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Robust Midpoint Classifier (RMC): A Simple and Robust Linear Alternative to Support Vector Machines

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Abstract

This paper proposes the Robust Midpoint Classifier (RMC), a simple and interpretable linear classification rule that connects centroid-based methods with margin-based approaches such as Support Vector Machines (SVM). RMC constructs the decision boundary as the perpendicular bisector between robust class centroids obtained via α-trimmed means, thereby reducing the influence of outliers while preserving a clear geometric interpretation. We present a unified formulation of RMC as a robustified nearest-centroid rule and analyse its behaviour in mean-shift settings. A simulation study based on repeated experiments compares RMC with a linear SVM under four scenarios: clean Gaussian data, outlier contamination, strong class overlap, and heterogeneous covariance structures. The results show that RMC matches SVM on clean and moderately contaminated data, slightly outperforms SVM in the overlap scenario, and remains competitive when covariances differ. Overall, RMC offers a computationally light and robust alternative for binary linear classification.

Keywords: Robust classification, Midpoint classifier, Support vector machines, α-trimmed means, Outlier contamination.

1 | Introduction

Support Vector Machines (SVMs) are among the most widely used and theoretically grounded supervised learning methods for classification and regression. By constructing a separating hyperplane that maximizes the margin between classes, SVMs achieve strong generalization performance, making them a central tool in statistical learning and modern Artificial Intelligence (AI) applications [1–3].

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SVMs have been successfully applied across diverse domains, including bioinformatics, image recognition, text categorization, signal processing, and financial modeling. Their ability to handle high-dimensional feature spaces, integrate kernel functions, and incorporate domain-specific regularization strategies contributes to their widespread adoption [1], [4].

Despite these advantages, classical SVMs are sensitive to outliers and mislabeled data. Since support vectors directly define the decision boundary, even a small number of atypical samples can substantially distort the hyperplane, especially in heavy-tailed distributions, label-noisy datasets, or heterogeneous covariance structures—common challenges in real-world AI applications [5–7].

Several approaches have been proposed to reduce this sensitivity, including robust loss functions, reweighting or trimming extreme samples, preprocessing techniques, and distributionally robust or adversarial optimization variants of SVM. Centroid- or prototype-based classifiers have also been explored, leveraging robust estimates such as α-trimmed means to achieve computational simplicity, interpretability, and enhanced robustness [5], [8], [9].

Motivated by these developments, we propose a novel robust centroid-based approach to mitigate SVM's sensitivity to outliers. Our method builds upon the Robust Midpoint Classifier (RMC), which constructs a decision boundary by estimating class centroids through α-trimmed robust measures and forming a perpendicular bisector between them. The proposed approach combines the geometric clarity of centroid-based rules with robustness against contamination.

The resulting RMC classifier is simple, fast, and considerably less sensitive to outliers than conventional linear SVM. Unlike many robust SVM variants, it does not rely on solving an optimization problem, making it computationally light and suitable for high-dimensional settings.

We evaluate RMC against standard linear SVM across various scenarios, including clean Gaussian data, moderate contamination with outliers or label noise, strong class overlap, and heterogeneous covariance structures. Performance metrics include accuracy, balanced accuracy, Receiver Operating Characteristic (ROC)-based measures, and computational efficiency.

The remainder of the paper is structured as follows. Section 2 reviews related work on robust classification methods. Section 3 presents the RMC methodology and its computational properties. Section 4 reports simulation studies, followed by the findings of the simulation studies in Section 5 and conclusions in Section 6.

2 | Related Work

To provide a context for the articulation of our method, in this section we refer to selected prior works ranging from general classification approaches to SVM–based methods and their robust variants.

Based on prior studies on classification methods conducted over the last decade, including works by Chandra and Bedi [10], Condran et al. [11], and Abdullah and Abdulazeez [4], research on classification methods has significantly advanced over the past decades, driven by the increasing demand for reliable, accurate, and interpretable machine learning models. In general, classification algorithms are designed to attribute labels to samples based on feature information, and their applications span a variety of domains. Early studies highlighted the importance of selecting appropriate models and hyperparameters to achieve high predictive performance, as well as addressing practical issues such as class imbalance and high-dimensional data.

Several works, such as those by Gou et al. [12], Sourati et al. [13], Saralajew et al. [14], and Wang and Zhang [15], have investigated different classification techniques, from nearest-neighbor and prototype-based approaches to ensemble methods and kernel-based learning. Prototype-based models, in particular, offer interpretability and conceptual simplicity, forming decision boundaries based on representative points for each class. While these methods provide robustness to small perturbations and clear geometric intuition, their predictive performance can be limited in complex or high-overlap scenarios.

Building on the extensive literature on SVM applications reported in studies by Wang and Shao [16], Guido et al. [17], Malashin et al. [18], and Abdullah and Abdulazeez [4], SVMs have emerged as one of the most powerful and widely used classifiers due to their solid theoretical foundations and strong performance across diverse domains, including healthcare, image analysis, text recognition, and industrial applications. SVMs construct decision boundaries that maximize the margin between classes, offering robustness and generalization capabilities. Numerous SVM variants, such as twin SVM, least-squares SVM, and kernel-based SVM, have been developed to enhance accuracy, reduce computational cost, and adapt to domain-specific challenges [10], [19], [20].

Considering the challenges of noise and data uncertainty highlighted in works by Ye et al. [21], Faccini et al. [22], Chuah et al. [23], and Asimit et al. [5], classical SVMs are sensitive to outliers, label noise, and heterogeneity in feature distributions. To address these limitations, several robust SVM formulations have been proposed, including models with nonconvex loss functions, distributionally robust optimization, and adaptive weighting schemes. These approaches aim to preserve predictive performance while mitigating the influence of atypical observations, but often at the expense of increased computational complexity and reduced interpretability [16], [19], [20], [24].

Summarizing the evidence from prior investigations [16], [19], [24], the literature highlights a clear trade-off between robustness, computational efficiency, and interpretability in linear classification methods. These findings motivate the development of alternative approaches, such as the proposed RMC, which leverages robust estimates of class centroids to construct a simple, fast, and interpretable linear decision boundary that mitigates the sensitivity of classical SVM to outliers.

3 | Methodology

In this section, we introduce a robust linear classifier, the RMC, based on a perpendicular bisector constructed from robust estimates of the class centroids. The method is designed to reduce the influence of outliers while retaining the geometric simplicity and interpretability of centroid-based linear decision rules.

3.1 | Problem Setup

Let

$$\mathcal{D}_n = \{(x_i, y_i)\}_{i=1}^{n},$$

denote a training sample, where each feature vector satisfies $x_i \in \mathbb{R}^d$ and each class label satisfies $y_i \in \{-1, +1\}$. We define the index sets of the two classes as

$$\mathcal{I}_+ = \{i: y_i = +1\},$$

$$\mathcal{I}_- = \{i: y_i = -1\},$$

with corresponding class sizes

$$n_+ = | \mathcal{I}_+ |,$$

$$n_- = | \mathcal{I}_- |,$$

$$n = n_+ + n_-.$$

A linear classifier is specified by a weight vector $w \in \mathbb{R}^d$ and a bias term $b \in \mathbb{R}$, and predicts the class label of a new point $x \in \mathbb{R}^d$ according to

$$g(x) = \mathrm{sign}\big(f(x)\big),$$

Where

$$f(x) = w^{\top}x + b.$$

The goal is to construct (w, b) in a way that balances classification accuracy and robustness to outliers.

3.2 | Classical Midpoint (Perpendicular Bisector) Classifier

Centroid-based classifiers are theoretically well-founded in high-dimensional settings, where they can achieve optimal classification performance under mild conditions on sparsity and dependence [25]. A natural geometric baseline is obtained by considering the empirical class centroids:

$$\hat{\mu}_+ = \frac{1}{n_+}\sum_{i\in\mathcal{I}_+} x_i,$$
$$\hat{\mu}_- = \frac{1}{n_-}\sum_{i\in\mathcal{I}_-} x_i. \tag{1}$$

The connecting vector between these centroids is then given by

$$v = \hat{\mu}_+ - \hat{\mu}_-, \tag{2}$$

and their midpoint is

$$m_0 = \frac{\hat{\mu}_+ + \hat{\mu}_-}{2}. \tag{3}$$

The hyperplane orthogonal to v that passes through m_0 is defined by

$$v^{\top}(x - m_0) = 0. \tag{4}$$

This Equation leads to the midpoint classifier:

$$g_{MC}(x) = \mathrm{sign}(v^{\top}(x - m_0)). \tag{5}$$

It is straightforward to verify that, under the Euclidean metric, the decision *Rule (5)* is equivalent to the nearest-centroid classifier based on $\hat{\mu}_+$ and $\hat{\mu}_-$. Moreover, under a Gaussian model with equal spherical covariances, the midpoint classifier coincides with the Bayes-optimal linear decision boundary. However, the empirical *Centroids (1)* are highly sensitive to outliers, which can severely distort both the direction v and the location m_0 of the separating hyperplane. This well-known limitation has motivated various regularized and robust alternatives in the literature [26]. This limitation motivates the use of robust location estimates.

3.3 | Robust Class Centroids via Trimmed Means

To mitigate the influence of outliers, we replace the empirical means $\hat{\mu}_+$ and $\hat{\mu}_-$ by robust class centers. In this work, we adopt a simple yet effective construction based on α-trimmed means, where a fixed proportion of the most distant observations in each class is discarded before computing the centroid [27].

For each class $k \in \{+, -\}$, the procedure is as follows:

Step 1 (Initial class center). We first compute the conventional empirical mean:

$$\hat{\mu}_k^{(0)} = \frac{1}{n_k}\sum_{i\in\mathcal{I}_k} x_i. \tag{6}$$

Step 2 (Distances from the initial center). For each observation x_i in class k, we compute its Euclidean distance from $\hat{\mu}_k^{(0)}$:

$$d_{i,k} = \| x_i - \hat{\mu}_k^{(0)} \|_2, \quad i \in \mathcal{I}_k. \tag{7}$$

Step 3 (Trimming of distant points). Let $\alpha \in [0,0.5)$ denote the trimming proportion. We sort the distances $\{d_{i,k}: i \in \mathcal{I}_k\}$ in ascending order and retain only the $(1-\alpha)n_k$ observations with the smallest distances. Denote the index set of these retained observations by $\mathcal{J}_k \subset \mathcal{I}_k$, with

$$| \mathcal{J}_k | = (1-\alpha)n_k. \tag{8}$$

Thus, approximately αn_k of the most distant points in each class are discarded.

Step 4 (Robust class center). The robust centroid for class k is then defined as the mean of the trimmed subset:

$$\tilde{\mu}_k = \frac{1}{| \mathcal{J}_k |} \sum_{i \in \mathcal{J}_k} x_i. \tag{9}$$

By construction, $\tilde{\mu}_k$ is less affected by a small fraction of extreme observations compared with $\hat{\mu}_k$. In particular, if the fraction of contaminated points in class k is below α, then, with high probability, most of the outliers will be excluded from the trimmed set $\mathcal{J}_k$, and the robust centroid $\tilde{\mu}_k$ will be primarily determined by the uncontaminated portion of the data [9].

3.4 | Robust Perpendicular Bisector Classifier

Given the robust class centers $\tilde{\mu}_+$ and $\tilde{\mu}_-$ defined in *Eq. (9)*, we construct a robust analogue of the midpoint classifier.

Robust connecting vector and midpoint: we define the robust connecting vector as

$$\tilde{v} = \tilde{\mu}_+ - \tilde{\mu}_-, \tag{10}$$

and the robust midpoint as

$$\tilde{m}_0 = \frac{\tilde{\mu}_+ + \tilde{\mu}_-}{2}. \tag{11}$$

Robust separating hyperplane: the robust separating hyperplane is defined as the set of points $x \in \mathbb{R}^d$ satisfying:

$$\tilde{v}^\top (x - \tilde{m}_0) = 0. \tag{12}$$

Equivalently, in the standard linear form $w^\top x + b = 0$, we can write:

$$w = \tilde{v}, \quad b = -\tilde{v}^\top \tilde{m}_0. \tag{13}$$

Decision function: the resulting RMC assigns class labels according to

$$g_{\mathrm{RMC}}(x) = \mathrm{sign}(\tilde{v}^\top (x - \tilde{m}_0)) = \mathrm{sign}(w^\top x + b). \tag{14}$$

In the absence of contamination, and under standard location-scale models such as Gaussian distributions with equal covariance matrices, the robust centroids $\tilde{\mu}_k$ converge to the true class means as $n_k \to \infty$, and the RMC decision boundary asymptotically coincides with that of the classical midpoint classifier or linear discriminant analysis [28]. In the presence of a moderate proportion of outliers, however, the robust centroids

$\tilde{\mu}_k$ remain stable, whereas the empirical means $\hat{\mu}_k$ can be severely distorted. Consequently, the RMC yields a separating hyperplane that is less sensitive to extreme observations [28], [29].

3.4.1 | Training algorithm

For completeness, we summarize the training procedure of the RMC in the following steps:

I. Class partition: construct the index sets:

$$\mathcal{I}_+ = \{i: y_i = +1\},$$

$$\mathcal{I}_- = \{i: y_i = -1\}.$$

II. Initial centroids: for each class $k \in \{+,-\}$, compute the initial centroid $\hat{\mu}_k^{(0)}$ using *Eq. (6)*.

III. Distance computation and trimming: for each class $k \in \{+,-\}$:

- *Compute distances $d_{i,k}$ according to Eq. (7) for all $i \in \mathcal{I}_k$.*
- *Sort $\{d_{i,k}: i \in \mathcal{I}_k\}$ in ascending order.*
- *Select the index set $\mathcal{J}_k$ of the $(1-\alpha)n_k$ observations with the smallest distances, as in Eq. (8).*

IV. Robust centroids: for each class $k \in \{+,-\}$, compute the robust centroid $\tilde{\mu}_k$ via *Eq. (9)* using the trimmed index set $\mathcal{J}_k$.

V. Robust decision parameters: compute the robust connecting vector $\tilde{v}$ and midpoint $\tilde{m}_0$ from *Eqs. (10)* and *(11)*, and set:

$$w = \tilde{v},$$

$$b = -\tilde{v}^\top \tilde{m}_0.$$

VI. Prediction: for a new instance $x \in \mathbb{R}^d$, predict its label as

$$g_{RMC}(x) = \text{sign}(w^\top x + b).$$

3.4.2 | Computational considerations

The computational cost of training the RMC is dominated by computing and sorting distances within each class. For each class k, the distance computation in *Eq. (7)* requires $O(n_k d)$ operations, where d is the feature dimension, and the sorting operation requires $O(n_k \log n_k)$ time. Hence, the overall training complexity is:

$$O(nd) + O(n_+ \log n_+) + O(n_- \log n_-),$$

which is linear in d and nearly linear in n up to logarithmic factors. Once the parameters (w, b) are obtained, the prediction cost for a new sample is $O(d)$, since only a single inner product and one scalar addition are required.

The RMC thus provides a computationally light and geometrically interpretable alternative to margin-based methods such as linear SVMs, while incorporating a tunable robustness parameter α that controls the fraction of potentially outlying observations to be trimmed from each class.

4 | Simulation Study

In this section, we present a compact simulation study comparing the proposed RMC with a linear SVM. The goal is to assess the behaviour of RMC across different data-generating mechanisms, with a particular focus on mean-shift settings, outlier contamination, class overlap, and heterogeneous covariance structures.

4.1 | Design

We consider binary classification in $\mathbb{R}^2$ with equal class sizes. For each scenario, $n_{train} = 200$ observations are generated for training and $n_{test} = 100$ for evaluation, with $\frac{n_{train}}{2}$ and $\frac{n_{test}}{2}$ instances per class. The following four scenarios are examined:

I. Clean: two well-separated Gaussian classes with distinct means and identical spherical covariances.

II. Outliers: same base distributions as in the clean scenario, but a fraction of training points in each class is replaced by extreme outliers located far from the main clusters.

III. Overlap: two Gaussian classes with closer means and identical spherical covariances, inducing substantial class overlap and higher Bayes error.

IV. Covariance: two Gaussian classes with separated means but markedly different covariance matrices, leading to heterogeneous spread and orientation across classes.

The RMC is trained with trimming level $\alpha = 0.10$, i.e., 10% of the most distant points (in Euclidean distance from the initial class mean) are discarded before computing the robust centroids. The SVM uses a linear kernel with cost parameter $C = 1$ and no feature scaling. Performance is evaluated on an independent test set using accuracy and F1-score; sensitivity, specificity, and precision exhibit analogous patterns and are therefore omitted for brevity.

"*Fig. 1*" illustrates the resulting decision boundaries of RMC and SVM across the four scenarios. For visualization purposes, the decision boundaries are shown for a single representative simulation run in each scenario.

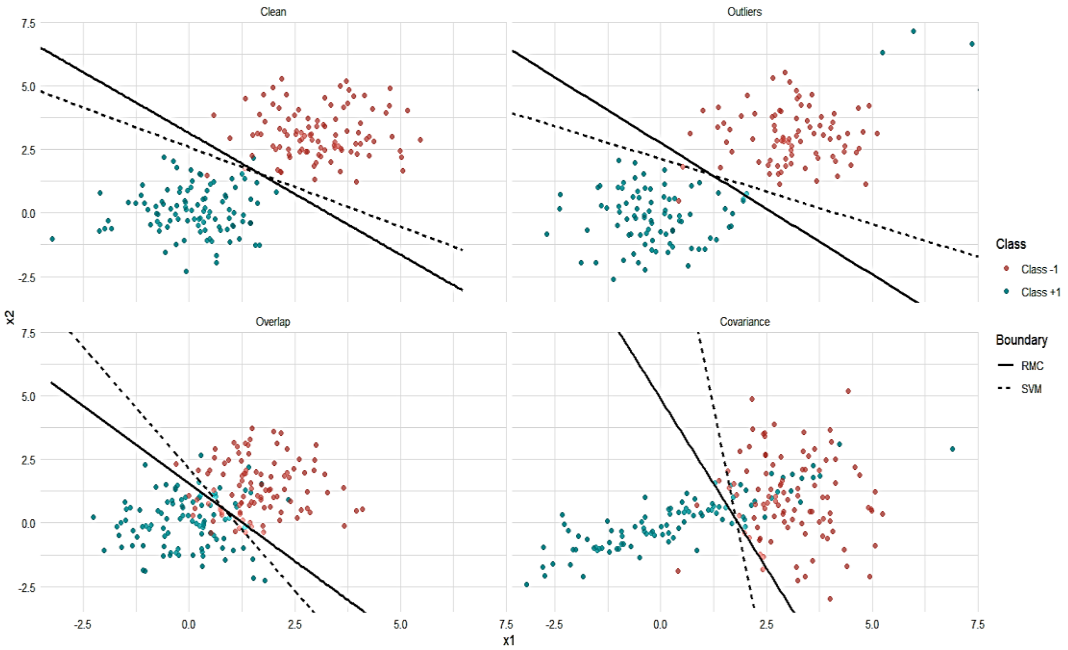

Fig. 1. RMC versus SVM: decision boundaries in the four simulation scenarios (clean, outliers, overlap, and heterogeneous covariance).

4.2 | Implementation and Simulation Details

All simulations were carried out in the R statistical computing environment. The RMC classifier was implemented from scratch following the training algorithm described in Subsection E. For the linear SVM, the svm function from the e1071 package was employed with a linear kernel, cost parameter $C = 1$, and feature scaling turned off. Artificial data were generated using the mvrnorm function from the MASS package, according to the mean and covariance specifications detailed in each scenario.

Outliers in the “Outliers” scenario were introduced by replacing $\varepsilon = 15\%$ of the training points in each class (independently of the trimming level $\alpha = 0.10$) with observations sampled from distant Gaussian clusters located at (8,8) for the positive class and (-8,-8) for the negative class, both with covariance $4I_2$.

To obtain reliable performance estimates, each scenario was independently repeated $N = 100$ times. In every replication, new training and test sets were generated, both classifiers were trained on the same training data, and their performance was evaluated on an independent test set of $n_{test} = 100$ observations. The mean and standard deviation of accuracy and F1-score over the 100 replications are reported in Section 5 (*Table 1*). All random number generation was controlled via unique seeds to ensure full reproducibility.

5 | Results

Figs. 2 and *3* provide a visual comparison of the F1-score and classification accuracy of RMC and SVM across the four simulation scenarios. *Table 1* summarizes the corresponding numerical results.

Table 1. Mean (± SD) test accuracy and F1-score over 100 independent replications for the RMC with α=0.10 and the linear SVM across four simulation scenarios.

Scenario	Method	Accuracy	F1-score
Clean	RMC	0.984 ± 0.015	0.984 ± 0.015
	SVM	0.982 ± 0.015	0.982 ± 0.016
Outliers	RMC	0.981 ± 0.013	0.981 ± 0.013
	SVM	0.807 ± 0.182	0.807 ± 0.179
Overlap	RMC	0.854 ± 0.040	0.854 ± 0.041
	SVM	0.852 ± 0.040	0.853 ± 0.040
Covariance	RMC	0.869 ± 0.039	0.860 ± 0.045
	SVM	0.878 ± 0.035	0.873 ± 0.039

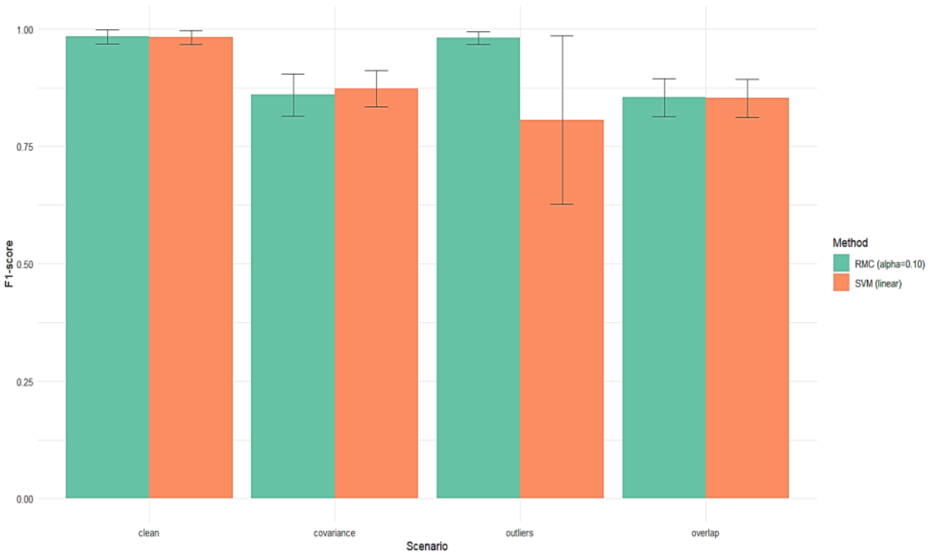

Fig. 2. Mean F1-score (± standard deviation) of RMC and linear SVM over 100 independent replications across the four simulation scenarios.

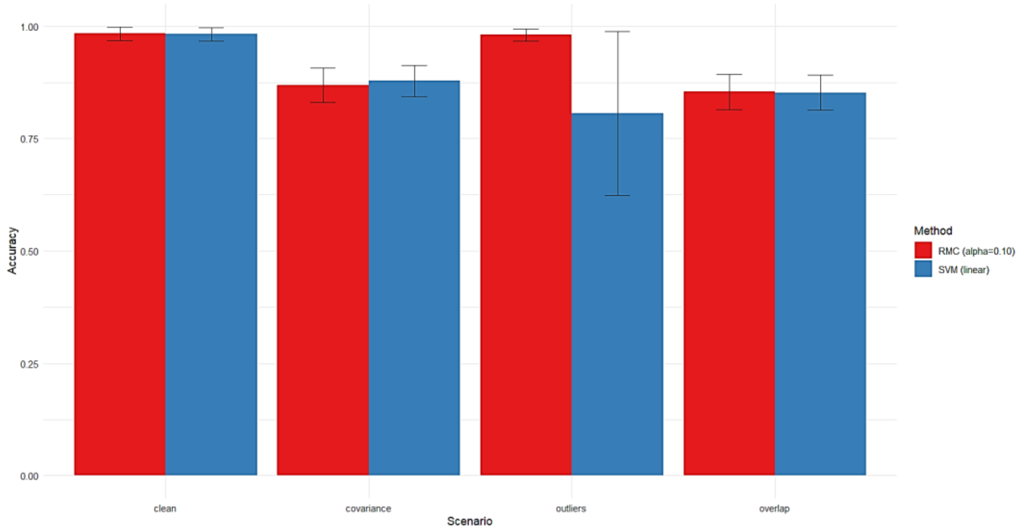

Fig. 3. Mean classification accuracy (± standard deviation) of RMC and linear SVM over 100 independent replications across the four simulation scenarios.

In the clean Gaussian setting, both RMC and linear SVM achieve near-optimal and virtually identical performance. Averaged over 100 independent replications, RMC attains a mean accuracy and F1-score of 0.984 ($\pm$ 0.015), while the linear SVM yields 0.982 (± 0.016). These results confirm that, when the underlying assumptions of mean-shift models with equal covariances are approximately satisfied, the midpoint-based decision boundary of RMC is fully competitive with the margin-based solution of SVM.

Under moderate contamination with outliers, RMC demonstrates clear robustness. The proposed method achieves a mean accuracy and F1-score of 0.981 with very small variability, whereas the linear SVM exhibits substantially degraded and highly variable performance (mean accuracy 0.807 with standard deviation 0.182). This pronounced instability highlights the sensitivity of margin-based methods to outlying observations, while the trimmed centroids employed by RMC ($\alpha = 0.10$) effectively stabilise the decision boundary.

In the overlap scenario, where the class means are closer and the classification task is intrinsically more challenging, both methods perform similarly. RMC slightly outperforms the linear SVM, achieving a mean accuracy of 0.854 versus 0.852, with comparable variability across replications. This behaviour is consistent with the fact that, in mean-shift models with similar covariances, a centroid-based hyperplane aligned with the difference of class means provides a good approximation to the Bayes decision boundary.

Finally, in the covariance scenario with heterogeneous covariance structures, the linear SVM marginally outperforms RMC. The SVM achieves a mean accuracy of 0.878 compared with 0.869 for RMC, reflecting a natural limitation of the proposed method. While RMC is specifically tailored to settings where class separation is primarily driven by location differences, margin-based approaches such as SVMs can better adapt to complex covariance structures. Overall, the simulation study demonstrates that RMC is a simple, computationally light, and robust alternative to linear SVM, particularly in mean-shift problems and in the presence of outliers.

6 | Conclusion

This paper introduced the RMC, a simple and interpretable linear classification rule constructed from robust estimates of class centroids. The method replaces empirical class means by trimmed class centres and defines the decision boundary as the perpendicular bisector of these robust locations. From a geometric viewpoint, RMC can be regarded as a robustified version of the classical midpoint (nearest-centroid) classifier. In location-shift models with approximately equal covariance structures, this construction naturally aligns with the Bayes-optimal linear decision boundary, while the trimming step enhances stability in the presence of contaminated observations.

A simulation study based on repeated experiments was conducted to compare RMC with a linear SVM across four representative scenarios: clean Gaussian data, moderate outlier contamination, strong class overlap, and heterogeneous covariance structures. In the clean setting, RMC matched the performance of the linear SVM, achieving near-perfect accuracy. Under moderate outlier contamination, RMC maintained stable and high classification performance, demonstrating that trimming a small fraction of extreme observations is sufficient to ensure robustness comparable to, and in some cases exceeding, that of margin-based regularisation. In the overlap scenario, RMC slightly outperformed the linear SVM, reflecting the advantage of a centroid-based decision boundary when class separation is primarily driven by location differences. Conversely, in the presence of strongly heterogeneous covariance structures, the linear SVM achieved marginally better results, highlighting a natural limitation of RMC in settings where discrimination depends heavily on covariance differences.

Overall, the proposed RMC provides a computationally light and conceptually transparent alternative to linear SVMs in mean-shift type problems, while remaining robust to moderate levels of contamination. Its reliance on robust location estimates, however, makes it less flexible in scenarios dominated by covariance heterogeneity or more complex nonlinear boundaries. Future work may explore extensions based on alternative robust location estimators, adaptive or data-driven selection of the trimming level, kernelised versions of the midpoint rule, and a more detailed asymptotic analysis of excess risk under various contamination models.

Authors' Contributions

All aspects of the research and manuscript preparation were carried out by the author. The author has read and approved the final version of the manuscript.

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Data Availability

All data supporting the reported findings in this research paper are provided within the manuscript.

Conflict of Interest

The author declares that they have no conflicts of interest.

Consent for Publication

The author confirms consent for the publication of this work

Ethics Approval and Consent to Participate

This article does not contain any studies with human participants performed by the author.

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