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Modeling Mechanical Component Classification Using Support Vector Machine with A Radial Basis Function Kernel

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Abstract

The process of identification and classification of products in the era of modern manufacturing industries has become a crucial pillar in enhancing efficiency, productivity, and product quality. In this research, the modeling of manufacturing product classification, such as mechanical components consisting of four classes: bolts, washer, nuts, and locating pin, was conducted. The proposed model in this study is the Support Vector Machine (SVM) with Radial Basis Function (RBF). The dataset used consists of digital images of mechanical components, with each component having 400 samples, resulting in a total of 1600 samples. The dataset is divided into training and testing data, with 300 samples for each component in the training set, and 100 samples removed from the training set for external testing as model validation. The best model parameters were determined using grid search by varying the parameter values of C and γ (gamma). The model was evaluated using K=3 fold cross-validation, and external testing utilized a confusion matrix to calculate Accuracy, Precision, Recall, and F1-Score values. The research results indicate that the SVM model with the RBF kernel, using the combination of C=10 and γ=scale, achieves the best performance in classifying the four mechanical components. This is evident from the training results of the model, which were able to obtain evaluation metrics such as Accuracy of 94.17%, Precision of 0.94, Recall of 0.94, and F1-Score of 0.94. Meanwhile, the validation results with new data not present in the training dataset show that the model can achieve evaluation metrics with an Accuracy of 93%, Precision of 0.93, Recall of 0.93, and F1-Score of 0.93. These results are consistent with the training performance, indicating that the SVM model with the RBF kernel excels in classifying digital images of mechanical components, such as bolts, nuts, washer, and locating pin.

Keywords: modeling, mechanical components, classification, support vector machine

1. Introduction

Manual tasks involving repetitive identification and classification of mechanical components tend to increase the risk of errors and require significant labor costs, especially when performed over an extended period. In the modern industrial era, the manufacturing process has become a key pillar in improving efficiency, productivity, and product quality [1]. Automation and modern manufacturing demand high reliability in the identification, classification, and placement of mechanical components. The success of automated recognition can reduce human involvement in repetitive tasks, enhance precision in assembly, and optimize overall production time [2]. Therefore, rapid and accurate identification is an urgent need in the scope of automation and manufacturing. Machine learning is one branch of artificial intelligence (AI) that enables computers or machines to learn from provided data, and these models can improve their performance as training data accumulates in the dataset [3], [4]. Machine learning can automatically learn through data processing and make predictions and decisions based on patterns in training data. Support Vector Machine (SVM) is one of the machine learning algorithms used for classification tasks. SVM is often employed in various applications such as text and image classification. SVM can separate two or more classes by finding the best hyperplane that maximizes the margin between these classes. The margin is the distance between the hyperplane and the nearest data points from each class, referred to as support vectors [5]. In many cases of complex image classification, the decision boundary between classes is non-linear [6]. SVM with Radial Basis Function (RBF) kernel is a type of SVM model capable of handling cases that cannot be linearly separated in the feature space. The RBF kernel projects data into a higher-dimensional feature space to find complex decision boundaries [7]. Many previous studies have applied SVM as one of the classification algorithms for manufacturing products. For instance, in [8], SVM is applied to Zero

Defect Manufacturing (ZDM), a strategy to eliminate defective components during production, a primary goal in the concept of Industry 4.0, as it can reduce operational costs associated with defective components. In this research, SVM enhances the efficiency, accuracy, and reliability of the production process, supporting ZDM objectives. In another study [9], SVM is used to detect damage on wood and metal surfaces. This research involves seven classifications of wood damage with 280 features extracted from each sample image, and an optimized set of 36 features is obtained using the sequential forward selection method. The results show that the SVM method can be applied to detect defects in wooden materials, with measured performance indicators such as sensitivity, specificity, misclassification, and accuracy. Based on the aforementioned issues, this research aims to develop an object classification model that can identify mechanical components such as bolts, washer, nuts, and locating pin with high accuracy using SVM with the RBF kernel. Thus, the application of this technology can contribute positively to cost management and enhance the competitiveness of companies in an increasingly competitive manufacturing environment.

2. Research Methodology

This study conducts a modeling of the classification of mechanical components, consisting of bolts, nuts, washer, and locating pin, using SVM with the RBF kernel. In this research, the search for the best model parameters is performed through grid search, and the model is evaluated using a confusion matrix to calculate accuracy, precision, recall, and F1-score. Additionally, the model with the best combination is validated through external testing using new data not present in the training set. The model is implemented using the Python programming language and executed on Google Colab. The stages of this research can be seen in Figure 1.

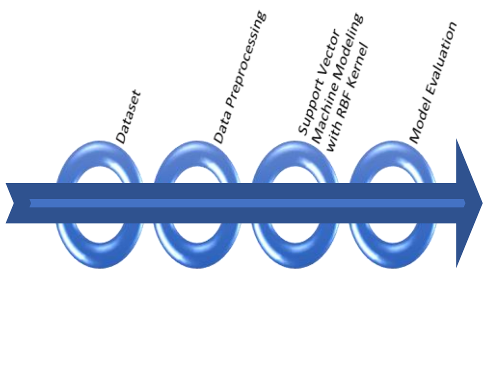

Figure 1. research scheme

1. Dataset

In this research, the dataset used consists of digital images comprising four types of mechanical components, namely bolts, nuts, washer, and locating pin. The dataset comprises 1600 samples, with each component having an equal number of samples, specifically 400 samples.

2. Data Preprocessing

Data preprocessing involves a series of steps to prepare and clean the data before utilizing it in the analysis or machine learning modeling process [9]. Common steps in data preprocessing include image processing such as resizing, cropping, image augmentation, and the division of training and testing data [10]. Additionally, at this stage, Principal Component Analysis (PCA) is applied to reduce the data dimensions, thus speeding up the model training time [11]. The primary objective of PCA is to reduce data complexity while retaining as much variation in information as possible [12]. PCA can be computed using equation 1.

$$Y = XW \tag{1}$$

Whereas, X is the data matrix with n rows and p columns, W is the weight matrix with p rows and k columns, where k is the desired number of principal components, and Y is the resulting transformation matrix with n rows and k columns. The weight matrix W can be determined using the eigen decomposition equation of the covariance matrix S of the data X, as shown in equation 2.

$$S = X\text{^}TX \tag{2}$$
$$Sv = \lambda v$$

Whereas, v is the eigen vector, and λ is the eigenvalue. The first principal component is the eigen vector corresponding to the largest eigenvalue, the second principal component is the eigen vector corresponding to the second-largest eigenvalue, and so forth [13].

3. Support Vector Machine Modeling with RBF Kernel

In this stage, SVM is trained using images of mechanical components with the application of the RBF kernel to transform image data into a higher-dimensional feature space. During the training process, SVM aims to find the optimal decision boundary that separates the four classes (bolts, washer, nuts, and locating pin) by maximizing the margin between these classes. SVM considers a subset of the training data referred to as Support Vectors. Support Vectors are data points that are close to or within the margin of the decision boundary. The decision boundary produced by SVM with the RBF kernel exhibits complex characteristics, allowing for better separation between classes in a high-dimensional feature space [7]. A visual illustration of how SVM can separate non-linear class data can be seen in Figure 2.

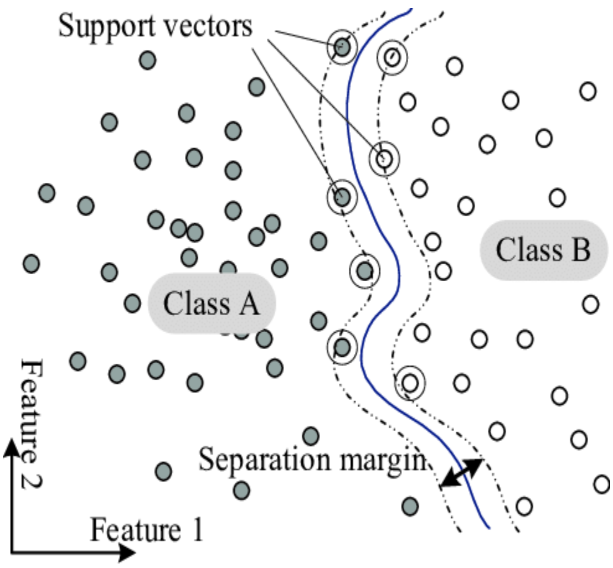

Figure 2. Illustration of non-linear SVM classification [14].

The RBF kernel is the most commonly used form of kernelization in non-linear cases due to its similarity to the Gaussian distribution. The RBF kernel can be mathematically represented as shown in equation 3

$$K(X_1, X_2) = \exp(-\gamma \| X_1 - X_2 \|^2) \quad (3)$$

Where γ is the hyperparameter, $\|X_1 - X_2\|$ is the Euclidean (L_2-norm) distance between two points X_1 and X_2. The maximum value of the RBF kernel is 1 and occurs when the distance between two points is 0, meaning the points are the same, i.e., $X_1=X_2$. When the points are the same, there is no distance between them, indicating their high similarity. When the points are separated by a significant distance, the kernel value is less than 1 and approaches 0, indicating dissimilarity between the points [15]. In this stage, the search for the best parameters is also conducted using grid search by varying the values of C and γ (gamma). The best combination will be evaluated using K-fold cross-validation and testing with data not present in the training data.

4. Model Evaluation

Model evaluation is performed using a confusion matrix to calculate accuracy, precision, recall, and F1-score [16].

a. Accuracy: It is the ratio of the number of correctly classified data (true positive and true negative) to the total amount of data. Accuracy describes how often the model can classify data correctly. Accuracy is expressed as a percentage, and the higher the accuracy value, the better the model's performance. Accuracy can be calculated using equation 4.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (4)$$

b. Precision: It is the ratio of the number of true positive classifications to the total number of data classified as positive by the model (true positive and false positive). This describes how accurately the model classifies data as positive, and precision can be calculated using equation 5.

$$Presisi = \frac{TP}{TP+FP} \quad (5)$$

c. Recall: It is the ratio of the number of true positive classifications to the total number of actual positive data (true positive and false negative). Recall describes how sensitive the model is in classifying truly positive data, and the recall value can be calculated using equation 6 [17].

$$Recall = \frac{TP}{TP+FN} \quad (6)$$

d. F1-score: It is the harmonic mean between precision and recall. This indicator illustrates the balance between precision and recall, and the F1-score can be calculated using equation 7.

$$F1 - Score = \frac{(Recall \ x \ Presisi)}{(Recall+Presisi)} \quad (7)$$

with TP, TN, FP, and FN representing true positive, true negative, false positive, and false negative.

3. Results and Discussion

1. Dataset

The dataset used in this research comprises four types of digital images of mechanical components, namely bolts, nuts, washer, and locating pin. This dataset consists of 1600 samples, with each component having an equal number of samples, specifically 400 samples. The data was obtained from Kaggle.com, which is one of the platforms providing datasets for learning, training, and machine learning modeling. Figure 3 displays some samples of the mechanical components present in the dataset.

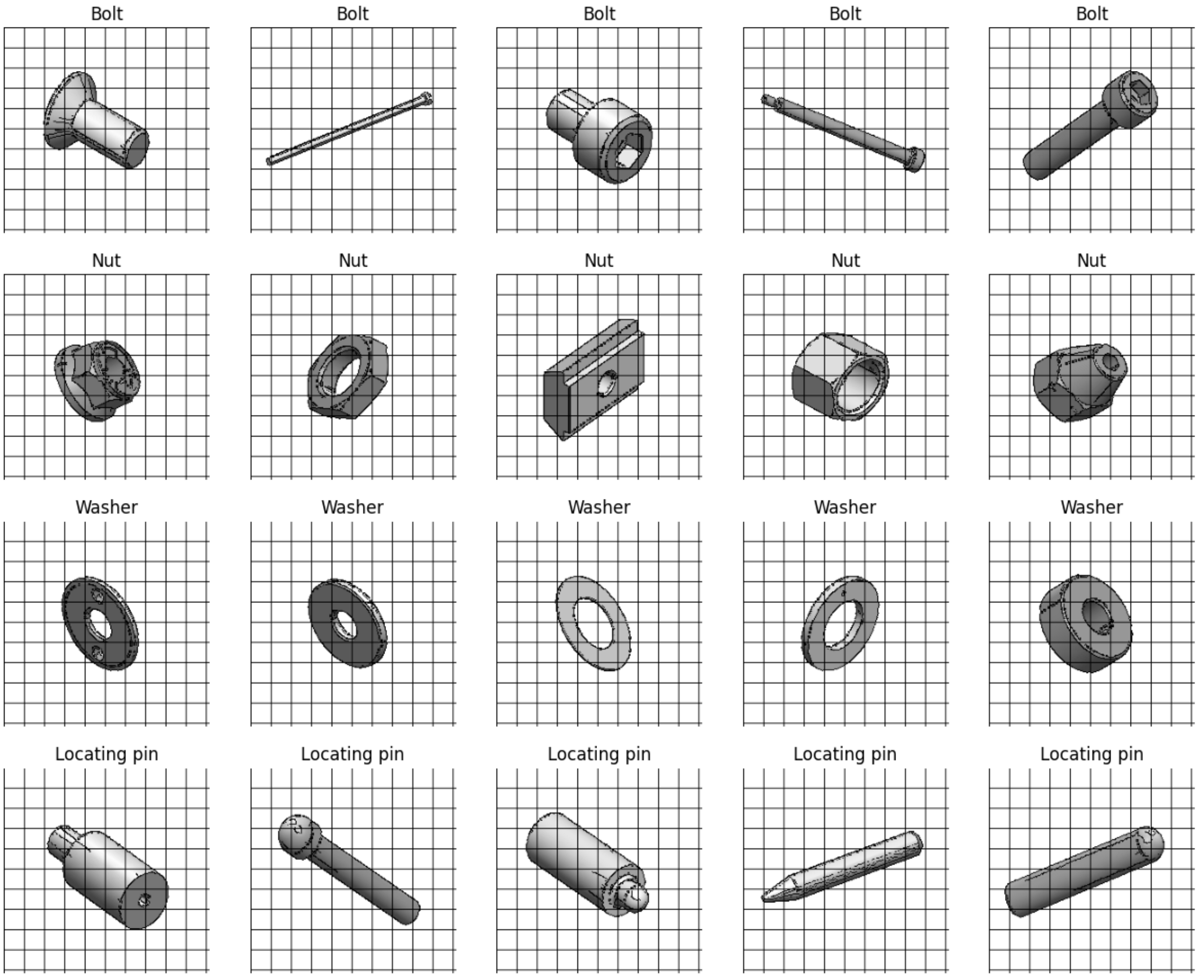

Figure 3. Digital images of the mechanical component dataset

2. Data Preprocessing
   In this stage, the dataset is divided into training and testing data, specifically 300 samples for each component that will be used during model training. Meanwhile, the remaining 100 samples for each component are separated from the training dataset and will be used for external testing in model evaluation. Even distribution of the dataset for each mechanical component helps prevent imbalance issues, ensures that the model learns well from each class, and produces fair and accurate evaluations when testing the model on previously unseen data [16]. The percentage balance of the dataset distribution used can be illustrated in Figure 4.

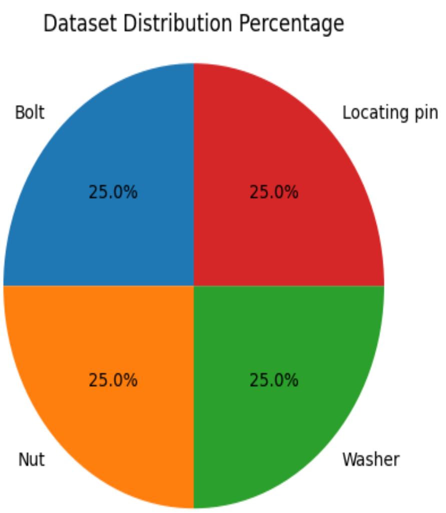

Figure 4. Percentage distribution of the dataset for each component.

In the classification model using SVM, digital images are transformed into vector form before being used as input for the model. This process is known as flattening or vectorization of the image. Each pixel in the image has an intensity value representing the brightness level at a specific location [18]. During vectorization, each pixel is considered a feature, and the intensity value of that pixel is taken as the feature value, as illustrated in Figure 5. Vectorization enables SVM to take a numerical representation of the image and work with matrices or vectors as input. This simplifies the use of machine learning algorithms, which are generally designed to handle data in vector or matrix formats.

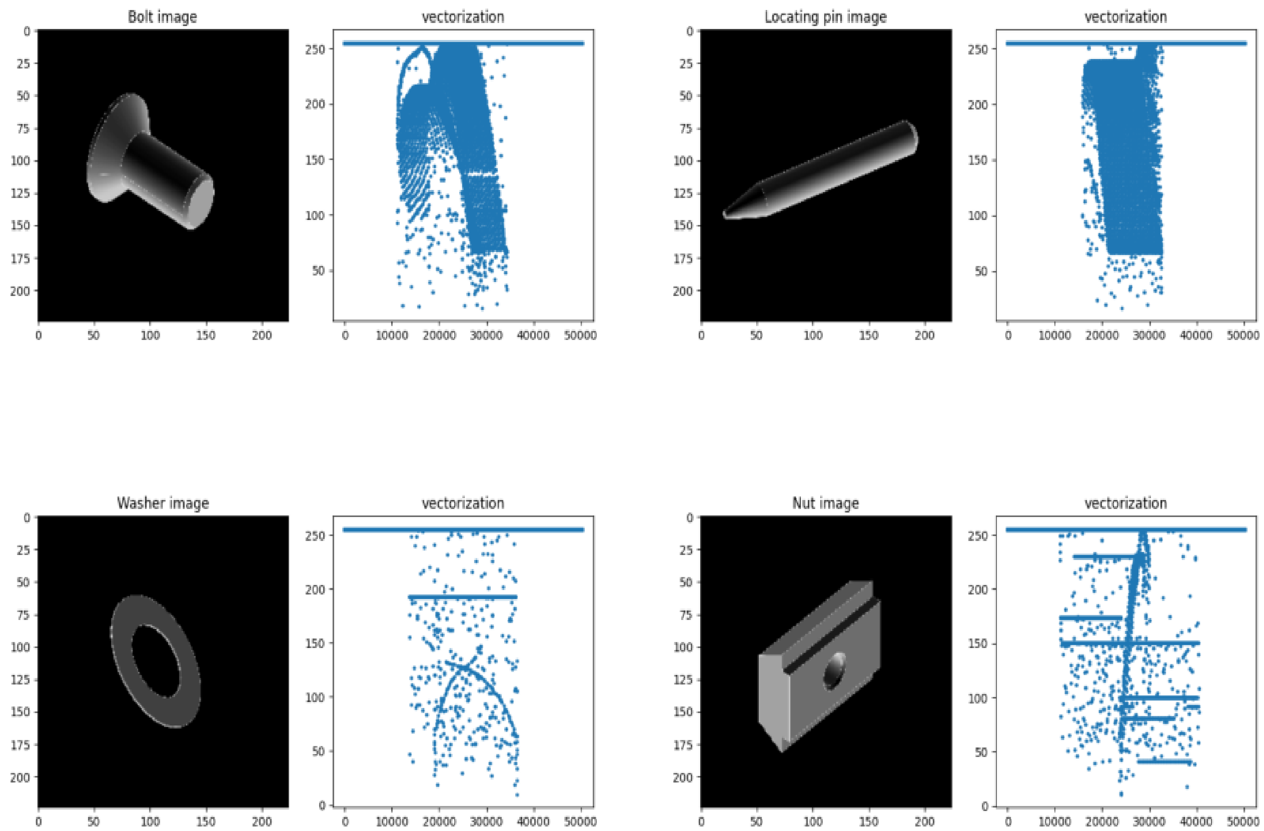

Figure 5. Result of vectorization of digital images of mechanical components

Based on Figure 5, differences in vector shapes for each mechanical component can be observed. These vectors will be used as input features in the SVM model. The results of vectorization show that when the image resolution is higher, the vector generated from that image will have more elements, making the vector denser. This is because each pixel in the image is represented by an element in the vector, and the higher the resolution, the more pixels there are. In some cases [19], [20], especially when the vector dimensions are very high, analyzing and modeling using the entire dimensions can be challenging. In such cases, dimension reduction techniques like Principal Component Analysis (PCA) can be useful. PCA is a method used to reduce the dimensions of data by projecting it into a lower-dimensional space, known as principal components. Principal components are linear combinations of the original features that have maximum variance [13]. By using PCA, it is possible to reduce the dimension of the image vectors without losing significant information. The results of dimension reduction for the four mechanical components using PCA can be seen in Figure 6.

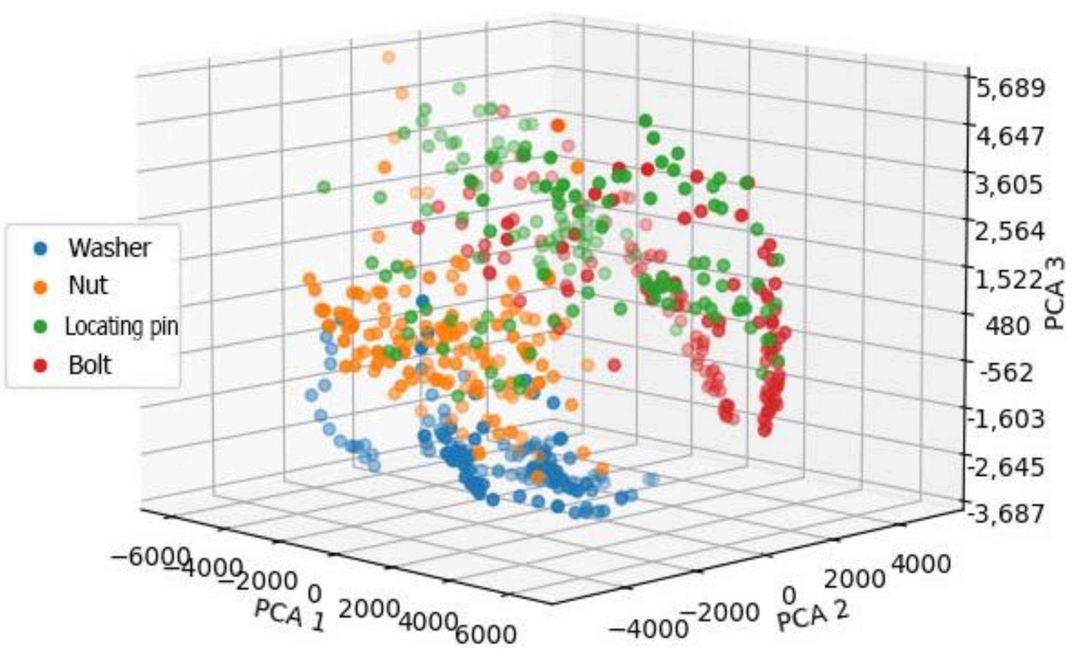

Figure 6. Dimension reduction using PCA

Based on the PCA results in Figure 6, it can be seen that the dowel has a more scattered data distribution compared to the other three components. The wider data distribution for the dowel indicates that this component has high variability or larger variations. This suggests that the dataset of dowel digital images tends to have significant differences between one another. High variability can pose a challenge in classification tasks, as the model needs to understand these variations to produce accurate predictions.

3. Support Vector Machine Modeling with RBF Kernel

In this stage, the dataset is divided into 260 samples for training and 60 samples for testing. The resolution of the digital images used in the model training is set at 100 pixels, allowing for model performance optimization considering factors such as task complexity and computational resource limitations. The selection of image resolution in the SVM model has a significant impact on model performance and efficiency [20]. High resolution produces images with more pixels, which can increase the complexity of the SVM model because the required number of features becomes larger. On the other hand, lower resolution can result in the loss of detailed information, causing the model to miss capturing significant characteristics of the classified object. However, high resolution can increase the risk of overfitting, where the model may learn irrelevant details specific to the training data. Meanwhile, low resolution can increase the risk of underfitting, where the model fails to capture important variations in the data. The SVM parameters with the RBF kernel being varied are C and γ (gamma). The parameter C in SVM controls the trade-off between classification errors on the training data and model complexity. In the implementation of the RBF kernel, the gamma parameter controls how much influence one data example has on the influence of other data examples. A high gamma value can cause the model to pay more attention to small details and may lead to overfitting. This parameter is searched using grid search with a range of values as shown in Table 1.

Table. 1 Parameter search variation.

No	Parameter	Value
1	C	0.1, 1, and 10
2	γ (gamma)	Scale, Auto, 0.1, 1, and 10

Based on the results of the model training, the best parameter combination was obtained with C = 10 and Gamma = scale. This can be seen from the confusion matrix presenting the prediction results for the four classes of mechanical components, as shown in Figure 7. In the case of the ring class, out of 60 samples, the model correctly predicted 57 samples, and 3 samples were predicted as nuts. For the nut class, the model correctly predicted 56 samples, and 4 samples were predicted as locating pin. In the dowel class, the model correctly predicted 53 samples, and there was a total of 7 mispredictions, 1 for nuts and 6 for bolts. Meanwhile, for the bolt class, the model correctly predicted all samples. This best parameter combination achieved an Accuracy of 94.17%, Precision of 0.94, Recall of 0.94, and F1-Score of 0.94.

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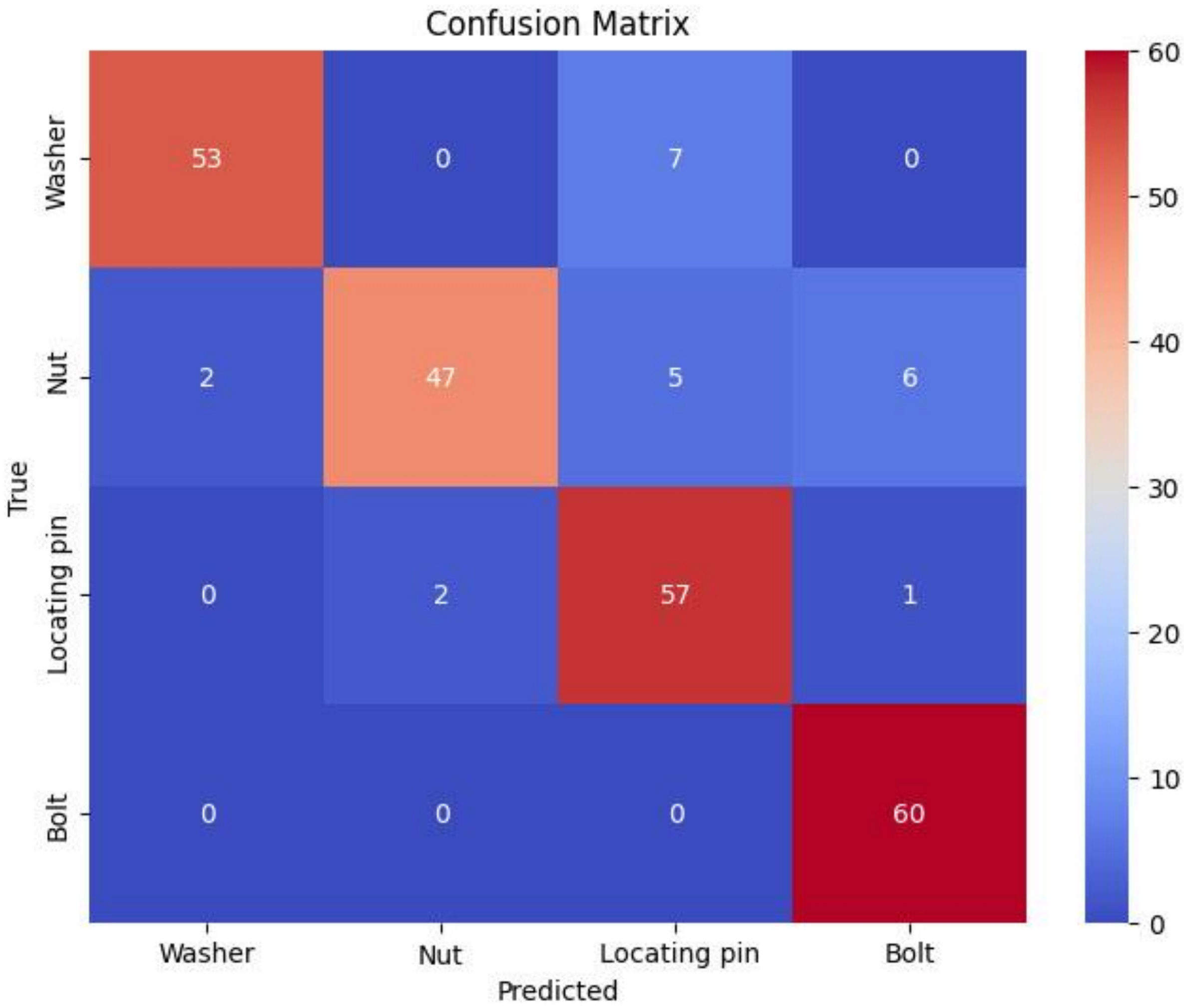

Figure 8. Confusion matrix

4. Model Evaluation

Model evaluation with K-Fold Cross Validation and external testing on data not present in the training data are two common approaches used to measure model performance more objectively and ensure good generalization [21]. K-Fold Cross Validation is a model evaluation method that divides the dataset into K folds of equal size. In this study, K=3 is used, so the dataset will be divided into 3 folds. The results of cross-validation can be seen in Figure 8, where the combination of parameters C=10 and Gamma = scale was able to achieve the highest accuracy, approximately 90%. This result is consistent with the best parameter search results during the previous model training, indicating that the SVM model with the RBF kernel is capable of making predictions with diverse training data.

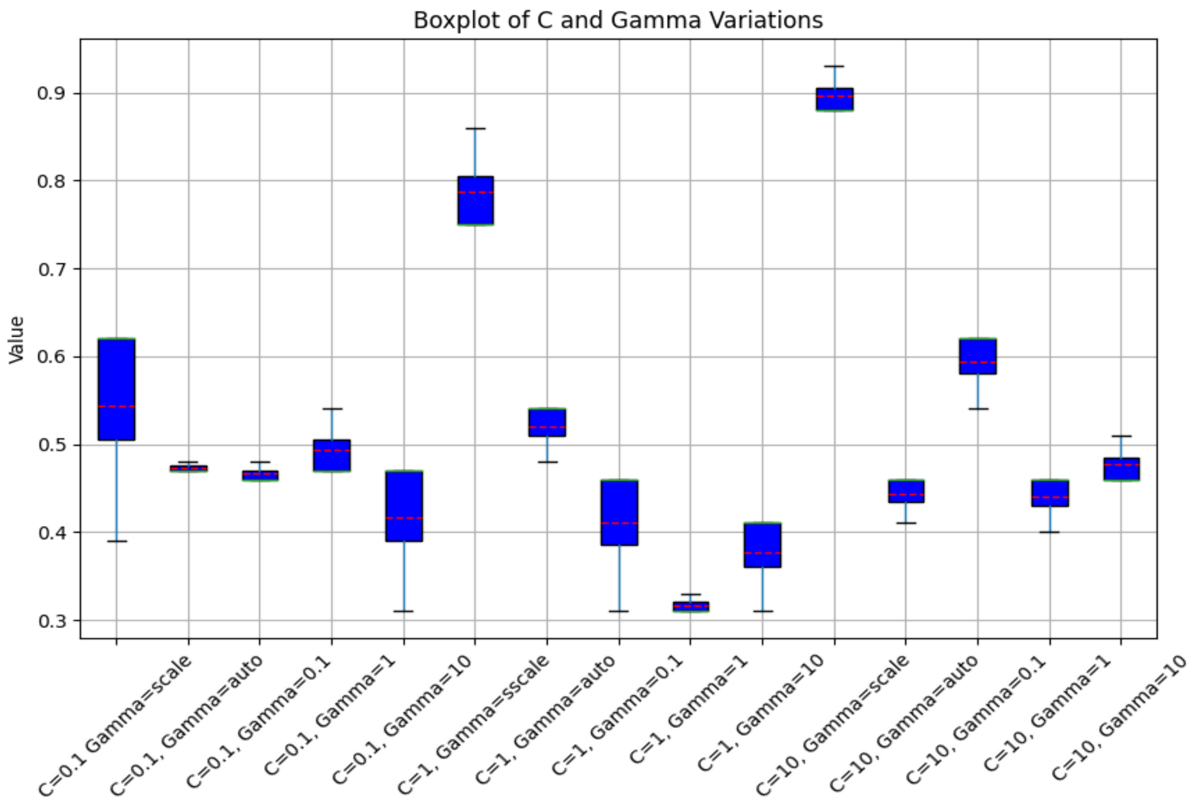

Figure 9. Comparison of model accuracy results on combinations of C and Gamma

Next, external testing was conducted with data not present in the training set. This data consists of 100 samples for each component. The tested model is the combination of the best parameters obtained earlier, namely C=10 and Gamma = scale. The results of testing with external data can be seen in the confusion matrix shown in Figure 10.

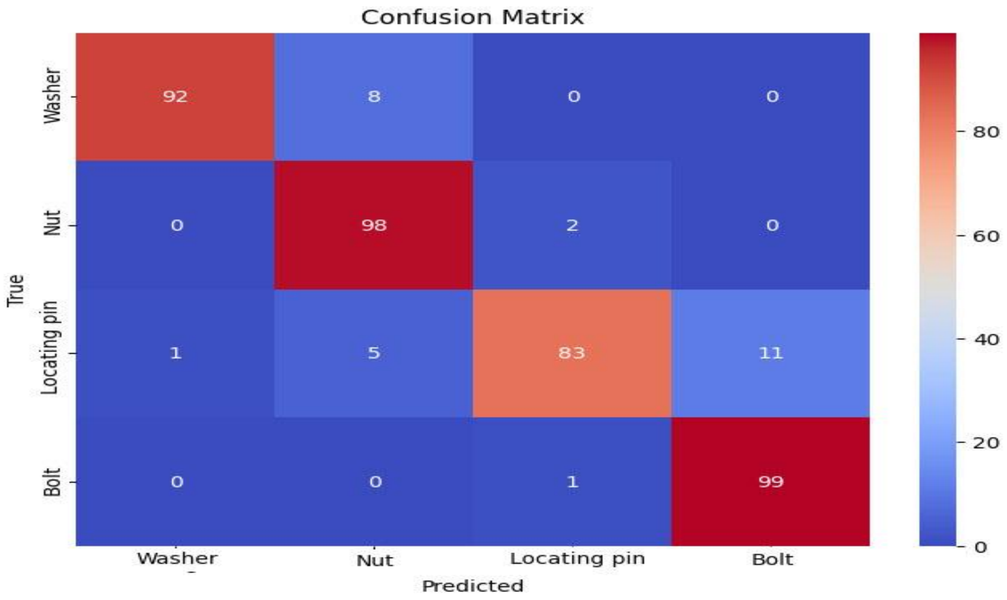

Figure 10. Confusion matrix

Based on the results of the confusion matrix from external testing, it can be observed that out of 100 samples of digital images of washer, the model was able to correctly predict approximately 92 samples, with 8 samples predicted as nuts. In the nut class, the model accurately predicted 98 digital images, and 2 images were predicted as locating pin. In the dowel class, there were 83 samples predicted correctly, 1 sample predicted as a ring, 5 samples predicted as nuts, and 11 samples predicted as bolts. Meanwhile, in the bolt class, the model correctly predicted 99 samples, and one sample was predicted as a dowel. The results of this external testing achieved evaluation metrics with an Accuracy value of 93%, Precision of 0.93, Recall of 0.93, and F1-Score of 0.93. These results are not significantly different from the previous model training, indicating that the SVM model with the RBF kernel can classify digital images of mechanical components such as bolts, washer, nuts, and locating pin very well. Based on the training and testing of the model, it can be seen that the dowel class is the least predictable class by the SVM model with the RBF kernel. This is attributed to the high data variability in the dowel class, making it challenging for the model to determine the correct class decisions for locating pin.

4. Conclusion

Based on the conducted research on the classification of mechanical components using SVM with the RBF kernel, it can be concluded that when high-resolution digital images are used, the results of data vectorization tend to be denser. Consequently, the data dimensions become more complex, which, in turn, can impact computation time and model accuracy. To address this issue, the implementation of Principal Component Analysis (PCA) proves to be an effective solution. PCA allows for dimension reduction in digital image data, enabling the SVM model with the RBF kernel to make more optimal and accurate classification decisions in determining the classes of mechanical components such as bolts, washer, nuts, and locating pin. This is evident from the evaluation metric values during both model training and testing with external data, where the SVM model with the RBF kernel is capable of achieving a sufficiently high level of model accuracy. The implementation of this model in a manufacturing environment can expedite the component identification process, minimize errors, and overall enhance production efficiency

Reference

[1]. Abubakr, M., Abbas, A. T., Tomaz, I., Soliman, M. S., Luqman, M., & Hegab, H. (2020). Sustainable and smart manufacturing: an integrated approach. Sustainability, 12(6), 2280.

[2]. Leni, D., & Selviaty, V. (2022). Estimasi Manufaktur Exspantion Joint di Bengkel Fabrikasi PT. Semen Padang. Jurnal Teknik Industri Terintegrasi (JUTIN), 5(1), 42-54.

[3]. Xu, C., & Zhu, G. (2021). Intelligent manufacturing lie group machine learning: Real-time and efficient inspection system based on fog computing. Journal of Intelligent Manufacturing, 32(1), 237-249.

[4]. Leni, D., & Sumiati, R. (2022). Perbandingan Alogaritma Machine Learning Untuk Prediksi Sifat Mekanik Pada Baja Paduan Rendah. Jurnal Rekayasa Material, Manufaktur dan Energi, 5(2), 167-174.

[5]. Sheykhmousa, M., Mahdianpari, M., Ghanbari, H., Mohammadimanesh, F., Ghamisi, P., & Homayouni, S. (2020). Support vector machine versus random forest for remote sensing image classification: A meta-analysis and systematic review. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13, 6308-6325.

[6]. Cervantes, J., Garcia-Lamont, F., Rodríguez-Mazahua, L., & Lopez, A. (2020). A comprehensive survey on support vector machine classification: Applications, challenges and trends. Neurocomputing, 408, 189-215.

[7]. Razaque, A., Ben Haj Frej, M., Almi'ani, M., Alotaibi, M., & Alotaibi, B. (2021). Improved support vector machine enabled radial basis function and linear variants for remote sensing image classification. Sensors, 21(13), 4431.

[8]. Papageorgiou, E. I., Theodosiou, T., Margetis, G., Dimitriou, N., Charalampous, P., Tzovaras, D., & Samakovlis, I. (2021, July). Short survey of artificial intelligent technologies for defect detection in manufacturing. In 2021 12th International Conference on Information, Intelligence, Systems & Applications (IISA) (pp. 1-7). IEEE.

[9]. Patel, A. K., Mandhala, V. N., Anguraj, D. K., & Nayak, S. R. (2021). Surface defect detection using SVM-based machine vision system with optimized feature. Machine Vision Inspection Systems, Volume 2: Machine Learning-Based Approaches, 109-127.

[10]. Maharana, K., Mondal, S., & Nemade, B. (2022). A review: Data pre-processing and data augmentation techniques. Global Transitions Proceedings, 3(1), 91-99.

[11]. Sarki, R., Ahmed, K., Wang, H., Zhang, Y., Ma, J., & Wang, K. (2021). Image preprocessing in classification and identification of diabetic eye diseases. Data Science and Engineering, 6(4), 455-471.

[12]. Huang, D., Jiang, F., Li, K., Tong, G., & Zhou, G. (2022). Scaled PCA: A new approach to dimension reduction. Management Science, 68(3), 1678-1695.

[13]. Ma, J., & Yuan, Y. (2019). Dimension reduction of image deep feature using PCA. Journal of Visual Communication and Image Representation, 63, 102578.

[14]. Kherif, F., & Latypova, A. (2020). Principal component analysis. In Machine Learning (pp. 209-225). Academic Press.

[15]. Alsheikh, M. A., Lin, S., Niyato, D., & Tan, H. P. (2014). Machine learning in wireless sensor networks: Algorithms, strategies, and applications. IEEE Communications Surveys & Tutorials, 16(4), 1996-2018.

[16]. Sadewo, W., Rustam, Z., Hamidah, H., & Chusmarsyah, A. R. (2020). Pancreatic cancer early detection using twin support vector machine based on kernel. Symmetry, 12(4), 667.

[17]. Leni, D., & Yermadona, H. (2023). Pemodelan Inspeksi Kerusakan Ban Mobil Menggunakan Convolutional Neural Network (CNN). Jurnal Rekayasa Material, Manufaktur dan Energi, 6(2), 176-186.

[18]. Chan, L., Hosseini, M. S., & Plataniotis, K. N. (2021). A comprehensive analysis of weakly-supervised semantic segmentation in different image domains. International Journal of Computer Vision, 129, 361-384.

[19]. Clement, D., Agu, E., Suleiman, M. A., Obayemi, J., Adeshina, S., & Soboyejo, W. (2023). Multi-class breast cancer histopathological image classification using multi-scale pooled image feature representation (mpifr) and one-versus-one support vector machines. Applied Sciences, 13(1), 156.

[20]. Chandra, M. A., & Bedi, S. S. (2021). Survey on SVM and their application in image classification. *International Journal of Information Technology*, *13*, 1-11.

[21]. Yan, T., Shen, S. L., Zhou, A., & Chen, X. (2022). Prediction of geological characteristics from shield operational parameters by integrating grid search and K-fold cross validation into stacking classification algorithm. Journal of Rock Mechanics and Geotechnical Engineering, 14(4), 1292-1303