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Intelligent Quality Management For Production Enhancement: A Review Of Ensemble Machine Learning Techniques

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Master's thesis in Industrial Engineering

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Abstract: Nowadays, the Artificial intelligence technology led to a rise in manufacturing innovation, including improvements in quality management. The expansive realm of artificial intelligence (AI) encompasses various branches, among which machine learning (ML) has evolved into a distinct science, notably, the field of ensemble learning (EL) that has gained heightened interest. This paper attempts to explore the novel concept of ensemble learning and its application in quality management with a narrow focus on quality control and quality assurance. In fact, we examine the performance of the three most popular tree-based algorithms (Random forest, Extream gradient boosting, and Adaptive boosting). Through an evaluation process, we select the most used models based on previous works and researches in order to reveal their underlying qualities. This research reveals that Random forest is the most used algorithm that can outperform not only the basic machine learning algorithms but also the deep learners due to its properties especially its simplicity, capacity and ability to handle multidimensional data.

Key-Words: Ensemble learning,RF,XGboost,Adaboost, Quality,Production

Contents

1. Introduction

In today's competitive manufacturing landscape, production processes optimization is faced to several challenges that are based on three major axes: reducing costs, environmental sustainability, and enhancing quality. In other words, improve efficiency and efficacy. New approaches based on emergent technologies have been developed and used to improve those crucial pillars so that the companies face the market demands and requirements.
As we already mentioned, quality stands as the cornerstone and essential pillar of a company's profitability that should be maintained by quality management system which is defined as a set of procedures followed to guarantee that a service or product meets the customer's expectations. This system is designed and implemented in a company in a way to ensure both effectiveness and efficiency.[1]. The goals of quality management include both achieving high standards for goods and services as well as ensuring profitability[2].
In the last century, quality paradigms have seen a continuous evolution. From the first paradigm of quality -*Quality inspection*- until the occurrence of *intelligent quality management*, several tools and methods have been exploited for the optimization and improvement of products, services and processes[3].
With the occurrence of artificial intelligence techniques, new insights have been discussed and recent approaches have been studied that improve the quality in the production process. Among those techniques, machine learning models. Machine learning is a trunk of a tree called artificial intelligence. It focuses on enabling computers to use existing knowledge in order to simulate human work and obtain new skills or knowledge[4]. In order to obtain superior knowledge and attend higher performance, multiple and basic machine learning models are combined, this approach is known as *ensemble learning*. If the ensemble models use the same kind of base machine learning model, the ensemble learning is homogeneous. As for the heterogeneous ensemble learning, different types of base algorithms are combined [5].
Both types are divided into parallel ensembles and sequential ensembles. The parallel ensembles algorithms simultaneously generate diverse base learners for example bagging and random forests models, while sequential ensembles train base models one after the other which is the case in boosting algorithms and stacking models where the result of one model can be used as input to another model [6].
Researches [7], [8], [9], [10], [11] have shown that AI, particularly machine learning techniques, offers a promising path to significantly enhance production quality. These advancements enable companies to achieve their goals of producing high-quality products by implementing policies based on ML-powered defect detection [12] and product quality prediction[13].
When basic ML models or individual models show varying performances and limitations, ensemble learning rises to the challenge. By combining the strengths of different models, ensemble methods improve overall accuracy and generalisation which means that ensemble models are mostly able to generate a wider range of relationships and patterns between the variables of the data set[6][14].
From individual to ensemble diving to deep learners, we have a variety of approaches, techniques and methods to improve quality from inspection to total quality management. This paper was written for the purpose of presenting alternatives and efficient methods to enhance quality of products and processes. For this reason we explored the literature of the ensemble learning approach assuming that it surpass the individual machine learning models. In this study, we aim to answer the following questions: How can EL applied to improve quality ? Do ensemble models consistently outperform individual models, and if so, which ensemble algorithms show the best performance under different circumstances?
The rest of the paper is organised as follows: Section 2 introduces the background needed to understand this research. Section 3 is devoted to the application of machine learning in quality management field. Section 4 presents a study on the application of EL in quality management. In section 5 we present a comparative study between ensemble tree based algorithms. Finally, in section 6 and 7 we discuss the results and the conclusion of this study respectively.

2. Background

2.1. Quality Management tools

Quality management tools and techniques are practical methods that can be applied to improve the quality management components (Figure 1) to achieve positive changes and improvements [15]. Seven essential quality tools can help organizations to solve problems and improve quality systems. The seven basic quality control tools are: [16]

Figure 1: Quality management components [2]

- The check sheet is a simple form used to tally the frequency of particular events during data collection. It helps organize data for later analysis.

- Histograms graphically represent the distribution and variation of data values and it aids in identifying the underlying distribution pattern of the variable under study.
- Pareto charts arrange data in descending order of frequency to identify a few key contributors. The cumulative percentage curve allows us to focus on the critical 20 per cent of errors that cause 80 per cent of the problems.
- Fishbone Diagram a cause-and-effect diagram that categorizes and displays all potential causes of a problem according to root cause categories.
- Control charts monitor process fluctuations over time and detect any out-of-control conditions that require corrective action. Statistical control limits are used to identify points that deviate from natural variation. Control charts are used to analyze dimensional errors defects.
- A flowchart provides a visual representation of the sequence of steps and decision points in a process. They help to examine processes, identify areas for improvement and communicate these clearly.
- Scatter Plot is a graph in which two variables are plotted against each other to analyze whether there is a correlation between them.The objective is to analyze the potential relationship between the two variables.

Several new quality tools have emerged, mainly for qualitative data like affinity diagrams, relationship diagrams, tree diagrams, matrix diagrams, arrow diagrams, process decision procedure diagrams (PDPC), and matrix data analysis[17]. From the above tools, those frequently used and appropriate for the quality systems, according to ISO 9001 are presented in Figure 2.

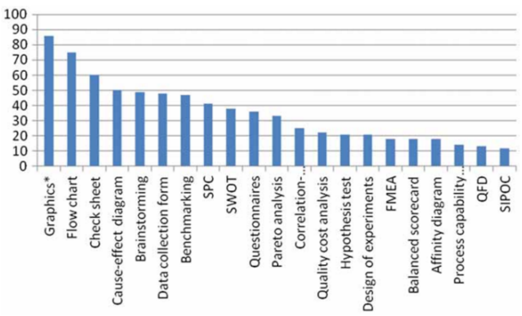

Figure 2: Level of use of tools/techniques[17].

With the advances of emergent technologies a new term has appeared *Intelligent quality management* which is a system of quality management that goes beyond traditional methods by using advanced data analysis techniques such as machine learning to improve quality[3]. There are several approaches for using machine learning. The ensemble learning approach is covered in the section that follows.

2.2. Ensemble learning

In this section we are going to introduce the most famous and commonly used algorithms of tree based ensemble learning (Figure 3):

2.2.1 Random Forest (RF)

Created by Leo Breiman (statistician and computer scientist), RF is an enhanced version of bagging, known as bagging of CARTs (Classification and Regression Trees)[18]. CARTs represent techniques for dividing the variable space according to a decision tree's embedded set of rules where a decision rule determines how each node divides [18]. RF technique is based on combining several tree predictors so that every tree in the forest is reliant on the values of a randomly distributed vector that is sampled individually for every tree in the forest[19]. The Figure 4 illustrates the architecture of a random forest model.

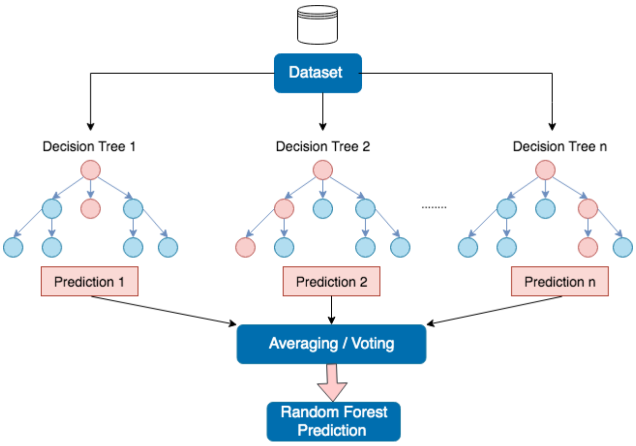

Figure 4: Random forest algorithm

Advantages:

- Prevents overfitting problems (Robust to overfitting issues)[20].
- The RF classifier is quite insensitive, even in cases when training data has been mislabeled[20].
- Handling large datasets with higher dimensionality [21].
- RF can handle missing data[21].
- RF has the capacity to simultaneously incorporate continuous and categorical data[22].
- Unlike other bagged ensembles, Random forest tries to minimise bias[23].
- Well known and effective[23].

Disadvantages :

- Not as easily understood as the other algorithms. Random forests are more challenging to understand and interpret than single trees[20][24].
- The calculations and instabilities could be more intricate than with the other techniques[20].
- Limitations of the algorithm in terms of using data to explicitly identify causal linkages[25].

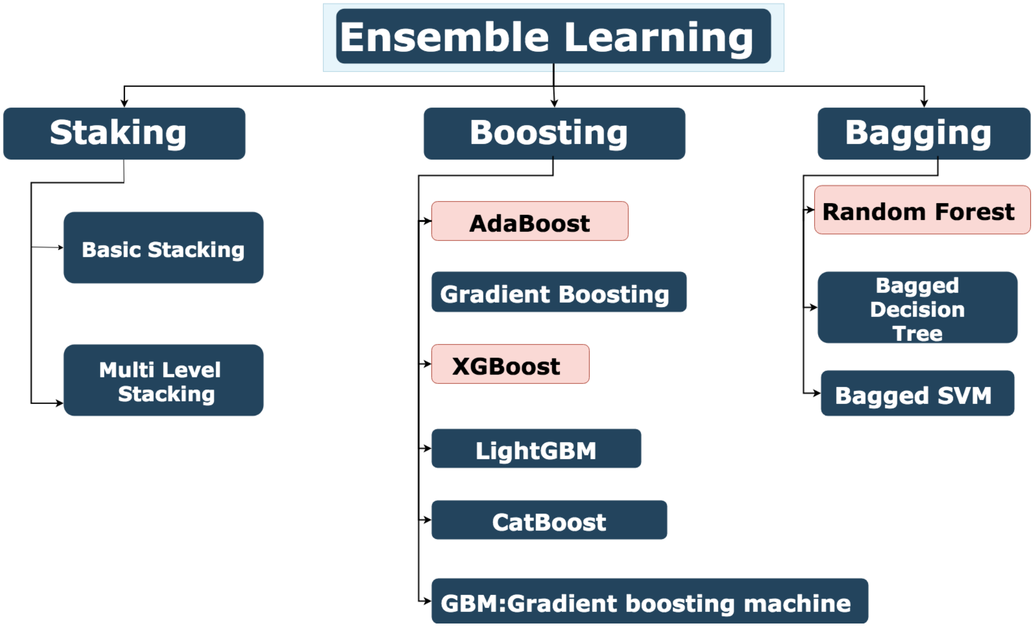

Figure 3: Ensemble learning algorithms

2.2.2 Extreme gradient Boosting (XGboost)

It has appeared in 2014, it is another type of boosting algorithms, it is constructed based on an ensemble of gradient boosting decision trees or a sequential ensemble approach known as a sequential decision tree[26]. Adding a regularisation parameter that lessens each regression tree's susceptibility to dataset outliers, which improves the gradient boosting algorithm[23]. With this approach, a weight value is assigned to each data value in the database, defining the likelihood that the value will be chosen for additional examination by a decision tree[27][26].
Afterwards, the sample class is predicted by adding the trees sequentially. Every tree seeks to recoup the discrepancy between the target and the previous ensemble of trees forecast[26]. The architecture of the XGboost is shown in Figure 5.

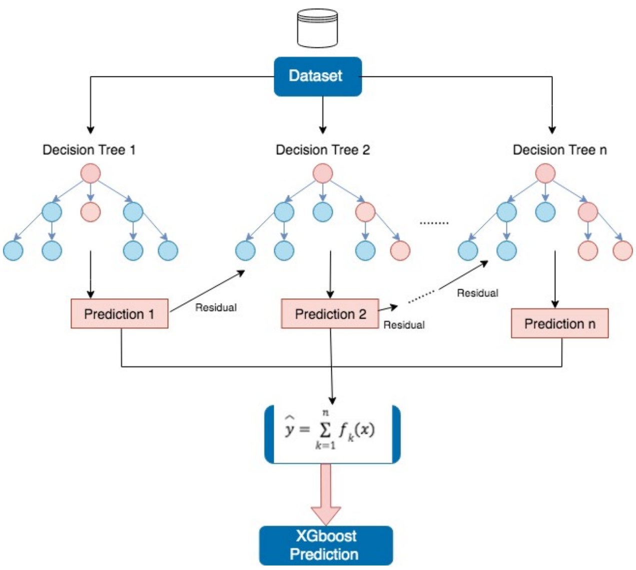

Figure 5: XGboost algorithm

Advantages:

- It performs better in classification compared to the typical neural network model[27].
- XGboost performs better across a variety of datasets[28].
- It works well with a variety of objective functions, including regression, classification, and ranking[28].
- XGboost is fast. Compared to GBM, it is typically over ten times quicker[28].
- XGboost accepts a variety of input formats for data [28][20].
- Capacity to reduce overfitting in an efficient manner[20].
- Have less variance than the one obtained using gradient boosting [23].

Disadvantages :

- Long training period(slow)[20].
- Restricted interpretability(limited)[20].
- XGboost is Sensitive to hyperparameters[20].

2.2.3 Adaptive Boosting (Adaboost)

FREUND Yoav et SCHAPIRE Robert were the first searchers who introduced and built this model in 1995. It is one of the boosting algorithms that was named accordingly because it adapts adaptively to the flaws of the weak hypotheses that WeakLearn returns, in contrast to other algorithms[29]. It may combine any number of base-learners and re-uses the same training set. This means that many classifiers of AdaBoost are trained one after the other. The efficiency of previously taught classifiers is the basis for training each new one[29][30].

Advantages:

- Adaboost has a solid theoretical base. It's applied in numerous domains[31][32].

- Does not need a large sample of data for training phase[33].
- It is quick, easy to use and program[34].

Disadvantages:

- Sensitive to noise and outliers. When noisy data is present, AdaBoost is prone to overfitting[35][33].
- Theory suggests that boosting could not be successful when there is insufficient data, when weak hypotheses are too weak, or when weak hypotheses are very complex[34].

3. Insights of Machine Learning applications in quality management

ML techniques are applied in so many fields and industry domains. For instance computer and electronics manufacturing, chemical manufacturing, metal industry uses those techniques to improve the performance of its discrete and continuous production lines and to solve various problems. Among the key areas where ML shines in order to enhance the performance of the production function, we mention quality optimization to achieve customer satisfaction[7].

The ML models can optimise quality either by detecting and minimising defects, therefore, achieving better product reliability or by optimising critical product performance parameters[7]. In other words, machine learning can be used indirectly as a diagnostic tool to detect anomalies for processes or products by analysing the underlying causes of quality issues and predicting product quality early on to avoid unfavourable outcomes. As for direct methods, they rely on identifying the best parameters to adjust based on the desired outcome and the characteristics of the product in order to attend high level of quality[8].

Another contribution of machine learning branches shines in the quality improvement tools such as lean management, six sigma, lean six sigma (LSS). In this case, it can be integrated directly for instance in root cause analysis for quality issues. The ML algorithm has shown to be successful in improving competitiveness and anticipatory identifying defects[8].

ABD ELNABY et al.[9] integrated machine learning in the analysis phase of the DMAIC approach (Define-Measure-Analyze-Improve-Control) in the context of lean six sigma to improve the quality of plastic bottles.

Another research by ALTUĞ Mehmet[10] was maintained to solve defective coating by implementing six sigma which lead to improved quality and reduce waste. After that, deep learning was integrated as an alternative solution. The deep learning model's performance closely matched actual outcomes, validating the effectiveness of the Six Sigma improvements.

As for lean combined with machine learning, ABUSAQ et al.[11] studied where ML was used with the lean principles to reduce idle time which led to substantial energy savings. Additionally, they developed a machine learning model using various factors to predict energy consumption which helped in optimising job scheduling, further reducing energy consumption and costs.

Even with the remarkable success of machine learning, Kuo-Yi Lin et al.[36] aptly point out, many production line challenges demand intelligent management solutions. They argue that ensemble learning surpasses traditional methods in quality control by eliminating nonconformity factors, ultimately leading to higher quality standards. EL's versatility extends beyond mere detection and isolation. It can pinpoint fault characteristics, predict imminent issues, and even forecast future problems before they manifest. From safeguarding quality control to bolstering inspections, ensemble learning offers a powerful toolkit for tackling production line hurdles and optimising performance.

4. Ensemble Learning for quality

This section provides an introduction to the use of ensemble learning in quality, with a focus on quality assurance and control.
Our study was based on 13 articles in different domains that are shown in Figure 6

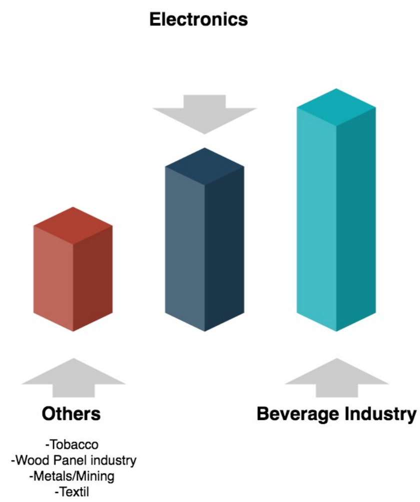

Figure 6: Articles' Domains

4.1. The beverage industry

Jain Khushboo et al. [37] aimed to predict wine quality using RF, DT, XGboost, Adaboost, Gradient boosting since the acquisition of wine certificates is quite important. For this purpose, they gathered information about the physical and chemical properties of wine from several websites. Then they created a binary classification in order to forecast the quality of wine if it's good or bad using the EL algorithms. This may help in wine quality modeling and identifying the importance of the characteristics used to determine the quality. As a result of testing the algorithms in different conditions, the XGboost showed good results with/without feature selection and key variables while RF had the best performance using the key variables. Another key finding of this study showed the effect of feature selection on the performance of the models.

For the same purpose, Dahal et al. [38] used ensemble model Gradient Boosting Regressor (GBR) and other machine learning and deep learning models. In this case they didn't transform the target variable into a variety of classes, they used regressors in order to identify the key factors that determine wine quality before the beginning of the production. Understanding these factors will empower winemakers to control quality from the very beginning of the wine production process. Similarly to the earlier case study they collected product dataset from a website (UCL repository). Unlike Schubert et al.[39], they checked and handled the outliers during the data preprocessing aiming to attend higher performance. The models' performance was assessed using correlation coefficient (R), mean squared error (MSE), and mean absolute percentage error (MAPE). The results showed that the gradient boosting regressor had the best results.

Another study was maintained in the beverage industry by Bhardwaj Piyush et al.[40] to test the performance of the ensemble models along with non ensemble models in predicting wine quality. The data used in this study were gathered from several producing areas and preprocessed using SMOTE analysis to balance and enhance the data. Additionally, a feature selection process was carried out to identify the top 10 significant features. The authors utilized Accuracy, Precision, Recall and F1 Score to rank the models in order of greatest performance. Consequently, random forest performance increased with critical feature attending at 1 accuracy, whereas Adaboost outperformed the other models with 1 accuracy both with and without feature selection.

Although the boosting algorithms were found to be effective in detecting and predicting defects in the three earlier studies, Nandan Mauparna et al.[41] tested the Random Forest classifier in conjunction with machine learners and deep learners in order to classify wine quality into three different categories.They found that it outperformed the other classifiers with an accuracy of 98.11 per cent.

In summary, ensemble learners are effectively used in both regression and classification problems to predict wine quality based on physicochemical properties. This prediction is crucial as it can improve product quality and assist in obtaining quality certifications.

4.2. Electronics

In order to make defect detection more efficient and distinguish genuine defects from false alarms, in other words, build a decision making tool to detect defects, Jabbar Eva et al.[42] used four tree based algorithms (CART, RF, XGboost, Adaboost). Unlike the case studies where they used SMOTE (Synthetic Minority Oversampling Technique) analysis to handle the imbalanced dataset, in this case ,they used data level procedures to modify the data sets by adding or removing entries. They tested the previously mentioned algorithms on the balanced dataset and using the metrics of Accuracy, Hamming loss, Precision, Recall and Computation time. They concluded that XGboost outperformed the other algorithms proving that the implementation of this algorithm is a promising approach.

In addition, the quality issue in battery manufacturing is critical, as it directly impacts the performance of the final product which addresses the need for an effective sensitivity analysis to quantify the importance and correlations of variables affecting electrode quality[43]. Iu Kailong et al.[43] proposed a boosting hybrid technique called random undersampling boosting (RUBoost) to predict quality. The ensemble learner was developed and used to verify electrode quality classification during battery manufacture. This technique outperformed the random forest algorithm in terms of Accuracy and forecast the characteristics of the produced electrode.

4.3. Tobacco

In this case study, Qioa shi et al. [44] aimed to predict quality by mining and analyzing data and integrating prediction ensemble learning models. This approach allows manufacturers to anticipate the quality of tobacco products and gain more time. To resolve the class imbalance in the datasets gathered from the tobacco industry's management information platform, a SMOTE study was performed. The ensemble methods were examined following the preprocessing of the data and feature selection. Recall, F1, and Training time were used to test each algorithm. Although it took longer, using the SMOTE analysis enhanced the algorithms' performance. Furthermore, in all scenarios, Xgboost performed better in categorization and product quality prediction than the random forest approach.

4.4. Software

While maintaining quality for physical items was the focus of the previous cases we saw, Saheed Yakub Kayode et al.[45] also examined software quality. In their study they aimed to predict the software defects during its life cycle by using a powerful approach then the basic ML. For this aim, several datasets were collected from the website and analyzed. A single method (logistic regression) as well as an ensemble of algorithms were used to train and evaluate the dataset. The models were assessed using the following metrics: F measure, AUC (area under the curve), Accuracy, Recall, Precision, and MCC (Matthew correlation coefficient). Overall, the ensemble models fared better than the individual models with the various datasets and the catboost algorithm performed the best among the ensemble models.

4.5. Wood fibre industry

Schubert et al.[39] used machine learning to predict pertinent wood fibre board qualities in real time for better quality control. They began by gathering and preparing data. The models used were assessed using the correlation coefficient R, the coefficient of determination R2, the mean absolute percentage error (MAPE), and the root-mean-square error (RMSE). Out of all the models that were used, the RF performed the best. It's also important to note that ensemble learners performed well despite the fact that just data generalization was employed during data preparation rather than data cleaning. The scientists viewed this as a benefit of ensemble learning over statistical methods, as ensemble learning is more resilient to outliers and noisy data.

4.6. Plastic Industry

Jung Jeon et al.[46] used machine learning techniques in an injection moulding company to address quality prediction issues and therefore optimize production efficiency. The injection moulding manufacturer provided the data utilized in this investigation, which were subsequently balanced using the SMOTE approach. Because of this, the autoencoder performed best in terms of Accuracy, Recall, Precision, and F1 score. Its recall score of 1 indicates that it can identify every flaw.

4.7. Metallurgy

Fucun et al.[47] aimed to propose an alternative solution for the quality control prediction system using stacking -ensemble learning approach- with ensemble base models. They first gathered the required data,then tested and evaluated the based algorithms with R2, RMSE and percentage of error. The boosting algorithms had better performance than the other ensemble. Then the based ensemble models were used with stacking and averaging ensemble models. The last two models showed better performance and were more robust predicting steel quality control.

4.8. Textile industry

In the paper of Demirel et al.[48], aimed to predict the quality properties of the products by introducing a novel concept with Regressor chain algorithms. In order to assess the quality of the textiles, data was gathered from the textile production process. The data was then separated into ten clusters, one of which had odd patterns. Before assessing the ensemble regressor chain performance, they examined the individual models to see which was the best. It was a really impressive performance by the random forest. The usage of ensemble regressor chains produced superior results when it came to odd data segments, according to statistical analysis. These results seem promising to further applications to automated quality control in the context of industry 4.0.

4.9. Manufacturing

In the work of Sankhye et al. [23], efficient quality control was achieved by the application of categorization machine learning in quality inspection. Following the manufacturing unit's data gathering, the dataset was processed and cleaned using feature engineering and SMOTE analysis. The algorithms were assessed using Accuracy and a different statistic known as Cohen Kappa after they were put into practice in order to gather further information about the algorithms'overall performance. XGboost and the RF were put through four tests. When the features were chosen, the performance of both models improved and was still rather decent. However, based on Cohen's kappa metric and confusion matrix, the XGboost had the best performance, indicating a significant degree of ability to forecast minority classifications.

In general, ensemble learning (EL) models are commonly used to predict quality and detect defects across various industries. These models can address regression problems to predict quality characteristics, as demonstrated in several studies [38] [47] [48]. Additionally, EL models are employed in classification problems to determine whether a product meets quality standards. In these cases, binary classification was used in some instances [37], while others involved more than two classes [41].

Table 1: Summary of Selected Articles in the Literature on the Use of Ensemble Learning for Quality

Articles	Domain	Problem	Algorithms used	Selected algorithm
[37]	Beverage	Classification	Decision Tree, Random Forests, Adaboost, XGBoost, Gradient Boosting	XGBoost and Random Forest
[41]	Beverage	Classification	Logistic Regression, Random Forest, Decision Tree, SVM, Gradient Boosting, AdaBoost, Multilayer Perceptron	Random Forest
[38]	Beverage	Regression	Ridge Regression (RR), Support Vector Machine (SVM), Gradient Boosting Regressor (GBR), Multi-layer Artificial Neural Network (ANN)	Gradient Boosting
[40]	Beverage	Classification	Adaboost, Random forest, XGboost, Stochastic Gradient Descent classifier, Support vector machine classifier, Decision tree classifier, Gaussian naive bias, KNN	Adaboost
[42]	Electronics	Classification	CART, Random Forest, XGboost, Adaboost	XGboost
[43]	Electronics	Classification	Random Forest, RUBoost	RUBoost
[44]	Tobacco	Classification	Random Forest, XGboost	XGboost
[45]	Software	Classification	CatBoost, Light Gradient Boosting Machine (LGBM), Extreme Gradient Boosting (XGBoost), Boosted CatBoost, Bagged Logistic Regression, Boosted LGBM, Boosted XGBoost Logistic Regression	CatBoost
[39]	Wood fibre industry	Regression	SVM, Artificial Neural Network, Random Forest	Random Forest
[46]	Plastic Industry	Classification	Random Forest, Gradient Boosting, XGBoost, CatBoost, LightGBM, Autoencoder, Logistic Regression, Support Vector	Autoencoder
[47]	Metallurgy	Regression	Stacking Linear Regression, Ridge Regression, Lasso Regression, SVM, KRR, KNN, RF, GBDT, LGBM, XGBoost	Stacking and Averaging Ensemble Model
[48]	Textile industry	Regression	RF, MARS (Multivariate Adaptive Regression Splines), DTR (Data trees regressor), Ensemble regressor chains	Random Forest
[23]	Manufacturing industry	Classification	RF, XGBoost	XGBoost

5. Comparative study of EL algorithms

Before we compare the various ensemble learning algorithms, it is crucial to highlight that numerous studies [41] [38] [40] [39] [47] [48] have demonstrated the superiority of ensemble learning models over basic machine learning models. These studies show that ensemble methods, typically achieve higher accuracy, better generalization, and increased robustness to overfitting compared to individual machine learning models. This consistent performance improvement is a key reason why ensemble techniques are widely adopted in industry applications.

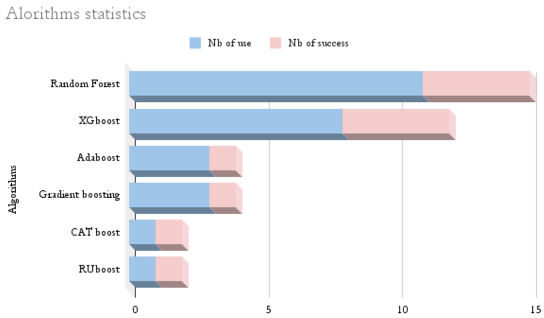

Figure 7: Statistics of algorithm used

In addition, as shown in Figure 7, we have found that the tree based ensemble learners are the most used. As a result, we have focused only on three models (Random forest, XGboost, Adaboost) in this part.
This approach was motivated by the article [45] in which the authors contrasted the ensemble algorithms' performance study in comparison to other papers. We assessed the performance of these models based on several metrics :
Accuracy in general: calculates a model's effectiveness as a percentage of actual outcomes over the total count of the instances[49][42].
Parametrisation : The required knobs that configure an algorithm are called parameters. These figures influence the behaviour of the algorithm in terms of duration and accuracy[49][42].
Overfitting Tendency: We refer to this as the overfitting problem while learning a noisy database. An excessively complicated model with too many parameters leads to overfitting[49].
Learning time (speed): The amount of time needed to train the dataset is called the "learning time," and it varies based on the size of the dataset and the technique being used[49][42].
Prediction time (speed): The amount of time needed to test the dataset is called prediction time. The magnitude of the data and the technique we employ determine this[49][42].
Flexibility: A network's flexibility is defined as its capacity to adjust to the patterns found in the database[49].
Interpretability: is the degree to which a human can consistently predict the model's result . This means that a model is more interpretable when it is easier for people to reason about and trace why the model made its predictions[50].
Robustness: refers to an algorithm's ability to uphold consistent performance, even in the presence of new samples that belong to the same subset as the testing samples. it signifies that when confronted with comparable samples, the algorithm's performance remains stable or predictable [51].

The evaluation of each method is indicated by the number of stars:

- In general : *** High **Average *Low
- For parametrisation: ***small number of parameters **Average number of parameters *Large number of parameters
- For Time: *** Slow **Average * Fast
- For Algorithm type : ** means that the algorithm is used for both classification and regression[49].

Table 2: Evaluation of algorithm according to selected criteria

Criteria	RF	XGBoost	AdaBoost
Accuracy	***	***	*
Parametrisation	**	*	***
Robust to Overfitting	***	**	**
Learning time	**	*	***
Prediction time	**	***	**
Flexibility	***	***	***
Interpretability	**	*	***
Algorithm Type	**	**	**
Robustness	***	**	**
Score	22	18	21

6. Discussion

Similar to how scientific experiments may yield different results in various conditions, machine learning al-

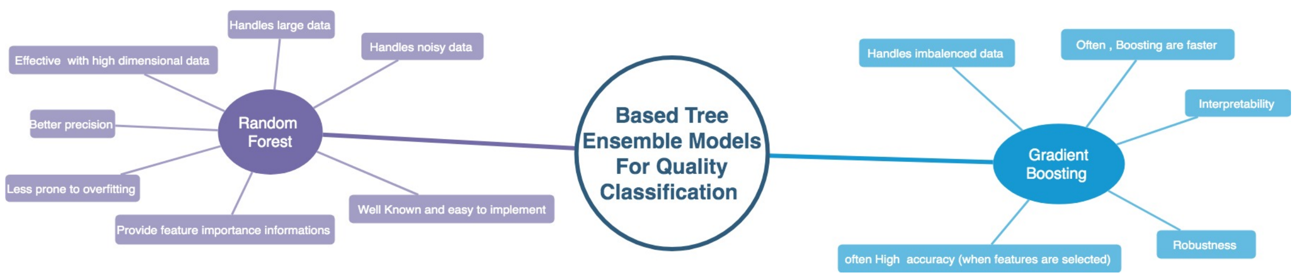

Figure 8: Criteria of selecting the algorithms based on this review

gorithms are also subject to this phenomenon. The selection of an appropriate algorithm is contingent upon a number of factors, including the data, the nature of the problem under investigation, and the requirements of the study. As we saw in the case studies presented previously, multiple algorithms have been employed and compared in the examined articles to determine which is the most appropriate. Among the different models and approaches applied, ensemble learning algorithms especially the tree based algorithms outperformed the other algorithms. This leads us to conclude that using ensemble learning for both regression and classification issues appears to be a viable strategy in the quality sector since it does not only surpass the basic machine learning, it also outperformed the deep learning models in cases.[38][39]
Although the authors Dahal et al.[38] showed preservation when it comes to neural networks assuming that ANN may have the best performance if the training set was larger or much more complex. Beside bagging and boosting algorithms stacking can also lead to very efficient results[47].

Despite the good performance of stacking algorithms, we focused on bagging and boosting techniques. Our evaluation of three commonly used tree-based algorithms (Random Forest, XGBoost, and AdaBoost) within quality systems suggests that Random Forest and AdaBoost are potentially the best models for this specific case. Even thought XGBoost may be faster and more flexible in generating predictions.
Furthermore, we draw conclusions about some of the factors shown in Figure 8 that might aid in choosing the appropriate model based on the case studies and the background research.

7. Conclusion

This review confirms that ensemble learning can be used as a technique to predict quality metrics or classify the defects components to improve quality. In this research, we introduced the most common boosting and bagging algorithms, then we collected articles to enrich our study. We found that tree based algorithms are well known and most used in quality prediction. Accordingly, we assessed the performance of the most used algorithms (RF, XGboost, Adaboost) based on several metrics. We found that RF and Adaboost are suggested due to their high score in the multicriteria analysis. RF with their simplicity, capacity and ability to handle multidimensional data is a good solution for quality regression and classification problems, while Gradient Boosting sequential learners are a suitable choice when precision is targeted.
Despite the results discussed, selecting an appropriate algorithm should be based on a number of principles, for instance the minimum description length (MDL) principle, which states that the optimal model is the one that minimises the total description length, which includes the complexity of the model and the encoded representation of the data[52].
In addition, further investigation and case studies are required in this work to deeply understand and highly assess the performance of the ensemble algorithms.

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A. Appendix A

- AI: Artificial intelligence.
- ML: Machine learning.
- EL: Ensemble learning.
- RF:Random Forest.
- CARTs:Classification and Regression Trees.
- XGboost: Exterme Gradient Boosting.
- GBM:Gradient Boosting Machines
- Adaboost:Adaptive Boosting
- SVM:Support vector Machine.
- ANN :Artificial Neural Network.
- KNN :k-nearest neighbors.
- GBDT:Gradient Boosting Decision Trees.

- Krr:Kernel ridge regression.
- DTR : Data trees regressor.
- RUBoost :Random undersampling. boosting.
- Tree Based Ensemble learning: Because the models studied combine multiple decision trees to improve overall model performance.
- SMOTE: Synthetic Minority Oversampling Technique