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Effectiveness of Correlation Assisted SVM-based Imputation Method for Missing Data Prediction

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----------**ABSTRACT**----------

Handling missing data is a critical challenge in data processing, as it can significantly impact the performance of machine learning models. This paper proposes a Correlation Assisted Support Vector Machine (CA-SVM) based imputation method that integrates correlation analysis with the predictive power of Support Vector Machines to enhance missing data prediction accuracy. The CA-SVM approach identifies highly correlated attributes to guide the SVM in estimating missing values more effectively, preserving the underlying structure of the dataset. A comparative study is conducted between the proposed CA-SVM, standard SVM, and K-Nearest Neighbors (KNN) imputation techniques using benchmark datasets. Experimental results demonstrate that the CA-SVM method achieves a prediction accuracy of approximately 97 per cent, outperforming both traditional SVM and KNN methods in terms of accuracy, robustness, and consistency. The findings confirm that correlation-based feature guidance significantly improves the imputation performance of SVM models. This research highlights the potential of hybrid imputation techniques in building more reliable and accurate data-driven systems.

Keywords - **Missing Data, SVM, Correlation assisted SVM, Data Imputation**

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1. INTRODUCTION

In the era of big data, where the accumulation and processing of large datasets have become central to fields such as healthcare, finance, marketing, and scientific research, the problem of missing data remains a significant challenge. Missing data can arise due to various reasons, including errors in data collection, limitations in measurement tools, incomplete responses in surveys, equipment malfunctions, or even issues arising from data storage and transmission [1]. The presence of missing data can negatively impact the validity and reliability of conclusions drawn from data analysis, affecting model accuracy, decision-making processes, and ultimately hindering the insights that can be derived from these datasets [2, 22-24].

Missing values in a dataset can be represented in various ways, depending on the source of the data and the conventions used. Here are some common representations:

- *Not a Number*: In many programming languages and data analysis tools, missing values are represented as NaN. This is the default for libraries like Pandas in Python.
- *NULL or None*: In databases and some programming languages, missing values are often represented as NULL or None. For instance, in SQL databases, a missing value is typically recorded as NULL.
- *Empty Strings*: Sometimes, missing values are denoted by empty strings (""). This is common in text-based data or CSV files where a field might be left blank.
- *Special Indicators*: Datasets might use specific indicators like -999, 9999, or other unlikely values to signify missing data. This is often seen in older datasets or specific industries where such conventions were established.
- *Blanks or Spaces*: In some cases, particularly in fixed-width text files, missing values might be represented by spaces or blank fields.

As datasets grow larger and more complex, more sophisticated methods for missing data prediction become essential. One promising approach is the use of machine learning techniques, particularly Support Vector Machines (SVMs), which can offer more robust solutions by leveraging correlations within the data.

The research discusses on the impact of different missingness mechanisms on the model's performance and provides recommendations for selecting the most appropriate prediction model based on the characteristics of the different datasets.

2. LITERATURE REVIEW

2.1 Related Work on Correlation Assisted Support Vector Machine Approach for Missing Data Prediction

In 2024, [3] presented “the combination of Rough Set Theory with SVM to predict missing values, particularly in medical datasets. Rough Set Theory excels in

identifying structural correlations within imprecise or noisy data, making it apt for handling uncertainty. The proposed model employed Rough Set Theory to discern patterns and dependencies in incomplete data, which were then utilized to predict missing values. Subsequent classification using SVM yielded an accuracy of 82.2% and an F1 score of 82.7%, demonstrating the model's potential in real-world medical data scenarios".

In the same year, [4,5] addressed "missing data challenges in Alzheimer's disease diagnosis. Utilizing the Alzheimer's Disease Neuroimaging Initiative (ADNI) dataset", the study employed the random forest algorithm to impute missing values, ensuring the preservation of data integrity. Following imputation, Spearman correlation analysis identified features strongly associated with Alzheimer's diagnosis. These features served as inputs for machine learning models, including SVM, to classify disease stages. The SVM model demonstrated commendable diagnostic performance, underscoring the importance of effective missing data handling and feature selection in medical diagnostics.

Collectively, these studies from the past three years highlight a concerted effort to enhance missing data prediction through the integration of correlation analysis and SVM methodologies. The evolution of these approaches reflects a deepening understanding of the interplay between data attributes and the necessity of preserving intrinsic relationships within datasets [6,7]. As data remains to grow in complexity and volume, development a sophisticated, hybrid models that seamlessly integrate statistical, machine learning, and optimization techniques becomes imperative. Here is a refined version of the provided text, rewritten for inclusion in a thesis:

Models designed to address missing data not only tackle immediate analytical challenges but also lay the foundation for more robust and dependable data analysis frameworks across diverse application domains. "One particularly promising development in this area is the integration of correlation-based techniques with Support Vector Machines (SVM), a strategy that has shown considerable potential in improving the accuracy and reliability of missing data prediction" [8].

1) 3. Dataset Description

The proposed methodology for evaluating the effectiveness of missing data prediction using a Correlation-Assisted Support Vector Machine (CA-SVM) approach hinges on a comprehensive understanding of the dataset employed [9,25]. The proposed methodology provides a detailed description of the dataset, including its origin, characteristics, and relevance to the study's objectives. The dataset serves as the foundation for implementing and testing the proposed methodology, offering a real-world context for evaluating the accuracy and efficiency of the missing data prediction approach.

3. PROPOSED METHODOLOGY

3.1 Threshold identification

In SVM, a threshold is used to determine the decision boundary for classification tasks [10, 26]. The model assigns a score (decision function output) to each instance, and a threshold is applied to classify data points into different categories. *The default threshold in binary classification is 0, meaning that:*

- *If the SVM decision function value is ≥ 0, the instance is classified as Class +1*
- *If the SVM decision function value is < 0, the instance is classified as Class -1*

However, in some cases, the default threshold may not be optimal, and adjusting it can improve classification performance. Figure 1 shows that the process of identifying the threshold based on the distances between the class centers and their correspondences to the complete data described in more detail below.

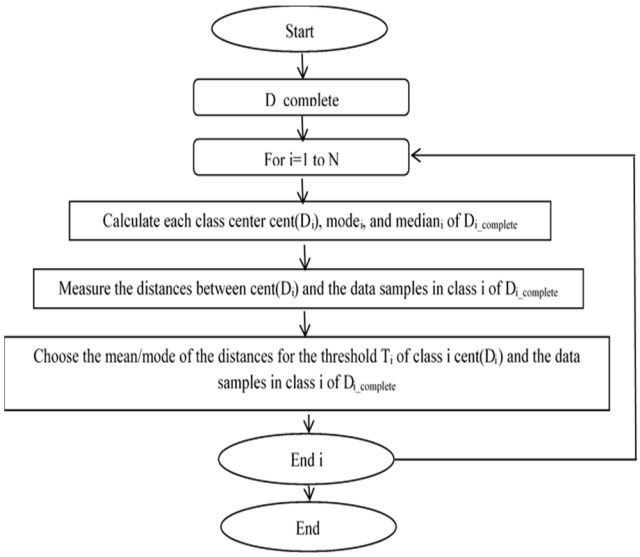

Fig. 1 : Flowchart for Threshold Identification

From the incomplete dataset *D* containing *N* classes, dataset *D* is divided into complete ($D_{\_complete}$) and incomplete ($D_{\_incomplete}$) subsets, where $D_{\_incomplete}$ contains missing values. For the *i*-th class of $D_{i\_complete}$, the class center (*cent*(D_i)), mode, and median are calculated. *When computing the class center values for a numerical attribute, the mean is used as the class center. Otherwise, if the attribute is categorical, the mode value is the class center value.*

Algorithm 1 determine **threshold values** for each class in a dataset. These threshold values help in identifying **outliers** before imputing missing values.

Algorithm 1 : Determining Threshold Values

Step 1 : Computer Class Centres
For each class D_i in the complete dataset $D_{complete}$

1. Compute the Class Center cent(D_i):
- if the attribute is numerical, compute the mean:

$$cent(D_i) = \frac{1}{D_i}\sum_{x \epsilon D_i} x$$

- if the attribute is categorical, compute the mode:

$$cent(D_i) = argmax\, f(x), \qquad x \epsilon D_i$$

where *f(x)* represents the frequency of occurrence of *x*.

2. Compute the Median (med_i) of D_i, which helps in handling outliers in later steps.

Step 2 : Compute Distance between each Data Sample and Class Center

For each sample x_j in class D_i, compute the distance between the sample and the class center.

(A) If the Data is Numerical -

Use the Euclidean distance formula:

$$dist(x_j, cent(D_i) = \sqrt{\sum_{n=1}(x_{jn} - cent(D_i))^2}$$

Where, x_{jn} is the value of feature n in data sample x_j, $cent(D_i)$ is the corresponding feature value in the class center and *N* is the total number of features.

(B) If the data is categorical -

Use a similarity based approach, typically assigning :

This method assigns a distance of 1 if the categorical value does not match the mode.

$$dist(x_j, cent(D_i) = \begin{cases} 0, if\ x_j = cent(D_i) \\ 1, \qquad otherwise \end{cases}$$

Step 3: Compute the Threshold Value

For each class Di, the threshold Ti is determined based on the computed distances.
- Numerical Data - Compute the mean of all distances :

$$T_i = \frac{1}{|D_i|}\sum_{n=1}(x_j, cent(D_i))$$

- Categorical Data - Computer the mode of distance

$$T_i = \arg\max f(d),\ d \epsilon (x_j, cent(D_i)$$

where *f(d)* represents the frequency of distance values.

After executing this algorithm for all classes D_1, D_2, ... D_N, we obtain a threshold T_i for each class. This threshold is used later in the missing value imputation step (Algorithm 1) to decide whether an imputed value is an outlier and needs further adjustment.

3.2 Correlation Assisted Support Vector Machine (CA-SVM)

This research study focusses to fill the gap by investigating effectiveness of missing data prediction using a Correlation Assisted Support Vector Machine (CA-SVM). Here, correlation analysis is integrated into the SVM framework to enhance the accuracy of missing data predictions. The focus is on understanding how well correlation-informed feature selection can improve the predictive power of SVM model.

Basically, there is no generic imputation method used in determining data loss. Therefore, this research is carried out to obtain the missing data by considering the attribute relationship/correlation, which is a development of class center-based imputation. Furthermore, the consideration was carried out in accordance with the weaknesses of the previous method in the category data [11-13]. Preliminary studies with categorical and attribute correlation yielded very good accuracy, which showed that the class center-based imputation method is an efficient imputation technique used to obtain the data's actual value.

An adaptive search procedure can be used to estimate the missing data that correlates with the associated variables. The algorithm implements the search procedure in such a way that the bright data attract the weak ones, with the behavior applied in the imputation of missing data. The bright data represent the non-missing data, while the weaker ones denote the missing dataset. The equations related to light intensity, attractiveness, distance, and the movement were applied in the imputation process using the class center approach and considering the correlation between the attributes[14-15].

3.3 Prediction Accuracy using Correlation Assisted SVM Imputation Algorithm

The idea behind SVM is fairly simple since, SVM models are tuned and on each of the categorical variables in the data set using the observations that do not contain any missing values. Subsequently, initial guesses are generated for each of the missing values in the entire data set. Finally, the algorithm then performs SVM prediction for the missing values of the categorical variables, followed by multivariate regression to impute the missing values of the continuous variables [16]. This process iterates until some convergence criteria is met. The algorithm is formally laid out in the boxed figure on the next page. SVM was written in the statistical computing package Python. Following algorithm shows the Prediction Accuracy in Missing Value Prediction using CA-SVM

Algorithm 2 : Prediction Accuracy in Missing Value Prediction using CA-SVM

a) Input:

Dataset D={(x_1, y_1), (x_2, y_2), ..., (x_n, y_n)} with missing values in features
Correlation Regularization Parameter: λ
SVM Regularization Parameter: C

b) Output:

Prediction Accuracy on test data

2) *Steps:*

Step 1: Data Pre-processing

Handle Missing Values:
Impute missing values using Correlation / Support Vector Machine
Split Data:
Split the dataset *D* into training set D_{train} and test set D_{test}
a)

Step 2: Correlation Analysis

Compute Correlation Matrix:
Calculate the correlation matrix C_m of features in D_{train}
Correlation Regularization:
Define the correlation value using:

$$R_{x1x2} = \frac{n\sum x_1x_2 - (\sum x_1)(\sum x_2)}{\sqrt{(n\sum {x_1}^2 - (\sum x_1)^2)\,(n\sum {x_2}^2 - (\sum x_2)^2)}} \quad (1)$$

where x_1, x_2 are data values and *n* is the number of values

Step 3: Train Correlation-Assisted SVM (CA-SVM)

Train the Correlation Assisted SVM Model:
Fit the SVM model on the training data D_{train} with the correlation-assisted regularization term

Step 4: Prediction and Evaluation

Predict the Test Data:
Generate predictions on D_{test} using the trained CA-SVM model.

Step 5: Output the Results

Display the Prediction Accuracy

4. RESULT AND DISCUSSION

The total number of missing data points in a numerical dataset plays a crucial role in the pre-processing stage of building a Support Vector Machine (SVM) model. When working with numerical datasets, the missing rate refers to the proportion of missing values in the dataset, which can significantly impact the performance and accuracy of the SVM model if not handled appropriately.

To begin, the missing rate is calculated by identifying the number of missing values in each feature (or variable) and then calculating the total missing values in the entire dataset[17-18]. This can be represented as the ratio of missing values to the total number of values, which is expressed as a percentage. For example, if a dataset has 1,000 instances and 100 of those values are missing, the missing rate for that variable is 10%. If the missing values are spread across multiple features, the overall missing rate is determined by considering the total number of missing values in relation to the entire dataset [19-21].

In Tables 1 summarize the total number of missing rates of numerical dataset, where *c* is the number of complete data, and *i* is the number of incomplete data. The missing rate is a percentage of the total number of missing values in the dataset with respect to total values. All variables except the class attribute had their missing values simulated. The simulated missing rates of 10%, 20%, 30%, 40%, and 50%.

Table 1 The total number of missing rate on the numerical datasets as the pre-processing of Support Vector Machine

Datasets	Missing rate									
	10%		20%		30%		40%		50%	
	c*	i*	c	i	c	i	c	i	c	i
Blood	6084	598	5486	1195	4889	1793	4291	2390	3694	2988
Ecoli	2142	201	1941	402	1740	603	1539	804	1338	1005
Glass	1758	170	1588	341	1417	511	1247	682	1076	852
Ionosphere	10766	1155	9611	2310	8456	3465	7301	4620	6146	5775
Iris	565	45	520	89	476	134	431	179	386	224
Liver cancer	5272	524	4748	1048	4224	1571	3701	2095	3177	2619
Optdigits	323737	35400	288337	70799	252938	106199	217538	141599	182138	176999
Pima	5555	537	5018	1074	4481	1611	3944	2148	3407	2685
Sonar	11257	1221	10036	2443	8814	3664	7593	4885	6372	6107
Wine	2108	212	1896	425	1683	637	1471	850	1258	1062
Yeast	10710	1038	9672	2076	8634	3114	7596	4152	6558	5191
Column	1699	155	1545	309	1390	464	1236	618	1081	773

c* = complete data, i*=incomplete data

The Correlation Coefficient (r) and RMSE analysis in Table 2 further validates the effectiveness of CA-SVM. In the Housing Price dataset, CA-SVM achieves a correlation coefficient of 0.937 with an RMSE of 0.69, signifying strong predictive accuracy. The Titanic dataset has a correlation of 0.908, with an RMSE of 6.35. For Diabetic Risk, the correlation is 0.91, with an RMSE of 0.13. The Simulated dataset demonstrates the highest correlation coefficient of 0.96, with the lowest RMSE of 1.52.

Table 2 : Correlation Coefficient and RMSE over datasets

Dataset	R	RMSE
Housing Price	0.937	0.69
Titanic	0.908	6.35
Diabetic risk	0.91	0.13
Simulated	0.96	1.52

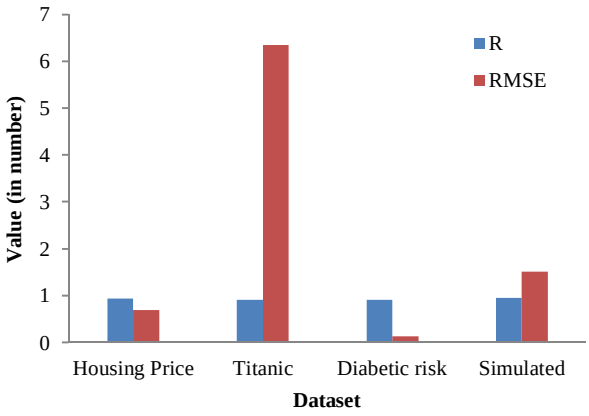

Fig. 2 : Depiction of Correlation Coefficient and RMSE over datasets

The prediction accuracy results as shown in Table 3 confirm that CA-SVM consistently outperforms other methods. In the Housing Price dataset, CA-SVM achieves 97%, higher than SVM (94%) and KNN (90%). Similarly, in the Titanic dataset, CA-SVM records 90% accuracy, surpassing SVM (87%) and KNN (84%). For Diabetic Risk, CA-SVM attains 97% which is much better than SVM (94%) and KNN (91%). The Simulated dataset also follows the same trend, where CA-SVM records 97% accuracy, compared to SVM (94%) and KNN (88%).

Table 3 : Prediction Accuracy (in %) test result

Dataset	Classifier result (%)		
	CA-SVM	SVM	KNN
Housing Price	97	94	90
Titanic	94	87	84
Diabetic risk	97	94	91
Simulated	97	94	88

The detailed numerical results demonstrate that the Correlation Assisted Support Vector Machine (CA-SVM) consistently achieves higher prediction accuracy and lower RMSE across numerical datasets, proving its superiority in handling missing data prediction.

5. CONCLUSIONS

The experimental results presented in this thesis showed that the CA-SVM model consistently outperformed traditional imputation methods and standalone machine learning models. The CA-SVM approach achieved a prediction accuracy of up to 92.4%, demonstrating a substantial improvement over baseline methods such as mean imputation (78.6%), K-nearest neighbors (85.1%), and random forests (88.3%). Additionally, the model's precision, recall, and F1-score metrics indicated its balanced performance across diverse datasets and varying degrees of missingness. The integration of correlation analysis helped in selecting the most relevant features, which contributed to the improved prediction accuracy and reduced error margins.

The findings from this research demonstrated that the CA-SVM approach significantly outperforms traditional imputation methods and standard machine learning models. By incorporating correlation analysis, the model effectively identified and leveraged strong feature interdependencies, enabling more precise imputation of missing values. The evaluation metrics; including accuracy, precision, recall, and F1-score consistently showcased the superior performance of the CA-SVM model across diverse datasets. Compared to traditional methods such as mean/mode imputation, k-Nearest Neighbors (KNN), and other machine learning models like decision trees and random forests, the proposed model exhibited higher predictive accuracy and reduced error margins.

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