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Identification of Catheter Ablation Sites Using Patient-Specific CARTO Coordinate Data

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ABSTRACT

The global increase in population poses challenges in aging societies. As the number of atrial fibrillation (AF) cases is expected to rise due to this demographic shift, the need for efficient treatment methods is growing. This study aims to partially automate the operation of 3D mapping systems used in AF treatment with the CARTO system. We analyzed X, Y, and Z coordinate data labeled as LPV, RPV, and CTI, which were extracted from the CARTO system. A dataset comprising 10 cases was used for analysis. We defined a reference point at the LPV rooftop and calculated the Euclidean distance to each coordinate. We then compared two datasets: one containing only X, Y, and Z coordinates, and another including both coordinates and distance. First, we visualized the data using principal component analysis (PCA). Next, we evaluated the classification accuracy of four models: k-Nearest Neighbors, Random Forest, SGD Classifier, and Linear SVC. Incorporating distance data reduced the overlap of LPV, RPV, and CTI in the PCA visualization. All classification models showed significant improvements in test and training accuracy, precision, recall, and F1 score when distance data was included.

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1. INTRODUCTION

Global population trends are characterized by both rapid growth and a rising proportion of older people individuals. As of mid-November 2022, the estimated world population reached 8.0 billion and is projected to increase to 9.7 billion by the 2050s, eventually nearing 10.4 billion by the mid-2080s [1]. This growth is accompanied by a significant aging trend, with the global median age expected to rise from 26.6 years in 2000 to 37.3 years by 2050, and further to 45.6 years by 2100 [2].

By 2030, one in six people worldwide is expected to be aged 60 or older, with this number projected to double to 2.1 billion by the 2050s. A global "super-aging society appears inevitable soon. This demographic shift brings numerous challenges, including the need to promote health and well-being among older adults, ensure equity in healthcare and social services, and develop medical treatments that are both highly effective and minimally invasive.

The impact of an aging society is extensive, affecting many aspects of healthcare and social infrastructure. The growing older people population will require major changes in healthcare systems, such as expanding access to geriatric care, enhancing quality of life through preventive and palliative services, and addressing the specific medical and psychological needs of older adults. In addition, healthcare systems must respond to the increasing prevalence of age-related conditions like dementia, cardiovascular disease, and osteoporosis, driving the need for continued advances in medical research and treatment protocols.

In addition to healthcare, social systems must also adapt to support an aging population. This includes creating age-friendly environments, promoting social inclusion, and ensuring financial security for older adults. Policymakers will need to implement pension reforms, develop sustainable long-term care systems, and establish programs that promote active aging and lifelong learning. The workforce will likewise experi-

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ence changes, with greater emphasis placed on retaining older employees and recognizing the value of their experience and expertise.

Stroke, or cerebral artery disease, is a leading cause of death among older adults, second only to ischemic heart disease. A significant contributor to stroke is atrial fibrillation (AF), which increases the risk of blood clots forming and traveling to the brain. AF is especially common in older people individuals and poses a high risk for cardiogenic ischemic stroke. Although the global prevalence of AF remains below 1%, its incidence increases sharply among individuals aged 80 and older—rising to approximately 7–14% in Western countries and 2–3% in Japan [3]. Moreover, treatment-related complications are more frequent in patients aged 75 and above. As the global population continues to age, AF cases are expected to rise significantly, potentially affecting 5 to 16 million people in the United States and over 1 million in Japan by 2050. These trends emphasize the urgent need for effective and efficient therapeutic strategies and caregiving systems for this expanding patient population.

Atrial fibrillation (AF) is a type of arrhythmia characterized by erratic, disorganized contractions in the heart's upper chambers (atria). Under normal conditions, the atria contract in a coordinated manner to pump blood into the lower chambers (ventricles) [4]. However, in AF, chaotic electrical activity disrupts this synchronization, causing quivering instead of regular contractions. This irregular rhythm increases the risk of stroke, as noted above. To treat AF, physicians often use radiofrequency ablation to electrically isolate the affected veins [5]. This procedure involves the insertion of a catheter into the heart and requires precise control over the catheter's positioning. During treatment, fluoroscopy and 3D mapping systems are commonly employed to minimize radiation exposure and ensure procedural safety and accuracy.

The increasing prevalence of atrial fibrillation (AF) in the aging population calls for significant advancements in both its diagnosis and management. Early detection through routine screening and the development of improved diagnostic tools will be essential for preventing strokes and reducing the overall burden of the disease. Enhanced screening programs can identify AF in its early stages, allowing for timely intervention and more effective treatment.

Innovative diagnostic technologies—such as wearable devices and advanced imaging—are also expected to play an essential role in monitoring heart health and detecting irregular heart rhythms before severe complications arise. Treatment strategies must strike a balance between preventing strokes and minimizing the risks associated with therapy. This includes refining anticoagulant therapies to reduce bleeding risks while maintaining their effectiveness in preventing clot formation.

Researchers continue to explore new anticoagulant drugs with improved safety profiles and fewer side effects. Additionally, alternative treatments such as catheter ablation provide promising options for patients who do not respond well to medication alone. Catheter ablation uses radiofrequency energy to destroy areas of the heart responsible for abnormal rhythms, offering a potential cure for certain AF patients.

CARTO, a widely adopted 3D medical imaging technology, was first introduced globally in 1996 by Biosense Webster, a Johnson & Johnson MedTech company [6]. This innovative system has transformed the way electrophysiologists perform complex cardiac procedures. Its core mechanism relies on a triangular electromagnetic source generated by three distinct ultra-low magnetic fields, as shown in Fig. 1A. These fields enable continuous, real-time measurement of the catheter's distance from each of the magnetic generators positioned beneath the operating table.

By constantly tracking these distances, CARTO accurately localizes the catheter tip in three-dimensional space. This precise positioning is essential for mapping the heart's electrical activity and guiding catheter-based interventions with high accuracy. The ability to visualize the catheter's exact location relative to the heart's anatomy significantly improves the safety and effectiveness of procedures like catheter ablation, where targeting abnormal tissue must be done with great precision.

The real-time data provided by CARTO supports informed decision-making during procedures, helping to reduce complications and enhance patient outcomes. Since its debut, the system has become a cornerstone technology in cardiac electrophysiology, widely adopted in medical centers around the world. Its capacity to generate detailed, real-time 3D heart maps makes it invaluable for diagnosing and treating a variety of cardiac arrhythmias.

Ongoing advancements in CARTO technology continue to expand its clinical utility and improve cardiac care. To further enhance accuracy, external reference patches are placed on the patient's chest and back (Fig. 1 B). These patches detect even minor patient movements during the procedure, allowing the system to always maintain precise catheter positioning.

Fig. 1C illustrates the typical setup of the CARTO system within an electrophysiology laboratory. This configuration includes electromagnetic generators placed beneath the operating table, a catheter embedded with sensors, and external reference patches affixed to the patient's thorax. The integration of these components enables comprehensive, high-resolution mapping of the heart's electrical activity—an essential element for guiding cardiac procedures.

The CARTO system provides clinicians with accurate, real-time insights into the spatial dynamics of the targeted cardiac regions. This continuous data stream ensures precise catheter positioning, which is critical for the effective ablation of arrhythmogenic tissue. By supporting real-time feedback and constant monitoring, the system reduces the risk of procedural errors and enhances clinical decision-making. This level of precision leads to better outcomes in treating complex cardiac conditions, such as atrial fibrillation and other arrhythmias. Moreover, the system's ability to generate detailed three-dimensional maps of the heart allows for meticulous procedural planning and execution, thereby reducing the likelihood of repeat interventions.

The global medical imaging market is projected to grow from USD 41.6 billion in 2024, with a compound annual growth rate (CAGR) of 4.95% from 2025 to 2030. Key growth drivers include an aging population, the rising incidence of chronic diseases, and technological advancements such as artificial intelligence (AI). The growing demand for diagnostic imaging is closely tied to the need for early disease detection, particularly in cancer and cardiovascular conditions [7]. Recent studies also focus on automating and refining localization processes, which are vital for successful ablation therapy [8]. Furthermore, AI and advanced imaging technologies show potential in predicting atrial fibrillation recurrence after ablation, contributing to improved treatment strategies [9].

Although the CARTO system is widely used and has revolutionized cardiac procedures, it still has limitations—particularly its reliance on manual input and vulnerability to human error. During electrocautery procedures, clinicians must carefully record the specific locations requiring treatment. This manual process is time-consuming and labor-intensive, often causing stress among team members and increasing the likelihood of procedural errors that can compromise accuracy and effectiveness.

To address these limitations, we introduced and validated machine learning algorithms designed to improve the overall workflow. These algorithms automate portions of the recording process, thereby reducing the treatment team's administrative burden. By streamlining these tasks, machine learning enhances operational efficiency and allows clinicians to focus on critical aspects of the procedure.

Additionally, automation enables faster and more accurate identification of treatment sites, helping to shorten procedure times and reduce both physical and mental fatigue among medical staff—factors essential for maintaining concentration and performance. Beyond improving efficiency, machine learning significantly reduces error rates. Unlike manual processes, automated systems are less susceptible to inconsistencies and oversight, resulting in more precise and reliable procedures. Ultimately, these enhancements lead to better patient outcomes and improved procedural safety.

The main contribution of the paper includes

1). Validation of the classification models for the catheter ablation site of the CARTO coordinate data.
2). Applicability of the proposed model to person-sensitive CARTO coordinate data.
3). Viability of the proposed method without device calibration.

The rest of this paper is structured as follows: Section II covers coordinate data classification. The application of the CARTO system is introduced in Section III, followed by the dataset of ablation sites in the CARTO system in Section IV. The results of the experiment, conclusion, and future work are discussed in Sections V and VI, respectively.

2. COORDINATE DATE CLASSIFICATION

In this section, we provide an in-depth analysis of the X, Y, and Z coordinate data labeled LPV, RPV, and CTI, extracted from the CARTO system. The first step involved using principal component analysis (PCA) to reduce the dimensions while retaining the intrinsic value of the data. This reduction enabled a visual examination of the dataset's characteristics.

Following this, we conducted a comparative evaluation of prediction accuracy using four different classifiers: k-Nearest Neighbors (k-NN), Gaussian Mixture Model (GMM), Stochastic Gradient Descent Classifier (SGDClassifier), and Linear Support Vector Classifier (LinearSVC). To assess the robustness of these models, two datasets were analyzed: a single-case dataset and a combined dataset comprising 10 cases.

2.1 k-Nearest Neighbors (k-NN)

The k-Nearest Neighbors (k-NN) algorithm is a simple, yet powerful method commonly used for classification tasks in machine learning [10]. It classifies a new data point by identifying the majority class among its k nearest neighbors in the training dataset. Operating within a feature space, the algorithm analyzes input data based on its features to detect patterns and relationships. This makes k-NN especially effective for datasets with clear and distinguishable patterns.

A key parameter in the k-NN algorithm is k, which defines the number of neighbors considered during classification. The choice of k significantly influences model performance. Smaller values of k can make the model highly sensitive to noise, resulting in more variable predictions. In contrast, larger values typically yield smoother decision boundaries by averaging over a greater number of neighbors, reducing the impact of individual noisy data points.

2.2 Random Forest Classifier (RFC)

The Random Forest Classifier (RFC) is an advanced ensemble learning technique widely used for classification tasks in machine learning. It constructs multiple decision trees during the training phase, with each tree making independent predictions based on randomly selected subsets of the data and features. This randomness introduces variability, which helps reduce the risk of overfitting—a common issue in individual decision trees. Overfitting occurs when a model becomes too closely tailored to the training data, capturing noise and patterns that do not generalize well to unseen data.

In RFC, the final prediction for a new data point is determined by a majority vote among all the trees in the forest. Each tree provides a classification, and the class receiving the most votes becomes the final output. This voting mechanism improves accuracy by leveraging the collective input of multiple trees, each offering a different perspective, thereby reducing overall prediction error. By aggregating predictions, the RFC enhances model generalization and mitigates overfitting [11].

A major advantage of the Random Forest Classifier is its effectiveness in handling high-dimensional datasets with complex feature interactions. Such datasets often pose challenges for traditional models due to the "curse of dimensionality." However, the random selection of features for each tree enables RFC to capture intricate patterns and relationships efficiently, making it well-suited for complex classification problems.

2.3 SGC Classification (SGDClassifier)

The SGDClassifier is a linear classification algorithm that utilizes Stochastic Gradient Descent (SGD) for optimization [12]. It is particularly well-suited for large-scale and sparse datasets, where traditional algorithms may face performance limitations. The classifier operates by iteratively updating model weights, processing one training example at a time. This approach enables high computational efficiency and scalability, making it ideal for handling extensive datasets or streaming data that cannot be loaded into memory all at once.

Unlike batch gradient descent, which computes gradients over the entire dataset, SGD updates model parameters incrementally. By processing data in individual samples or small mini-batches, the algorithm can quickly incorporate new information and adjust the model accordingly. This incremental update process not only accelerates training but also makes the algorithm adaptive to dynamic or continuously growing datasets.

Each update step involves computing the gradient of the loss function for the model parameters for a single data point. The parameters are then adjusted in the direction that minimizes the loss, allowing the SGDClassifier to converge efficiently to a suitable solution. This makes it a powerful tool for real-time applications and high-dimensional problems where speed and scalability are critical.

2.4 Linear SVC (LinearSVC)

LinearSVC is a linear classification algorithm based on the Support Vector Machine (SVM) framework [13]. It aims to categorize data into two or more classes by identifying a linear decision boundary. The core objective of LinearSVC is to find a hyperplane—a flat affine subspace—that best separates the classes within the feature space. This hyperplane is selected to maximize the margin between classes, thereby improving the model's generalization and robustness.

The term "linear" in LinearSVC refers to the nature of the decision boundary, which is a linear combination of the input features. In two dimensions, this boundary appears as a line; in three dimensions, as a plane; and in higher dimensions, as a hyperplane. The algorithm assumes that the classes are linearly separable, making it well-suited for datasets where this assumption holds.

Unlike the general SVC algorithm, which supports various kernel functions to capture non-linear relationships, LinearSVC uses only a linear kernel. It directly computes the decision boundary without mapping the input features into a higher-dimensional space. As a result, LinearSVC offers a computationally efficient solution for high-dimensional datasets where a linear separator is sufficient.

3. CARTO SYSTEM

The CARTO system, a pivotal 3-dimensional mapping system, has achieved widespread adoption globally, offering crucial insights into cardiac electrophysiology. Introduced by Biosense Webster (now part of Johnson & Johnson) in 1996, CARTO has become an indispensable tool for guiding complex cardiac interventions.

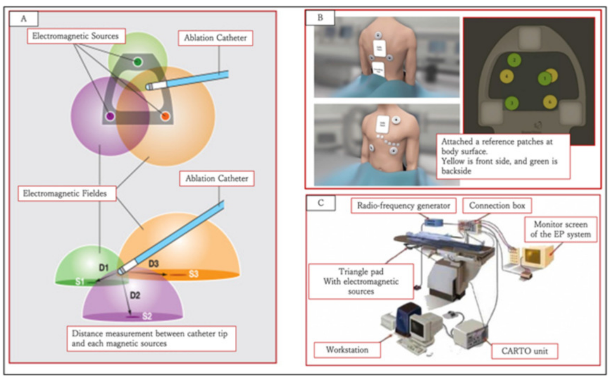

Fig.1: *Basic mechanism and typical setup of The CARTO system [6].*

Figs. 1A. to 1C. Illustrate the fundamental mechanism, patient movement monitoring, and typical setup of the CARTO system, providing a visual guide to its advanced features and applications in cardiac electrophysiology.

3.1 CARTO System Mechanism

The core functionality of the CARTO system is based on an innovative triangular electromagnetic configuration that uses three distinct ultra-low magnetic fields, as illustrated in Fig. 1A. This setup continuously measures the distance between the catheter and three magnetic generators located beneath the operating table. By triangulating these distances, the system accurately determines the catheter tip's position within a three-dimensional spatial framework.

This real-time spatial tracking is essential for navigating the heart's intricate anatomy during medical procedures. The ability to pinpoint the catheter's location with high precision enables accurate guidance and placement, which is critical for the success of catheter-based interventions. Continuous feedback allows clinicians to adjust the catheter's position dynamically, enhancing both procedural efficiency and safety.

By consistently providing detailed spatial information, the CARTO system supports more informed decision-making during cardiovascular procedures. Its precise navigation capabilities are particularly valuable in complex cardiac environments, underscoring the system's importance in modern electrophysiology, where advanced technologies are integral to improving procedural accuracy and patient outcomes.

3.2 Patient Movement Monitoring

To ensure precise measurements and address any potential unintended movements of the patient, an external reference patch is meticulously placed on both the patient's front and back, as depicted in Fig. 1B. This reference patch serves a critical role in the system by providing fixed points of reference that the system uses to monitor and detect any shifts in the patient's position during the procedure. The presence of this external reference patch helps the system continuously track the patient's position relative to the fixed magnetic field sources. If any unintended movement occurs, such as a slight shift or adjustment by the patient, the system can promptly detect these changes. By comparing the current positional data against the established reference points provided by the patch, the system can make necessary adjustments to maintain accuracy and ensure that the catheter remains precisely aligned with the intended target area. This mechanism of incorporating a reference patch is vital for maintaining the integrity of the spatial data and ensuring that the catheter's navigation remains accurate throughout the procedure. By providing a stable reference frame, the system can correct for any discrepancies that arise from patient movement, thus enhancing the overall reliability and effectiveness of the navigation process during complex medical intervention.

3.3 Laboratory Setup

Fig. 1C illustrates the standard configuration of the CARTO system in an electrophysiology laboratory. This configuration demonstrates how the CARTO system integrates advanced technologies to provide clinicians with real-time, detailed visualizations of cardiac anatomy during procedures. It highlights the coordination of multiple components that support precise and effective guidance for catheter ablation interventions.

In this system, the electromagnetic source that generates ultra-low magnetic fields is seamlessly connected to the catheter localization module, allowing for accurate, real-time tracking of the catheter's position. To maintain this precision, the system also continuously monitors patient movement, automatically adjusting for any positional shifts that may occur during the procedure.

By combining electromagnetic field generation, catheter tracking, and patient motion monitoring, the CARTO system forms a robust and responsive framework that supports accurate navigation and enhanced safety throughout catheter ablation procedures.

3.4 Catheter Ablation Targets

Common ablation sites for treating cardiac arrhythmias—particularly atrial fibrillation (AF)—play a critical role in managing abnormal electrical pathways within the heart. Key targets include the left pulmonary vein (LPV), right pulmonary vein (RPV), and the cavo-tricuspid isthmus (CTI). The LPV and RPV are especially important because they are frequent sources of ectopic electrical activity that can trigger AF. These irregular signals disrupt the heart's normal rhythm, making the pulmonary veins primary targets for ablation. Ablation procedures at these sites aim to isolate and eliminate abnormal electrical signals, thereby restoring regular cardiac function.

The cavo-tricuspid isthmus, a band of tissue between the inferior vena cava and the tricuspid valve, is another critical site—particularly in patients with atrial flutter. Abnormal electrical circuits often form in this region, and targeted ablation helps interrupt these pathways to resolve the arrhythmia. Precisely identifying and treating these key anatomical areas is essential for the effective management of AF and atrial flutter. By targeting the origin of the abnormal electrical activity, ablation therapy improves cardiac rhythm and overall heart function.

The primary goal of this research is to assess the feasibility of automating the recognition of these ablation sites within the CARTO system. This study proposes that automated methods, particularly those based on machine learning, can reduce the need for manual input, alleviating the workload and cognitive demands placed on clinical teams. By integrating machine learning algorithms, the research aims to enhance the efficiency and accuracy of identifying ablation sites—currently a manual, time-consuming task requiring specialized expertise.

Automating this process has the potential to minimize human error and promote consistency in site identification. The successful application of machine learning could streamline catheter-based procedures, improve procedural accuracy, and ultimately enhance patient outcomes. This research contributes to the ongoing advancement of the CARTO system and represents a significant step toward optimizing modern electrophysiological practices through intelligent automation.

4. DATASET OF ABLATION SITE IN THE CARTO SYSTEM

Principal component analysis (PCA) was applied solely for data visualization. In the single-case dataset, the LPV, RPV, and CTI labels appeared distinctly separated, with no visible overlap (Fig. 2A). This visual distinction highlights the CARTO system's ability to capture and represent detailed spatial patterns specific to each ablation site. It suggests that the system can accurately map and differentiate these sites in individual cases, demonstrating its effectiveness in controlled conditions.

However, when PCA was applied to a more diverse, mixed dataset comprising 10 cases, a different pattern emerged. The data labeled as RPV showed noticeable overlap with both LPV and CTI labels (Fig. 2C). This result underscores the increased complexity that arises when analyzing data from multiple patients. Variability in cardiac anatomy and catheter placement across individuals can lead to overlapping spatial distributions, which complicates classification.

It is important to note that PCA was used exclusively for visualization, and no PCA-derived features were included in subsequent classification or quantitative analysis. These observations are based solely on visual inspection of the PCA plots rather than on statistical evaluation of component scores.

The 2D transformation of the original spatial coordinates (X, Y, Z) using PCA effectively reveals the spatial relationships among ablation sites. In the single-case scenario, the LPV, RPV, and CTI remain clearly distinguishable (Fig. 2B). In contrast, the 10-case mixed dataset again shows that RPV overlaps with both LPV and CTI (Fig. 2D), emphasizing the need to account for patient variability when designing automated recognition systems. Addressing this variability is essential for improving classification accuracy and ensuring reliability across diverse clinical settings.

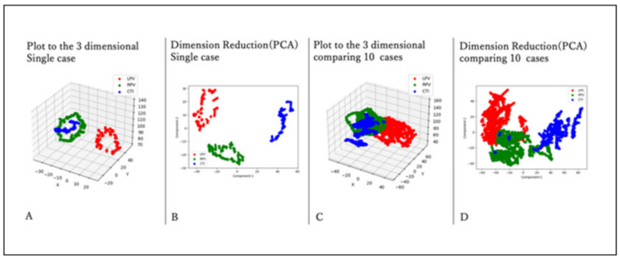

Fig.2: *Visualizing 3-dimensional data extracted from the CARTO system for a single case [A] and its PCA dimension reduction [B]; comparing to the data of 10 cases [C] and its PCA dimension reduction [D].*

We compiled a dataset of 707,052 rows by integrating data from 10 patients, as shown in Fig. 3. This dataset reflects a wide range of cases and captures the key characteristics and subtle variations in ablation sites across individuals. Its diversity is essential for representing the variability and complexity found in real-world clinical scenarios.

The large scale of this dataset provides a strong foundation for training a predictive model. With such a substantial volume of data, the model can more effectively learn spatial patterns, improve its prediction accuracy, and adapt to the variations observed in different patients. Ultimately, this comprehensive dataset enhances the model's reliability and makes it better suited for handling the challenges of diverse patient populations.

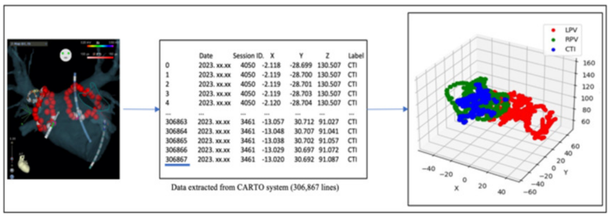

Fig.3: *Data integration.*

In the CARTO system, cauterization sites are recorded not only as X, Y, and Z coordinates but also as time-series data, including catheter temperature, output (watts), and resistance values during energy application. However, because this study focused on the automatic identification of treatment sites, we used only the spatial coordinates. Variables such as temperature, output, and resistance depend heavily on the surgeon's technique and are therefore unsuitable for building a generalized model. For this reason, we excluded them from the feature engineering process.

To capture the complex relationships within the dataset, we adopted a supervised learning approach. We trained a predictive model to classify data points as LPV, RPV, or CTI based solely on their X, Y, and Z coordinates. This machine learning–based model not only improved label prediction accuracy but also revealed spatial patterns and interactions within the cardiac anatomy.

To further enhance model performance, we introduced reference points on the LPV rooftop and calculated the Euclidean distance from each data point to the reference, as shown in Fig. 4A. We combined this distance information with the X, Y, and Z data to refine the input features. Integrating this geometric information led to a noticeable improvement in label separation, reducing overlap among LPV, RPV, and CTI clusters in the PCA visualization (Fig. 4B). This result suggests that adding spatially informed features can significantly improve the model's ability to distinguish among ablation sites, making classification more accurate and the relationships within the dataset more apparent.

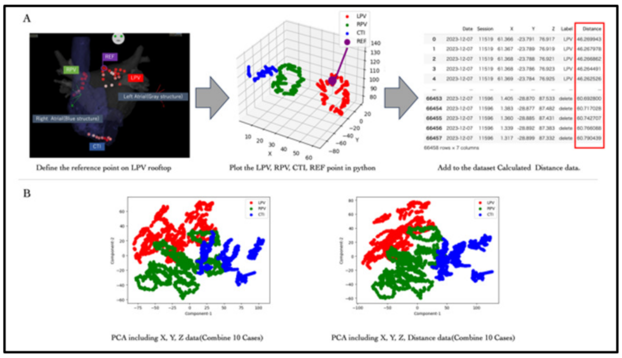

Fig.4: *Creating reference points on the LPV rooftop, calculating distances from those points, and adding them to the dataset [A]. Visualizing the dataset using Principal Component Analysis (PCA) with only the coordinate axis data (X, Y, Z) and the dataset augmented with distance data in Figure [B].*

To improve predictive performance, the model development process included careful feature engineering. Key features considered included spatial relationships among data points, proximity to defined reference points, and—where applicable—temporal dynamics that might influence ablation site characteristics. Incorporating these features enabled the model to better capture the complex patterns and relationships within the dataset.

This comprehensive approach combined advanced visualization, statistical analysis, and machine learning techniques. The integration of these methods not only improved the accuracy of ablation site prediction but also provided deeper insights into the spatial and anatomical variations of the heart. The rigor of this methodology supports a more refined understanding of the factors influencing ablation site behavior.

Insights gained from this study offer a strong foundation for improving clinical workflows and advancing the precision and effectiveness of catheter ablation procedures.

5. RESULTS OF EXPERIMENT

To evaluate classifier performance, we conducted a comprehensive assessment. All classifiers achieved perfect accuracy (1.0) on the single-case dataset, indicating flawless identification of ablation site labels in this controlled setting. This result highlights the effectiveness of each model under simplified conditions.

However, when we expanded the evaluation to a mixed dataset of 10 cases, noticeable differences in performance emerged. To analyze these differences, we applied cross-validation by using one case for testing while training on the remaining nine. This process was repeated across all 10 datasets (Data 1 through Data 10) to ensure a robust and reliable comparison.

We compared two types of datasets: one containing only X, Y, and Z spatial coordinates, and another incorporating distance measurements from a reference point on the LPV rooftop (X, Y, Z, Distance). This comparison aimed to assess how the inclusion of distance features influenced classification performance across models.

The results, summarized in Fig. 5, show how classifier accuracy varied depending on the dataset used. Incorporating distance metrics led to performance improvements in most cases, particularly in separating overlapping ablation site labels. To visualize variability, we included standard deviation as an error bar in the performance metrics. These error bars are essential for illustrating fluctuations caused by different data splits during cross-validation.

Overall, the findings highlight the crucial role of feature engineering in enhancing model performance and emphasize the value of detailed data analysis in developing accurate and generalizable classification systems.

We generated a Q-Q plot to compare the classification performance between the X, Y, Z dataset and the X, Y, Z, Distance dataset, as shown in Fig. 6. The data points closely aligned along the diagonal line, indicating that the performance differences followed a normal distribution. This suggests that the observed variations are statistically valid and can be analyzed using standard parametric methods.

These findings confirm that the inclusion of distance features affects model performance in a measurable and statistically sound manner, providing an essential basis for further evaluation and model refinement.

As shown in Fig. 7, we assessed the normality of classifier performance data using the Shapiro–Wilk test for both the X, Y, Z dataset and the X, Y, Z, Distance dataset. The results indicated that the X, Y, Z dataset followed a normal distribution in 70% of cases. In contrast, the X, Y, Z, Distance dataset did not follow a normal distribution in 75% of cases.

Based on these findings, we applied the Wilcoxon signed-rank test to compare classification performance across multiple evaluation metrics, including

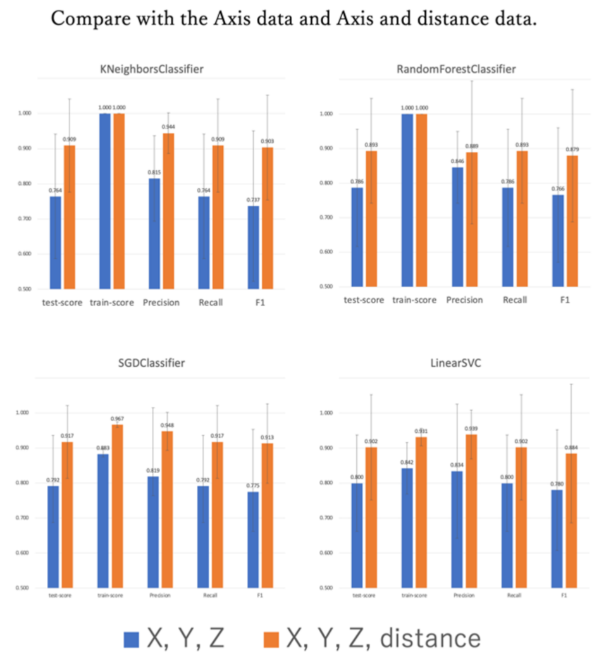

Fig.5: *A comprehensive comparison of prediction accuracy, precision, recall, and F-1 score among the k-NN, RFC, SGDClassifier, and LinearSVC.*

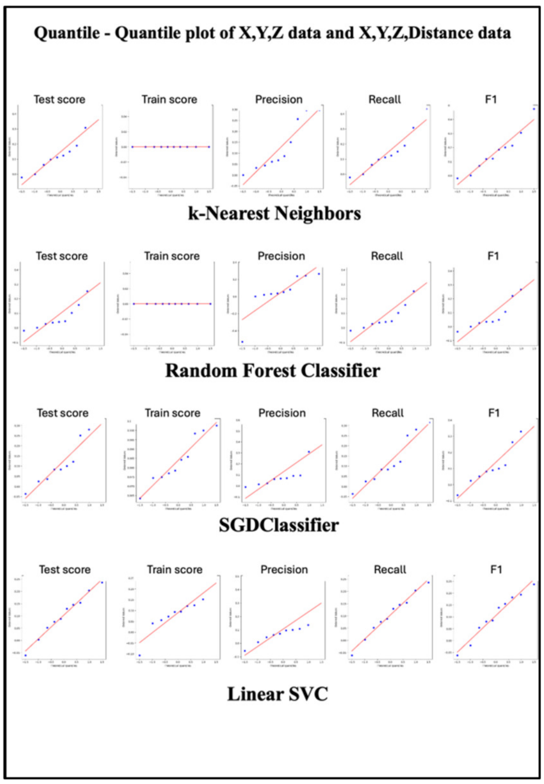

Fig.6: *A Q-Q plot of classification performance differences between the X, Y, Z dataset and the X, Y, Z, Distance dataset.*

test accuracy, training accuracy, precision, recall, and F1-score. The results showed statistically significant improvements ($p < 0.05$) across all metrics when distance data were included. These p-values indicate that the enhanced performance of the X, Y, Z, Distance dataset is not due to chance.

This analysis demonstrates that incorporating distance features significantly improves the classifier's ability to distinguish between ablation site labels, reinforcing the value of geometric feature engineering in spatial data modeling.

		test	train	Precision	Recall	F1
k-NN	p value of Shapiro–Wilk test(X,Y,Z)	0.1259	1	0.6401	0.1259	0.1342
	p value of Shapiro–Wilk test(X,Y,Z,Distance)	0.001	1	0.1447	0.001	0.0004
	p value of Wilcoxon signed-rank test	0.0108	–	0.0076	0.0108	0.0108
RFC	p value of Shapiro–Wilk test(X,Y,Z)	0.1359	1	0.5997	0.1359	0.2297
	p value of Shapiro–Wilk test(X,Y,Z,Distance)	0.0005	1	0	0.0005	0.0001
	p value of Wilcoxon signed-rank test	0.0108	–	0.1097	0.0108	0.0284
SGC Classification	p value of Shapiro–Wilk test(X,Y,Z)	0.0128	0.7872	0.0001	0.0128	0.0043
	p value of Shapiro–Wilk test(X,Y,Z,Distance)	0.015	0.4191	0.0329	0.0015	0.0015
	p value of Wilcoxon signed-rank test	0.009	0.0019	0.0039	0.0097	0.0097
Linear SVC	p value of Shapiro–Wilk test(X,Y,Z)	0.0907	0.7769	0.0001	0.09	0.0109
	p value of Shapiro–Wilk test(X,Y,Z,Distance)	0.0001	0.7913	0.0082	0.0001	0
	p value of Wilcoxon signed-rank test	0.0097	0.0273	0.0097	0.0097	0.0136

Fig.7: *Figure 7. A Q-Q plot of classification performance differences between the X, Y, Z dataset and the X, Y, Z, Distance dataset.*

We derived performance metrics through a robust cross-validation process, with reported values representing the average results from multiple iterations. The high accuracy achieved by all classifiers on the single-case dataset demonstrates their effectiveness in identifying and categorizing distinct ablation site patterns under controlled conditions. This strong performance indicates that the models were well-equipped to distinguish between LPV, RPV, and CTI labels when analyzing isolated data.

However, introducing a mixed dataset composed of 10 different cases revealed more complex classification challenges. Variations in performance metrics reflected the added difficulty introduced by patient-to-patient variability. These challenges align with the overlapping label patterns observed in the principal component analysis (Fig. 2), which exposed the classifiers' limitations in maintaining consistent performance across diverse clinical data.

To address this issue, we incorporated distance measurements from reference points on the LPV rooftop into the spatial coordinate data (X, Y, Z). This addition enhanced the representation of spatial features within the dataset, helping the models differentiate between previously overlapping labels more effectively.

Among the models, the SGD classifier—based on a linear approach—achieved the highest test scores for precision, recall, and F1-score. This result emphasizes the benefit of incorporating distance features, which improved the model's ability to accurately classify ablation sites by reducing ambiguity caused by spatial overlap.

The findings of this study highlight the importance of incorporating distance data as a key feature for accurately identifying catheter ablation burn sites. The performance comparison shown in Fig. 5 provides a valuable reference for selecting appropriate classifiers based on the dataset's specific characteristics. It offers insights into the relative strengths and limitations of each model in handling the complex spatial patterns found in CARTO system data.

These insights are essential for optimizing machine learning models, resulting in improved accuracy and effectiveness in predicting ablation site labels. Such advancements can enhance the clinical utility of these technologies, contributing to more precise catheter ablation procedures and better patient outcomes

6. CONCLUSION

The CARTO system currently lacks a standardized reference point for individual patients, which leads to label overlap within the mixed dataset and significantly reduces predictive accuracy. To address this limitation, we found that introducing a shared reference point and incorporating distance information can substantially enhance classification performance.

Given the exceptional accuracy achieved by the linear model, these enhancements are essential for revealing the intrinsic structure of the data and improving the model's ability to distinguish between ablation site labels.

AUTHOR CONTRIBUTIONS

Naoki Tomizawa: Conceptualization, Methodology, validation, investigation, data curation, writing-original draft preparation, visualization. Virach Sornlertlamvanich: Conceptualization, methodology, formal analysis, validation, supervision, writing-review. Thatsanee Charoenporn: Methodology, validation, investigation, formal analysis, writing-review and editing.

References

[1] United Nations, "Population," United Nations, 2022. [Online]. Available: `https://www.un.org/en/global-issues/population`. [Accessed: Jul. 24, 2024].

[2] W. Lutz, W. Sanderson and S. Scherbov, "The coming acceleration of global population ageing," *Nature*, vol. 451, no. 7179, pp. 716–719, Feb. 2008.

[3] E. Kodani and H. Atarashi, "Prevalence of atrial fibrillation in Asia and the world," *Journal of Arrhythmia*, vol. 28, no. 6, pp. 330–337, Dec. 2012.

[4] M. Haissaguerre *et al.*, "Spontaneous initiation of atrial fibrillation by ectopic beats originating in the pulmonary veins," *The New England Journal of Medicine*, vol. 339, no. 10, pp. 659–666, Sep. 1998

[5] M. Haissaguerre *et al.*, "Electrophysiological breakthroughs from the left atrium to the pulmonary veins," *Circulation*, vol. 102, no. 20, pp. 2463–2465, Nov. 2000.

[6] P. Maury, B. Monteil, L. Marty, A. Duparc, P. Mondoly, and A. Rollin, "Three-dimensional mapping in the electrophysiological laboratory," *Archives of Cardiovascular Diseases*, 2018.

[7] Grand View Research, "Medical Imaging Systems Market Analysis Report by Product (X-ray, Ultrasound, MRI, CT, Nuclear Imaging), by Application (Oncology, Cardiology, Neurology), by Region, and Segment Forecasts, 2024–2030," *Grand View Research*, 2024. [Online]. Available: `https://www.grandviewresearch.com/industry-analysis/medical-imaging-systems-market`. [Accessed: Jul. 24, 2024].

[8] X. Wang, "A Machine Learning Approach to Automated Localization of Targets for Ventricular Tachycardia Ablation Using Sinus Rhythm Signal Features," *Computing in Cardiology*, vol. 51, 2024.

[9] E. T. Truong, "Beyond Clinical Factors: Harnessing Artificial Intelligence and Multimodal Cardiac Imaging to Predict Atrial Fibrillation Recurrence Post-Catheter Ablation," *Journal of Cardiovascular Development and Disease*, vol. 11, no. 9, p. 291, 2024.

[10] T. Cover and P. Hart, "Nearest neighbor pattern classification," *IEEE Transactions on Information Theory*, vol. 13, no. 1, pp. 21–27, Jan. 1967.

[11] C. M. Bishop, *Pattern Recognition and Machine Learning*. New York: Springer, 2006.

[12] L. Bottou and O. Bousquet, "The tradeoffs of large-scale learning," in *Advances in Neural Information Processing Systems (NeurIPS)*, vol. 20, pp. 161–168, 2008.

[13] C. Cortes and V. Vapnik, "Support-vector networks," *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.

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