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Vibration-based monitoring of agro-industrial machinery using a k-Nearest Neighbors (kNN) classifier with a Harmony Search (HS) frequency selector algorithm

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ABSTRACT

Monitoring the status of rotating components is important in modern machinery. The goal of this study is to evaluate the feasibility of using a k-Nearest Neighbors (kNN) classifier combined with a Harmony Search (HS) algorithm, to detect the operational status of rotating components within agricultural machines. Vibration data, the source data, were acquired from four accelerometers located along the chassis of a harvester. Five operational statuses of three rotating components of the harvester were studied: engine (*low/maximum speed*), thresher, and chopper *(on/off* and *balanced/unbalanced*). The methodology includes vibration signal acquisition, data pre-processing, smoothing, preselection of frequencies, Brute Force (BF) and Harmony Search frequency selection, and classification with kNN. The input frequencies for the classifier were chosen with either BF search or HS. The main results of the study were: i) the preselection of frequencies reduced the training time between 92.2% and 95.6%; ii) the smoothing stage improved accuracy; iii) HS reduced the training time between 82% and 90% in comparison with BF, reaching accuracies of nearly 100% in the five operational statuses with only 2 input frequencies; iv) similar levels of accuracy were obtained when using data from the accelerometers at different locations. The results suggested that it was feasible to predict the operational status of rotating components of agricultural machines using a kNN classifier with the combination of preselection, smoothing, and the HS algorithm. This feasibility was achieved both in terms of accuracy and computational burden, building upon previously proposed methods.

1. Introduction

Maintenance in industrial and agricultural machines can be performed in three ways: corrective, preventive, and predictive maintenance (Mobley et al., 2008; Sullivan et al., 2002). Predictive maintenance, also referred to as condition-based maintenance, refers to continual evaluations of the actual operating conditions of the machine and maintenance operations are then planned based on the results of the evaluation (Ali and Abdelhadi, 2022). In this paper, predictive maintenance will be addressed.

The rotating components of industrial and agricultural machines can fail, mainly because of rotating imbalance within the machine casing (Reda and Yan, 2019), and bearing faults (Ali and Abdelhadi, 2022). Imbalance and faulty bearings can be detected by analyzing vibration data from sensors attached near the rotating components (Cecchini et al., 2021; Mohd Ghazali et al., 2021) Vibration signals can mainly be acquired in three ways: (i) measuring relative displacement between a sensor and a device or mark, (ii) sensor measurements of absolute speed, and (iii) sensor measurements of absolute acceleration. The most popular way to measure vibrations in rotating machines is measuring absolute acceleration with piezoelectric accelerometers (Randall, 2004a, 2004b).

Methods for predicting faults by processing vibration data can be grouped into two categories: model-based methods and data-driven

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methods. Model-based methods, on the one hand, employ specific knowledge and vibration faults and their effects, in order to implement a model that is able to predict faults (Mohd Ghazali et al., 2021; Randall, 2004a). Data-driven methods, on the other hand, use machine learning methods to train the model once the data have been acquired, without using previous knowledge of this process for the model implementation (Mohd Ghazali et al., 2021). Data-driven methods normally implement a feature extraction stage where signals, once acquired, are processed to obtain features, which are parameters related with the status of the monitored machine (Yang et al., 2015). Some features are obtained from the signals acquired within the time domain (Althubaiti et al., 2022; Mystkowski et al., 2022; Prakash Kumar et al., 2022), and others are obtained in the frequency domain, employing, among others, the Fast Fourier transform (FFT) (Riaz et al., 2017). After the feature extraction, a selection of features usually follows to identify the most relevant features of a dataset for the input information. This feature selection process reduces computation cost and increases the performance of the classification system. Many algorithms have been designed and developed for feature selection, inspired by phenomena that can be seen in nature, such as Cuckoo search, Bat algorithm, Firefly algorithm, Flower pollination algorithm, Krill herd algorithm, Grey wolf optimizer, Ant lion optimizer, and Dragonfly algorithm (Agrawal et al., 2021). In contrast to the previously stated algorithms, the Harmony Search (HS) algorithm is based on an artificial phenomenon: the so-called music Improvisation process (Woo Geem et al., 2001). These algorithms have been implemented in combination with various types of classifiers, such as Support Vector Machine (SVM), Artificial Neural Network (ANN), Naïve Bayesian, Decision Tree, and k-Nearest Neighbors (kNN), in order to select the best set of features for the input information and therefore to reduce computational complexity (Sudhir et al., 2017).

Numerous researchers have made significant contributions to methods for processing vibration data to predict faults in rotating machinery: (Henriquez et al., 2014; Liang et al., 2014; Liu et al., 2018; Riaz et al., 2017; Tiboni et al., 2022; Wang et al., 2019). Several fault detection diagnosis methods have been proposed in this field involving the use of ANN (Bin et al., 2012; Guo et al., 2018; Paulraj et al., 2013; Tian and Liu, 2019; Tseng et al., 2014; Tseng et al., 2018), Deep learning (Chen et al., 2020; Li et al., 2016), kNN (Liang et al., 2015), K-means (Lu et al., 2015), Multi-output neuro-fuzzy classifiers (Rajabi et al., 2022), and other methods (Nembhard et al., 2015). Moreover, some fault diagnosis techniques have also been implemented in the literature applied to rotating machinery based on algorithms such as Fuzzy kNN and Kernel Independent Component Analysis (KICA) (Li et al., 2013), Bat algorithm (Tseng et al., 2018), Genetic algorithms (Lu et al., 2015), and HS (Chen et al., 2020). Nevertheless, there is little research within the field of agriculture (Xu et al., 2014; Yao et al., 2017, 2022; Zhang, 2015).

Our team has conducted research on guidance of tractors (Alonso-Garcia et al., 2011; Garcia Martin and Gomez Gil, 2008; Gomez-Gil et al., 2011a–c, 2013; Gómez et al., 2006), machine vision in agriculture (Arribas et al., 2011; Guevara-Hernandez and Gomez-Gil, 2011; Martínez-Martínez et al., 2018; Ruiz-Ruiz et al., 2009; Silva Junior et al., 2012), crop drying (Martínez-Martínez et al., 2012, 2015b), acoustics applied to agricultural sprayers (Ruiz-Gonzalez et al., 2017), improving the health of farmers (Gomez-Gil et al., 2014), yield mapping of harvesters (Gómez-Gil et al., 2011), and the optimization of agricultural spreaders (Gomez-Gil et al., 2009). Moreover, to the best of the authors' knowledge, we are the only team to have published three papers over the past few years focused on predictive maintenance and condition monitoring in agricultural machinery. Specifically, vibration signals from one or various accelerometers placed on a combine harvester were analyzed using different techniques, such as SVM (Ruiz-Gonzalez et al., 2014), ANN (Martínez-Martínez et al., 2015a) and Composite Spectrum (Feijoo et al., 2020), to detect the working status of rotating components. The accuracy reached by Ruiz-Gonzalez *et al.* and Martínez-Martínez *et al.* ranged from 80 % to 85 % except in one case, the engine, that reached 100 % in the ANN study. In these previous research articles on predictive maintenance the use of other processing techniques was proposed as a future line of research, in order to improve the previous accuracies and to simplify the computational burden of the data. For example, analyzing the vibration data from the same harvester, and applying a different pattern recognition of the rotating components with less computational complexity.

The kNN classifier is a classic pattern recognition method. Conventional kNN predicts the test sample category according to the *k* training samples which are the nearest neighbors to the test sample, assigning it to the most probable category (Puspadini et al., 2020; Zhang et al., 2018). The kNN classifier has shown very good performance in medical data classification (Hans et al., 2020; Liang et al., 2015; Satria et al., 2021; Singh et al., 2022), software defect prediction (Goyal, 2022), engineering (Swarna et al., 2022), facial recognition (Sugiharti et al., 2020), predicting economic events (Imandoust and Bolandraftar, 2013), and the detection of gases (Yang et al., 2016). In agriculture, kNN has been applied to weather situations and forecasts (Kaur et al., 2014; Kim et al., 2016), and seed classification (Sabancı and Akkaya, 2016). kNN has three major limitations: great calculation complexity, full dependence on a training set, and no weight difference between each class (Lubis et al., 2020). To overcome these limitations, the computational burden can be reduced by pre-processing algorithms, to select the set of components for the input information of the classifier.

The HS algorithm is a global optimization algorithm introduced by Z. W. Geem and J. H. Kim in 2001, inspired by the principle of musical improvisation (Geem, 2006; Woo Geem et al., 2001). A heuristic method is used in the HS algorithm to solve discrete optimization problems. Despite not finding the optimal solution, it has the advantage of finding a suboptimal solution within a shorter time and within lower computational times. An alternative to HS is the Brute Force (BF) algorithm, which evaluates all the possible options for the problem and considers the best one as the solution to the problem. The HS algorithm with different classifiers has been applied in many areas as a feature selection method, mainly using biodata in healthcare systems (Abdulkhaleq et al., 2022), for benchmark datasets (Yusup et al., 2019), in data mining (Assad and Deep, 2016), and renewable energy (Geem and Yoon, 2017). Nevertheless, HS with a kNN classifier has been specifically used in only a few studies on image classification (Chen et al., 2012), benchmark dataset (Krishnaveni and Arumugam, 2013), and spam detection (Rajamohana et al., 2017). To the best of our knowledge, neither the HS algorithm for selecting the set of frequencies for the input nor the kNN classifier have been applied to rotating component fault detection in vibration-based monitoring of agro-industrial machinery.

The main goal of this article is to assess the feasibility of the application of an HS algorithm combined with a kNN classifier, in order to estimate the state of the three rotating components of a harvester, engine, thresher, and chopper, by analyzing vibration signals acquired from accelerometers on the chassis. Four specific sub-objectives are proposed to accomplish this main objective. First, to compare classifier accuracy and training time when all the frequencies or a preselection of frequencies are employed as the classifier input. Second, to assess whether smoothing the vibration signal in the pre-processing stage will produce any improvement in accuracy. Third, to compare classifier accuracy and training time when applying the HS algorithm or when employing BF to select the frequencies given as the kNN inputs. And fourth, to compare classifier accuracy when data from accelerometers at different locations are individually evaluated.

2. Materials and methods

2.1. Equipment

A twelve-year-old *New Holland TC56* harvester (New Holland Agriculture, New Holland, PA, USA) with 4050 working hours on the clock, equipped with a *Moresil 718* seven-row sunflower header (Moresil SL, Posadas, Córdoba, Spain) was used for the experiments.

Four *Brüel & Kjaer 4507-B-006* uniaxial accelerometers (HBK - Hottinger Brüel & Kjær A/S, London, United Kingdom) were used to measure vibration signals. Accelerometers a1, a2, and a3 were located on the left side of the chassis, oriented in the lateral direction, at a distance from the rear wheel axle of 300, 1980, and 3006 mm, respectively, and at a height from the floor of 1010, 1040, and 1560 mm, respectively. The fourth accelerometer, a4, was located on the left side of the lower rear beam of the header, at 1520 mm from the header center, oriented in the longitudinal direction. The accelerometer positions are represented in Fig. 1. The sensors were inserted in mounting clips that were adhered to the harvester chassis.

The data-acquisition instruments consisted of a *National Instrument (NI) 9234* data acquisition module for acquisition of analogic input vibration signals, and a *NI compact DAQ chassis* (*NI cDAQ-9172)*, to connect the module to the laptop. *NI Sound and Vibration Assistant* software was used for data acquisition and the *MATLAB* software package for data analysis (The MathWorks Inc., Natick, MA, USA) running on a laptop *Asus K72J*.

2.2. Methodology

The methodology consisted of several stages: 1) Acquisition of the vibration signal from the chassis of a harvester combining the different statuses of the three rotating components of the machine: engine, thresher, and chopper; 2) dataset preprocessing; 3) smoothing and preselection of the most relevant frequencies; 4) dimensional reduction in which BF and HS algorithms were applied to select the frequencies with most information on the status of the components; 5) kNN classification; and 6) comparison of the results. A brief description of each step is provided in the following subsections. The schematic diagram of the proposed method is shown in Fig. 2.

2.2.1. Data acquisition of vibrations and rotating component status

The machine was operating in threshing mode, was stationary, and the header was deactivated when the vibration signal was acquired on the harvester chassis.

Several working conditions were performed in the harvester depending on the status of three rotating components: engine (*low rpm/maximum rpm*); thresher (*on/off*); thresher (*balanced/imbalanced*); chopper (*on/off*); chopper (*balanced/imbalanced*).

Imbalances in the chopper are typically caused by blade breakage against pebbles within the straw, an effect that was generated in this study by removing one of the chopper blades. Thresher imbalances are usually caused by non-uniform wear of the bars, due to usage. An effect that was simulated by attaching an eccentric weight to the thresher.

As shown in Table 1, with the combination of the status of the three rotating components, eighteen different data-acquisition processes were performed. A total of 18 vibration signals, each one with a length of 60 s,

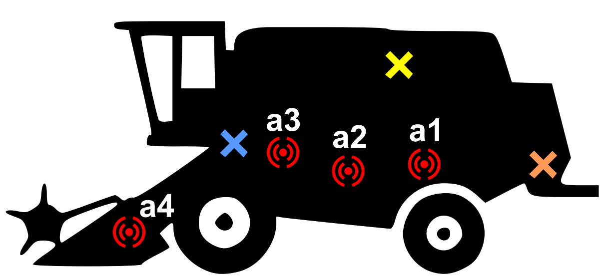

Fig. 1. Harvester diagram in which the red symbols represent the location of the four accelerometer sensors on the chassis: a1, a2, a3, and a4. Moreover, the yellow cross represents the location of the engine, the blue cross represents the location of the thresher cylinder, and the orange cross represents the location of the straw chopper.

were acquired from each of the four accelerometers, at a sampling frequency of 1706 Hz. Thus, 102,360 samples were obtained in each of the 18 working conditions that were studied (1–18).

2.2.2. Preprocessing stage

Once acquired, each data sequence was preprocessed in two substages: *splitting* and *transforming* to the frequency domain. Before the *splitting* substage there were 18 vibration signals, of 60 s each, for each of the 4 accelerometers. In the *splitting* substage each signal of 60 s, consisting of 102,360 samples, was divided into 10 epochs of 6 s, thereby obtaining 10,236 samples for each epoch.

In the *transforming* substage, the Discrete Fourier Transform (DFT) of each epoch was calculated, using FFT to obtain a symmetrical spectrum of 10,236 frequencies. Negative frequency components were removed, because the FFT of a real signal is a conjugate symmetric signal, so the absolute value of its corresponding negative and positive frequencies are the same. Hence, only the non-negative frequency components were considered, obtaining a 5118-frequency spectrum. The separation of two consecutive frequencies, which is the frequency resolution, was $\Delta f = \frac{f_s}{N} = 0.17$ Hz, where f_s is the sampling rate (1706 Hz), and N is the number of frequencies of the spectrum (10236).

2.2.3. Smoothing and preselection of frequencies

This stage was divided into two substages, *smoothing* and *preselection,* that were or were not applied to assess the effects on final performance of the system.

The *smoothing* substage reduces the noise of the preprocessed signal. It was applied with a moving-average smoothing low-frequency filter with a window size of 5 and was implemented with the convolution of the FFT vector input with a five-element vector, all of whose components had a value of 1/5. This window size was selected via a *trial-and-error* procedure, selecting the one that visually reduced most noise without affecting the vibration signal data.

The *preselection* substage removes the elements of the vectors that add no relevant information, in order to reduce the size of the vectors, by eliminating the least relevant frequencies. To do so, the *mean value, the variance*, and the *coefficient of variation (*variance divided by the mean value) were calculated for each of the 5118 frequencies of the epoch spectrums. A *threshold* was then selected by an expert with a *trial-and-error* procedure, in order to reduce the elements with low *coefficients of variation*, obtaining vectors with fewer than 400 elements, thereby reducing the number of elements to around 7 % (1 for each 14).

2.2.4. Selection of the input data for the classifier stage: The Brute Force and the Harmony Search (HS) algorithms

The set of frequencies as input information for the classifier was selected with the application of either the Brute Force or the HS algorithm.

2.2.4.1. Brute Force. Brute Force, also called exhaustive search, is characterized by an evaluation of all possible options of an optimization problem, so as to select the best one. The best option among all possible options can be found, but it has the disadvantage of needing a lot of computation time to obtain the result. It cannot therefore be employed in some scenarios, because the computational power needed to solve the problem is not feasible.

2.2.4.2. Harmony Search (HS) algorithm. The HS algorithm involves several steps that were explained in Geem *et al.* (Woo Geem et al., 2001) and in Abdulkhaleq *et al.* (Abdulkhaleq et al., 2022). The HS algorithm works with a group of solution vectors, with each vector containing elements that are the harmonies, or in this case the frequencies. This group of solution vectors is stored in an element called Harmony Memory (HM), which is initialized with a set of random solution vectors and is updated on each iteration of the HS algorithm. HM Size (HMS) is

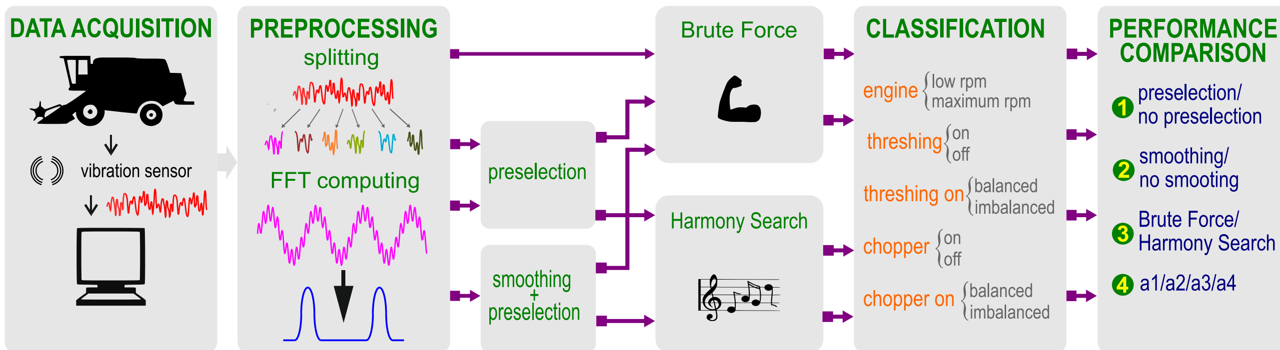

Fig. 2. Schematic diagram of the proposed method developed for predicting the status of rotating components in a harvester by processing vibration signals.

the number of selected solution vectors stored in the HM. In this work, it was set at 50, because that figure was big enough to have a representative set of solutions for our problems, but also small enough to execute each iteration within a reasonable time. Harmony Memory Considering Rate (HMCR) is the rate of choosing one vector element from those stored in HM in the following iteration. In our work, HMCR was set at 0.75, meaning that there was a 25 % probability of selecting one frequency from among all the frequencies and a 75 % probability of selecting one frequency from the HM. This HMCR value was selected with a *trial-and-error* procedure and considering the number of possible frequencies, lending more importance to the frequencies in the HM, but helping the HS algorithm to select frequencies that were not stored in the HM. The Pitch Adjusting Rate (PAR) determines whether the decision variables can change to a neighboring value. In this study, it was set to 0.10, which is the same PAR as the one proposed by Geem *et al.* (Woo Geem et al., 2001). In other words, there is a 10 % probability that the frequency can change to a neighboring value. The PAR window, that is, the maximum distance from the replaced frequency to a new frequency using the pitch adjustment operator, was set at 5. Finally, the number of algorithmic iterations was set at 5000, because the initial experiments showed that this number of iterations allowed the HS to converge, satisfying in most cases the termination criteria of reaching a 100 % accuracy.

Table 1
Working conditions studied according to the combination of the status of the engine (*low rpm/maximum rpm*); thresher (*on/off*); thresher (*balanced/imbalanced*); chopper (*on/off*); chopper (*balanced/imbalanced*).

Working conditions	Engine status	Thresher status		Chopper status	
1	Low RPM	Off (Deactivated)		Off	
2				On	Balanced
3					Imbalanced
4		On (Activated)	Balanced (healthy)	Off	
5				On	Balanced
6					Imbalanced
7			Imbalanced (faulty)	Off	
8				On	Balanced
9					Imbalanced
10	Max RPM	Off (Deactivated)		Off	
11				On	Balanced
12					Imbalanced
13		On (Activated)	Balanced (healthy)	Off	
14				On	Balanced
15					Imbalanced
16			Imbalanced (faulty)	Off	
17				On	Balanced
18					Imbalanced

2.2.5. Classification: k-Nearest neighbors (kNN)

A kNN classifier (Houssein et al., 2021) was used to estimate the operational status for each of the five statuses, which were described in Table 1, and the classifier performance was analyzed calculating mean accuracy, precision, recall, and F1 score obtained using a leave-one-out cross-validation. The value of k was chosen beforehand, in such a way that it resulted in the highest classification accuracy while also keeping the number of neighbors as low as possible. Thus, it was set at $k = 5$ neighbors for all the subsequent results after having determined that value by *trial-and-error*. Furthermore, Euclidean distance was employed as the distance metric to calculate the nearest neighbors.

2.2.6. Comparative performance analysis

A comparative analysis of performance was carried out by comparing the following four scenarios: (i) evaluation of the influence of the *preselection* substage, comparing the performance achieved when using it or not to reduce the number of candidate frequencies to the later substage; (ii) evaluation of the influence of the *smoothing* substage and the number of frequencies used as input for the kNN classifier; (iii) evaluation of the performance achieved when input frequencies were chosen with HS versus BF; and (iv) evaluation of the influence of the location of the accelerometer, comparing the performance achieved at four different locations.

The performance was considered by analyzing the following metrics: training time, accuracy, precision, recall, and F1 score. It was necessary to consider the different operational statuses as either positive or negative states, in order to calculate some of these metrics. In our case, we considered the most common condition as the negative condition. Thus, "*maximum rpm*" engine status, "*off*" thresher and chopper status and "*balanced*" thresher and chopper status were considered as negative while "*low rpm*" engine status, "*on*" thresher and chopper status and "*imbalanced*" thresher and chopper status were considered as positive to calculate the metrics when necessary.

3. Results

3.1. Evaluation of the influence of preselection

The results obtained with the kNN classifier using BF to select the frequencies, using accelerometer a1, and without preselection (number of frequencies analyzed 5118), can be seen in Table 2.

With 1 selected frequency as input for the kNN classifier, the accuracy reached was between 82.5 % and 100 % for the five operational statuses that were considered. And the range of the training time was between 1.2 min and 2 min. Precision, recall and F1 score metrics are presented in Table A1, where slight differences between precision,

Table 2
Accuracy and training time obtained with kNN combined with Brute Force, without preselection (5118 frequencies), from the accelerometer a1, using 1 input frequency, in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*). Precision, recall and F1 score results can be seen in Table A1.

Accelerometer	Total Frequencies (n)	Input Frequencies (n)	Operational Statuses	Accuracy	Training time (minutes)
a1	5118	1	Engine (low/max.)	99.44 %	1.73
	5118		Thresher (on/off)	100 %	1.66
	5118		Thresher (bal./im.)	82.50 %	1.21
	5118		Chopper (on/off)	82.78 %	2.00
	5118		Chopper (bal./im.)	82.50 %	1.78

recall, F1 score and accuracy were obtained. For this reason, both in this table and in subsequent tables the results with these metrics will be included in Appendix A, as they add no further information to the results of the accuracy metric. Analogous results as presented in Table 2, but with instead of without preselection, can be seen in Table 3.

As shown in Table 3, the range of selected frequencies was between 365 and 389. The range of the accuracy achieved was between 80 % and 100 %. And the range of the training time was between 0.095 min and 0.117 min.

Fig. 3 shows the comparison of the results obtained with kNN without preselection (Table 2) and kNN with preselection (Table 3), in the five operational statuses that were studied, and using 1 input frequency.

As shown in Table 3 and Fig. 3, whether or not using preselection, the accuracy was the same for four out of five operational statuses, where only for the balanced chopper a difference of less than 2.5 % was observed. The training time with the preselection was reduced between 92.2 % and 95.6 % (a 1.2–2 min range using all the frequencies and a 0.095–0.117 min range applying preselection of frequencies).

3.2. Evaluation of the influence of smoothing and the number of input frequencies on the accuracy

Accuracy with and without the *smoothing* substage and using 1-to-3 input frequencies was compared, so as to assess the influence of smoothing and the number of input frequencies. HS frequency selection was applied for the purposes of the comparison, and under the following conditions: using accelerometer a1, considering the five operational statuses that were studied and with preselection. The *preselection* substage was employed, as it was verified in subsection 3.1 that it reduced the training time, although accuracy was hardly reduced. Table 4 and Fig. 4 show the results of this comparison.

As shown in Table 4 and Fig. 4, the accuracy improves with smoothing, reaching an accuracy of 100 % with 2 input frequencies in four of the five conditions that were analyzed, versus only two statuses when smoothing was not applied. Moreover, with 3 input frequencies, 100 % accuracy is reached in all the operational statuses that were analyzed with smoothing. In the light of the results, the smoothing substage was applied in the following subsection (3.3) and only the solutions with 2 frequencies were considered.

3.3. Comparison of accuracy and training time between BF and HS for frequency selection

The results obtained with kNN when using BF to select the frequencies were compared with the results of kNN when employing the HS algorithm to select the frequencies under the same conditions: using accelerometer a1, with *preselection* and *smoothing*, with a number of selected frequencies as input for the classifier equal to 2 and considering the five operational statuses that were studied (Table 5 and Fig. 5).

As shown in Table 5 and Fig. 5, the accuracy obtained was nearly 100 % for the five operational statuses, obtaining the same accuracy with BF and HS. However, with HS a reduction in training time was achieved between 82 % and 90 % (from a range of 7.6–22.8 min with BF to 1.3–2.4 min with HS).

3.4. Comparison of the accuracy of the four accelerometers using HS

Finally, the accuracy obtained with each of the four accelerometers was compared under the same conditions: using HS to select the frequencies, with preselection and smoothing, with 3 input frequencies and in the five operational statuses that were studied. The number of input frequencies chosen was 3 because with this number the accuracy was 100 % in the five operational statuses that were studied.

As shown in Table 6 and Fig. 6, the accuracy was similar using the data obtained from the four accelerometers; of 100 % in all but two cases (99.4 % with accelerometer a2 and chopper; 96 % with accelerometer a3 and balanced thresher).

4. Discussion

The main results of the study suggest that, for the detection of the working status of rotating components within agro-industrial machinery: (i) it is feasible to estimate the status of the rotating components using a kNN classifier; (ii) the *preselection* and *smoothing* stages were important for reducing the training time and improving the accuracy, respectively; (iii) using HS instead of BF for the frequency selection reduced classifier training time; (iv) the position of the accelerometers appeared to have no significant influence on the accuracy when applying the proposed methodology; and (v) in our particular experimental setup, a 100 % classification accuracy could be achieved with

Table 3
Accuracy and training time obtained with kNN combined with Brute Force, with preselection (365 to 380 frequencies), from the accelerometer 1, using 1 frequency as the input of the classifier, and in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*). Precision, recall and F1 score results can be seen in Table A2.

Accelerometer	Preselected Frequencies (n)	Input Frequencies (n)	Operational statuses	Accuracy	Training time (minutes)
a1	365	1	Engine (low/max.)	99.44 %	0.103
	361		Thresher (on/off)	100 %	0.109
	380		Thresher (bal./im.)	82.50 %	0.095
	371		Chopper (on/off)	82.78 %	0.117
	346		Chopper (bal./im.)	80.00 %	0.079

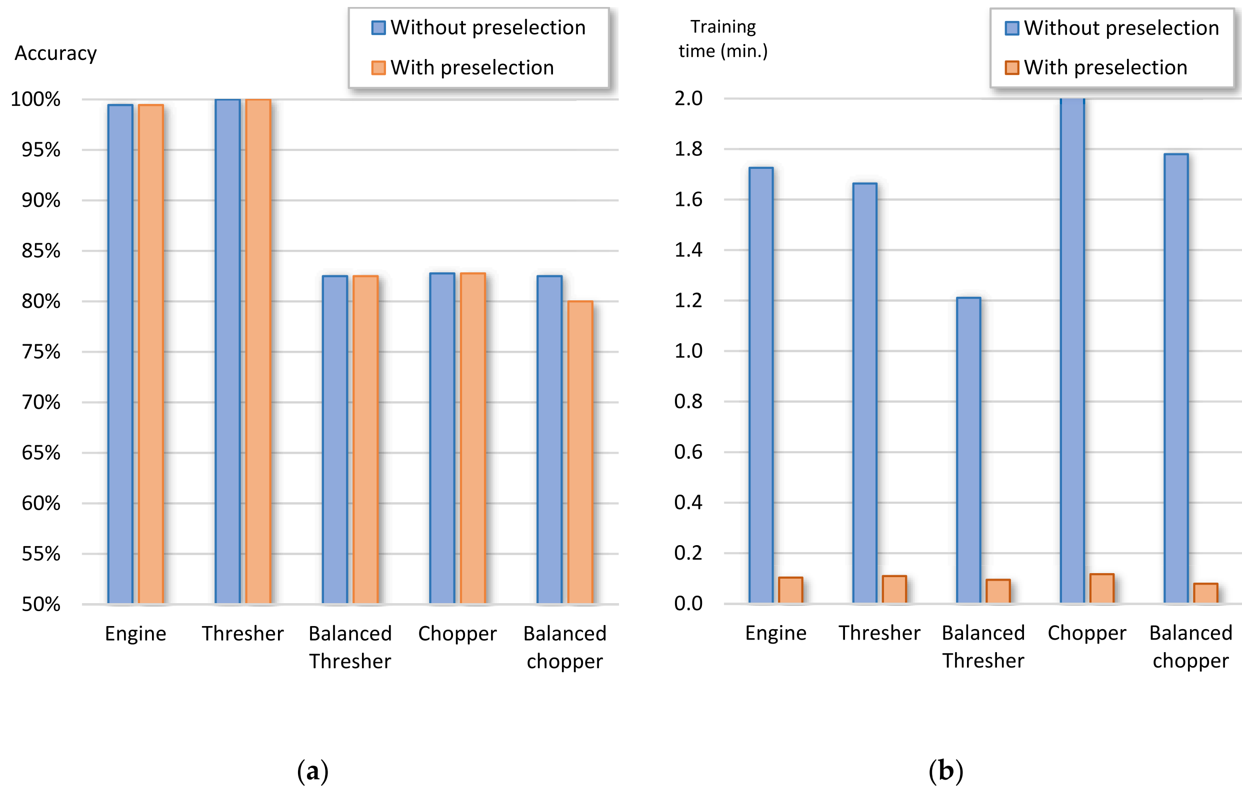

Fig. 3. Comparison of (**a**) accuracy and (**b**) training time, obtained with kNN combined with Brute Force, without preselection (5118 frequencies) and with preselection (346 to 380 frequencies), from the accelerometer a1, using 1 input frequency, and for the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*).

Table 4
Accuracy and training time obtained with Harmony Search (HS) algorithm with and without smoothing under the same conditions: with preselection (346 to 380 frequencies), from the accelerometer a1, using 1-to-3 input frequencies, and in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*). Precision, recall and F1 score results can be seen in Table A3 and Table A4.

Accelerometer	Preselected Frequencies (n)	Input Frequencies (n)	Operational Statuses	Accuracy Without smoothing HS	Accuracy With smoothing HS
a1	365	1	Engine (low/max.)	99.44 %	100 %
	361		Thresher (on/off)	100 %	100 %
	380		Thresher (bal./im.)	82.50 %	80.83 %
	371		Chopper (on/off)	82.78 %	85.56 %
	346		Chopper (bal./im.)	80.00 %	92.50 %
	365	2	Engine (low/max.)	100 %	100 %
	361		Thresher (on/off)	100 %	100 %
	380		Thresher (bal./im.)	98.33 %	100 %
	371		Chopper (on/off)	92.22 %	98.89 %
	346		Chopper (bal./im.)	99.17 %	100 %
	365	3	Engine (low/max.)	100 %	100 %
	361		Thresher (on/off)	100 %	100 %
	380		Thresher (bal./im.)	99.17 %	100 %
	371		Chopper (on/off)	96.67 %	100 %
	346		Chopper (bal./im.)	100 %	100 %

only 3 frequencies as input. These results are consistent with the objective of the study which sought to optimize the classifier and reduce the complexity and computational burden of other techniques proposed in previous works from the literature to detect the operational statuses of the rotating components of agricultural machines by applying data pre-processing, the HS algorithm, and the kNN classifier.

In this research, using 1 selected frequency as input for the classifier, the accuracy was similar with or without preselection of frequencies (between 82.5 % and 100 %). However, the training time with preselection of frequencies was reduced between 92.2 % and 95.6 %. A result that suggested that the preselection of frequencies is an important stage in the application of the classifier, in order to reduce the training time.

In this study, the *smoothing* substage improved accuracy. When smoothing was applied, accuracy levels of 100 % were reached with 2 input frequencies in four of the five operational statuses that were analyzed. In contrast, when smoothing was not applied, 100 % accuracy was only reached in two of the five statuses. In addition, with 3 kNN

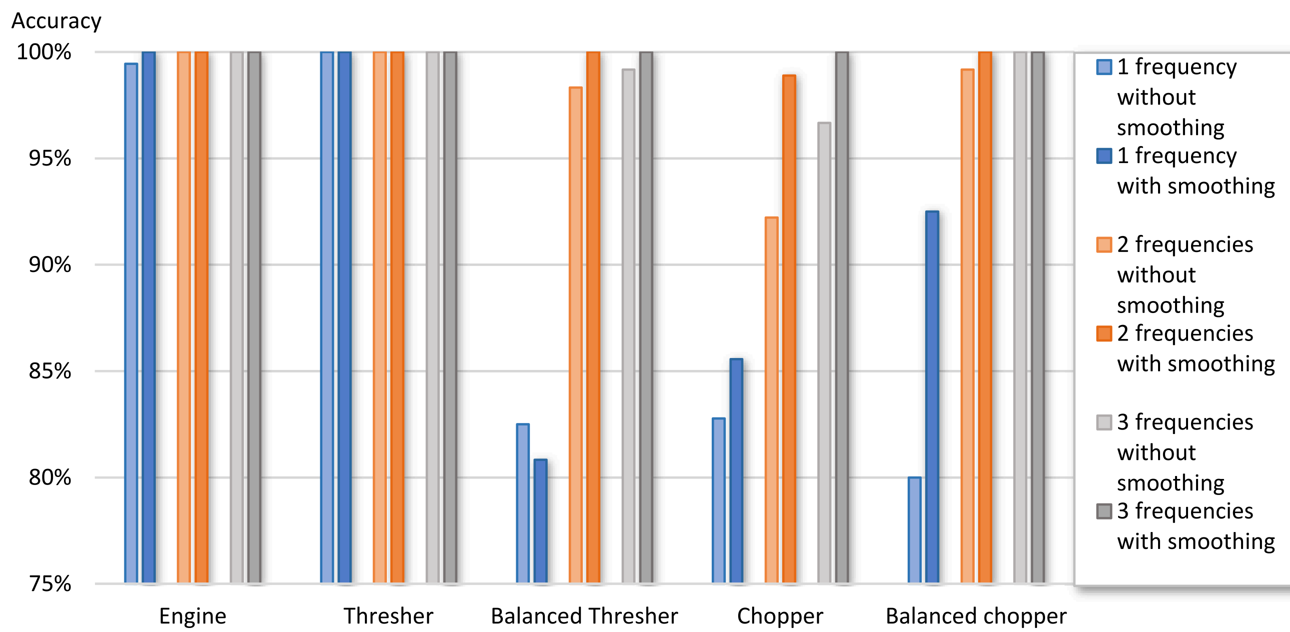

Fig. 4. Comparison of accuracy obtained applying Harmony Search (HS) with and without smoothing under the same conditions: with preselection (346 to 380 frequencies) and smoothing, using 1-to-3 input frequencies, and in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*).

Table 5
Accuracy and training time obtained with Brute Force (BF) and with Harmony Search (HS) under the same conditions: with preselection (346 to 380 frequencies), from the accelerometer a1, using 2 input frequencies, and in the five operational statuses studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*). Precision, recall and F1 score results can be seen in Table A5.

Accelerometer	Preselected Frequencies (n)	Input Frequencies (n)	Operational Statuses	Accuracy		Training time (minutes)	
				BF	HS	BF	HS
a1	365	2	Engine (low/max.)	100 %	100 %	18.42	2.39
	361		Thresher (on/off)	100 %	100 %	22.85	2.20
	380		Thresher (bal./im.)	100 %	100 %	8.95	1.39
	371		Chopper (on/off)	98.89 %	98.89 %	24.10	2.30
	346		Chopper (bal./im.)	100 %	100 %	7.69	1.39

input frequencies, 100 % accuracy was reached in all operational statuses analyzed with smoothing. This can be explained because smoothing combines information from adjacent frequencies and reduces the noise, thus improving the accuracy of the method.

One of the main sub-objectives of the study was to compare the accuracy of HS and the BF search in the frequency selection. An accuracy of nearly 100 % with both BF and HS was found for the five operational statuses. However, a reduction in training time was achieved with HS between 82 % and 90 % (from a range of 7.6 to 22.8 min with BF and from 1.3 to 2.4 min with HS). It should be noted that the training time when using BF for frequency selection greatly increased as the number of frequencies increased, ranging between 0.079 and 0.117 min with 1 input frequency (Table 3) and between 7.69 and 24.10 min with 2 input frequencies (Table 5). That increase happens because BF explores all the combinations of frequencies, whereas the HS algorithm selects only a set of frequencies, finding a suboptimal solution within less time.

Finally, the accuracy obtained when employing HS to select the frequencies was similar in the four accelerometers placed in different locations of the machine, nearly 100 % accuracy in all operational statuses with 3 inputs (Table 6). It therefore suggests that when testing different locations, the position of the accelerometers had no significant influence on the accuracy that was achieved.

When analyzing the performance metrics of the proposed method, it can be seen that the values of accuracy, precision, recall and F1 score were similar for all the experiments. The proposed method therefore generated classifiers with balanced precision and recall. In the case of needing greater precision than recall or *vice versa*, the HS algorithm fitness value should be modified, replacing the accuracy with a parameter based on the metric of interest.

Little attention has been given to predictive maintenance, condition monitoring, and fault detection systems for agricultural machinery (Zhang, 2015). Moreover, to the best of our knowledge, no research has previously been published in which a kNN classifier employing a HS algorithm to select the classifier inputs has been used in real agricultural machinery. Analyzing the literature on the evaluation of predictive maintenance or fault detection using vibration signals revealed that accuracy values between 90 % and 98 % were obtained (Guo et al., 2018; Li et al., 2013; Paulraj et al., 2013; Tseng et al., 2014); values that are numerically within the range of the results presented in this article. Nevertheless, the vibration patterns analyzed in the literature have not been applied in a real machine but in simple experimental models for the detection of damages such as in a gearbox (Li et al., 2013), a steel plate (Paulraj et al., 2013), in a motor (Guo et al., 2018; Tseng et al., 2014), or in a rotating experimental machine (Guo et al., 2018).

Our team has published three articles on the predictive maintenance of agricultural machinery in which vibration signals are analyzed on a combine harvester, applying different techniques: an SVM-based classifier (Ruiz-Gonzalez et al., 2014), an ANN-based expert system (Martínez-Martínez et al., 2015a), and a Composite Spectrum data-fusion technique (Feijoo et al., 2020). These works can be compared to this

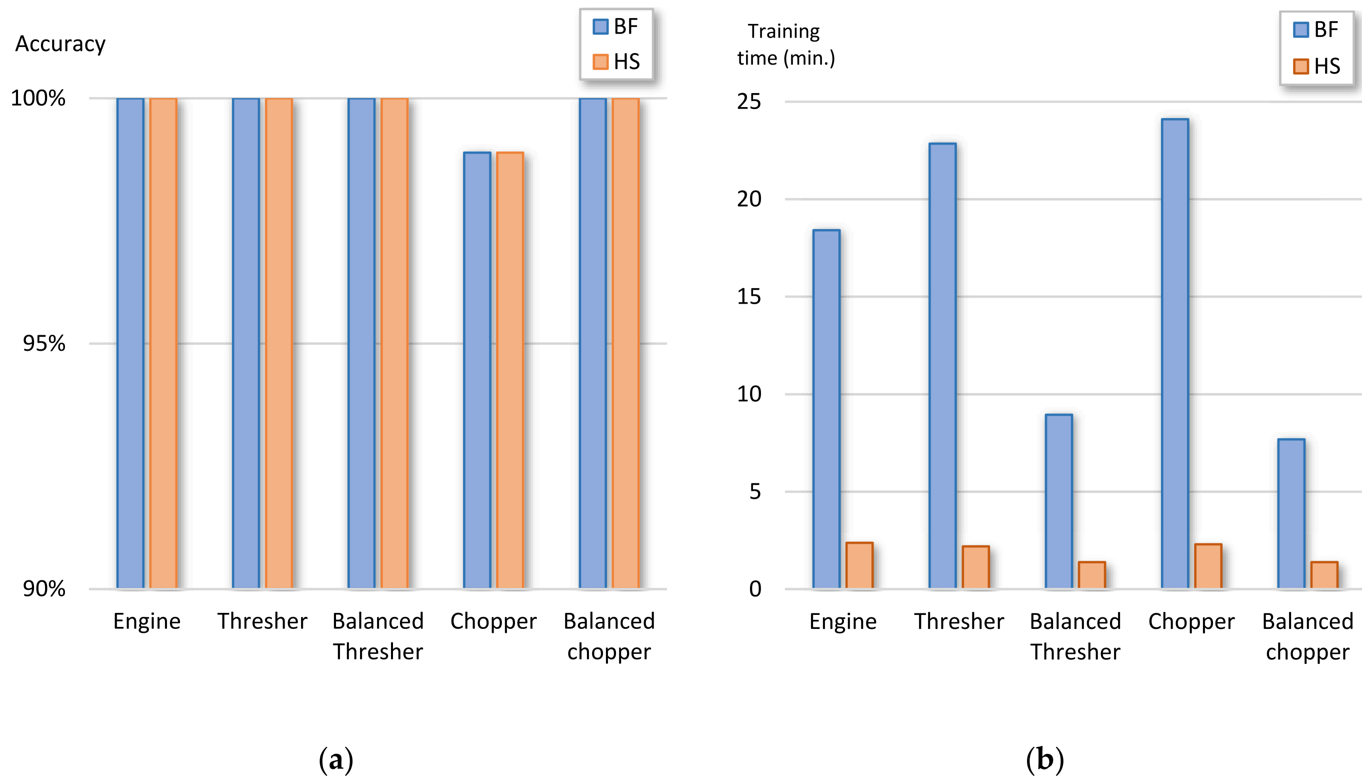

Fig. 5. Comparison of (**a**) accuracy and (**b**) training time obtained with Brute Force (BF) and with Harmony Search (HS) under the same conditions: from the accelerometer a1, with preselection (346 to 380 frequencies) and smoothing, using 2 input frequencies, and in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*).

study because a similar research design was applied: the analysis of vibration signals from one or various accelerometers placed on a combine harvester, in order to detect the working status of several rotating components.

In 2014, an SVM-based classifier using a vibration signal acquired from a single point on the machine chassis was applied (Ruiz-Gonzalez et al., 2014). An 85 % mean cross-validation accuracy was reached with this classifier, using a maximum of 7 features as its input. In comparison, in our study the accuracy ranged 100 % in four of the five operational statuses studied with only 2 input frequencies. It was not possible to compare the training time, because Ruiz-Gonzalez *et al.* did not analyze that parameter.

In 2015, Martínez-Martínez *et al.*, using a single vibration signal from one accelerometer and applying an ANN-based expert system, found that the status of several rotating components placed meters away from the accelerometer could be estimated to a high degree of accuracy (Martínez-Martínez et al., 2015a). In this article, a GA-based learning method was proposed to fit the ANN weights and biases. High levels of accuracy were obtained, but lower than those obtained with the current method: the maximum accuracy using ANN (100 %) was only reached in one case (engine speed study), and the lowest was 80 %. In contrast, in this present study, accuracies of between 98.89 % and 100 % were achieved in all cases by applying the HS algorithm and setting the number of kNN input frequencies to 2. It was not possible to compare the training time, because Martínez-Martínez *et al.* only considered the number of iterations of their proposed model when they analyzed that parameter.

In 2020, Feijoo *et al.* conducted a composite spectrum analysis of the signals from four accelerometers situated at four points on a combine harvester. Their work demonstrated that the rotating imbalances of various components can be detected with a reduced number of accelerometers located in non-optimal positions, and that it is feasible to simplify the monitoring (Feijoo et al., 2020). In the present study, the results obtained with the vibration signals of four accelerometers were also analyzed and compared, and similar results when testing different locations were obtained. It is therefore also suggested in our study that accelerometers can be placed in any position for high accuracy detection of machine component vibrations: engine, thresher, and straw chopper.

Overall, it has been suggested in the present study that the application of a relatively simple kNN classifier with techniques such as preselection, smoothing, and the HS algorithm for the detection of the working status of rotating components of agro-industrial machines, builds upon and outperforms any other previous approach in terms of accuracy.

Precise calibrated piezoelectric accelerometers were employed in this study. However, similar levels of accuracy could be expected using less costly accelerometers in real-world applications, such as MEMS accelerometers used in mobile phones, despite their lower precision. Another feature to be considered, if less costly accelerometers were used, should be the sampling frequency: in our study the sampling frequency was 1706 Hz, while most mobile telephone devices do not exceed 200 Hz. Future work could study how the accuracy of the method varies with the precision of the accelerometer and the sampling frequency. Nevertheless, in the previous work of Ruiz-Gonzalez *et al.*, an effective sampling frequency of 400 Hz was employed after applying downsampling, which suggests that further reductions could still achieve similar accuracies (Ruiz-Gonzalez et al., 2014).

The proposed monitoring system could be easily implemented in other types of real-world agricultural machines for two reasons. First, no specific information on the machine is needed in the design of the method and no experts are needed to implement the prediction system and to supervise the process. Second, the data-acquisition stage can be simplified, as only one vibration sensor can be used to monitor several components of the machine, dramatically reducing the number of sensors required and simplifying the wiring. That is a great advantage in modern agricultural machines, which have multiple shafts rotating at

Table 6
Accuracy obtained using Harmony Search (HS) to select the frequencies recorded in the four accelerometers under the same conditions: with preselection (346 to 380 frequencies), using 3 input frequencies, and in the five operational statuses: engine (*low rpm/maximum rpm*), thresher (*on/off*); thresher (*balanced/imbalanced*), chopper (*on/off*), chopper (*balanced/imbalanced*). Precision, recall and F1 score results can be seen in Table A6.

Accelerometer	Preselected Frequencies (n)	Input Frequencies (n)	Operational Statuses	Accuracy HS
a1	365	3	Engine (low/max.)	100 %
	361		Thresher (on/off)	100 %
	380		Thresher (bal./im.)	100 %
	371		Chopper (on/off)	100 %
	346		Chopper (bal./im.)	100 %
a2	365		Engine (low/max.)	100 %
	361		Thresher (on/off)	100 %
	380		Thresher (bal./im.)	100 %
	371		Chopper (on/off)	100 %
	346		Chopper (bal./im.)	100 %
a3	365		Engine (low/max.)	100 %
	361		Thresher (on/off)	100 %
	380		Thresher (bal./im.)	95.83 %
	371		Chopper (on/off)	100 %
	346		Chopper (bal./im.)	100 %
a4	365		Engine (low/max.)	100 %
	361		Thresher (on/off)	100 %
	380		Thresher (bal./im.)	100 %
	371		Chopper (on/off)	100 %
	346		Chopper (bal./im.)	100 %

different speeds where monitoring each individual component would require a high number of accelerometers. Furthermore, this unique vibration sensor can be arbitrarily positioned at quite some distance from the bearing supports, whereas previous studies refer to vibration sensors that were placed on the supports of the rotating components. Although this arbitrary positioning could make detection and monitoring of rotating imbalance more difficult, the results of this study have proven its feasibility. This study on a combine harvester, one of the most complex agricultural machines with multiple rotating and moving elements, has been successfully completed. The vibration signal that was processed contained the combined signals from both the three components under analysis and many other components of the machine. Altogether, it suggests that the proposed system could be successfully implemented in any other type of agricultural machinery, and could lead to fast and low-cost machinery inspections, avoiding many mechanical faults and replacing expensive, time-consuming inspections that are frequently required nowadays.

The current study has several strengths. First, the study has been applied to a real machine with the rotating components of the machine working. To our knowledge only our team has completed research on condition monitoring in real agricultural machinery and using a single accelerometer to monitor several rotating components. Second, the study builds upon and in terms of simplicity outperforms our previous approaches to real machines: only 1-to-3 inputs for the classifier, and accuracy levels better than or at least comparable to the accuracy obtained with other more complex classifiers (Martínez-Martínez et al., 2015a; Ruiz-Gonzalez et al., 2014). Third, the study has followed the line of research of our research team and has a similar experimental design to previous works, thereby improving upon the reliability of the comparisons between these studies. Fourth, the proposed system can be easily implemented in other types of machines.

Finally, when compared with recent works in the literature in which the status of components using a vibration signal are evaluated, our method has some advantages: (i) despite the accuracy obtained being within the same range that in the literature, between 90 % and 98 % (Feijoo et al., 2020; Guo et al., 2018; Li et al., 2013; Martínez-Martínez et al., 2015a; Paulraj et al., 2013; Ruiz-Gonzalez et al., 2014; Tian and Liu, 2019; Tseng et al., 2014), in our study 100 % accuracy is reached under some operational statuses; (ii) our work estimated the status of three rotating components whereas most of them usually estimated the status of a single rotating component (Liang et al., 2014; Tian and Liu, 2019; Tseng et al., 2014; Yang et al., 2015); and (iii) in previous works that estimated the status of several rotating components the accelerometers were placed close to each of these components (Bin et al., 2012; Guo et al., 2018; Li et al., 2013; Lu et al., 2015; Nembhard et al., 2015), whereas in our study they were placed far from each other and from each rotating component.

Nevertheless, there are some limitations to this work that should be taken into account before implementing the proposed method. The main limitation is that the data were gathered from a stationary harvester, that is, with the harvester wheels stopped, to facilitate the acquisition procedure. If the proposed estimation method is used when the monitored machine is in motion, low-frequency interference signals would appear due to the unevenness of the terrain and the elasticity of the combine wheels. However, these signals are not expected to cause problems, because the frequencies of interest in the rotating components of these machines will almost certainly be much higher than the interference frequencies. Moreover, other components that generate vibration, such as the beater cylinder, the sieves box, the cleaning fan, the hydrostatic pump, the elevator chains, the augers, and the drum variators, were not studied in this work. Some of these components also generate friction-induced vibration. Despite these additional sources of vibrations, the imbalanced components under study have been detected with the present method. According to the experience of the authors, it is expected that the proposed method, evaluated in a stationary machine, could be applied in real-word conditions, and the results are expected to be similar to the results of a machine harvesting in the field.

Futures lines of research that could be conducted are the evaluation and adjustment of the proposed methods working in real conditions, while the machine is harvesting in the field. Another future line could be to compare the performance of the proposed method with high-end and low-end accelerometers, evaluating the influence of accelerometer precision and the sampling frequency. Classification improvements could also be studied when a combination of vibration signals from several accelerometers is analyzed.

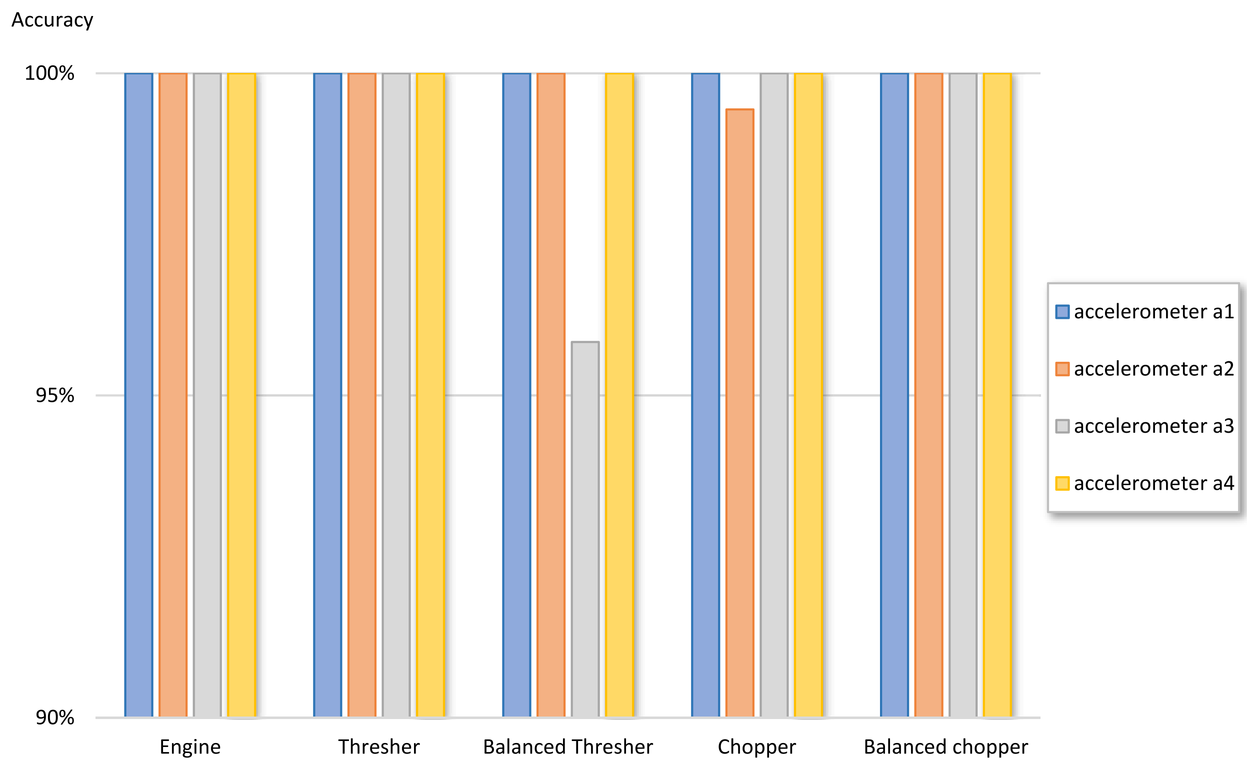

Fig. 6. Comparison of the accuracy applying Harmony Search (HS) with the four accelerometers, under the same conditions: with preselection (346 to 380 frequencies) and smoothing, using 3 input frequencies, and in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*).

5. Conclusions

The results obtained in this study have provided evidence that (i) it is possible to estimate with a high degree of accuracy the status of the rotating components of an agricultural machine from the vibration signal using a kNN classifier; (ii) applying the HS algorithm, it is possible to reduce the training time between 82 % and 90 % compared with BF; and (iii) there are no substantial differences in the accuracy between the different locations of the sensor.

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Conflicts of interest

The authors declare no conflict of interest.

CRediT authorship contribution statement

Francisco Javier Gomez-Gil: Conceptualization, Data curation, Investigation, Writing – original draft, Writing – review & editing. **Víctor Martínez-Martínez:** Conceptualization, Methodology, Software, Investigation, Writing – original draft, Writing – review & editing. **Ruben Ruiz-Gonzalez:** Conceptualization, Methodology, Software, Data curation, Investigation, Writing – original draft, Writing – review & editing. **Lidia Martínez-Martínez:** Conceptualization, Software, Investigation, Writing – original draft. **Jaime Gomez-Gil:** Conceptualization, Data curation, Investigation, Writing – original draft.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A

See Table A1-A6.

Table A1
Accuracy, precision, recall and F1 score obtained with BF without preselection (5118 frequencies), from accelerometer a1, using 1 kNN input frequency, in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*).

Component Statuses	Accuracy BF	Precision BF	Recall BF	F1 score BF
Engine (low/max.)	99.44 %	98.90 %	100 %	99.45 %
Thresher (on/off)	100 %	100 %	100 %	100 %
Thresher (bal./im.)	82.50 %	84.21 %	80.00 %	82.05 %
Chopper (on/off)	82.78 %	86.18 %	88.33 %	87.24 %
Chopper (bal./im.)	82.50 %	83.05 %	81.67 %	82.35 %

Table A2
Accuracy, precision, recall and F1 score obtained with Brute Force (BF) with preselection (346 to 380 frequencies), from accelerometer a1, using 1 frequency as the input of the kNN classifier, in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*).

Operational statuses	Accuracy BF	Precision BF	Recall BF	F1 score BF
Engine (low/max.)	99.44 %	98.90 %	100 %	99.45 %
Thresher (on/off)	100 %	100 %	100 %	100 %
Thresher (bal./im.)	82.50 %	84.21 %	80.00 %	82.05 %
Chopper (on/off)	82.78 %	86.18 %	88.33 %	87.24 %
Chopper (bal./im.)	80.00 %	80.00 %	80.00 %	80.00 %

Table A3
Accuracy, precision, recall and F1 score without smoothing, obtained with Harmony Search (HS) with preselection (346 to 380 frequencies), from accelerometer a1, using 1-to-3 kNN input frequencies, in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*).

kNN Input Frequencies (n)	Operational Statuses	Without smoothing HS			
		Accuracy	Precision	Recall	F1 score
1	Engine (low/max.)	99.44 %	98.90 %	100 %	99.45 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	82.50 %	84.21 %	80.00 %	82.05 %
	Chopper (on/off)	82.78 %	86.18 %	88.33 %	87.24 %
	Chopper (bal./im.)	80.00 %	80.00 %	80.00 %	80.00 %
2	Engine (low/max.)	100 %	100 %	100 %	100 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	98.33 %	100 %	96.67 %	98.31 %
	Chopper (on/off)	92.22 %	92.74 %	95.83 %	94.26 %
	Chopper (bal./im.)	99.17 %	98.36 %	100 %	99.17 %
3	Engine (low/max.)	100 %	100 %	100 %	100 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	99.17 %	100 %	98.33 %	99.16 %
	Chopper (on/off)	96.67 %	98.31 %	96.67 %	97.48 %
	Chopper (bal./im.)	100 %	100 %	100 %	100 %

Table A4
Accuracy, precision, recall and F1 score with smoothing, obtained with Harmony Search (HS) with preselection (346 to 380 frequencies), from accelerometer a1, using 1-to-3 kNN input frequencies, in the five operational statuses that were studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*).

kNN Input Frequencies (n)	Operational Statuses	With smoothing HS			
		Accuracy	Precision	Recall	F1 score
1	Engine (low/max.)	100 %	100 %	100 %	100 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	80.83 %	78.46 %	85.00 %	81.60 %
	Chopper (on/off)	85.56 %	91.23 %	86.67 %	88.89 %
	Chopper (bal./im.)	92.50 %	91.80 %	93.33 %	92.56 %
2	Engine (low/max.)	100 %	100 %	100 %	100 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	100 %	100 %	100 %	100 %
	Chopper (on/off)	98.89 %	100 %	98.33 %	99.16 %
	Chopper (bal./im.)	100 %	100 %	100 %	100 %
3	Engine (low/max.)	100 %	100 %	100 %	100 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	100 %	100 %	100 %	100 %
	Chopper (on/off)	100 %	100 %	100 %	100 %
	Chopper (bal./im.)	100 %	100 %	100 %	100 %

Table A5
Accuracy, precision, recall and F1 score obtained with Brute Force (BF) and Harmony Search (HS), with preselection (346 to 380 frequencies), from accelerometer a1, using 2 kNN input frequencies, in the five operational statuses studied: engine (*low rpm*, *maximum rpm*), thresher (*on/off*), thresher (*balanced/imbalanced*), chopper (*on/off*), and chopper (*balanced/imbalanced*).

Preselected Frequencies (n)	Operational Statuses	Accuracy		Precision		Recall		F1 score	
		BF	HS	BF	HS	BF	HS	BF	HS
365	Engine (low/max.)	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
361	Thresher (on/off)	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
380	Thresher (bal./im.)	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %
371	Chopper (on/off)	98.89 %	98.89 %	100 %	100 %	98.33 %	98.33 %	99.16 %	99.16 %
346	Chopper (bal./im.)	100 %	100 %	100 %	100 %	100 %	100 %	100 %	100 %

Table A6
Accuracy, precision, recall, and F1 score, obtained with kNN + Harmony Search (HS) algorithm and kNN (HS + kNN) in the four accelerometers under the same conditions: with preselection (346 to 380 frequencies), using 3 input frequencies, and in the five operational statuses studied: engine (*low rpm/maximum rpm*); thresher (*on/off*); thresher (*balanced/imbalanced*); chopper (*on/off*); chopper (*balanced/imbalanced*).

Accelerometer	Operational Statuses	Accuracy HS	Precision HS	Recall HS	F1 score HS
a1	Engine (low/max.)	100 %	100 %	100 %	100 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	100 %	100 %	100 %	100 %
	Chopper (on/off)	100 %	100 %	100 %	100 %
	Chopper (bal./im.)	100 %	100 %	100 %	100 %
a2	Engine (low/max.)	100 %	100 %	100 %	100 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	100 %	100 %	100 %	100 %
	Chopper (on/off)	100 %	100 %	100 %	100 %
	Chopper (bal./im.)	100 %	100 %	100 %	100 %
a3	Engine (low/max.)	100 %	100 %	100 %	100 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	95.83 %	95.83 %	96.61 %	95.00 %
	Chopper (on/off)	100 %	100 %	100 %	100 %
	Chopper (bal./im.)	100 %	100 %	100 %	100 %
a4	Engine (low/max.)	100 %	100 %	100 %	100 %
	Thresher (on/off)	100 %	100 %	100 %	100 %
	Thresher (bal./im.)	100 %	100 %	100 %	100 %
	Chopper (on/off)	100 %	100 %	100 %	100 %
	Chopper (bal./im.)	100 %	100 %	100 %	100 %

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