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Determinación de características físicas de elementos mecánicos mediante machine learning

Determination of physical characteristics of mechanical elements using machine learning

[1] Rodrigo Rigoberto Moreno Pallares https://orcid.org/0000-0003-1877-6942
Faculty of Mechanics, Polytechnic School of Chimborazo, Riobamba, Ecuador, Ecuador.
rodrigo.moreno@espoch.edu.ec

[2] Edwin Fernando Mejia Penafiel https://orcid.org/0000-0001-6888-4621
Chimborazo Polytechnic School, Riobamba, Ecuador, Ecuador.
efmejia@espoch.ed.ec

[3] Edgar Fabian Sanchez Carrion https://orcid.org/0000-0002-8027-2799
Faculty of Mechanics, Polytechnic School of Chimborazo, Riobamba, Ecuador, Ecuador.
edgar.sanchez@espoch.edu.ec

[4] Diego Alejandro Caceres Veintimilla https://orcid.org/0000-0003-0498-1240
Chimborazo Polytechnic School, Riobamba, Ecuador, Ecuador.
diego.caceres@espoch.edu.ec

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Palabras claves: Control, calidad, ingeniería, red neuronal, clasificación, imágenes

Resumen

Introducción. Uno de los problemas cotidianos de las personas es verificar el estado de diversas autopartes que se distribuyen en grandes cantidades, debido a que de ello dependen varios almacenes de repuestos que distribuyen piezas mecánicas para satisfacer a los clientes y su entorno en general. Para cubrir tales necesidades se han desarrollado redes neuronales artificiales que clasificarán estos elementos según sus características físicas. La adquisición de piezas mecánicas en la industria del automóvil se repite en innumerables ocasiones, por lo que pueden comprar piezas mecánicas defectuosas. **Objetivo.** Clasificación de elementos mecánicos mediante redes neuronales artificiales para su uso en control de calidad en sus características físicas. **Metodología.** Se aplica una metodología de recopilación de datos que ayudarán a entrenar a la red neuronal artificial. La red neuronal artificial podrá determinar el estado de calidad del elemento mecánico basándose en los datos de imágenes recopiladas y actuará como entrenamiento de la red neuronal en el siguiente proceso. **Resultados.** En la prueba final se utilizaron 200 uniones metálicas de estas clasificadas y se observó que 10 tenían defectos físicos. **Conclusión.** Las redes neuronales convolucionales se pueden utilizar para clasificar piezas mecánicas, extraer sus características de imágenes y luego utilizarlas como base de datos de redes neuronales. **Área de estudio general:** Ingeniería. **Área de estudio específica:** Ingeniería automotriz. **Tipo de estudio:** original.

Keywords: Control, quality, engineering, neural network, classification, images

Abstract

Introduction. One of people's daily problems is verifying the status of various auto parts that are distributed in large quantities, because several spare parts warehouses that distribute mechanical parts depend on it to satisfy customers and their environment in general. To cover such needs, artificial neural networks have been developed that will classify these elements according to their physical characteristics. The acquisition of mechanical parts in the automobile industry is repeated countless times, so they can purchase defective mechanical parts. objective. Classification of mechanical elements using artificial neural networks for use in quality control of their physical characteristics. Methodology. A data collection methodology is applied that will help train the artificial neural network. The artificial neural network will be able to determine the quality status of the mechanical element based on the collected image data and will act as training of the neural network in the following process. Results. In the final test, 200 of these classified metal joints were used and it was observed that 10 had physical defects. Conclusion. Convolutional neural networks can be used to classify mechanical parts, extract their features from images, and then use them as a neural network database.

Introduction

Nowadays, talking about artificial neural networks can be very complicated as we understand them, but their application to various everyday problems has solved countless of the same problems and has helped people improve their daily tasks (Olabe, 2016). In the automotive industry, the inspection carried out on each of its parts obeys not only design criteria, but also a safety factor (Gamarra & Bertel, 2014).

One of the everyday problems people face is checking the status of various auto parts that are distributed in large quantities, because several spare parts warehouses that distribute mechanical parts to satisfy customers and their environment in general depend on it (Poblet, 2022). To meet such needs, artificial neural networks have been developed that will classify these elements according to their properties and determine their status (Mateo-Jiménez et al., 2021).

Convolutional Neural Networks (CNR) (Aljure, 20215) have been developed, with Principal Component Analysis (PCA) and Convolutional Neural Networks without PCA (Artola2019), to classify metal parts based on their geometry (regular or irregular). In experiments, an accuracy of at least 93% was achieved using a factorial design with variables including: illumination, number of hidden layer neurons, type of optimization, and number of components (Aguilar-Alvarado & Campoverde-Molina, 2019). The metal parts are exposed to cold and warm light at three light levels: 1000 lux, 1500 lux and 2000 lux, based on the official Mexican standard NOM-025-STPS-2008. The image is pre-processed using principal component analysis to remove noise from redundant data (usually due to dimensionality) and produce a smaller dimension than the original dimension, allowing the convolutional neural network to receive a small amount of input material (Mateo-Jiménez et al., 2021).

Methodology

This research work is based on a quantitative approach using data collection and analysis using statistical tools to support the proposed research hypotheses (Arispe et al., 2020, p. 57).

In this case we use the deductive method, based on the theoretical framework and the information obtained we will draw conclusions that meet the objectives of the study to find solutions to the research problems. This method involves collecting data that will help train the artificial neural network itself. The artificial neural network will be able to determine the quality status of the metal joint based on the database of collected images and will act as a training of the neural network in the following process: Through the hidden ANN layer, the data obtained will be used to determine the quality of a certain quantity of metal parts purchased from an auto parts distributor (Lubinus et al., 2021).

The research offers a descriptive level, which aims to clarify the characteristics of the object of analysis, that is, it only measures and collects information independently of the variables studied and indicates the reasons for collecting this data.

Correlation ranges are found to relate variables using predictable patterns, each variable is initially measured, then quantified, analyzed, and then related (Cadena & Heredia, 2018). This allows the real-time collection of physical data on metal assemblies obtained by auto parts distributors and linking this information to an image database in the hidden layer of the ANN (Chirinos & Calero,2021).

A statement located in the Statistical Bulletin and Auto Parts issued by the Chamber of the Automotive Industry of Ecuador (CINAE) shows that between March 2022 and March 2023, a significant increase was recorded in the volume of imports of auto parts in US dollars. In March 2022, the total import volume of auto parts in US dollars was 1,210,503,288.06 (Gila, 2022).

The Association of Automotive Companies of Ecuador(AEADE, 2022), concluded that the majority of Ecuadorians prefer stores that distribute universal or spare parts, while a minority is clearly inclined to buy. Without exclusive, or original spare parts. Currently, approximately 75% of spare parts are generic and 25% original. Taking this into account, a survey was conducted in a General Motors warehouse or spare parts dealership that meets the necessary requirements for auto parts that can be purchased in large quantities and distributed very quickly, based on this information the survey was conducted at General Motors located in Latacunga, the “Motor Solutions” spare parts warehouse.

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Results

For this group, 1,000 images were defined that contained the most common defects in metal assemblies resulting from storage, transportation, manufacturing, etc. (Basulto, 2018). In addition, 1,000 images of metal assemblies in good condition were identified, since some of these defects were extremely small and can be distributed without problems.

The tests and results obtained during the validation of a Convolutional Neural Network (CNN) using the code presented in the previous chapter. Among them, Yvalidation is the input variable, YPred is the output, which becomes the final result of CNN, and then calculates the "PRECISION and ACCURACY" scores for each neural network (Narciso & Manzano, 2021). Figure 1 shows the confusion matrix of a convolutional neural network.

Figure 1

CNN Confusion Matrix #1

The focus is on the results of both programs. The "flawed" result is that 345 images are correctly classified, which corresponds to a "flawed" accuracy of 77.4%. There are 48 images with an accuracy of 10.9%. CNN #1 in this study successfully classified 393 images out of 446 test images, which, expressed as a percentage, correctly classified 88.1% and 11.9% of false negatives, false positives, and false positives, respectively. A true case of negative evaluation.

Table 1

Variables of the confusion matrix model No. 1

Worth	TP	FP	TN	FN
Defective	345	0	48	53
Faultless	48	53	345	0

"Defective" value

$Accuracy$= 345+48345+0+48+53=0.88

$Precision$= 345345+0=1

"No defect" value

$Accuracy$= 48+345345+0+48+53=0.88

$Precision$= 4848+53=0.47

CNN confusion matrix evaluation #2

The "defective" result is that 397 images are correctly classified, corresponding to an accuracy of 89.0%. For this model, out of a total of 446 validation images, 443 images were correctly classified as a percentage, with a correct classification rate of 99.3% for false negatives, 0.7% for false positives, and 0.7% for true negatives for each evaluation case.

Table 2

Variables of the confusion matrix model No. 2

Worth	TP	FP	TN	FN
Defective	397	2	46	1
Faultless	46	1	397	2

"Defective" value

$Accuracy$= 397+46397+2+46+1=0.99

$Precision$= 397397+2=0.99

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"No defect" value

$Accuracy = 46+39746+1+397+2=0.99$

$Precision = 4646+1=0.98$

Table 3

Comparison of values from the confusion table

CNN	Worth	TP	FP	TN	FN
N. 1	Defective	345	0	48	53
	Faultless	48	53	345	0
N. 2	Defective	397	2	46	1
	Faultless	46	1	397	2

Table 4 and 5 compare the "accuracy" metric for the two CNN models, with CNN #2 having the best "Accuracy" metric relative to CNN #1.

Table 4

Accuracy metric comparison

CNN	Worth	Precision	Total average %
N. 1	Defective	1	73.5
	Faultless	0.47	
N. 2	Defective	0.99	98.5
	Faultless	0.98	

Table 4-6 compares the accuracy metric for the two CNN models, also giving the best evaluation to the accuracy metric of CNN #2.

Table 5

Accuracy metric comparison

CNN	Worth	Precision	Total average %
N. 1	Defective	0.88	88
	Faultless	0.88	
N. 2	Defective	0.99	99
	Faultless	0.99	

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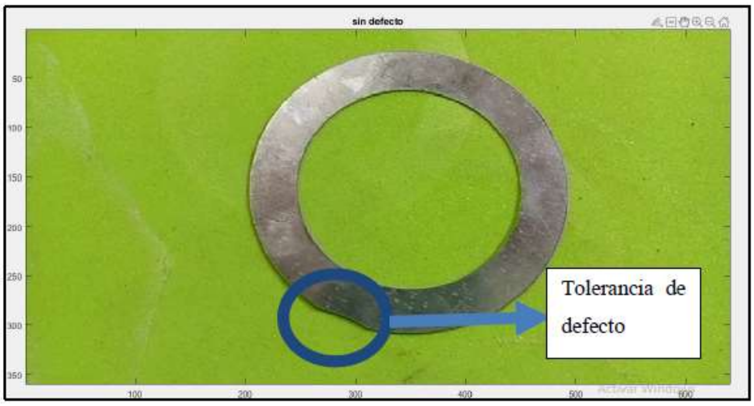
The final test used a batch of 200 metal joints recently purchased from a Motor Solutions parts store. However, they suggested a small error in CNN training due to the stored error tolerance; joints classified with this tolerance can be used without problems. Figure 2 shows fault-tolerant links.

Figure 2

Sorting tolerance



Discussion

Convolutional Neural Networks (CNR) with Principal Component Analysis (PCA) and Convolutional Neural Networks without PCA have been developed to classify metal parts based on their geometry (regular or irregular). In experiments, an accuracy of at least 93% was achieved using a factorial design with variables including: illumination, number of hidden layer neurons, optimization type, and number of components. Metal parts are exposed to cold and warm light at three light levels: 1000 lux, 1500 lux, and 2000 lux, based on the Mexican official standard NOM-025-STPS-2008. The image is preprocessed using principal component analysis to remove noise from redundant data (usually due to dimensionality) and obtain a smaller dimension than the original dimension, allowing the convolutional neural network to receive a small amount of input information.(Mateo-Jiménez et al., 2021).

Conclusions

- Convolutional ANNs can be applied to the classification of mechanical parts, extracting their features through images that will later serve as a database for the ANN.
- From the wide variety of spare parts, metal gaskets were selected since they have a higher sales demand. Through historical data, it was determined that, when

purchasing 200 metal gaskets per month in 2022, a total of 43 of them were defective.

- 1000 images were used for each study group and were used for training the ANN in order for its application to be successful.

Conflict of interest

The authors declare that there are no conflicts of interest in the submitted manuscript.

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