# Convolutional Neural Networks using the SMOTE Algorithm and Features Fusion for Wind Turbine Fault Prediction

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***Abstract*—This research introduces an innovative method using Convolutional Neural Networks (CNNs) to identify mass imbalances in wind turbine rotors through a feature fusion strategy. To address the issue of class imbalance, the Synthetic Minority Oversampling Technique (SMOTE) is applied. A detailed simulation was carried out using a 1.5 MW three-bladed Wind Turbine model, employing tools such as Turbsim, FAST, and Matlab Simulink, to collect rotor speed data under different wind conditions. Mass imbalances were simulated by modifying blade density in the software. The fusion architecture combines feature extraction with Power Spectral Density analysis, improving the CNN's ability to work across both frequency and time domains. The effectiveness of this approach was confirmed through a comparative analysis with 9 classifiers and 4 different dataset combinations, demonstrating its capability in detecting mass imbalances.**

**Link to graphical and video abstracts, and to code: https://latamt.ieeer9.org/index.php/transactions/article/view/9269**

***Index Terms*—Machine Learning;Convolutional Neural Networks; Wind turbine fault detection; Wind turbine failure predict.**

## I. Introduction

In 2020, new wind farm installations exceeded 93 Gigawatts generating the largest amount of power added in a year until now. Globally, wind power is responsible for producing 744 Gigawatts, which is enough to supply 7% of the world's total energy demand [1]. However, almost 200 Gigawatts installed have already surpassed ten years of operation. This situation has driven an increase in research focused on wind turbine failures, wind assessment, and condition monitoring systems (CMS), all aimed at enhancing the performance and reliability of wind energy systems.( [2] [3] [4] [5]). One of the most essential points in evaluating power generation is efficiency. Any part or process that does not achieve the normal behaviour of the power system causes a large loss in the total amount of energy generated, which leads to a monetary loss for businesses and customers and inappropriate use of resources and space. To avoid this loss, it is common for most system operators to spend a lot of time and resources on system maintenance. Previous research estimates that in an offshore wind farm 20-35% of the total amount of energy is spent on maintenance ( [6]- [7]). All these resources impact heavily the Levelized Cost of Energy (Lcoe) of those Wind Turbines.

To reduce maintenance costs, [8] developed a technique for classifying failures in the gearbox of a wind turbine. The proposed method uses vibration signals processed by the Integral Empirical Load Mode Decomposition (IELMD) technique. These signals are used to classify the type of failure using the Least Squares Support Vector Machine (LSSVM).

Proposing a classifying method for fault diagnosis in wind turbines with insufficient data [9] [10] use a transfer of knowledge method to improve accuracy results. The transfer of knowledge uses a similar wind turbine with a large amount of data to improve the training set. The improved training set is then used to train a Convolutional Neural Network.

Additionally, using artificial neural networks, [11] proposes a diagnostic method to identify different fault types. The approach integrates Kalman filters to track the blade pitch angle and employs an artificial neural network to classify six different fault types in wind turbines. Also in [12] proposed a method that employs generator current/voltage and rotor speed as source for fault detection.

In order to provide a more robust classification, [13] proposes a Deep Learning Network with parallel Convolutional Layers. The network is structured with multiple branches, each containing multiple layers. This model demonstrates effectiveness in extracting discriminative features and accurately classifying data, even under noisy conditions.

This study proposes a diagnostic method to identify mass imbalances in wind turbine blades. Mass imbalances can arise from various sources, including ice accumulation, manufacturing defects, environmental exposure, transportation challenges, and improper installation [14] [15]. Such imbalances often result in fluctuations in rotor speed, indicating that the wind turbine is no longer functioning within its optimal operating parameters. The mass imabalance may lead to a loss in energy production but also because it will reduce the useful life of the rotor.

The main contributions of this work are:

(i) The extraction of features from the time series data and from the PSD in Frequency domain.

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TABLE I
SIMULATED WT SPECIFICATIONS

| Parameter | Value |
|---|---|
| Nominal Power | 1.5 MW |
| Generator type | permanent magnet synchronous |
| Hub height | 84 m |
| Rotor diameter | 70 m |
| Rotor orientation | Upwind |
| Rotor configuration | 3 blades |
| Nominal speed | 2.14 rad/s (20 RPM) |
| Nominal rotor torque | 736.79 kNm |

(ii) The Fusion of time and frequency features using a vector encoding.

(iii)The usage of Gramian Angular Difference Field and Convolutional Neural Networks as a diagnosis tool for mass imbalance at Wind Turbines

(iv) The usage of SMOTE to solve class imbalance problems in Wind Turbine applications.

(v) Comparison with 9 others classifiers for results consolidation.

The paper is composed of 5 sections: Introduction, Material and Methods, Proposed Approach, Results and Conclusion.

## II. THEORETICAL BACKGROUND

This section describes the simulation setup used for the experiments in the wind turbine and also the techniques and algorithms used for the classification.

### A. Dataset

This study used the dataset from [16], which consists of simulated data generated using Turbsim, FAST, and Simulink. Turbsim simulates three-component wind, while FAST models a 1.5 MW, three-blade, upwind, variable-speed wind turbine. To introduce mass imbalances ranging from -5% to +5%, the search varied the density of the blade material for each state. Tab. I provides the specifications of the simulated wind turbine, and Fig. 1 visually illustrates the software interactions.

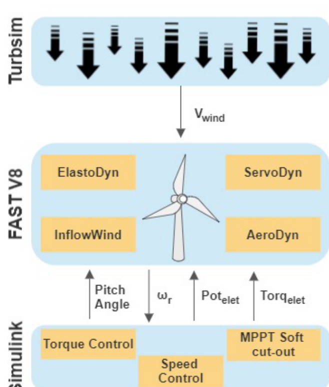


Fig. 1. Software Flowchart for database generation.

The dataset captures samples from each simulation at a frequency of 2 kHz for a duration of 180 seconds, with the first 60 seconds removed from the final dataset. This initial cut-off is applied to eliminate the transient period and focus on the steady-state regime. The choice of a 2 kHz sampling frequency is due to the method used to estimate wind turbine rotational speed from electrical measurements (current and voltage), which requires a high sampling rate. Once the estimated speed is obtained, the primary frequency of interest for classifying rotor imbalance is the 1p frequency (approximately 0.34 Hz in operating region 3), as mass imbalances typically manifest at this frequency [16]. For each level of mass imbalance, the search conducted 390 simulations, while 273 simulations were performed for balanced blades. These 390 simulations for each class of mass imbalance are split, though not evenly, into positive and negative imbalance percentages. For example, the 5% mass imbalance class comprises 117 simulations for a -5% imbalance and 273 simulations for a +5% imbalance. Since we have 5 different classes of imbalance, we have a total of 1950 simulations on mass imbalanced blades situations. Adding the 273 simulations performed for balanced blades, the dataset is composed by 2223 simulations.

Each simulation is then filtered to discard samples that fall outside a specific boundary around the target rotational speed of 188 rad/s, ensuring that the generator operates within its nominal range (region 3). Fig. 2 shows the distribution of samples after this filtering process. The final time-series dataset consists of 1,574 samples across 11 classes, as illustrated in Fig. 2, with each sample containing 240,000 features.

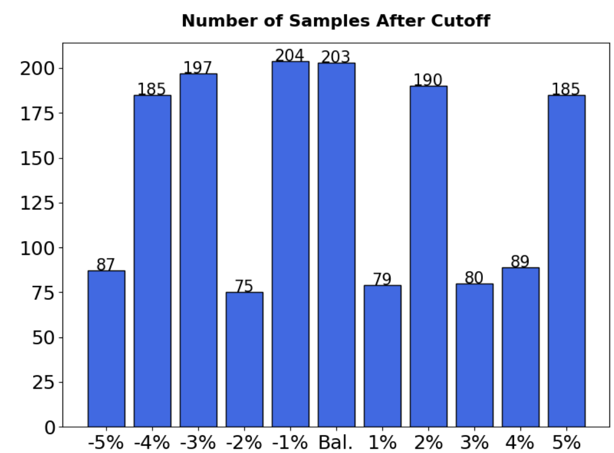


Fig. 2. Number of Samples for each percentage of mass imbalance after cutoff

### B. SMOTE

In the method outlined in this paper, the dataset balancing technique employed is the Synthetic Minority Oversampling Technique (SMOTE), an oversampling algorithm as the name suggests.

Proposed by [17] this technique is a form of data augmentation. Fig. 3 shows a hypothetical usage of SMOTE algorithm to balance a dataset. In Fig. 3, X axis represents 15 values of frequency that are around the frequency 0.33hz, and Y axis represents the normalized Power Spectral Density of those points.

On the other hand, SMOTE creates new samples by selecting a k number of neighbors for every sample and then,

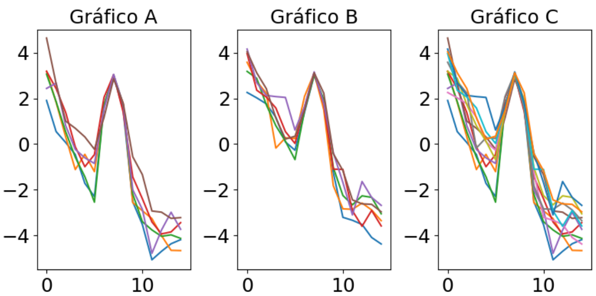


Fig. 3. Figure presents a hypothetical dataset to exemplify the oversampling: a)Original data; b)Synthetic data produced by SMOTE; c)Final dataset with an oversampled class

depending on how many new samples need to be created, randomly choosing between those neighbors. Synthetic data is generated between the sample and the neighbor. The distance between the synthetic data and the original sample is the distance between the original sample and its chosen neighbor multiplied by a random factor between 0 and 1. It is import the use of SMOTE because an imbalanced dataset can lead to misclassification, especially of the minority classes [18].

### C. Convolutional Neural Network

For this work, the type of neural network [19] [20] used was a Convolutional Neural Network (CNN). CNN is a class of neural networks that have contributed significantly to the field of Computer Vision [21] [22].

Standards CNN's are composed of 4 different types of layers: Convolution Layers, Pooling Layers (max pooling was used in this work as it is usually the most rewarding pooling strategy in terms of accuracy [23], Fully-Connected layers and Dropout layers to prevent data overfitting [24]. The CNN will process the time series data that has been converted to the frequency domain with the PSD technique ( [25], [26]), the information in the frequency domain will be converted into an image using a Gramian Angular Matrix [27].

## III. Proposed Approach

### A. General Architecture

This section will describe the process of training and testing the CNN and the other 8 classifiers used for comparison. Fig. 4 presents a flowchart outlining the entire sequence of steps in the proposed approach discussed in this article. The imbalanced dataset through a process of data augmentation using the SMOTE algorithm is balanced. Features are extracted in the time and frequency domain and using theses features is created an image using the Gramian Angular Matrix technique. the image is the input data of the convolutional neural entwork.

### B. Feature Fusion and Vector Encoding

Firstly, the dataset that has 2223 samples is imported. Every sample has 240,000 characteristics. Samples that surpass either the top or bottom limit were excluded. After this cut-off, 1574 samples remain. In this set of 1574 samples the first feature extraction is performed [28] [29], generating a dataset

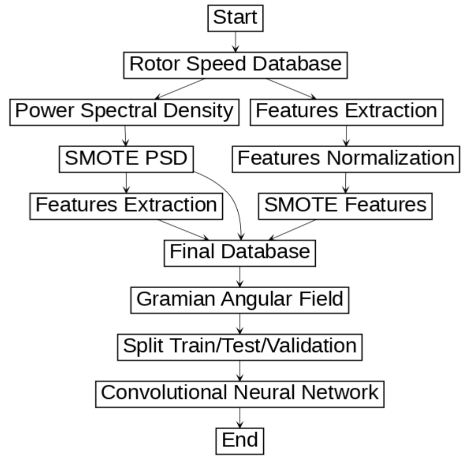


Fig. 4. Flowchart of the method.

which we will call 'Time's Features (TF)', with the following features: Maximum Value, Kurtosis, Median Absolute Deviation, Mean Absolute Deviation, Standard Deviation, Variance, Total Energy, Trimmed mean, Peak to peak value, Mean and Minimal Value. Since these 1574 samples are divided into imbalanced classes. The SMOTE algorithm was used to create synthetic samples, ending up with 2244 samples in 11 balanced classes. Unifying both minus percent classes and plus percent classes, like -5% and 5%, we end up with 2244 samples in 6 classes, but, since we double all classes except normal functioning (0% imbalance), we need to create more Synthetic Data, ending with 2448 samples divided into 6 perfect balanced classes.

Then, we calculate the Power Spectral Density of the original 1574 time series. Since we know that the mass imbalance malfunction affects mainly generation at low frequencies, we used only the first 15 values of the whole Spectrum. The process of creating synthetic data is identical to the one used with the time-series features. At this point it was made a second feature extraction, generating a dataset, which we will call 'PSD's Features (PF)', with the following features: Kurtosis, Median Absolute Deviation, Mean Absolute Deviation, Standard Deviation, Variance, Total Energy, Trimmed mean, Peak to peak value, Mean, RMS Value and Zero cross value. The final data-set is composed of the concatenation of the PSD values, the PSD's Features and the Time Series's features such as Fig. 5 shows.

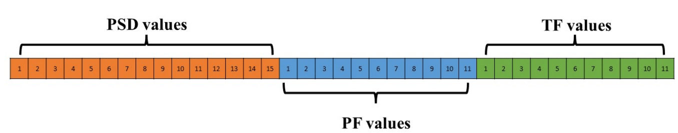


Fig. 5. Illustrative representation of the Final Data Set

The 2448 samples with 37 features, every sample is converted to an image of 37x37 with three dimensions of color, this encoding process is made using the Gramian Angular Difference Field algorithm. Those images are split into the train, test and validation sets. The train set represents 68% of the images, the validation set represents 12% and the test set represents the last 20%.

### C. CNN Architecture

The CNN model is composed of three convolutional layers, the first one has 256 nodes and the last layers with 128 nodes, three Max Polling layers, four dropout layers, four activation layers, one flatten layer and two fully connected layers. The whole summary model is in Fig. 6.

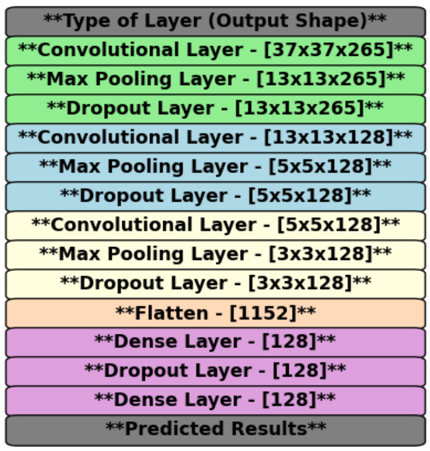


Fig. 6. Convolutional Neural Network structure

Besides the CNN, other 9 classifiers were used for comparative matters. The nine classifiers utilized are : Nearest Neighbours, Linear SVM, RBF SVM, Decision Tree, Random Forest, Multi-layer Perceptron Neural Network, Ada Boost, Gaussian Naive Bayes and QDA. Each was trained using 80% of the data and tested on the remaining 20%.

## IV. RESULTS

The results are divided into 6 sets of experiments: In the first one, only data in the frequency domain was used to feed the convolutional neural network; in the second set, the technique of SMOTE to create synthetic samples was employed; in the third set was used the data in the frequency domain with the SMOTE algorithm and the addition of statistical features of the time domain; in the fourth set was used the data in the frequency domain with the SMOTE algorithm and the addition of statistical features of the frequency domain; in the fifth set was used the data in the frequency domain with the smote algorithm and statistical data from time and frequency domain. Finally, in the last set of experiments was made a comparison of the technique proposed in this paper with other machine learning algorithms for classification.

I) Experiments with CNN

The simulation using only data in the PSD data resulted in a low accuracy rate. The main reason for this poor result is likely to be the small number of features, resulting in a final image of a 15x15 pixel size. The final accuracy was 56,51% for six classes. The training and validation curve is showed in Fig. 7 and the confusion matrix is depicted in Fig. 8.

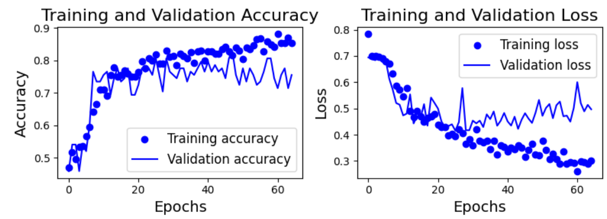


Fig. 7. Training of the Convolutional Neural Networks using PSD data

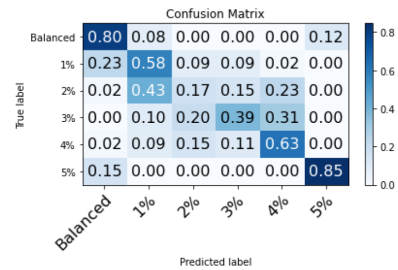


Fig. 8. Confusion matrix obtained after training the Convolutional Neural Network using PSD data

II) Experiments with CNN and SMOTE

The simulation using the frequency data and synthetic samples also resulted in a low accuracy rate. Although there is a small improvement in accuracy, the results are still far from acceptable. The final accuracy reached was 57,55%. The training and validation curves and the confusion matrix can be found in Figs. 9 and 10 .

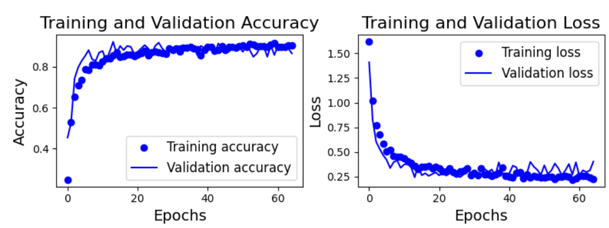


Fig. 9. Training of the Convolutional Neural Network using the PSD data and the SMOTE Algorithm

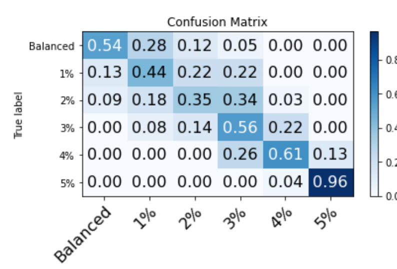


Fig. 10. Confusion matrix obtained after training the Convolutional Neural Network using PSD data and the SMOTE algorithm

III) Experiments with the CNN adding Time Statistical Features

Adding the time statistical features impacted a lot on the results of the CNN. The new features not only increase the image size but also bring new information for the data. The final accuracy reached 87.75%, which means that the system started to be a solid diagnosis tool. The training and validation curves and the confusion matrix can be found in Figs. 11 and 12.

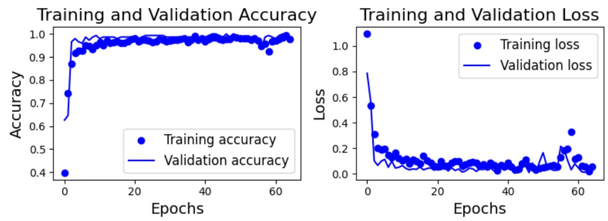


Fig. 11. Training of the Convolutional Neural Network using the PSD data, the SMOTE algorithm and the Time statistical features

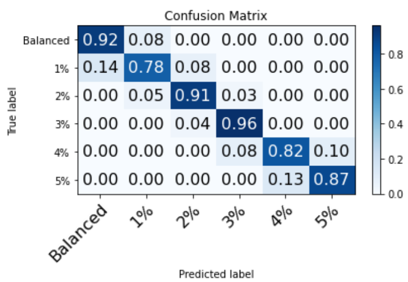


Fig. 12. Confusion matrix obtained after training the Convolutional Neural Network using PSD data, SMOTE algorithm and the time statistical features

IV) Experiments with CNN adding Frequency Statistical Features

Using the statistical metrics features instead of the time statistical features also improved the results of the CNN. This is an indicative that the information extracted from the frequency domain data series is, in some way, more valuable to define the classification borders. The new accuracy rate reached 89.18%. The training and validation curves and the confusion matrix can be found in Figs. 13 and 14.

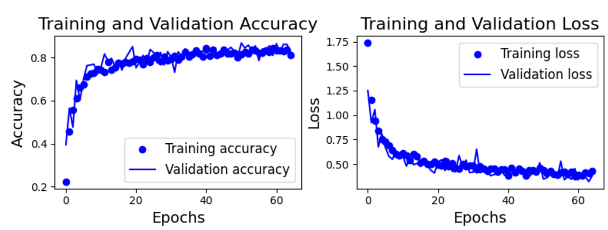


Fig. 13. Training of the Convolutional Neural Network using the PSD data, the SMOTE algorithm and the PSD statistical features

V) Experiments with the CNN and Fusion of Frequency and Time Statistical Features

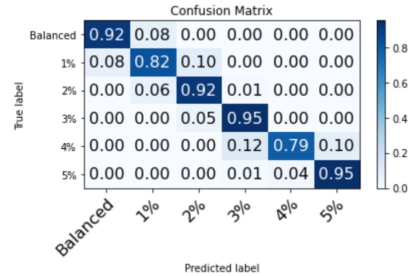


Fig. 14. Confusion matrix obtained after training the Convolutional Neural Network using PSD data, SMOTE algorithm and the PSD statistical features

Finally, using the dataset composed using both frequency and time statistical features the accuracy rate was 91,84%. This result is the best one so far for the CNN. Using both statistical features brought a lot of new information for the dataset and the neural network was able to find the patterns in this new data. The training and validation curves and the confusion matrix can be found in Figs. 15 and 16.

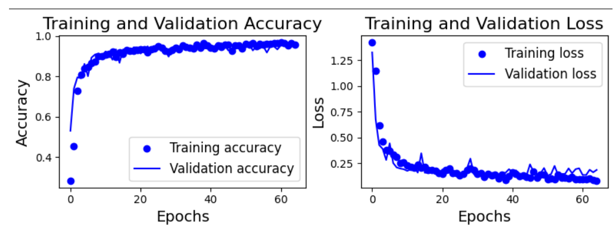


Fig. 15. Training of the Convolutional Neural Network using the PSD data, the SMOTE algorithm and both Time and PSD statistical features

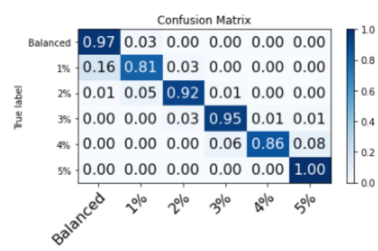


Fig. 16. Confusion matrix obtained after training the Convolutional Neural Network using PSD data, SMOTE algorithm and both Time and PSD statistical features

VI) Experiments with other Classifiers and Comparison with CNN Results

The proposed algorithm in this work was compared in experiments with 9 other classifiers. The Parameters used with these classifiers can be found at: GIT Hub Repository.All of them showed improvement by adding the Synthetic samples with SMOTE algorithm. Most of them achieve their best results using only the PSD dataset, without any statistical feature addition. MLP Neural Network was the algorithm that showed the biggest similarities with the CNN proposed in this paper, improving its results when adding the statistical features, much likely because MLP is also a neural network. The best result of each classifier is exposed in Table 2.

TABLE II
BEST ACCURACY RESULT FOR ALL TESTED MACHINE LEARNING ALGORITHM. FOR EVERY ALGORITHM MULTIPLE TESTS WERE MADE WITH DIFERENT DATASET COMBINATIONS

| Classifier | Accuracy |
|---|---|
| Linear SVM | 89,79% |
| MLP Neural Net | 88,57% |
| QDA | 88,16% |
| Decision Tree | 86,32% |
| RBF SVM | 84,48% |
| Nearest Neighbors | 84,08% |
| Naive Bayes | 72,24% |
| Random Forest | 72,04% |
| AdaBoost | 58,57% |
| CNN | 91,84% |

## V. CONCLUSIONS

This work proposed the diagnosis of mass imbalance in the rotor of a wind turbine using a convolutional neural network. Through the process it was also used the SMOTE algorithm and the Gramian Angular Difference Field algorithm to prepare the data. The final accuracy of the CNN was 91,84%, which proved that the proposed technique is promising to detect mass imbalance. This result also showed to be relevant when compared to other common classifiers. Another important result of the paper is the usage of the features extraction as a pre-processing method in order to fusion time and frequncy data, focused on improving the accuracy result of artificial neural network algorithms, the results improved dramatically with the utilization of the method. For reference, the accuracy using only the data from PSD reached only 56,51% , but when we add Time or Frequency Features, the result improves to 87.75% and 89.18% respectively, and reaches 91.84% when used both features together. Also, the article applies successfully a convolutional Neural Network and the SMOTE technique for classification of mass imbalance in wind turbine, the Convolutional neural network for this problem is a different approach from what have been presented before and the SMOTE algorithm application shows great relevancy when it comes to real scenarios, where is common the problem of imbalanced datasets. The CNN performed better than most of methods presented before and the SMOTE improved the results of all classifiers. Finally, a comparison with 9 different classifiers was implemented, which proves that the CNN is a viable algorithm. For further work, the most essential step forward is use the same methodology with real data from a operating wind turbine.

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