# Singular Value Decomposition with Optimal Rank Thresholding and RUSTICO in Burr Classification

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***Abstract*—Burrs are unwanted protrusions formed during machining, have adverse effects on workpiece quality. The process of deburring, which involves removing these burrs, is expensive and time-consuming, and it can potentially compromise the safety of the workers. To address this issue, the paper uses a methodology called RUSTICO and classification using C-Support Vector Classification (C-SVC) to reduce both cost and time associated with the negative impact of burrs on workpieces within the manufacturing industry. Since images often have high-dimensional data, Singular Value Decomposition is used to reduce the dimensionality. Reducing the dimension by more than 50% using the optimal rank using threshold creates a better model without using SVD. By using SVD-Optimal Rank Threshold, the model could extract more features in lesser vertical divisions than the original method. The precision using the proposed method achieved on average 83.92%, the recall reaches 81.54%, while the F1-Score yielded 80.89%.**

***Index Terms*—RUSTICO, Burr Classification, Singular Value Decomposition (SVD), Support Vector Machine (SVM), Image Processing.**

## I. Introduction

Burrs are undesirable protrusions formed during machining, have detrimental effects on the quality of workpieces. Removing burrs manually through deburring is a time-consuming and expensive process. It can also lead to injuries for the person handling it and cause damage to the surfaces that come into contact with it, resulting in wear and reduced efficiency in the assembly process. This obstacle significantly hampers efforts to achieve high productivity and automate machining processes. This research is motivated by the impact that burrs have on manufacturing costs and time, since it is necessary for machined workpieces to meet certain quality criteria, such as ensuring that there are no burrs in the edge finishing [1].

In the manufacturing industry, there exists a pressing necessity to optimize the edge finishing of machined components with the objective of achieving the desired levels of quality and cost-efficiency. Conventionally, this analysis has heavily relied upon the subjective visual assessment conducted by human operators, introducing inherent variability across different individuals. The existence of burrs along the edges of manufactured parts is highly undesirable, consequently prompting extensive research endeavors dedicated to comprehending and addressing this phenomenon [2]. This research concentrates on detecting and studying end milling workpieces, which traditionally rely on visual assessment by human operators based on their experience. By replacing human judgment with computer algorithms, this automated process ensures consistent and objective evaluation of the machined workpiece. The extraction of meaningful information and quality metrics from captured images is accomplished by computer vision and image processing methods, effectively eliminating the need for subjective evaluations.

This paper implements Singular Value Decomposition to improve feature extraction. The purpose of this algorithm is not only to reduce dimension but also to confirm that the features chosen are the most significant. As images are always different from picture to picture, lighting, rotational, saturation level and many other factors, many factors will influence image classification. By using SVD (Singular Value Decomposition), it could extract the most important features and improve the model.

SVD has always been a big part of image classification implementations in manufacturing area. The research of Wu et al. of tool wear prediction uses SVD to filter out noise from the original matrix, leaving behind only the essential features, which enhances the algorithm's robustness and effectiveness [3]. Singular Value Decomposition (SVD) provides a way to obtain numerically stable decomposition matrices for linear algebraic calculations [4]. Determining the rank for SVD usually is done manually, by capturing a certain percentage of eigenvalue while still holding most of the value. Most of the time, it is just based on pure guessing and instinct. Using optimal rank thresholding, it is possible to find the best rank automatically according to the value of the matrix so the large dimensions from image could be reduced while keeping the most important features intact.

Acting as a cornerstone of computer vision, edge detection pinpoints the edges of objects and shapes embedded within images. Its significance extends across a spectrum of image processing applications, encompassing image segmentation, feature extraction, and target recognition. By pinpointing the edges, we can effectively delineate objects and extract meaningful features that aid in image analysis and interpretation [5]. With RUSTICO (RobUST Inhibition-augmented Curvilinear Operator), Li et al. [6] have proposed combining CSW (Circle-Shaped Window) with RUSTICO to detect SAR images and the result is resilient against speckle noise and effectively extracts complete and continuous edges. To detect burrs, it is important to distinguish between the different types of edges. With that, this paper combines RUSTICO and SVD with Optimal Rank Thresholding for distinguishing burrs in machining to measures the impact of SVD in burr classification using RUSTICO.

V. Riego et al have conducted a study about burr classification using RUSTICO and C-SVC [7], but the accuracy of the method aren't quite reproducible using other seeds of the provided dataset. Hence, this paper tries to improve the feature extraction and dimension reduction using SVD in burr classification.

This paper is explained in detail into five sections. Section 1 gives an explaination of the research background and the problem being addressed. Section 2 delves into the underlying theory and reviews relevant studies. Section 3 details the methodology employed in this research, specifically the C-SVC Classification with SVD and Optimal rank thresholding approach. Section 4 presents an analysis of the research findings. Finally, Section 5 summarizes the research outcomes and highlights key findings.

## II. Base Theory

### A. RUSTICO

RUSTICO, an advanced method for curvilinear pattern detection, employs morphological operations and topological analysis to extract workpiece contours. It leverages the B-COSFIRE filter framework, known for its pattern recognition prowess. By combining multiple filter responses, RUSTICO robustly detects curvilinear patterns, even amidst noise and false textures. Inspired by the push-pull mechanism in certain visual neurons, RUSTICO incorporates noise suppression for enhanced pattern detection [8].

Initially, the system detects changes in contrast by using a specific filter, known as the Difference-of-Gaussians (DoG) filter. This filter is mathematically defined as:

$$\mathrm{DoG}_\sigma(x,y) = \frac{1}{2\pi(0.5\sigma)^2} e^{-\frac{x^2+y^2}{2(0.5\sigma)^2}} - \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

$\sigma = w/1.92$ is the standard deviation of the outer Gaussian function. Next, (x, y) are coordinates from each pixel from the image. The calculation of the response $r_B(x,y)$ of a B-COSFIRE filter B involves five sequential steps: convolution, ReLU activation, blurring, shifting, and combination. The first step is using input image I and then convolving it with DoG $\sigma_i$. After that using the activation function rectifier linear unit (ReLU) which is $|\cdot|+$, and lastly forms the feature map Ci(x, y) as this equation below:

$$C_i(x,y) = \left| \sum_{x'\in\Omega} \sum_{y'\in\Omega} I(x,y) DoG_{\sigma_i}(x-x', y-y') \right|^+ \quad (2)$$

RUSTICO is characterized by two complementary components, $P_\lambda(B, B_\lambda)$ excitatory and inhibitory, which receive input from DoG filters with opposing polarities. To calculate its response $r_{P\lambda}(\mathrm{x,y})$, the next step is to subtract a portion $\xi$ of the inhibitory response $r_{B\lambda}(\mathrm{x,y})$ from the excitatory response and then apply a ReLU operation like below:

$$r_{P_\lambda}(x,y) = |r_B(x,y) - \xi r_{B_\lambda}(x,y)|^+ \quad (3)$$

The positive parameter $\zeta$ represents the inhibition strength, which determines the degree to which the excitatory response is reduced.

### B. C-SVC

The SVM (Support Vector Machine) algorithm is a widely used machine learning technique that has proven effective in various domains for classification tasks. It has different formulations and is recognized as a powerful classification tool. SVM works by categorizing data points into two distinct categories. Once all the points are categorized, the algorithm proceeds to identify lines that lie at the boundaries between the two classes. The objective is to maximize the separation distance between these lines. The line that achieves the greatest distance represents the optimal separation between the classes. However, in real-world scenarios, data points are often not linearly separable.

SVM employs a penalty parameter, C, that affects the error term. C controls the balance between creating a smooth decision boundary and correctly classifying the training points. Unnecessarily high values of C can result in overfitting to the training data, potentially hindering the algorithm's ability to generalize effectively [9] [10].

C-support vector classification (C-SVC) is a classification technique that expands the data into a higher-dimensional space, with the regularization parameter C (cost) controlling the extent of regularization. C-SVC employs the primal-dual relationship to solve the primal optimization problem. The resulting C-SVC decision incorporates kernel parameter information, which serves as a predictive model.

### C. SVD

In the realm of image classification, Singular Value Decom position (SVD) stands as a powerful mathematical tool. This factorization method, rooted in linear algebra, decomposes a rectangular matrix into three distinct matrices: U, S, and V.

The U matrix, with dimensions m x m, comprises orthogonal vectors, where m represents the number of rows in the original matrix. The diagonal matrix S, of dimensions m x n, contains the singular values arranged in descending order, where n denotes the number of columns in the original matrix. Finally, the V matrix, with dimensions n x n, consists of orthogonal vectors. SVD decomposes the orginal matrix into:

$$A = USV^T \tag{4}$$

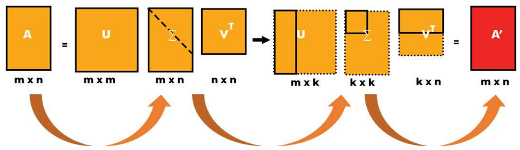



Fig. 1. Diagram of SVD

A more complete way of decomposing a non-square matrix is mentioned below [11]:

1) From a non-square matrix A, a square matrix can be obtained by multiplying $A^T$ by A.
2) After that, we can find the eigenvalues of the previous matrix multiplication using the formula $(A^T \cdot A)V_i = \lambda_i \cdot V_i$. Here, V represents the right singular vector.
3) $\lambda_i$ is eigenvalue meanwhile $\sigma_i$ is $\lambda_i$ which represents the singular value.
4) $U_i = \frac{1}{} AV_i$ ; And U represents the left singular vector.
5) The singular values are then sorted in descending order, from the largest to the smallest. Singular values can be used to describe matrix approximation, and the singular value decomposition can be defined as follows:

$$A_{mxn} \approx A_{mxr} S_{rxr} V^T_{rxn} \tag{5}$$

6) r is a number smaller than m and n, therefore the multiplication will be as follows:
7) The multiplication of these three matrices will approximate A, where r will be closer to n. The entire area of the resulting matrix will be smaller than the original matrix. In the end, it is only necessary to store U, S, and V to approximate A.

### D. Optimal value of rank r

One of the optimal way to get the optimal value of r is by using . Truncated SVD (TSVD) has a number of singular values, which must be optimal so that it can perform the most effective dimension reduction with an approximation of rank r which is close to the original matrix A. A matrix of order m x n where m <n and the noise level is unknown. In general, all matrices have these conditions, so only these conditions will be discussed at this time [12] [13]. To determine which singular value to retain, the following formula is used:

$$\hat{\tau}_* = \omega(\beta) \cdot y_{med} \tag{6}$$

$y_{med}$ is the median value of the vector $\Sigma$ singular value, $\omega(\beta)$ is the correct factor, and $\hat{\tau}_*$ only the threshold value will change according to an algorithm. $\beta$ is $\frac{m}{n}$, and $\omega(\beta)$ can be approximated with:

$$\omega(\beta) \approx 0.56\beta^3 - 0.95\beta^2 + 1.82\beta + 1.43 \tag{7}$$

**Algorithm 1** Optimal r determination

**Require:** $S \epsilon R^{1 \times n}$, where S is the singular value row vector
Compute the value of $\hat{\tau}_*$
Compute r number of singular values $> \hat{\tau}_*$

## III. Research Methods

The proposed method can be seen in Figure 2. It starts with Burr dataset with 224 pictures of containing knife-burr, saw-burrs, and burr-breakage types [14]. These data also have been categorized manually according to one of the categories, saved in a csv. Then, all RGB images are converted into grayscale which are then duplicated for the one that will go through SVD and the other one that doesn't. After decomposed into three matrices, using the method mentioned in equation 4. After that, it's reconstructed back after thresholding and goes to identification and classification like the non processed dataset. In classification, the prediction process uses 30% of the whole dataset. Then research ends with analysis.

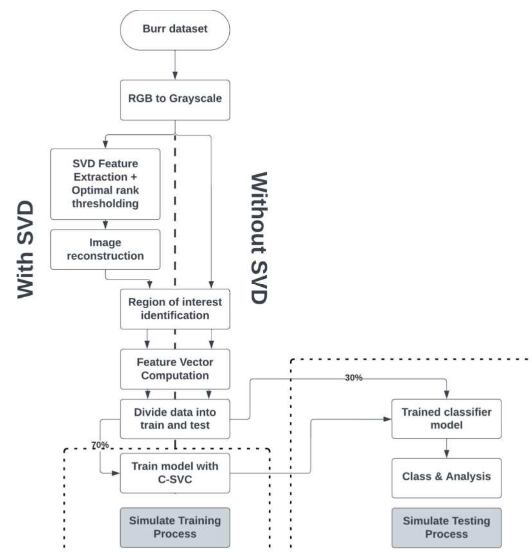



Fig. 2. Flowchart of proposed method

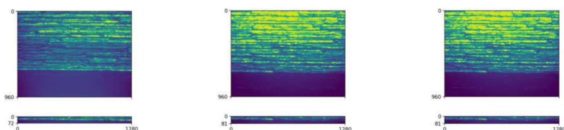
### A. Burr Dataset

The provided dataset by V. Riego et al. [14] provides with 224 pictures of containing knife-burr, saw-burrs, and burr-breakage types [14]. Images of burrs have been categorized manually according to the three categories, saved in a csv file. By utilizing the same dataset as V. Riego et al. [7]'s study, this paper facilitates a straightforward comparison of the proposed enhanced method to the conventional approach. The images are captured by boroscope, at a resolution of 2592 × 1994 pixels. These images serve as the input for the classification task. Each image is labeled by domain experts based on the presence of imperfections in the workpiece's edge shape. The classification task involves three distinct categories:

1) The first category represents the ideal situation where no imperfections are present, commonly referred to as

knife-type burr (K). This category indicates a workpiece without any significant deviations or irregularities in its edge shape, making it suitable for use.

2) The second category corresponds to images that exhibit small splinters, known as saw-type burr (S). The acceptance of such imperfections depends on the intended use of the machined piece. In certain cases, these small splinters may be deemed acceptable without compromising the functionality or performance of the workpiece.
3) The third category comprises images showing a large deformation, resulting in burr-breakage (B). Workpieces falling under this category are considered unusable due to the extent of the deformation, rendering them ineffective for their intended purpose.



(a) Knife-type burr (K) (b) Saw-type burr (S) (c) Burr-breakage (B)

Fig. 3. Three distinct burr types

The goal of the developed system is to accurately classify the captured images into these three categories, providing valuable insights for quality control and decision-making in the manufacturing process.

### *B. RGB to Grayscale*

This experiment uses automatic threshold SVD for image compression. As the images are RGB which have 3 different channels, each channel may have a different rank after SVD and create a non-cohesive (different rank per channel) image. So to avoid biased results, all images after acquiring are converted into grayscale, so the experiment only runs on one channel to create a non-biased experiment.

### *C. SVD and Optimal Rank Thresholding*

The primary focus of existing literature revolves around enhancing image classification methods. The contribution lies in enhancing the process of data enrollment rather than repeatedly emphasizing the classification process itself. This approach ultimately leads to improved classification outcomes. Achieving this entails utilizing the SVD method, which typically requires establishing the dataset prior to commencing the classification process.

### *D. Region of Interest Identification*

The definition of a region of interest (ROI) is a specific area within an image or dataset that is of particular importance or relevance to a specific task or analysis. Due to the typical location of burrs at the workpiece's extremity, the region of interest (ROI) is determined to be the vicinity of that end.

1) Optimizing the RUSTICO algorithm involves fine-tuning various parameters: $\sigma_0$ and $\alpha$ control the algorithm's ability to handle distortions in the patterns of interest, while $\lambda$ and $\xi$ determine its resilience to image noise. Additionally, $\rho$ and $\sigma$ represent the polar coordinates of the considered DoG responses relative to the reference point. In this study, these parameters are set as follows: $\sigma_0 = 3$, $\alpha = 0.1$, $\lambda = 0.5$, $\xi = 1.5$, $\rho = 16$, and $\sigma = 2.5$. Finally, a manually selected threshold of 0.2 is applied to binarize the image
2) Perform a morphological closing operation on the image generated by RUSTICO using a disk of radius 67 pixels to eliminate small holes. Next, divide the image into 100 horizontal sections. Identify the region of interest, which includes points where the difference between a point and its previous point is greater than 5. Exclude any sections where the position on the *x*-axis is greater than 10, effectively removing noisy sections.

### *E. Feature Vector Computation*

The feature vector is extracted from the RUSTICO-provided image through a series of steps:

1) Image Dilation and Border Addition: The image is dilated using a $31 \times 79$ pixel kernel to expand and merge lines, distinguishing between the background and the object of interest. A 10-pixel border is then added around the image.
2) Morphological Closing and Contour Extraction: Morphological closing operations are performed to remove small objects and regions near the image edges. Contours are then extracted and filled using topological structural analysis.
3) Feature Vector Calculation: The division of the region of interest into vertical sections is followed by an analysis of each section to identify the largest closed area. The determination of a bounding rectangle from the workpiece edge to the end of the region of interest is carried out. The height of this rectangle in each section is used to form the final feature vector.
4) Overexposure Handling: Overexposed images can lead to the loss of essential information. Therefore, the method removes images where the region of interest cannot be precisely identified or where contour detection fails in all vertical divisions.

### *F. Classification*

The categorization of images are provided by experts was achieved through the implementation of a supervised machine learning approach. C-Support Vector Classification (C-SVC), a particular implementation of Support Vector Machines (SVM), was employed for the classification process in this study. The choice of the C-SVC algorithm was driven by its adaptability to classification tasks and its established record of success in various domains. For the SVM, the Radial Basis Function (RBF) kernel is utilized in this experiment. The burr images are then divided into 70% for training. The rest of the images are then used for testing.

### G. Performance Analysis

To assess the accuracy of classification models, this study employs three crucial metrics: precision, recall, and f1-score. In the realm of classification, TP (true positive) signifies the number of correctly classified instances as positive, while TN (true negative) is the amount of instances accurately classified as negative. Furthermore, FP (false positive) means the amount of negative instances incorrectly classified as positive, and lastly FN (false negative) describes the amount of positive instances are incorrectly classified as negative. Precision, recall, and F1-Score are defined as follows, respectively [15] [16]:

$$\text{Precision } = \frac{TP}{TP+FP}, \quad (8)$$

$$\text{Recall } = \frac{TP}{TP+FN}, \quad (9)$$

$$F1- \text{ Score } = \frac{2\times TP}{2\times TP+FP+FN}, \quad (10)$$

## IV. Experiments and Analysis

This section explores the outcomes derived from processing the dataset using SVD-Optimal Rank Threshold and contrasts them with the original method. The classification process commences by partitioning the dataset into two distinct sets: a training set dedicated to constructing the classification model and a testing set intended for evaluating its performance. A 70:30 split was employed, allocating 70% of the data for training and the remaining 30% for testing. After the image has been obtained and converted into grayscale, the image are then factorized into U, S, and V to gain the matrices to be used for SVD. By using optimal rank thresholding it could decrease the original rank by more than 50%. For example, even though the original rank is 960, by using optimal thresholding that is catered per image, the optimal rank ranges from 301 to 358. Which is more effective than previous methods of determining optimal rank using hand-picked parameters. This method also ease the burden of choosing the rank manually.

The features of the dataset exhibit a significant overlap (see Figure 4) in their mean and standard deviation, especially between knife-type (K) and saw-type (S) burrs. This indicates that the proposed method successfully distinguishes burr breakage (B) and knife-type (K) instances, which are the prevalent edge finishing categories. However, there are occasional misclassifications with saw-type (S) burrs as they are quite similar. In order to optimize the configuration parameters, grid search was conducted, accompanied by a 12-fold cross-validation approach. An optimization process identified the optimal value of the regularization parameter C to be 9. This parameter serves to counteract overtraining, an issue that arises when a model becomes overly attuned to the training data and exhibits poor performance on unfamiliar examples.

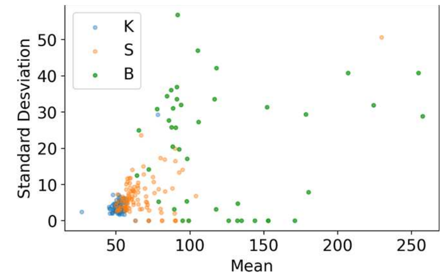


Fig. 4. Scatter of standard deviation and mean of each class

By comparing different amount of vertical divisions the results of testing and training could be obtained. From Figure 5 and 6 we could infer that on average, the precision and recall test of the model using SVD is better than the model without SVD. During test using SVD, on average the precision is 83.92%, recall is 81.54%, and f1-score reached 80.89%. On the other end, during test without using SVD, on average the precision is 81.09%, recall is 79.88%, and f1-score reached 79.63%.

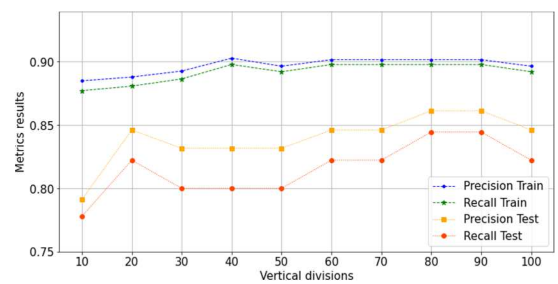


Fig. 5. Final Results SVD

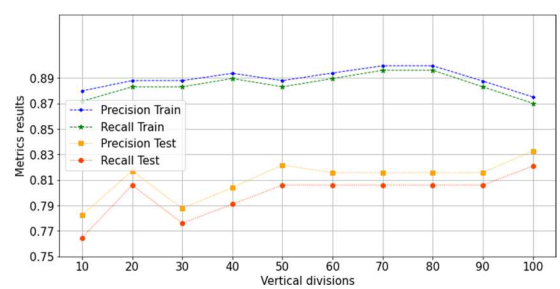


Fig. 6. Final Results Non-SVD

During test, SVD-Optimal Rank Thresholding achieved the highest precision (86.12%) and recall (84.44%) in 80 and 90 vertical divisions. In comparison, the original method achieved the highest in 100 vertical divisions with 83.28% in precision and 82.09% in recall. Both methods exhibit lowest precision and accuracy in 10 vertical divisions. This is caused by lower divisions produce bigger frames and hence can't pick up as much details to create the model as higher vertical divisions. But too much vertical divisions may pick too much noise and hence create a model that overfits. The optimal vertical division for SVD-Optimal Rank Thresholding is 80 divisions, which is caused by the feature extraction ability of SVD to be able pick more features in lower divisions. In comparison, the original method have to make up for feature extraction by increasing the amount of vertical divisions to 100. In the end, there's slight improvement in precision, recall, and F1-Score after optimal rank thresholding.

## V. Conclusion

The SVD-RUSTICO model, presented in this paper, can be employed for predicting burr classification, and it enhances the prediction accuracy. The model has been developed and evaluated using a burr classification dataset acquired online. SVD with Optimal Rank Thresholding could reduce the dimension by more than 50% and extract more features from the original image. A comparative experiment between burr classification prediction models using SVD features and non-SVD features revealed that the SVD feature-based model achieved superior burr classification prediction accuracy. The method using SVD-Optimal Rank Thresholding are able to extract more features even in lesser vertical divisions, the original method have to increase the amount of vertical divisions to make up for that. From the comparison experiments of C-SVC, it can be found that the method of SVD and Optimal Rank Thresholding with RUSTICO combined into the precision, reached an impressive on average 83.92%, the recall reaches 81.54%, while the F1-Score yielded 80.89%.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## References


[1] S. Y. Jin, A. Pramanik, A. Basak, C. Prakash, S. Shankar, and S. Debnath, "Burr formation and its treatments—a review," *The International Journal of Advanced Manufacturing Technology*, vol. 107, pp. 2189–2210, 2020.

[2] V. R. del Castillo, L. Sánchez-González, L. Fernández-Robles, and M. Castejón-Limas, "Burr detection using image processing in milling workpieces," in *International Workshop on Soft Computing Models in Industrial and Environmental Applications*. Springer, 2020, pp. 751–759.

[3] X. Wu, J. Li, Y. Jin, and S. Zheng, "Modeling and analysis of tool wear prediction based on svd and bilstm," *The International Journal of Advanced Manufacturing Technology*, vol. 106, pp. 4391–4399, 2020.

[4] S. L. Brunton and J. N. Kutz, *Data-driven science and engineering: Machine learning, dynamical systems, and control*. Cambridge University Press, 2022.

[5] N. Ofir, M. Galun, S. Alpert, A. Brandt, B. Nadler, and R. Basri, "On detection of faint edges in noisy images," *IEEE transactions on pattern analysis and machine intelligence*, vol. 42, no. 4, pp. 894–908, 2019.

[6] J. Li, W. Yu, Z. Wang, Y. Luo, and Z. Yu, "A robust statistic-aided edge detector for sar images based on rustico," *Electronics Letters*, vol. 58, no. 10, pp. 393–395, 2022.

[7] V. Riego, L. Sánchez-González, L. Fernández-Robles, A. Gutiérrez-Fernández, and N. Strisciuglio, "Burr detection and classification using rustico and image processing," *Journal of computational science*, vol. 56, p. 101485, 2021.

[8] N. Strisciuglio, G. Azzopardi, and N. Petkov, "Robust inhibition-augmented operator for delineation of curvilinear structures," *IEEE Transactions on Image Processing*, vol. 28, no. 12, pp. 5852–5866, 2019.

[9] C.-C. Chang and C.-J. Lin, "Libsvm: a library for support vector machines," *ACM transactions on intelligent systems and technology (TIST)*, vol. 2, no. 3, pp. 1–27, 2011.

[10] L. Jiang and R. Yao, "Modelling personal thermal sensations using c-support vector classification (c-svc) algorithm," *Building and Environment*, vol. 99, pp. 98–106, 2016.

[11] Y. Wang and L. Zhu, "Research and implementation of svd in machine learning," in *2017 IEEE/ACIS 16th International Conference on Computer and Information Science (ICIS)*. IEEE, 2017, pp. 471–475.

[12] D. L. Donoho and M. Gavish, "The optimal hard threshold for singular values is 4," *arXiv preprint arXiv:1305.5870*, 2013.

[13] H. Lyu, N. Sha, S. Qin, M. Yan, Y. Xie, and R. Wang, "Advances in neural information processing systems," *Advances in neural information processing systems*, vol. 32, 2019.

[14] V. Riego, L. Sánchez, L. Fernández, A. Gutiérrez, N. Strisciuglio, "Burr detection and classification using rustico and image processing." [Online]. Available: https://open.scayle.es/dataset/burr-detection-and-classification-using-rustico-and-image-processing

[15] D. M. Powers, "Evaluation: from precision, recall and f-measure to roc, informedness, markedness and correlation," *arXiv preprint arXiv:2010.16061*, 2020.

[16] D. Chicco and G. Jurman, "The advantages of the matthews correlation coefficient (mcc) over f1 score and accuracy in binary classification evaluation," *BMC genomics*, vol. 21, no. 1, pp. 1–13, 2020.