# ML-Based Classification Models for Assessing Workpiece Dimensional Accuracy

**Pavle STEPANIĆ[1], Nedeljko DUČIĆ[2], Jelena BARALIĆ[2], Nebojša STANKOVIĆ[2], Đorđe DAMNJANOVIĆ[2]*, Vladan GRKOVIĆ[3]**

[1] Research and Development Institute Lola Ltd., Kneza Viseslava 70A, 11030, Belgrade, Serbia
pavle.stepanic@li.rs

[2] Faculty of Technical Sciences Čačak, University of Kragujevac, Svetog Save 65, 32102, Čačak, Serbia
nedeljko.ducic@ftn.kg.ac.rs, jelena.baralic@ftn.kg.ac.rs, nebojsa.stankovic@ftn.kg.ac.rs, djordje.damnjanovic@ftn.kg.ac.rs (**Corresponding author*)

[3] Faculty of Mechanical and Civil Engineering in Kraljevo, University of Kragujevac, Dositejeva 19, 36000, Kraljevo, Serbia
grkovic.v@mfkv.kg.ac.rs

**Abstract:** The integration of machine learning (ML) into manufacturing processes has significantly improved predictive maintenance and quality assessment, particularly in Computer Numerical Control (CNC) machining. This study presents the development and evaluation of four types of ML classification models, namely Support Vector Machine (SVM), k-Nearest Neighbors (KNN), Naïve Bayes, and Artificial Neural Network (ANN) models for assessing the dimensional accuracy for workpieces produced via step drilling on a horizontal CNC machining center. Vibration signal features were extracted during the machining process, resulting in 27 statistical features per workpiece. The models were trained on a dataset from 2019 and tested on an independent dataset from 2021 in order to evaluate their temporal robustness. The Medium Gaussian SVM model and the ANN model with the 27-21-2 architecture achieved the highest training accuracy, namely 98.77%, and the latter showed a perfect generalization ability with a 100% accuracy for the 2021 test dataset. These findings confirm the suitability of ML-based models for quality assessment in the context of machining processes, and their potential for integration into real-time smart manufacturing systems.

**Keywords**: Step drilling, CNC machining, Vibration signal, Machine learning, Classification models.

## 1. Introduction

The companies that embrace the principles of smart production rely on the systematic recording, collection, and analysis of data throughout all phases of manufacturing, embodying the essence of Industry 4.0. Within the Industry 4.0 paradigm, smart manufacturing systems constitute a cornerstone for the development of high value-added processes and services (Banța et al., 2024). This concept encompasses areas such as the Internet of Things (IoT), Internet of Services (IoS), Artificial Intelligence (AI), and data mining (DM), allowing for the management of big data and its utilization to develop effective maintenance strategies. The manufacturing equipment typically has a lifespan of up to 20 years or more (Stock & Seliger, 2016), and integrating it with the existing brownfield components and controllers can hinder the implementation of scalable real-time applications. The shift towards Industry 4.0, particularly through Cyber-Physical Systems and the Internet of Things (IoT), has facilitated the digital transformation and retrofitting of older machines with connected sensors, edge computing, cloud connectivity, and other technologies (Quatrano et al., 2017; Lins et al., 2017). The integration of artificial intelligence (AI) and machine learning (ML) into the realm of Computer Numerical Control (CNC) machines has significantly transformed predictive maintenance practices in manufacturing. The advent of Industry 4.0 has catalyzed this transformation, enabling the development of smart factories characterized by interconnected systems and advanced data analytics capabilities. These advancements necessitate customized approaches to address the unique requirements of diverse manufacturing environments, particularly in the context of condition-based maintenance (CBM) and predictive maintenance solutions (Polenghi et al., 2023; Rahal et al., 2023).

The integration of machine learning (ML) techniques, particularly neural networks and support vector machines (SVM), into the area of machining and CNC (Computer Numerical Control) machines has garnered significant attention in recent years. These technologies are pivotal in enhancing manufacturing processes by improving efficiency, accuracy, and predictive capabilities. Machine learning, especially through the use of neural networks, has shown great

https://doi.org/10.24846/v34i4y202502 

promise in optimizing CNC machining processes (Arotaritei et al., 2014). For instance, Mongan et al. (2023) demonstrated the effectiveness of an ensemble neural network specifically designed for optimizing CNC milling operations, which highlights the potential of ML to enhance traditional machining methods. Similarly, Liu et al. (2021) explored the application of a bidirectional long short-term memory (BiLSTM) network for thermal error modeling in CNC machines, emphasizing the ability of deep learning to capture complex temporal patterns that influence machining accuracy. These studies illustrate how neural networks can be utilized to address specific challenges in CNC machining, such as thermal errors and process optimization.

Support vector machines (SVM) also play a crucial role in the context of machining. Gao et al. (2020) developed a machine learning-based approach for cutting chatter identification from vibration datasets. They applied support vector machine (SVM) for classification, achieving a high identification accuracy of 92.57%. Sharp et al. (2018) discussed the advantages of SVM in cost estimation for manufacturing processes, noting its capacity to incorporate new data rapidly, which is essential for maintaining accurate cost models in dynamic manufacturing environments.

This adaptability is particularly beneficial in CNC machining, where operational conditions can frequently change. Moreover, the work of Yang & Rai (2019) on machine auscultation using convolutional neural networks (CNNs) for diagnosing CNC lathe operations further underscores the versatility of ML techniques in enhancing machine performance and reliability. Furthermore, the application of unsupervised learning methods, such as the Gaussian mixture models, has been explored for contextual classification in smart machining environments. Wang et al. (2020) highlighted how these models can analyze machine-tool signals to improve the operational insights and decision-making processes. This is particularly relevant in modern manufacturing settings where data-driven approaches are essential for optimizing the machine-tool performance and ensuring quality control. The integration of machine learning with traditional machining processes not only enhances operational efficiency but it also facilitates predictive maintenance. For instance, Bencheikh et al. (2022) proposed a model that combines production scheduling with predictive maintenance, utilizing deep learning algorithms for optimizing both aspects simultaneously. This approach is crucial in CNC machining, where unplanned downtimes can significantly impact productivity. In summary, the incorporation of machine learning, particularly through neural networks and SVM, into CNC machining processes represents a transformative shift in manufacturing practices. These technologies provide robust solutions for optimizing machining operations, improving predictive maintenance, and enhancing the overall efficiency and accuracy.

All the above provides the foundation and motivation for this research, which evaluates the performance of machine learning algorithms in classifying the correctness of machining processes in a horizontal CNC machining center during the step drilling operation. Four ML algorithms - SVM, KNN, Naïve Bayes, and ANN - are investigated in order to develop classification models capable of accurately assessing the dimensional conformity of workpieces based on vibration signals acquired during drilling.

The key novelty of this study lies in validating the employed models on a dataset collected two years after training, thereby assessing their long-term generalization ability and stability. This demonstrates the potential of the developed models for real-time industrial monitoring. Additionally, this paper presents a comprehensive methodology for preparing and processing real industrial data using ML algorithms and performing detailed result analysis. The remainder of the paper is structured as follows. Section 2 describes the data collection and preprocessing methodology, while Section 3 presents and discusses the obtained results. Finally, Section 4 concludes this paper with the key findings and outlines possible future work directions.

## 2. Data Collection and Preprocessing

The dataset employed in this study originated from the Bosch CNC Machining Dataset (Tnani et al., 2022), which was collected at a production facility using a horizontal CNC machining center between October 2018 and August 2021. The dataset includes vibration intensity values along three axes (X, Y, and Z) recorded during the machining process. Data acquisition took place during the step drilling process for aluminum workpieces, where sequential drilling was performed to create holes of varying diameters on a single part. The data was gathered (sampling rate of 2 kHz) using an indirect measurement approach, utilizing accelerometers from Bosch CISS sensors, which were positioned at the rear of the spindle housing. The sensor was mounted such that its distance from the tool center point remained constant, and its three accelerometer axes were aligned with the machine's linear motion axes. The sensor coordinate system is shown in Figure 1.

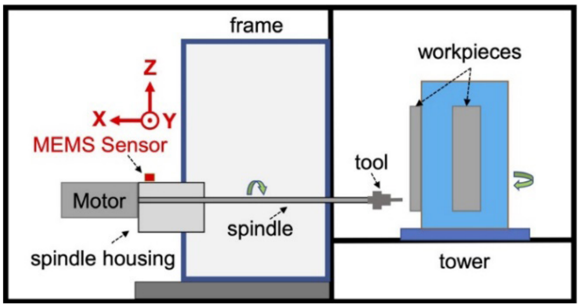



**Figure 1.** Experimental setup: 4-axis CNC machining center with sensor installation (Tnani et al., 2022)

Drilling is one of the most important metal cutting operations, which after turning and milling is the most common in the process of metal cutting. Drilling is the process of machining openings and holes. The openings and holes that are made can be of constant diameter or step holes. Two drills of different diameters or one step drill can be used to make step holes.

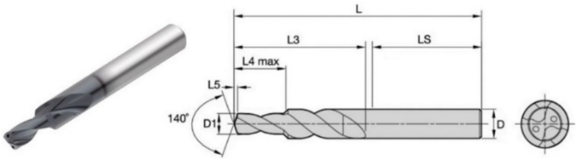



**Figure 2.** Step drill (Kennametal, n.d.)

The main rotating and auxiliary linear movements are performed by the drill tool. The main movement is defined by the cutting speed V, measured in m/min or the number of revolutions n, expressed as rev/min, and the auxiliary movement is defined by feed f, the axial movement of the tool for one revolution of the tool measured in mm/rev or the feed rate $V_f$, measured in mm/min. When calculating the cutting speed and feed of two-diameter drills like center drills, step drills and sub-land drills, the largest cutting diameter is used for calculating the cutting speed and the smallest diameter is used for selecting the feed. In this paper, the utilized workpiece material is aluminum alloy. Aluminum is the second most used metal because of its low density, high conductivity, high strength and other characteristics. The machining of aluminum alloys can be done with general-purpose tools, but it is best to choose tools specially designed for these materials. The advantages of machining materials such as aluminum alloys include processing with high cutting speeds, low cutting forces, low temperatures in the cutting zone and minimal tool wear. The problems that occur when machining aluminum alloys include achieving the desired machined surface quality and accuracy and built-up edges on the tool edges. The choice of cutting speed and feed is very important. Their correct selection reduces the size of built-up edges and prevents chip breaking. Table 1 provides an overview of the values of the process parameters used during the collection of experimental data for the step drill process.

**Table 1.** The process parameter values

| Designation of the step drilling operation | n (rev/min) | $V_f$ (mm/min) |
|---|---|---|
| OP00 | 15000 | 100 |
| OP01 | 15000 | 100 |
| OP03 | 15000 | 330 |
| OP04 | 15000 | 100 |
| OP05 | 12000 | 50 |
| OP06 | 15000 | 50 |
| OP07 | 12000 | 50 |
| OP08 | 15000 | 50 |
| OP10 | 15000 | 50 |
| OP11 | 15000 | 50 |
| OP12 | 15000 | 50 |
| OP14 | 15000 | 50 |

The data was collected for 81 workpieces in 2019 and 22 workpieces in 2021. Out of the 81 workpieces from 2019, 49 exhibited satisfactory dimensional characteristics after processing, while 32 were classified as scrap. Regarding the workpieces manufactured in 2021, 15 had satisfactory dimensional characteristics after processing, and 7 were classified as scrap. Figures 3–5 depict the data collected during the step drilling process for one workpiece that met the dimensional requirements and one that did not meet them, under the process parameters defined for the OP10 operation. The vibrations are shown in the time domain, where the ordinate represents the vibration intensity and the abscissa represents the number of samples. The vibrations associated with a poor processing quality are labeled as Not OK (NOK) on the graphs, while those corresponding to acceptable processing quality are labeled as OK.

Feature extraction was performed for the vibration signals collected along all the three axes (X, Y, and Z) for all workpieces using digital signal processing in the time domain. The following statistical parameters were employed for characterizing the vibration signals:

- Arithmetic mean - $\overline{x} = \frac{1}{N}\sum_{i=1}^{N} x(i)$
- Root Mean Square - $x_{rms} = \left(\frac{1}{N}\sum_{i=1}^{N} x^2(i)\right)^{1/2}$
- Square Mean Root - $x_r = \left(\frac{1}{N}\sum_{i=1}^{N} |x(i)|^{1/2}\right)^2$

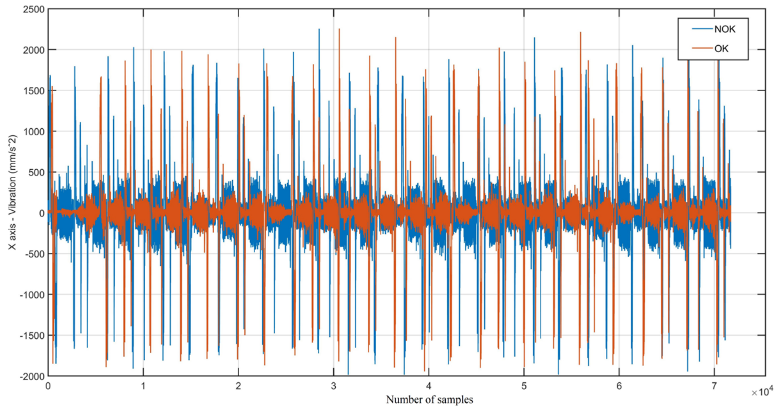



**Figure 3.** Vibration intensity along the X axis

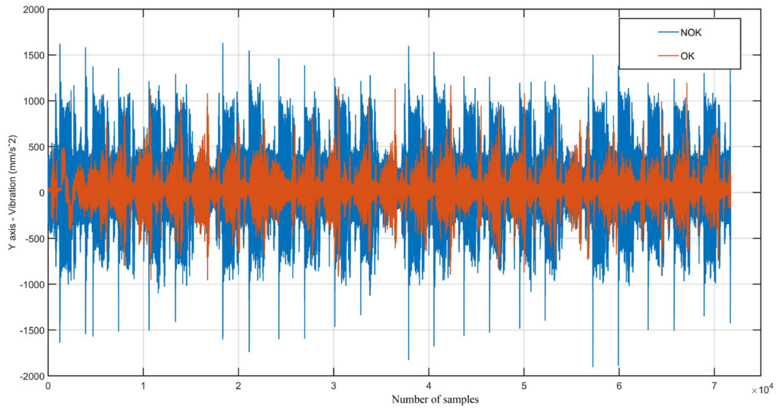



**Figure 4.** Vibration intensity along the Y axis

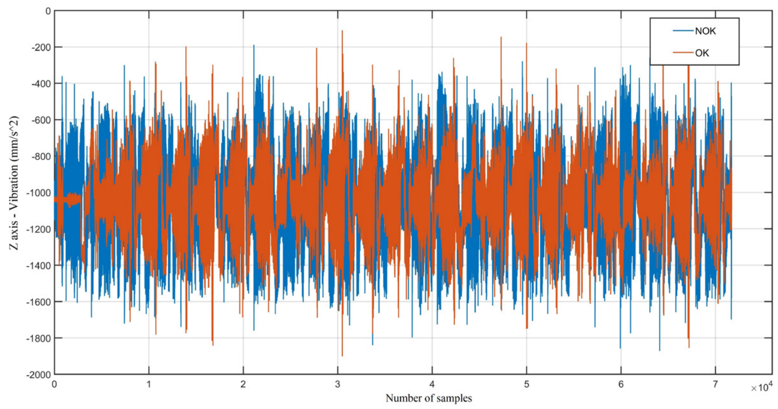



**Figure 5.** Vibration intensity along the Z axis

- Skewness Index - $x_{ske} = \dfrac{\frac{1}{N}\sum_{i=1}^{N}\left(x(i)-\overline{x}\right)^3}{x_v^{3/2}}$, the variance - $x_v = \frac{1}{N}\sum_{i=1}^{N}\left(x(i)-\overline{x}\right)^2$
- Kurtosis Index - $x_{kur} = \dfrac{\frac{1}{N}\sum_{i=1}^{N}\left(x(i)-\overline{x}\right)^4}{x_v^2}$
- C factor - $C = \frac{PP}{x_{rms}}$, where *PP* is the peak-to-peak value: $PP = \max_i\left(x(i)\right) - \min_i\left(x(i)\right)$
- L factor - $L = \frac{PP}{x_r}$
- S factor - $S = \frac{x_{rms}}{\overline{x}}$
- I factor - $I = \frac{PP}{\overline{x}}$, where $x(i)$ is the vibration signal sample at discrete time point $i\Delta t$, and $\Delta t = 1/2kHz$.

In this way, each workpiece is described by 27 statistical features of the vibration signals (9 features per axis) recorded during signal processing.

## 3. Machine Learning Algorithms for Machined Parts Recognition

As highlighted in the introduction, four types of ML algorithms (SVM, KNN, Naïve Bayes, and ANN) were employed in order to develop a classification model that evaluates, based on 27 statistical characteristics of the signal, whether the machined part is dimensionally correct or classified as scrap. The dataset collected in 2019 was used for developing the classifier models. As it was previously mentioned, it consists of 81 samples, corresponding to 81 workpieces. The classifier models were developed using the MATLAB software package, and their performance was assessed using standard evaluation techniques such as a confusion matrix and the receiver operating characteristic (ROC) curve. For every prediction by a classification model, a matrix called the confusion matrix can be constructed which indicates the number of cases which were correctly and incorrectly classified. The terms used in the confusion matrix are described below:

- True Positive (TP): These are the positive cases, which the model correctly predicted as positive;
- False Positive (FP): These are the cases that are not positive, but the model predicted them as positive;
- True Negative (TN): These are the negative cases, which the model correctly predicted as negative;
- False Negative (FN): These are the cases that are actually positive, but the model has incorrectly predicted them as negative cases.

Based on the aforementioned components of the confusion matrix, it is possible to calculate important model characteristics, such as:

- Precision = TP/(TP+FP),
- Negative Predictive Value = TN/(TN+FN)),
- Recall (Sensitivity) = TP/(TP+FN),
- Specificity = TN/(TN+FP),
- Accuracy = (TP+TN)/(TP+FP+TN+FN) and
- F1 Score = 2*(Precision*Recall)/(Precision+Recall).

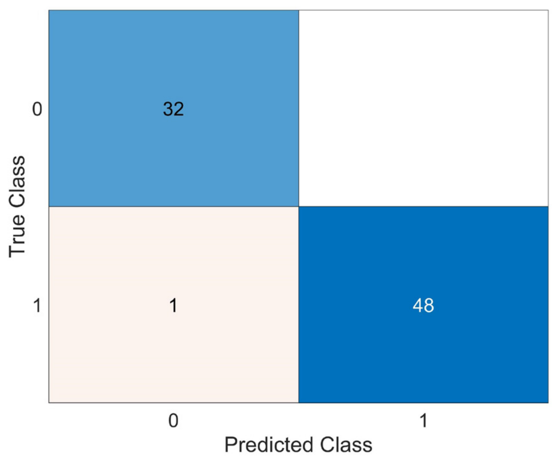
Accuracy is a basic evaluation metric, calculated as the ratio of correctly predicted instances to the total number of instances. This metric is most meaningful when the dataset is balanced, that is when each class has an equal number of instances. However, in the case of imbalanced datasets, accuracy may be misleading, as it does not provide a comprehensive understanding of a model's performance. The precision score measures the proportion of correctly predicted positive cases to all the cases predicted as positive by the employed model. It is particularly useful when minimizing false positives is a priority. The recall score, also known as sensitivity, represents the true positive rate, which is calculated as the proportion of correctly predicted positive cases to the total number of actual positive cases. It is important when minimizing false negatives is a priority. The F1 score is the harmonic mean of precision and recall, combining both metrics into a single value. It is particularly useful when both precision and recall need to be balanced in the evaluation of a model.

### 3.1 SVM Classification Models

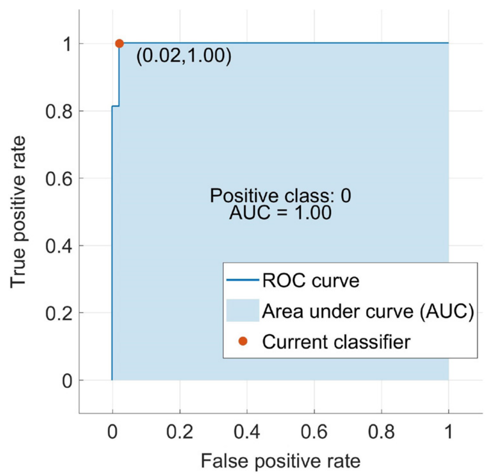
Support Vector Machines (SVMs) represent a powerful class of supervised learning algorithms primarily utilized for classification tasks. At the core of SVMs is the concept of hyperplanes, which are decision boundaries that separate different classes in the feature space. The optimal hyperplane is defined as the one that maximizes the margin between the closest data points of each class, known as support vectors. In scenarios where the data is not linearly separable, SVMs employ kernel functions to map the input features into a higher-dimensional space, where a linear separation becomes feasible. The commonly used kernels include polynomial, radial basis function (RBF), and sigmoid kernels, each providing a different mechanism for transforming the data. Among the SVM classification models, the Medium Gaussian SVM exhibited the best performance (see Table 2 and Figure 6), with only one misclassification and an overall accuracy of 98.77%. The Medium Gaussian SVM model employs the most commonly used kernel for SVM – the Gaussian (RBF) kernel expressed in equation (1):

$$K(x_i, x_j) = e^{\left(-\frac{\|x_i - x_j\|^2}{2\sigma^2}\right)} \tag{1}$$

where: $x_i$,$x_j$ are the input vectors, and σ is the kernel scale (the width parameter of the Gaussian function). The kernel scale (σ) in the case of the Medium Gaussian SVM model is 5.7 and this model provides a good balance between accuracy and robustness. The kernel scale in the case of the Fine Gaussian SVM and Coarse Gaussian SVM models is 1.4 and 23, respectively. The results provided by the aforementioned models are significantly weaker than those obtained by the other algorithms in Table 2. The parameter of the SVM classifier, which relates to the balance between classification accuracy and decision boundary smoothness, is C=1 for all the developed SVM models.




(a)




(b)

**Figure 6**. (a) Confusion matrix and (b) ROC curve of the Medium Gaussian SVM model

**Table 2**. The six SVM classification models – evaluation results

| Classifier | TP | FP | TN | FN | Precision (%) | Negative Predictive Value (%) | Recall (%) | Specificity (%) | Accuracy (%) | F1 Score (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| Linear SVM | 48 | 4 | 28 | 1 | 92.31 | 96.55 | 97.96 | 87.50 | 93.83 | 95.05 |
| Quadratic SVM | 48 | 2 | 30 | 1 | 96.00 | 96.77 | 97.96 | 93.75 | 96.30 | 96.97 |
| Cubic SVM | 49 | 4 | 28 | 0 | 92.45 | 100 | 100 | 87.50 | 95.06 | 96.08 |
| Fine Gaussian SVM | 49 | 16 | 16 | 0 | 75.38 | 100 | 100 | 50 | 80.25 | 85.96 |
| Medium Gaussian SVM | 48 | 0 | 32 | 1 | 100 | 96.97 | 97.96 | 100 | 98.77 | 98.97 |
| Coarse Gaussian SVM | 44 | 8 | 25 | 4 | 84.62 | 86.21 | 91.67 | 75.76 | 85.19 | 88 |

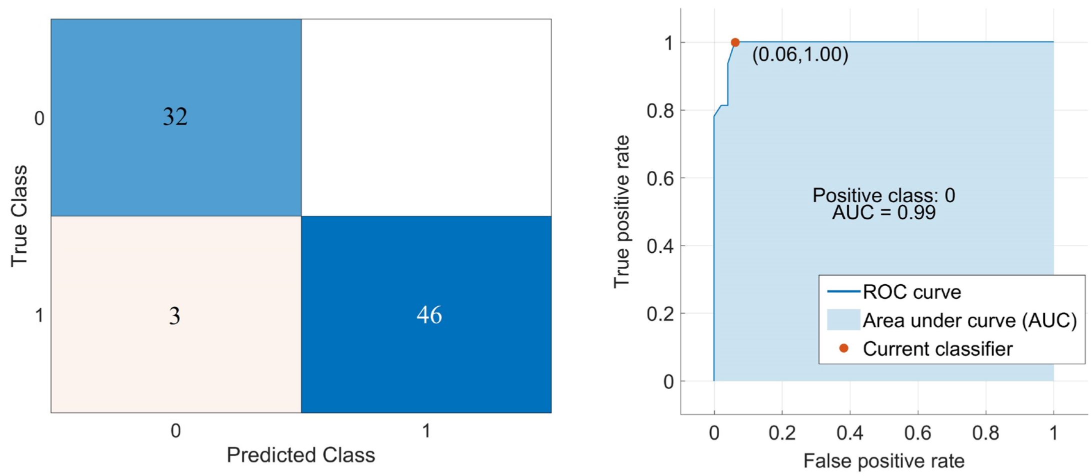
## 3.2 KNN Classification Models

The K-Nearest Neighbors (KNN) classification algorithm is a widely utilized non-parametric method in machine learning, primarily due to its simplicity and effectiveness in various classification tasks. The mathematical foundation of KNN is rooted in the concept of distance metrics, which are used for determining the proximity of data points in a multi-dimensional space. The algorithm operates by identifying the 'k' nearest neighbors for a query point from a labeled training dataset and assigning the most common class among these neighbors to the query point. The distance between points can be measured using various metrics, such as the Euclidean, Cosine, or Minkowski distances, depending on the nature of the data and the specific requirements of the classification task. The choice of 'k', the number of neighbors to consider, is crucial, as it can significantly impact the algorithm's performance. A small 'k' may lead to noise sensitivity, while a large 'k' can smooth out class boundaries, potentially misclassifying data points. The KNN algorithm is particularly effective in scenarios where class boundaries are not well-defined, as it can adapt to the local structure of the data. Among the KNN classification models, the Fine KNN exhibited the best performance (see Table 3 and Figure 7), with three misclassifications and an overall accuracy of 96.3%. The Fine KNN model featured a number of neighbors $k=1$, and used the Euclidean distance metric in equation (2), which is the square of the Euclidean distance between the two vectors $x_s$ and $y_t$:

$$d^2_{st} = (x_s - y_t)(x_s - y_t)' \qquad (2)$$

## 3.3 Naive Bayes Classification Models

The Naive Bayes classification algorithm is grounded in Bayes' theorem, which provides a probabilistic framework for classification tasks. The fundamental principle behind the Naive Bayes classification algorithm is the assumption of conditional independence among the features




(a) (b)

**Figure 7.** (a) Confusion matrix and (b) ROC curve of the Fine KNN model

**Table 3.** The six KNN classification models – evaluation results

| Classifier | TP | FP | TN | FN | Precision (%) | Negative Predictive Value (%) | Recall (%) | Specificity (%) | Accuracy (%) | F1 Score (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| Fine KNN | 46 | 0 | 32 | 3 | 100 | 91.43 | 93.88 | 100 | 96.3 | 96.84 |
| Medium KNN | 43 | 4 | 28 | 6 | 91.49 | 82.35 | 87.76 | 87.50 | 87.65 | 89.58 |
| Coarse KNN | 47 | 32 | 1 | 1 | 59.49 | 50 | 97.92 | 3.03 | 59.26 | 74.02 |
| Cosine KNN | 42 | 1 | 31 | 7 | 97.67 | 81.58 | 85.71 | 96.88 | 90.12 | 91.30 |
| Cubic KNN | 44 | 4 | 28 | 5 | 91.67 | 84.85 | 89.80 | 87.50 | 88.89 | 90.72 |
| Weighted KNN | 48 | 5 | 27 | 1 | 90.57 | 96.43 | 97.96 | 84.38 | 92.59 | 94.12 |

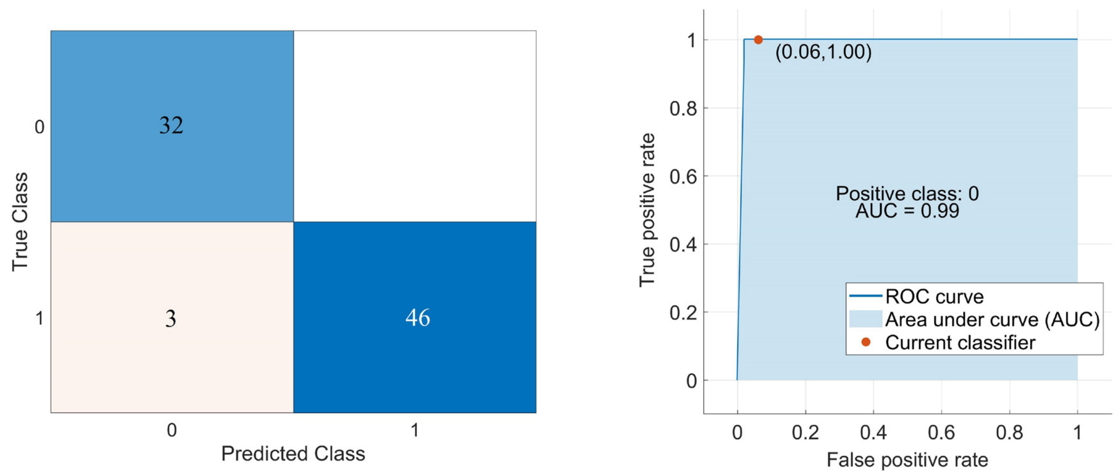
considering the class label. This assumption simplifies the computation of the posterior probability for a class given the features, allowing for an efficient classification even in high-dimensional spaces. Its mathematical formulation is given in equation (3).

$$P(C|X)=\frac{P(X|C)P(C)}{P(X)} \tag{3}$$

where P(C|X) is the posterior probability of class (C) given the features denoted by (X), P(X|C) is the likelihood of features for class (C), P(C) is the prior probability of class (C), and P(X) is the evidence. Among the Naive Bayes classification models, the Kernel Naive Bayes model demonstrated the best performance (see Table 4 and Figure 8), with three misclassifications and an overall accuracy of 96.3%. The Kernel Naive Bayes model, instead of assuming a specific distribution shape, uses a nonparametric probability density estimation method called Kernel Density Estimation (KDE). This means that for each class and each feature, the distribution P(X|C) is estimated based on real data using a "kernel" function (Gaussian in this case).

### 3.4 ANN Classification Models

Artificial Neural Networks (ANNs), while not very frequently compared directly with the aforementioned algorithms, are recognized for their ability to model complex relationships among data through their layered architecture. They are mathematical models inspired by biological neural networks, designed to process complex data through interconnected nodes that mimic the behavior of neurons in the human brain. During the development of the corresponding neural network, several architectures with a different number of hidden layers and neurons were designed and tested. The best performance was achieved by the architecture consisting of a single hidden layer with 21 neurons. This network was trained using the scaled conjugate gradient backpropagation algorithm. The training process converged after 54 epochs, when the cross-entropy loss function - the key performance metric of the neural network - reached a value of $5.36\times10^{-5}$. A comparative analysis of the performance of five neural network architectures is presented in




(a) (b)

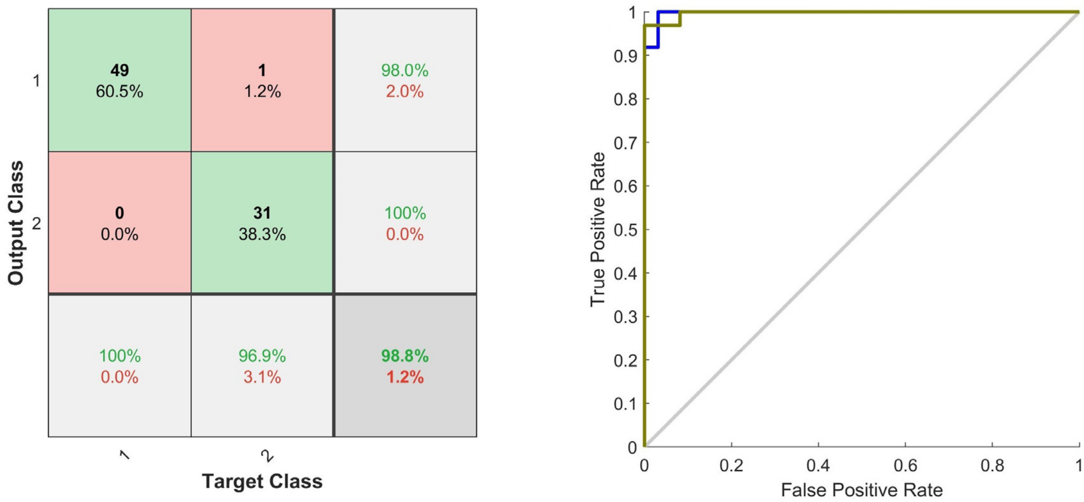
**Figure 8.** (a) Confusion matrix and (b) ROC curve of the Kernel Naive Bayes model

**Table 4.** The Naive Bayes classification models – evaluation results

| Classifier | TP | FP | TN | FN | Precision (%) | Negative Predictive Value (%) | Recall (%) | Specificity (%) | Accuracy (%) | F1 Score (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| Kernel Naive Bayes | 46 | 0 | 32 | 3 | 100 | 91.43 | 93.88 | 100 | 96.3 | 96.84 |
| Gausian Naive Bayes | 41 | 0 | 32 | 8 | 100 | 80 | 83.67 | 100 | 90.12 | 91.11 |

Table 5, clearly showing that this configuration achieved the best results (one misclassification and an overall accuracy of 98.77%). Figure 9 shows the two criteria that also reflect the success of the developed architecture.

Therefore, the classifier models with the best performance are the Medium Gaussian SVM, Kernel Naive Bayes, Fine KNN, and ANN27-21-2 models. Each of the four classifier models presented above was tested on a dataset collected in 2021, consisting of 22 samples (22 workpieces) that were not used in the model development process. The primary objective of this testing was to evaluate the models' accuracy and consistency over a two-year period. Table 6 presents the performance results for these four models on the test dataset.




(a) (b)

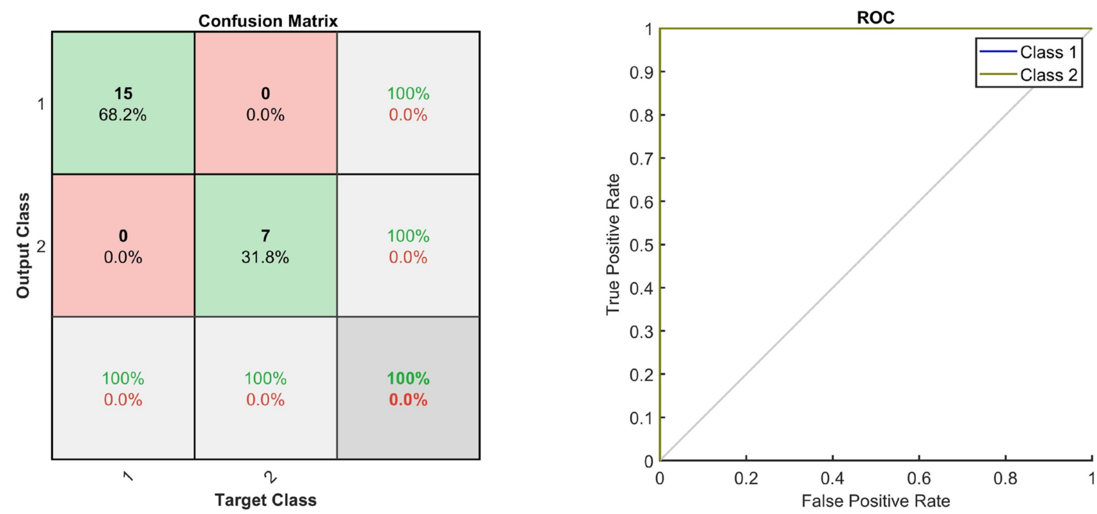
**Figure 9.** (a) Confusion matrix and (b) ROC curve of the ANN 27-21-2 model

**Table 5.** The five ANN classification models – evaluation results

| Classifier | TP | FP | TN | FN | Precision (%) | Negative Predictive Value (%) | Recall (%) | Specificity (%) | Accuracy (%) | F1 Score (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| ANN 27-21-2 | 49 | 0 | 31 | 1 | 100 | 96.88 | 98 | 100 | 98.77 | 98.99 |
| ANN 27-40-2 | 41 | 8 | 31 | 1 | 83.67 | 96.88 | 97.62 | 79.49 | 88.89 | 90.11 |
| ANN 27-32-2 | 49 | 0 | 30 | 2 | 100 | 93.75 | 96.08 | 100 | 97.53 | 98 |
| ANN 27-27-2 | 49 | 0 | 28 | 4 | 100 | 87.50 | 92.45 | 100 | 95.06 | 96.08 |
| ANN 27-54-2 | 48 | 1 | 30 | 2 | 97.96 | 93.75 | 96.00 | 96.77 | 96.30 | 96.97 |

**Table 6.** The four ML classification models – evaluation results for the test dataset

| Classifier | TP | FP | TN | FN | Precision (%) | Negative Predictive Value (%) | Recall (%) | Specificity (%) | Accuracy (%) | F1 Score (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| Medium Gaussian SVM | 13 | 2 | 7 | 0 | 86.67 | 100 | 100 | 77.78 | 90.91 | 92.86 |
| Kernel Naive Bayes | 9 | 6 | 7 | 0 | 60 | 100 | 100 | 53.85 | 72.73 | 75.00 |
| ANN 27-21-2 | 15 | 0 | 7 | 0 | 100 | 100 | 100 | 100 | 100 | 100 |
| Fine KNN | 14 | 1 | 6 | 1 | 93.33 | 85.71 | 93.33 | 85.71 | 90.91 | 93.33 |




(a) (b)

**Figure 10.** (a) Confusion matrix and (b) ROC curve of the ANN 27-21-2 model in the testing phase

Among the four tested models, three achieved an accuracy rate exceeding 90%. Notably, the artificial neural network model, ANN 27-21-2, outperformed the other models, demonstrating the highest and maximal overall performance (see Figure 10).

## 4. Conclusion

This study presents a systematic investigation of machine learning (ML) algorithms for classifying machined parts according to dimensional accuracy. Four types of algorithms, namely Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Naive Bayes (NB), and Artificial Neural Network (ANN) models were trained using vibration signal data acquired during the step drilling process on a horizontal CNC machining center at Bosch company. The statistical features extracted from tri-axial vibration signals (27 in total) were used for characterizing each manufactured workpiece.

The experimental results indicate that the Medium Gaussian SVM and ANN 27-21-2 models achieved the highest classification accuracy (98.77%), while the Fine KNN and Kernel Naive Bayes models also exhibited a strong performance (96.3%). Model validation on an independent dataset confirmed model robustness, with the ANN (27-21-2 architecture) reaching a perfect classification rate (100%).

These findings demonstrate the feasibility of ML-based classification for quality assessment in machining operations. Future work will focus on extending this approach to other manufacturing processes and developing real-time inference modules for integrating them into CNC control systems.

## Acknowledgements

This research has been supported through the research grants of the Serbian Ministry of Science, Technological Development and Innovations, namely grant No. 451-03-137/2025-03/200132, grant No. 451-03-136/2025-03/200066 and grant No. 451-03-137/2025-03/200108.

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