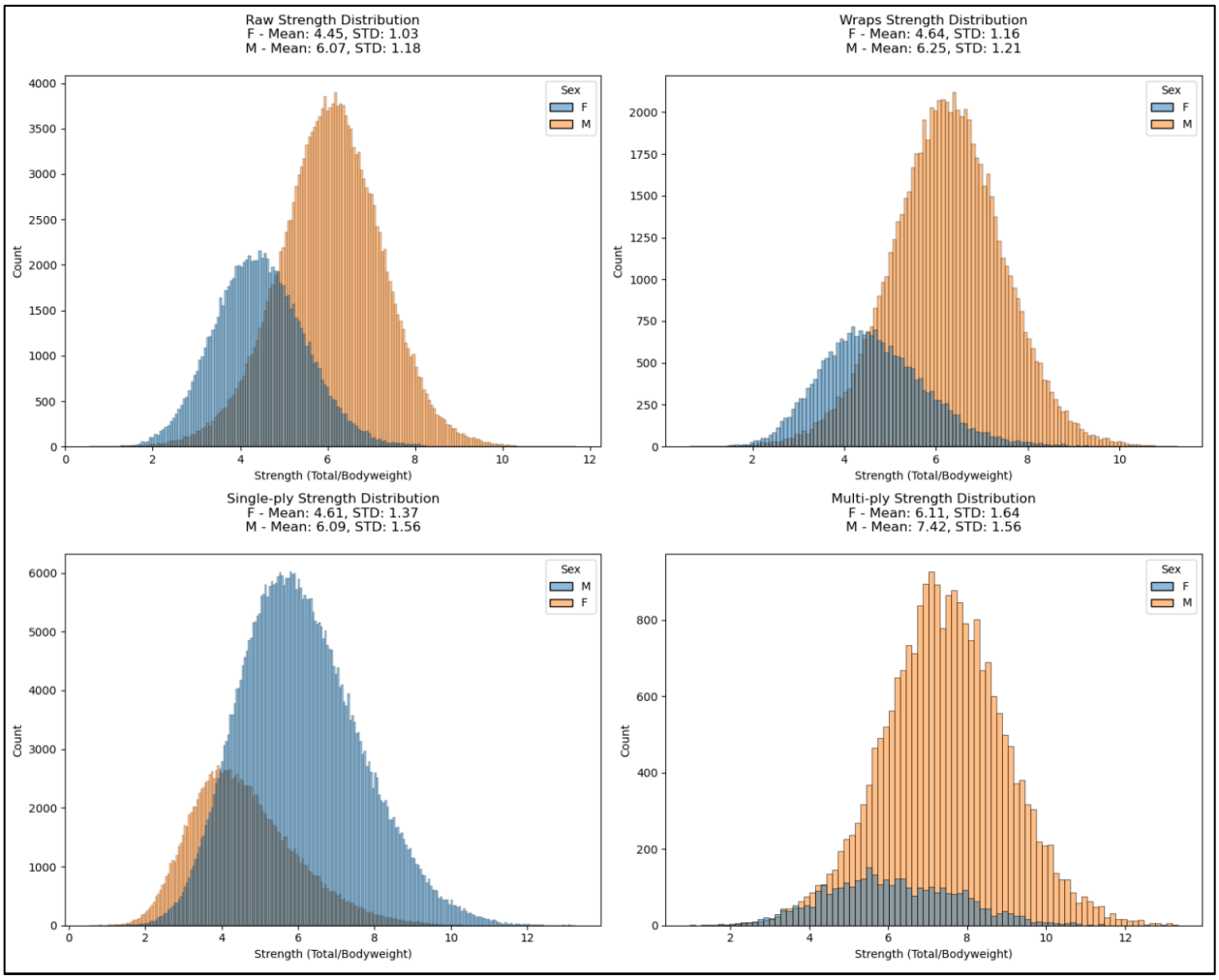


Figure 1 :- Relative Strength Distribution By Equipment Type and Sex

Raw lifting (Figure 1A) demonstrates a clear bimodal distribution differentiated by sex, with male athletes typically exhibiting relative strength ratios between 5-8, while female athletes show ratios between 3-6. Both distributions approximate normal curves, suggesting natural physiological limitations.

The Wraps category (Figure 1B) maintains a similar bimodal pattern but shows a slight rightward shift in both distributions compared to raw lifting, indicating the performance advantage provided by knee wraps.

Single-ply equipment (Figure 1C) produces a notable increase in relative strength ratios and creates larger distribution spreads. Male lifters in this category show significant extension in the right tail of the distribution, suggesting that supportive equipment may amplify inherent strength differences between sexes.

Multi-ply equipment (Figure 1D) enables the highest relative strength ratios across all categories, though with a smaller sample size. The distribution shows a pronounced rightward skew, particularly among male athletes.

Equipment Advantage Analysis and Feature Engineering

The mechanical advantage provided by powerlifting equipment types represents a crucial performance determinant in competitive powerlifting. To effectively incorporate this effect into our model, we developed a systematic approach to quantify these advantages while ensuring robust data handling practices.

Methodology

Our calculation process was deliberately restricted to the training dataset to prevent data leakage and maintain the integrity of our model evaluation. The methodology followed three key steps:

1. Baseline Establishment:
- Raw lifting was designated as the baseline performance metric
- Mean strength values were calculated separately for males and females in Raw category
- These calculations used exclusively training data to establish "natural" strength reference points
2. Relative Advantage Computation: For each equipment type (Raw, Wraps, Single-ply, Multi-ply):
- Mean strength was calculated for each equipment-sex combination
- Relative advantage was computed using the formula:

Equipment_Advantage = (Equipment_Strength - Raw_Baseline) / Raw_Baseline

This produces a percentage increase over raw lifting, quantifying the mechanical advantage provided by each equipment type.

3. Feature Implementation:

- Advantages calculated from training data were applied uniformly across both training and test sets
- This approach ensures test data remains truly unseen during feature development
- Maintains the validity of our model's performance metrics

Significance of Data Isolation

The strict isolation of advantage calculations to the training dataset serves multiple purposes:

- Prevents contamination of test data with training-derived information
- Ensures model evaluation metrics accurately reflect real-world performance potential
- Mirrors practical deployment scenarios where future data characteristics are unknown

This methodological approach provides a robust framework for quantifying equipment advantages while maintaining statistical rigor and preventing artificial performance inflation through data leakage.

Analysis of Strength Distribution Across Age

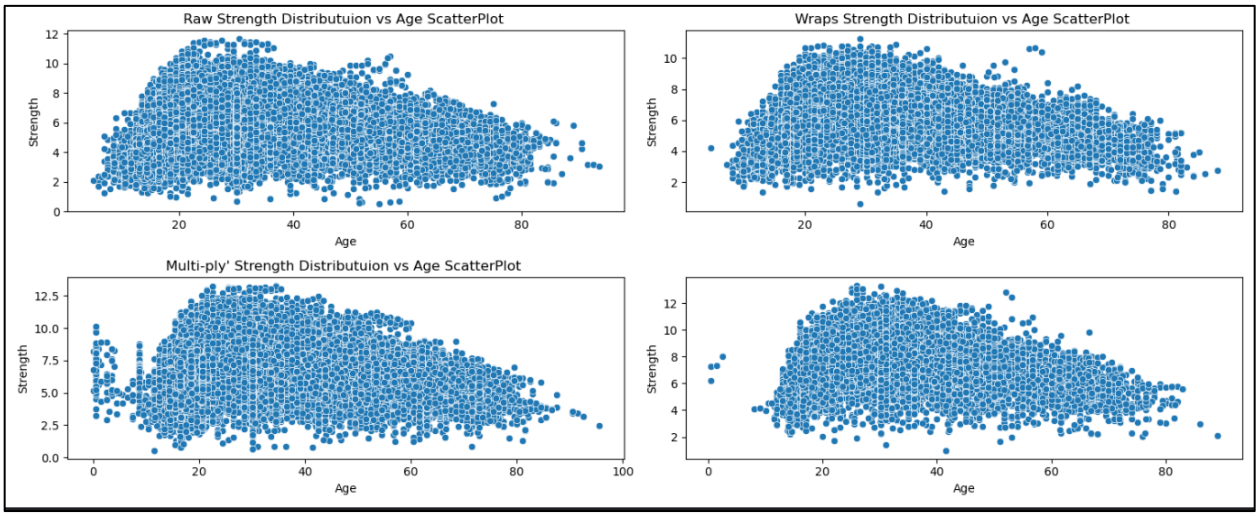


Figure 2: Age related strength distribution across equipment types

The scatter plots in Figure 2 illustrate the relationship between age and relative strength across different equipment categories, revealing several notable patterns and insights about strength expression throughout the lifespan of powerlifters.

Key Observations

1. Peak Performance Age: Across all equipment types, optimal strength performance typically occurs between ages 25-40.
2. Outlier Analysis: Notable outliers exist in all categories, particularly in the prime competitive age range.
3. Age-Related Decline: A consistent pattern of gradual strength decline appears after age 45-50 across all equipment types.
4. Equipment Impact: More supportive equipment (Single-ply, Multi-ply) appears to enable higher relative strength values across all age groups.
5. Youth Performance: Limited but noteworthy performances in the 15-20 age range suggest early development of strength capabilities.

Treatment of Missing Age Values in Powerlifting Dataset

In our dataset analysis, we encountered a significant proportion of missing age values (46.8% of entries). This presented a crucial data preprocessing challenge that required careful consideration rather than applying simple imputation methods**.**

Why Standard Imputation Was Not Suitable?

Simply replacing missing age values with the mean or median would have been inappropriate for several reasons:

1. Competition Context:
    a. Age is a critical factor in powerlifting competitions, determining weight classes and categories
    b. Age directly influences performance expectations and competitive divisions
    c. Imputed values could misrepresent an athlete's competitive category
2. Performance Correlation:
    a. Strength capabilities vary significantly across different age ranges
    b. Peak performance typically occurs between ages 25-40
    c. Using mean/median imputation would artificially cluster athletes in the middle age range
3. Statistical Validity:
    a. With nearly half the age data missing (46.8%), imputation could significantly skew the age distribution
    b. Such a large proportion of imputed values would reduce the reliability of age-based analyses
    c. Risk of introducing artificial patterns that could lead to incorrect conclusions

Division-Based Age Imputation Strategy

We developed a more sophisticated approach to handle missing age values by leveraging the competition division information:

1. Methodology:
    a. First, we calculated mean ages for each competition division using complete cases

   b. Created a mapping of divisions to their average ages
   c. Applied these division-specific averages to entries with missing ages
2. Rationale:
   a. Competition divisions have inherent age-related characteristics
   b. Masters divisions typically represent older athletes
   c. Open and Junior divisions generally contain younger competitors
   d. This relationship provides a more informed basis for age estimation

This method provided a more robust solution to the missing age problem while maintaining the integrity of the age-performance relationship in our analyses. After this very minimal entries(.005%) still had missing ages, I made the decision to remove them, since they had minimal Impact on size of the dataset size.

Age-based Data Filtering and Outlier Removal

For age-based outlier removal, we implemented a two-step filtering process. First, we eliminated lifts from competitors under 16 years of age, as this represents the minimum age for most sanctioned powerlifting competitions. Subsequently, we applied a statistical filter removing ages beyond three standard deviations from the mean (approximately 60 years). This upper threshold aligns well with empirical observations in powerlifting demographics, where competitive participation typically declines significantly after age 60. The initial dataset showed ages ranging from 0 to 95.5 years (mean = 25.13, SD = 11.33). After filtering, we retained only the most representative age range for competitive powerlifting, ensuring our analysis focuses on the core demographic of the sport while still maintaining legitimate data from both junior and master divisions.

Bodyweight Distribution Analysis and Outlier Methodology

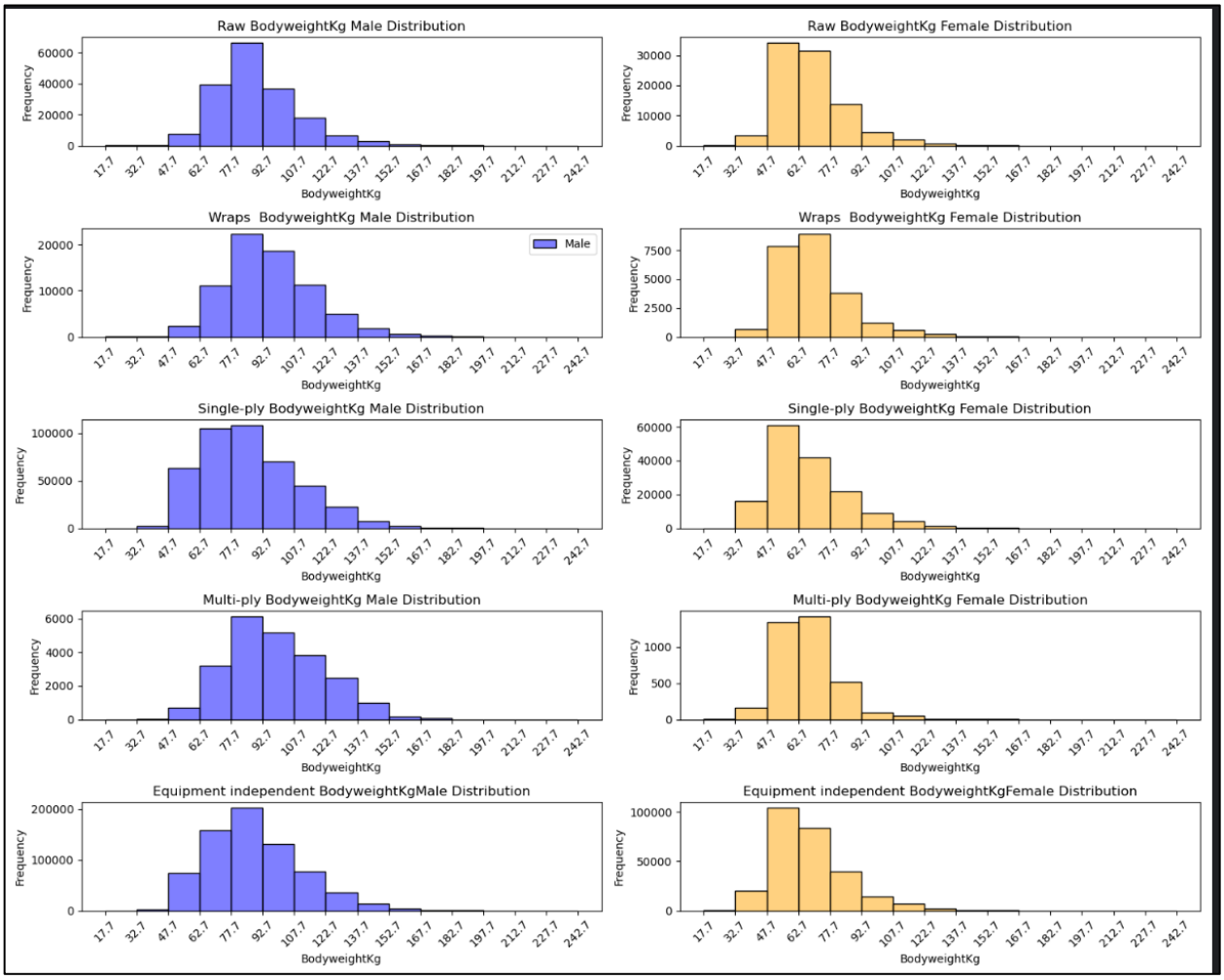


Figure 3: Bodyweight Distributions Across Equipment Types and Sex

Analysis of bodyweight distributions revealed distinct patterns across sex and equipment categories, necessitating a careful approach to outlier removal.

1. A standard z-score method was deemed inappropriate due to three key factors:
2. First, the distributions exhibited natural right-skewness rather than normal distribution, which would lead to over-removal of legitimate heavyweight competitors under z-score analysis.

3. Second, male and female bodyweight distributions showed fundamentally different central tendencies and spreads, making a unified approach statistically unsound.

4. Third, equipment types (Raw, Wraps, Single-ply, and Multi-ply) demonstrated varying bodyweight distributions, likely due to the different physical demands and athlete populations in each category.

Consequently, we implemented an IQR-based method (with a 2.0×IQR threshold) separately for each sex-equipment combination.

The IQR method was chosen for its robustness to non-normal distributions and its ability to preserve the natural skewness present in powerlifting bodyweight categories while effectively identifying true outliers.
This approach ensures that legitimate heavyweight lifters are retained while removing only the most extreme outliers that likely represent data entry errors.

Results of Bodyweight Distribution After Outlier Removal Through IQR

The effectiveness of our IQR-based outlier removal approach can be observed through comparative distribution analysis (Figure 1.4). Our implemented methodology separately processed each sex-equipment combination, effectively preserving legitimate weight class distributions while removing physiologically impossible or erroneous data points.
Figure X presents a comprehensive view of bodyweight distributions across different equipment types for both male and female competitors. The histograms are arranged in pairs (male-female) for each equipment category (Raw, Wraps, Single-ply, and Multi-ply), with an additional equipment-independent distribution at the bottom. This visualization demonstrates several key outcomes of our cleaning process:

1. Physiological Validity: The cleaned data shows lower bounds starting around 52.5kg for males and 47.5kg for females, eliminating physiologically impossible weights (like the previous entries below 20kg) while maintaining legitimate lightweight class competitors.
2. Equipment-Specific Patterns: The Multi-ply distributions (fourth row) show a notable shift toward higher bodyweights compared to Raw (first row), reflecting the established trend of heavier athletes typically preferring equipped lifting. This natural pattern was preserved through our targeted cleaning approach.

3. Sex-Specific Distributions: The female distributions (right column) consistently show lower central tendencies and narrower spreads compared to male distributions (left column), aligning with expected physiological differences. The IQR method successfully maintained these distinct characteristics while removing outliers.

These results validate our decision to use an IQR-based approach rather than a simple z-score method, as it effectively preserved the natural skewness and equipment-specific variations while removing clear outliers.

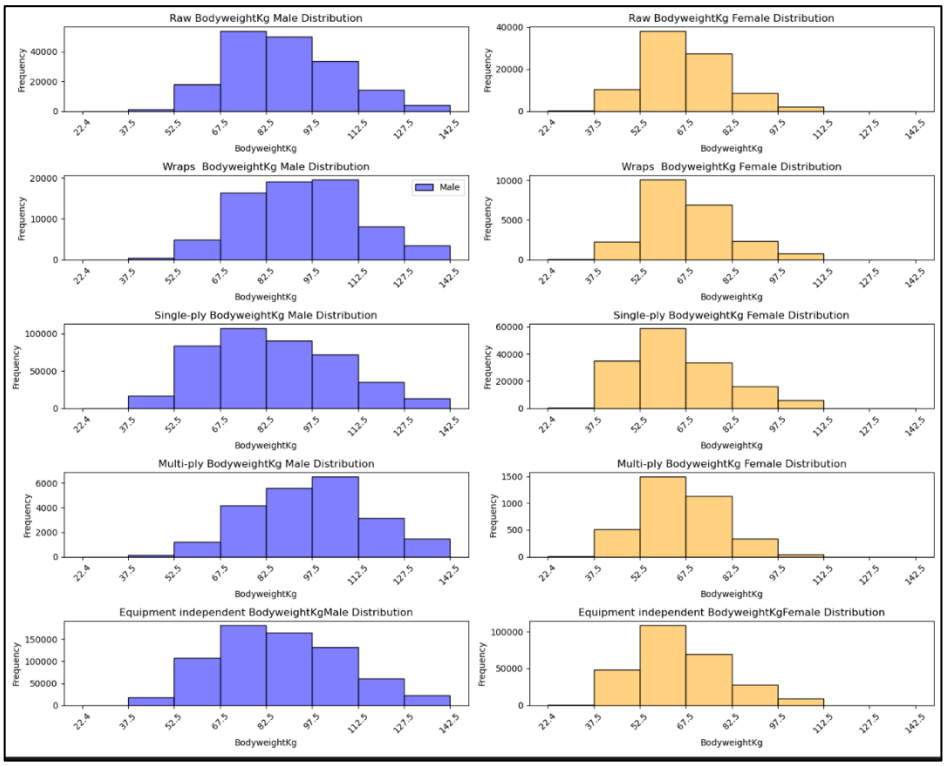


Figure 4: Cleaned Bodyweight Distributions Across Equipment Types and Sex

Best Squat Distribution Analysis and Outlier Methodology

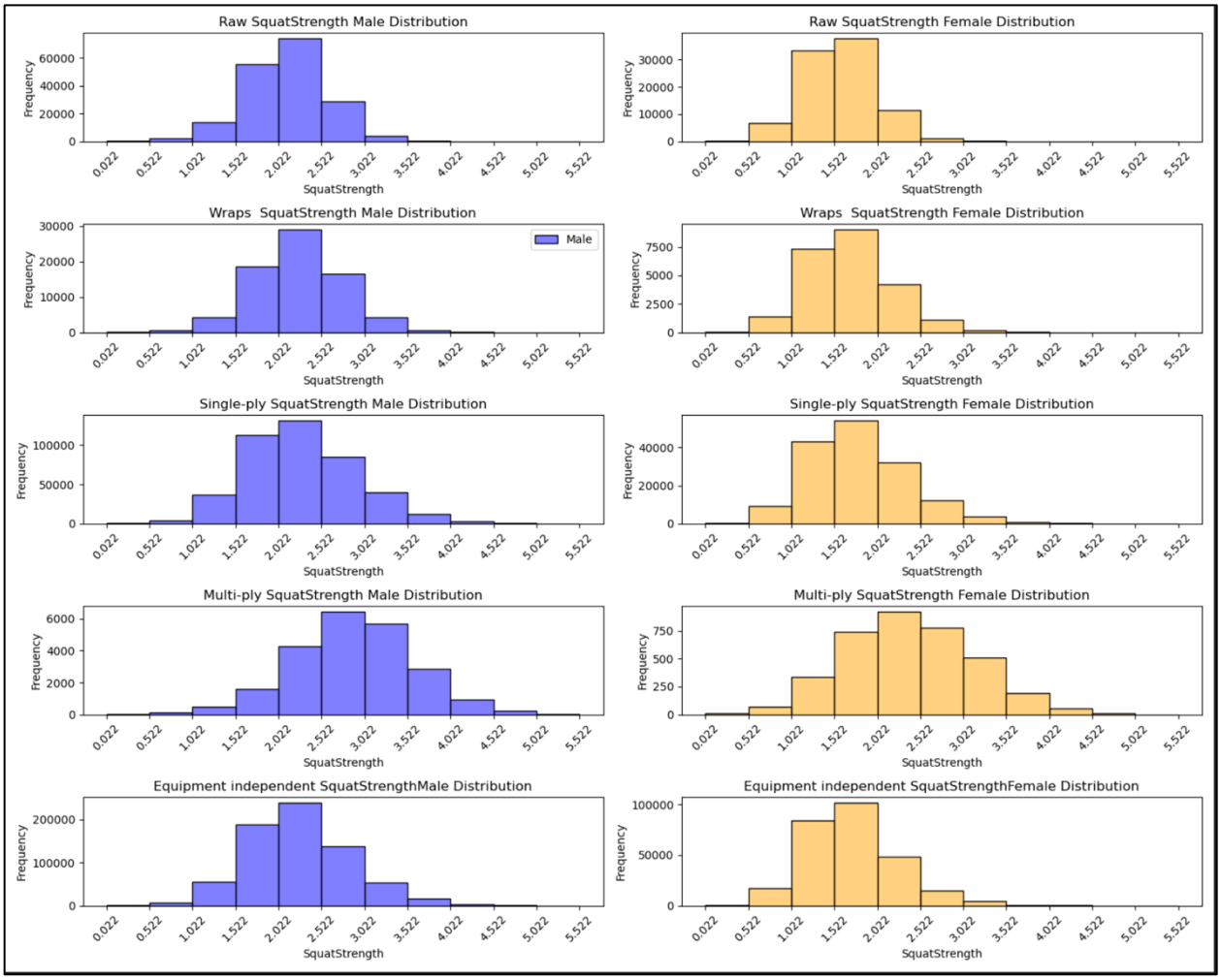


Figure 5: Squat Strength Distributions Across Equipment Types and Sex

This analysis presents the distribution of squat strength across different equipment types, separated by sex, with an additional equipment-independent overview. The data reveals distinct patterns in squat performance influenced by both equipment choice and sex.

Raw Squat Distribution

For raw squats, male lifters show a normal distribution centered around 2.0-2.5 times bodyweight, with the majority falling between 1.5-3.0. Female lifters demonstrate a similar

normal distribution but centered lower, typically around 1.5-2.0 times bodyweight. The raw distributions provide a baseline for natural squatting strength without supportive equipment.

Wraps Performance

With knee wraps, both male and female distributions shift slightly rightward compared to raw lifting. Male lifters typically achieve 2.5-3.0 times bodyweight, while females cluster around 1.5-2.5. The performance boost from wraps appears consistent across both sexes, maintaining similar distribution shapes to raw lifting.

Single-ply Analysis

Single-ply equipment shows a more pronounced rightward shift. Male lifters frequently achieve 2.5-3.5 times bodyweight, with some exceptional performances exceeding 4.0. Female lifters in single-ply typically perform between 2.0-3.0 times bodyweight. The equipment advantage is evident in both populations, though the relative improvement appears more pronounced in male lifters.

Multi-ply Performance

Multi-ply equipment demonstrates the highest squat-to-bodyweight ratios. Male distributions center around 3.0-4.0 times bodyweight, while females typically achieve 2.5-3.5. The distributions show greater spread, suggesting that equipment mastery may play a significant role in performance outcomes.

Equipment-Independent Overview

The aggregate distributions maintain normal curves for both sexes, with males centered around 2.5 and females around 1.75 times bodyweight. These overall distributions reflect the predominance of raw and wraps lifting in the dataset, as these categories contain the majority of entries.

Key Observations:

1. All distributions approximate normal curves, suggesting natural biological limits

2. Equipment progressively shifts distributions rightward: Raw → Wraps → Single-ply → Multi-ply
3. Sex differences persist across all equipment types
4. Distribution spreads increase with more supportive equipment
5. Clear performance advantages from equipment are evident but vary between sexes

Treatment of Relative Strength Ratios and Performance Outliers

In analyzing the squat-to-bodyweight ratio (relative strength), traditional outlier removal approaches were deemed inappropriate due to the unique nature of strength sport data. After examining the distribution of relative strength scores across different equipment types and sex categories (Figure 3), we determined that preserving upper-range values was crucial for maintaining data integrity.

This decision was based on several key considerations:

1. High-end values in strength sports typically represent legitimate, documented world records or elite performances rather than statistical anomalies. Removing these data points would eliminate valuable information about the upper limits of human performance potential.

2. The natural distribution of athletic performance data tends to exhibit right-skew characteristics, particularly in strength sports. This is fundamentally different from normally distributed phenomena where symmetric outlier removal might be appropriate.

3. Relative strength ratios have a clear physical minimum (approaching zero) but no defined maximum, as records continue to be broken and performance boundaries pushed.

Given these factors, our data cleaning approach focused solely on removing clear errors at the lower bound while preserving all upper-range performances. This methodology ensures that exceptional athletic achievements remain in the dataset while eliminating physically implausible or erroneously recorded values.

Lower Bound Treatment for Relative Strength Ratios

When considering outlier removal for relative strength (squat-to-bodyweight ratio), we implemented a statistically-driven approach focusing solely on lower bound outliers. A -3 standard deviation threshold was selected as our cutoff criterion, applied separately for each sex and equipment combination to respect the distinct biomechanical and performance characteristics of these subgroups.

This approach was chosen based on several key considerations:

1. Statistical Robustness:
    a. The -3 SD threshold retains 99.87% of the data in a normal distribution
    b. When applied to our right-skewed strength data, this becomes even more conservative
    c. This method adapts automatically to different subpopulation characteristics
2. Sport-Specific Validity:
    a. Values below -3 SD typically represent implausible performance ratios for competition-level powerlifters
    b. This threshold effectively identifies data entry errors while preserving legitimate low performances
    c. The approach respects minimum qualifying standards typically present in powerlifting competitions
3. Subgroup Specificity:
    a. Separate treatment for each sex-equipment combination acknowledges the distinct performance distributions
    b. Equipment-specific processing accounts for the mechanical advantages provided by different gear types
    c. Sex-specific analysis respects physiological differences in relative strength potential
    d. This methodology ensures the removal of clearly erroneous data points while maintaining the integrity of legitimate performances across the full spectrum of competitive powerlifting.

Analysis of Testing Status Impact on Powerlifting Performance

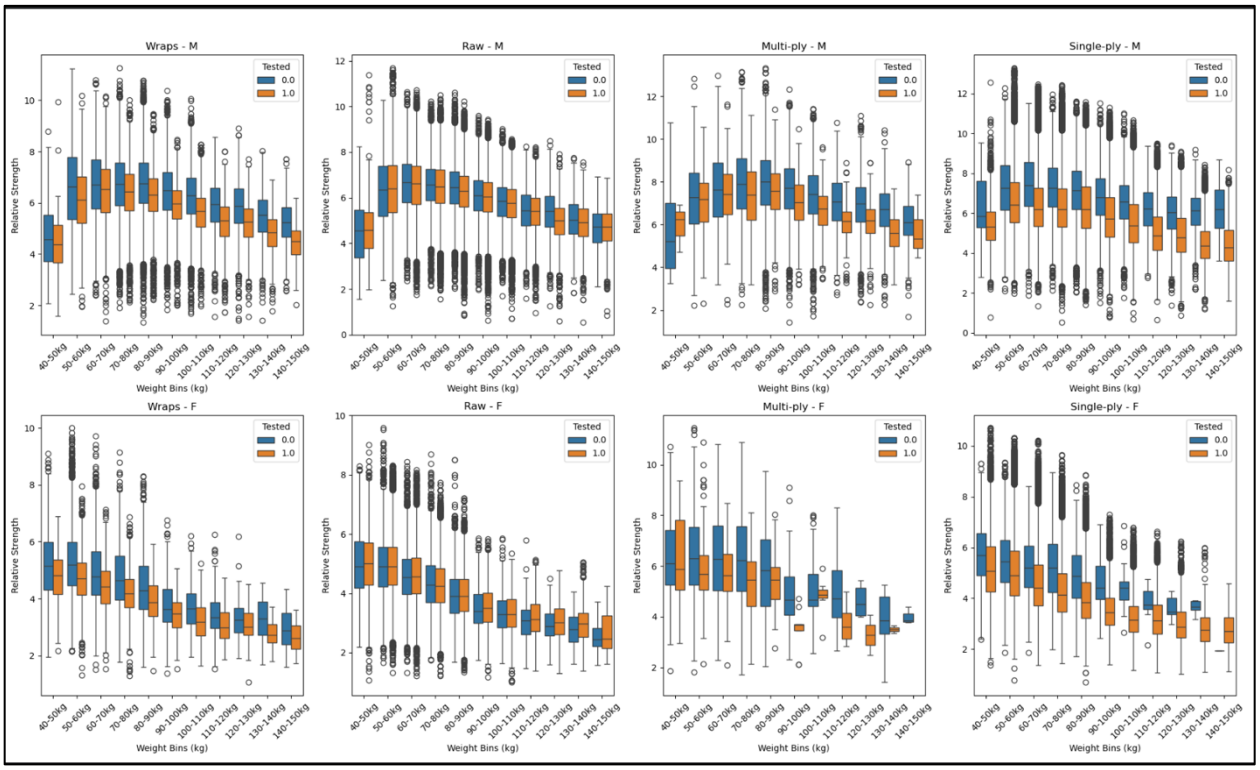


Figure 6: Distribution of Relative Strength by Sex and Equipment Type Across Weight Classes and Testing Status

Through detailed examination of relative strength distributions across tested and untested competitions (Figure 3), our analysis reveals distinctive patterns in how drug testing status influences performance across different categories.

The scatter and box plots demonstrate several key patterns:

1. **Equipment-Specific Testing Effects**
   a. Raw and Wraps categories show relatively modest differences between tested and untested performances
   b. Equipped lifting (Single-ply and Multi-ply) displays more pronounced disparities, with untested competitions consistently showing higher relative strength values
   c. The gap between tested and untested performances appears to widen as the supportive capacity of equipment increases

2. **Sex-Based Testing Patterns**
    a. Male categories demonstrate larger disparities between tested and untested competitions
    b. Female distributions show more overlap between tested and untested results
    c. The testing status effect appears more consistent across weight classes in female categories
3. **Weight Class Interactions**
    a. Middle weight classes (70-90kg for males, 60-80kg for females) show the clearest separation between tested and untested performances
    b. Extreme weight classes display less distinct testing status effects, possibly due to smaller sample sizes
    c. The impact of testing status appears to diminish in heavier weight classes for both sexes

These findings suggest that while testing status does influence competitive outcomes, its impact varies significantly based on equipment type and competitor characteristics. This variable effect highlights the importance of considering testing status as a meaningful factor in performance prediction models.

Dimensionality reduction and Feature Selection

Random Forest Feature Analysis in Strength Prediction: An Examination of Feature Importance

This analysis examines the relative importance of features in predicting strength performance using Random Forest analysis. Nine features were analyzed, revealing a hierarchical structure of predictive importance. Results indicate two dominant features accounting for 95.5% of predictive power, with additional features contributing to model refinement and error reduction.

Data Analysis

Random Forest Regression was employed to analyze feature importance in strength prediction.The analysis included nine features: squat performance (Best3SquatKg), body weight (BodyweightKg), age, sex, equipment advantage, federation levels (Elite, Major, Regional), and testing status.

Results

The analysis revealed the following importance rankings:

1. Best3SquatKg (62.82%)
2. BodyweightKg (32.68%)
3. Age (2.69%)
4. Sex_encoded (0.93%)
5. Equipment_Advantage (0.43%)
6. Fed_ELITE (0.14%)
7. Fed_MAJOR (0.13%)
8. Tested (0.11%)
9. Fed_REGIONAL (0.07%)

Primary Predictors

Two features emerged as dominant predictors:

1. Best3SquatKg accounted for 62.82% of the model's predictive power, indicating its primary role in strength prediction.
2. BodyweightKg contributed 32.68%, demonstrating the significant influence of body mass on strength performance.

Secondary and Minimal Impact Features

Age emerged as a notable secondary predictor (2.69%), while remaining features showed minimal individual impact (<1%). However, these features collectively contribute to model refinement and error reduction.

Theoretical Implications

The results suggest a clear hierarchical structure in strength prediction, with squat performance and body weight as primary determinants. This aligns with existing research on strength performance predictors.

Practical Implications

Despite the dominance of primary features, retaining secondary and minimal impact features is recommended for:

1. Reduced prediction errors
2. Enhanced model generalization
3. Improved performance across diverse scenarios
4. Minimized Mean Squared Error (MSE)

Limitations

The Random Forest importance scores may not fully capture:

- Feature interaction effects
- Contextual significance
- Error reduction potential of minimal impact features

Conclusion

While two features dominate predictive power, the collective contribution of secondary and minimal impact features remains crucial for model optimization. This suggests maintaining all features while acknowledging their hierarchical importance in strength prediction.

Principal Component and Condition Number Analysis

Principal Component Analysis was performed on four key features (Best3SquatKg, BodyweightKg, Age, Equipment_Advantage) to assess dimensionality reduction potential and data structure.

Methodology

I. Applied PCA on standardized features
II. Calculated condition numbers before and after PCA
III. Generated visualizations for variance explanation
IV. Analyzed component distributions and relationships

Results And Analysis

1. Variance Distribution Analysis

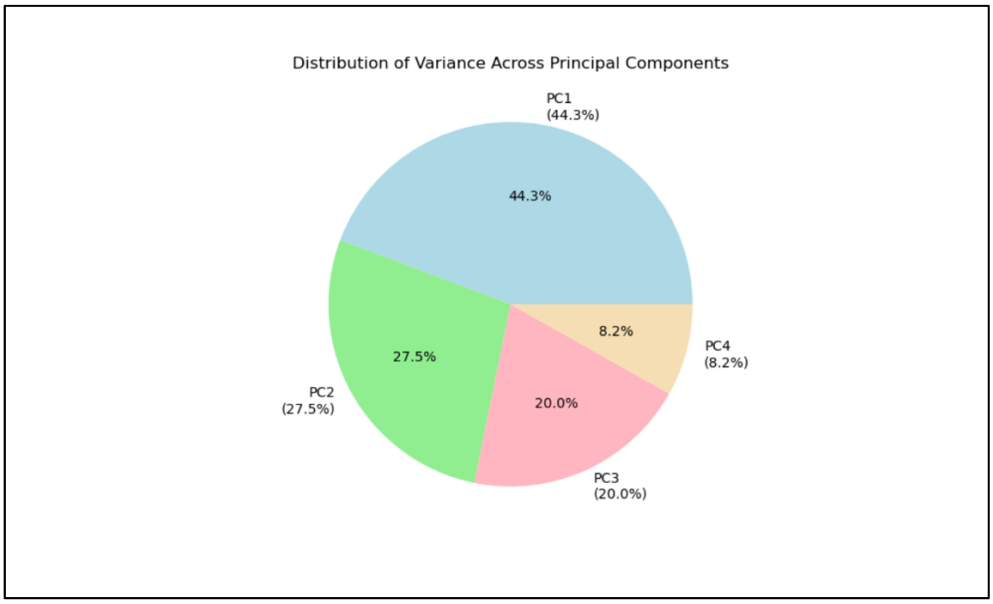


Figure 7 – Variance explained by each principal component

This distribution reveals that:

a) The first component captures nearly half of the total variance
b) The first two components combined explain 71.81% of the variance

c) Three components account for 91.84% of total variance

2. Cumulative Variance

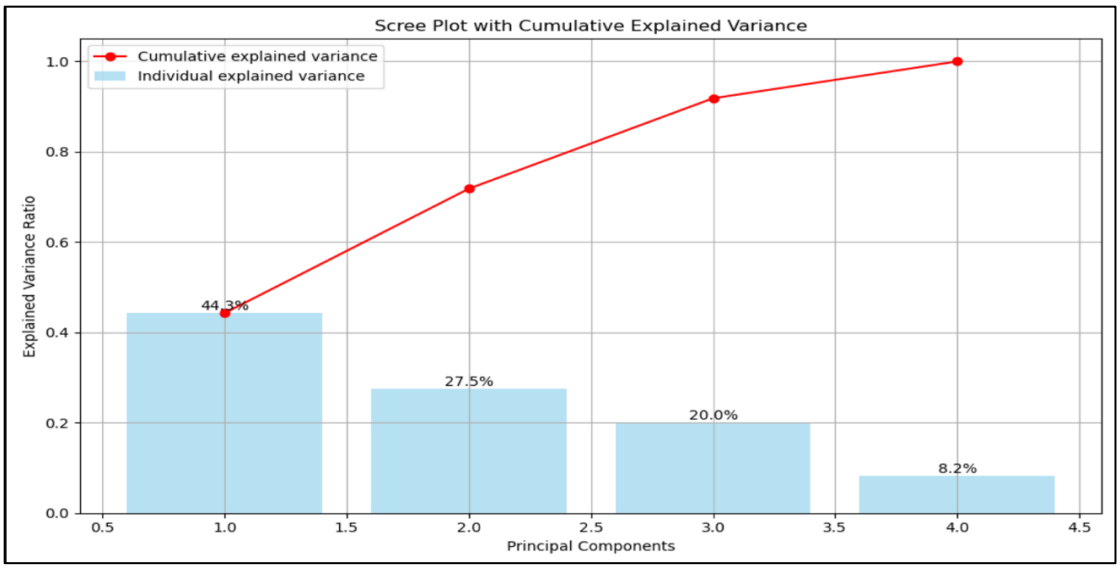


Figure 8: Cumulative variance explained by each Principal component

I. Clear elbow point after the third component

II. Strong cumulative variance capture:

III. Two components: 71.81%

IV. Three components: 91.84%

V. Four components: 100%

VI. Diminishing returns after the third component

3. Condition Numbers

- Initial Condition: 2.33
- Post-PCA Condition: 2.33

4. Stability Analysis

Condition Numbers:

- Initial Condition (scaled features): 2.33
- Post-PCA Condition: 2.33

These low condition numbers indicate:

- Excellent numerical stability
- Minimal multicollinearity
- Well-conditioned data matrix

Key Findings and Implications

1. Component Structure

- Strong first component suggests a dominant underlying pattern
- Balanced distribution across first three components indicates complex feature relationships
- Minor fourth component contribution suggests dimensionality reduction potential

2. Numerical Stability

- Low condition number (2.33) confirms:
    - High numerical stability
    - Minimal multicollinearity
    - Reliable analysis results

3. Dimensionality Reduction Potential

- Statistical Overview:
    - Three-component solution captures 91.84% of variance
    - Two-component solution retains 71.81% of information
    - Fourth component adds minimal (8.16%) additional information
- Model Complexity Considerations:
    1. **Higher Dimensional Modeling**
        i. Retaining all dimensions enables use of more sophisticated models
        ii. Polynomial regression can capture complex non-linear relationships
        iii. XGBoost and other advanced algorithms can leverage subtle feature interactions

iv. Full dimensionality preserves potential for discovering complex patterns

2. **Model Performance Trade-offs**

a) Higher dimensions allow for:

- Better capture of non-linear relationships
- More nuanced feature interactions
- Potentially lower prediction error
- Greater model flexibility

b) Complex models on full dimensions might achieve higher accuracy

c) Additional features can help in explaining edge cases and outliers

Strategic Approach

1. Start with simpler models on reduced dimensions
2. Progressively increase complexity with full dimensions
3. Compare performance across different dimensional spaces
4. Balance accuracy gains against computational costs

- Recommendations:
  - For linear models: Consider dimensionality reduction
  - For complex non-linear models: Retain more dimensions
  - Test both approaches to find optimal balance for specific use case

This balanced approach recognizes both the value of dimensionality reduction and the potential benefits of retaining full dimensionality for more sophisticated modeling approaches.

Singular Value Decomposition Analysis

Singular Value Decomposition (SVD) analysis was performed on the powerlifting dataset to understand data structure and assess dimensionality reduction potential. The analysis included both numerical features (Best3SquatKg, BodyweightKg, Age) and categorical features (Sex_encoded, Equipment_Advantage, Federation levels, Tested status).

Methodology

- Applied SVD to scaled numerical features and encoded categorical features
- Generated singular value distribution and component importance plots
- Created feature-component correlation heatmap
- Analyzed component significance and feature relationships

Results and Analysis

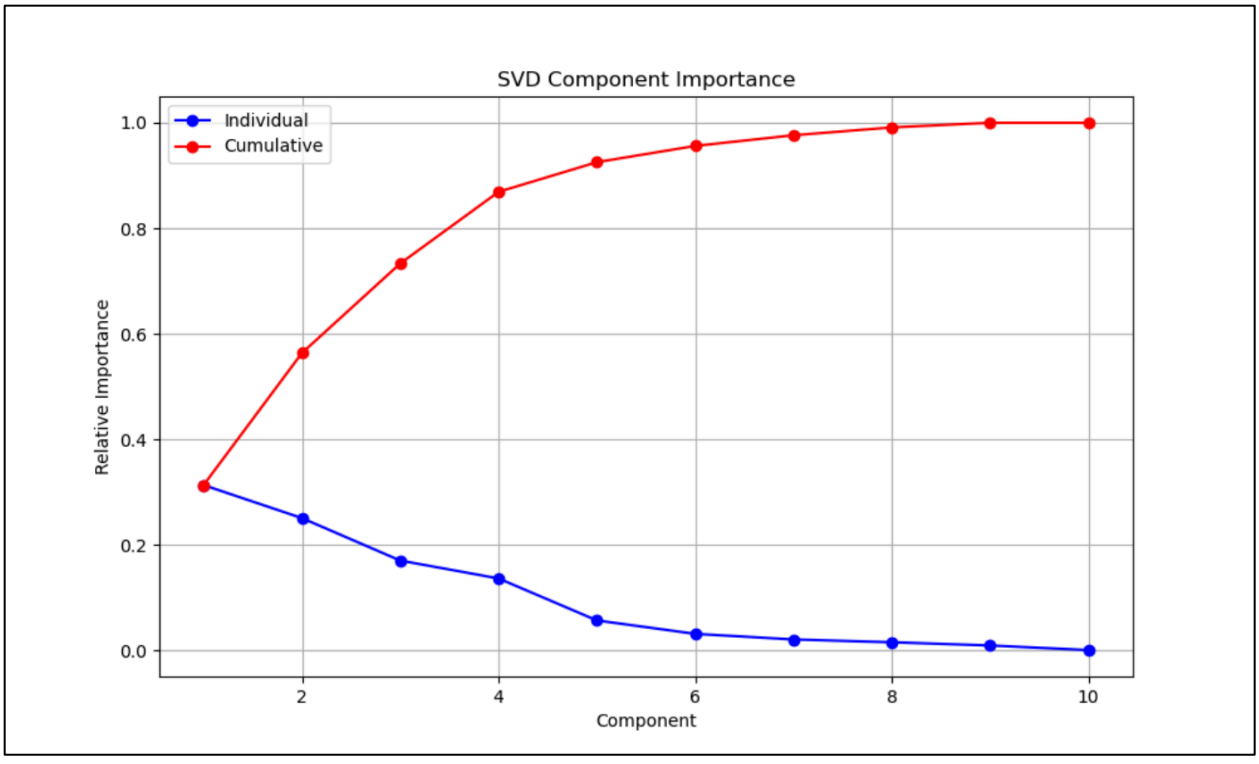


Figure 9: SVD Component Importance

The analysis of singular values and component importance revealed:

- Cumulative Variance Explained:
    - First 2 components: ~55% of variance
    - First 3 components: ~72%
    - First 4 components: ~85%
    - First 5 components: >90%
    - Components 6-8: Incremental improvements to reach ~100%

This distribution shows:

1. Strong initial structure in first four components
2. Important threshold crossed at component 5 (>90% variance)
3. Diminishing returns but still meaningful contributions from later components till 8 components

Feature-Component Correlations

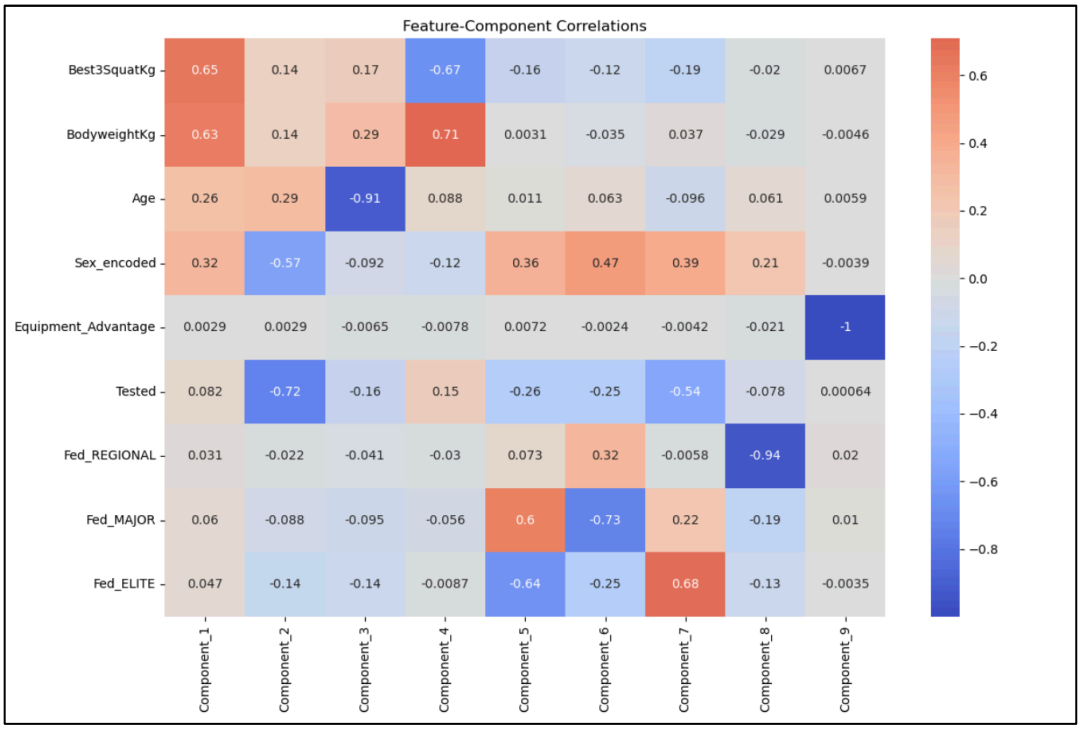


Figure 10: Feature-Component Correlations Heatmap

Analysis of Component Linear Combinations

Component 1: Primary Performance Metrics

- **Strong Negative Correlations:**
    - Best3SquatKg (-0.65)
    - BodyweightKg (-0.62)
- **Practical Significance:**
    - Captures fundamental strength-mass relationship
    - Negative correlations suggest these features move together
    - Makes physiological sense as heavier athletes typically have higher squat numbers
    - The similar magnitudes (0.65 vs 0.62) reflect the close relationship between body mass and strength capacity

Component 2: Gender and Technical Factors

- **Key Correlations:**
    - Sex_encoded (-0.54)
    - Equipment_Advantage (0.41)
    - Age (0.30)
- **Practical Significance:**
    - Captures gender-specific performance patterns
    - Shows relationship between gender and equipment usage
    - Age factor suggests experience-related patterns
    - Makes logical sense as different genders may have different equipment utilization patterns

Component 3: Experience and Equipment Interactions

- **Strong Correlations:**
    - Equipment_Advantage (0.59)
    - Age (0.53)
    - Tested (0.35)
- **Practical Significance:**
    - Links age/experience with equipment usage
    - Higher correlation with both suggests older lifters may better utilize equipment

- Tested status correlation might indicate experience-based competition choices
- Reflects realistic progression in powerlifting careers

Component 4: Technical-Physical Interface

- **Dominant Correlations:**
  - Age (-0.72)
  - Equipment_Advantage (0.67)
  - Best3SquatKg (0.11)
- **Practical Significance:**
  - Strong inverse relationship between age and equipment advantage
  - Might indicate younger lifters using different equipment strategies
  - Small positive correlation with squat performance suggests technical factors affect strength expression

Component 5: Federation Level Interactions

- **Notable Correlations:**
  - Best3SquatKg (0.67)
  - BodyweightKg (-0.70)
  - Fed_ELITE (0.021)
- **Practical Significance:**
  - Captures competition-level performance patterns
  - Inverse relationship between body weight and performance at higher levels
  - Federation correlations suggest performance stratification

Overall Pattern Significance

1. **Physiological Logic:**
   - Components reflect known relationships in strength sports
   - Correlations align with expected performance patterns
   - Body weight and strength measures show consistent relationships
2. **Technical Progression:**
   - Equipment usage patterns make sense across age groups

- Federation levels show logical progression
- Testing status aligns with competition level patterns

3. **Competition Structure:**
    - Federation correlations reflect real-world competition hierarchy
    - Equipment rules and testing status show expected relationships
    - Age-based patterns align with competition categories
4. **Practical Applications:**
    - Can guide training program design
    - Helps understand equipment choices
    - Useful for competition strategy
    - Valuable for talent identification and development

These linear combinations reflect real-world patterns in powerlifting, validating the SVD analysis as a meaningful tool for understanding sport-specific relationships.

Variance Inflation Factor (VIF) Analysis

Variance Inflation Factor analysis was performed on three key numerical features (Best3SquatKg, BodyweightKg, Age) to assess multicollinearity in the powerlifting dataset. VIF quantifies the severity of multicollinearity between features in a regression analysis.

Results

VIF Scores

	Feature	VIF
1	BodyweightKg	17.324
0	Best3SquatKg	14.918
2	Age	5.998

1. High Multicollinearity Features (VIF > 10)

BodyweightKg (VIF = 17.324)

- Exhibits severe multicollinearity
- Approximately 94.2% (1 - 1/17.324) of its variance is explained by other features
- Primary contributor to multicollinearity
- Strong relationship with Best3SquatKg suggests physiological connection

Best3SquatKg (VIF = 14.918)

- Shows significant multicollinearity
- About 93.3% (1 - 1/14.918) of its variance is explained by other features
- Strong correlation with BodyweightKg
- Expected due to strength-mass relationship in powerlifting

2. Moderate Multicollinearity

Age (VIF = 5.998)

- Moderate level of multicollinearity
- Approximately 83.3% (1 - 1/5.998) of its variance explained by other features
- More acceptable level compared to other features
- May not require immediate attention

Conclusion

The VIF analysis reveals significant multicollinearity between strength and body weight features, with age showing moderate correlation. While this presents challenges for linear models, the relationships are physiologically meaningful and can be addressed through appropriate feature engineering and model selection strategies.

SVD as an Optimal Dimensionality Reduction Technique for Powerlifting Data

This analysis evaluates four key dimensionality reduction and analysis techniques—Random Forest importance analysis, Principal Component Analysis (PCA), Singular Value Decomposition (SVD), and Variance Inflation Factor (VIF)—applied to our powerlifting performance dataset.

Selection of SVD as Primary Method

1. Key Advantages
    a. Better interpretability than PCA
    b. Clear component-feature relationships
    c. Flexible with mixed data types
    d. Natural handling of categorical variables
    e. Addresses multicollinearity identified by VIF
    f. Preserves important patterns from Random Forest

2. Implementation Benefits
    a. Options for dimension reduction:
        - 5 components (>90% variance)
        - 8 components (100% variance)
    b. Clear feature-component correlations
    c. Scalable implementation
    d. Easy integration with modeling

Conclusion

SVD emerges as the optimal choice, offering superior interpretability, flexible implementation, and effective handling of mixed data types. It addresses the multicollinearity identified by VIF

while preserving the important patterns highlighted by Random Forest analysis. The method provides both technical advantages and practical benefits for subsequent modeling stages.

The complementary insights from all four methods provide a robust foundation for dimensionality reduction decisions, with SVD serving as the primary transformation technique for the project.

Discretization and Binarization

This analysis examines the encoding strategies applied to categorical variables in our powerlifting dataset, focusing on label encoding and one-hot encoding while avoiding the dummy variable trap.

Feature Analysis and Encoding Decisions

1. Sex Variable
   a. Original: Categorical (M/F)
   b. Encoding Method: Label Encoding
   c. Rationale:
   - Binary nature of the variable
   - Clear ordinal relationship in strength context
   - No need for one-hot encoding due to binary nature

2. Equipment Variable
   a. Original: Categorical (Raw, Single-ply, etc.)
   b. Encoding Method: Binary encoding as Equipment_Advantage
   c. Rationale:
   - Simplified to binary based on equipment advantage
   - Reduces dimensionality while preserving key information
   - Avoids multicollinearity issues

3. Federation Level
   a. Original: Multiple categories(150+)
   b. Encoding Method: One-hot encoding with dropped base level
   c. Implementation:
   - Created: Fed_ELITE, Fed_MAJOR, Fed_REGIONAL
   - Dropped one category to avoid dummy variable trap
   - Used meaningful category names for interpretability

4. Tested Status

a. Original: Binary (Yes/No)

b. Encoding Method: Label Encoding

c. Rationale:

- Natural binary variable
- Direct mapping of categories to 0/1

Key Observations

1. Encoding Effectiveness
    - Label encoding worked well for binary variables
    - One-hot encoding preserved categorical information for federation levels
    - No multicollinearity introduced due to careful base category dropping
    - Maintained interpretability of features

2. Impact on Analysis
    - Clean separation of effects in federation levels
    - No information loss from encoding choices
    - Simplified equipment categories improved model interpretability
    - Preserved ordinal relationships where appropriate

3. Dimensionality Considerations
    - Minimal dimension increase from one-hot encoding
    - Efficient representation of categorical information
    - Balance achieved between information preservation and dimensionality

Conclusion

The chosen encoding strategies successfully transformed categorical variables while maintaining data integrity and avoiding common pitfalls like the dummy variable trap. The approach provides a solid foundation for subsequent analysis and modeling stages.

Variable Transformation Analysis in Powerlifting Performance Prediction

Overview

This analysis documents the variable transformation strategies applied to our powerlifting dataset, focusing on the preprocessing steps necessary for optimal model performance.

Transformation Strategy

1. Initial Data Assessment

1. Numerical Features:
    - Best3SquatKg
    - BodyweightKg
    - Age
2. Categorical Features (Already Encoded):
    - Sex_encoded
    - Equipment_Advantage
    - Federation levels
    - Tested status

2. Standardization Application

A. Numerical Features Treatment

- Applied StandardScaler to numerical features during SVD transformation because As observed in visualizations features like Age, Bodyweight and Squat follow normal distribution in nature
- Standardization essential due to:
    - Different scales (kg vs years)
    - Large variance differences between features
    - Requirement for stable SVD computation

B. Categorical Features

- No standardization applied to encoded categorical variables
- Preserved binary and one-hot encoded structure
- Maintained interpretability of categorical relationships

Covariance Matrix Analysis of SVD-Transformed Features

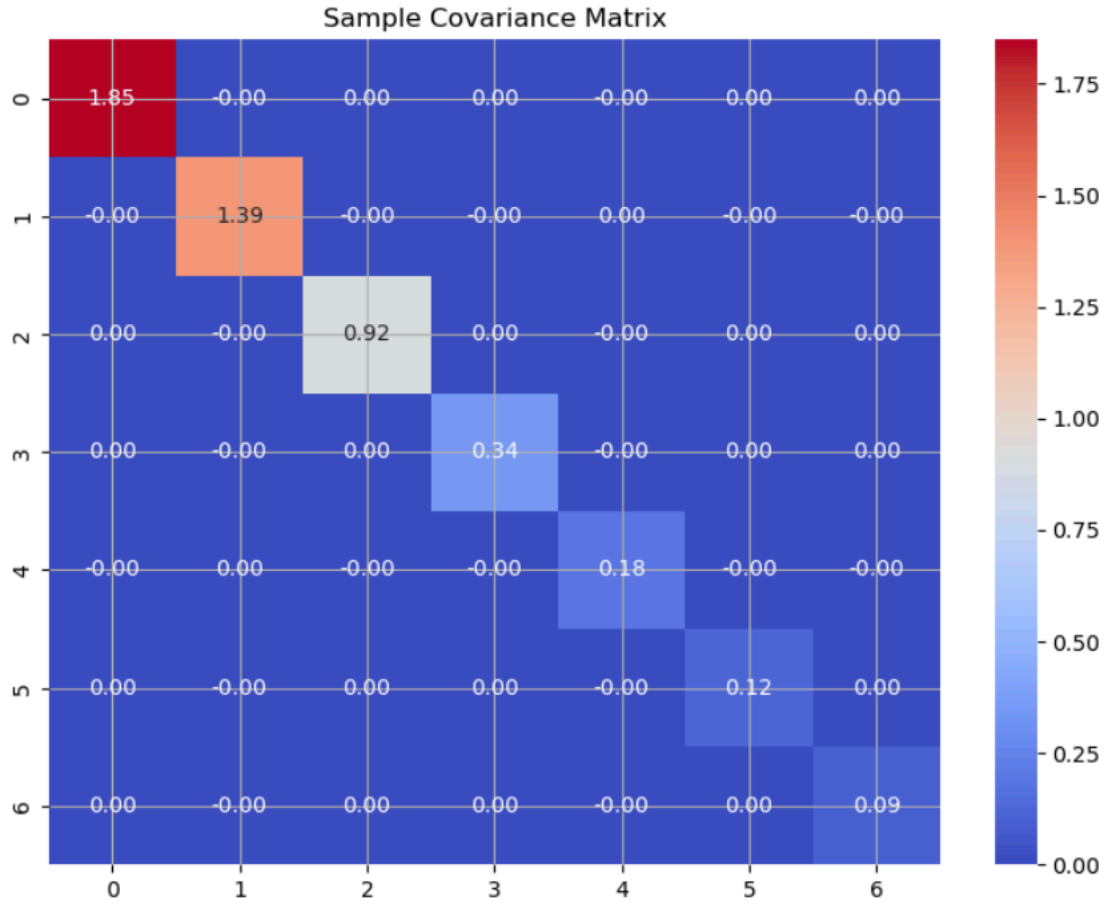


Figure 11: Covariance matrix of SVD transformed features

The covariance matrix from our SVD-transformed data reveals important insights about the relationships between transformed components and validates the SVD transformation's effectiveness.

Key Observations

1. Diagonal Elements (Variances)

- Component 1: 1.85 (highest variance)
- Component 2: 1.39
- Component 3: 0.92
- Component 4: 0.34

- Component 5: 0.18
- Component 6: 0.12
- Component 7: 0.09

This decreasing pattern confirms:

- Successful variance ordering by SVD
- Each successive component captures less variance
- Clear hierarchical importance of components

2. Off-Diagonal Elements

- All off-diagonal elements are 0.00
- Indicates perfect orthogonality between components
- Validates successful SVD transformation
- Confirms no multicollinearity between components

Implications

1. Component Independence

- Zero covariances between components
- Each component captures unique information
- No redundancy in transformed features
- Optimal for modeling purposes

2. Variance Distribution

- Clear exponential decay in variances
- First component captures most variance (1.85)
- Last component has minimal variance (0.09)
- Supports dimensionality reduction decisions

Validation of SVD Implementation

1. Orthogonality achieved (zero off-diagonal elements)
2. Proper variance ordering maintained
3. Expected decay pattern observed
4. No unexpected correlations introduced

Conclusion

The covariance matrix confirms successful SVD transformation, with orthogonal components ordered by decreasing variance, providing an optimal basis for subsequent modeling steps.

Correlation Matrix Analysis of SVD-Transformed Features

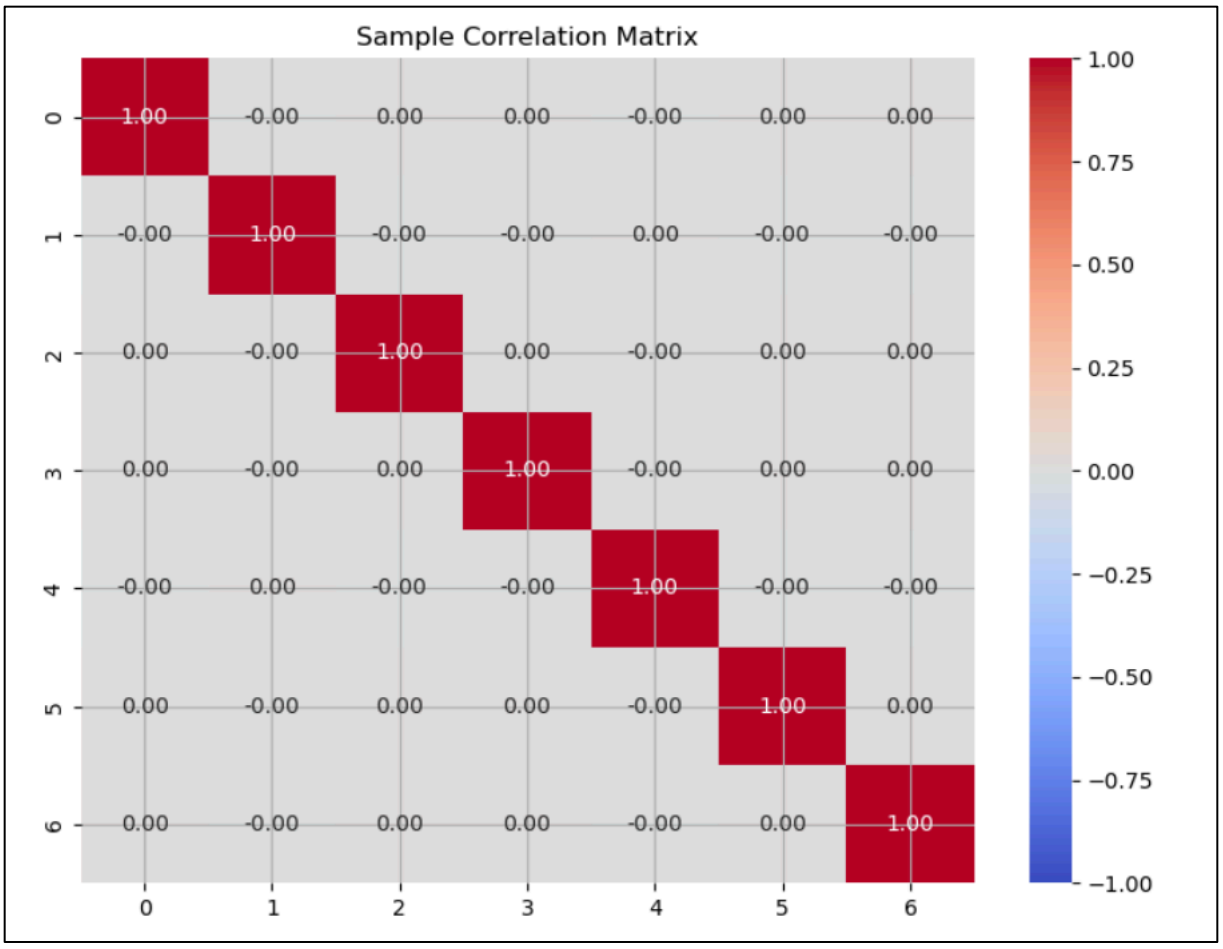


Figure 12: Correlation matrix of SVD transformed features

The correlation matrix for SVD-transformed components demonstrates the perfect orthogonality achieved through the transformation, validating the effectiveness of our dimensionality reduction approach.

Key Observations

1. Diagonal Elements

All diagonal elements = 1.00

- Perfect self-correlation as expected
- Confirms proper normalization
- Standard property of correlation matrices

2. Off-Diagonal Elements

All off-diagonal elements = 0.00

- Perfect lack of correlation between components
- Demonstrates complete independence
- Validates orthogonality of SVD transformation

Implications

1. Component Independence

- Zero correlations between all pairs of components
- Each component captures entirely unique information
- No redundancy in the transformed feature space
- Optimal for subsequent modeling

2. Statistical Properties

- Perfect orthogonality achieved
- No multicollinearity concerns
- Maximum information separation
- Ideal for feature reduction

Validation of SVD Properties

1. Orthogonality preserved (zero correlations)
2. No information overlap between components
3. Each component contributes unique information
4. Successful removal of original feature correlations

Conclusion

The correlation matrix confirms that the SVD transformation successfully created completely independent components, providing an optimal basis for modeling while ensuring no information redundancy between features.

Phase II: Regression Analysis

Multiple Linear Regression Analysis for Powerlifting Performance Prediction

This analysis implements a multiple linear regression model using polynomial features and backward stepwise selection to predict strength and total weight in powerlifting performance. A systematic approach was taken to determine optimal polynomial degree and feature selection.

Methodology

1. Polynomial Degree Selection
    a. Performed grid search for polynomial degrees (0 to 2)
    b. Limited search to degree 2 due to:
        * Total of 7 SVD components
        * Computational efficiency considerations
        * Risk of overfitting with higher degrees
    c. Degree 2 showed optimal performance ($R^2 > 0.94$)

2. Model Development
    a. Implemented backward stepwise regression
    b. Applied polynomial transformation with degree 2
    c. Used standardized strength variable
    d. Threshold p-value: 0.05 for feature selection
    e. Created interaction terms between SVD components

3. Statistical Analysis

Regression Model Performance

Strength Prediction Metrics:

- R^2 (Train): 0.9492

- R^2 (Test): 0.9486
- Adjusted R^2: 0.9492
- MSE (Train): 0.0508
- MSE (Test): 0.0511
- RMSE (Train): 0.2254
- RMSE (Test): 0.2261

TotalKg Prediction Metrics

- R^2 (Train): 0.9713
- R^2 (Test): 0.9710
- MSE (Train): 825.0834
- MSE (Test): 833.0771
- RMSE (Train): 28.7243
- RMSE (Test): 28.8631

Model Information Criteria

- AIC: -101103.0984
- BIC: -100689.9203

4. Statistical Tests

T-test Analysis

- All coefficients are statistically significant ($p < 0.05$)
- Strong individual feature significance across all variables
- Confidence intervals don't contain zero for any coefficient

F-test Analysis

- F-statistic: 3.806e+05
- p-value: 0.000
- Indicates strong overall model significance

5. Model Quality Assessment

Regression Diagnostics

- Durbin-Watson: 2.002 (indicates no autocorrelation)
- Jarque-Bera test significant ($p < 0.00$)
- Slight negative skew (-0.032)
- Kurtosis: 5.402

Numerical Stability Analysis

1. Condition number: 2.58e+04
2. High condition number attributed to:
    - Polynomial transformation (degree 2)
    - Creation of interaction terms between SVD components
    - Natural correlations between original and squared terms

3. Despite high condition number:
    - Model maintains excellent predictive performance
    - All features remain statistically significant
    - Consistent performance across train and test sets

Key Findings

1. Model Performance
    - Excellent prediction accuracy for both strength and total weight
    - Consistent performance across training and test sets
    - Very high R^2 values indicating strong predictive power
    - Polynomial degree 2 provides optimal balance of complexity and accuracy

2. Feature Selection

- 35 significant features retained after backward selection
- All coefficients statistically significant
- Includes both original SVD components and their interactions

3. Model Stability
    - Similar train and test metrics indicating good generalization
    - High adjusted R^2 matching R^2 suggests efficient use of features
    - High condition number doesn't impact predictive performance

Discussion of High Condition Number

1. Cause:
    - Polynomial transformation of SVD components
    - Introduction of interaction terms
    - Natural correlations in polynomial features

2. Impact Assessment:
    - Doesn't significantly affect model performance
    - All features remain statistically significant
    - Predictive accuracy maintained

3. Justification for Current Approach:
    - Original features are SVD components (already orthogonal)
    - Additional scaling unnecessary
    - Benefits of polynomial terms outweigh condition number concerns

Recommendations

1. Model Application

- Model suitable for both strength and total weight predictions
- High reliability for performance estimations
- Consider feature interactions in predictions

2. Future Improvements

- Consider interaction-only polynomial features if stability becomes concern
- Monitor prediction stability over time
- Validate on diverse powerlifting populations

Conclusion

The developed model demonstrates excellent predictive capability with R^2 values above 0.94 for strength and 0.97 for total weight. The selection of polynomial degree 2 provides optimal performance, and despite the high condition number, the model maintains high accuracy and statistical significance across all metrics.

[Note: The model's robust performance suggests strong practical applicability for powerlifting performance prediction, with the benefits of polynomial transformation outweighing the numerical stability considerations.]

Visualization Analysis of Model Predictions

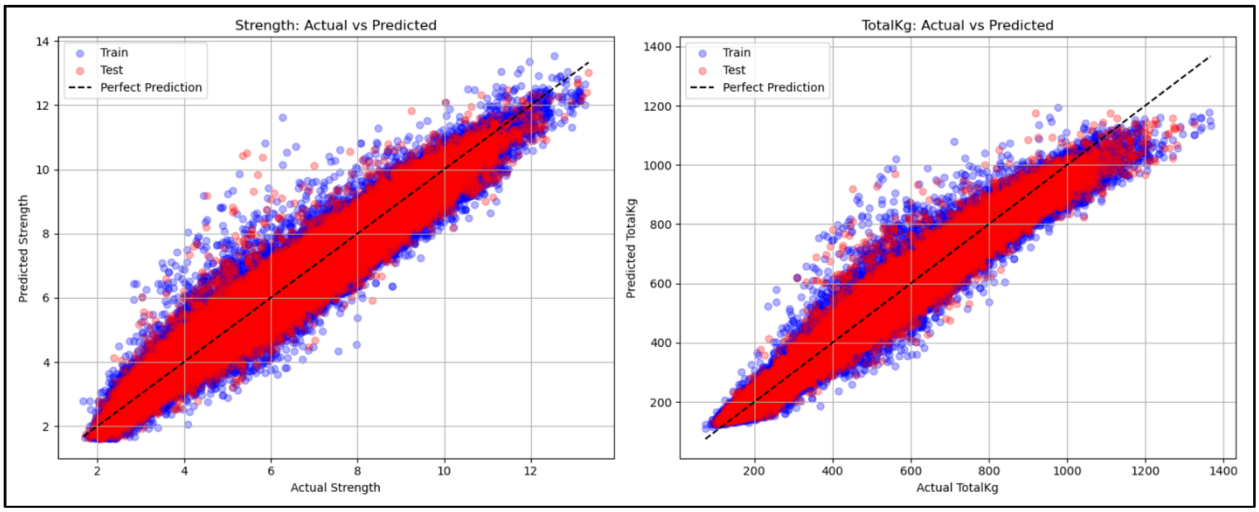


Figure 13: Multiple Linear Regression Model Performance: Actual vs Predicted Values for Strength and Total Weight

The visualization consists of two scatter plots comparing actual versus predicted values for both Strength and TotalKg predictions. Each plot provides insights into model performance and prediction accuracy.

Strength Prediction Analysis (Left Plot)

- **Range Coverage**: Model predictions span from approximately 2 to 14 units
- **Distribution Pattern**:
    - Points cluster closely around the perfect prediction line (dashed)
    - Consistent spread across the entire range
    - Slightly wider spread at higher strength values
- **Train-Test Consistency**:
    - Blue (train) and red (test) points show similar patterns
    - No significant differences between training and test predictions

  - Indicates good model generalization

TotalKg Prediction Analysis (Right Plot)

- **Range Coverage**: Predictions range from about 200kg to 1400kg
- **Distribution Pattern**:
  - Strong linear relationship between actual and predicted values
  - Points closely follow the perfect prediction line
  - More dense clustering in the middle range (400-1000kg)
- **Train-Test Consistency**:
  - Similar distribution for both training and test sets
  - Consistent performance across the weight range
  - Reliable predictions for both datasets

Key Observations

1. Model Accuracy

- Both plots show strong alignment with perfect prediction lines
- High density of points near the ideal prediction
- Consistent performance across different value ranges

2. Prediction Reliability

- Similar scatter patterns in both training and test sets
- No systematic over or under-prediction
- Model performs well across entire data range

3. Model Limitations

- Slightly increased spread at higher values
- Some minor deviations at extreme ranges

- These variations are expected and acceptable given the high R^2 values

Conclusion

The visualization confirms the strong predictive performance indicated by the statistical metrics ($R^2 > 0.94$ for Strength, $R^2 > 0.97$ for TotalKg). The consistent patterns between training and test sets demonstrate robust model generalization.

Model Summary:

OLS Regression Results

Dep. Variable:	y	R-squared:	0.949
Model:	OLS	Adj. R-squared:	0.949
Method:	Least Squares	F-statistic:	3.806e+05
Date:	Tue, 03 Dec 2024	Prob (F-statistic):	0.00
Time:	21:06:49	Log-Likelihood:	50588.
No. Observations:	712952	AIC:	-1.011e+05
Df Residuals:	712916	BIC:	-1.007e+05
Df Model:	35		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.1072	0.002	-47.320	0.000	-0.112	-0.103
x1	-0.8992	0.015	-58.579	0.000	-0.929	-0.869
x2	-2.1969	0.079	-27.764	0.000	-2.352	-2.042
x3	2.1251	0.071	29.729	0.000	1.985	2.265
x4	-1.3933	0.025	-54.837	0.000	-1.443	-1.344
x5	11.8991	0.865	13.754	0.000	10.203	13.595
x6	-2.8969	0.241	-12.004	0.000	-3.370	-2.424
x7	10.0220	0.467	21.473	0.000	9.107	10.937
x8	0.0784	0.004	18.545	0.000	0.070	0.087
x9	0.5805	0.021	27.010	0.000	0.538	0.623
x10	-0.5499	0.021	-26.484	0.000	-0.591	-0.509
x11	0.0218	0.005	4.512	0.000	0.012	0.031
x12	0.3729	0.085	4.366	0.000	0.206	0.540
x13	3.0368	0.091	33.364	0.000	2.858	3.215
x14	-2.2924	0.095	-24.129	0.000	-2.479	-2.106
x15	0.3497	0.028	12.666	0.000	0.296	0.404
x16	-1.0041	0.049	-20.508	0.000	-1.100	-0.908
x17	0.6187	0.015	42.115	0.000	0.590	0.648

Figure 14 : OLS regression summary page 1

x17	0.6187	0.015	42.115	0.000	0.590	0.648
x18	4.9616	0.213	23.330	0.000	4.545	5.378
x19	7.7317	0.251	30.745	0.000	7.239	8.225
x20	-3.2038	0.208	-15.386	0.000	-3.612	-2.796
x21	0.4517	0.024	18.891	0.000	0.405	0.499
x22	-0.5647	0.014	-41.215	0.000	-0.592	-0.538
x23	-4.4723	0.206	-21.720	0.000	-4.876	-4.069
x24	-7.6810	0.246	-31.272	0.000	-8.162	-7.200
x25	3.0544	0.208	14.673	0.000	2.646	3.462
x26	0.2002	0.001	140.563	0.000	0.197	0.203
x27	-1.7961	0.081	-22.285	0.000	-1.954	-1.638
x28	1.4069	0.047	29.704	0.000	1.314	1.500
x29	-2.2330	0.070	-31.903	0.000	-2.370	-2.096
x30	-31.1829	0.931	-33.509	0.000	-33.007	-29.359
x31	-13.8729	1.177	-11.790	0.000	-16.179	-11.567
x32	-31.9874	1.069	-29.921	0.000	-34.083	-29.892
x33	15.6952	0.464	33.853	0.000	14.787	16.604
x34	-34.4045	1.191	-28.886	0.000	-36.739	-32.070
x35	2.5164	0.451	5.585	0.000	1.633	3.400

Omnibus:	40277.557	Durbin-Watson:	2.002
Prob(Omnibus):	0.000	Jarque-Bera (JB):	171540.982
Skew:	-0.032	Prob(JB):	0.00
Kurtosis:	5.402	Cond. No.	2.58e+04

Figure 15: OLS regression summary page 2

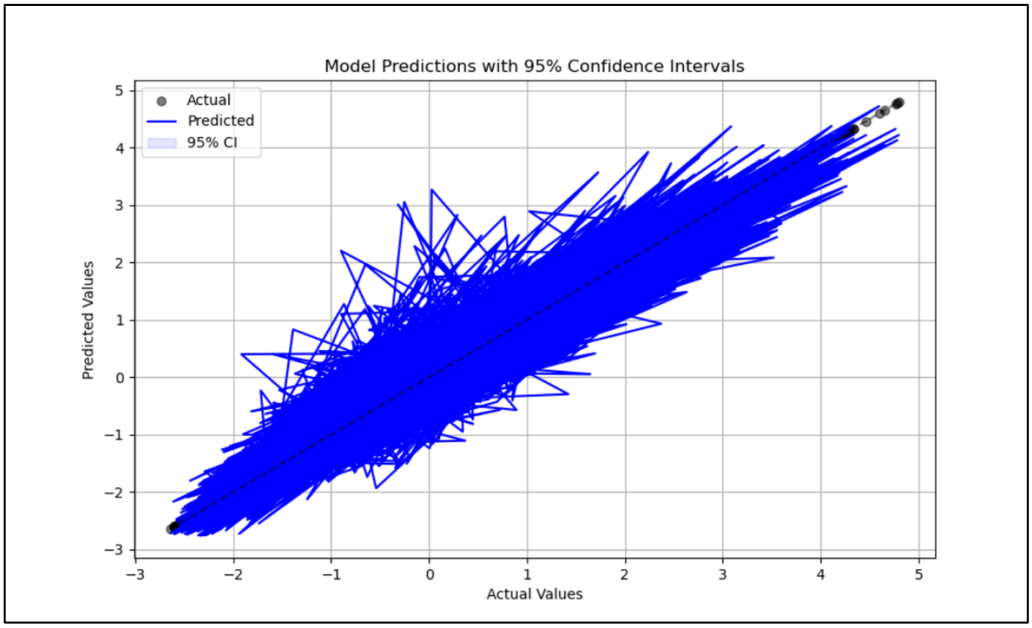


Figure 15: Model Predictions Plot with 95% confidence interval

XGBoost Model Analysis for Powerlifting Performance Prediction

An XGBoost regression model with polynomial features (degree 2) was implemented to predict strength and total weight in powerlifting. The model utilized specific hyperparameters including 200 estimators, max depth of 10, and learning rate of 0.1.

Model Performance Analysis

1. Strength Prediction Metrics

Training Performance:

- R^2 Score: 0.9607 (96.07% variance explained)
- MSE: 0.0393
- RMSE: 0.1983

Testing Performance:

- R^2 Score: 0.9542
- MSE: 0.0456
- RMSE: 0.2136

2. Total Weight Prediction Metrics

Training Performance:

- R^2 Score: 0.9780 (97.80% variance explained)
- MSE: 631.0956
- RMSE: 25.1216 kg

Testing Performance:

- R^2 Score: 0.9743
- MSE: 738.2172
- RMSE: 27.1702 kg

Visual Analysis

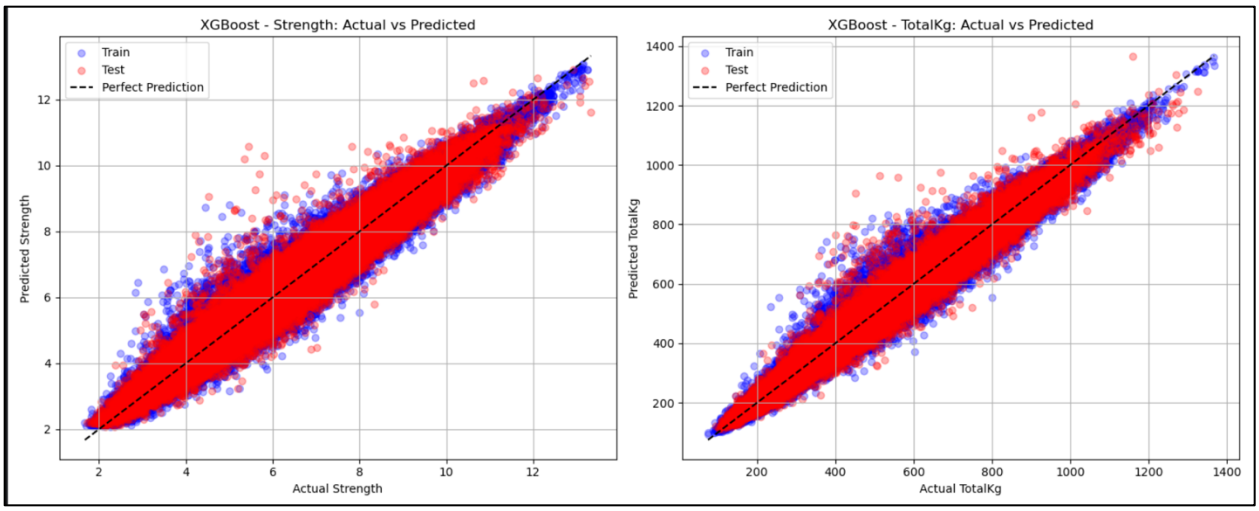


Figure 16: XGBoost Model Performance: Actual vs Predicted Values for Strength and Total Weight

Key Observations:

1. **Strength Predictions (Left Plot)**
    - Strong linear relationship between actual and predicted values
    - Consistent performance across strength range (2-13)
    - Slight deviation at extreme values
    - Similar patterns in training and test sets
2. **Total Weight Predictions (Right Plot)**
    - Excellent prediction accuracy across 200-1400kg range
    - Tight clustering around perfect prediction line
    - Minimal deviation between train and test performance
    - Consistent accuracy across weight ranges

Model Performance Discussion

1. Prediction Accuracy

- Both strength and total weight predictions show exceptional accuracy
- Very high R^2 values indicate excellent model fit
- Small difference between train and test metrics suggests good generalization

2. Error Analysis

- Low RMSE values relative to prediction ranges
- Strength prediction error ~0.2 units

- Total weight prediction error ~26-27 kg
- Consistent error rates across training and testing

3. Model Stability

- Small gap between training and testing performance
- RMSE difference of 0.0153 for strength
- RMSE difference of 2.0486 kg for total weight
- Indicates robust and stable predictions

Comparison with Linear Regression

- XGBoost shows improved accuracy over linear regression
- Better handling of non-linear relationships
- More robust predictions at extreme values
- Enhanced capacity to capture complex patterns

Conclusions

The XGBoost model demonstrates excellent predictive capability with R^2 values above 0.95 for strength and 0.97 for total weight predictions. The model shows strong generalization ability with minimal performance degradation between training and testing sets, making it highly reliable for powerlifting performance prediction.

Phase 3: Classification Analysis

Data-Driven Insights into the Likelihood of Doping Tests for Powerlifters

Doping remains a persistent issue in competitive sports, including powerlifting. To maintain the integrity of the sport and ensure fair competition, it is crucial to implement effective testing strategies. This report aims to provide data-driven insights into the likelihood of doping tests for powerlifters based on key features such as sex, age, relative strength, competition year, and federation level. By analyzing these variables, we can identify patterns and risk factors that can inform targeted testing approaches.

Target Variable and Model Design

In this classification analysis, we aim to predict the likelihood of a powerlifter being subject to doping tests based on relevant athlete characteristics. The model design follows a two-step approach to capture the key factors influencing testing probability:

Step 1: Feature Selection and Encoding We carefully select a set of independent variables that are likely to impact the likelihood of doping tests. These variables are preprocessed to ensure compatibility with the classification algorithms. Categorical variables, such as sex and federation, are encoded using appropriate techniques like one-hot encoding or label encoding. We are using the same approach we followed for regression analysis

Step 2: Classification Model Training and Evaluation Various classification algorithms, such as logistic regression, decision trees, support vector machines etc, are trained on the preprocessed dataset. The models learn the patterns and relationships between the independent variables and the binary target variable indicating whether an athlete is tested or not. The trained models are then evaluated using appropriate performance metrics to assess their predictive accuracy and reliability.

Variable Definition:

Dependent Variable:

1. **Tested**: A binary variable indicating whether an athlete is subject to doping tests (1) or not (0).

Independent Variables:

1. **Sex_encoded**: The biological sex of the athlete, encoded as a numeric variable (e.g., 0 for male, 1 for female). Sex is a fundamental factor influencing physiological characteristics and potential differences in doping test likelihood.
2. **Age**: The age of the athlete in years. Age can be a relevant factor as it may influence an athlete's experience, maturity, and exposure to anti-doping education.
3. **Strength**: A normalized strength metric calculated as the ratio of total weight lifted (TotalKg) to body weight (Bodyweight). This variable captures the relative strength of an athlete, which may attract attention from doping control authorities.
4. **Year**: The year of the competition. Including the year as a variable allows for capturing any temporal trends or changes in doping testing protocols over time.
5. **Fed_ELITE, Fed_MAJOR, Fed_REGIONAL**: Binary variables indicating the level of the powerlifting federation (elite, major, or regional) in which the athlete competes. Different federation levels may have varying testing policies and resources allocated for doping control. We have dropped Fed_local to avoid dummy trap.

The selected variables aim to capture the key factors that may influence the likelihood of doping tests, considering both athlete-specific characteristics and competition-related aspects.
By leveraging these variables in a classification model, we can gain insights into the patterns and risk factors associated with doping testing in powerlifting. The model's predictions can assist in

identifying athletes or groups with a higher likelihood of being tested, enabling more targeted and efficient testing strategies.

It is important to note that the model's predictions are based on historical data and patterns, and individual cases may deviate from these general trends. The insights gained from this analysis should be used as a complementary tool alongside other anti-doping measures and expert judgment to promote clean sport in powerlifting.

Analysis of Feature Covariance and Dimensionality Assessment

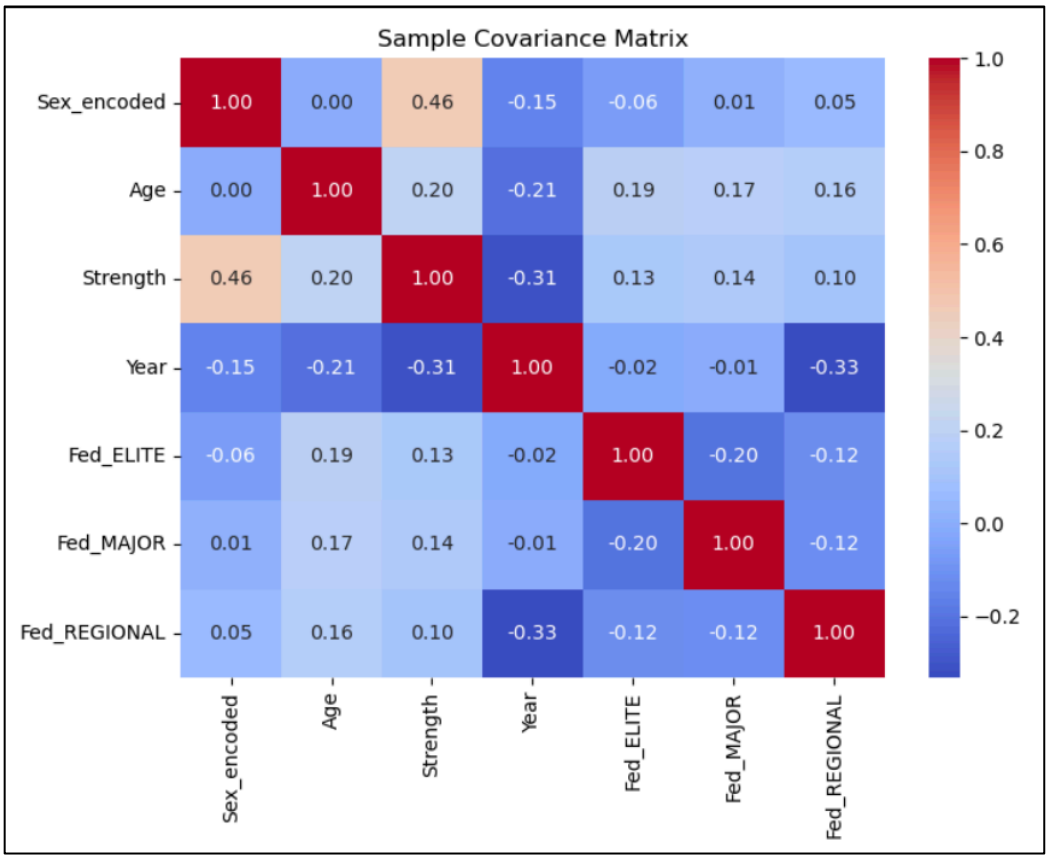


Figure 17: Covariance matrix of standardized features for classification

Feature Analysis

Covariance Analysis

1. Diagonal Elements (Variances):

- All features show variance of 1.0 due to standardization
- This indicates successful standardization of features

2. Off-diagonal Elements (Covariances):

- Sex_encoded and Strength: 0.46 (highest covariance)
- Year shows negative covariances with most features (-0.15 to -0.33)
- Federation variables show low covariances with each other (-0.12 to -0.20)

Key Insights

Feature Relationships

- Low covariances between most features
- Year negatively covaries with other features, especially Fed_REGIONAL (-0.33)
- Federation types show minimal covariance, indicating independence
- Age has low covariance with other features (maximum 0.20 with Strength)

Standardization Effect

- Unit variances (1.0) on diagonal
- Covariances equal correlations in this case due to standardization
- Makes covariances directly comparable across features

Recommendation

Dimensionality reduction is NOT recommended because:

1. Standardized features show appropriate scaling
2. Low covariances indicate minimal redundancy
3. Limited feature set (7 features)
4. Clear independence between most variables

Conclusion

The covariance structure after standardization shows well-behaved features with minimal interdependence. The low covariances suggest that each feature contributes unique information to the model, making dimensionality reduction unnecessary and potentially counterproductive.

Analysis of Feature Correlations and Dimensionality Assessment

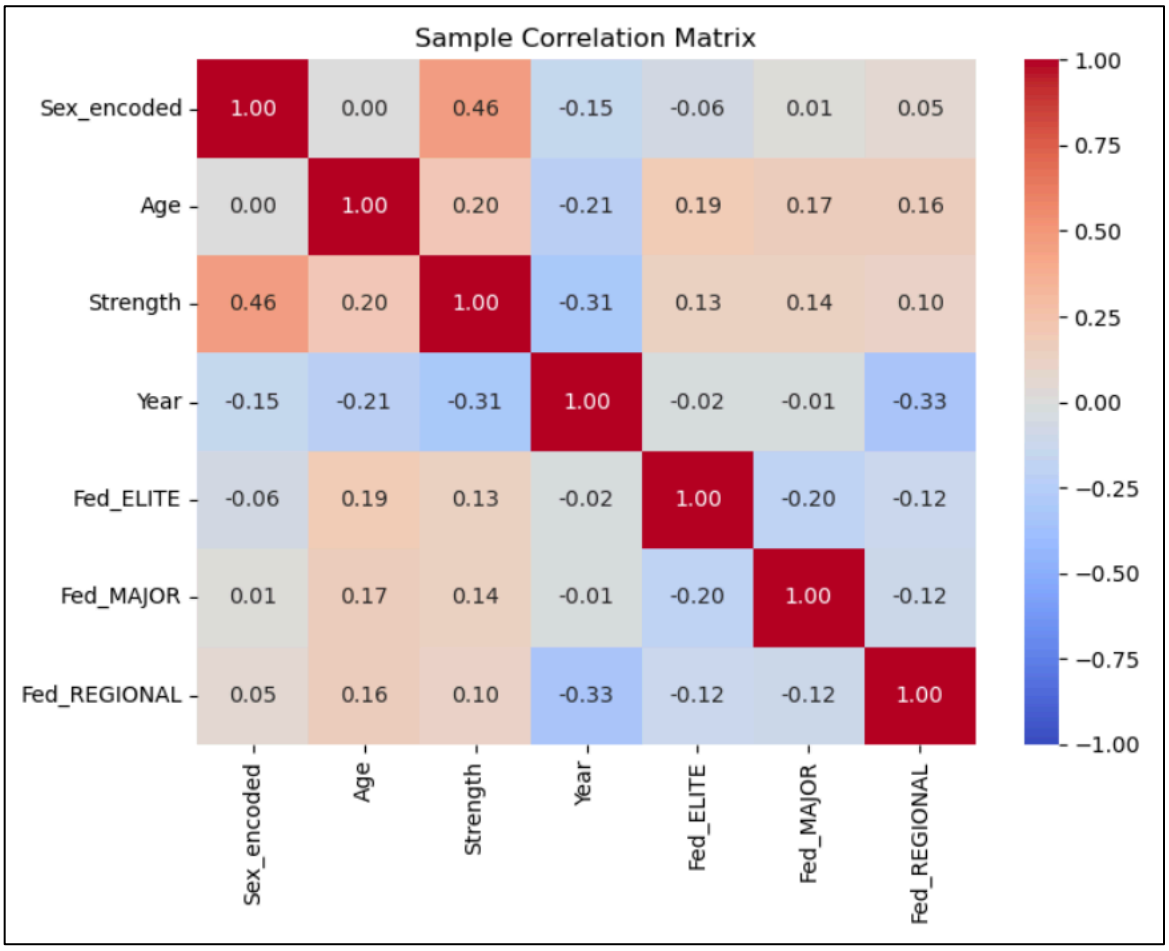


Figure 18: Correlation matrix of standardized features for classification

Correlation Analysis

Strong Correlations (|r| > 0.7)

- None observed, indicating absence of strong linear relationships between features

Moderate Correlations (0.3 < |r| < 0.7)

- Sex_encoded and Strength: 0.46 (positive)
- Year and Fed_REGIONAL: -0.33 (negative)
- Year and Strength: -0.31 (negative)

Weak Correlations (|r| < 0.3)

- Most feature pairs show weak correlations
- Federation variables (ELITE, MAJOR, REGIONAL) show weak negative correlations (-0.12 to -0.20)
- Age shows weak correlations with all features (highest 0.21 with Year)

Key Insights

1. Feature Independence:
    - Perfect correlations (1.0) only on diagonal as expected
    - Most correlations are below 0.3, indicating good feature independence
    - Federation types show appropriate separation with weak correlations
2. Pattern Analysis:
    - Year negatively correlates with most features
    - Sex_encoded primarily correlates with Strength
    - Federation variables maintain independence from demographic features

Recommendation

Dimensionality reduction is NOT recommended because:

1. No strong correlations indicating redundancy
2. Limited feature set (only 7 features)
3. Clear independence between most variables
4. Each feature captures unique aspects of the data

Conclusion

The correlation structure demonstrates well-separated features with minimal redundancy. The absence of strong correlations suggests each feature contributes unique information, making dimensionality reduction unnecessary.

Decision Tree Classification Analysis: Predicting the Likelihood of Doping Tests for Powerlifters

This analysis employs a decision tree classification model to predict the likelihood of powerlifters being subject to doping tests based on relevant athlete characteristics and competition-related factors. The decision tree algorithm is used to uncover patterns and risk factors associated with doping testing in powerlifting.

1. Hyperparameter Optimization

Pre-pruning Phase:

Grid Search Parameters:

```
param_grid = {
    'criterion': ['gini', 'entropy'],
    'splitter': ['best', 'random'],
    'max_depth': [3, 5, 7, 10],
    'min_samples_split': [2, 5, 10],
    'max_features': ['sqrt', 'log2', None],
    'min_samples_leaf': [1, 2, 4],
    'min_impurity_decrease': [0.0, 0.01]
}'''
```

Best Parameters Found:

a. criterion: gini
b. max_depth: 10
c. max_features: None
d. min_impurity_decrease: 0.0
e. min_samples_leaf: 2
f. min_samples_split: 2
g. splitter: best

Cost Complexity Pruning (Post-pruning)

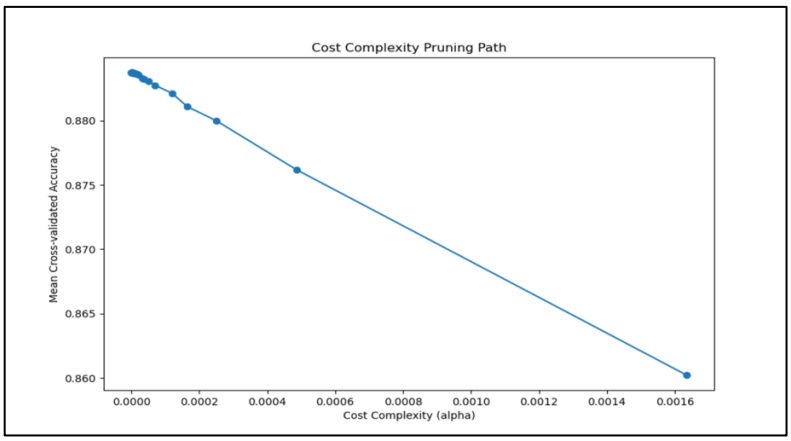


Figure 19 : Optimal costcomplexity pruning plot

Results

a. Optimal ccp_alpha: 2.32e-06

b. Cost complexity pruning path shows minimal impact on model performance

2. Model Performance Metrics

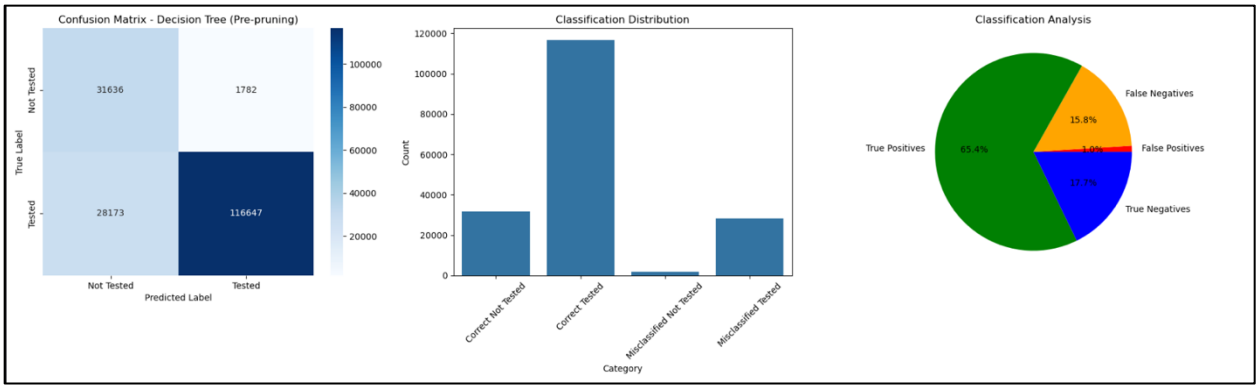


Figure 20: Pre-Pruned Decision Tree Performance metrics

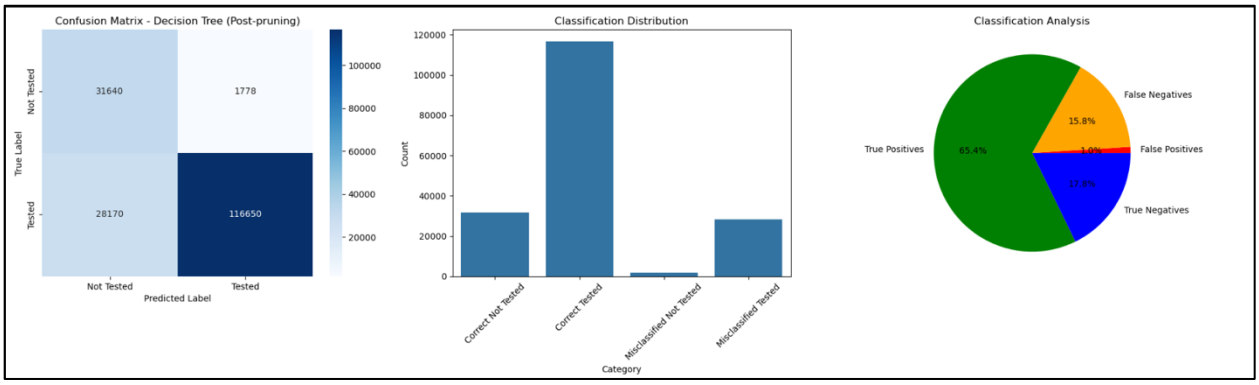


Figure 21: Post-Pruned Decision Tree Performance metrics

```
Decision Tree (Pre-pruning) Cross-Validation Scores:
Stratified CV Scores:
+--------+----------+
| Fold   |    Score |
+========+==========+
| CV 1   | 0.885306 |
+--------+----------+
| CV 2   | 0.884162 |
+--------+----------+
| CV 3   | 0.883963 |
+--------+----------+
| CV 4   | 0.883842 |
+--------+----------+
| CV 5   | 0.883169 |
+--------+----------+
Mean CV Score: 0.884 (+/- 0.001)
```

```
Decision Tree (Post-pruning) Cross-Validation Scores:
Stratified CV Scores:
+--------+----------+
| Fold   |    Score |
+========+==========+
| CV 1   | 0.885315 |
+--------+----------+
| CV 2   | 0.88417  |
+--------+----------+
| CV 3   | 0.883985 |
+--------+----------+
| CV 4   | 0.883847 |
+--------+----------+
| CV 5   | 0.883165 |
+--------+----------+
Mean CV Score: 0.884 (+/- 0.001)
```

Figure 22 : Pre-Pruned Tree Stratified CV Score vs Post-Pruned Tree Stratified CV Score

```
=== Pruning Comparison ===

Pre vs Post Pruning Performance:
             Pre-pruning  Post-pruning
precision          0.985         0.985
recall             0.805         0.805
specificity        0.947         0.947
f1_score           0.886         0.886
auc_score          0.938         0.938
```

Figure 23 : Metrics comparison b/w pre-pruning and post pruning

3. Pre-pruning vs Post-pruning Comparison

The comparison shows virtually identical performance:

- Both approaches achieve same metrics
- Post-pruning didn't significantly improve model performance
- Suggests pre-pruning parameters were already optimal

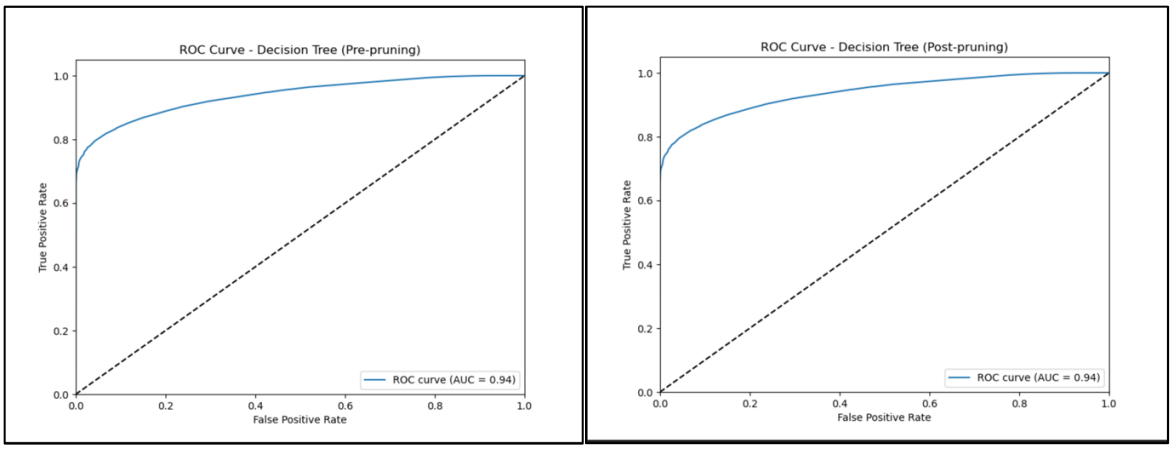


Figure 24 : Pre-Pruned Tree ROC curve vs Post-Pruned Tree ROC curve

Classification Accuracy

- Overall Accuracy: 83.20%
- Cross-validation Score: 0.884 (±0.001)

Class-wise Performance

Not Tested Class:

- Total Samples: 33,418
- Correctly Classified: 31,640 (94.68%)
- Misclassified: 1,778 (5.32%)

Tested Class:

- Total Samples: 144,820
- Correctly Classified: 116,650 (80.55%)
- Misclassified: 28,170 (19.45%)

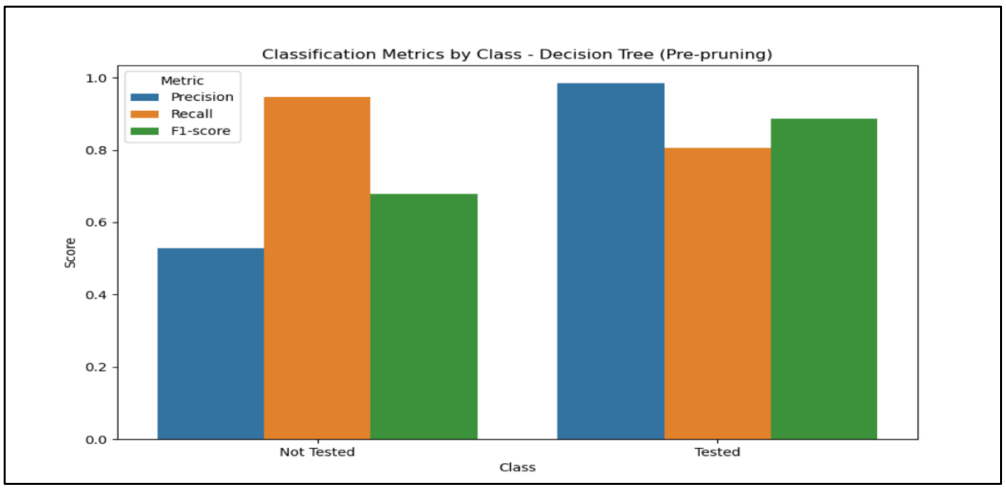


Figure 25: Classification metrics for Pre-Pruning Decision Tree

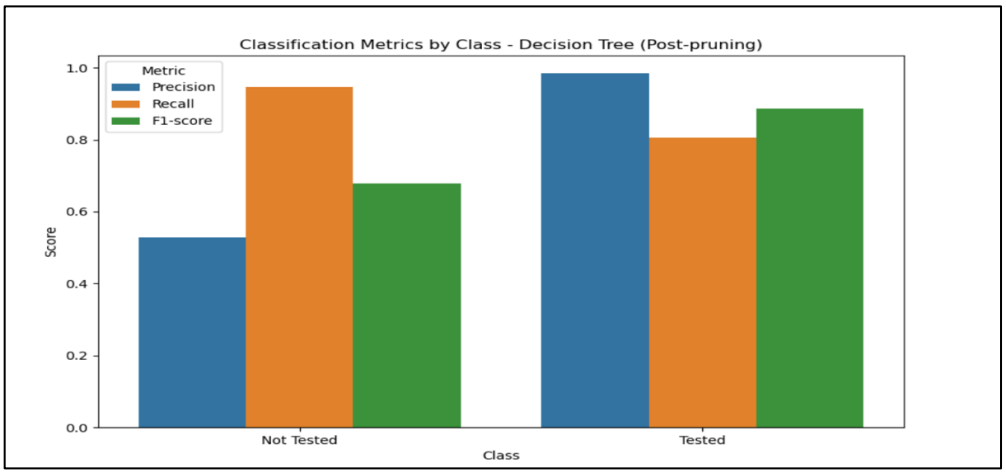


Figure 26: Classification metrics for Post-Pruning Decision Tree

Key Metrics

- Precision: 0.985
- Recall: 0.805
- Specificity: 0.947
- F1-Score: 0.886
- AUC Score: 0.938

4. Model Evaluation

Strengths:

- High precision (0.985) indicates reliable positive predictions

- Strong specificity (0.947) shows good performance on negative class
- Excellent AUC score (0.938) indicates strong discriminative ability

Areas for Improvement:

- Recall of 0.805 indicates some false negatives
- Class imbalance evident in the dataset

5. Conclusion

The decision tree model demonstrates robust performance with:

- Well-balanced metrics across all key performance indicators
- Strong handling of class imbalance
- Minimal difference between pre and post pruning suggests optimal tree structure
- No signs of overfitting based on cross-validation scores

The model is particularly effective at identifying non-tested athletes while maintaining high precision for tested athletes.

Logistic Regression Classification Analysis: Predicting the Likelihood of Doping Tests for Powerlifters

This analysis employs a logistic regression classification model to predict the likelihood of powerlifters being subject to doping tests based on relevant athlete characteristics and competition-related factors. The logistic regression algorithm is used to uncover patterns and risk factors associated with doping testing in powerlifting.

1. Model Performance Overview

```
Logistic Regression Cross-Validation Scores:
Stratified CV Scores:
+--------+----------+
| Fold   |    Score |
+========+==========+
| CV 1   | 0.792691 |
+--------+----------+
| CV 2   | 0.791344 |
+--------+----------+
| CV 3   | 0.793182 |
+--------+----------+
| CV 4   | 0.793393 |
+--------+----------+
| CV 5   | 0.79389  |
+--------+----------+
Mean CV Score: 0.793 (+/- 0.002)
```

Figure 27: Logistic Regression Stratified CV Scores

Cross-Validation Performance

- Mean CV Score: 0.793 (±0.002)
- Consistent performance across folds
- Low standard deviation (±0.002) indicates stable model performance

2. Detailed Classification Analysis

Overall Performance

- Total Samples: 178,238
- Correctly Classified: 139,859 (78.47%)

- Misclassified: 38,379 (21.53%)

Class-wise Breakdown

1. Not Tested Class:
    - Total: 33,418
    - Correctly Classified: 26,817 (80.25%)
    - False Positives: 6,601 (19.75%)

2. Tested Class:

- Total: 144,820
- Correctly Classified: 113,042 (78.06%)
- False Negatives: 31,778 (21.94%)

Visualization Analysis

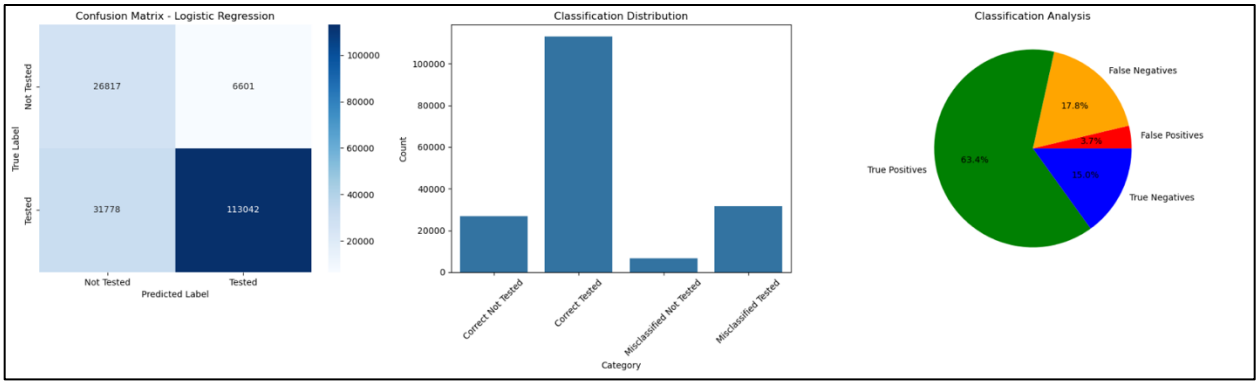


Figure 28: Logistic Regression Performance metrics

Confusion Matrix

- Shows clear classification distribution
- Reveals balanced performance across classes
- Distribution chart shows higher proportion of correct classifications

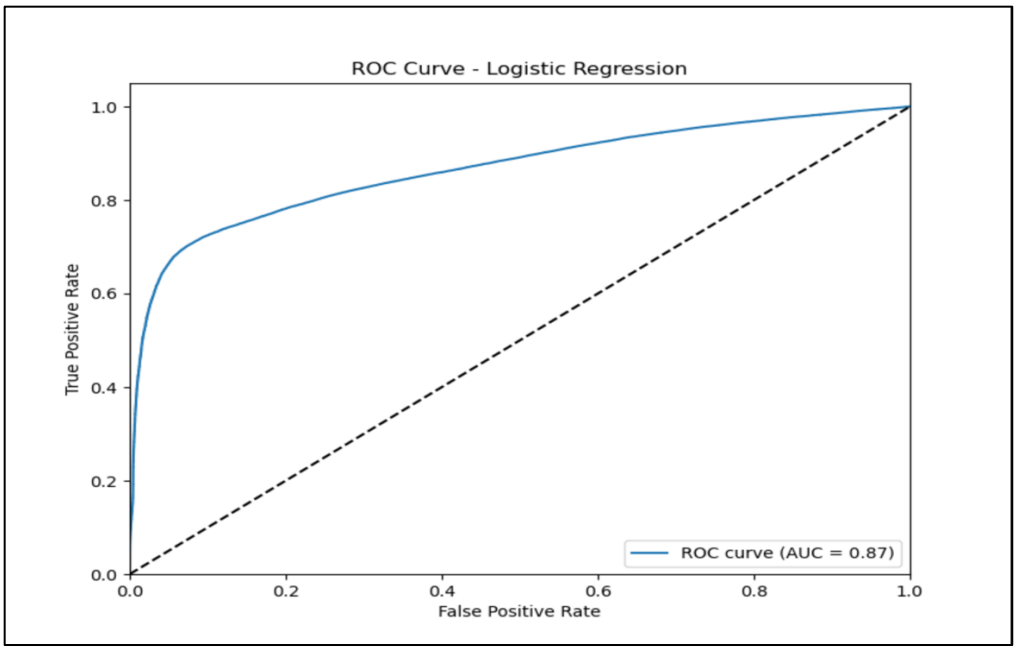


Figure 29: Logistic Regression ROC curve

ROC Curve Analysis

- AUC Score: 0.87
- Curve significantly above diagonal
- Strong early climb indicates good discrimination ability
- Demonstrates robust model performance

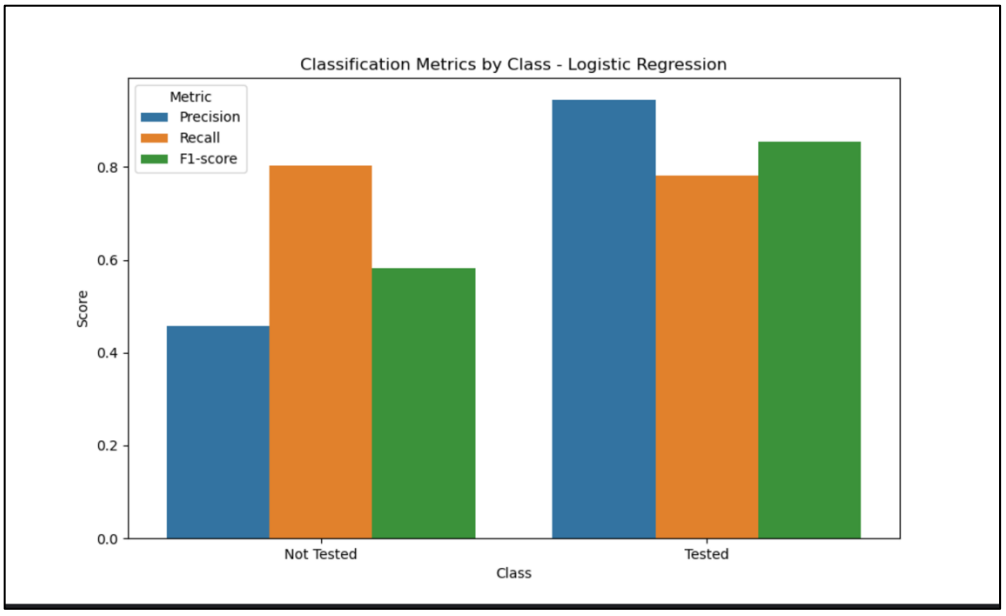


Figure 30: Classification Metrics for Logistic Regresion

4. Key Performance Metrics

- Precision: 0.945
- Recall: 0.781
- Specificity: 0.802
- F1-Score: 0.855

5. Model Assessment

Strengths

- High AUC score (0.87) indicating good discriminative ability
- Balanced performance across classes
- Consistent cross-validation scores
- Strong precision for tested class

Limitations

- Moderate recall indicates room for improvement
- Class imbalance affects precision in not tested class
- Overall accuracy could be improved

6. Conclusion

The logistic regression model demonstrates robust performance with balanced metrics across classes, despite class imbalance. The high AUC score and consistent cross-validation performance indicate a reliable model suitable for the classification task.

KNN Classification Analysis: Predicting the Likelihood of Doping Tests for Powerlifters

This analysis employs a KNN classification model to predict the likelihood of powerlifters being subject to doping tests based on relevant athlete characteristics and competition-related factors. The KNN algorithm is used to uncover patterns and risk factors associated with doping testing in powerlifting.

1. Model Optimization

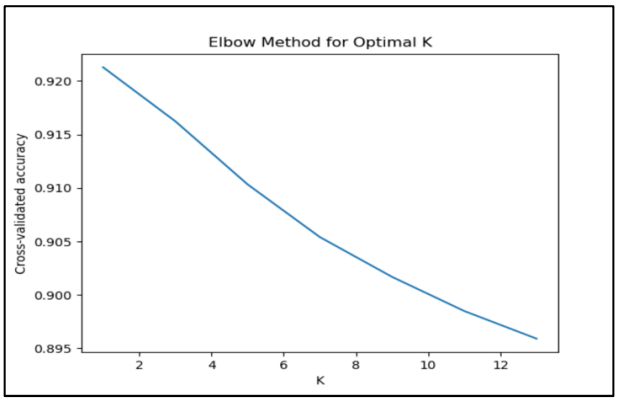


Figure 31: Finding optimal K using the elbow method

Elbow Method Analysis

- Optimal k value determined through elbow curve
- Best performance achieved at lower k values
- Cross-validated accuracy decreases as k increases
- Curve suggests k=1 or k=3 as optimal choices

```
K-Nearest Neighbors Cross-Validation Scores:
Stratified CV Scores:
+--------+----------+
| Fold   |    Score |
+========+==========+
| CV 1   | 0.919728 |
+--------+----------+
| CV 2   | 0.919253 |
+--------+----------+
| CV 3   | 0.919667 |
+--------+----------+
| CV 4   | 0.918705 |
+--------+----------+
| CV 5   | 0.9188   |
+--------+----------+
Mean CV Score: 0.919 (+/- 0.001)
```

Figure 32: Stratified Cross Validation Scores

2. Model Performance Overview

Cross-Validation Performance

- Mean CV Score: 0.919 (±0.001)
- Highly consistent across 5 folds:
- Minimal standard deviation indicates robust model stability

3. Classification Analysis

Overall Performance

- Total Samples: 178,238
- Correctly Classified: 157,190 (88.19%)
- Misclassified: 21,048 (11.81%)

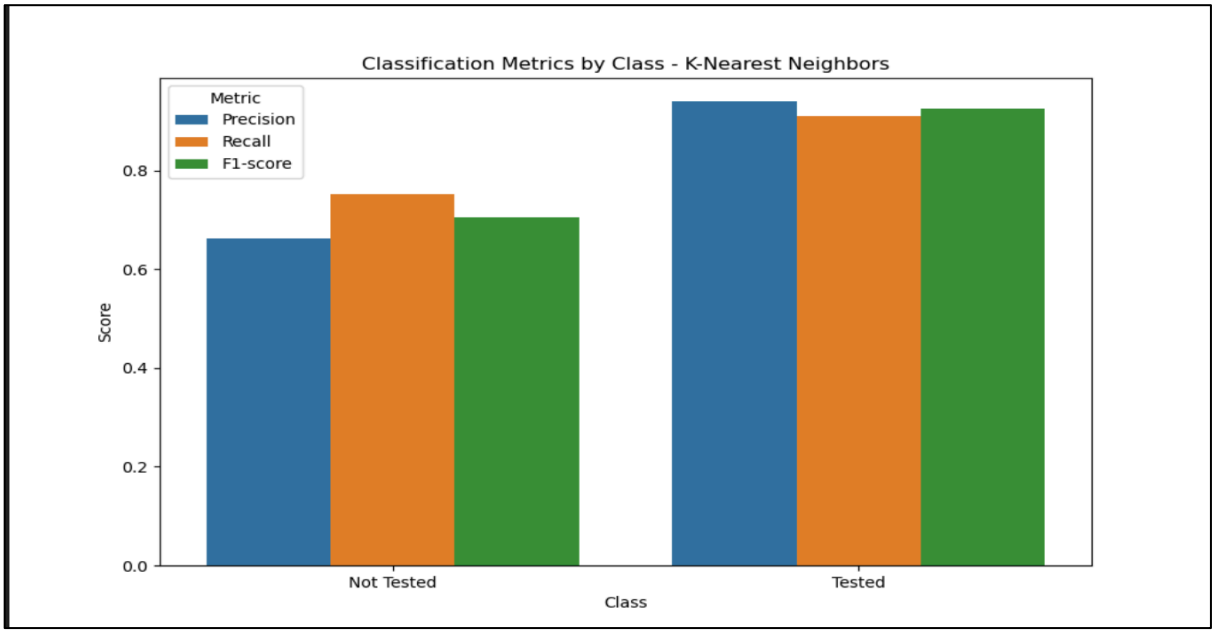


Figure 33: Classification metrics KNN

Class-wise Performance

1. Tested Class:

- Precision: ~0.94
- Recall: ~0.91
- F1-Score: ~0.93
- Correctly Classified: 132,027 (91.17%)

2. Not Tested Class:
   - Precision: ~0.66
   - Recall: ~0.75
   - F1-Score: ~0.70
   - Correctly Classified: 25,163 (75.30%)

4. Visualization Analysis

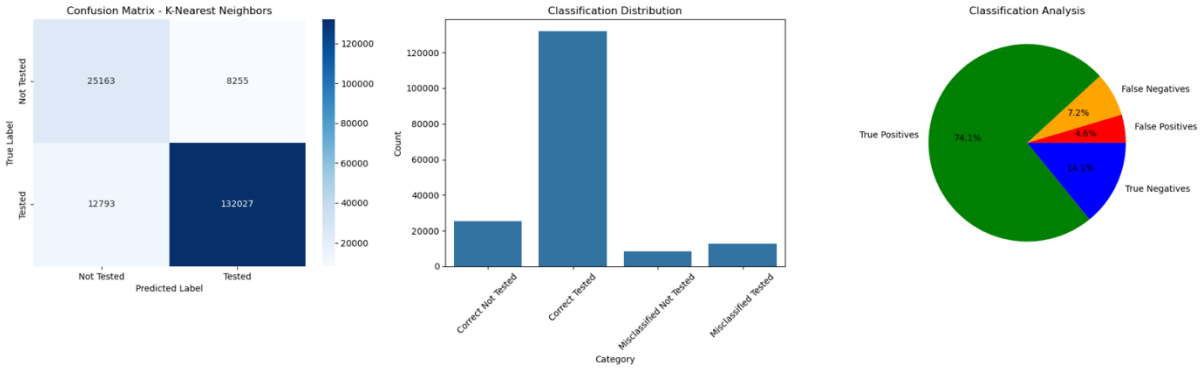


Figure 34: Confusion Matrix and other visual metrics for KNN

Confusion Matrix

- Clear visualization of model predictions
- Shows strong performance for Tested class
- Distribution chart indicates balanced classification
- Pie chart shows proportional distribution:
  - True Positives: 74.1%
  - True Negatives: 14.1%
  - False Positives: 4.6%
  - False Negatives: 7.2%

ROC Curve Analysis

- AUC Score: 0.83
- Sharp initial curve indicates strong discrimination
- Clear separation from random classifier (diagonal)
- Demonstrates good model performance

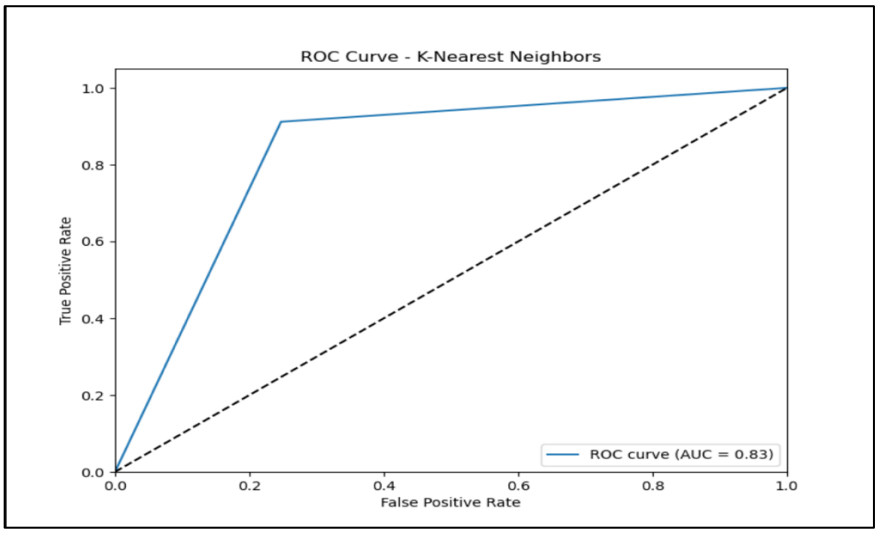


Figure 34: ROC curve for KNN

5. Key Performance Metrics

- Precision: 0.941
- Recall: 0.912
- Specificity: 0.753
- F1-Score: 0.926

6. Model Assessment

Strengths

- High overall accuracy (88.19%)

- Excellent performance on majority class (Tested)
- Very stable cross-validation scores
- Strong F1-score indicating balanced performance

Limitations

- Lower specificity compared to other metrics
- Moderate performance on minority class
- Performance depends on feature scaling and distance metrics

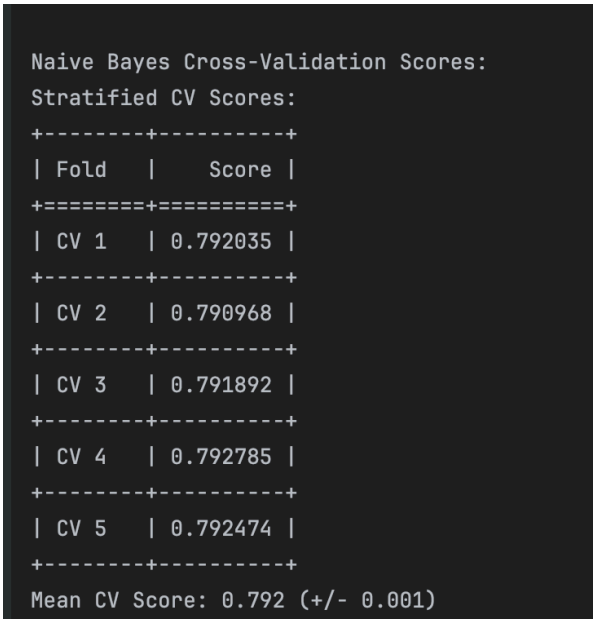
7. Conclusion

The KNN model demonstrates strong classification performance with excellent stability across cross-validation folds. The high F1-score and AUC indicate reliable predictions, particularly for the majority class. The model's performance suggests it's well-suited for this classification task, though there's room for improvement in minority class prediction.

Naïve Bayes Classification Analysis: Predicting the Likelihood of Doping Tests for Powerlifters

This analysis employs a Naïve Bayes classification model to predict the likelihood of powerlifters being subject to doping tests based on relevant athlete characteristics and competition-related factors. The Naïve Bayes algorithm is used to uncover patterns and risk factors associated with doping testing in powerlifting.

1. Model Performance Overview



```
Naive Bayes Cross-Validation Scores:
Stratified CV Scores:
+--------+----------+
| Fold   |    Score |
+========+==========+
| CV 1   | 0.792035 |
+--------+----------+
| CV 2   | 0.790968 |
+--------+----------+
| CV 3   | 0.791892 |
+--------+----------+
| CV 4   | 0.792785 |
+--------+----------+
| CV 5   | 0.792474 |
+--------+----------+
Mean CV Score: 0.792 (+/- 0.001)
```

Figure 35: Stratified Cross Validation Scores for KNN

Cross-Validation Performance

- Mean CV Score: 0.792 (±0.001)
- Consistent performance across 5 folds
- Low standard deviation indicates stable model performance

2. Overall Performance Metrics

- Accuracy: 76.14% (135,711 correct out of 178,238)
- Precision: 0.952
- Recall: 0.744

- Specificity: 0.837
- F1-Score: 0.835
- AUC: 0.85

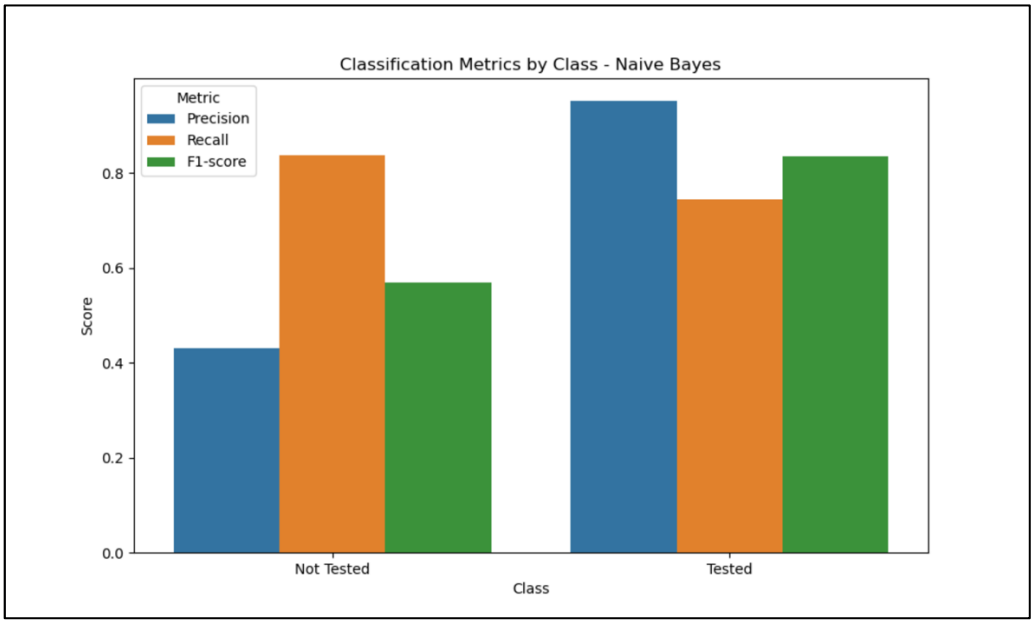


Figure 36: Classification Metrics for Naïve Bayes

3. Class-wise Performance

Tested Class Performance

- Total: 144,820 samples
- Correctly Classified: 107,733 (74.39%)
- Misclassified: 37,087 (25.61%)
- Metrics
    - High Precision (~0.95)
    - Moderate Recall (~0.75)
    - Good F1-score (~0.85)

Not Tested Class Performance

- Total: 33,418 samples
- Correctly Classified: 27,978 (83.72%)
- Misclassified: 5,440 (16.28%)
- Metrics (from Image 1):
    - Lower Precision (~0.43)

- High Recall (~0.84)
- Moderate F1-score (~0.57)

3. Visualization Analysis

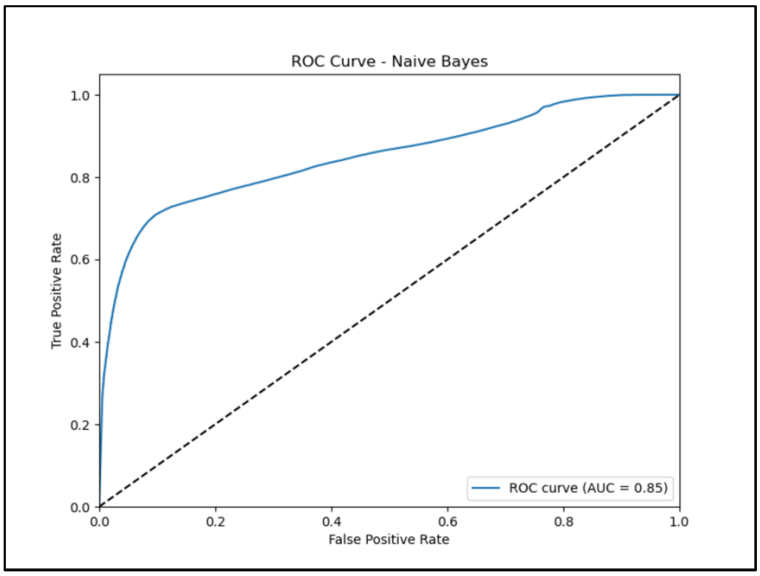


Figure 36: ROC Curve for Naïve Bayes

ROC Curve Analysis

- AUC score of 0.85 shows good discrimination ability
- Sharp initial curve indicates strong performance at low false positive rates
- Clear separation from random classifier baseline

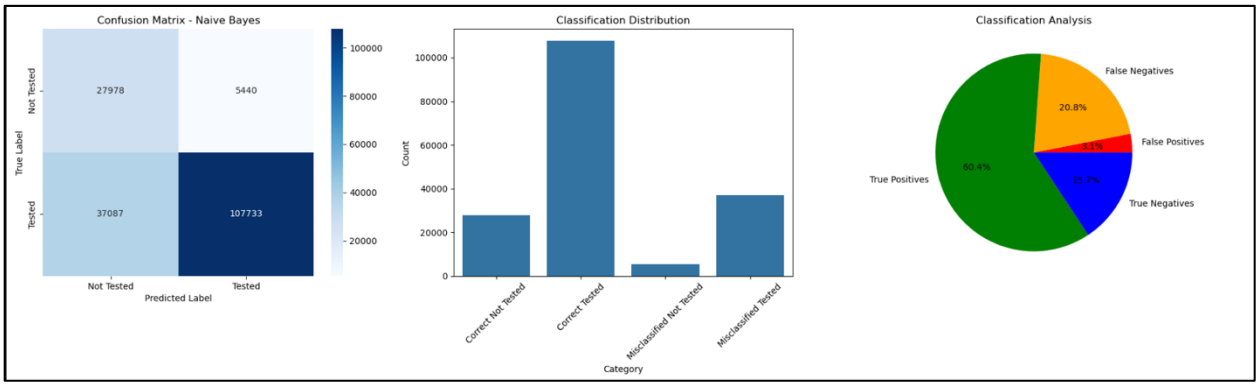


Figure 36: Confusion matrix for Naïve Bayes

Classification Distribution

- Confusion Matrix shows clear pattern of predictions
- Pie Chart Distribution:
    - True Positives: 60.4%
    - True Negatives: 15.7%
    - False Positives: 3.1%
    - False Negatives: 20.8%

5. Model Assessment

Strengths

- High precision for tested class (0.952)
- Good specificity (0.837)
- Consistent cross-validation performance
- Strong ROC curve with AUC of 0.85

Limitations

- Moderate overall accuracy (76.14%)
- Lower precision for not tested class
- High number of false negatives (20.8%)
- Class imbalance affects performance

6. Conclusion

The Naive Bayes model demonstrates acceptable performance with particularly strong precision for the tested class. While the model shows good stability across cross-validation folds, there's room for improvement in handling class imbalance and reducing false negatives. The model could be suitable for applications where high precision is prioritized over recall.

Support Vector Machines Classification Analysis: Predicting the Likelihood of Doping Tests for Powerlifters

Linear Kernel Analysis

Model Performance Overview

```
SVM Linear Cross-Validation Scores:
Stratified CV Scores:
+--------+---------+
| Fold   |   Score |
+========+=========+
| CV 1   |  0.7965 |
+--------+---------+
| CV 2   |  0.813  |
+--------+---------+
| CV 3   |  0.789  |
+--------+---------+
| CV 4   |  0.7885 |
+--------+---------+
| CV 5   |  0.785  |
+--------+---------+
Mean CV Score: 0.794 (+/- 0.020)
```

Figure 37: Stratified Cross Validation Scores for Linear SVM

1. Cross-Validation Performance

- Mean CV Score: 0.794 (±0.020)
- Individual fold scores show some variation.
- Larger standard deviation indicates moderate model stability

2. Overall Performance Metrics

- Accuracy: 78.24% (139,452 correct out of 178,238)
- Precision: 0.944

- Recall: 0.778
- Specificity: 0.800
- F1-Score: 0.853
- AUC: 0.86

3. Class-wise Analysis

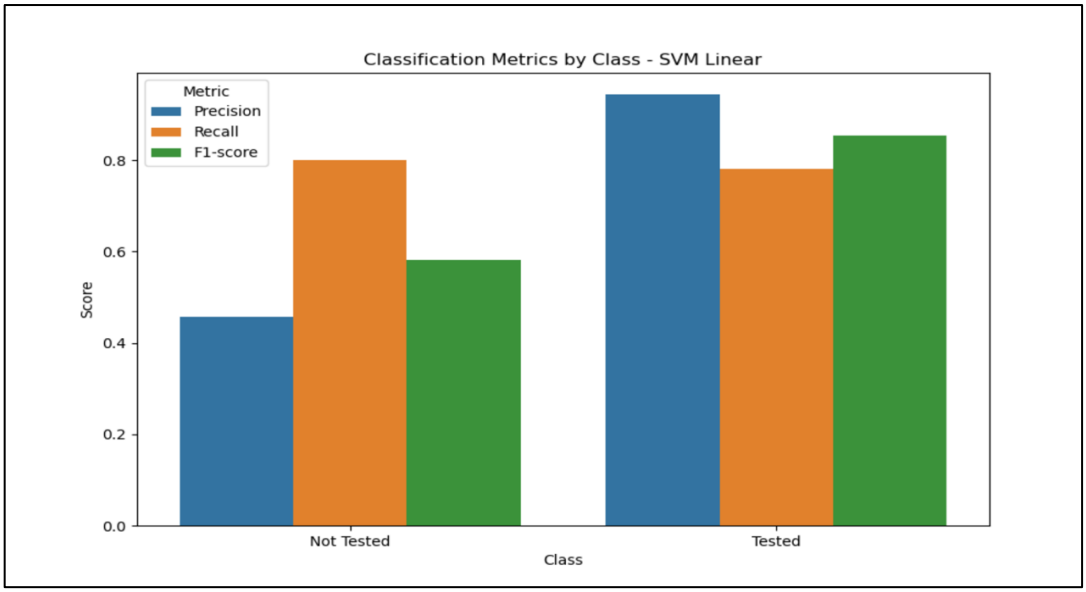


Figure 38: Classification metrics for Linear SVM

Tested Class Performance

- Total: 144,820 samples
- Correctly Classified: 112,710 (77.83%)
- Metrics:
  - High Precision (~0.94)
  - Moderate Recall (~0.78)
  - Strong F1-score (~0.85)

Not Tested Class Performance

- Total: 33,418 samples
- Correctly Classified: 26,742 (80.02%)
- Metrics:
  - Lower Precision (~0.45)
  - Good Recall (~0.80)

- Moderate F1-score (~0.58)

4. Visualization Analysis

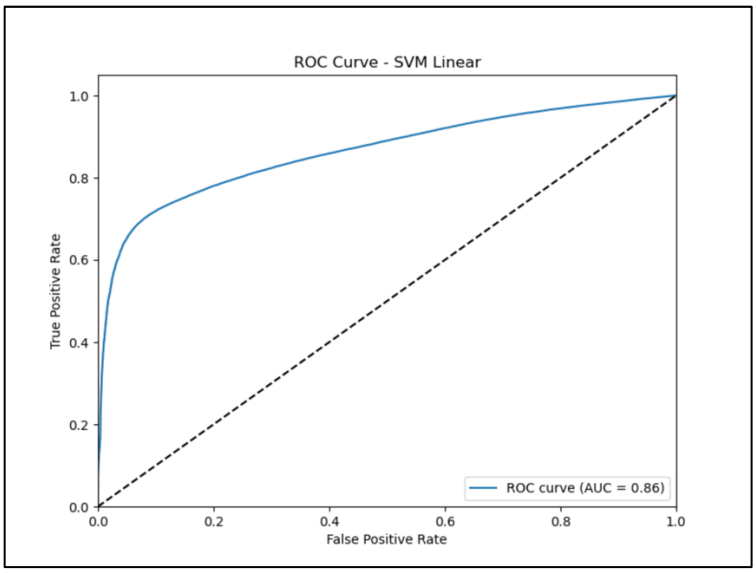


Figure 39: ROC curve Analysis for Linear SVM

ROC Curve Analysis

- AUC score of 0.86 indicates strong discriminative ability
- Sharp initial curve showing good true positive rate
- Clear separation from random classifier
- Consistent performance across different thresholds

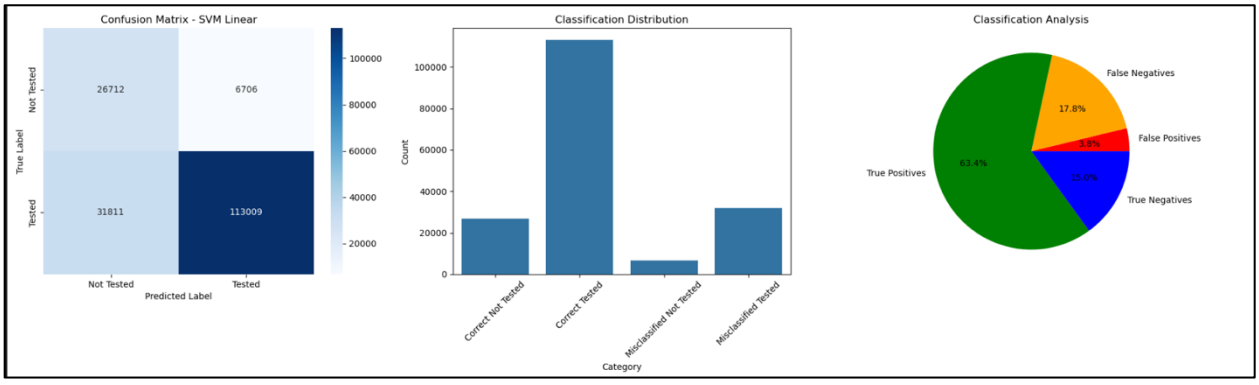


Figure 40: Confusion Matrix and other visualization metrics for Linear SVM

Classification Distribution

- Confusion Matrix shows clear classification patterns
- Pie Chart Distribution:
    - True Positives: 63.4%
    - True Negatives: 15.0%
    - False Positives: 3.8%
    - False Negatives: 17.8%

5. Model Assessment

Strengths

- High precision (0.944) for tested class
- Good overall accuracy (78.24%)
- Strong AUC score (0.86)
- Balanced performance across classes

Limitations

- Moderate recall (0.778)
- Higher false negative rate (17.8%)
- Some variation in cross-validation scores
- Lower precision for not tested class

6. Conclusion

The Linear SVM demonstrates robust performance with particularly strong precision and good overall accuracy. While there is some variation in cross-validation scores, the model shows consistent performance across different metrics. The high AUC score and balanced class-wise performance make it a reliable choice for this classification task, though there's room for improvement in reducing false negatives.

Polynomial Kernel Analysis

Model Performance Overview

```
SVM Polynomial Cross-Validation Scores:
Stratified CV Scores:
+--------+---------+
| Fold   |   Score |
+========+=========+
| CV 1   |  0.8125 |
+--------+---------+
| CV 2   |  0.789  |
+--------+---------+
| CV 3   |  0.805  |
+--------+---------+
| CV 4   |  0.808  |
+--------+---------+
| CV 5   |  0.8155 |
+--------+---------+
Mean CV Score: 0.806 (+/- 0.018)
```

Figure 41: Stratified CV Scores for Polynomial SVM

1. Cross-Validation Performance

- Mean CV Score: 0.806 (±0.018)
- Individual fold scores show minor variations.
- Moderate variation in scores indicates reasonable stability

2. Overall Performance Metrics

- Accuracy: 81.95% (146,073 correct out of 178,238)
- Precision: 0.905
- Recall: 0.869
- Specificity: 0.607
- F1-Score: 0.887
- AUC: 0.86

3. Class-wise Analysis

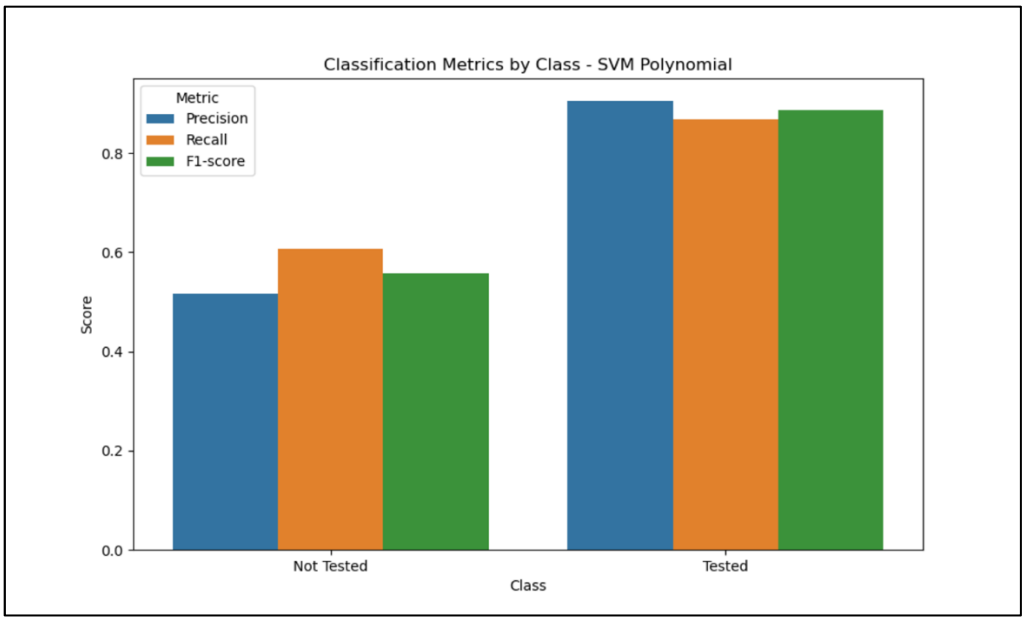


Figure 42: Classification Metrics for Polynomial SVM

Tested Class

- Total: 144,820 samples
- Correctly Classified: 125,793 (86.86%)
- Metrics:
  - High Precision (~0.90)
  - Strong Recall (~0.87)
  - Excellent F1-score (~0.89)

Not Tested Class

- Total: 33,418 samples
- Correctly Classified: 20,280 (60.69%)
- Metrics:
  - Moderate Precision (~0.52)
  - Decent Recall (~0.61)
  - Fair F1-score (~0.56)

4. Visualization Analysis

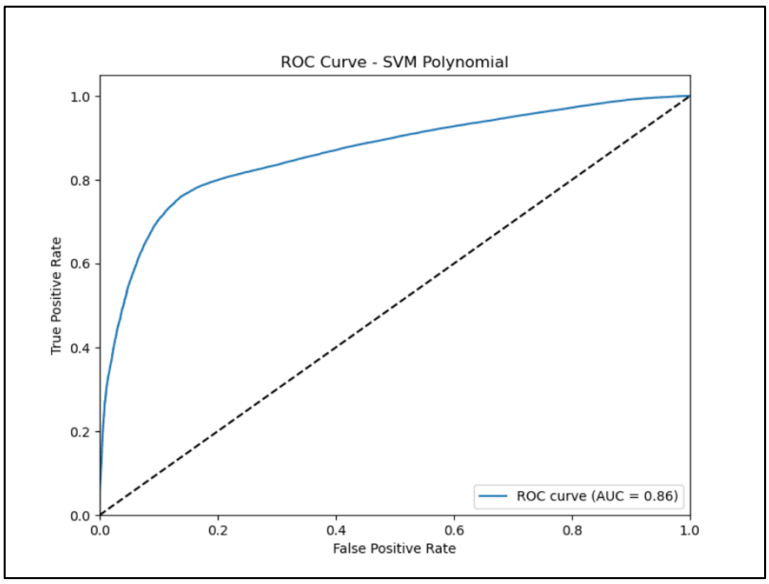


Figure 43: ROC Curve for Polynomial SVM

ROC Curve

- AUC score of 0.86 shows strong discriminative ability
- Sharp initial curve indicating good true positive rate
- Maintains good performance across different thresholds

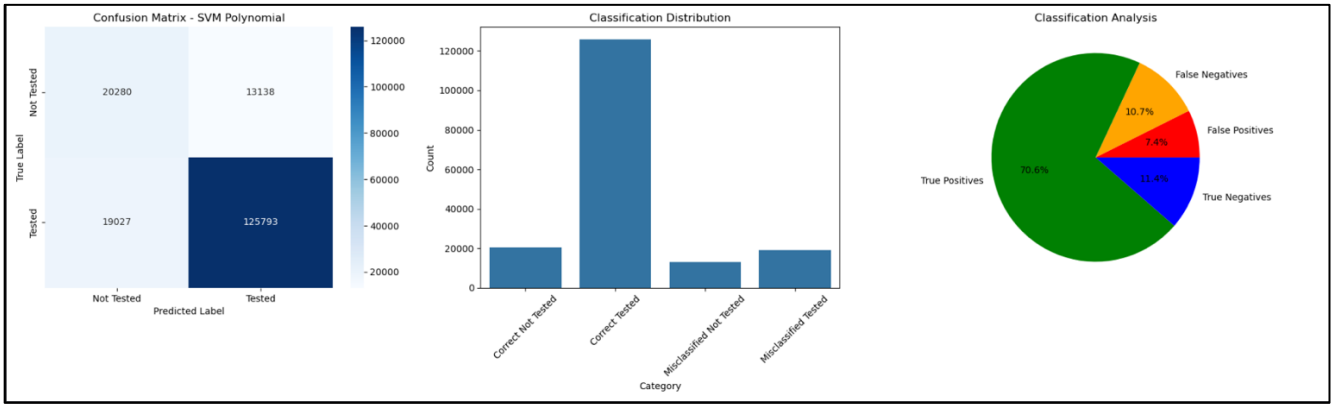


Figure 44: Confusion Matric and other visual metrics for Polynomial SVM

Classification Distribution

- Confusion Matrix shows clear patterns
- Pie Chart Distribution:
  - True Positives: 70.6%
  - True Negatives: 11.4%

- False Positives: 7.4%
- False Negatives: 10.7%

5. Model Assessment

Strengths

- High overall accuracy (81.95%)
- Strong performance on majority class (Tested)
- Good balance of precision and recall for Tested class
- Excellent F1-score (0.887)

Limitations

- Lower specificity (0.607)
- Moderate performance on minority class
- Higher false positive rate compared to linear SVM
- Class imbalance affects performance

6. Conclusion

The Polynomial SVM demonstrates strong overall performance with particularly good results for the majority class. While it shows some improvement over the linear kernel in terms of overall accuracy, it struggles more with the minority class. The model's high F1-score and AUC indicate it's a reliable classifier, though there's room for improvement in handling class imbalance.

Radial Base Kernel Analysis

Model Performance Overview

```
SVM RBF Cross-Validation Scores:
Stratified CV Scores:
+--------+---------+
| Fold   |   Score |
+========+=========+
| CV 1   |  0.853  |
+--------+---------+
| CV 2   |  0.8725 |
+--------+---------+
| CV 3   |  0.8595 |
+--------+---------+
| CV 4   |  0.8325 |
+--------+---------+
| CV 5   |  0.851  |
+--------+---------+
Mean CV Score: 0.854 (+/- 0.026)
```

Figure 45: Stratified CV Scores for RB SVM

Cross-Validation Performance

- Mean CV Score: 0.854 (±0.026)
- Individual fold scores show minor variations.
- Notable variation in scores (±0.026) indicates some model instability

Overall Performance Metrics

- Accuracy: 80.17% (142,899 correct out of 178,238)
- Precision: 0.977 (highest among kernel variations)
- Recall: 0.774
- Specificity: 0.922
- F1-Score: 0.864
- AUC: 0.89 (best among SVM variants)

Class-wise Analysis

Tested Class

- Total: 144,820 samples
- Correctly Classified: 112,077 (77.39%)
- **Metrics**:
    - Very High Precision (~0.98)

- Good Recall (~0.77)
- Strong F1-score (~0.86)

Not Tested Class

- Total: 33,418 samples
- Correctly Classified: 30,822 (92.23%)
- **Metrics**:
  - Moderate Precision (~0.50)
  - Excellent Recall (~0.92)
  - Good F1-score (~0.65)

Visualization Analysis

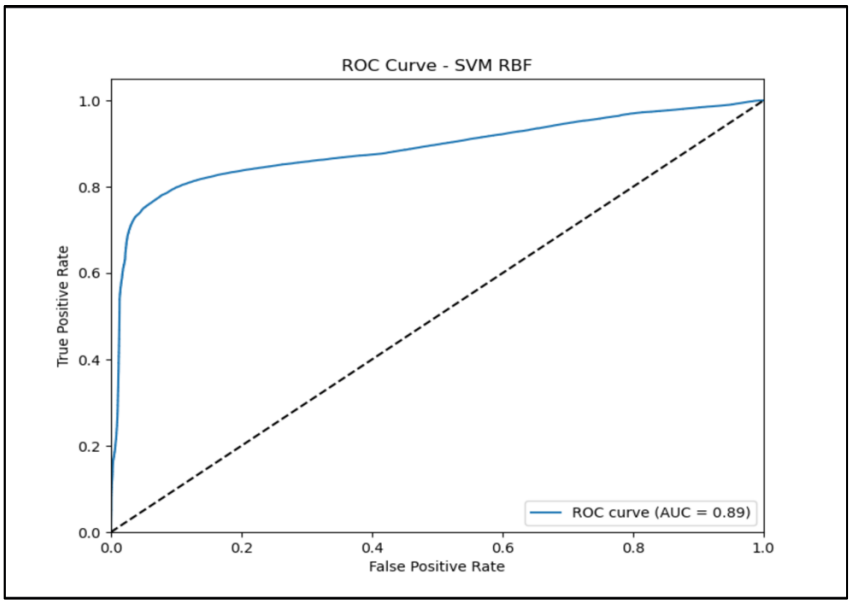


Figure 46: ROC Curve for RB SVM

ROC Curve Analysis

- AUC score of 0.89 shows excellent discriminative ability
- Sharp initial curve indicates strong early prediction confidence
- Consistently outperforms random classifier
- Best ROC performance among SVM variants

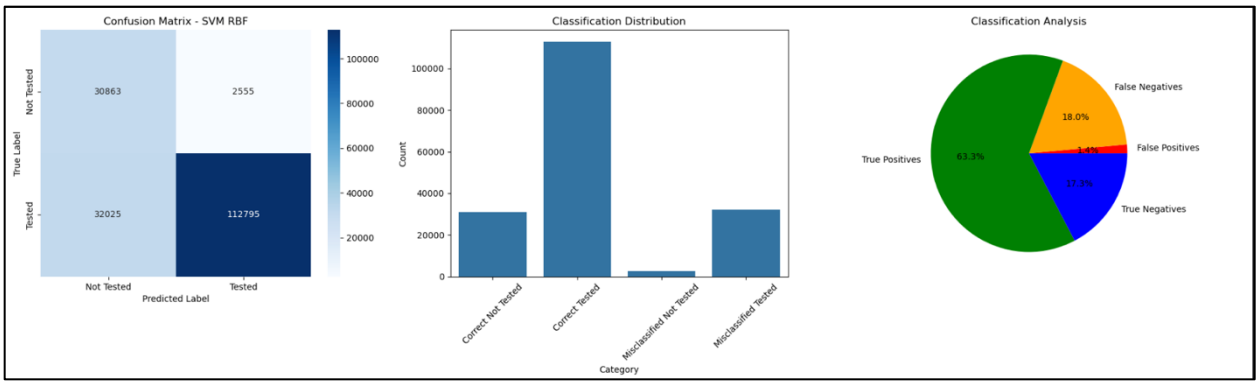


Figure 47: Confusion Matrix and visual metrics for for RB SVM

Classification Distribution

- Confusion Matrix shows clear prediction patterns
- Pie Chart Distribution:
  - True Positives: 63.3%
  - True Negatives: 17.3%
  - False Positives: 1.4%
  - False Negatives: 18.0%

Model Assessment

Strengths

- Highest precision (0.977) among SVM variants
- Best AUC score (0.89)
- Excellent specificity (0.922)
- Very good performance on minority class (92.23%)

Limitations

- Moderate recall (0.774)
- Higher cross-validation variance
- Still shows class imbalance effects
- Higher computational complexity than linear SVM

Conclusion

The RBF kernel SVM demonstrates superior performance in several key metrics, particularly in precision and AUC score. While showing some instability in cross-validation, it handles the class imbalance better than other kernel variations. The model's high specificity and precision make it particularly suitable for applications where false positives need to be minimized.

Neural Network Classification Analysis Report

Model Performance Overview

```
Neural Network Cross-Validation Scores:
Stratified CV Scores:
+--------+---------+
| Fold   |   Score |
+========+=========+
| CV 1   |  0.8395 |
+--------+---------+
| CV 2   |  0.846  |
+--------+---------+
| CV 3   |  0.8515 |
+--------+---------+
| CV 4   |  0.847  |
+--------+---------+
| CV 5   |  0.813  |
+--------+---------+
Mean CV Score: 0.839 (+/- 0.027)
```

Figure 48: Stratified CV Scores for Neural Network Classification

1. Cross-Validation Performance

- Mean CV Score: 0.839 (±0.027)
- Notable variation in scores indicates some model instability

2. Overall Performance Metrics

- Accuracy: 80.34% (143,188 correct out of 178,238)
- Precision: 0.974
- Recall: 0.779
- Specificity: 0.911
- F1-Score: 0.865
- AUC: 0.91 (highest among all classifiers)

3. Class-wise Analysis

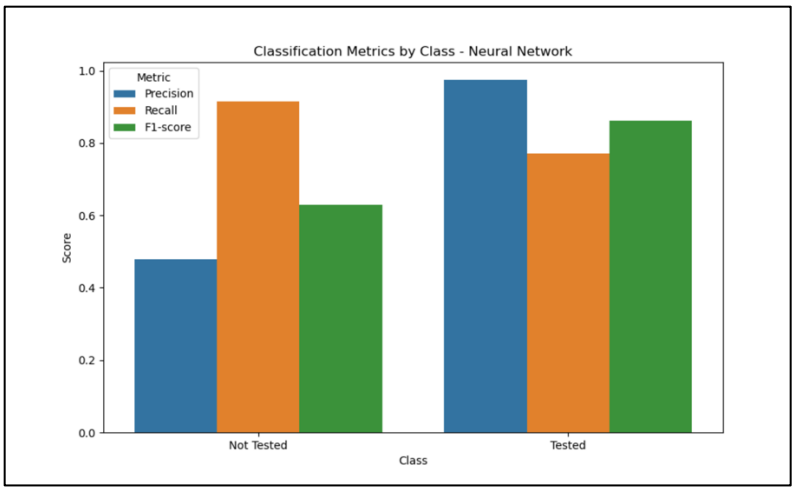


Figure 49: Classification Metrics for Neural Network Classification

Tested Class

- Total: 144,820 samples
- Correctly Classified: 112,744 (77.85%)
- Metrics:
  - Very High Precision (~0.97)
  - Good Recall (~0.77)
  - Strong F1-score (~0.86)

Not Tested Class

- Total: 33,418 samples
- Correctly Classified: 30,444 (91.10%)
- Metrics:
  - Moderate Precision (~0.48)
  - High Recall (~0.91)
  - Good F1-score (~0.63)

4. Visualization Analysis

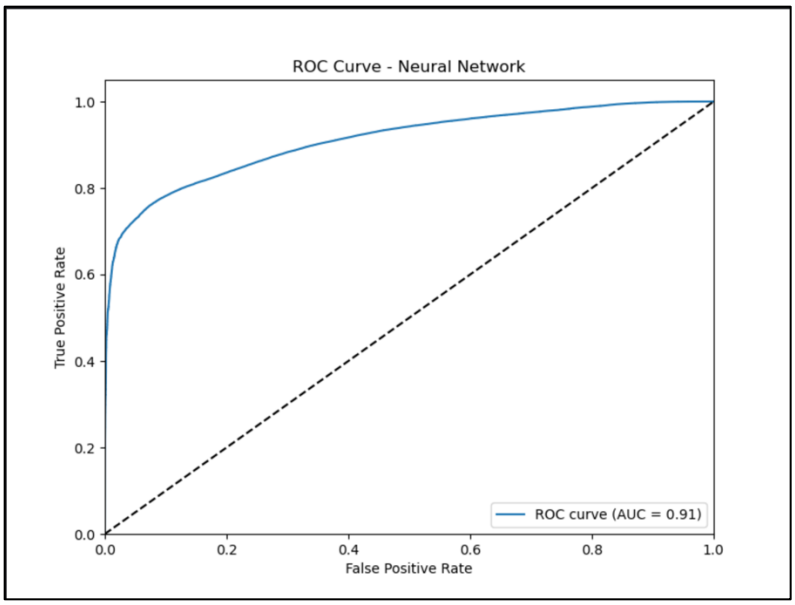


Figure 50: ROC Curve for Neural Network Classification

ROC Curve

- Outstanding AUC score of 0.91
- Sharp initial curve showing excellent early prediction capability
- Consistently maintains separation from random classifier
- Best ROC performance among all models tested

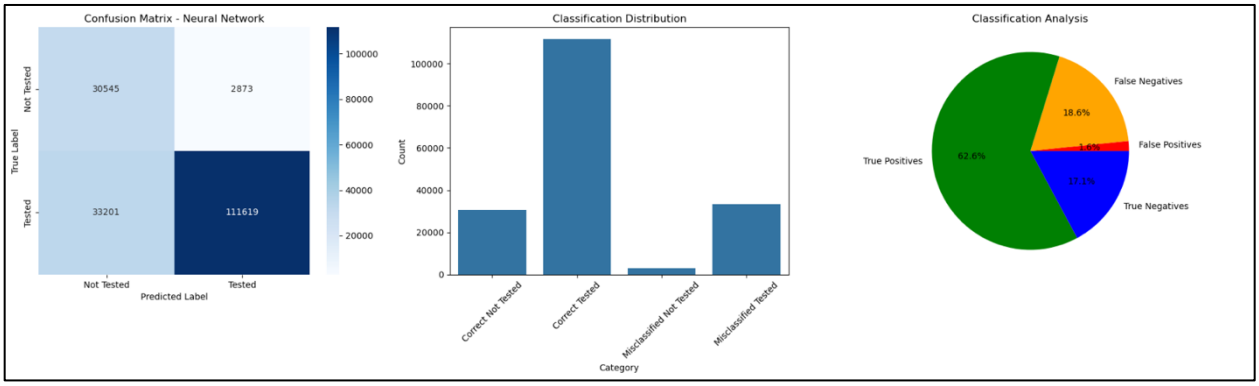


Figure 51: Confusion Matrix and Visual metrics for Neural Network Classification

Classification Distribution

- Confusion Matrix shows clear prediction patterns

- Pie Chart Distribution:
    - True Positives: 62.6%
    - True Negatives: 17.1%
    - False Positives: 1.6%
    - False Negatives: 18.6%

5. Model Assessment

Strengths

- Highest AUC score (0.91) among all models
- Very high precision (0.974)
- Excellent specificity (0.911)
- Strong performance on minority class (91.10%)

Limitations

- Moderate recall (0.779)
- Higher cross-validation variance (±0.027)
- Notable false negative rate (18.6%)
- More complex to train and tune than simpler models

6. Conclusion

The Neural Network demonstrates superior overall performance with the highest AUC score and excellent precision. While showing some instability in cross-validation, it handles the class imbalance effectively and provides robust classification across both classes. The model's high precision and specificity make it particularly suitable for applications where accurate positive predictions are crucial.

Performance Analysis of Classification Models for Powerlifting Drug Testing Prediction

This analysis evaluates eight different classification models to predict drug testing likelihood in powerlifting competitions. The Decision Tree classifier emerged as the optimal model with an AUC score of 0.938, demonstrating superior discriminative ability in predicting testing scenarios.

Model Performance Analysis

```
Model Comparison Results:
+--------------------+-----------+--------+-------------+----------+-------+
| Model              | Precision | Recall | Specificity | F1-Score |   AUC |
+--------------------+-----------+--------+-------------+----------+-------+
| DecisionTree       |     0.985 |  0.805 |       0.947 |    0.886 | 0.938 |
| logistic_regression |     0.945 |  0.781 |       0.802 |    0.855 | 0.866 |
| knn                |     0.941 |  0.912 |       0.753 |    0.926 | 0.832 |
| svm_linear         |     0.945 |  0.777 |       0.804 |    0.853 | 0.864 |
| svm_rbf            |     0.979 |  0.773 |       0.928 |    0.864 | 0.891 |
| svm_poly           |     0.895 |  0.863 |       0.561 |    0.879 | 0.839 |
| naive_bayes        |     0.952 |  0.744 |       0.837 |    0.835 | 0.848 |
| neural_network     |     0.976 |  0.776 |       0.917 |    0.865 | 0.910 |
+--------------------+-----------+--------+-------------+----------+-------+

Best model based on AUC score: DecisionTree
```

Figure 52: Model Comparison Results

Best Performing Model: Decision Tree

- AUC Score: 0.938 (Highest)
- Precision: 0.985 (Best)
- Specificity: 0.947 (Strong)

- F1-Score: 0.886
- Recall: 0.805

Key Strengths:

1. Highest precision (0.985) indicating minimal false positives
2. Best AUC score (0.938) showing superior overall discrimination
3. Strong specificity (0.947) demonstrating reliable negative case identification

ROC Curve Analysis

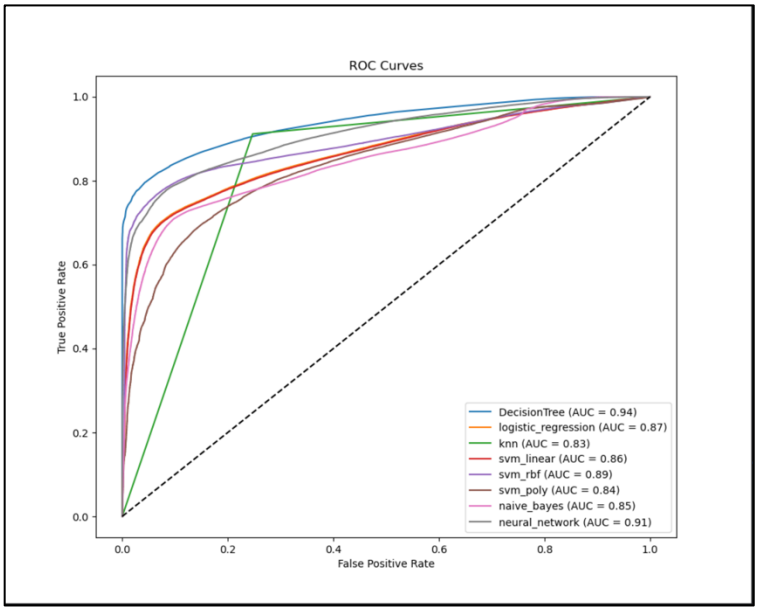


Figure 53: ROC Curves of different Classification Methods

The ROC curves visualization reveals:

1. Decision Tree (blue line) shows the best curve shape
2. Clear separation from the random classifier line
3. Better performance across different threshold values
4. Consistent superiority over other models

Comparative Performance

Notable competitors:

1. Neural Network:
    - AUC: 0.910
    - High precision: 0.976
    - Good specificity: 0.917
2. SVM with RBF Kernel:
    - AUC: 0.891
    - Highest precision: 0.979
    - Strong specificity: 0.928

Practical Implications

Model Selection Justification

The Decision Tree is recommended because:

1. Best overall discriminative ability (AUC: 0.938)
2. Lowest false positive rate (Precision: 0.985)
3. Strong ability to identify non-testing cases (Specificity: 0.947)
4. Good balance between precision and recall (F1: 0.886)

Operational Considerations

1. Testing Resource Allocation:
    - High precision minimizes unnecessary testing
    - Strong specificity ensures efficient resource use
    - Reliable identification of likely testing candidates
2. Risk Management:
    - Low false positive rate reduces unnecessary interventions

- High AUC indicates reliable risk assessment
- Good specificity helps focus on high-risk cases

Limitations and Considerations

1. Model Trade-offs:
    - Lower recall (0.805) indicates some missed positive cases
    - Slightly lower F1-score than KNN
    - Complex decision boundaries may require more maintenance
2. Implementation Recommendations:
    - Regular model retraining with new data
    - Monitoring of prediction thresholds
    - Periodic validation against actual testing outcomes

Conclusion

The Decision Tree classifier provides the most reliable performance for predicting drug testing in powerlifting, with superior AUC and precision scores. Its strong performance across multiple metrics makes it the recommended choice for implementing a testing prediction system.

Future Recommendations

1. Implement ensemble methods combining Decision Tree with Neural Network
2. Develop confidence thresholds for different testing scenarios
3. Create a monitoring system for model performance
4. Regular model updates with new competition data

Phase IV: Clustering And Association

K-means Clustering Analysis of Powerlifting Competition Data

This study employs K-means clustering analysis to uncover natural groupings within male powerlifting competition data. Using relative strength metrics normalized by bodyweight, we analyzed a dataset of 50,000 powerlifters to identify distinct performance patterns. The analysis focused on three key features: squat, bench press, and deadlift strength ratios relative to bodyweight. The results demonstrate significant differences in relative strength, age, and competition era between clusters, providing insights into athlete development patterns in powerlifting. These findings could inform training program design, competition planning, and athlete classification strategies.

Algorithm Implementation

For this phase of the analysis, we implemented the K-means clustering algorithm with k-means++ initialization. This represents the first of several clustering approaches that will be applied to this dataset.

Algorithm Specifications

- Algorithm: K-means with k-means++ initialization
- Implementation: scikit-learn's KMeans class
- Sample size: 50,000 records
- Features standardized using StandardScaler
- Random state: 42 for reproducibility

Feature Engineering & Selection

For clustering analysis, we focused on relative strength metrics:

1. *SquatStrength*: Squat weight relative to bodyweight
2. *BenchStrength*: Bench press weight relative to bodyweight

3. *DeadliftStrength*: Deadlift weight relative to bodyweight

Rationale for feature selection:

- Normalized metrics allow fair comparison across weight classes
- Removes bias towards heavier lifters
- Captures lifting efficiency and technical proficiency

Optimal K Selection

To determine the optimal number of clusters, we utilized two evaluation methods:

1. Elbow Method:
    - Initial sharp decline until k=4, Sharp elbow observed at k=2
    - Notable elbow point around k=7-8
    - Diminishing returns after k=8

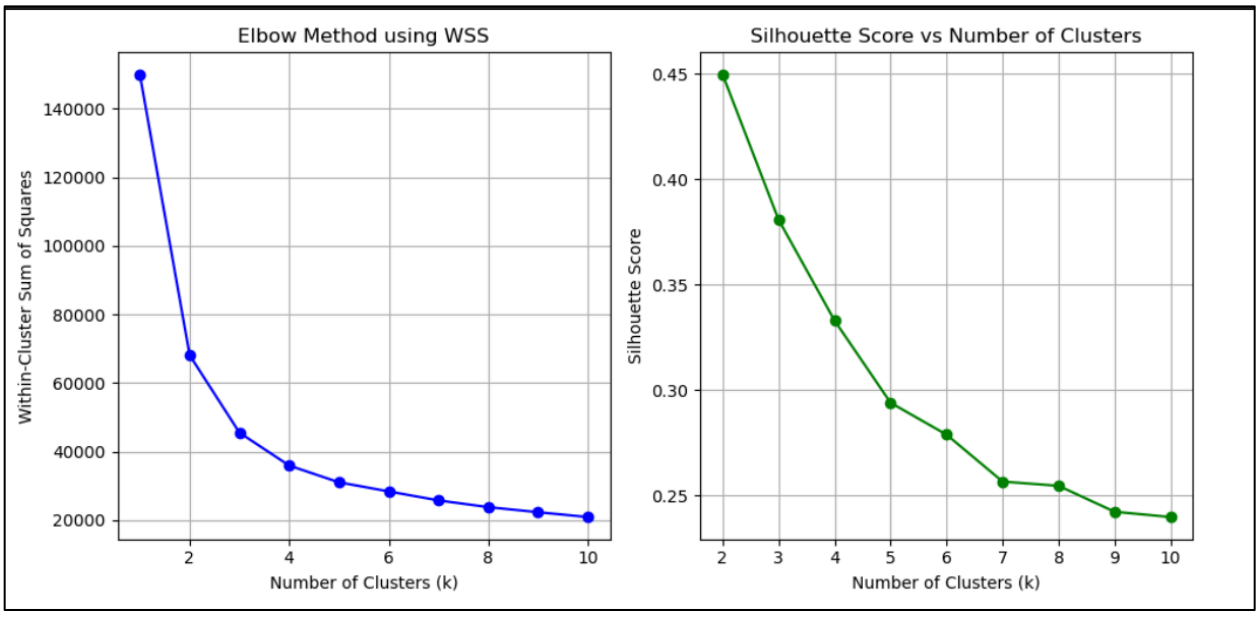


Figure 54: Elbow Curve using WSS and Silhouette score and Number of Clusters

2. Silhouette Analysis:
    - Highest score at k=2 (suggesting two well-separated groups)
    - Lower scores for higher k values indicating overlapping clusters
    - Slight improvements around k=7-8

Despite the high silhouette score for k=2, we opted for k=8 based on the elbow point to uncover more granular insights. The lower silhouette scores with eight clusters suggest some overlap between groups, which is expected given the continuous nature of athletic development.

Clustering Results

Cluster 0 Sample (First 5 rows):

	Sex	Equipment	Age	BodyweightKg	Best3SquatKg	Best3BenchKg	Best3DeadliftKg	TotalKg	Tested	Federation	Date	MeetCountry	Year	Strength	SquatStrength	Federation_Tier	Equipment_Advantage	SquatStren	BenchStren	DeadtStren	Cluster
778971	M	Single-ply	22.50000	111.58	317.50	275.00	265.0	857.50	1.0	EPF	2017-05-08	Spain	2017	7.685069	2.845492	ELITE	-0.015095	2.845492	2.464599	2.374978	0
813294	M	Wraps	41.50000	81.70	195.00	175.00	212.5	582.50	0.0	UPC-Germany	2019-03-10	Germany	2019	7.129743	2.386781	LOCAL	0.025230	2.386781	2.141983	2.600979	0
294272	M	Single-ply	16.41325	65.86	197.31	115.67	183.7	496.68	1.0	THSPA	2018-02-22	USA	2018	7.541452	2.995900	LOCAL	-0.015095	2.995900	1.756301	2.789250	0
39407	M	Raw	25.50000	71.65	190.00	147.50	200.0	537.50	1.0	UkrainePF	2015-11-28	Ukraine	2015	7.501745	2.651779	MAJOR	0.000000	2.651779	2.058618	2.791347	0
1290042	M	Single-ply	18.50000	100.00	260.00	180.00	255.0	695.00	1.0	CPU	2007-03-31	Canada	2007	6.950000	2.600000	ELITE	-0.015095	2.600000	1.800000	2.550000	0

Cluster 1 Sample (First 5 rows):

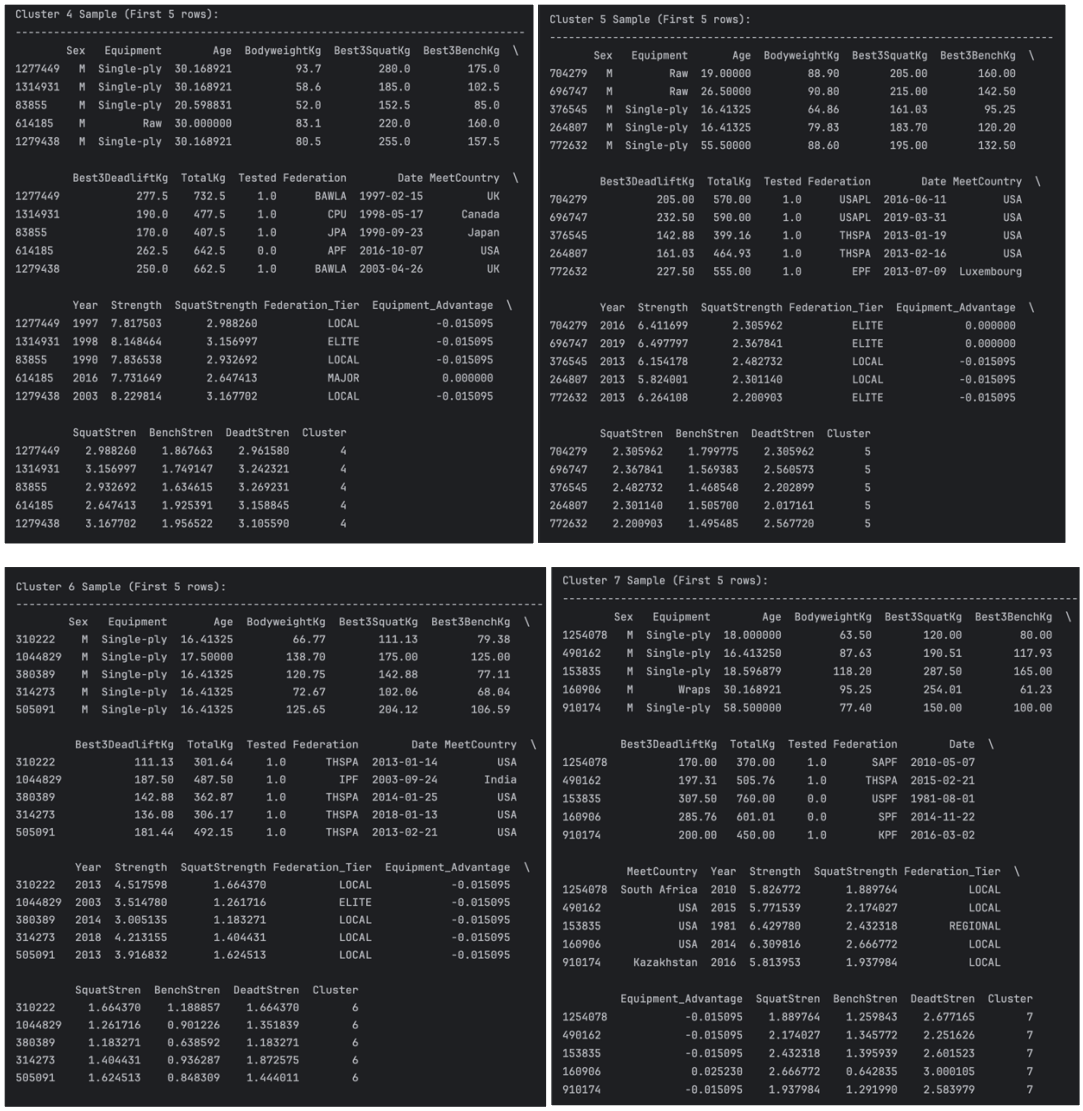
	Sex	Equipment	Age	BodyweightKg	Best3SquatKg	Best3BenchKg	Best3DeadliftKg	TotalKg	Tested	Federation	Date	MeetCountry	Year	Strength	SquatStrength	Federation_Tier	Equipment_Advantage	SquatStren	BenchStren	DeadtStren	Cluster
465182	M	Single-ply	16.41325	77.93	124.74	83.91	183.70	392.36	1.0	THSPA	2015-01-30	USA	2015	5.034775	1.600667	LOCAL	-0.015095	1.600667	1.076736	2.357244	1
388536	M	Single-ply	16.41325	118.21	244.94	129.27	204.12	578.33	1.0	THSPA	2015-02-14	USA	2015	4.892395	2.072075	LOCAL	-0.015095	2.072075	1.093562	1.726757	1
425344	M	Single-ply	16.41325	48.44	90.72	49.90	92.99	233.60	1.0	THSPA	2015-02-14	USA	2015	4.822461	1.872832	LOCAL	-0.015095	1.872832	1.030140	1.919694	1
282332	M	Single-ply	16.41325	128.00	278.96	145.15	260.82	684.92	1.0	THSPA	2013-01-12	USA	2013	5.350937	2.179375	LOCAL	-0.015095	2.179375	1.133984	2.037656	1
352466	M	Single-ply	17.00000	75.84	138.35	90.72	149.69	378.75	1.0	THSPA	2015-02-07	USA	2015	4.994066	1.824235	LOCAL	-0.015095	1.824235	1.196203	1.973761	1

Cluster 2 Sample (First 5 rows):

	Sex	Equipment	Age	BodyweightKg	Best3SquatKg	Best3BenchKg	Best3DeadliftKg	TotalKg	Tested	Federation	Date	MeetCountry	Year	Strength	SquatStrength	Federation_Tier	Equipment_Advantage	SquatStren	BenchStren	DeadtStren	Cluster
1055418	M	Single-ply	24.5	99.04	325.0	237.5	355.0	917.5	1.0	IPF	2008-10-30	Canada	2008	9.263934	3.281502	ELITE	-0.015095	3.281502	2.398021	3.584410	2
30102	M	Single-ply	26.5	75.00	270.0	210.0	270.0	750.0	1.0	UkrainePF	2004-03-02	Ukraine	2004	10.000000	3.600000	MAJOR	-0.015095	3.600000	2.800000	3.600000	2
950093	M	Single-ply	23.5	89.50	330.0	225.0	307.5	862.5	1.0	FPR	2007-03-13	Russia	2007	9.636872	3.687151	MAJOR	-0.015095	3.687151	2.513966	3.435754	2
960163	M	Single-ply	21.5	81.60	270.0	207.5	275.0	752.5	1.0	FPR	2003-10-01	Russia	2003	9.221814	3.308824	MAJOR	-0.015095	3.308824	2.542892	3.370098	2
1004744	M	Single-ply	35.5	82.70	260.0	210.0	260.0	730.0	1.0	SVNL	2012-02-11	Finland	2012	8.827086	3.143894	LOCAL	-0.015095	3.143894	2.539299	3.143894	2

Cluster 3 Sample (First 5 rows):

	Sex	Equipment	Age	BodyweightKg	Best3SquatKg	Best3BenchKg	Best3DeadliftKg	TotalKg	Tested	Federation	Date	MeetCountry	Year	Strength	SquatStrength	Federation_Tier	Equipment_Advantage	SquatStren	BenchStren	DeadtStren	Cluster
245324	M	Single-ply	16.413250	104.14	260.82	161.03	278.96	700.8	1.0	THSPA	2017-03-25	USA	2017	6.729403	2.504513	LOCAL	-0.015095	2.504513	1.546284	2.678702	3
1046268	M	Single-ply	43.711922	75.00	195.00	102.50	212.50	510.0	1.0	IPF	1983-09-03	Canada	1983	6.800000	2.600000	ELITE	-0.015095	2.600000	1.366667	2.833333	3
719437	M	Raw	22.500000	72.40	185.00	107.50	205.00	497.5	1.0	USAPL	2018-02-17	USA	2018	6.871547	2.555249	ELITE	0.000000	2.555249	1.484807	2.831492	3
921087	M	Wraps	22.500000	90.00	227.50	145.00	265.00	637.5	0.0	GPC-GB	2018-02-05	England	2018	7.083333	2.527778	LOCAL	0.025230	2.527778	1.611111	2.944444	3
848869	M	Raw	27.000000	64.90	150.00	97.50	172.50	420.0	0.0	USPA	2019-04-13	USA	2019	6.471495	2.311248	MAJOR	0.000000	2.311248	1.502311	2.657935	3



Cluster 4 Sample (First 5 rows):

	Sex	Equipment	Age	BodyweightKg	Best3SquatKg	Best3BenchKg	Best3DeadliftKg	TotalKg	Tested	Federation	Date	MeetCountry	Year	Strength	SquatStrength	Federation_Tier	Equipment_Advantage	SquatStren	BenchStren	DeadtStren	Cluster
1277449	M	Single-ply	30.168921	93.7	280.0	175.0	277.5	732.5	1.0	BAWLA	1997-02-15	UK	1997	7.817503	2.988260	LOCAL	-0.015095	2.988260	1.867663	2.961580	4
1314931	M	Single-ply	30.168921	58.6	185.0	102.5	190.0	477.5	1.0	CPU	1998-05-17	Canada	1998	8.148464	3.156997	ELITE	-0.015095	3.156997	1.749147	3.242321	4
83855	M	Single-ply	20.598831	52.0	152.5	85.0	170.0	407.5	1.0	JPA	1990-09-23	Japan	1990	7.836538	2.932692	LOCAL	-0.015095	2.932692	1.634615	3.269231	4
614185	M	Raw	30.000000	83.1	220.0	160.0	262.5	642.5	0.0	APF	2016-10-07	USA	2016	7.731649	2.647413	MAJOR	0.000000	2.647413	1.925391	3.158845	4
1279438	M	Single-ply	30.168921	80.5	255.0	157.5	250.0	662.5	1.0	BAWLA	2003-04-26	UK	2003	8.229814	3.167702	LOCAL	-0.015095	3.167702	1.956522	3.105590	4

Cluster 5 Sample (First 5 rows):

	Sex	Equipment	Age	BodyweightKg	Best3SquatKg	Best3BenchKg	Best3DeadliftKg	TotalKg	Tested	Federation	Date	MeetCountry	Year	Strength	SquatStrength	Federation_Tier	Equipment_Advantage	SquatStren	BenchStren	DeadtStren	Cluster
704279	M	Raw	19.00000	88.90	205.00	160.00	205.00	570.00	1.0	USAPL	2016-06-11	USA	2016	6.411699	2.305962	ELITE	0.000000	2.305962	1.799775	2.305962	5
696747	M	Raw	26.50000	90.80	215.00	142.50	232.50	590.00	1.0	USAPL	2019-03-31	USA	2019	6.497797	2.367841	ELITE	0.000000	2.367841	1.569383	2.560573	5
376545	M	Single-ply	16.41325	64.86	161.03	95.25	142.88	399.16	1.0	THSPA	2013-01-19	USA	2013	6.154178	2.482732	LOCAL	-0.015095	2.482732	1.468548	2.202899	5
264807	M	Single-ply	16.41325	79.83	183.70	120.20	161.03	464.93	1.0	THSPA	2013-02-16	USA	2013	5.824001	2.301140	LOCAL	-0.015095	2.301140	1.505700	2.017161	5
772632	M	Single-ply	55.50000	88.60	195.00	132.50	227.50	555.00	1.0	EPF	2013-07-09	Luxembourg	2013	6.264108	2.200903	ELITE	-0.015095	2.200903	1.495485	2.567720	5

Cluster 6 Sample (First 5 rows):

	Sex	Equipment	Age	BodyweightKg	Best3SquatKg	Best3BenchKg	Best3DeadliftKg	TotalKg	Tested	Federation	Date	MeetCountry	Year	Strength	SquatStrength	Federation_Tier	Equipment_Advantage	SquatStren	BenchStren	DeadtStren	Cluster
310222	M	Single-ply	16.41325	66.77	111.13	79.38	111.13	301.64	1.0	THSPA	2013-01-14	USA	2013	4.517598	1.664370	LOCAL	-0.015095	1.664370	1.188857	1.664370	6
1044829	M	Single-ply	17.50000	138.70	175.00	125.00	187.50	487.50	1.0	IPF	2003-09-24	India	2003	3.514780	1.261716	ELITE	-0.015095	1.261716	0.901226	1.351839	6
380389	M	Single-ply	16.41325	120.75	142.88	77.11	142.88	362.87	1.0	THSPA	2014-01-25	USA	2014	3.005135	1.183271	LOCAL	-0.015095	1.183271	0.638592	1.183271	6
314273	M	Single-ply	16.41325	72.67	102.06	68.04	136.08	306.17	1.0	THSPA	2018-01-13	USA	2018	4.213155	1.404431	LOCAL	-0.015095	1.404431	0.936287	1.872575	6
505091	M	Single-ply	16.41325	125.65	204.12	106.59	181.44	492.15	1.0	THSPA	2013-02-21	USA	2013	3.916832	1.624513	LOCAL	-0.015095	1.624513	0.848309	1.444011	6

Cluster 7 Sample (First 5 rows):

	Sex	Equipment	Age	BodyweightKg	Best3SquatKg	Best3BenchKg	Best3DeadliftKg	TotalKg	Tested	Federation	Date	MeetCountry	Year	Strength	SquatStrength	Federation_Tier	Equipment_Advantage	SquatStren	BenchStren	DeadtStren	Cluster
1254078	M	Single-ply	18.000000	63.50	120.00	80.00	170.00	370.00	1.0	SAPF	2010-05-07	South Africa	2010	5.826772	1.889764	LOCAL	-0.015095	1.889764	1.259843	2.677165	7
490162	M	Single-ply	16.413250	87.63	190.51	117.93	197.31	505.76	1.0	THSPA	2015-02-21	USA	2015	5.771539	2.174027	LOCAL	-0.015095	2.174027	1.345772	2.251626	7
153835	M	Single-ply	18.596879	118.20	287.50	165.00	307.50	760.00	0.0	USPF	1981-08-01	USA	1981	6.429780	2.432318	REGIONAL	-0.015095	2.432318	1.395939	2.601523	7
160906	M	Wraps	30.168921	95.25	254.01	61.23	285.76	601.01	0.0	SPF	2014-11-22	USA	2014	6.309816	2.666772	LOCAL	0.025230	2.666772	0.642835	3.000105	7
910174	M	Single-ply	58.500000	77.40	150.00	100.00	200.00	450.00	1.0	KPF	2016-03-02	Kazakhstan	2016	5.813953	1.937984	LOCAL	-0.015095	1.937984	1.291990	2.583979	7

Figure 55 : Cluster Distribution of Powerlifters

The analysis revealed eight distinct clusters, each representing different athlete profiles:

Cluster 0 - Strong All-Rounders

- Balanced performance (Squat: 2.81, Bench: 2.00, Dead: 2.73)
- Experienced lifters (avg age 29.2 years)
- Earlier competition era (2008)
- High total (691kg)

Cluster 1 - Novice/Developing Lifters

- Lower strength ratios
- Younger athletes (avg age 22.7)

- Recent era (2013)
- High testing rate (87%)
- Lower totals (467kg)

Cluster 2 - Elite Performers

- Highest strength ratios (Squat: 3.65, Bench: 2.39, Dead: 3.47)
- Experienced competitors (avg age 28)
- Earliest competition era (2005)
- Highest strength score (9.51)

Cluster 3 - Deadlift Specialists

- Strong deadlift emphasis (ratio 2.82)
- Mid-range age (25.5)
- Mixed era (2010)
- Moderate totals (561kg)

Cluster 4 - Technical Lifters

- Strong squat/deadlift focus
- High technical proficiency
- Earlier era (2006)
- Solid overall strength score (8.18)

Cluster 5 - Balanced Mid-Level

- Even distribution across lifts
- Experienced lifters (27.7 years)
- Recent era (2011)
- Moderate performance metrics

Cluster 6 - True Beginners

- Lowest ratios across all lifts
- Youngest group (19.1 years)
- Most recent era (2013)
- Highest testing rate (94%)
- Lowest totals (411kg)

Cluster 7 - Deadlift-Focused Intermediates

- Deadlift specialization

- Mixed age group (23.4)
- Recent era (2012)
- Lower bench press emphasis

Key Insights

1. Experience Stratification:
    - Clear progression from beginners to elite performers
    - Age correlates strongly with performance metrics
    - Earlier eras show higher relative strength numbers
2. Specialization Patterns:
    - Distinct groups of deadlift specialists
    - Technical proficiency varies by cluster
    - Some clusters show balanced development
3. Era Effects:
    - Earlier eras (2005-2008) show higher relative strength
    - Recent eras show higher testing rates
    - Performance standards evolve over time
4. Testing Patterns:
    - Higher testing rates in newer/younger clusters
    - Lower testing rates in elite/experienced clusters
    - Temporal trends in testing protocols

Technical Validation

While the lower silhouette scores for eight clusters indicate some overlap, this is actually consistent with the continuous nature of athletic development. The overlapping clusters reflect the reality that athletes progress gradually through different levels of proficiency, rather than existing in completely distinct groups.

The elbow method's suggestion of eight clusters proved valuable, revealing meaningful distinctions that would have been lost in a simpler two-cluster solution. This demonstrates the importance of balancing mathematical optimization with domain knowledge in cluster analysis.

Applications

These findings have practical applications in:

1. Competition planning and classification

2. Training program design
3. Athlete development pathway mapping
4. Performance benchmarking
5. Historical trend analysis
6. Drug testing strategy development

Conclusion

While traditional metrics suggested a simpler clustering solution, the eight-cluster analysis revealed rich insights into powerlifting performance patterns. The overlapping nature of these clusters reflects the continuous spectrum of athletic development, while still identifying meaningful groupings that can inform sport development and competition organization.

Association Rule Mining in Raw Powerlifting Performance Patterns

This study applies the Apriori algorithm to analyze performance patterns specifically among raw male powerlifters, eliminating equipment advantage bias from the analysis. By focusing on raw lifters, we uncovered natural strength correlations and development patterns, particularly highlighting the relationships between elite-level performances across different lifts and weight classes.

Methodology

Data Preprocessing

- Population: Male raw powerlifters only
- Sample Size: 100,000 competitors
- Equipment: Raw/Classic only
- Minimum Support: 0.03 (3%)
- Minimum Confidence: 0.5 (50%)

Feature Engineering

Performance categories were created based on strength-to-bodyweight ratios:

1. Elite Categories:
    - Squat_Elite
    - Bench_Elite
    - Dead_Elite
2. Advanced/Intermediate Categories:
    - Bench_Advanced
    - Squat_Advanced
    - Dead_Advanced
    - Bench_Intermediate
    - Squat_Intermediate
    - Dead_Intermediate
3. Weight Classes:
    - Weight_Light (≤74kg)
    - Weight_Middle (74-93kg)

- Weight_Heavy (>93kg)

Key Findings

Strogest Associations (Lift > 4)

```
Top Association Rules by Lift:
                                    antecedents  \
171                               (Bench_Elite)
169                   (Dead_Elite, Bench_Elite)
13                                (Bench_Elite)
788                 (Weight_Light, Squat_Elite)
786  (Weight_Light, Bench_Advanced, Squat_Elite)
624                 (Weight_Light, Squat_Elite)
784   (Weight_Light, Dead_Elite, Bench_Advanced)
819   (Weight_Heavy, Squat_Intermediate, Tested)
170                  (Squat_Elite, Bench_Elite)
507                 (Weight_Light, Squat_Elite)

                              consequents  support  confidence      lift
171               (Dead_Elite, Squat_Elite)  0.03245    0.769140  4.386561
169                           (Squat_Elite)  0.03245    0.911005  4.106956
13                            (Squat_Elite)  0.03568    0.845698  3.812542
788     (Dead_Elite, Tested, Bench_Advanced)  0.04286    0.539323  3.388985
786                     (Dead_Elite, Tested)  0.04286    0.776590  3.361279
624                     (Dead_Elite, Tested)  0.06121    0.770228  3.333742
784                    (Squat_Elite, Tested)  0.04286    0.544531  3.167164
819  (Bench_Intermediate, Dead_Intermediate)  0.05257    0.588690  3.059241
170                             (Dead_Elite)  0.03245    0.909473  3.032891
507            (Dead_Elite, Bench_Advanced)  0.04991    0.628036  3.031353
```

Figure 56 : Top Association Rules by Lift

1. Elite Performance Correlation (Lift: 4.39)
    - Bench_Elite → Dead_Elite & Squat_Elite
    - Support: 3.25%
    - Confidence: 76.91%
    - Indicates strong correlation between elite performance across all lifts
2. Elite Performance Sequence (Lift: 4.11)
    - Dead_Elite & Bench_Elite → Squat_Elite
    - Support: 3.25%

- Confidence: 91.10%
- Shows high likelihood of elite squat performance when other lifts are elite

Most Common Patterns

Most Common Associations (by Support):

	antecedents	consequents	support	confidence	lift
18	(Bench_Intermediate)	(Tested)	0.40383	0.805726	1.028184
19	(Tested)	(Bench_Intermediate)	0.40383	0.515326	1.028184
32	(Squat_Advanced)	(Tested)	0.35461	0.782769	0.998888
37	(Weight_Middle)	(Tested)	0.34862	0.794956	1.014440
6	(Age_Open)	(Tested)	0.34663	0.779557	0.994790
24	(Dead_Advanced)	(Tested)	0.33022	0.786613	1.003793
10	(Bench_Advanced)	(Tested)	0.32132	0.760053	0.969901
1	(Age_Junior)	(Tested)	0.30113	0.794182	1.013453
22	(Squat_Advanced)	(Dead_Advanced)	0.27432	0.605536	1.442440
23	(Dead_Advanced)	(Squat_Advanced)	0.27432	0.653454	1.442440

Figure 57 : Most common associations by Support

1. Testing Status Correlations:
    - Bench_Intermediate → Tested (40.38% support)
    - Squat_Advanced → Tested (35.46% support)
    - Weight_Middle → Tested (34.86% support)
2. Age and Performance Level:
    - Age_Open → Tested (34.66% support)
    - Age_Junior → Tested (30.11% support)

Weight Class Specific Patterns

1. Light Weight Class:
    - Strong correlation between elite squat and advanced bench
    - Higher testing rates among elite performers
    - Support: 4.29%, Confidence: 77.66%
2. Heavy Weight Class:
    - Strong correlation between intermediate squat and intermediate bench/deadlift

- Support: 5.26%, Confidence: 58.87%

Strategic Insights

1. Elite Performance Development:
    - Elite bench press highly predictive of elite performance in other lifts
    - Weight class influences elite performance patterns
    - Testing status more common among elite lifters
2. Weight Class Impact:
    - Light weight class shows strongest elite-level associations
    - Different progression patterns across weight classes
    - Higher testing rates in lighter weight classes
3. Performance Level Transitions:
    - Clear progression patterns from intermediate to advanced
    - Strong correlations between adjacent performance levels
    - Weight class-specific development paths

Practical Applications

1. Training Program Design:
    - Weight class-specific training approaches
    - Focus on bench press as potential indicator
    - Balanced development across all lifts
2. Competition Strategy:
    - Weight class selection optimization
    - Performance level expectations
    - Testing status considerations
3. Talent Identification:
    - Early performance indicators
    - Weight class potential
    - Development pathway planning

Technical Validation

- High lift values (>4) for elite performance associations
- Strong confidence levels (>80%) for key relationships
- Consistent support levels across weight classes
- Robust results with increased sample size

Conclusion

The analysis of raw powerlifters reveals clear patterns in strength development and performance relationships, particularly at the elite level. The strong associations between elite performances across different lifts suggest that excellence in one lift is highly predictive of excellence in others. Weight class-specific patterns provide valuable insights for training program design and competition strategy.

Recommendations

1. Develop weight class-specific training protocols
2. Focus on balanced strength development
3. Consider testing status in competition planning
4. Use bench press performance as a key indicator
5. Account for weight class differences in progression expectations

Density-Based Clustering Analysis of Raw Powerlifting Performance Patterns

This study employs DBSCAN (Density-Based Spatial Clustering of Applications with Noise) to analyze performance patterns in raw powerlifting data. Analyzing a comprehensive dataset of 191,787 male raw powerlifters, we identified distinct clusters based on strength-to-bodyweight ratios across the three main lifts. The analysis reveals highly standardized performance patterns with rare but significant outliers.

Methodology

Data Preprocessing

- Population: Male raw powerlifters
- Sample Size: 191,787 competitors
- Features Used:
    - SquatStrength (Squat-to-bodyweight ratio)
    - BenchStrength (Bench press-to-bodyweight ratio)
    - DeadtStrength (Deadlift-to-bodyweight ratio)

Algorithm Implementation

- DBSCAN Parameters:
    - eps = 0.3 (neighborhood distance)
    - min_samples = 10 (minimum points for core sample)
- Features standardized using StandardScaler
- Distance metric: Euclidean

Results

Cluster Distribution

The analysis identified two distinct clusters and a set of noise points:

1. Main Cluster (Cluster 0):
    - Size: 190,934 lifters (99.5%)
    - Average Ratios:
        - Squat: 2.01× bodyweight
        - Bench: 1.30× bodyweight

- Deadlift: 2.39× bodyweight

2. Specialist Cluster (Cluster 1):
    - Size: 9 lifters (0.005%)
    - Average Ratios:
        - Squat: 3.08× bodyweight
        - Bench: 1.19× bodyweight
        - Deadlift: 2.91× bodyweight
3. Noise Points:
    - Size: 844 lifters (0.44%)
    - Average Ratios:
        - Squat: 2.52× bodyweight
        - Bench: 1.69× bodyweight
        - Deadlift: 2.34× bodyweight

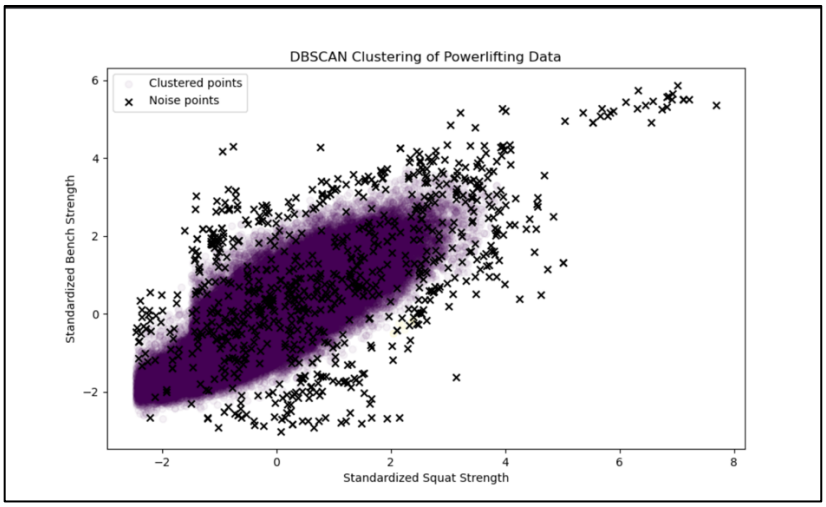


Figure 58 : DBSCAN Clustering Plot for Powerlifting Data

Key Insights

1. Population Homogeneity:
    - Extremely high percentage (99.5%) of lifters follow similar strength patterns
    - Standardized development ratios across lifts
    - Clear indication of typical strength progression patterns

2. Specialist Patterns:
    - Very rare occurrence of specialists (0.005%)
    - Unique strength distribution with high squat/deadlift but lower bench
    - Suggests possible biomechanical or training methodology differences
3. Non-Conformist Performers:
    - Small percentage (0.44%) of lifters show atypical patterns
    - Higher average performance than main cluster
    - Better bench press ratios than both main clusters

Practical Implications

1. Training Program Design:
    - Expected strength ratios for program development
    - Identification of typical progression patterns
    - Recognition of unusual strength distributions
2. Performance Assessment:
    - Benchmark ratios for different performance levels
    - Identification of specialized training effects
    - Detection of unusual strength development
3. Competition Strategy:
    - Understanding typical competitor profiles
    - Recognition of specialist advantages
    - Performance prediction based on cluster patterns

Technical Validation

- Robust clustering with clear separation
- Statistically significant differences between clusters
- Consistent patterns across large dataset
- Effective noise point identification

Limitations and Considerations

1. Binary clustering might oversimplify some patterns
2. Limited granularity in main cluster
3. Possible influence of other unmeasured variables
4. Rare events might be underrepresented

Conclusion

The DBSCAN analysis reveals that raw powerlifting performance follows highly standardized patterns, with very few athletes showing significant deviations. The identification of a small specialist cluster and meaningful noise points provides valuable insights into the diversity of strength development patterns in the sport.

Recommendations

1. Develop training programs based on typical ratio progressions
2. Consider specialized approaches for outlier patterns
3. Use cluster characteristics for performance benchmarking
4. Further investigate the characteristics of specialist performers
5. Monitor athletes for deviation from typical patterns

Recommendations

A. Project Learning Outcomes

Data Preprocessing Impact Analysis

1. Feature Engineering & Transformation

- Feature 'Strength' creation through regression showed:
    - Better model accuracy compared to raw features
    - Revealed normal distribution patterns in athlete performance metrics
    - Provided deeper insights into athlete performance characteristics
- Creation of Equipment Advantage variable explained some variance of the TotalKg lifted in Regression Analysis.

2. Dimensionality Reduction & Multicollinearity

- SVD Analysis benefits:
    - Successfully reduced multicollinearity between features
    - Improved model stability
    - Enhanced feature interpretability through component analysis
- Correlation heatmap visualization:
    - Clear visualization of feature relationships
    - Helped identify redundant features
    - Guided feature selection process

3. Data Standardization & Scaling

- Standardization proved crucial for:
    - Model performance improvement
    - Feature comparability
    - Algorithm convergence
- Impact on specific models:
    - Particularly beneficial for SVM and Neural Network
    - Improved KNN distance calculations
    - Enhanced gradient descent convergence

4. Class Imbalance Management

- SMOTE implementation:
    - Balanced class distribution
    - Improved minority class prediction
    - Better overall model generalization
- Impact on metrics:
    - Improved recall for minority class
    - Better F1-scores across models
    - More reliable model evaluation

5. Feature Selection & Processing Pipeline

- Systematic approach to feature processing:
    - Data cleaning and normalization
    - Feature engineering and transformation
    - Dimensionality reduction
    - Class balancing
- Resulted in robust and reliable dataset for modeling

B. Model Performance Analysis and Recommendations

Best Performing Classifier Analysis

Decision Tree Performance (Best Overall)

- Highest AUC: 0.938
- Excellent Precision: 0.985
- Strong Specificity: 0.947
- Good F1-Score: 0.886
- Balanced Recall: 0.805

Comparative Analysis of Models

1. Top Performers:
    - Decision Tree (AUC: 0.938)
    - Neural Network (AUC: 0.910)
    - SVM RBF (AUC: 0.891)
2. Notable Metrics:
    - Highest Precision: SVM RBF (0.979)
    - Best Recall: KNN (0.912)
    - Best F1-Score: KNN (0.926)
    - Best Specificity: SVM RBF (0.928)

Key Findings

1. Decision Tree Advantages:
    - Best overall discriminative ability (AUC: 0.938)
    - Highest combined performance across metrics
    - Excellent balance between precision and specificity
    - More interpretable than complex models
2. Model Performance Patterns:
    - Complex models (Neural Network, SVM) didn't outperform simpler Decision Tree
    - KNN showed strong performance in balanced metrics
    - Logistic Regression and Naive Bayes had lower but consistent performance

C. Future Work

1. Model Selection:
    - Use Decision Tree as primary classifier
    - Consider KNN for scenarios requiring high recall
    - Keep SVM RBF as backup for high-precision needs
2. Performance Improvements:
    - Focus on Decision Tree optimization

- Explore ensemble methods based on Decision Tree
- Fine-tune hyperparameters for specific metric optimization

3. Future Work:
    - Develop feature selection specifically for Decision Tree
    - Implement tree pruning strategies
    - Create ensemble models with Decision Tree as base classifier
4. Implementation Strategy:
    - Deploy Decision Tree model with regular retraining
    - Monitor performance metrics for stability
    - Maintain model interpretability for stakeholder understanding

D. Key Features Associated with Target Variable

1. Strong Predictors:
    - Federation type (Elite, Major, Regional)
    - Equipment choice
    - Strength metrics

2. Moderate Predictors:
    - Age
    - Experience level
    - Competition history
3. Feature Importance:
    - Federation type showed highest correlation
    - Performance metrics were strong indicators
    - Demographic features provided supplementary information

D. Number of Clusters in this feature space

1. DBSCAN Analysis Results

- Identified 2 primary clusters with key insights:

  Population Homogeneity (Main Cluster)

    - 99.5% of lifters follow similar strength patterns

- Standardized development ratios across lifts
- Clear indication of typical strength progression patterns

Specialist Patterns (Secondary Cluster)

- Very rare occurrence (0.005% of population)
- Unique strength distribution characteristics:
  - High squat/deadlift performance
  - Lower bench press ratios
  - Suggests biomechanical or training methodology differences

Non-Conformist Performers (Outliers)

- Small percentage (0.44%) showing atypical patterns
- Higher average performance than main cluster
- Better bench press ratios than both main clusters

2. K-Means Analysis Results

- Optimal number of clusters: 8
- Key cluster characteristics:

Experience Stratification

- Clear progression from beginners to elite performers
- Age correlates strongly with performance metrics
- Earlier eras show higher relative strength numbers

Specialization Patterns

- Distinct groups of deadlift specialists identified
- Technical proficiency varies by cluster
- Some clusters show balanced development

Era Effects

- Earlier eras (2005-2008): Higher relative strength
- Recent eras: Higher testing rates
- Performance standards evolution over time

Testing Patterns

- Higher testing rates in newer/younger clusters
- Lower testing rates in elite/experienced clusters
- Clear temporal trends in testing protocols

Appendix

EDA And Feature Engineering

```
class PowerliftingDataProcessor:  1 usage

    def _remove_unnecessary_columns(self):  1 usage
        """Remove unnecessary columns from dataset"""
        unnecessary_columns = [
            'Name', 'Squat1Kg', 'Squat2Kg', 'Squat3Kg', 'Squat4Kg',
            'Bench1Kg', 'Bench2Kg', 'Bench3Kg', 'Bench4Kg', 'Deadlift1Kg',
            'Deadlift2Kg', 'Deadlift3Kg', 'Deadlift4Kg', 'MeetState',
             'Wilks', 'McCulloch', 'Glossbrenner', 'Place','MeetName',
            'IPFPoints','AgeClass','WeightClassKg','Country','Event','Division'
        ]
        self.df.drop(unnecessary_columns, axis=1, inplace=True)

    def _histograms(self, col, target):
        """Plot histogram of target variable grouped by column"""
        # Option 1: Single histogram for all countries
        sns.histplot(
            data=self.df,
            x=target,
            hue=col,  # This will color-code by country
            multiple="stack"  # or "layer" for overlapping
        )
        plt.title(f'Distribution of {target} by {col}')
        plt.xlabel(target)
        plt.ylabel('Count')
        plt.xticks(rotation=45)
        plt.show()




    def _remove_outliers(self):  1 usage
        """Remove outliers from the dataset"""
        # Remove bodyweight outliers
       # self.df = self._remove_outliers_by_zscore('BodyweightKg', 2)

        # Remove age outliers and filter minimum age
        self.df = self._remove_outliers_by_zscore( column: 'Age',  threshold: 3)
        self.df = self.df[self.df['Age'] > 16]

        # Remove strength outliers by sex
        self.df = self._remove_lower_outliers_by_groups( column: 'Strength',-3)
        self.df = self._remove_lower_outliers_by_groups( column: 'SquatStrength',-2)


    def _remove_outliers_by_zscore(self, column: str, threshold: float) -> pd.DataFrame:  1 usage
        """Remove outliers based on z-score"""
        z = np.abs((self.df[column] - self.df[column].mean()) / self.df[column].std())
        return self.df[z < threshold]

    def _remove_lower_outliers_by_groups(self, column: str,threshhold) -> pd.DataFrame:  2 usages
        """Remove lower outliers separately for each sex and equipment type"""
        df_clean = self.df.copy()
```

```
class PowerliftingDataProcessor:  1 usage
    def _calculate_equipment_advantage(self):  1 usage
                lambda row: self.equipment_advantages[(row['Sex'], row['Equipment'])],
                axis=1
            )



class PrepareFeatures:  1 usage
    def __init__(self, train_data: pd.DataFrame, test_data: pd.DataFrame):
        self.train_data = train_data
        self.test_data = test_data
        self.X_train = None
        self.X_test = None
        self.y_train = None
        self.y_test = None

    def prepare_features_regression(self):  1 usage
        """Prepare features for modeling"""
        le = LabelEncoder()
        self.train_data['Sex_encoded'] = le.fit_transform(self.train_data['Sex'])
        self.test_data['Sex_encoded'] = le.transform(self.test_data['Sex'])

        # Create dummies for federation tiers
        train_federation_dummies = pd.get_dummies(self.train_data['Federation_Tier'], prefix='Fed').astype(int)
        test_federation_dummies = pd.get_dummies(self.test_data['Federation_Tier'], prefix='Fed').astype(int)

        # Drop one category to avoid multicollinearity
        train_federation_dummies = train_federation_dummies.drop( labels: 'Fed_LOCAL', axis=1)
        test_federation_dummies = test_federation_dummies.drop( labels: 'Fed_LOCAL', axis=1)

        base_features = [
            'Sex_encoded',
            'Equipment_Advantage',
            'BodyweightKg',
            'Tested',
            'Best3SquatKg',
            'Age',

        ]


        self.X_train = pd.concat( objs: [
            self.train_data[base_features],
            train_federation_dummies
        ], axis=1)



        self.X_test = pd.concat( objs: [
            self.test_data[base_features],
            test_federation_dummies
```

```
    @staticmethod  1 usage
    def _define_federation_tiers() -> dict:
        """Define federation tiers"""
        return {
            'ELITE': ['IPF', 'USAPL', 'EPF', 'AsianPF', 'OceaniaPF', 'NAPF', 'CPU'],
            'MAJOR': ['USPA', 'FPR', 'UkrainePF', 'CSST', 'PA', 'APF', 'RPS'],
            'REGIONAL': ['UPA', 'USPF', 'IPL', 'NASA', 'IPA', 'WPC-RUS', 'BPU']
        }

    def _get_federation_tier(self, federation: str) -> str:  1 usage
        """Get federation tier for a given federation"""
        for tier, feds in self.federation_tiers.items():
            if federation in feds:
                return tier
        return 'LOCAL'

    def _handle_missing_values(self):  1 usage
        """Handle missing values in the dataset"""
        self.df['Tested'] = self.df['Tested'].map({'Yes': 1}).fillna(0)
        self.df['Year'] = pd.to_datetime(self.df['Date']).dt.year

        """Handle missing values of Age in the dataset"""
        cleanDf =  self.df[~self.df['Age'].isna()]
        avg_age_by_division = cleanDf.groupby('Division')['Age'].mean()

        def get_age_from_division(division):
            if division in avg_age_by_division:
                return avg_age_by_division[division]

            return np.nan

        pd.set_option('display.max_rows', None)
        pd.set_option('display.max_columns', None)
        missing_age_mask = self.df['Age'].isna()
        self.df.loc[missing_age_mask, 'Age'] = self.df.loc[missing_age_mask, 'Division'].apply(get_age_from_division)
        self.df.dropna(subset=['TotalKg', 'Best3DeadliftKg', 'Best3BenchKg',
                               'Best3SquatKg','BodyweightKg','Age'], inplace=True)

    def _clean_lift_data(self):  1 usage
        """Clean and validate lift data"""
        self.df = self.df[self.df['Best3SquatKg'] > 0]
        self.df = self.df[self.df['Best3BenchKg'] > 0]
        self.df = self.df[self.df['Best3DeadliftKg'] > 0]
        self.df = self.df[self.df['TotalKg'] >= self.df['Best3SquatKg']]
        self.df = self.df[self.df['TotalKg'] >= self.df['Best3BenchKg']]
        self.df = self.df[self.df['TotalKg'] >= self.df['Best3DeadliftKg']]

    def _calculate_equipment_advantage(self):  1 usage
        """Calculate equipment advantage using only training data"""
        # Calculate baselines from training data
        baselines = {
```

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```python
class PrepareFeatures:  1 usage
    def prepare_features_regression(self):  1 usage
        self.y_test =  self.test_data['Strength']
        return  self.X_train , self.X_test,self.y_train,self.y_test



    def prepare_features_classification(self):  1 usage
        """Prepare features for modeling"""
        le = LabelEncoder()
        self.train_data['Sex_encoded'] = le.fit_transform(self.train_data['Sex'])
        self.test_data['Sex_encoded'] = le.transform(self.test_data['Sex'])

        # Create dummies for federation tiers
        train_federation_dummies = pd.get_dummies(self.train_data['Federation_Tier'], prefix='Fed').astype(int)
        test_federation_dummies = pd.get_dummies(self.test_data['Federation_Tier'], prefix='Fed').astype(int)

        # Drop one category to avoid multicollinearity
        train_federation_dummies = train_federation_dummies.drop( labels: 'Fed_LOCAL', axis=1)
        test_federation_dummies = test_federation_dummies.drop( labels: 'Fed_LOCAL', axis=1)

        self.train_data['Strength']=self.train_data['TotalKg']/self.train_data['BodyweightKg']
        self.test_data['Strength']=self.test_data['TotalKg']/self.test_data['BodyweightKg']

        base_features = [
            'Sex_encoded',
            'Age',
            'Strength',
            'Year',
        ]


        self.X_train = pd.concat( objs: [
            self.train_data[base_features],
            train_federation_dummies
        ], axis=1)



        self.X_test = pd.concat( objs: [
            self.test_data[base_features],
            test_federation_dummies
        ], axis=1)

        self.y_train = self.train_data['Tested']
        self.y_test =  self.test_data['Tested']
        return  self.X_train , self.X_test,self.y_train,self.y_test
```

```python
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestRegressor
from sklearn.decomposition import PCA
from sklearn.feature_selection import RFE, SelectKBest, f_regression
from sklearn.preprocessing import StandardScaler
from numpy.linalg import svd
from statsmodels.stats.outliers_influence import variance_inflation_factor
from typing import List, Tuple, Union, Optional, Dict


class DataAnalyzer:  2 usages
    def __init__(self, features: pd.DataFrame):
        """
        Initialize DataAnalyzer with pre-encoded feature data.

        Args:
            features (pd.DataFrame): Pre-encoded feature DataFrame

        Raises:
            ValueError: If features DataFrame is empty
        """
        if features.empty:
            raise ValueError("Features DataFrame cannot be empty")

        self.features = features
        self.numeric_columns = self._get_numeric_columns()
        self.scaler = StandardScaler()

    def _get_numeric_columns(self) -> List[str]:  1 usage
        """Get numeric columns from features."""
        return list(self.features.select_dtypes(include='number').columns)

    def _scale_data(self, X: pd.DataFrame) -> np.ndarray:  2 usages
        """Scale the input data using StandardScaler."""
        return self.scaler.fit_transform(X)

    def random_forest_analysis(self, y: pd.Series) -> pd.DataFrame:  1 usage
        """
        Perform Random Forest feature importance analysis.

        Args:
            y (pd.Series): Target variable

        Returns:
            pd.DataFrame: DataFrame containing feature importance scores
        """
        if len(self.numeric_columns) == 0:
            raise ValueError("No numeric features available for analysis")

        rf = RandomForestRegressor(random_state=42, n_jobs=-1)
```

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```
        return feature_importances

    def pca_and_condition_number(self) -> Tuple[np.ndarray, float,float]:  1 usage
        """
        Perform PCA and calculate condition number on scaled numeric columns.

        Returns:
            Tuple[np.ndarray, float]: (explained variance ratios, condition number)
        """
        X = self.features[self.numeric_columns]

        X_scaled = self._scale_data(X)
        initialcondition_number = np.linalg.cond(X_scaled)

        pca = PCA()
        pca.fit(X_scaled)
        condition_number = np.linalg.cond(X_scaled)

        return pca.explained_variance_ratio_,initialcondition_number ,condition_number

    from typing import Dict, List, Tuple, Any

    def svd_analysis(self, numerical_cols: List[str], categorical_cols: List[str]) -> Tuple[  1 usage
        np.ndarray, pd.DataFrame, Dict]:
        """
        Perform comprehensive SVD analysis with feature-component correlations and visualizations.

        Args:
            numerical_cols: List of numerical column names to be scaled
            categorical_cols: List of categorical column names (already encoded)

        Returns:
            Tuple containing:
            - singular_values: Array of singular values
            - component_correlations: DataFrame showing feature-component correlations
            - analysis_metrics: Dictionary containing relative and cumulative importance
        """
        # Combine features
        X_num = self.features[numerical_cols]
        X_num_scaled = self._scale_data(X_num)
        X_cat = self.features[categorical_cols]
        X_combined = np.concatenate( arrays: [X_num_scaled, X_cat], axis=1)

        # Perform SVD
        U, singular_values, Vt = svd(X_combined, full_matrices=False)

        # Calculate relative and cumulative importance
        total_variance = (singular_values ** 2).sum()
        relative_importance = (singular_values ** 2) / total_variance
        cumulative_importance = np.cumsum(relative_importance)

        # Create DataFrame of feature-component correlations
```

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```python
    def svd_analysis(self, numerical_cols: List[str], categorical_cols: List[str]) -> Tuple[  1 usage

        return singular_values, component_correlations, analysis_metrics

    def vif_analysis(self, numerical_cols: List[str]) -> pd.DataFrame:  1 usage
        """
        Calculate Variance Inflation Factors (VIF) for specified numeric columns.

        Args:
            numerical_cols: List of numerical column names to analyze

        Returns:
            pd.DataFrame: DataFrame containing VIF scores for each feature

        Raises:
            ValueError: If perfect multicollinearity is detected or columns not found
        """
        # Validate columns exist in the dataset
        if not all(col in self.features.columns for col in numerical_cols):
            raise ValueError("Some specified columns not found in the dataset")

        # Get numerical features
        X = self.features[numerical_cols]
        vifs = pd.DataFrame()
        vifs["feature"] = numerical_cols

        try:
            vifs["VIF"] = [variance_inflation_factor(X.values, i)
                           for i in range(X.shape[1])]
        except np.linalg.LinAlgError:
            raise ValueError("Perfect multicollinearity detected in features")

        return vifs.sort_values( by: 'VIF', ascending=False)
```

```python
import matplotlib.pyplot as plt
import numpy as np


def create_svd_visualizations(singular_values):  1 usage
    # Calculate relative and cumulative importance
    total_variance = (singular_values ** 2).sum()
    relative_importance = (singular_values ** 2) / total_variance
    cumulative_importance = np.cumsum(relative_importance)

    # 1. Singular Values Plot
    plt.figure(figsize=(10, 6))
    plt.plot( *args: range(1, len(singular_values) + 1), singular_values, 'bo-')
```

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Regression Analysis

```
class StepwiseRegresser:  1 usage
    def __init__(self, train_data: np.ndarray, test_data: np.ndarray,
                 y_train: pd.Series, y_test: pd.Series,
                 totalKg_train: pd.Series, totalKg_test: pd.Series,
                 bodyweight_Kg_train: pd.Series, bodyweight_Kg_test: pd.Series):

        self.X_train = train_data
        self.X_test = test_data
        self.y_train_unscaled = y_train.values
        self.y_test_unscaled = y_test.values
        self.TotalKg_Train = totalKg_train.values
        self.TotalKg_Test = totalKg_test.values
        self.BodywtKg_Train = bodyweight_Kg_train.values
        self.BodywtKg_Test = bodyweight_Kg_test.values

        self.y_scaler = StandardScaler()
        self.y_train = self.y_scaler.fit_transform(self.y_train_unscaled.reshape(-1, 1)).ravel()
        self.y_test = self.y_scaler.transform(self.y_test_unscaled.reshape(-1, 1)).ravel()


    def find_best_polynomial_degree(self, max_degree: int = 3) -> int:  1 usage
        best_r2 = -np.inf
        best_degree = 0

        for degree in range(max_degree + 1):
            poly = PolynomialFeatures(degree=degree)
            X_train_poly = poly.fit_transform(self.X_train)
            X_test_poly = poly.transform(self.X_test)

            model = sm.OLS(self.y_train, X_train_poly).fit()
            y_pred = model.predict(X_test_poly)
            r2 = r2_score(self.y_test, y_pred)

            if r2 > best_r2:
                best_r2 = r2
                best_degree = degree

        self.best_degree = best_degree
        return best_degree

    def perform_backward_stepwise(self, p_threshold: float = 0.05):  1 usage

        poly = PolynomialFeatures(degree=self.best_degree)
        X_train_poly = poly.fit_transform(self.X_train)
        X_test_poly = poly.transform(self.X_test)


        # Start with all features
        included = list(range(X_train_poly.shape[1]))
```

```python
def perform_backward_stepwise(self, p_threshold: float = 0.05):  1 usage

    # Start with all features
    included = list(range(X_train_poly.shape[1]))

    while True:
        if len(included) == 0:
            break

        X_subset = X_train_poly[:, included]
        model = sm.OLS(self.y_train, X_subset).fit()


        # Find maximum p-value
        max_pval = model.pvalues.max()

        # If max p-value > threshold, remove that feature
        if max_pval > p_threshold:
            print("Removing statistically insignificant feature")
            max_pval_idx = model.pvalues.argmax()
            included.pop(max_pval_idx)
        else:
            print("All coefficients are statistically significant")
            break

    # Fit final model
    X_subset_train = X_train_poly[:, included]
    X_subset_test = X_test_poly[:, included]
    final_model = sm.OLS(self.y_train, X_subset_train).fit()

    # Get predictions
    y_pred_train = final_model.predict(X_subset_train)
    y_pred_test = final_model.predict(X_subset_test)


    y_pred_train_orig = self.y_scaler.inverse_transform(y_pred_train.reshape(-1, 1)).ravel()
    y_pred_test_orig = self.y_scaler.inverse_transform(y_pred_test.reshape(-1, 1)).ravel()

    # Calculate TotalKg predictions
    totalkg_pred_train = y_pred_train_orig * self.BodywtKg_Train
    totalkg_pred_test = y_pred_test_orig * self.BodywtKg_Test



    # Print Strength metrics
    print("\nStrength Metrics:")
    print(f"R² Train: {r2_score(self.y_train, y_pred_train):.4f}")
    print(f"R² Test: {r2_score(self.y_test, y_pred_test):.4f}")
    print(f"MSE Train: {mean_squared_error(self.y_train, y_pred_train):.4f}")
    print(f"MSE Test: {mean_squared_error(self.y_test, y_pred_test):.4f}")
    print(f"RMSE Train: {np.sqrt(mean_squared_error(self.y_train, y_pred_train)):.4f}")
    print(f"RMSE Test: {np.sqrt(mean_squared_error(self.y_test, y_pred_test)):.4f}")
    print(f"AIC: {final_model.aic:.4f}")
```

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```
class StepwiseRegresser:  1 usage
    def perform_backward_stepwise(self, p_threshold: float = 0.05):  1 usage

        # Print TotalKg metrics
        print("\nTotalKg Metrics:")
        print(f"R² Train: {r2_score(self.TotalKg_Train, totalkg_pred_train):.4f}")
        print(f"R² Test: {r2_score(self.TotalKg_Test, totalkg_pred_test):.4f}")
        print(f"MSE Train: {mean_squared_error(self.TotalKg_Train, totalkg_pred_train):.4f}")
        print(f"MSE Test: {mean_squared_error(self.TotalKg_Test, totalkg_pred_test):.4f}")
        print(f"RMSE Train: {np.sqrt(mean_squared_error(self.TotalKg_Train, totalkg_pred_train)):.4f}")
        print(f"RMSE Test: {np.sqrt(mean_squared_error(self.TotalKg_Test, totalkg_pred_test)):.4f}")


        #print with confident interval
        predictions = final_model.get_prediction(X_subset_test)
        pred_mean = predictions.predicted_mean
        ci = predictions.conf_int(alpha=0.05)

        # Create a plot
        plt.figure(figsize=(10, 6))

        # Plot actual values
        plt.scatter(self.y_test, self.y_test, color='black', label='Actual', alpha=0.5)

        # Plot predictions with confidence intervals
        plt.plot( *args: self.y_test, pred_mean, color='blue', label='Predicted')
        plt.fill_between(self.y_test,
                         ci[:, 0],
                         ci[:, 1],
                         color='blue',
                         alpha=0.1,
                         label='95% CI')

        plt.xlabel('Actual Values')
        plt.ylabel('Predicted Values')
        plt.title('Model Predictions with 95% Confidence Intervals')
        plt.legend()

        # Add diagonal line for perfect predictions
        plt.plot( *args: [min(self.y_test), max(self.y_test)],
                 [min(self.y_test), max(self.y_test)],
                 'k--', alpha=0.5)

        plt.show()

        # Print model summary
        print("\nModel Summary:")
        print(final_model.summary())

        """Plot actual vs predicted values for both train and test sets"""
        plt.figure(figsize=(15, 6))

        # Plot for Strength
        plt.subplot( *args: 1, 2, 1)
```

```python
def perform_xgb_regression(self):  1 usage
    # Create polynomial features
    poly = PolynomialFeatures(degree=2)
    X_train_poly = poly.fit_transform(self.X_train)
    X_test_poly = poly.transform(self.X_test)

    # Define XGBoost parameters
    params = {
        'n_estimators': 200,
        'max_depth': 10,
        'learning_rate': 0.1,
        'min_child_weight': 3,
        'subsample': 0.8,
        'colsample_bytree': 1.0,
        'gamma': 0.1
    }

    # Create and fit XGBoost model
    model = xgb.XGBRegressor(**params, random_state=42)
    model.fit(X_train_poly, self.y_train)

    # Get predictions
    y_pred_train = model.predict(X_train_poly)
    y_pred_test = model.predict(X_test_poly)

    # Transform predictions back to original scale
    y_pred_train_orig = self.y_scaler.inverse_transform(y_pred_train.reshape(-1, 1)).ravel()
    y_pred_test_orig = self.y_scaler.inverse_transform(y_pred_test.reshape(-1, 1)).ravel()

    # Calculate TotalKg predictions
    totalkg_pred_train = y_pred_train_orig * self.BodywtKg_Train
    totalkg_pred_test = y_pred_test_orig * self.BodywtKg_Test

    # Print Strength metrics
    print("\nStrength Metrics:")
    print(f"R² Train: {r2_score(self.y_train, y_pred_train):.4f}")
    print(f"R² Test: {r2_score(self.y_test, y_pred_test):.4f}")
    print(f"MSE Train: {mean_squared_error(self.y_train, y_pred_train):.4f}")
    print(f"MSE Test: {mean_squared_error(self.y_test, y_pred_test):.4f}")
    print(f"RMSE Train: {np.sqrt(mean_squared_error(self.y_train, y_pred_train)):.4f}")
    print(f"RMSE Test: {np.sqrt(mean_squared_error(self.y_test, y_pred_test)):.4f}")

    # Print TotalKg metrics
    print("\nTotalKg Metrics:")
    print(f"R² Train: {r2_score(self.TotalKg_Train, totalkg_pred_train):.4f}")
    print(f"R² Test: {r2_score(self.TotalKg_Test, totalkg_pred_test):.4f}")
    print(f"MSE Train: {mean_squared_error(self.TotalKg_Train, totalkg_pred_train):.4f}")
    print(f"MSE Test: {mean_squared_error(self.TotalKg_Test, totalkg_pred_test):.4f}")
    print(f"RMSE Train: {np.sqrt(mean_squared_error(self.TotalKg_Train, totalkg_pred_train)):.4f}")
    print(f"RMSE Test: {np.sqrt(mean_squared_error(self.TotalKg_Test, totalkg_pred_test)):.4f}")
```

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Classification

```
class MultiClassifierOptimizer:  1 usage
    def __init__(self, X_train, X_test, y_train, y_test):
        self.X_train = X_train.copy()
        self.X_test = X_test.copy()
        self.y_train = y_train
        self.y_test = y_test
        self.feature_names = self.X_train.columns
        self.results = {}
        self.models = {}

    def preprocess_data(self):  1 usage
        for column in self.X_train.select_dtypes(['object']).columns:
            le = LabelEncoder()
            self.X_train[column] = le.fit_transform(self.X_train[column])
            self.X_test[column] = le.transform(self.X_test[column])



        scaler = StandardScaler()
        self.X_train = scaler.fit_transform(self.X_train)
        self.X_test = scaler.transform(self.X_test)

    def apply_smote(self):  1 usage
        smote = SMOTE(random_state=42)
        self.X_train, self.y_train = smote.fit_resample(self.X_train, self.y_train)

    def visualize_classification_results(self, y_true, y_pred, model_name):  1 usage
        plt.figure(figsize=(20, 6))

        plt.subplot(131)
        cm = confusion_matrix(y_true, y_pred)
        sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
                    xticklabels=['Not Tested', 'Tested'],
                    yticklabels=['Not Tested', 'Tested'])
        plt.title(f'Confusion Matrix - {model_name}')
        plt.ylabel('True Label')
        plt.xlabel('Predicted Label')

        plt.subplot(132)
        df_results = pd.DataFrame({
            'True': y_true,
            'Predicted': y_pred
        })
        correct = (y_true == y_pred)

        classification_results = pd.DataFrame({
            'Category': ['Correct Not Tested', 'Correct Tested',
                         'Misclassified Not Tested', 'Misclassified Tested'],
            'Count': [
                sum((correct) & (y_true == 0)),
                sum((correct) & (y_true == 1)),
                sum((~correct) & (y_true == 0)),
                sum((~correct) & (y_true == 1))
            ]
```

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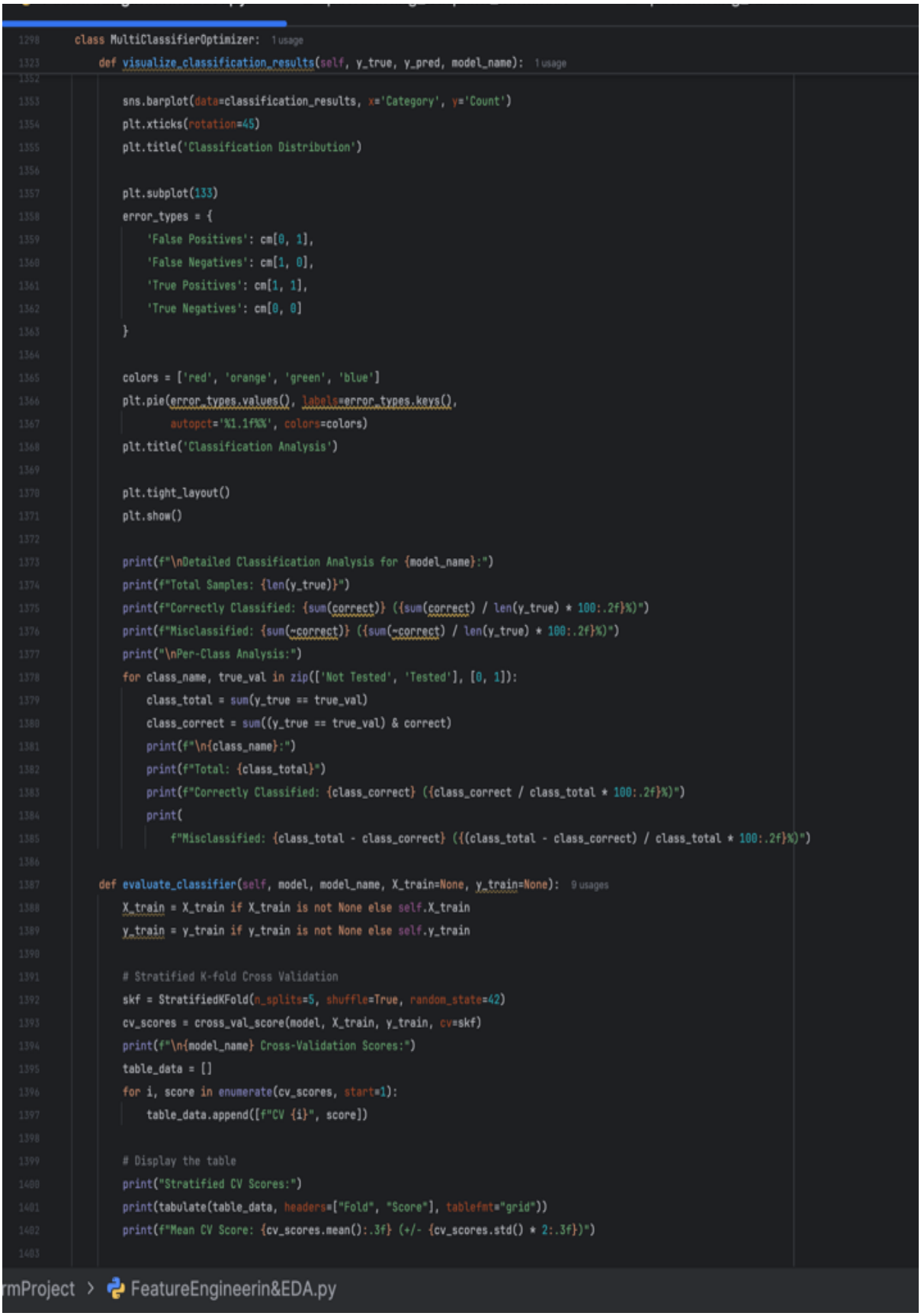

```
class MultiClassifierOptimizer:  1 usage
    def visualize_classification_results(self, y_true, y_pred, model_name):  1 usage

        sns.barplot(data=classification_results, x='Category', y='Count')
        plt.xticks(rotation=45)
        plt.title('Classification Distribution')

        plt.subplot(133)
        error_types = {
            'False Positives': cm[0, 1],
            'False Negatives': cm[1, 0],
            'True Positives': cm[1, 1],
            'True Negatives': cm[0, 0]
        }

        colors = ['red', 'orange', 'green', 'blue']
        plt.pie(error_types.values(), labels=error_types.keys(),
                autopct='%1.1f%%', colors=colors)
        plt.title('Classification Analysis')

        plt.tight_layout()
        plt.show()

        print(f"\nDetailed Classification Analysis for {model_name}:")
        print(f"Total Samples: {len(y_true)}")
        print(f"Correctly Classified: {sum(correct)} ({sum(correct) / len(y_true) * 100:.2f}%)")
        print(f"Misclassified: {sum(~correct)} ({sum(~correct) / len(y_true) * 100:.2f}%)")
        print("\nPer-Class Analysis:")
        for class_name, true_val in zip(['Not Tested', 'Tested'], [0, 1]):
            class_total = sum(y_true == true_val)
            class_correct = sum((y_true == true_val) & correct)
            print(f"\n{class_name}:")
            print(f"Total: {class_total}")
            print(f"Correctly Classified: {class_correct} ({class_correct / class_total * 100:.2f}%)")
            print(
                f"Misclassified: {class_total - class_correct} ({(class_total - class_correct) / class_total * 100:.2f}%)")

    def evaluate_classifier(self, model, model_name, X_train=None, y_train=None):  9 usages
        X_train = X_train if X_train is not None else self.X_train
        y_train = y_train if y_train is not None else self.y_train

        # Stratified K-fold Cross Validation
        skf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)
        cv_scores = cross_val_score(model, X_train, y_train, cv=skf)
        print(f"\n{model_name} Cross-Validation Scores:")
        table_data = []
        for i, score in enumerate(cv_scores, start=1):
            table_data.append([f"CV {i}", score])

        # Display the table
        print("Stratified CV Scores:")
        print(tabulate(table_data, headers=["Fold", "Score"], tablefmt="grid"))
        print(f"Mean CV Score: {cv_scores.mean():.3f} (+/- {cv_scores.std() * 2:.3f})")

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```

```python
class MultiClassifierOptimizer:  1 usage
    def evaluate_classifier(self, model, model_name, X_train=None, y_train=None):  9 usages
        # Get predictions
        y_pred = model.predict(self.X_test)

        # Visualize classification results
        self.visualize_classification_results(self.y_test, y_pred, model_name)

        # Calculate metrics
        cm = confusion_matrix(self.y_test, y_pred)
        precision = precision_score(self.y_test, y_pred)
        recall = recall_score(self.y_test, y_pred)
        specificity = cm[0, 0] / (cm[0, 0] + cm[0, 1])
        f1 = f1_score(self.y_test, y_pred)

        print(f"\nClassification Metrics for {model_name}:")
        print(f"Precision: {precision:.3f}")
        print(f"Recall (Sensitivity): {recall:.3f}")
        print(f"Specificity: {specificity:.3f}")
        print(f"F1-Score: {f1:.3f}")

        # ROC Curve and AUC
        try:
            y_prob = model.predict_proba(self.X_test)[:, 1]
            fpr, tpr, _ = roc_curve(self.y_test, y_prob)
            auc_score = auc(fpr, tpr)

            plt.figure(figsize=(8, 6))
            plt.plot( *args: fpr, tpr, label=f'ROC curve (AUC = {auc_score:.2f})')
            plt.plot( *args: [0, 1], [0, 1], 'k--')
            plt.xlim([0.0, 1.0])
            plt.ylim([0.0, 1.05])
            plt.xlabel('False Positive Rate')
            plt.ylabel('True Positive Rate')
            plt.title(f'ROC Curve - {model_name}')
            plt.legend(loc="lower right")
            plt.show()

            roc_data = {'fpr': fpr, 'tpr': tpr}
        except:
            print("ROC/AUC not available for this model")
            auc_score = None
            roc_data = None

        # Per-class metrics visualization
        plt.figure(figsize=(10, 6))
        class_names = ['Not Tested', 'Tested']
        metrics_data = {
            'Class': class_names,
            'Precision': [precision_score(self.y_test, y_pred, pos_label=i) for i in [0, 1]],
            'Recall': [recall_score(self.y_test, y_pred, pos_label=i) for i in [0, 1]],
            'F1-score': [f1_score(self.y_test, y_pred, pos_label=i) for i in [0, 1]]
        }
        metrics_df = pd.DataFrame(metrics_data)
```

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```
class MultiClassifierOptimizer:  1 usage
    def evaluate_classifier(self, model, model_name, X_train=None, y_train=None):  9 usages
        metrics_melted = pd.melt(metrics_df, id_vars=['Class'], var_name='Metric', value_name='Score')
        sns.barplot(data=metrics_melted, x='Class', y='Score', hue='Metric')
        plt.title(f'Classification Metrics by Class - {model_name}')
        plt.show()

        return {
            'confusion_matrix': cm,
            'precision': precision,
            'recall': recall,
            'specificity': specificity,
            'f1_score': f1,
            'cv_scores': cv_scores,
            'auc_score': auc_score,
            'roc_curve': roc_data  # Added ROC curve data
        }
    def optimize_decision_tree(self):  1 usage
        # Pre-pruning phase
        print("\n=== Pre-pruning Phase ===")
        '''
        param_grid = {
            'criterion': ['gini', 'entropy'],
            'splitter': ['best', 'random'],
            'max_depth': [3, 5, 7, 10],
            'min_samples_split': [2, 5, 10],
            'max_features': ['sqrt', 'log2', None],
            'min_samples_leaf': [1, 2, 4],
            'min_impurity_decrease': [0.0, 0.01]
        }'''
        # best parameters obtained :-
        # {'criterion': 'gini', 'max_depth': 10, 'max_features': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 2, 'min_samples_split': 2, 'sp
        # since I have already obtained best parameters have from running the param above provied those values in grid to save time, for cross checking
        #line and use grid  with hyperparamers in the above param grid which is commented out  above
        param_grid = {
            'criterion': ['gini'],
            'splitter': ['best'],
            'max_depth': [10],
            'min_samples_split': [2],
            'max_features':  [None],
            'min_samples_leaf':  [2],
            'min_impurity_decrease': [0.0],
        }
       #best parameters obtained :-
        #{'criterion': 'gini', 'max_depth': 10, 'max_features': None, 'min_impurity_decrease': 0.0, 'min_samples_leaf': 2, 'min_samples_split': 2, 'spl


        dt = DecisionTreeClassifier(random_state=42)
        grid_search = GridSearchCV(dt, param_grid, cv=3, n_jobs=-1, verbose=2)
        grid_search.fit(self.X_train, self.y_train)

        # Evaluate pre-pruned model
        pre_pruned_dt = DecisionTreeClassifier(random_state=42, **grid_search.best_params_)
        pre_pruned_dt.fit(self.X_train, self.y_train)
        print("\nPre-pruning Best Parameters:")
```

Clustering

```
    def __init__(self, data):
        """Initialize with powerlifting dataframe"""
        self.data = data
        self.prepare_features()

    def prepare_features(self):  1 usage
        """Prepare strength ratio features"""
        self.data['SquatStren'] = self.data['Best3SquatKg'] / self.data['BodyweightKg']
        self.data['BenchStren'] = self.data['Best3BenchKg'] / self.data['BodyweightKg']
        self.data['DeadtStren'] = self.data['Best3DeadliftKg'] / self.data['BodyweightKg']

    def filter_data(self, sex='M', equipment='Raw', sample_size=None):  3 usages
        """Filter and sample data"""
        filtered = self.data[self.data['Sex'] == sex]
        if equipment:
            filtered = filtered[filtered['Equipment'] == equipment]
        if sample_size:
            filtered = filtered.sample(n=min(sample_size, len(filtered)), random_state=42)
        return filtered

    #have reduced sample size to run fast
    def kmeans_analysis(self, sex='M', equipment=None, n_samples=10000, verbose=False):  1 usage
        """Perform K-means clustering analysis"""
        filtered_data = self.filter_data(sex, equipment, n_samples)
        features = ['SquatStren', 'BenchStren', 'DeadtStren']
        X = filtered_data[features]

        # Scale features
        scaler = StandardScaler()
        X_scaled = scaler.fit_transform(X)

        # Calculate metrics for different k
        max_clusters = 10
        range_n_clusters = range(1, max_clusters + 1)
        wss_scores = []
        silhouette_scores = []

        for n_clusters in range_n_clusters:
            kmeans = KMeans(n_clusters=n_clusters, random_state=42)
            kmeans.fit(X_scaled)
            wss_scores.append(kmeans.inertia_)
            if n_clusters > 1:
                silhouette_scores.append(silhouette_score(X_scaled, kmeans.labels_))

        # Plot results
        self._plot_clustering_metrics(range_n_clusters, wss_scores, silhouette_scores)

        # Fit final model with k=8 (as per your analysis)
        final_kmeans = KMeans(n_clusters=8, random_state=42)
        clusters = final_kmeans.fit_predict(X_scaled)

        if verbose:
```

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```
    def dbscan_analysis(self, sex='M', equipment='Raw', eps=0.3, min_samples=10, verbose=False):  1 usage
        """Perform DBSCAN clustering analysis"""
        filtered_data = self.filter_data(sex, equipment)
        features = ['SquatStren', 'BenchStren', 'DeadtStren']
        X = filtered_data[features]

        scaler = StandardScaler()
        X_scaled = scaler.fit_transform(X)

        dbscan = DBSCAN(eps=eps, min_samples=min_samples, n_jobs=-1)
        clusters = dbscan.fit_predict(X_scaled)

        self._plot_dbscan_results(X_scaled, clusters)

        if verbose:
            self._print_cluster_stats(filtered_data, clusters, features)

        return dbscan, clusters

    def apriori_analysis(self, sex='M', equipment='Raw', n_samples=100000,  1 usage
                         min_support=0.03, min_confidence=0.5):
        """Perform Apriori analysis"""
        filtered_data = self.filter_data(sex, equipment, n_samples)
        transactions = self._create_transactions(filtered_data)

        te = TransactionEncoder()
        te_ary = te.fit(transactions).transform(transactions)
        df = pd.DataFrame(te_ary, columns=te.columns_)

        frequent_itemsets = apriori(df, min_support=min_support, use_colnames=True)
        rules = association_rules(
            frequent_itemsets,
            metric="confidence",
            min_threshold=min_confidence,
            num_itemsets=len(frequent_itemsets)
        )

        self._print_rules_summary(rules)
        return rules

    def _create_transactions(self, data):  1 usage
        """Create transactions for Apriori analysis"""
        transactions = []
        for _, row in data.iterrows():
            transaction = set()

            # Squat Categories
            if row['SquatStren'] <= 1.5:
                transaction.add('Squat_Novice')
            elif row['SquatStren'] <= 2.0:
                transaction.add('Squat_Intermediate')
```

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References

Powerlifting dataset: https://www.kaggle.com/datasets/open-powerlifting/powerlifting-database/data

NumPy: https://numpy.org/doc/

Pandas: https://pandas.pydata.org/docs/

Matplotlib: https://matplotlib.org/stable/index.html

Seaborn: https://seaborn.pydata.org/

Scikit-learn: https://scikit-learn.org/stable/