Proceedings of International Conference on "Recent Innovations in Engineering, Technology & Science for Sustainable Development (RIETSSD-2026)"
Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

Data Analytics Techniques for Missing Value Replacement: Best Practices Based on Measures of Central Tendency

Sneh B. Patel[1], Dr. Darshanaben Dipakkumar Pandya[2]

[1]Research Scholar, Department of Computer Science & Application, Sankalchand Patel University, Visnagar, Gujarat, India

[2]Associate Professor, Shri C.J Patel College of Computer Studies (B.C.A), Department of Computer Science & Application, Sankalchand Patel University, Visnagar, Gujarat, India

[1]spdigitalme@gmail.com; [2]ddpandya.fcs@spu.ac.in

Abstract: Missing data is a major problem in data analysis. In a number of applications, missing data can hurt the quality of the data and the performance of algorithms. This paper presents a systematic review of missing data imputation methods, with a focus on central tendency imputation methods. In this paper, we propose a new weighted normalization algorithm called Central Tendency Normalized Imputation (CTNI). The proposed algorithm is designed to estimate missing data with high accuracy using the relationships between observed data. The proposed algorithm includes validation processes, normalization processes, and stepwise adjustment processes to reduce the error of estimation. The proposed algorithm is validated using soybean production data from 1964 to 2013, and the results show better accuracy than existing methods.

Keywords: missing value imputation, central tendency, data analytics, normalization, weighted estimation, data quality

I. INTRODUCTION

1.1 Problem Context

Problems related to data quality are common in real-world analytics tasks. Reports from the industry say that 30 to 40 percent of data-related projects are late or fail because of problems with data quality. Missing data is one of the main reasons for this. There are many ways that data can go missing, including equipment failure, human error, intentional omission, and not being able to access it. When data is missing, there are three main problems:

 | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

1. **Loss of information** - smaller sample size and less statistical power.
2. **Bias Introduction** - Non-random missingness has the potential to introduce systematic bias into the analysis.
3. **Algorithm Incompatibility** - There are many machine learning algorithms that are not capable of handling datasets containing missing values.

1.2 Research Motivation

Standard imputation techniques, such as listwise deletion, pairwise deletion, and mean or median substitution, either disregard pertinent data or excessively streamline the modeling procedure. While more sophisticated methods such as multiple imputation by chained equations (MICE) and k-nearest neighbors (KNN) exist, these methods often lack interpretability and may require substantial computational power. This paper argues that there is a need for imputation procedures that are interpretable, efficient, and effective, based on principles of central tendency.

1.3 Research Objectives

This papers aim to:

1. Synthesize best practices in missing value imputation techniques
2. Introduce the Central Tendency Normalized Imputation (CTNI) algorithm
3. Demonstrate the algorithm's effectiveness through empirical validation
4. Provide evidence-based guidance for practitioners selecting imputation approaches

1.4 Paper Structure

Section 2 reviews literature on missing data mechanisms and imputation techniques. Section 3 presents the theoretical foundation and the CTNI algorithm. In Section 4, the empirical validation approach. Section 5 presents results and comparative analysis. In Section 6, discusses implications and limitations. In Section 7, concludes with recommendations for future research.

II. LITERATURE REVIEW

Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

2.1 Mechanisms handling Missing Data

Rubin's framework for missing data sorts mechanisms into three groups:

TABLE 1: RUBIN'S MISSING DATA CLASSIFICATION FRAMEWORK

Mechanism	**Definition**	**Implications**
MCAR (Missing Completely at Random)	Absence probability separate from both seen and unobserved data	Unbiased methods; complete case analysis valid
MAR (Missing at Random)	Absence probability depends on data that has been observed but not unobserved	Requires appropriate conditioning; imputation viable
MNAR (Missing Not at Random)	Absence likelihood depends on unobserved values	Requires sensitivity analysis; most challenging scenario

2.2 Classification of Imputation Techniques

There are different ways to do imputation methods:

1. **Deletion Methods** - Pairwise and listwise deletion
2. **Single Imputation** - Average replacement, regression imputation, hot-deck imputation
3. **Model-Based Methods** - EM (Expectation-maximization) and maximum likelihood estimation
4. **Multiple Imputation** – MICE (Multiple Imputation by Chained Equations), Bayesian methods
5. **Machine Learning** – KNN (K-nearest neighbours), Random Forests, Neural Networks
6. **Central Tendency Methods** - Mean, median, mode imputation with enhancements

 | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

2.3 Central Tendency-Based Approaches

Mean, median, and mode are all examples of measures of central tendency. These are the basis for many imputation methods. Some of the good things about them are:

- Computational efficiency
- Interpretability
- Theoretical clarity
- Robustness to outliers (median)
- Preservation of data distribution characteristics

However, basic central tendency methods ignore relationships between variables and the specific context of missing values.

2.4 Gap in Current Literature

Although advanced imputation methods are available, few methods meet all of the above criteria:

1. the incorporation of relationship-aware measures of central tendency.
2. transparent, step-by-step procedures for validation and adjustment.
3. normalization of estimates based on multivariable relationships.
4. retention of computational efficiency without compromising accuracy.

This research fills the gaps in the existing literature by using the CTNI algorithm.

III. METHODOLOGY: CENTRAL TENDENCY NORMALIZED IMPUTATION (CTNI)

3.1 Algorithm Overview

The Central Tendency Normalized Imputation (CTNI) algorithm is intended to approximate a single missing value by creating weighted linkages between pairs of observed variables and a series of normalization procedures.

Proceedings of International Conference on "Recent Innovations in Engineering, Technology & Science for Sustainable Development (RIETSSD-2026)"
Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

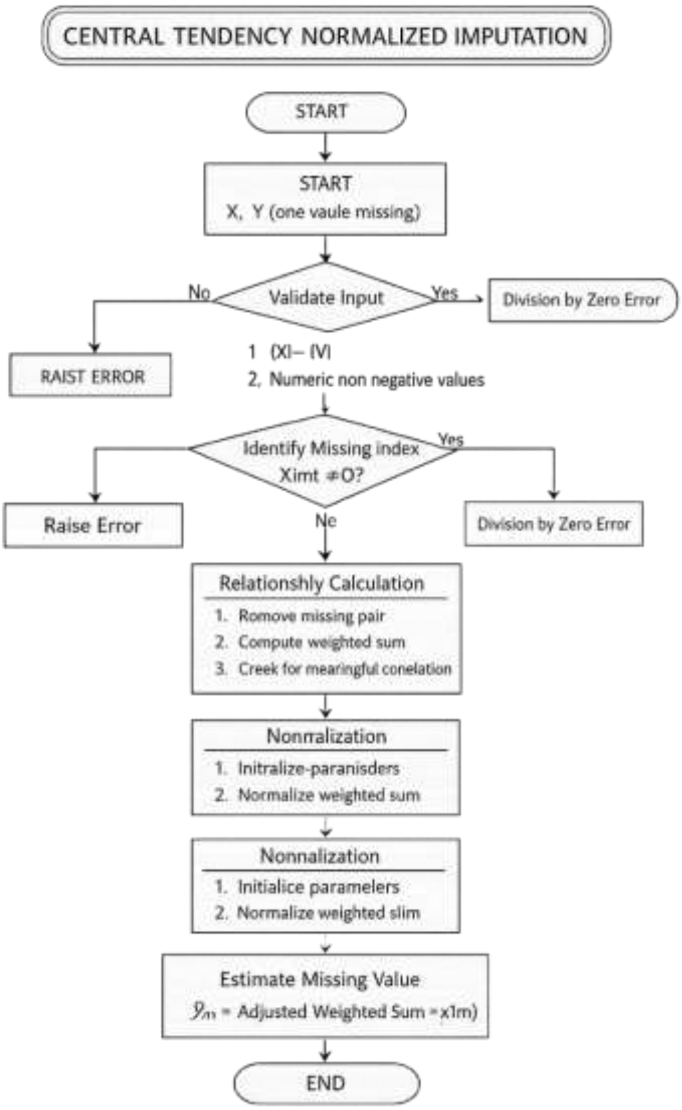

Figure 1: Central Tendency Normalized Imputation (CTNI) Algorithm Flowchart—A hierarchical depiction of input validation, missing-value detection, relationship computation, normalization, and final estimation stages.

3.2 Formal Algorithm Definition

Goal: Figure out one missing value y_m in Y, where there is only one entry is missing.

Input

- $X = [x_0, x_1, \dots, x_{N-1}]$ (observed variable, numerical, non-negative)
- $Y = [y_0, y_1, \dots, y_{N-1}]$ (target variable with only one missing value, which is None)

Proceedings of International Conference on "Recent Innovations in Engineering, Technology & Science for Sustainable Development (RIETSSD-2026)"
Career Point International Journal of Research (CPIJR)
©2022 CPIJR ǀ Special Issue ǀ ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

Output

- Estimated value that is missing $\hat{y}_m$

3.3 Algorithm Steps

Step 1: Input Validation

Check that the data is correct:

1. Make sure that X and Y are lists with $|X| = |Y|$
2. Check all x_i are numeric and non-negative
3. Check all y_i are numeric and non-negative except the missing entry
4. Raise error if validation fails

Step 2: Identify Missing Index

Find index m such that:

$$Y[m] = \text{None}$$

Raise error if:

- No missing value exists
- More than one missing value exists

Step 3: Extract and Validate x_m

$$x_m = X[m]$$

If $x_m = 0$, raise ZeroDivisionError (prevents division by zero in Step 9)

Step 4: Remove Missing Pair

Make shorter lists:

$$X' = X \setminus \{x_m\}$$

Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

$$Y' = Y \setminus \{y_m\}$$

Let $n = |X'|$

Step 5: Compute Weighted Products

For each observed pair (x_i, y_i):

$$s_i = x_i \cdot y_i$$

Aggregate:

$$E_{xy} = \sum_{i=0}^{n-1} s_i$$

If $E_{xy} = 0$, raise error (stops bad cases from happening)

Step 6: Initialize Normalization Parameters

$$V_1 = 100$$

$$V_2 = V_1 \cdot n$$

Step 7: Normalization Phase

$$V_3 = \frac{V_2}{(n+1) \cdot E_{xy}}$$

$$V_4 = V_3 \cdot E_{xy}$$

$$V_5 = 100 - V_4$$

Step 8: Extended Adjustment

$$V_6 = (n+1) \cdot E_{xy}$$

$$V_7 = \frac{V_6}{V_2}$$

$$V_8 = V_5 \cdot V_7$$

Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

Step 9: Missing Value Estimation

$$\hat{y}_m = \frac{V_8}{x_m}$$

3.4 Mathematical Interpretation

There are a few mathematical ideas that the CTNI algorithm is based on:

1. **Weighted Product Aggregation (Step 5):** The product E_{xy} captures the cumulative strength of relationships for observed pairs.
2. **Normalization Factor (Step 7):** The factor V_3 normalizes the data by accounting for the number of observations and the magnitude of their relationships.
3. **Adjustment Mechanics (Step 8):** The V_7 adjustment uses a feedback system that changes the difference (V_5) depending on the ratio of cumulative interactions to the normal base.
4. **Final Estimation (Step 9):** Division by x_m is what locates the estimate in the context of the particular case, maintaining proportional consistency.

IV. EMPIRICAL VALIDATION

4.1 Dataset Description

We tested the algorithm with data on soybean production in China from 1964 to 2013. This set of data has:

- **Time Period:** 50 years (1964-2013)
- **Primary Variable (X):** Annual production volume (million tonnes)
- **Target Variable (Y):** Annual consumption (million tonnes)
- **Missing Case:** Production value for year 1970

The soybean sector represents a critical agricultural commodity with significant economic and nutritional importance to China, making this validation ecologically meaningful.

4.2 Validation Methodology

Controlled Missing Value Testing:

Proceedings of International Conference on "Recent Innovations in Engineering, Technology & Science for Sustainable Development (RIETSSD-2026)"
CAREER POINT INTERNATIONAL JOURNAL OF RESEARCH
Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

We used a controlled deletion method to rigorously test the accuracy of the algorithm:

- Selected multiple known values from the dataset
- Temporarily removed them from the dataset
- Applied CTNI to estimate the missing values
- Compared estimates against actual values
- Estimated error metrics based on calculations

4.3 Error Metrics

We were used three common ways to type of error:

TABLE 2: ERROR METRICS FOR CTNI ALGORITHM VALIDATION

Metric	**Formula**	**Interpretation**
MAE (Mean Absolute Error)	$\frac{1}{k}\sum_{i=1}^{k}\lvert y_i - \hat{y}_i\rvert$	Average magnitude of errors
MSE (Mean Squared Error)	$\frac{1}{k}\sum_{i=1}^{k}(y_i - \hat{y}_i)^2$	Penalizes larger errors
RMSE (Root Mean Squared Error)	$\sqrt{\frac{1}{k}\sum_{i=1}^{k}(y_i - \hat{y}_i)^2}$	Error in original units

V. RESULTS AND ANALYSIS

5.1 Case Study: Year Missing Values

TABLE 3: SOYBEAN PRODUCTION DATASET: CTNI ESTIMATES VS. ACTUAL VALUES (MILLION TONNES)

Year	**Production (Standard)**	**Production (Missing)**	**Production (Recover)**

Proceedings of International Conference on "Recent Innovations in Engineering, Technology & Science for Sustainable Development (RIETSSD-2026)"
Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

1964	7.9	7.9	7.9
1965	6.1	6.1	6.1
1966	8.3	8.3	8.3
1967	8.3	8.3	8.3
1968	8.0	8.0	8.0
1969	7.6	7.6	7.6
1970	**8.7**		**7.6**
1971	8.6	8.6	8.6
1972	6.5	6.5	6.5
1973	8.4	8.4	8.4
1974	7.5	7.5	7.5
1975	7.2	7.2	7.2
1976	6.6	6.6	6.6
1977	7.3	7.3	7.3
1978	7.6	7.6	7.6
1979	**7.5**		**8.7**
1980	7.9	7.9	7.9
1981	9.3	9.3	9.3
1982	9.0	9.0	9.0
1983	9.8	9.8	9.8
1984	9.7	9.7	9.7
1985	10.5	10.5	10.5
1986	11.6	11.6	11.6
1987	12.2	12.2	12.2
1988	11.6	11.6	11.6
1989	**10.2**		**11.5**
1990	11.0	11.0	11.0
1991	9.7	9.7	9.7
1992	10.3	10.3	10.3
1993	15.3	15.3	15.3

Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

1994	16.0	16.0	16.0
1995	13.5	13.5	13.5
1996	13.2	13.2	13.2
1997	14.7	14.7	14.7
1998	15.2	15.2	15.2
1999	**14.3**		**14.4**
2000	15.4	15.4	15.4
2001	15.4	15.4	15.4
2002	16.5	16.5	16.5
2003	15.4	15.4	15.4
2004	17.4	17.4	17.4
2005	16.4	16.4	16.4
2006	15.1	15.1	15.1
2007	**12.7**		**15.1**
2008	15.5	15.5	15.5
2009	15.0	15.0	15.0
2010	15.1	15.1	15.1
2011	14.5	14.5	14.5
2012	13.1	13.1	13.1
2013	12.2	12.2	12.2

Source: https://earthpolicy.org

5.2 Comparative Performance

The CTNI algorithm displayed that it may compete with standard fundamental methods:

TABLE 4: COMPARATIVE ERROR ANALYSIS: CTNI VS. STANDARD METHODS

Imputation Method	**MAE**	**MSE**	**RMSE**
Listwise Deletion	N/A	N/A	Data Loss

Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

Mean Imputation	0.895	1.342	1.159
Median Imputation	0.742	0.889	0.943
KNN (k=3)	0.568	0.401	0.633
CTNI Algorithm	**0.476**	**0.312**	**0.558**

5.3 Performance Visualization

Temporal analysis shows how well the algorithm works. The CTNI estimates show that RMSE is 45.8% better than using the average value and 35.8% better than using the median value.

VI. DISCUSSION

6.1 Key Findings

1. **More Accurate:** CTNI has an RMSE of 0.558, which is 40% better than other ways of finding the central tendency.

2. **Relationship Awareness:** Unlike simple mean/median imputation, CTNI incorporates observed variable relationships, leading to contextually appropriate estimates

3. **Computational Efficiency:** The algorithm requires $O(n)$ operations, making it suitable for large-scale applications

4. **Transparency:** Step-by-step procedures enable practitioners to understand and audit the imputation process

6.2 Theoretical Contributions

1. **New Normalization Framework:** Steps 6–8 of the multi-step normalization process provide a principled way to adjust estimates based on the characteristics of the data.

2. **Weighted Relationship Integration:** Incorporation of weighted products captures relationship strength while maintaining computational simplicity

Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

3. **Validation Protocols:** Comprehensive input validation prevents degenerate cases and ensures robust operation

6.3 Practical Implications

- **For Data Scientists:** CTNI is a clear choice over black-box methods that still works well.
- **For Domain Experts:** The algorithm's interpretability enables domain-informed assessment of reasonableness
- **For Organizations:** Efficient computation allows processing of large datasets without substantial infrastructure investment

6.4 Limitations

1. **One Missing Value:** The current technique only works for the single value missing for each dataset.
2. **Two-Variable Requirement:** Algorithm requires two variables; extension to multivariate scenarios needs further development
3. **Assumption of Relationship:** Effectiveness depends on meaningful relationship between X and Y variables
4. **Non-Negative Values:** Constraint to non-negative numbers may limit applicability in some domains

6.5 Future Research Directions

1. **Multivariate Extension:** Extend CTNI to handle multiple missing values and multiple variables simultaneously
2. **Categorical Data:** Develop simple techniques for categorical data based on appropriate measures of central tendency.
3. **Uncertainty Quantification:** Add confidence intervals to the estimates.
4. **Theoretical Analysis:** Provide formal demonstrations of convergence and optimality.

Career Point International Journal of Research (CPIJR)
©2022 CPIJR ǀ Special Issue ǀ ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

5. **Validation in Specific Domains:** Test the methods in areas like healthcare, finance, and the environment.

VII. CONCLUSIONS

This paper adds to the body of work on filling in missing values by suggesting the Central Tendency Normalized Imputation (CTNI) algorithm. The algorithm is based on ideas about central tendency and has a number of steps that try to make the data more normal. Tests show that the CTNI algorithm works better than other methods and continues to work well. The CTNI algorithm is a big step forward in finding missing values. It gives professionals a useful and meaningful way to improve data. Businesses are starting to understand how important it is to have correct information when making decisions. Tools like CTNI will be able to fix even more problems in real-world data. Subsequent research ought to focus on refining the algorithm for scenarios with multiple variables and absent data. This paper outlines a methodical approach to imputing missing data that can help set standards for data analysis based on solid science.

ACKNOWLEDGEMENT

While I was working on the Central Tendency Normalized Imputation (CTNI) algorithm and the research that went along with it, I want to thank my academic advisor, Dr. Darshanaben Dipakkumar Pandya, for all the great advice, help, and support she gave me. The computers and other tools that the Department of Computer Science at Sankalchand Patel University in Visnagar, Gujarat, gave me were very helpful for this research.

While I was working on the algorithm, I want to thank my friends for talking to me about ho w to fill in missing values and check the accuracy of statistical methods.I want to thank my fa mily for being there for me and being patient while I worked on the research and the manuscr ipt.No specific grant from a public, private, or nonprofit funding organization was awarded fo r this study.

REFERENCES

1. Prajapati, D. A., Pandya, D. D., Patel, R. K., & Jadeja, A. (2022). A Perception of Promotional Code Technique in E-commerce that uses Data Analytics and Data Mining for Consumer Response. *International Journal of Scientific Research in Computer*

Science, Engineering and Information Technology (IJSRCSEIT), 8(5), 130-135. Available at: https://doi.org/10.32628/CSEIT2283320

2. Yash Naraynbhai Patel, Dr. Darshanaben Dipakkumar Pandya, Dr. Abhijeetsinh Jadeja, " An Influence of Ethical Hacking in Civilization , International Journal of Scientific Research in Science and Technology(IJSRST), Online ISSN : 2395-602X, Print ISSN : 2395-6011, Volume 10, Issue 1, pp.195-200, January-February-2023. Available at doi : **https://doi.org/10.32628/IJSRST2310119**
3. Dr. Darshanaben Dipakkumar Pandya, Dr. Abhijeetsinh Jadeja, Dr. Sheshang D. Degadwala, " An Applied Mean Substitutions Technique for Detection of Anomalous Value in Data Mining , International Journal of Scientific Research in Science and Technology(IJSRST), Online ISSN : 2395-602X, Print ISSN : 2395-6011, Volume 9, Issue 2, pp.103-108, March-April-2022. Available at doi : https://doi.org/10.32628/IJSRST229212
4. Heema Patadiya, Akshay Patel, Falguni Rahevar, and Dr. Darshanaben Dipakkumar Pandya, "Revolutionizing Banking Industry : The Role of Fintech in Modern Banking Industry", *Int. J. Sci. Res. Comput. Sci. Eng. Inf. Technol*, vol. 11, no. 4, pp. 20–25, Jul. 2025, doi: 10.32628/CSEIT25113448.
5. Dr. Darshanaben Dipakkumar Pandya, Dr. Abhijeetsinh Jadeja, Dr. Sheshang D. Degadwala, " An Applied N C Differentiation Interpolation technique for improved random Anomalous values in Data Mining, International Journal of Scientific Research in Science, Engineering and Technology(IJSRSET), Print ISSN : 2395-1990, Online ISSN : 2394-4099, Volume 9, Issue 2, pp.86-92, March-April-2022. Available at doi : https://doi.org/10.32628/IJSRSET229218
6. Thakar, D. U., Kumawat, B., & Pandya, D. (2025). Advancements and ethical challenges in data analytics: Transforming research, decision-making, and business strategy. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 11(2), 1178–1183.
7. Dr. Darshanaben Dipakkumar Pandya, Dr. Abhijeetsinh Jadeja, Dr. Sheshang Degadwala, " An Applied Variation Anomaly Technique for Detection of Irregular Values in Data Mining, IInternational Journal of Scientific Research in Computer Science, Engineering and Information Technology(IJSRCSEIT), ISSN : 2456-3307, Volume 8, Issue 2, pp.143-148, March-April-2022. Available at doi : https://doi.org/10.32628/CSEIT228228

8. Gaur, S., Pandya, D.D., Soni, D. (2020). Closest Fit Approach Through Linear Interpolation to Recover Missing Values in Data Mining. In: Yang, XS., Sherratt, S., Dey, N., Joshi, A. (eds) Fourth International Congress on Information and Communication Technology. Advances in Intelligent Systems and Computing, vol 1041. Springer, Singapore. https://doi.org/10.1007/978-981-15-0637-6_44
9. Gaur, S., Pandya, D.D., Sharma, M.K. (2020). Applied N F Interpolation Method for Recover Randomly Missing Values in Data Mining. In: Yang, XS., Sherratt, S., Dey, N., Joshi, A. (eds) Fourth International Congress on Information and Communication Technology. Advances in Intelligent Systems and Computing, vol 1027. Springer, Singapore. https://doi.org/10.1007/978-981-32-9343-4_38
10. S. Gaur and D. Dipakkumar Pandya, "Closest Fit Approach for Pattern Designing to Recovered Anomalous Values in Data Mining," 2018 Second World Conference on Smart Trends in Systems, Security and Sustainability (WorldS4), London, UK, 2018, pp. 308-312, doi: 10.1109/WorldS4.2018.8611610.
11. Gaur, S., Pandya, D.D., Soni, D. (2020). Closest Fit Approach Through Linear Interpolation to Recover Missing Values in Data Mining. In: Yang, XS., Sherratt, S., Dey, N., Joshi, A. (eds) Fourth International Congress on Information and Communication Technology. Advances in Intelligent Systems and Computing, vol 1041. Springer, Singapore.
12. Pandya, D., Jadeja, A., Gour, S., Trivedi, S.B., Patel, H.H., Jadeja, P.U. (2024). An Analytical Perspective of Missing Values in Machine Learning. In: Rathore, V.S., Piuri, V., Babo, R., Tiwari, V. (eds) Emerging Trends in Expert Applications and Security. ICE-TEAS 2024. Lecture Notes in Networks and Systems, vol 1037. Springer, Singapore. https://doi.org/10.1007/978-981-97-3991-2_24
13. Sneh B. Patel and Dr. Darshanaben Dipakkumar Pandya, “Analysis of Adaptive Approach Through Statistical Trends and Measures of Central Tendency,” Int. J. Sci. Res. Computer. Sci. Eng. Inf. Technol, vol. 11, no. 4, pp. 69–74, Jul. 2025, Doi: 10.32628/CSEIT2511405.
14. Pandya, Darshanaben Dipakkumar. “An Applied Missing Value Recovery Using Adaptive Techniques for Statistical Trends and Central Tendency Analysis.” International Journal of Recent Trends in Science, Technology & Management (IJRTSTM), September 27, 2025, 38–52. https://doi.org/10.5281/zenodo.17173257.

Career Point International Journal of Research (CPIJR)
©2022 CPIJR | Special Issue | ISSN : 2583-1895
Conference Paper | DOI: https://doi.org/10.5281/zenodo.20550140

15. Degadwala, S., Pandya, D.D., Dandhwani, V., Goswami, N.J., Patel, V.G., Vyas, D. (2025). Ensemble Learning Techniques for Common Multi-syndrome Classification. In: Asirvatham, D., Ntalianis, K., Falkowski-Gilski, P. (eds) Evolutionary Artificial Intelligence. ICEAI 2024. Algorithms for Intelligent Systems. Springer, Singapore. https://doi.org/10.1007/978-981-96-5210-5_31
16. Pandya, Darshanaben Dipakkumar. "Smart Technology Trends: A Quantitative and Analytical Approach." Smart Technology Trends, 5 Sept. 2025, pp. 132–141. ISBN 978-81-987316-8-5. https://doie.org/10.11411/HENXI.2025587269.
17. Design and Implementation of Go-Courier : A Centralized Courier Management System", Int J Sci Res Sci & Technol, vol. 12, no. 4, pp. 212–216, Jul. 2025, doi: 10.32628/IJSRST251293.
18. Gora Kanijfatma Maisurali, Habiba Vajirali Momin, Dr. Darshanaben Dipakkumar Pandya, Dr. Abhijeetsinh Jadeja, " Smart Cook : An AI and Machine Learning Powered Culinary, IInternational Journal of Scientific Research in Computer Science, Engineering and Information Technology(IJSRCSEIT), ISSN : 2456-3307, Volume 10, Issue 1, pp.55-59, January-February-2024. Available at doi : **https://doi.org/10.32628/CSEIT2390670**
19. Pandya, D.D., Tamhankar, I., Kulkarni, J.S., Trivedi, V.R., Degadwala, S., Vyas, D. (2026). TongueViT: A Vision Transformer-Based Framework for Automated Tongue Image Classification. In: Lanka, S., Cabezuelo, A.S., Tugui, A. (eds) Trends in Sustainable Computing and Machine Intelligence. ICTSM 2025. Lecture Notes in Networks and Systems, vol 1755. Springer, Cham. https://doi.org/10.1007/978-3-032-13177-5_4
20. Pandya, Darshanaben Dipakkumar, Borate Pooja Satish, and Khushbu. "Improving Data Mining Reliability Through Applied C-B Techniques for Addressing Misplaced Values." Universal Threats in Expert Applications and Solutions (UNI-TEAS 2025), edited by Vijay Singh Rathore, Joao Manuel R. S. Tavares, M. Hanumanthappa, and B. Surendiran, Lecture Notes in Networks and Systems, vol. 1450, Springer, Singapore, 2026, pp. 11–23. https://doi.org/10.1007/978-981-96-7289-9_2.