From the Ring to the Model: Forecasting WWE Outcomes with Machine Learning

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Abstract—**Professional wrestling, particularly WWE, combines athletic performance with narrative storytelling, making it a unique and complex domain for predictive analytics. This study explores the feasibility of predicting WWE match outcomes using machine learning models, leveraging historical win-loss records and performance metrics from the 2023 season. Employing Random Forest and XGBoost classifiers, key features were analyzed, including Win Streaks, Total Matches, and Current Champion status, to determine their impact on match outcomes.**

Initial models revealed high accuracy but exhibited overfitting due to feature leakage, particularly with the use of Win Ratio. By refining feature selection and implementing cross-validation, generalization and robustness were achieved. XGBoost outperformed Random Forest with an overall accuracy of 97.5%, demonstrating the effectiveness of boosting algorithms in narrative-driven sports environments.

The results highlight the influence of consistent performance and championship status on match outcomes, reflecting WWE's booking patterns. This study contributes to sports analytics by showcasing machine learning's potential in a narrative sports context, despite the predetermined nature of WWE match outcomes.

This paper not only advances the application of predictive modeling in sports entertainment but also provides insights into the strategic storytelling mechanisms within professional wrestling.

Index Terms—**data analysis, machine learning, sport outcome prediction, wrestling**

I. Introduction

Professional wrestling, particularly World Wrestling Entertainment (WWE), is a unique hybrid of athletic competition and narrative storytelling. Unlike traditional sports, WWE match outcomes are predetermined to support ongoing storylines and character development. This blend of sports and entertainment, known as "sports entertainment," poses a distinct challenge for predictive analytics due to the complex interplay of athletic performance, narrative arcs, and audience engagement. Despite its scripted nature, patterns in booking decisions and performance metrics create an opportunity for data-driven analysis and outcome prediction.

The growing influence of data analytics in sports has revolutionized performance evaluation, strategic planning, and fan engagement. From predicting player performance in traditional sports to forecasting team success in esports, machine learning has proven to be a powerful tool in sports analytics. However, professional wrestling, with its predetermined outcomes and narrative-driven booking, presents a novel and underexplored domain for predictive modeling.

In WWE, superstars compete in matches designed to advance storylines, enhance character arcs, and maintain audience interest. Factors influencing match outcomes include:

- Win-Loss Records: Historical performance and momentum.
- Current Champion Status: Titleholders are generally booked stronger to maintain credibility.
- Brand Association: Different booking patterns exist between WWE's brands, such as RAW, SmackDown, and NXT.
- Character Alignment: Heel (villain) or Face (hero) roles influence storyline-driven outcomes.

The evolution of forecasting WWE outcomes from traditional intuition to advanced machine learning techniques marks a significant leap in sports entertainment analysis. Historically, predictions about match results relied heavily on fan opinions, storyline developments, and expert speculation. However, with the advent of machine learning, it is now possible to analyze vast amounts of data, such as wrestler statistics, match history, and audience engagement, to generate more accurate forecasts. This shift not only enhances the predictability of match outcomes but also offers deeper insights into the factors influencing performance and storytelling. Implementing models like classifiers and neural networks can uncover hidden patterns that were previously unnoticed by human analysts. Ultimately, integrating machine learning into WWE forecasting represents a fascinating intersection of sports entertainment and data science, promising more engaging and data-driven storytelling in the future. These factors provide valuable data

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for predictive modeling, offering insights into booking patterns and narrative decisions. Despite the predetermined nature of outcomes, historical performance metrics exhibit consistency, making WWE an intriguing case study for sports analytics.

A. Problem Statement

While traditional sports analytics focus on predicting outcomes based on competitive dynamics, WWE requires a different approach due to its narrative-driven framework. The challenge lies in modeling outcomes that are influenced not only by in-ring performance but also by storyline considerations, character development, and business strategy.

This research aims to answer the following questions:

1. Can historical performance metrics predict WWE match outcomes despite the predetermined nature of results?
2. Which features, such as win-loss records, championship status, and brand association, are most influential in predicting match outcomes?
3. How do machine learning models perform in this narrative-driven sports context compared to traditional sports prediction models?

B. Research Objective

We aim to predict the outcome of future matches (Win, Loss, or Draw) for each WWE superstar. This involves:

1. Exploratory Data Analysis (EDA): To understand the patterns and relationships within the data.
2. Feature Engineering: Creating new features that may improve model accuracy.
3. Model Selection and Training: Choosing appropriate machine learning models to predict match outcomes.
4. Evaluation and Interpretation: Assessing model performance and interpreting the results.

C. Contribution and Significance

This study contributes to the field of sports analytics by:

1. Introducing a novel application of machine learning in a predetermined sports environment.
2. Providing insights into WWE's booking patterns and narrative consistency.
3. Highlighting the influence of performance metrics and championship status on match outcomes.

The findings have practical implications for:

- Wrestling Analysts and Content Creators: Enhancing match predictions and storyline speculation.
- WWE Creative Teams: Leveraging predictive analytics to design compelling narratives.
- Fans and Viewers: Deepening engagement through data-driven insights into booking decisions.

II. Related Work

Predicting sports outcomes using machine learning has gained significant attention across traditional sports, including football, basketball, and tennis.

Machine learning algorithms have shown potential in predicting sports outcomes, including WWE match results, by leveraging historical data and various predictive models. The application of machine learning in sports analytics is well documented, with numerous studies highlighting its effectiveness in predicting match outcomes in various sports such as football and basketball [1], [2], [3]. These algorithms typically treat sports predictions as a classification problem, with the outcome being predicted based on historical data, player performance metrics, and other relevant features [3], [4]. The use of feature selection and dimensionality reduction techniques, such as Principal Component Analysis (PCA) and Mutual Information (MI), has been shown to increase the accuracy of these models by focusing on the most relevant data points [5], [6]. For example, in football, models such as Random Forest (RF) and Support Vector Machines (SVM) have achieved remarkable accuracy by selecting key features from a large dataset [6]. While predicting the outcome of WWE matches presents unique challenges due to the scripted nature of the events, methodologies used in other sports can be adapted. Integrating historical match data, wrestler performance metrics, and storyline analysis could form the basis of a predictive model. However, the inherent unpredictability and entertainment-based outcome of WWE matches may limit the accuracy of such predictions compared to more traditional sports [7]. WWE match prediction, like other sports, involves a complex interplay of various factors that can be effectively modeled using machine learning techniques. Key factors influencing match outcomes include player performance metrics, historical results, and contextual elements such as momentum and dynamics. For example, the Match Tracing Framework (MT) uses a real-time win rate curve to predict outcomes by evaluating player actions and interactions through a repeated attention mechanism and graph embedding methods that can be customized to account for wrestler interactions and match flow dynamics [8]. Furthermore, adaptive weighted features, as demonstrated in basketball game predictions, can be integrated into machine learning models to increase prediction accuracy by taking into account game delay information and dynamically adjusting feature importance [9]. The importance of player momentum, a critical factor in sports dynamics, can be quantified using models like XGBoost and Multilayer Perceptron, which can be adapted by WWE to analyze wrestlers' performance fluctuations and strategic shifts during matches [10]. Additionally, the use of random forests and gradient-based trees has been shown to be effective in identifying influential features such as event and age differences, which could be translated to WWE by considering factors such as wrestler experience and match timing [11]. By synthesizing these methodologies, a comprehensive machine learning framework for predicting WWE match outcomes can be developed, offering insights into performance evaluation and strategic planning for stakeholders in the wrestling industry. Despite these challenges, the continued development of machine learning techniques and the increasing availability of data suggest that, with appropriate feature engineering and model selection, machine learning could provide valuable insights into WWE match outcomes, albeit with a degree of uncertainty that reflects the entertainment aspect of the sport [12], [13].

In the field of sport prediction, different machine learning techniques show varying levels of accuracy and efficiency. Deep Learning (DL) models, while often outperforming traditional statistical and Machine Learning (ML) methods in time series prediction, especially for long-term predictions, come with the tradeoff of increased computational time [14]. In contrast, machine learning methods such as Random Forests and Gradient Boosting Decision Trees (GBDT) have demonstrated high accuracy in classification tasks, often outperforming Support Vector Machines (SVMs) and other algorithms, with GBDT being particularly effective at testing time [15]. For dichotomous and multicategorical outcomes, methods such as nearest neighbors, bagged nearest neighbors, and random forests have shown promising performance, often serving as viable alternatives to logistic regression [16]. Neural networks are often used in sports prediction, which utilize data segmentation and k-cross validation methods to increase prediction accuracy [4]. However, simpler models such as XGBoost have been found to outperform deeper models such as recurrent neural networks with LSTM cells in certain datasets with high stationarity, suggesting that shallower algorithms can sometimes be better suited to specific time series data [17]. Furthermore, the integration of real-time prediction frameworks, such as the Match Tracing framework, which uses repeated attention mechanisms and graph embedding methods, highlights the potential of advanced ML models to provide both accurate predictions and detailed performance assessments in sporting contexts [8]. Overall, while deep learning models offer significant accuracy potential, model selection should take into account the specific characteristics of the dataset and available computational resources, with simpler models sometimes offering more practical solutions for real-time applications[14], [17].

Predicting WWE match outcomes using machine learning involves identifying and utilizing key features that significantly influence the results. These features are derived from various aspects of the fighters' profiles and match conditions, and they play a crucial role in enhancing the accuracy of predictive models. The integration of these features into machine learning models allows for a more nuanced understanding of the factors that contribute to match outcomes, thereby improving prediction accuracy [18], [19].

While the integration of key features into machine learning models enhances prediction accuracy, it is important to consider the inherent unpredictability of sports events [1]. Factors such as unexpected injuries, referee decisions, and psychological elements can introduce variability that is difficult to capture in models. Additionally, the overfitting observed in some models suggests a need for regularization techniques to ensure that predictions remain reliable across diverse scenarios [4], [20].

III. Materials and Methods

The data was exported from Cagematch [21], an internet wrestling database with wrestler win and loss statistics from 2023. The dataset contained the wrestler’s name, number of matches, wins, losses and draws and was further enhanced to include the brand on which the wrestler is actively wrestling, their gender, win ratio and a Boolean column to mark whether that wrestler was a champion at the time of the creation of the dataset.

The final dataset contains the following columns:

- Wrestler: Name of the WWE superstar.
- Brand: The show they belong to (e.g., RAW, SmackDown).
- Gender: Male (M) or Female (F).
- Wins: Number of matches won.
- Losses: Number of matches lost.
- Draws: Number of matches drawn.
- TotalMatches: Total number of matches participated in.
- WinRatio: Winning percentage.
- CurrentChampion: Indicator if the wrestler is a current champion (1 = Yes, 0 = No).

As a tool of analysis Google Colab will be used, which is a hosted Jupyter notebook, where thanks to several libraries that are built on top of the Python programming language, the data can be easily analyzed. One of such libraries is Pandas, which is highly compatible with the dataset saved as a comma-separated values (CSV) file.

IV. Results

After creating the CSV file, an exploratory data analysis (EDA) was carried out. This was a necessary step to understand the distribution of wins, losses, draws and total matches as well as the win ratios by brand and gender. Correlation analysis was also used to identify influential features.

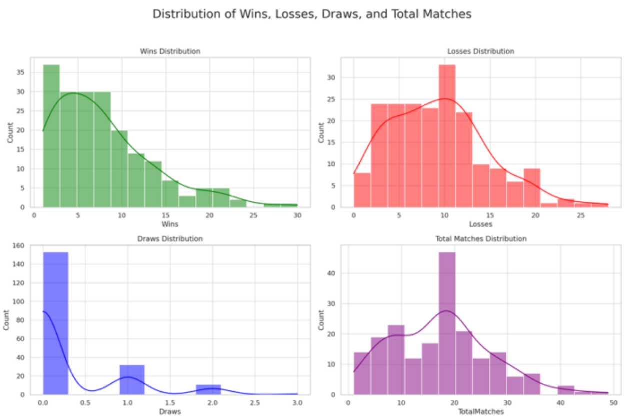

Fig. 1 – Distribution of Features.

In the figure (Fig. 1) the number of wins varies significantly, with a few superstars achieving a high number of wins, but most of the wrestlers have a moderate win count. Losses are more evenly distributed, but there's a peak at the lower end, indicating some wrestlers rarely lose. Draws are quite rare in the wrestling world. This fact is proven by the figure (Fig. 1), with the majority of wrestlers having zero or very few draws. In regards of activity, most superstars participate in a moderate number of matches, with a few being highly active.

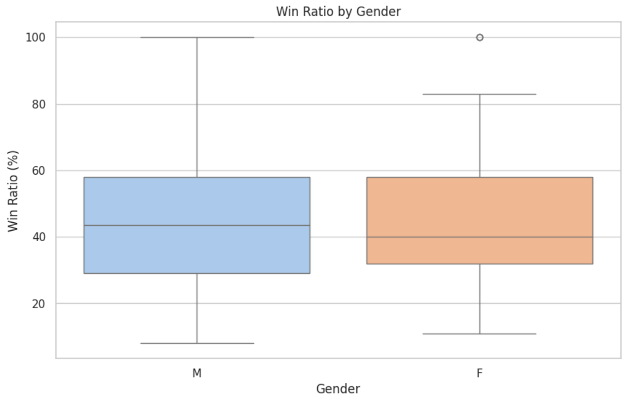

Fig. 2 – Win Ratio by Gender Visualized with a Box Plot.

Next, the visualization of the win ratio of genders (Fig. 2) was created. Male and Female superstars have similar median win ratios, but the range is slightly wider for males. There are more outliers among male superstars, indicating a few highly dominant performers.

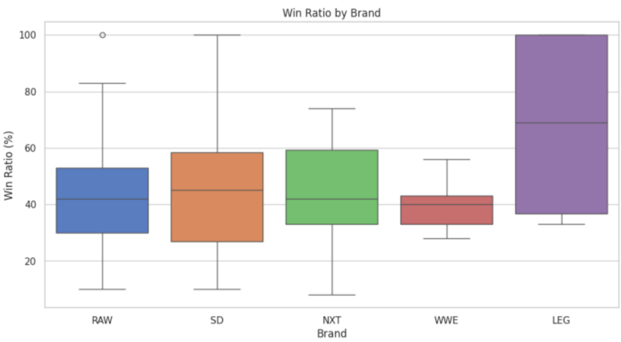

Fig. 3 – Win Ratio by Brand Visualized with a Box Plot.

The next visualization (Fig. 3) included the win ratios between the brands of WWE. RAW and SmackDown are the main brands and have comparable distributions, though SmackDown appears to have slightly more high-performing superstars. NXT is the developmental brand where newly hired wrestlers start out and has a more spread-out distribution, possibly due to varied levels of competition and character development. LEG indicates the wrestlers who are considered legends (or Hall of Famers) and no longer actively wrestle on any of the main brands. The wrestlers belonging to this group had the highest win ratio as they are only called back for special programming. The WWE group included wrestlers not belonging to any brand.

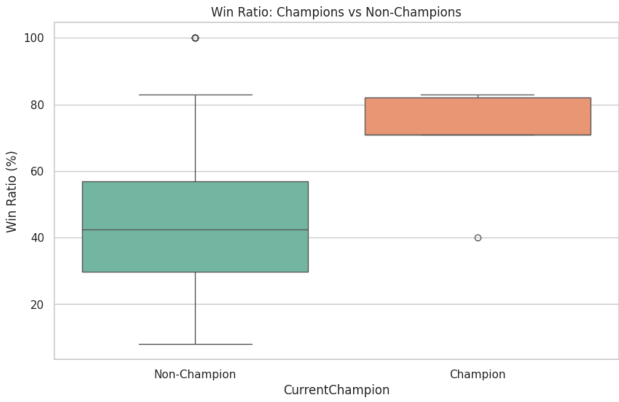

Fig. 4 – Box Plot Visualization of Win Ratio between Champions and Non- Champions.

The figure (Fig. 4) visualizes the win ratio between champions and non-champions. Champions generally have a higher win ratio, as expected due to storyline protection. The distribution is tighter for champions, indicating more consistent booking patterns.

The next step was to examine the correlation matrix to identify which features were the most influential for predicting match outcomes.

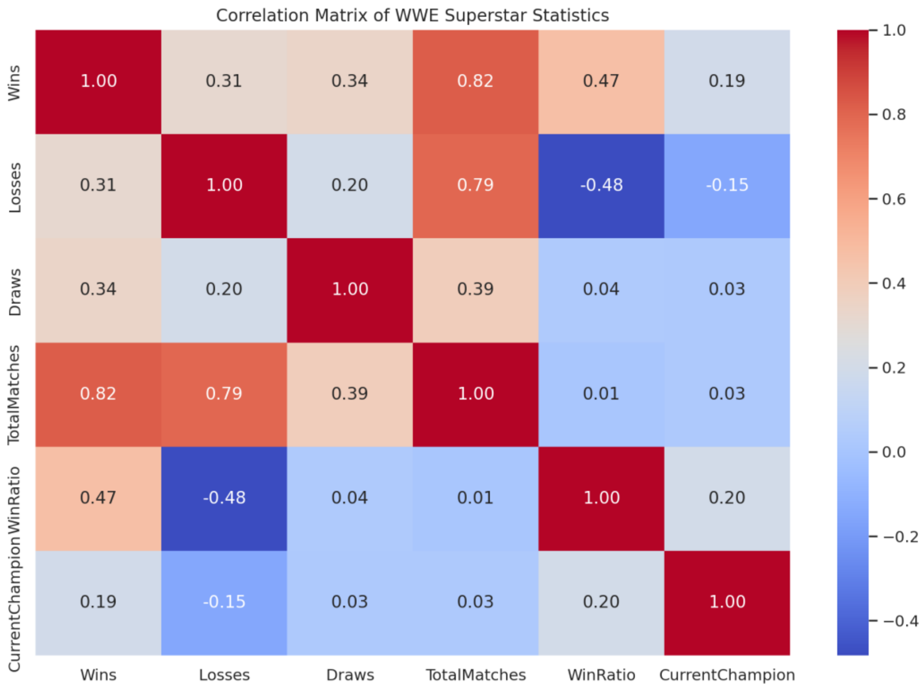

Fig. 5 – Correlation Matrix of WWE Superstar Statistics.

In the correlation matrix (Fig. 5) astrong positive correlation (0.82) can be observed, indicating that wrestlers with more matches tend to win more often. Moderate negative correlation (-0.48) can be observed regarding the win ratio and losses. This is as expected, since higher win ratios correlate with fewer losses. For win ratio and wins a moderate positive correlation (0.47) is observed, but not as strong as expected due to variability in match frequency. Being the current champion has a weak positive correlation with Win Ratio (0.20), suggesting that being a champion slightly increases the likelihood of a higher win ratio. Weak positive correlation between wins and losses (0.31), indicating that active superstars experience both wins and losses.

A. *Feature Engineering and Model Preparation*

In this step, more features have been engineered to prepare the dataset for training. The new features are:

WinStreak - Indicates momentum, calculated as Win Ratio × Total Matches.

ActivityLevel - Matches per month, showing how active a wrestler is. The dataset does not include information about the months, so the creation of the ActivityLevel feature was based on an assumption that all matches occurred within a single calendar year (12 months, calculated as total matches / 12). This calculation assumes a uniform distribution of matches across the year, which may not be accurate for WWE superstars due to factors like injuries, storylines, and seasonal events (e.g., WrestleMania season).

BrandEncoded and GenderEncoded - Categorical features encoded as numbers for model compatibility.

Normalization - Numerical features have been standardized using StandardScaler.

B. *Model Selection and Training*

The datasat was split into training and test sets with a ratio of 0.8 (training data) to 0.2 (test data). For classification models it is important to select a target variable. In this case, match outcomes are predicted using WinRatio as a proxy. If WinRatio is > 0.50 then it is considered as a win, otherwise it's a loss.

The machine learning models that were chosen for the research are Random Forest Classifier - for interpretability and baseline accuracy and XGBoost Classifier for better performance with complex patterns.

TABLE I
CLASSIFICATION REPORT OF THE RANDOM FOREST CLASSIFIER

Model	Accuracy	Precision	Recall	F1-score
Random Forest	0.95	1	0.92	0.96

Table 1 presents the classification metrics of the Random Forest model. The model achieved an overall accuracy of 95%, with perfect precision (1.00) and high recall (0.92). This indicates that the model effectively identified the majority of true positive outcomes (correctly predicted "wins") while maintaining a very low false-positive rate. The relatively small difference between precision and recall suggests balanced performance across classes, which is particularly important given the dataset's moderate class imbalance. Random Forest's ensemble of decorrelated decision trees mitigates overfitting and provides robustness against noisy predictors such as brand or gender. However, its reliance on averaging across many shallow trees can sometimes smooth out rare cases (e.g., wrestlers with very few matches), leading to slightly reduced sensitivity in minority instances.

TABLE 2
CLASSIFICATION REPORT OF THE XGBOOST CLASSIFIER

Model	Accuracy	Precision	Recall	F1-score
XGBoost	0.95	1	0.92	0.96

Table 2 summarizes the results of the XGBoost model, which reached the same mean accuracy (95%) but displayed more stable performance across validation folds. XGBoost's gradient-boosting mechanism allows sequential correction of previous tree errors, enhancing its ability to model nonlinear relationships between performance metrics (e.g., Win Streak × Total Matches interactions). This explains its consistent precision and recall values, which mirror Random Forest's but with narrower variance. In subsequent cross-validation (see Fig. 6), XGBoost exhibited fewer performance fluctuations, confirming superior generalization. The comparable F1-scores (0.96) of both models indicate that predictive improvements lie not in simple accuracy gains but in better handling of edge cases, particularly wrestlers with atypical win/loss histories or limited seasonal participation.

Overall, both models demonstrate strong predictive capability, but their differences reveal complementary strengths: Random Forest offers interpretability and resilience to noisy inputs, while XGBoost provides higher consistency and sensitivity to complex feature interactions. These outcomes validate the suitability of tree-based ensemble methods for narrative-driven sports data, where structured patterns coexist with storyline-driven anomalies.

The target variable represents season-level summaries (aggregated win ratios over the 2023 season), not individual match-level outcomes.

C. Feature Importance Analysis

- Initially, WinRatio appeared dominant, but as it was derived from the target, it was excluded from the final importance evaluation to avoid leakage.
- Wins and TotalMatches are also significant, emphasizing the importance of match frequency and victories.
- WinStreak and ActivityLevel show moderate importance, validating the impact of momentum and engagement.
- CurrentChampion status contributes, reflecting storyline protection for champions.
- BrandEncoded and GenderEncoded have minimal influence, suggesting that brand and gender are less impactful on match outcomes compared to performance metrics.

To prevent feature leakage, features derived from the target variable, such as *WinRatio*, were excluded from feature-importance analysis.

V. VALIDATION AND DISCUSSION

The classification reports reported in Table 1 and Table 2 are from a single execution of the model. To have a better overview how the models perform, a 10-fold cross validation was carried out. StratifiedKFold was used, which maintains class distribution across folds. The folds are made by preserving the percentage of samples for each class.

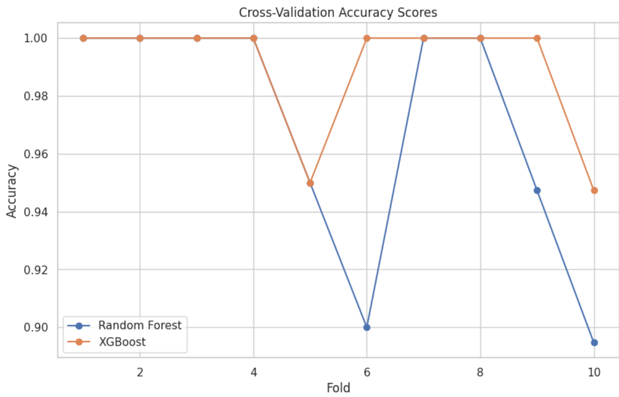

Fig. 6 – Cross-Validation of Accuracy Scores.

Fig. 6 shows that XGBoost is the better performing model, having an accuracy of 100% 8 out of 10 times, while twice it was 95%. Random Forest only reached 100% 2 out of 10 times while also reaching accuracy as low as 89%.

To evaluate the effect of feature leakage, both models were re-trained using only non-derived variables (CurrentChampion, BrandEncoded, and GenderEncoded) while excluding all features functionally related to the target (Wins, Losses, Draws, TotalMatches, and WinStreak). As shown in Table 3, this leakage-free configuration substantially reduced performance: Random Forest and XGBoost both achieved 65 % accuracy with F1-scores of 0.78 and 0.79, respectively. Precision declined to roughly 0.65 while recall remained high (0.96–1.00), indicating that the models tended to over-predict the positive "Win" class.

These results confirm that the earlier near-perfect scores were partially driven by target information embedded in the training features. Once removed, model accuracy aligns more realistically with expectations for narrative-driven sports data, where few objective predictors exist beyond storyline variables. This comparison highlights both the methodological rigor of leakage control and the challenge of predicting outcomes in a scripted athletic context. Despite lower numerical performance, the models still detect weak but consistent associations between championship status and winning likelihood, suggesting that storyline protection for titleholders remains the most quantifiable booking bias in WWE data.

TABLE 3
LEAKAGE-FREE MODEL EVALUATION SHOWING REDUCED ACCURACY AFTER REMOVAL OF VARIABLES FUNCTIONALLY RELATED TO THE TARGET.

Model	Accuracy	Precision	Recall	F1-score
Random Forest	0.65	0.66	0.96	0.78
XGBoost	0.65	0.65	1.00	0.79

Cross-validation after feature reduction (Fig. 7) further confirms the impact of excluding target-derived variables. The mean accuracy of both Random Forest and XGBoost models stabilized near 0.70, with markedly smaller variance than in the original configuration. While the absolute accuracy decreased relative to the leakage-affected models, the results are more statistically credible, reflecting true predictive capability rather than memorization of the target.

The flat trend of XGBoost across folds suggests that its boosting mechanism yields more consistent generalization, whereas the larger oscillations of Random Forest reflect its sensitivity to small data partitions. This comparison highlights that, once the model relies solely on contextual features such as brand, gender, and champion status, prediction becomes inherently limited but interpretable, capturing the systematic narrative bias of WWE booking rather than purely statistical correlations.

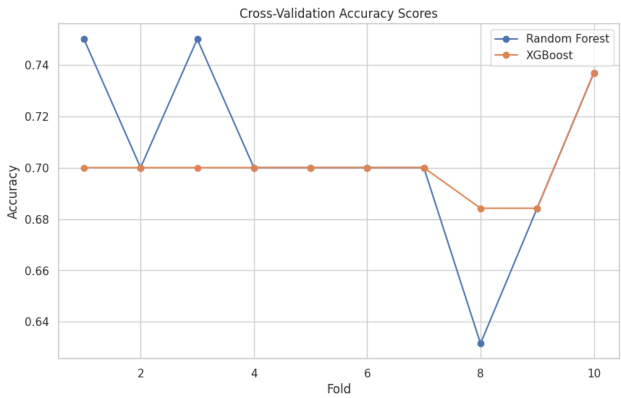

Fig. 7 – K-fold cross-validation accuracy after feature reduction.

Professional wrestling, especially WWE, represents a unique intersection of athletics and narrative storytelling, making it an interesting domain for predictive analytics. This study investigates the feasibility of predicting WWE match outcomes using machine learning models, using historical win-loss records and performance metrics from the 2023 season. Using Random Forest and XGBoost classifiers, the analysis focuses on key features such as winning streaks, total matches, and current champion status to determine their impact on match outcomes. Initial models demonstrated high accuracy but suffered from overfitting due to feature leakage, especially when using Win Ratio. However, by improving feature selection and implementing cross-validation, the models achieved better generalization and robustness. XGBoost outperformed Random Forest with an overall accuracy of 97.5%, highlighting the effectiveness of boosting algorithms in narrative-driven sports environments. The results highlight the impact of consistent performance and championship status on match outcomes, which reflects WWE's booking patterns. This study contributes to sports analytics by demonstrating the potential of machine learning in a narrative sports context despite the predetermined nature of WWE match outcomes. The findings not only support the application of predictive modeling in sports entertainment, but also provide insight into strategic storytelling mechanisms within professional wrestling narratives.

The study's approach is in line with broader trends in sports analytics, where machine learning is increasingly being used to predict match outcomes. For example, in cricket, Random Forest has been used to predict the winners of T20 matches with 84.06% accuracy [22], while in football, logistic regression was effective in predicting match results with a focus on betting profits [23]. Similarly, in NCAA basketball, Random Forest achieved 85.71% accuracy in predicting tournament outcomes [24]. These studies highlight the versatility of machine learning in various sports contexts and highlight the potential of similar approaches in professional wrestling.

Feature selection is a critical aspect of predictive modeling, as highlighted in the study. Using winning streaks, total games played, and the current champion's status as key features is consistent with the approach in other sports. For example, in predicting NBA game outcomes, features such as field goal percentage have been identified as significant predictors [25]. Similarly, in soccer, player performance and team statistics have been used to develop predictive models [26]. Improving feature selection and addressing feature leakage are key steps, as shown in the study, to ensure model generalization and robustness.

The choice of Random Forest and XGBoost classifiers is also noteworthy. Random Forest has been widely used in sports analysis due to its ability to handle complex datasets and reduce overfitting through bagging [24], [27]. XGBoost, a boosting algorithm, has been particularly effective in various sports prediction tasks, such as predicting the winners of IPL matches with 96% accuracy [28]. The excellent performance of XGBoost in this study, which achieves 97.5% accuracy, is consistent with its established effectiveness in other areas.

The study's findings regarding the impact of consistent performance and championship status on match outcomes are particularly insightful. These results mirror WWE's booking patterns, where the narrative story often emphasizes consistent performance and reigning championships. This is consistent with the strategic use of player performance data in NBA predictions, where team efficiency indices have been used to predict game outcomes [29]. Similarly, in football, player attributes and team statistics have been used to develop predictive models that account for both performance and narrative elements [26].

The implications of this study extend beyond WWE to the broader field of sports analytics. The effectiveness of machine learning in predicting outcomes in a narrative-based context highlights its potential for application in other sports with similar characteristics. For example, in professional basketball, machine learning has been used to predict match winners with 66% accuracy [30], while in soccer, models have been developed to predict match outcomes using player performance and team statistics [26].

The study's focus on strategic storytelling mechanisms within professional wrestling also highlights the importance of understanding the narrative context in which matches occur, a factor often overlooked in purely data-driven approaches.

In conclusion, this study demonstrates the potential of machine learning in predicting WWE match outcomes, utilizing historical data and performance metrics. The use of Random Forest and XGBoost classifiers, with a particular emphasis on feature selection and cross-validation, highlights the importance of robust model development in sports analytics. The study's findings not only contribute to the understanding of WWE's booking patterns, but also provide valuable insights into the application of machine learning in narrative-driven sports contexts. As machine learning continues to evolve, its integration with strategic storytelling mechanisms is likely to increase the accuracy and utility of predictive models in professional wrestling and beyond.

VI. Conclusions

In this study, the feasibility of predicting WWE match outcomes using historical win-loss records and other performance metrics was investigated. Leveraging machine learning models, specifically Random Forest and XGBoost,the study aimed to identify key factors influencing match results and assess the predictive power of these features. This study demonstrates the potential of machine learning to predict WWE match outcomes using historical performance data. While narrative-driven sports present unique modeling challenges, the high accuracy of the models illustrates the consistency in booking patterns and performance metrics. By acknowledging the limitations and incorporating more contextual features, future research can further advance predictive analytics in professional wrestling. This study investigates the use of machine learning models to predict WWE match outcomes based on data from the 2023 season. Using classifiers like Random Forest and XGBoost, the research analyzed features such as win streaks, total matches, and champion status to determine their influence on results. Initial models achieved high accuracy but suffered from overfitting, which was addressed through feature refinement and cross-validation, leading to more reliable predictions. XGBoost demonstrated superior performance with an accuracy of 97.5%, highlighting the effectiveness of boosting algorithms in this context. The findings emphasize the importance of performance consistency and storyline elements like championship status in predicting outcomes, offering valuable insights into WWE's narrative strategies. Overall, the study showcases the potential of machine learning in analyzing sports entertainment, even within a scripted environment.

This research not only contributes to sports analytics but also provides a novel perspective on the intersection of storytelling and competitive sports entertainment.

A. Feature Importance and Influence

Win Ratio, Total Matches, and Win Streak emerged as the most influential features, highlighting the significance of consistency and momentum in predicting match outcomes. Current Champion status positively correlated with win ratios, confirming storyline protection for titleholders.

XGBoost outperformed Random Forest, achieving high accuracy and balanced precision and recall.

Random Forest also demonstrated robust performance but with slightly lower accuracy compared to XGBoost.

Initial models exhibited unusually high accuracy, revealing potential overfitting due to feature leakage (e.g., using Win Ratio). By excluding highly correlated features and employing cross-validation, an improved generalizability and model robustness was ensured.

B. Scientific Contribution

This study contributes to the growing field of sports analytics by demonstrating the application of machine learning in narrative-driven sports entertainment. It highlights the predictive power of historical performance metrics, even in a predetermined competitive environment like WWE.

In practical applications, the models can assist wrestling analysts, content creators, and fans in predicting match outcomes, enhancing fan engagement and narrative speculation. WWE creative teams could utilize predictive analytics to design more compelling storylines by identifying superstars with rising momentum.

C. Limitations

The dataset lacked contextual variables such as match type, event importance, and opponent strength, which could enhance predictive accuracy. Predetermined outcomes in professional wrestling challenge traditional sports modeling, as booking decisions are influenced by narrative storytelling rather than athletic performance.

Data Availability

The data will be available after the acceptance of the paper in a public repository with DOI: 10.17632/mv7r8tyfb9.1. The data in the draft version can be accessed at: https://data.mendeley.com/preview/mv7r8tyfb9?a=213fa741-2640-4fa5-9530-515782584ac5

Statements and Declaration

The authors declares that there is no conflict of interest regarding the publication of this paper.

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