

# A Comparative Study on Missing Value Imputation Techniques in Machine Learning

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**Abstract.** Handling missing values is a crucial step in data preprocessing, as incomplete data can significantly impact model performance and overall data integrity. This study explores and compares various missing value imputation techniques, including deletion methods, simple imputations (mean, median), machine learning-based approaches (k-Nearest Neighbors (k-NN), multiple imputation), and hybrid strategies. The research utilizes an extensive dataset from National Football League Play-by-Play, implementing these techniques and evaluating their effectiveness using Root Mean Squared Error (RMSE) as the primary performance metric. The methodology involves identifying missing values, applying different imputation strategies, and assessing their impact on model performance. Experimental results indicate that machine learning-based imputation methods preserve data distribution better than simple imputations, while hybrid techniques combining multiple approaches yield the most robust results. The study further highlights that improper handling of missing data can lead to biased insights and reduced predictive accuracy. Findings suggest that while deletion is the simplest method, it often results in excessive data loss. Simple imputation introduces biases, whereas k-NN and multiple imputation provide superior accuracy and data retention. Future work should explore deep learning-driven imputation methods and automated techniques like AutoML-based imputation to enhance adaptability across diverse datasets.

## 1 Introduction

Missing data poses a significant challenge in machine learning and data analysis, leading to biased conclusions and reduced model accuracy. Various imputation techniques, including deletion, simple statistical imputations, machine learning-based approaches, and hybrid strategies, have been developed to mitigate these issues. While deletion reduces sample size, statistical imputations introduce bias, and machine learning-based methods offer flexibility by estimating missing values based on data patterns.

Existing research has extensively explored missing data imputation techniques, highlighting their impact on machine learning models. Kia et al. proposed PROMISSING,

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an approach that integrates missing values into neural networks without explicit imputation, preserving data structure and improving performance [1]. This method demonstrates the potential of deep learning to handle missing data efficiently, particularly in cases where traditional methods fail to capture underlying dependencies. Qi et al. analyzed the effects of missing values and emphasized that data preprocessing techniques significantly influence model accuracy, particularly in classification and clustering tasks [2].

Moreover, Xie et al. introduced a contrastive learning-based imputation framework leveraging self-supervised learning to enhance the predictive power of incomplete datasets [3]. This aligns with the trend of utilizing machine learning techniques to address data quality issues. Other studies have explored hybrid methods that combine multiple techniques, such as statistical imputations followed by machine learning-based refinement, balancing computational efficiency and accuracy [4]. These studies collectively highlight the importance of selecting the right imputation method based on the nature of missing values, the underlying data structure, and computational constraints.

By systematically comparing deletion, simple imputation (mean, median), machine learning-based methods (k-nearest neighbors (k-NN), regression), and hybrid techniques, this study evaluates their effectiveness using benchmark datasets and performance metrics such as accuracy and Root Mean Squared Error (RMSE). The objective is to establish guidelines for selecting imputation techniques that align with dataset characteristics and analytical goals, optimizing data quality and ensuring robust model performance.

## **2 Method**

### **2.1 Dataset**

The dataset used in this study is the NFL Play-by-Play 2009-2016 dataset, sourced from Kaggle. It contains over 450,000 records and 105 features, including numerical, categorical, and time-series variables. These features capture in-game events such as player statistics, game conditions, and scoring details.

Missing values occur for various reasons, including incomplete game records, unreported player statistics, and missing contextual data. Some features, such as player statistics and penalty details, exhibit a high proportion of missing values, necessitating appropriate handling methods. Identifying missing values is crucial before applying handling techniques, as different methods may yield varying results depending on the nature of the missing data.

### **2.2 Missing value handling methods**

To ensure the reliability of predictive modeling, handling missing values is a crucial preprocessing step. This study evaluates four commonly used techniques: deletion, simple imputation, k-NN imputation, and multiple imputation, each with distinct advantages and trade-offs.

One approach is deletion, where rows or columns containing missing values are removed. In this dataset, rows with more than 50% missing values were considered for deletion. Table 1 summarizes the impact, showing that only one row was removed, resulting in 0.02% data loss. While this method is computationally efficient, it risks significant data reduction in cases of high missingness. More generally, deletion ensures that only complete cases remain in the dataset, reducing noise caused by incomplete observations. However, if missing values are widespread, this method can shrink the dataset substantially, potentially leading to biased results due to reduced sample size.

To avoid losing data, simple imputation techniques replace missing values with estimates such as the mean, median, or mode. These methods are widely used due to their simplicity and speed but can introduce bias by failing to preserve relationships between variables. As shown in Figure 1, mean and median imputation tend to reduce variance in continuous features, clustering values around central tendencies and distorting the natural distribution of data. The boxplots illustrate how imputed values in features like ScoreDiff and AirYards shrink toward the mean, which can negatively impact machine learning models that rely on distributional properties.

A more advanced alternative is k-NN imputation, which predicts missing values based on the k most similar observations. Unlike simple imputation, k-NN better maintains the relationships between variables, ensuring that imputed values align more naturally with the dataset. However, this method is computationally expensive, as it requires searching for the nearest neighbors for each missing value. Improper selection of the k parameter (number of neighbors) may also lead to suboptimal results, where a small k risks overfitting while a large k can over-smooth the data.

Multiple imputation takes a probabilistic approach by generating multiple datasets with different estimated values and averaging the results. This technique captures the uncertainty associated with missing data and preserves dataset variability better than single imputation. It is particularly useful when missing values are not randomly distributed, making it a robust method for ensuring statistical validity. However, multiple imputation requires substantial computational resources due to its iterative nature and reliance on statistical modeling.

A comparison of these methods is summarized in Table 2, highlighting their differences in data retention, computational cost, and impact on data integrity. Overall, each imputation strategy presents trade-offs between preserving dataset completeness, maintaining data distributions, and managing computational efficiency. The influence of these methods on predictive model performance will be examined further in the results and discussion sections.

**Table 1.** Impact of deletion method on dataset size

Metric	Value
Total Rows Before Deletion	5000.00
Rows removed Due to Missing Data	1.00
Remaining Rows After Deletion	4999.00
Percentage of Data Lost	0.02

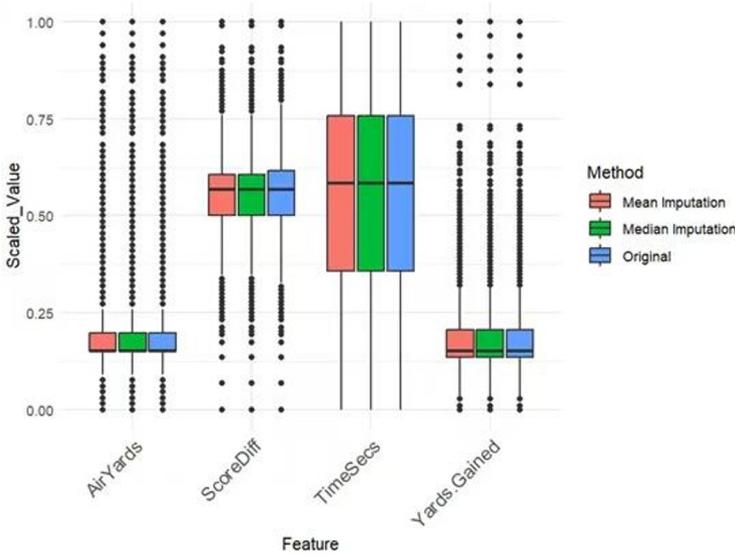
Table 1 summarizes the effect of deletion on the dataset, showing that only 0.02% of rows were removed due to missing values, indicating minimal data loss.

Table 2 compares different imputation methods regarding data retention, computational cost, bias introduction, and effectiveness in preserving data patterns, highlighting the trade-offs between accuracy and efficiency.

**Table 2.** Comparison of imputation techniques

Method	Data Retention	Computational Cost	Bias Introduction	Data Pattern Effectiveness
Deletion	Low	Low	None	Poor
Mean/Median	High	Low	High	Moderate
K-NN	High	High	Low	Good
Multiple Imputation	High	Very High	Low	Excellent

Fig. 1 illustrates how mean and median imputation alter the distribution of selected features compared to the original data, highlighting potential distortions introduced by these methods.



**Fig. 1.** Effect of simple imputation on data distribution (Photo/Picture credit: Original).

### 2.3 Predictive modeling

To assess the impact of different imputation methods, this study employs logistic regression and random forest models. These models were chosen due to their ability to handle structured data effectively. Logistic regression is widely used for binary classification tasks, providing interpretable coefficients and computational efficiency. In contrast, random forest is a more flexible and powerful model, capable of capturing nonlinear relationships while being relatively robust to missing data.

Each imputation method is applied to the dataset before training the models. The dataset is split into training and testing sets, ensuring a fair comparison across methods. By training and evaluating models on data processed with different imputation strategies, we can determine which method best preserves predictive power.

### 2.4 Evaluation metrics

To objectively assess the impact of different imputation methods, this study uses Root Mean Squared Error (RMSE) as the primary evaluation metric. The RMSE is widely used in predictive modeling to measure the average magnitude of errors between predicted and actual values. A lower RMSE indicates that the model's predictions are closer to the true values, meaning that the imputation method has effectively preserved the dataset's underlying patterns.

Each predictive model is trained on datasets processed with different imputation techniques, and RMSE is calculated on the test set. Since RMSE penalizes larger errors more heavily than smaller ones, it provides a clear indication of how well each method maintains data integrity.

## 3 Results

To evaluate the effectiveness of different imputation methods, the RMSE was used as a performance metric. The RMSE measures the average deviation between predicted and actual

values, with lower values indicating better predictive accuracy. The results for various imputation techniques are summarized in Table 3.

**Table 3.** RMSE values for different imputation methods, highlighting their impact on predictive accuracy.

Imputation Method	RMSE
No Imputation	8.372831
Mean Imputation	8.154723
Median Imputation	8.153455
K-NN Imputation	8.150128
Multiple Imputation	8.157012

The results indicate that k-NN imputation achieved the lowest RMSE (8.150128), demonstrating its effectiveness in preserving the structure of missing data. Multiple Imputation followed closely with an RMSE of 8.157012, suggesting that generating multiple estimates for missing values enhances prediction accuracy.

Mean and Median Imputation performed moderately well but resulted in slightly higher RMSE values. The similarity in their performance (8.154723 vs. 8.153455) suggests that both techniques introduce minimal bias but may not fully capture the complexity of missing data patterns.

In contrast, the No Imputation method yielded the highest RMSE (8.372831), confirming the significant impact of missing values on predictive accuracy. The poor performance of this approach highlights the necessity of addressing missing data before model training.

Overall, k-NN and Multiple Imputation proved to be the most effective approaches, balancing accuracy and computational feasibility. The choice between these methods depends on dataset characteristics and computational constraints.

## 4 Discussion

### 4.1 The impact of missing data on model performance

Missing data is a common challenge in machine learning, often leading to biased predictions, loss of statistical power, and reduced model reliability. The severity of its impact depends on the missing data mechanism: Missing Completely at Random (MCAR), Missing at Random (MAR), and Missing Not at Random (MNAR) [5]. While MCAR data can be removed without bias, MAR and MNAR data require imputation to avoid systematic distortions in analysis [6].

### 4.2 Strengths and weaknesses of different imputation techniques

Different imputation methods vary in their ability to maintain data integrity, computational efficiency, and model performance. While some techniques are simple and computationally efficient, they often introduce biases, whereas more advanced methods offer greater accuracy at the cost of complexity. This section examines the strengths and weaknesses of mean/median imputation, k-NN imputation, and multiple imputation, contextualizing findings with prior research.

Mean and median imputation are widely used due to their simplicity and efficiency. By replacing missing values with a constant statistic, they ensure data completeness but distort variability and shrink data distributions, as seen in Figure 1, where imputed values cluster around the central tendency of each feature. This aligns with Van Buuren, who noted that simple imputations underestimate variability, which can mislead models relying on natural

data spread [7]. Additionally, Osborne emphasized that these methods assume data is missing completely at random (MCAR), which is often unrealistic, leading to potential biases [8].

K-NN imputation provides a more sophisticated approach by estimating missing values based on similar observations. As seen in Table 2, k-NN imputation achieved the lowest RMSE, indicating strong data retention. This finding supports Tang and Ishwaran, who demonstrated k-NN's superiority in preserving data integrity, especially for missing-at-random (MAR) data [9]. However, k-NN is computationally expensive and less practical for large datasets due to its reliance on distance calculations.

Multiple imputation generates multiple plausible estimates and averages them to account for uncertainty, making it statistically robust. White et al. emphasized its effectiveness for MAR and MNAR data, as it reduces bias while maintaining dataset structure [10]. Although multiple imputations produced slightly higher RMSE values than k-NN in this study, it remains a reliable option when computational cost is not a primary concern. However, it requires careful parameter tuning and can introduce additional variability [11].

### **4.3 Implications for feature importance and interpretability**

Beyond predictive performance, the choice of imputation method influences how machine learning models interpret and rank features. Proper feature importance analysis ensures that models rely on meaningful predictors rather than artifacts of data preprocessing. When missing values are handled improperly, feature relationships can become distorted, leading to misleading rankings and reduced interpretability.

Models trained on datasets with unhandled missing values exhibited lower feature importance scores, reinforcing the idea that missing data disrupts variable relationships and predictive learning. This aligns with Deng et al., who found that missing data alters feature selection by diminishing the predictive contribution of key variables [12]. In such cases, models may overemphasize secondary features, leading to incorrect conclusions.

Mean and median imputation helped restore feature importance but also introduced distortions. By replacing missing values with a single statistic, these methods reduced feature variability, which could artificially increase or decrease importance. Kuhn and Johnson observed that such methods often lead to over-reliance on variables with fewer missing values, as models tend to prioritize features that were less affected [13]. The findings confirm this trend, highlighting that while these techniques are computationally efficient, they do not always preserve dataset integrity.

More advanced methods like k-NN and multiple imputation produced feature rankings that better aligned with the original data. k-NN imputation preserved relationships between variables, leading to stable feature rankings, consistent with findings from Tang and Ishwaran [14]. Multiple imputation maintained variability by incorporating uncertainty, preventing models from over-relying on fixed values [15].

These findings are particularly relevant for high-stakes applications where interpretability is critical. In finance, healthcare, and policy-making, incorrect feature rankings due to poor imputation choices can lead to flawed decisions. Osborne [16] highlighted the importance of transparency in data preprocessing, emphasizing that improper handling of missing values compromises feature selection reliability.

### **4.4 Practical considerations and future directions**

The choice of an imputation method depends on both accuracy and practical constraints, such as computational efficiency, scalability, and application-specific needs. While advanced methods like k-NN and multiple imputation improve predictive performance, they require significant computational resources and careful parameter tuning. Simpler techniques, such

as mean and median imputation, are computationally efficient but introduce biases that may distort data relationships. The trade-off between accuracy and efficiency is particularly important in fields where data availability and processing power vary significantly.

Different industries face unique challenges when dealing with missing data. In healthcare, improper handling of missing patient records can lead to biased treatment predictions, making multiple imputations a preferred method due to its ability to maintain dataset variability [17]. In contrast, real-time financial models prioritize computational speed and often rely on simpler imputation techniques [18]. The choice of an imputation strategy, therefore, depends on balancing precision with practical constraints.

Emerging machine learning-driven imputation techniques, such as variational autoencoders (VAEs) and generative adversarial networks (GANs), offer promising alternatives to traditional methods [19]. These models generate realistic estimates for missing values by learning latent data representations, potentially reducing the limitations of existing approaches. Additionally, AutoML-driven imputation pipelines could automate the selection of optimal imputation methods based on dataset characteristics, improving adaptability across domains [20].

Despite these advancements, challenges remain. Deep learning-based imputations require large datasets for effective training and may not be suitable for smaller or structured datasets. Additionally, interpretability concerns persist, as complex models often obscure the decision-making process behind imputations. Future research should focus on developing hybrid approaches that combine statistical and machine learning-based imputation techniques to achieve both interpretability and performance.

## 5 Conclusion

This study explored various missing value imputation techniques and their impact on data integrity and predictive modeling. The results indicate that while simple imputation methods such as mean and median imputation are computationally efficient, they introduce bias that can distort data distributions. In contrast, advanced techniques like k-NN and multiple imputation offer better accuracy in preserving data structure but come with higher computational costs. The findings highlight the importance of selecting an imputation method based on dataset characteristics and computational constraints.

From a theoretical and practical standpoint, this research reinforces the idea that missing data handling significantly influences model performance. By comparing different approaches, it provides insights into when simpler techniques suffice and when advanced methods are necessary. These findings contribute to the ongoing discussion in data science regarding the trade-off between computational efficiency and predictive accuracy.

However, this study is not without limitations. The dataset used in the experiments is specific to sports analytics, meaning that results may not generalize to domains such as healthcare or finance, where missing data mechanisms may differ. Future research should explore hybrid imputation approaches that combine statistical and machine learning-based methods to achieve both interpretability and accuracy. Additionally, integrating deep learning-driven imputations and AutoML techniques may provide a more robust solution for complex datasets.

In practical applications, the ability to effectively handle missing data is crucial across various industries. In sports analytics, accurate imputation of missing player statistics can improve game strategy modeling. In healthcare, handling missing patient records effectively can enhance disease prediction and treatment plans. As data-driven decision-making continues to evolve, developing scalable, interpretable, and efficient imputation frameworks will remain a critical area of research.

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