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Application of Artificial Neural Networks for Quality Classification in Electromobility Manufacturing Processes

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Abstract

INTRODUCTION: Modern manufacturing requires proactive, data-driven quality control methods that support process stability, reduce non-conformities and improve product reliability.

OBJECTIVES: The objective of this paper is to evaluate the applicability of selected artificial neural network models for quality classification in an electromobility-related manufacturing process.

METHODS: The study used empirical production data, SIPOC process analysis and five neural network models evaluated with accuracy, error rate, validation cost, operational indicators, confusion matrices and ROC/AUC analysis.

RESULTS: The analysed models achieved validation accuracy above 95%, with the Narrow Neural Network obtaining the best overall result of 97.0% accuracy, 3.0% error rate and the lowest validation cost.

CONCLUSION: The results confirm that artificial neural networks can effectively support quality classification and proactive quality management in electromobility manufacturing processes.

Keywords: quality control, artificial neural networks, machine learning, predictive quality, electromobility, manufacturing process, product classification, data-driven quality management.

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1. Introduction

In modern production systems, quality is one of the key factors determining a company's competitiveness, operational performance, market position and ability to meet customer expectations. In an increasingly demanding industrial environment, consistently delivering products that meet specified requirements has become one of the key determinants of organisational success. Quality is now seen as an integral element of the entire production system, embedded in every stage of the manufacturing process, rather than just the final characteristic of a finished product.

In manufacturing environments, quality control plays a key role in maintaining stable and repeatable processes that comply with both technical specifications and customer expectations. When a production process is properly

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controlled and stable, it is possible to achieve consistent product quality and reduce the number of items that fail to meet defined standards, dimensional tolerances, or specification requirements [1].

Furthermore, maintaining process stability facilitates the early detection and resolution of hidden quality issues that could otherwise remain unnoticed until later stages of production or even after product delivery to the customer [2]. Such non-conformities can generate additional costs, including rework, scrap, warranty claims, complaints, and loss of customer trust.

In the traditional approach, quality control was mainly associated with final inspection, where products were checked after the completion of the manufacturing process. The main purpose of this practice was to identify and separate non-conforming items before they reached the customer [3]. Although such an approach helped detect visible defects and reduce the risk of delivering faulty products, it was largely corrective rather than preventive. As a result, the underlying causes of defects often remained unresolved, which could lead to repeated quality problems, higher production costs, lower process efficiency and interruptions in production flow.

However, in recent years, manufacturing companies have increasingly shifted from traditional, inspection-based quality control towards a more proactive approach. This modern approach places greater emphasis on prevention than on detection. It involves real-time monitoring of production parameters, the early detection of deviations, the systematic analysis of process variability and the implementation of corrective and preventive actions before defects occur. This enables organisations to identify quality issues more quickly and understand their root causes, thereby reducing the probability of recurrence.

Statistical process control tools play an important role in proactive quality management by enabling the systematic observation and evaluation of process behaviour over time. Using methods such as control charts, process capability analysis and trend monitoring enables companies to detect deviations from normal operating conditions at an early stage. This enables them to intervene before the process produces non-conforming products, thereby improving process stability and reducing waste. Additionally, the increasing use of digital technologies, sensors, data acquisition systems and advanced analytics further enhances the capacity to monitor production processes in real time and facilitate data-driven decision-making.

Consequently, contemporary quality control is becoming increasingly integrated with broader concepts such as continuous improvement, lean manufacturing, predictive quality, and Industry 4.0. These approaches facilitate the development of production systems that are more reliable, flexible and efficient. By focusing on prevention, process optimisation and systematically reducing variability, manufacturing companies can improve product quality, lower operational costs, enhance customer satisfaction and strengthen their long-term competitiveness. Therefore, quality control should be regarded not only as a corrective activity, but also as a proactive, data-driven element of production management.

The increasing use of production data, sensor technologies and digital monitoring systems has opened new possibilities for implementing artificial intelligence and machine learning in quality control. These approaches make it possible to identify complex dependencies between process parameters and product quality, support the early recognition of non-conformities and strengthen decision-making in manufacturing environments.

2. Literature Review

The development of Industry 4.0 has transformed the concept and implementation of quality control in modern manufacturing systems. Traditional methods, which are mainly based on manual inspection, statistical sampling and end-of-line verification, are becoming increasingly inadequate in environments characterised by high production speeds, complex product structures and strict customer requirements. Contemporary production systems require methods that enable continuous monitoring, the early detection of deviations and rapid decision-making. In this context, artificial intelligence (AI) and machine learning (ML) have become important tools in supporting quality control, predictive quality management and zero-defect manufacturing strategies [4, 5].

AI and ML are applied in manufacturing quality control to perform various tasks, such as visual inspection, defect detection, anomaly detection, process monitoring, and prediction of product conformity. These methods are particularly valuable when product quality is influenced by multiple process variables, machine settings, material characteristics, and operator-related factors. In such cases, conventional rule-based approaches may be inadequate, whereas ML models can identify complex, non-linear relationships between input variables and quality outcomes. This is particularly important for production processes where minor variations in technological parameters can result in non-conforming products or hidden defects that are challenging to identify during routine inspections.

Recent research has mainly focused on automated visual inspection using deep learning methods. Convolutional neural networks and object detection models, such as YOLO-based architectures, have proven highly effective at identifying surface defects, dimensional deviations and assembly errors in industrial settings [6]. These models can extract hierarchical features from images and detect defects under different lighting conditions, with various surface textures and complex product geometries. Studies indicate that deep learning systems can achieve very high inspection accuracy in real time, making them suitable for integration with production lines. However, such solutions typically require image data and suitable vision systems, which are not always available in every production environment.

Apart from image-based inspection, supervised machine learning methods are widely used for predictive quality control based on process data. These methods use historical production records to predict whether a product will meet quality requirements. Models such as artificial neural networks, random forests and support vector machines have been used to identify tolerance violations, detect non-conformities and support early quality decisions. In automotive manufacturing, for instance, ML models have been employed to predict dimensional deviations and facilitate proactive interventions before defects propagate to subsequent production stages [7]. This approach is particularly important in processes where the early detection of quality risks can reduce the need for rework, scrap, production delays and customer complaints.

Artificial neural networks are particularly useful for predicting quality because they can model non-linear relationships between multiple input variables and output classes. Multilayer perceptrons, consisting of fully connected layers of neurons, are commonly used for classification tasks, where the objective is to categorise observations. In the context of manufacturing quality control, for example, neural networks can be trained to classify products as either conforming or non-conforming based on process parameters, machine settings, material data and other production-related variables. Their flexibility makes them suitable for processes in which the relationship between causes and quality effects is unclear or cannot be easily described using traditional statistical models.

Despite their potential, the implementation of ML and neural network models in industrial quality control is not without limitations. A key challenge is the shortage of representative data describing defective products. In well-controlled manufacturing systems, defects usually occur infrequently, which may result in an imbalanced dataset and complicate the model training process. In such cases, a model can obtain a high overall accuracy while still being ineffective in recognising the less frequent class, which often represents non-conforming products. Therefore, recent research highlights the need to assess classification models using a broader set of measures, including precision, recall, F1 score, confusion matrices, ROC curves and AUC, rather than accuracy alone [8]. These indicators allow for a more reliable evaluation of model performance, especially when overlooking a defective product may lead to serious quality and operational consequences.

In order to address the issue of limited labelled data, researchers have explored various approaches, including semi-supervised learning, active learning, anomaly detection and the generation of synthetic data. Semi-supervised learning makes use of both labelled and unlabelled data, which is useful when expert labelling would be costly or time-consuming. Active learning reduces the required amount of labelled data by selecting the most informative cases for expert annotation. Anomaly detection methods are valuable, too, because they learn the characteristics of normal products or processes and can identify deviations that may indicate defects. These approaches are particularly useful in manufacturing environments where new or rare defect types may appear unexpectedly.

Another important area of research concerns the practical implementation of ML-based quality control systems in industrial environments. A model intended for real production use must be accurate, fast, compact, robust and easy to integrate with existing production infrastructure. Therefore, prediction speed, training time, memory requirements and interpretability are important criteria in model selection. Edge-based and embedded AI solutions are increasingly being discussed as a means of performing quality assessments directly on the production line, thereby reducing latency and enabling real-time decision-making. At the same time, integration with manufacturing execution and quality management systems remains essential for successful industrial deployment [10].

The literature also highlights the increasing significance of explainable AI in manufacturing quality control. In industrial practice, a model must provide more than just a classification result. Engineers and quality specialists often need to understand why a product has been classified as defective, and which process variables have contributed most to this decision. Explainability fosters trust in AI systems, facilitates root cause analysis and enables corrective and preventive action. This is particularly important in quality control processes, since model recommendations can influence production decisions, customer safety and compliance with technical requirements [5].

With regard to the production of electric vehicle charging connector components, the reviewed literature confirms the relevance of applying machine learning (ML)-based classification models to support quality control. The analysed process involves several operations, such as cable unwinding, cutting to length and insulation stripping. Each of these operations may be affected by technical, material, organisational and human factors. As product conformity depends on the interaction of these variables, neural network models can be useful for identifying patterns associated with quality deviations. Using such models may enable the earlier detection of non-conforming products, reduce hidden defects and improve process stability [11].

Further studies have demonstrated the effectiveness of convolutional neural networks (CNNs) in improving the visual quality of manufacturing processes by enhancing the detection and classification of defects [12]. The potential of hybrid machine learning models to increase manufacturing reliability and enable more accurate quality prediction has also been emphasised [13]. Additionally, reinforcement learning (RL) techniques have been suggested as a promising method for adapting inspection systems dynamically to changing production conditions and process variability [14]. A broader discussion of machine learning applications in quality control, particularly with regard to error reduction, process optimisation and continuous improvement, can be found in [15].

Recent studies show that AI and ML technologies are becoming an important part of modern quality control systems. Their main advantages include processing large amounts of data, detecting complex relationships, supporting real-time monitoring and improving decision-making in manufacturing. However, successful implementation requires attention to data quality, class imbalance, model validation, interpretability and integration with existing production systems. Therefore, when applying neural network models to the analysed connector production process, it is important to consider them not only as a classification tool, but also as a step towards data-driven quality management and continuous improvement in electromobility manufacturing.

The article is organised as follows. The first section introduces the research background and the main context of the study. Section 3 describes the research methodology, including process analysis, data preparation and the configuration of the analysed neural network models. Section 4 presents and discusses the obtained results. Finally, Section 5 summarises the main findings, limitations and directions for future research. This paper is a continuation of the work presented in [16].

3. Materials and methods

3.1. Research methodology

This study adopted a research methodology designed to assess the applicability of selected machine learning methods for quality monitoring in the production process of electric vehicle charging connectors (Figure 1). This approach involves process analysis, identifying quality-related variables, preparing empirical data and comparing classification models.

Production data was obtained from the manufacturing process of connector components used in electric vehicle charging systems for the study. The analysed process includes key operations such as cable unwinding, cutting to length and insulation stripping. The occurrence of product non-conformities may be influenced by technical, material, organisational, and human-related factors affecting these stages.

The first stage of the research involved analysing the process using the SIPOC method. This tool enabled the identification of suppliers, inputs, process stages, outputs and customers, as well as the main areas where quality risks and process variability may occur. The results of this analysis were then used to define the scope of the research and select the variables for further machine learning analysis.

The research problem was formulated as a binary classification task aimed at predicting whether a product would be classified as conforming or non-conforming. Input variables included selected parameters relating to the process, materials, machines, environment, and operators, while the output variable represented the final quality status of the product.

Prior to model development, the collected data were prepared for analysis through verification, coding of categorical variables, and standardisation of selected numerical variables. The prepared dataset was then used to train and evaluate five supervised artificial neural network models: Bilayered Neural Network (BNN), Medium Neural Network (MNN), Narrow Neural Network (NNN), Trilayered Neural Network (TNN), and Wide Neural Network (WNN). The models differed in terms of network architecture, including the number of hidden layers and the number of neurons, which enabled the assessment of how model complexity influenced classification performance

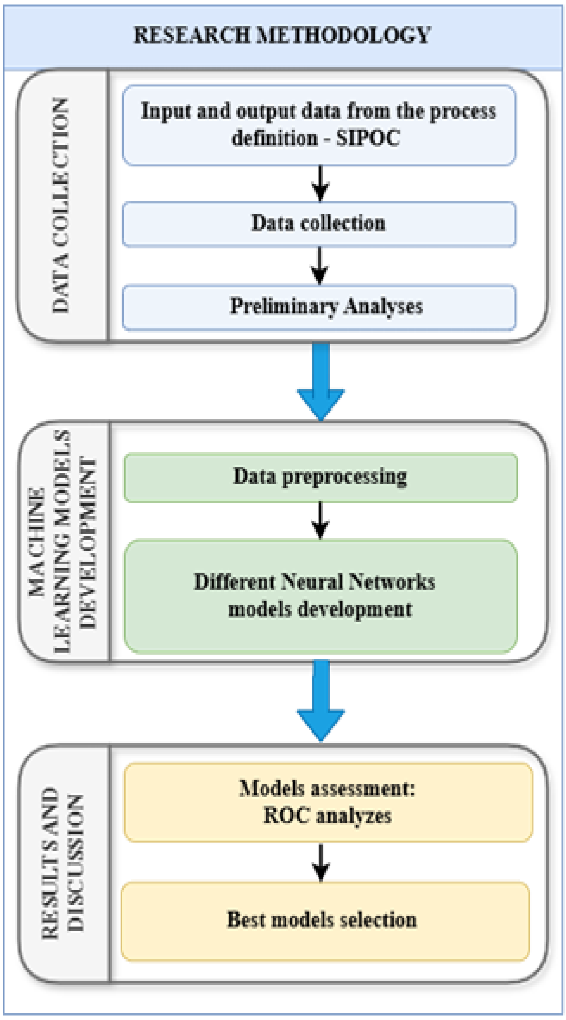


Figure 1. Research methodology

Model performance was evaluated using standard classification measures, including accuracy, error rate, precision, recall and the F1 score. Confusion matrices and ROC curve analysis were also employed to provide a more detailed interpretation of the results of the predictions. Additionally, practical considerations such as training time, prediction speed and model size were taken into account when evaluating the models' suitability for industrial implementation.

The proposed methodology provides a structured basis for comparing machine learning models in the context of quality monitoring. It facilitates the identification of methods that can enhance the early detection of non-conformities, minimise quality losses, and optimise the stability and efficiency of the analysed production process.

3.2. Description of the case study process

In an era of rapid electromobility development, ensuring the quality, reliability and safety of electric vehicle components has become a priority for manufacturers in this sector. The growing demand for electric vehicles and charging infrastructure is putting increasing pressure on production systems to deliver components that meet strict technical, functional and regulatory requirements. The charging connector is particularly important, as it is responsible for ensuring safe and efficient energy transfer between the charging station and the vehicle. Therefore, the manufacturing process must be carried out with high precision and under controlled conditions to guarantee durability, electrical safety, dimensional accuracy and long-term operational reliability.

The manufacturing process of cable components includes several key operations, among which cable feeding from the reel, cutting to the required length and removing insulation from cable ends are particularly important. The quality of the final product may be affected at each of these stages, as the process is exposed to different sources of variation. These include technical aspects, such as machine condition, tool wear and equipment calibration, as well as organisational and human-related factors, including operator skills, compliance with work instructions and the correctness of technological and order data. Small deviations in cable length, stripping depth or insulation removal may lead to non-conformities that can disrupt later assembly stages or reduce the functional reliability of the final component.

To examine the analysed production process in a systematic way, the SIPOC approach was used. SIPOC, meaning Supplier–Input–Process–Output–Customer, is a process mapping method that helps structure the main elements of a process and show the relationships between them. Its application enables the identification of suppliers, required inputs, process activities, outputs and customers. In the analysed case, the SIPOC diagram supported a clearer understanding of material and information flows within the company and helped indicate process areas that may have a significant impact on product quality and process stability.

The supplier category includes both external and internal sources that support the analysed production process. External suppliers provide cables with defined technical characteristics, including conductor cross-section, insulation type, flexibility and dimensional tolerances. The stability and quality of these materials are crucial, as variations in cable properties may influence the accuracy of cutting and insulation stripping operations. Internal suppliers include the materials warehouse, which delivers auxiliary components, such as guide sleeves and other elements required for production. The maintenance department also plays an important role by ensuring the proper technical condition of key equipment, including the cutting knife, encoder, feeding mechanism and stripping unit. The condition and reliability of these machine components have a direct impact on process repeatability and the dimensional accuracy of the prepared cable elements.

The inputs to the process include physical materials, information, and human resources. Material inputs consist primarily of cables and production accessories, while informational inputs include order specifications, technical documentation, machine settings, quality requirements and production schedules. Operator competencies are also a significant input, since correct machine operation, interpretation of documentation and response to process deviations depend largely on the knowledge and experience of production personnel. Proper training and standardised work instructions are therefore essential for maintaining process stability and reducing the risk of errors.

The analysed production process can be divided into five main stages. The first stage consists of feeding the cable from the reel into the cutting machine, where smooth material flow, appropriate cable tension and correct positioning in the feeding system must be maintained. The second stage involves cutting the cable to the specified length. At this point, the accuracy of the encoder, the technical condition of the cutting knife and the correctness of machine settings are critical for achieving the required dimensional precision. The third stage involves stripping the cable ends to the specified depth and length. High precision is required for this operation, as excessive or insufficient stripping may damage the conductor, leave insulation residues, or cause problems during subsequent assembly. The fourth stage is quality control, during which selected parameters such as cable length, stripping length, insulation condition and visual appearance are verified against established requirements. The final stage is to decide whether to accept the product, rework it, or reject it.

Disruptions may occur at any stage of the process, resulting from environmental, technical, material or human factors. For instance, incorrect cable tension during unwinding can cause feeding errors, and a worn cutting knife can result in uneven cuts or cable end deformation. Improper machine calibration can result in length deviations, while insufficient operator attention may lead to incorrect data entry or failure to detect visible defects. Environmental conditions such as contamination, temperature or workplace organisation may also affect process stability. For this reason, it is necessary to systematically monitor key process parameters and identify deviations early on in order to maintain consistent product quality.

The main outputs of the process are cut and stripped cables that are ready for further assembly operations. These outputs must meet all the dimensional and quality requirements defined in the technical documentation. In addition to physical products, the process generates quality control records and production documentation, providing evidence of compliance and supporting traceability. Products that do not meet the required specifications are classified as non-conforming and may be redirected for rework, additional inspection or disposal. Such non-conformities can affect production efficiency, increase costs, disrupt logistics and delay subsequent assembly stages.

The process has both internal and external customers. The internal customers are primarily the assembly department, which uses the prepared cable components in subsequent production stages, and the quality control department, which ensures compliance with customer and technical specifications. External customers include companies operating in the electromobility sector, such as electric vehicle and charging infrastructure manufacturers. These customers expect reliable, safe components that are fully compliant with specifications and ready for integration into final products.

Using SIPOC mapping to analyse the process makes it possible to clearly define the relationships between suppliers, inputs, process operations, outputs and customers. It also supports the identification of critical points where quality risks may arise. Consequently, SIPOC provides a useful basis for further process analysis, including the development of corrective and preventive actions, improvement of process control, standardisation of work procedures and reduction of variability. Thus, the method not only improves understanding of the connector production process, but also enhances product quality, process stability and operational efficiency in electromobility manufacturing.

3.3. Machine learning methods methodology

In this research, five artificial neural network classifiers were analysed for binary quality prediction in the manufacturing process. The same dataset was used for training and evaluation of all models and included 402 observations described by 20 input variables. The target variable had two classes and represented the final quality status of the product, indicating whether it met the required specifications or was identified as non-conforming. To ensure a more robust evaluation and limit the influence of a single data split on the results, 3-fold cross-validation was applied.

Because the available industrial dataset was relatively small, the evaluation was treated as a process-specific feasibility study rather than as a universal comparison of all machine learning methods. To reduce the influence of a single train-validation split, all analysed architectures were assessed using the same 3-fold cross-validation protocol, identical preprocessing assumptions and the same set of predictive and operational metrics. The comparative interpretation therefore focuses on the relative behaviour of the neural-network variants under the same data conditions.

Artificial neural networks were chosen because they are capable of capturing complex and non-linear dependencies between production process variables and quality outcomes. In manufacturing quality assurance, machine learning and deep learning techniques are increasingly used to support predictive quality control, defect detection and process monitoring, especially when product quality is shaped by the interaction of multiple process parameters [17,18]. In this context, multilayer perceptrons are particularly relevant, as feedforward neural networks can approximate complex relationships when an appropriate network structure and number of hidden units are used [19, 20].

The analysed models were fully connected feedforward neural networks with different architectural configurations. All networks used the rectified linear unit (ReLU) activation function, which is widely used in modern neural networks because it supports efficient training and reduces issues associated with saturating activation functions [21, 22]. In all cases, the iteration limit was set to 1000, the regularisation strength parameter lambda was set to 0 and the input data were standardised prior to training. Data standardisation was applied to improve numerical stability and support more efficient model convergence during training.

The comparison performed in this study should therefore be understood as an intra-family benchmark of feedforward neural network architectures. Alternative non-neural classifiers, including random forests, support vector machines and gradient boosting models, were identified as a relevant extension of the benchmarking framework and are discussed in the limitations and future research section.

The first model was a Bilayered Neural Network consisting of two fully connected hidden layers, each with 10 neurons. This architecture enabled the model to represent more complex non-linear dependencies while maintaining a relatively small model size. The model achieved a validation accuracy of 95.9%, an error rate of 4.1%, a total validation cost of 23, a prediction speed of around 8,900 observations per second and a training time of 2.1871 seconds. It also had a compact model size of around 18 kB.

The second model was a Medium Neural Network composed of one fully connected hidden layer with 25 neurons. This configuration represents an intermediate solution between narrow and wide architectures. It increases the number of trainable parameters compared to a narrow network while maintaining a relatively simple structure. This model achieved a validation accuracy of 95.4%, an error rate of 4.6%, a total validation cost of 26, a prediction speed of around 8,200 observations per second, a training time of 4.0812 seconds and a compact model size of around 21 kB.

The third model was a Narrow Neural Network containing one fully connected hidden layer with 10 neurons. As the simplest analysed neural architecture, it was characterised by a limited number of parameters, which reduced the risk of overfitting and improved generalisation, particularly for relatively small datasets. Despite its simplicity, this model achieved the best validation performance: an accuracy of 97.0%, an error rate of 3.0%, a total validation cost of 17, a prediction speed of around 8,700 observations per second, a training time of 4.755 seconds and a compact model size of around 17 kB.

The fourth model was a Trilayered Neural Network consisting of three fully connected hidden layers, each with 10 neurons. This architecture increased the model's depth, thereby enhancing its ability to represent complex nonlinear relationships. However, deeper architectures may require more training time and may not always improve performance with limited datasets. In this study, the Trilayered Neural Network achieved a validation accuracy of 96.2%, an error rate of 3.7%, a total validation cost of 21, a prediction speed of around 7,400 observations per second and a training time of 5.5655 seconds. The model size was also compact at around 20 kB.

The fifth model was a Wide Neural Network composed of one fully connected hidden layer with 100 neurons. This architecture increased the width of the network, enabling it to capture a broader range of non-linear relationships between the input variables and the output class. However, the larger number of neurons also increased the model size. The wide neural network achieved a validation accuracy of 96.8%, an error rate of 3.2%, a total validation cost of 18, a prediction speed of around 8,300 observations per second, a training time of 3.649 seconds and a compact model size of around 45 kB.

A comparison of the models indicates that the narrow neural network provided the most favourable balance of predictive accuracy, error rate, computational efficiency and model compactness. Although the wide neural network also achieved high accuracy, its model size was significantly larger. Despite its deeper structure, the Trilayered Neural Network did not outperform the simpler models and required the longest training time. These findings suggest that increasing the depth or width of the neural network did not necessarily lead to improved classification performance for the analysed production dataset. This is consistent with the practical assumption that model complexity should be adjusted according to the size and structure of the dataset rather than being increased automatically.

The quality of each model was evaluated using predictive and operational performance metrics. The main predictive metrics included accuracy, error rate, precision, recall, the F1 score, a confusion matrix analysis, a ROC curve analysis and an AUC. Accuracy assessed the proportion of correctly classified observations overall, while the error rate provided complementary information about incorrect predictions.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

where TP denotes true positives, meaning correctly classified observations belonging to class 1, while TN denotes true negatives, meaning correctly classified observations belonging to class 0. FP refers to false positives, i.e. observations from class 0 that were incorrectly assigned to class 1, whereas FN refers to false negatives, i.e. observations from class 1 that were incorrectly assigned to class 0. Error rate is defined as:

$$ErrorRate = 1 - Accuracy \tag{2}$$

Precision and recall were also considered because they are particularly important in binary quality classification problems, where misclassifying defective products as acceptable can be costly. The F1 score combines precision and recall into a single measure, which is useful when the class distribution is imbalanced [23, 24].
The F1 score is defined as:

$$F1score = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \tag{3}$$

In addition to classification quality, the study also considered operational characteristics, including prediction speed, training time and model size. These parameters are important from an implementation perspective, as models intended for industrial use should combine high accuracy with low computational requirements and fast response times. Their inclusion made it possible to evaluate the analysed models not only in terms of predictive performance, but also with regard to their suitability for practical application in production quality control systems.

4. Results

Five artificial neural network models were evaluated on their ability to classify products as either acceptable or defective: The models were the Bilayered Neural Network (BBN), the Medium Neural Network (MNN), the Narrow Neural Network (NNN), the Trilayered Neural Network (TNN) and the Wide Neural Network (WNN).

All models were trained and validated using the same dataset, and their performance was assessed based on validation accuracy, error rate, total validation cost, prediction speed, training time and model size. All analysed models were fully connected feedforward neural networks that used the ReLU activation function. The input data were standardised prior to training and the iteration limit was set to 1000. No regularisation was applied as the regularisation strength parameter, Lambda, was set to 0. The models differed primarily in terms of their network architecture, specifically the number of fully connected layers and the number of neurons in each layer (Table 1).

Table 1. Training parameters and validation results for the analysed neural network models

Parameter	BNN	MNN	NNN	TNN	WNN
Network architecture (layers /neurons in each layer)	2/10	1/25	1/10	3/10	1/100
Accuracy % (Validation)	95.9	95.4	97.0	96.2	96.8
Error rate % (Validation)	4.1	4.6	3.0	3.7	3.2
Total cost (Validation)	23	26	17	21	18
Prediction speed (obs/sec)	~8900	~8200	~8700	~7400	~8300
Training time (sec)	2.1871	4.0812	4.7550	5.5655	3.6490
Model size (kB)	~18	~21	~17	~20	~45

The BBN model consisted of two fully connected hidden layers, each containing 10 neurons. This architecture achieved a validation accuracy of 95.9% and an error rate of 4.1%. It also demonstrated the fastest prediction speed (approximately 8,900 observations per second) and the shortest training time (2.1871 seconds). Its compact model size was approximately 18 kB. The MNN was based on a single fully connected hidden layer containing 25 neurons. It achieved a validation accuracy of 95.4%, an error rate of 4.6% and a total validation cost of 26. The prediction speed was around 8,200 observations per second and the training time was 4.0812 seconds. The compact model size was approximately 21 kB. The NNN consisted of one fully connected hidden layer with 10 neurons. This model achieved the best classification performance of all the tested variants: a validation accuracy of 97.0%, an error rate of 3.0% and a total validation cost of 17. It could predict approximately 8,700 observations per second, took 4.755 seconds to train and had a compact model size of approximately 17 kB.

The TNN comprised three fully connected hidden layers, each containing 10 neurons. Despite its deeper structure, however, it did not outperform simpler models. It achieved a validation accuracy of 96.2%, an error rate of 3.7% and a total validation cost of 21. This model also had the lowest prediction speed of approximately 7,400 observations per second and the longest training time of 5.5655 seconds. Its compact model size was approximately 20 kB.

The WNN consisted of one fully connected hidden layer with 100 neurons. This model achieved the second-best validation accuracy of 96.8%, with an error rate of 3.2% and a total validation cost of 18. It had a prediction speed of approximately 8,300 observations per second and a training time of 3.649 seconds. However, this model had the largest compact size of approximately 45 kB, which may be less favourable for implementation in systems with limited computational resources.

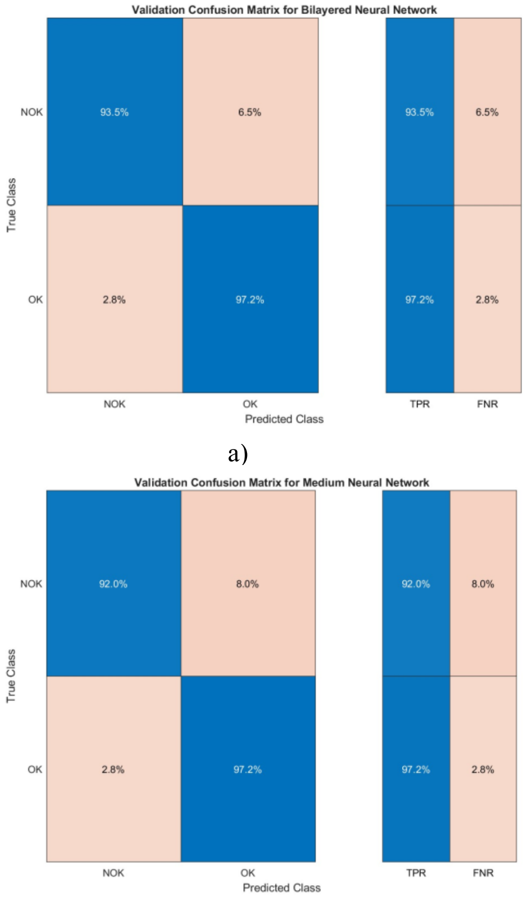
A comparison shows that the NNN provided the best overall classification performance. It achieved the highest validation accuracy (97.0%), the lowest error rate (3.0%) and the lowest total validation cost (17). At the same time, it maintained a compact model size of around 17 kB and a high prediction speed of approximately 8,700 observations per second. These results suggest that a relatively simple neural network architecture is sufficient for modelling the relationship between production process variables and product quality outcomes.

The WNN also demonstrated strong predictive performance, achieving a validation accuracy of 96.8% and an error rate of 3.2%. However, its model size was significantly larger than that of the other models at around 45 kB. This suggests that, while increasing the number of neurons improved performance compared with some variants, it also increased memory requirements.

In terms of prediction speed and training time, the BBN was the fastest model. However, its validation accuracy was lower than that of the NNN and WNN models. Despite having the deepest architecture, the TNN did not achieve the best results and required the longest training time. This suggests that increasing network depth does not necessarily improve classification performance for this dataset.

Moreover, the analysed results suggest that greater model complexity does not necessarily lead to better predictive performance. In this case study, the NNN offered the most favourable balance of accuracy, error rate, computational efficiency and model compactness. Therefore, this model is the most suitable solution for supporting quality classification in the analysed manufacturing process.

To analyse the classification performance of the neural network models further, validation confusion matrices were generated for each classifier. Figure 2 shows the relationship between the true and predicted classes for two quality categories: NOK and OK. In the analysed quality control problem, particular attention should be paid to cases in which products classified as 'Not OK' (NOK) are incorrectly predicted as 'OK', because such errors may result in defective products being accepted for further production or delivery. Errors in the opposite direction, where OK products are incorrectly classified as NOK, are also important because they may lead to unnecessary rework, additional inspections, or the rejection of products that conform to specifications.



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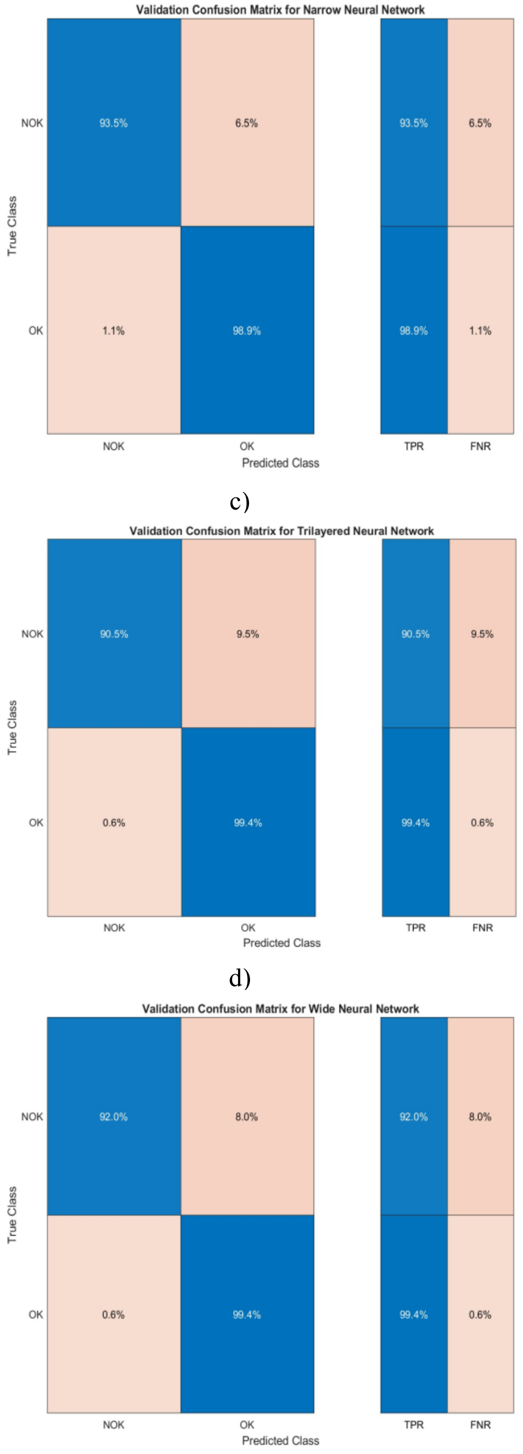


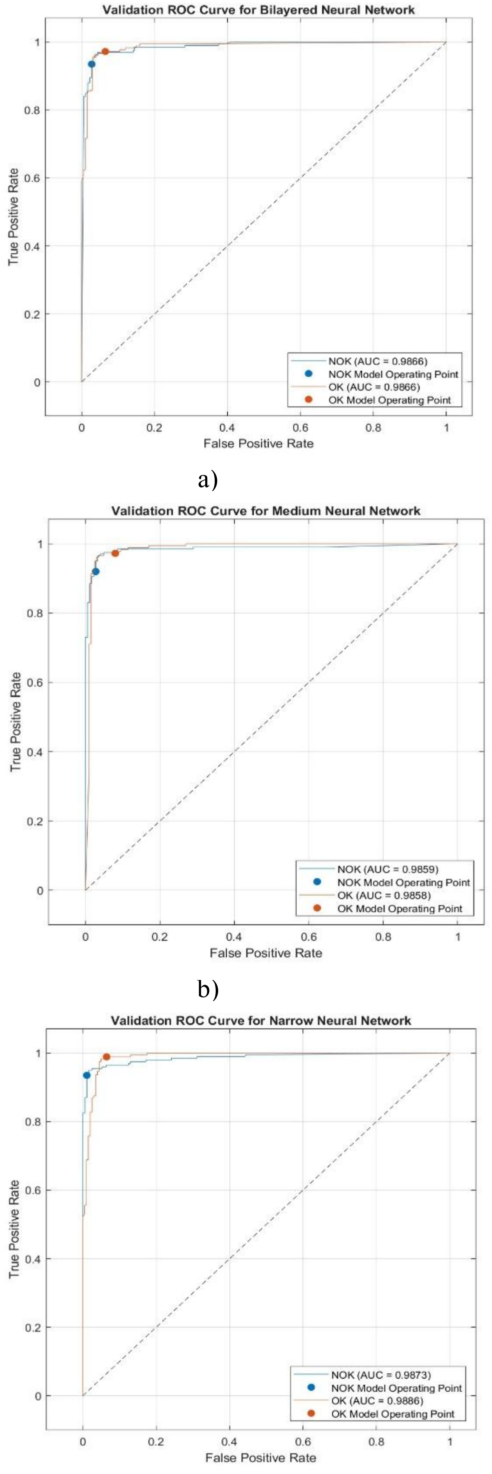
c)

d)

e)

Figure 2. Validation confusion matrices for the analysed neural network models: a) BBN, b) MNN, c) NNN, d) TNN and e) WNN

Figure 3 shows the ROC curves for the validated neural network models, providing an additional evaluation of their classification performance at various decision thresholds.



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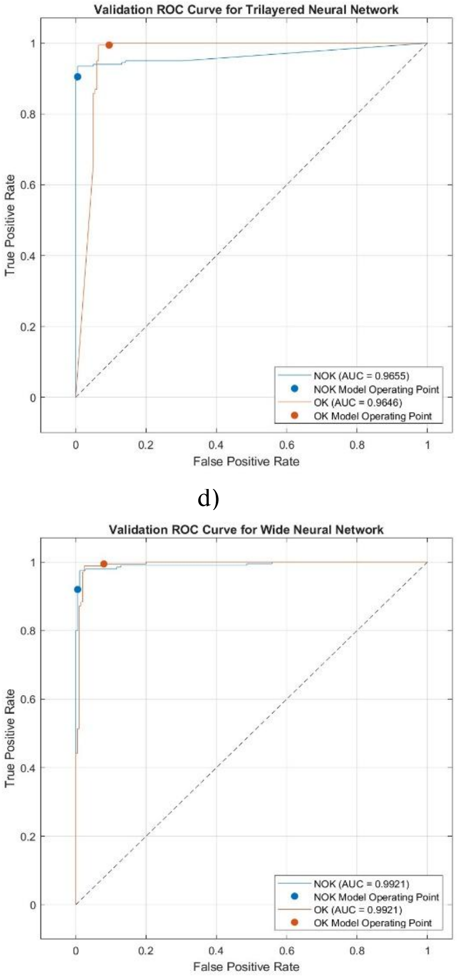
b)

c)



d)

e)

Figure 3. Validation ROC curves for the analysed neural network models: a) BBN, b) MNN, c) NNN, d) TNN and e) WNN

ROC analysis differs from the confusion matrix in that it evaluates the model's ability to distinguish between the two quality classes, NOK and OK, independently of the selected threshold. The closer the ROC curve is to the top-left corner of the plot, the greater the model's discriminative ability.

The obtained ROC curves indicate that all analysed neural network models achieved very high discriminative capability, as their curves were located far above the diagonal reference line representing random classification. This confirms that the models could effectively distinguish between conforming and non-conforming products in the analysed manufacturing process. The area under the curve (AUC) is used as a summary measure of this performance (Table 2).

Table 2. AUC values for the analysed neural network models

Model	AUC for NOK class	AUC for OK class
BBN	0.9866	0.9866
MNN	0.9859	0.9858
NNN	0.9873	0.9886
TNN	0.9655	0.9646
WNN	0.9921	0.9921

The BBN achieved an AUC value of 0.9866 for both the NOK and OK classes, indicating very strong and balanced classification capability. The MNN obtained similarly high results, with an AUC value of 0.9859 for the NOK class and 0.9858 for the OK class. While these results confirm that both models could separate the two classes effectively, their performance was slightly lower than that of the best-performing models.

The NNN achieved an AUC of 0.9873 for NOK and 0.9886 for OK. These results confirm its strong classification ability, supporting earlier findings from the accuracy and confusion matrix analysis where this model demonstrated the most favourable balance between detecting NOK products and correctly recognising OK products. The high AUC values demonstrate that the NNN maintained consistent performance across various decision thresholds.

The TNN achieved the lowest AUC values of all the analysed models: 0.9655 for NOK and 0.9646 for OK. While these values still indicate good classification performance, they are notably lower than those achieved by the other neural network variants. This suggests that increasing the network's depth did not improve its ability to separate the two quality classes in the analysed dataset.

The WNN achieved the highest AUC values, with 0.9921 for both the NOK and OK classes. This indicates the strongest threshold-independent discriminative capability among the analysed models. However, when considered alongside the confusion matrix and operational indicators, it was found that the WNN also had the largest model size. Therefore, while it performed best in terms of the AUC, it may require more computational resources for practical implementation than simpler models.

ROC and AUC analysis confirms the high effectiveness of neural network models in the analysed quality classification problem. The WNN demonstrated the best ability to distinguish between the NOK and OK classes in terms of AUC, while the NNN provided the most favourable overall compromise when accuracy, error rate, confusion matrix results, model size, and computational efficiency were considered together. Therefore, the ROC results strengthen the conclusion that neural network models can effectively support quality control decisions in the analysed manufacturing process, particularly in applications requiring early identification of non-conforming products.

5. Conclusions

The literature review shows that quality control in contemporary manufacturing is increasingly evolving from final inspection and defect detection towards proactive, data-driven quality management. As production systems become more complex and customer requirements more demanding, artificial intelligence and machine learning are gaining importance as tools for process monitoring, defect identification and predictive quality control. This is especially significant in electromobility-related manufacturing, where component quality and reliability have a direct impact on product safety, operational effectiveness and customer confidence.

This study assessed the applicability of selected artificial neural network models in supporting quality control in the production process of electric vehicle charging connector components. The analysed case focused on the binary classification of products into two categories: conforming products (marked as OK) and non-conforming products (marked as NOK). The research combined SIPOC-based process analysis, empirical data preparation, and a comparative evaluation of five neural network architectures.

The results confirm that artificial neural networks can effectively support quality classification in the analysed process. All of the tested models achieved a validation accuracy of over 95%, which indicates their ability to identify the relationships between the variables of the production process and the final quality of the product. This demonstrates the effectiveness of data-driven methods in processes where product conformity depends on a variety of technical, material, organisational, and human factors.

Among the analysed models, the NNN achieved the best overall performance. It achieved the highest validation accuracy (97.0%), the lowest error rate (3.0%) and the lowest total validation cost (cost = 17). It also maintained a compact model size (approximately 17 kB) and a high prediction speed (approximately 8,700 observations per second). These results demonstrate that a relatively simple neural network architecture consisting of a single hidden layer with ten neurons was sufficient to achieve excellent classification performance.

The results also suggest that increasing model complexity does not necessarily improve predictive performance. Despite having the deepest architecture, the TNN did not outperform the simpler models and required the longest training time. The WNN achieved the highest AUC values, at 0.9921 for both quality classes, but its model size was significantly larger. Therefore, while the WNN demonstrated the strongest threshold-independent discriminative ability, the NNN offered the most favourable balance of accuracy, error rate, model size, and computational efficiency.

Confusion matrix analysis confirmed the practical importance of the selected model. In industrial quality control, particular attention must be paid to the misclassification of non-conforming (NOK) products as conforming (OK), as such errors may allow defective products to proceed to further production stages or reach the customer. From this perspective, the NNN provided an optimal balance between identifying NOK products and correctly recognising OK products while minimising the rejection of conforming products.

ROC and AUC analyses confirmed the high discriminative capability of all the analysed neural network models. The ROC curves were located far above the random classification line, demonstrating that the models could effectively distinguish between acceptable (OK) and unacceptable (NOK) products at different decision thresholds. From a practical point of view, the results suggest that neural network models could be employed as decision support tools in manufacturing quality control systems to facilitate the earlier detection of non-conformities, reduce quality losses, and improve process stability.

Despite the promising results, several limitations should be noted. Firstly, the study was based on a single industrial case concerning electric vehicle charging connector components, meaning that the findings are specific to the analysed process and require further verification in other manufacturing contexts. The dataset consisted of 402 observations and 20 input variables; therefore, the obtained results should be interpreted as preliminary and process-specific. Although 3-fold cross-validation, confusion matrices and ROC/AUC analysis were used to reduce the dependence on a single split and to provide a broader assessment of the classifiers, larger datasets collected over longer production periods would enable a more comprehensive evaluation of model robustness, repeatability and generalisation ability.

Another limitation is that the study only considered selected artificial neural network architectures. Therefore, the present comparison constitutes an intra-family benchmark of feedforward neural networks rather than a complete benchmark of all possible machine learning methods. Other techniques, such as random forests, gradient boosting, support vector machines and ensemble methods, were not included in the final empirical comparison and should be analysed in future work using the same preprocessing pipeline and validation protocol. Additionally, the classification problem was formulated as a simple OK/NOK task, providing no information about defect types, severity or root causes. The study also did not include an analysis of interpretability, which may limit the practical acceptance of the models by quality engineers.

Therefore, future research should include larger and more diverse production datasets collected under different operating conditions and from different production lines. Further studies should compare neural networks with classical and ensemble machine learning algorithms and should include repeated cross-validation and, where the number of observations allows, statistical significance testing of differences between models. The use of explainability methods, such as SHAP values, permutation importance and sensitivity analysis, would help identify the most influential process variables and support root cause analysis.

Future work should also consider multiclass classification models that can distinguish between different defect types, as well as anomaly detection methods that can identify rare or previously unknown defects. Finally, the selected model should be integrated with real-time production monitoring systems and validated under actual operating conditions.

The results presented in this study confirm that artificial neural networks have significant potential to support proactive, data-driven quality control in electromobility manufacturing. The proposed approach could help companies transition from traditional, inspection-based quality control to predictive quality management, enabling the earlier identification of process deviations and the more effective prevention of non-conforming products.

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