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Learning Model Based on Artificial Intelligence to Determine Wood Quality: A Systematic Review

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ABSTRACT

Prediction models that are aimed at identifying patterns, attributes and conditions allow identifying quality aspects to generate results with better forecasts for the decision of a strategic framework. A review procedure was considered based on different bibliographic resources such as contribution articles and systematic literature reviews to know the state of the art on different studies carried out with prediction models that managed to obtain more precise and reliable results for the determination of wood quality. Likewise, the analysis of various contributions was carried out through a systematic process where models such as automatic, deep and alternative learning were considered. Three (39) research questions and essential activities for the treatment were considered: model identification, calculation of metrics and determination of factors. The metrics were considered with the development of two (2) formulas: the average precision (APREC) and the average accuracy (AAUC), where the results obtained from the various algorithms of the models under study were used. The review consists of: Introduction, method, related works, evaluation and analysis, discussion of results, conclusions and recommendations.

1. INTRODUCTION

Wood is a construction resource that is most in demand worldwide and due to its renewable nature, it is very economically attractive for the industry in terms of structural and architectural use. In this regard, it was specified that the world consumption of wood in 2024 was between 1,400 and 1,900 m^3, which made up 40% of the demand as a construction input [1]. It is considered that by 2050 the increase of 30% in consumption is estimated compared to 2024. Likewise, wood comes in a variety of species, sizes, and categories, allowing for widespread use as a source of fuel, building material, furniture, wooden beams, and other diverse applications. Among non-renewable materials, they use considerably more energy per unit of production than wood. The study [2] indicate that wood is a very abundant, renewable material and requires respect for the environment for numerous practical applications. In this way, we offer a sustainable recovery of the species.

In this context, one of the initial forms of inspection was the conventional method, which involved human operators physically inspecting the wood to identify and classify [3]. Wood recognition is necessary to work in commercial timber activities.

Cross-sectional images were used to identify wood species and quality. Investigations were defined in two types: traditional machine learning algorithms and deep learning algorithms [4, 5].

It is considered that forest companies possess datasets from the base of forest inventory, environmental monitoring, soil and relief maps [6]. However, these datasets are primarily used for daily operations and are not typically utilized to assess the quality of the wood.

The precise identification of wood quality is deemed important as it aids in determining its value and appropriate use [2]. This identification process often relies on characteristics such as color, texture, smell, the amount of pores, and the distribution of porosity, which are essential for evaluating the quality aspects of the wood.

Currently, conventional techniques and empirical applications are employed to evaluate wood quality [7]. These methods, however, do not yield highly accurate results and may have precision metrics ranging between 30% and 50%.

Given the impact it has on productivity and cost reduction, decision-making is one of the most required aspects in the industry [8]. In the manufacture of panels, the quality of the product is a function of multiple variables, especially the variability of the wood. This quality depends, among other factors, on the adhesion between sheets or perpendicular tensile strength. The objective was to evaluate a machine learning approach that allowed predicting adhesion under industrial operating conditions, at the gluing and pre-pressing stage. They also pointed out that various studies carried out over time in the plywood industry have not considered the entire production process. This is mainly due to the variability of wood, as it is a material of biological origin, which plays an essential role. The number of variables and parameters to be taken into account during the process confirm the complexity to be controlled.

On the other hand, it was pointed out that detecting defects in wood is crucial as it aids in securing assurances within manufacturing processes [3]. It was identified that these processes are often conducted manually and lack stringent control. Therefore, it is important to implement controls that ensure quality and help routine inspection through techniques that allow reducing costs and improving processes. The technique used consisted of incorporating and improving images, grouping, extraction and selection of characteristics.

In this context, it is identified various supervised learning methods, where they considered that the decision tree has favorable characteristics to adapt to a learning model to guide an effective decision through the classification of premises and the deployment of conditional blocks [6]. Likewise, it is important to point out that by applying optimization techniques, the model can be improved and more precise results can be obtained.

Supervised learning algorithms are known to evolve with the processing of more data, thereby enhancing decision-making and forecasting capabilities [9].

In order to fully automate the evaluation of wood quality, a precise classification technique is required that is related to the form of image processing [10]. In this framework, various devices such as laser scanners or propagation antennas were used. Likewise, it was identified that the quality of wood has various acceptance percentages where its own characteristics were considered. They used the analysis model with graphics to recognize the central rot process of wood.

The justification is specified from the practical and methodological point of view, where the practice referred to the use of various techniques for the search for suitable documents as input for the review, which were considered to be relevant to the topic according to the criteria and objectives set. The methodology consisted of specifying the way of working with the collected articles aimed at research and the development of new approaches.

The article provides an overview of previous work on the various machine learning, deep learning and other models and approaches using contemporary algorithms and techniques that have been implemented for wood quality identification. The results after performing the method, related works, evaluation and analysis, discussion of results, conclusions and recommendations were specified.

2. METHOD OF ANALYSIS

2.1 Methodology

The methodology considered for the review was carried out with the PRISMA guide according to the clarifications [11], where the documentation of the collected articles and the contribution made by the authors that allowed generating the link with the questions raised within the research framework were considered. The methodology is the basis for the development of systematic reviews of the literature where the available evidence related to the research is identified, analyzed and interpreted. Within this framework, precise inclusion and exclusion criteria were considered for the collected articles. All of this allowed the incorporation of search and selection activities, analysis and results of the works chosen for study. The PRISMA guide has various activities and a structured framework that allows the efficient organization of bibliographic references. Likewise, its use is essential in research to guarantee the transparency of the documented sources that promote an adequate analysis and the subsequent discussion of results generating a conclusive analysis. In addition to this, it was considered that the process applied with PRISMA was carried out through the generation of research questions, database consultation through search chains, selection and orientation towards results.

2.2 Research questions

For the systematic review of the literature, three research questions were proposed:

Qi1: What are the learning models based on artificial intelligence to determine wood quality?

Qi2: What is the ideal AI-based learning model to determine wood quality?

Qi3: What are the factors that influence the learning model based on artificial intelligence to determine the quality of wood?

2.3 Inclusion and exclusion criteria

Various criteria were considered for the inclusion of suitable articles and for the exclusion of articles that do not respond to the nature of the study. It is considered that these are characteristics that determine whether a study or article is suitable to be included in the review stage [11]. Likewise, the inclusion criteria are the characteristics that make a study eligible to be included and the exclusion criteria make a study ineligible. For the review process, 10 criteria were determined, 5 for inclusion and 5 for exclusion. Likewise, the selection of the criteria was determined with the guide related to PRISMA, where it was specified that an adequate systematic review of the literature considers specific criteria that allow the information to be included within the scope of the research, thus motivating the generation of indicators and metrics. Among the identified criteria, the deployment for primary articles related to the subject and published in journals indexed in the Scopus and Science Direct databases was specified. All of this was the starting point for more specific criteria such as the English language, year of publication no more than 5 years ago, among others. The criteria were specified in Table 1.

Table 1. Criteria

Inclusion	Exclusion
Cri1: Articles from the thematic area	Cre1: Review articles, volumes, books, posters
Cri2: Articles in English	Cre2: Articles that are not from the thematic area
Cri3: Period from 2019 to 2024	Cre3: Outside the period
Cri4: Articles with open access	Cre4: Paid or closed
Cri5: Articles related to the questions	Cre5: Unrelated articles

2.4 Development of the review

The review of articles that were published in journals indexed by Scopus and also by Science Direct was carried out. The period was between the years 2019 and 2024. The following variables were used: Quality, wood, machine learning and models.

The initial result was specified in Figure 1 where the following was obtained: Scopus: 194, Science Direct: 108. After that, the criteria (inclusion and exclusion) were applied. The final result was: Scopus: 18 and Science Direct: 23.

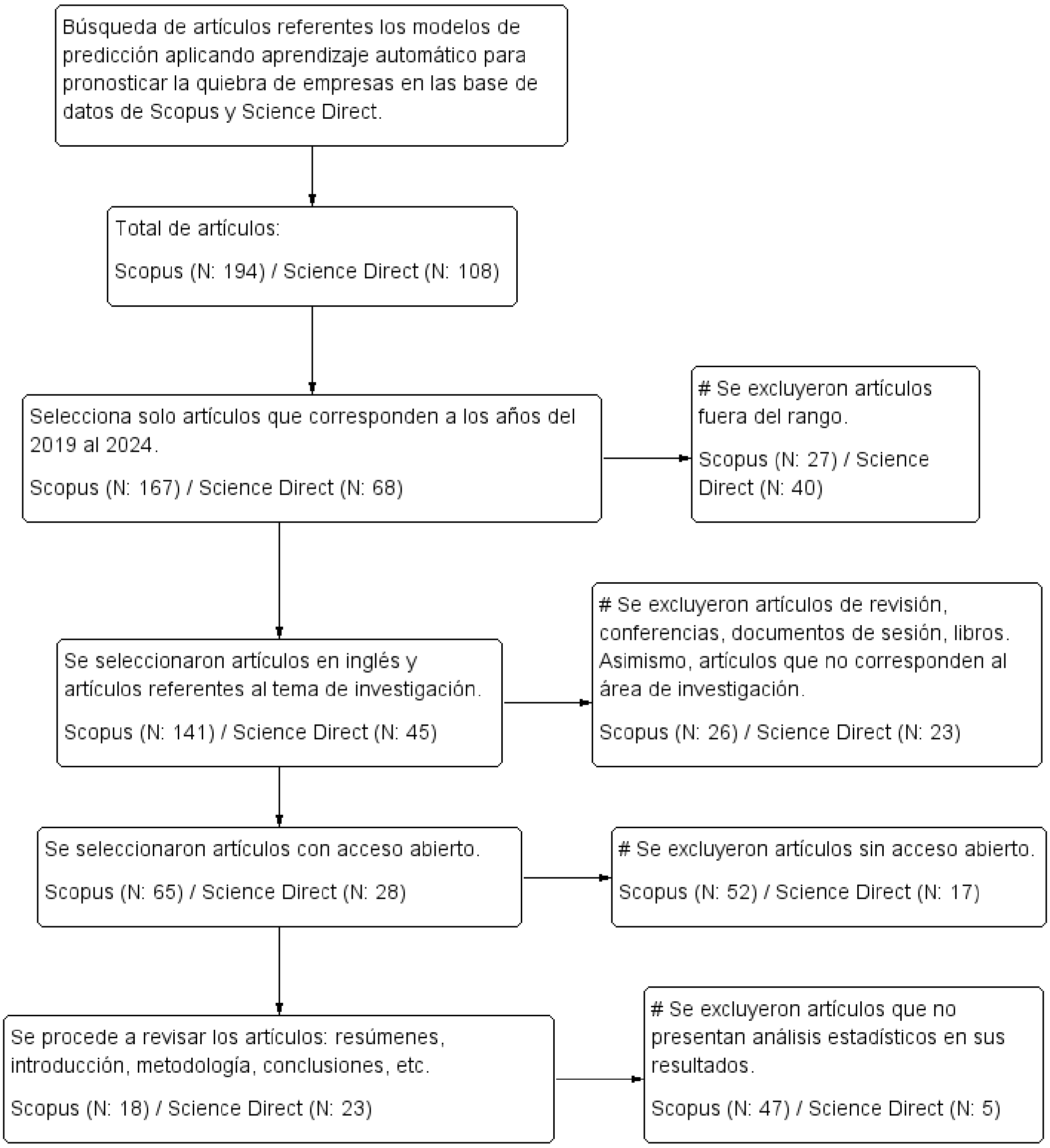

Figure 1. Prism diagram

2.5 Dataset and approaches of the reviewed articles

The dataset generated after the collection and review of articles is the product of various methods and procedures to determine the quality of wood and obtain its main characteristics. In this context, research was identified that focuses on methods for detecting anomalies or defects in wood. This has facilitated the identification of an ideal model that delivers optimal results, as evidenced by the best outcomes obtained from various performance metrics [12].

Traditional AI-based learning models for determining the quality in a dataset contain specialized algorithms: neural networks (ANN [13-15], RNA [8], RNN [16], CNN [3, 17-21]), alternative models (big data [22], U-Net [23], integrated model [7], OCSVM [4, 5], optical regression [24], SGO [25]), and machine learning (classification [26], decision tree [6, 27-30], K-MEANS [10], random forest [31, 32], random tree [33-36], SVM [2, 19, 37-40]).

The generation of data with wood-specific characteristics begins with identifying the components of the input [41], followed by recording the relevant data. Subsequently, the incorporation of correlations between variables has been proposed to enhance the generation of more accurate results [42].

3. RELATED STUDIES

Simple neural networks were evaluated with the RNA algorithm using the R studio program, where they changed the initial variables and the number of neurons [8]. They also performed the activation function (logistic and tangential). The analyses were carried out so that the quality of the wood generates optimal results to avoid loss of raw material and generate good practices to improve the results. The results were obtained after performing the R2 (Coeff-determination) and RMSE (Root-square-error) operations. The precision and accuracy metrics were considered, where 66% and 72% were obtained, respectively. The results obtained required a lower yield compared to other algorithms because wood was considered as a result after treatment and processing of the input; that is, it did not consider the percentage of loss of the input. Likewise, the study [13] deployed with the ANN model, where the results did not generate a significant change compared to other models. The results were obtained after the wood treatment process. In this sense, they recommended making better adjustments and establishing correlations between variables to improve results. The results obtained were: Accuracy 92% and accuracy 94%. Similarly, it is considered that the ANN algorithm is ideal for obtaining optimal results to determine the quality of wood through the density and morphological aspects of the wood [15]. A precision of 95% and accuracy of 96% were obtained. The study [3] determined the quality of wood as a complex process in the wood industry; therefore, they considered that a manual inspection has a risk of error by the person who performs the evaluation. In this sense, the proposal was to develop an automated vision inspection process, which would be complemented by an intelligent system, the proposal was to work with a CNN model where 90% precision and 91.20% accuracy were obtained. The results obtained have great recurrence with the study [14] who used the neural network model with CNN algorithms to identify if a wood has ideal characteristics within the quality levels, they considered the results of precision 90.35% and accuracy 93.00%.

Maturity indices are necessary to be applied with a recurrent neural network (RNN) using the K-Means algorithm, which is ideal for identifying the degree of quality of the wood [16]. The RNN algorithm was applied with the color factor for the input and the maturity indices (6) for the output. The results obtained required adequate values to verify the improvement in the prediction of wood quality. The study provided an adequate identification of the maturity degrees in the processing stage. Similar techniques were applied on the identification of relevant characteristics and variables such as ripeness, density, color, odor, humidity, among others [17-21]. In this way, the following accuracy metrics were obtained: 96.50%, 97.22%, 95%, 93% and 94 respectively. Likewise, the accuracy metrics were obtained: 96%, 97%, 96.40%, 95% and 94.30% respectively.

A multifaceted algorithm, known as the multi-tackle decision tree (DTM), was developed to identify patterns in training datasets [6]. This model was designed to improve the forecast of quality and productivity in the extraction of Eucalyptus by predicting decisions for new datasets. The algorithm achieved high accuracy rates, with results showing 94.50% and 96% accuracy. In a similar study [29] focusing on the quality of western hemlock wood, a decision tree algorithm was applied to 336 records featuring 15 wood characteristics, yielding accuracies of 94.85% and 96%. Further studies [27-30] utilizing the decision tree algorithm reported precision and accuracy rates of 97.7% and 98%, 97.65% and 98%, and 97.40% and 97.60%, respectively. The DTM algorithm offers several advantages, including ease of interpretation, simplicity, the capacity to handle heterogeneous data and nonlinear relationships, identification of relevant variables, flexibility in evaluation metrics, and the ability to process unstructured data. These features significantly contribute to achieving efficient results in wood quality assessments.

A model utilizing classification algorithms was developed, taking into account six strategic variables to assess quality aspects of wood finishes. Additionally, it was identified that density and temperature are key factors to consider in this process [26]. Accuracy of 90% and accuracy of 92% were obtained. A technique was employed to scan and classify wood chips, assessing material quality and providing rapid responses to conveyor belt deficiencies in real time. This approach achieved accuracies of 93.50% and 92.60% [10].

It has been proposed that the random forest algorithm is well-suited for addressing wood quality issues, particularly in managing wood density and the decrease in stiffness and strength as the diameter grows, achieving 92% precision and 93% accuracy [31]. Similarly, the random forest algorithm was applied by incorporating odor and color variables, resulting in 94% accuracy [32].

An initial model was implemented to predict wood defects using three variables: density, temperature, and durability [33]. The random tree algorithm was employed, yielding accuracies of 93% and 92.50%. A more detailed analysis [34] of these variables was conducted to determine wood quality, resulting in accuracies of 95.10% and 93.20%. Subsequently, the model [36] was enhanced by incorporating color, odor, and hardness variables, achieving accuracies of 94% and 93.60%. Another model [35], utilizing an open-source structure with machine learning techniques, was proposed to gather pertinent data on wood. Tests and studies were conducted on climate impacts and tree growth, leading to the generation of data on tree rings used to assess wood quality. This approach resulted in a precision of 90% and an accuracy of 92.50%.

A support vector machine (SVM) model was proposed to enhance manual techniques for predicting wood defects, achieving a precision of 90.50% and an accuracy of 91.00% [37]. Similar results were obtained after implementing an SVM model to determine the main characteristics of wood for quality identification, with a precision of 97.20% and an accuracy of 98% [39]. This model was further enriched with additional variables, resulting in a precision of 92.10% and an accuracy of 93.50% [40]. These studies [2, 38-43] formed the foundation for subsequent research, which improved the model by incorporating relevant wood variables such as odor, color, and humidity. The results of these enhancements showed precision and accuracy rates of 92.89% and 93%, 98% and 97.40%, and 96% and 95.80%, respectively.

Various alternative models have been proposed for assessing wood quality. These include a big data model with a forecast of 91.20% and an accuracy of 93.00% [22]; a U-Net model with accuracies of 85% and 89.50% [23]; an integrated model that reached 94.30% and 95.00% accuracy [7]; an OCSVM model with accuracies of 85% and 86.20% [4]; an optical regression model that obtained 94% and 95.30% accuracy [24]; and an SGO model with accuracies of 87.32% and 89.00% [25]. Each of these models utilized variables aligned with the characteristics of the input data to determine wood quality. However, the models have not considered the incorporation of new variables for other types of inputs and training to improve the model. The results obtained by the models considered the wood after treatment and processing, for this reason no significant changes were identified between the models. Likewise, another fundamental reason was that the models did not consider the residual percentage to identify any change or complement in the result.

4. ANALYSIS

4.1 Analysis of the questions

The research questions were determined in section 2, so the calculation of the average formulas for the precision and accuracy metrics was performed. Likewise, the study [44] proposed that the results after the calculation of the formulas would generate answers to the research questions through the involvement of three stages: Identification for the parameters, results of the formulas by model and determination of factors. The analysis for each question was specified:

Qi1: What is the AI-based learning models for determining wood quality?

Table 2. Parameters identified in articles

References	Parameters	Models	Nro Models
[13-15]	Deep learning	ANN	3
[22]	Alternative models	Big Data	1
[26]	Machine learning	Clasification	1
[3, 17-21]	Deep learning	CNN	6
[6, 27-30]	Machine learning	Decision Tree	5
[10]		K-MEANS	1
[7]	Alternative models	Integrated Model	1
[4, 5]		OCSVM	2
[31, 32]	Machine learning	Random Forest	2
[33-36]		Random Tree	4
[24]	Alternative models	Optical Regression	1
[8]	Deep learning	ANN	1
[16]		RNN	1
[25]	Alternative models	SGO	1
[2, 37-40, 43]	Machine learning	SVM	6
[23]	Alternative models	U-Net	1
Grand total			**37**

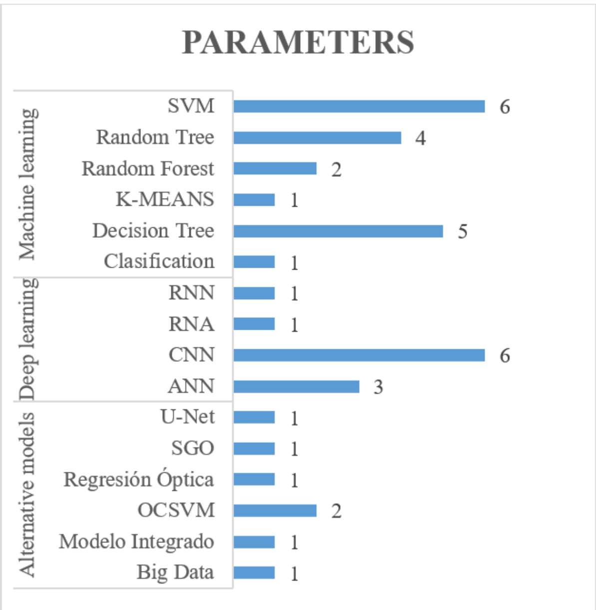

Figure 2. Parameters used

In the previous works of section 3, the various models that have been studied and applied in obtaining suitable results for calculating wood quality metrics were specified. In this framework, it was identified that some models are more relevant than others and that they are determined according to the nature of the problem and the work carried out. Likewise, the objective of the proposal and the scope according to the characteristics of the wood were considered. Next, in Table 2, the various parameters identified in the articles reviewed (directly or indirectly) were specified, where the number of articles referred to and the models identified on the determination of wood quality were considered.

It can be seen that in Figure 2 the parameters mean the number of articles studied (references) that have similar models, specifying that they correspond to the context of predictability and the determination of wood quality through the incorporated variables.

Qi2: What is the most suitable AI-based learning model for determining wood quality?

The question was formulated to identify the most suitable AI-based model for determining wood quality, which is achieved by calculating the average precision and accuracy for each type of model. Table 3 shows the results of the metrics.

Table 3. Algorithm metrics according to model (parameters)

Parameters	Algorithm	APREC	AAUC
Deep learning	ANN	92.62%	94.33%
	ANN	66.00%	72.00%
	RNN	93.60%	93.50%
	CNN	94.29%	94.98%
Alternative models	Big Data	91.20%	93.00%
	U-Net	85.00%	89.50%
	Integrated Model	94.30%	95.00%
	OCSVM	85.00%	86.20%
	Optical Regression	94.00%	95.30%
	SGO	87.32%	89.00%
Machine learning	Clasification	90.00%	92.00%
	Decision Tree	96.42%	97.12%
	K-MEANS	93.50%	92.60%
	Random Forest	93.00%	93.50%
	Random Tree	93.03%	92.95%
	SVM	94.45%	94.78%

4.2 Formulation and evaluation of metrics

The study metrics were formulated with the consideration that treating solid metrics across various algorithms, as proposed in the reviewed models, yields efficient results and enables the generation of accurate conclusions on a specific topic, thereby addressing the research questions [44]. Likewise, he considered that analyzing the ideal metrics means an important step in any study, which allows identifying behaviors on the determination of the forecast and the predictability of a set of data. In this context, it was determined that the precision and accuracy metrics are the ideal ones for this type of study of predictability and forecasting of wood quality. Then, the calculation was determined according to the division of the sum of the precision metric and the sum of the number of models.

$$APREC = \frac{\sum Precision\ Modelo}{\sum Modelos} \tag{1}$$

To calculate AAUC, the division of the sum of the accuracy metric and the sum of the number of models is required.

$$AAUC = \frac{\sum Exactitud\ Modelo}{\sum Modelos} \tag{2}$$

According to the study [45], the calculation of metrics related to the studied models means a transcendental event to obtain results that allow answering the research questions.

With this, representative values are obtained for each algorithm and model.

4.3 Classification of techniques

In order to achieve an adequate classification of the techniques, it is necessary to specify the formulas for calculating the results. In this framework, it was considered that the method applied to obtain the APREC and AAUC metrics are ideal for documents and studies that involve model reviews [45]. Likewise, the study [46] indicated that the results obtained resolve the research questions if they have similar characteristics to the object of study. Next, the 16 algorithms used in the relevant models were specified. Table 3 specifies the results applied by the proposed formula to each type of model.

It is observed in Figure 3 that the Decision Tree algorithm has greater accuracy (96.42%), where the APREC formula was used. Similarly, the Decision Tree algorithm was obtained with greater accuracy (97.12%), as in Figure 4, where the AAUC formula was used.

Qi3: What are the factors that influence the learning model based on artificial intelligence to determine the quality of wood?

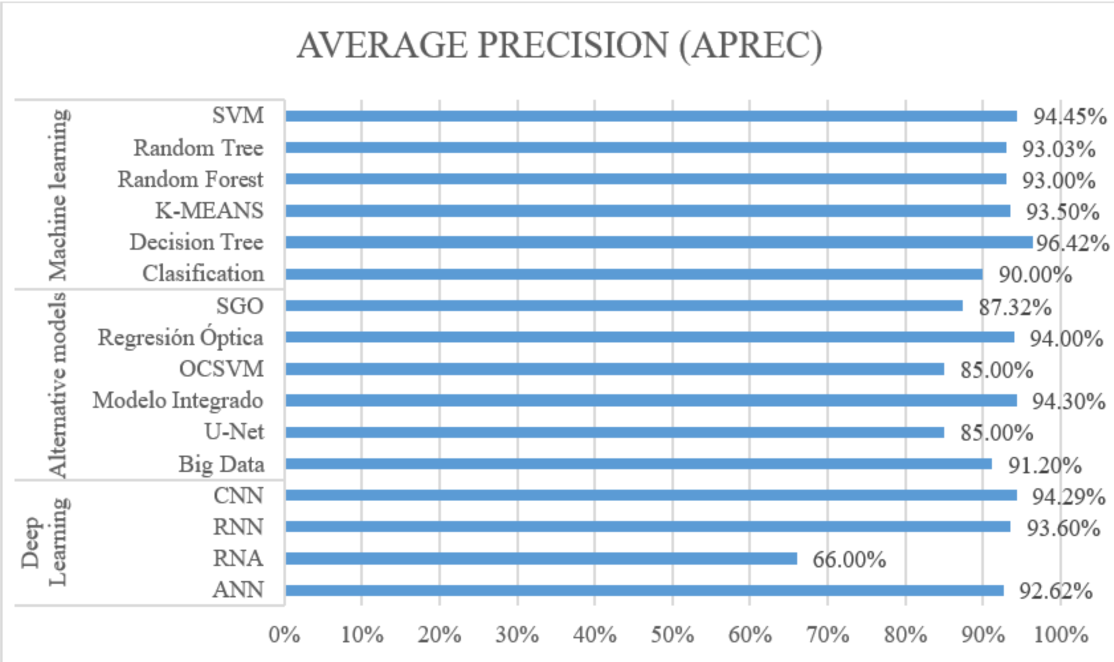

Figure 3. APREC of learning models

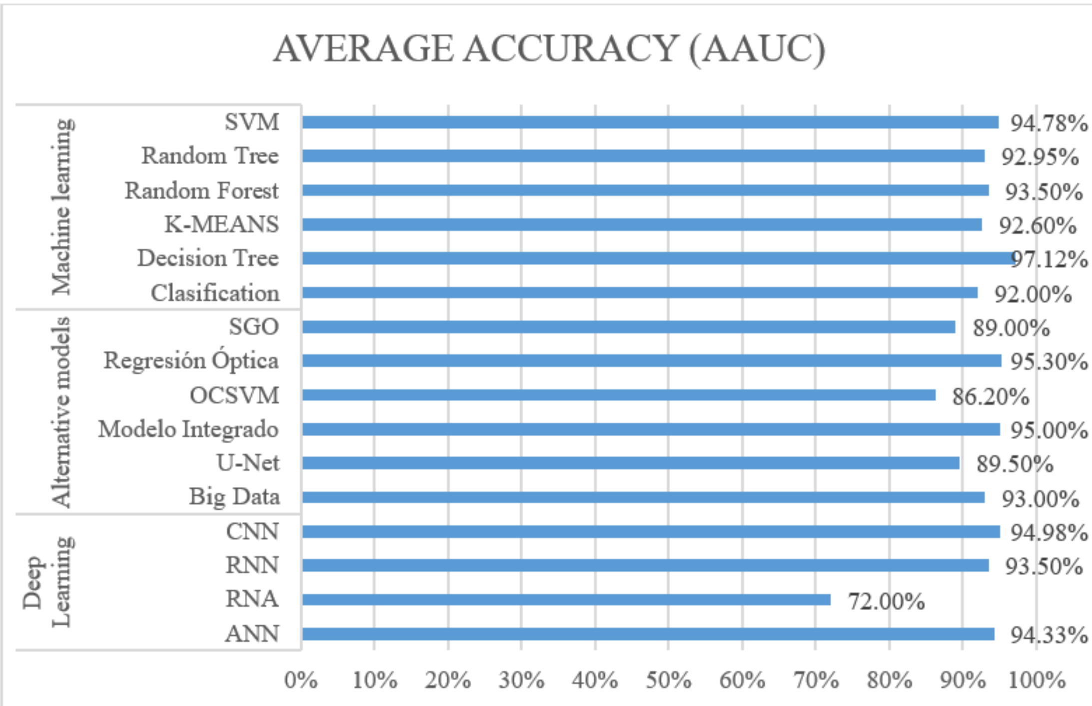

Figure 4. AAUC of learning models

It has been identified that the factors with the greatest relevance are those that have a higher percentage of incidence in the quality of wood. Likewise, the study specified the formulas for the calculation where the factors are those that influence the results. The procedure for determining the relevant factors was carried out by adding up the times that the aforementioned factor was used as a calculation variable. This procedure is underpinned by the understanding that the factors significantly influencing model outcomes necessitate dedicated and personalized treatment [47]. The number of times where the factors were presented in the articles under review was specified in Table 4.

The factors with the greatest impact on the reviewed articles were identified. These are considered to be of greatest relevance in determining product quality, in this case wood. Figure 5 details the identified factors.

Table 4. Alignment of factors and references

Factors	Nro	References
Strength	28	[2-8, 13-19, 22, 23, 27, 28, 31-40]
Durability	28	[2, 3, 6-8, 13-23, 26-28, 33-40]
Appearance	8	[6, 20, 21, 23-27]
Sustainability	6	[10, 13-15, 23, 26]
Hardness	4	[10, 16, 22, 26]
Humidity	4	[4, 5, 10, 22]
Sustainability	3	[4, 5, 22]
Colour	7	[6, 24, 25, 27-30]
Odor	7	[6, 24, 25, 27-30]
Density	25	[2-5, 7, 8, 13-15, 17-21, 31-40]

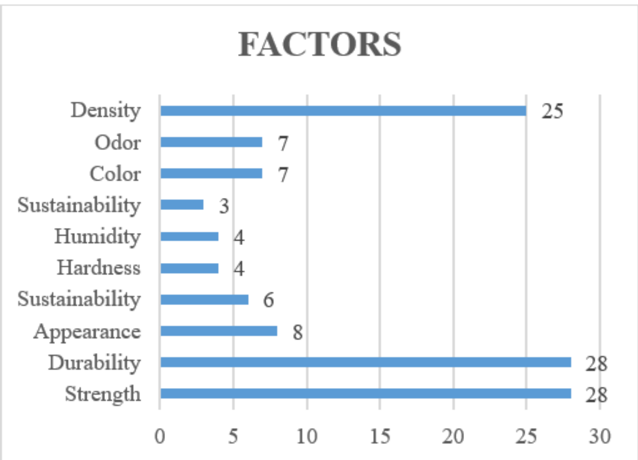

Figure 5. Factor identification

5. DISCUSSION OF THE RESULTS

This study allowed us to identify the relevance of each model by calculating the formulas proposed by obtaining results on the data set of the variables that determine the quality of wood. The proposed models were specified after the analysis and review of each article. It was identified that the model with the best results was machine learning (decision tree algorithm), where it obtained significant metrics. The models analyzed were machine learning, deep learning and other alternative models, where ANN, RNA, RNN, CNN, Big Data, U-Net, Integrated Model, OCSVM, Optical Regression, SGO, Classification, Decision Tree, K-MEANS, Random Forest, Random Tree and SVM algorithms were identified, which are associated to determine the quality of wood according to its own characteristics and according to the treatment of the data.

In determining the ideal model, the formulas specified for the calculation of the APREC and the AAUC were used, which correspond to the averages of precision and accuracy, which were found in each article reviewed. For this reason, the decision tree algorithm was identified as the most suitable when obtaining 5 articles that deal with the subject of wood quality. Likewise, it was identified that the authors considered that each model requires adequate data treatment according to the nature of the product and the specific variables. The study [44] considered that the treatment for the prediction of a specific context generated precision and accuracy metrics; similar conclusions were specified by the study [9], where they indicated that the variables needed data with precise characteristics in order to promote an adequate level of quality. Within this framework, a machine learning model utilizing a decision tree algorithm achieved notable results [6, 27-30], with an average precision of 96.42% and an average accuracy of 97.12%. Comparable outcomes were observed when employing the SVM algorithm, which yielded an average precision of 94.45% and an accuracy of 94.78% [2, 37-40, 43]. The inclusion of variables such as odor, color, and humidity were suggested to further enhance the results. Various proposals have been made to improve the understanding of wood characteristics, including classification methods [26], random forest [31, 32], random tree [33-36], and K-Means algorithms [10]. Likewise, it is specified that the algorithms did not carry out a more exhaustive analysis to identify variables that improve the results of the metrics; therefore, it was considered to choose the decision tree algorithm as the most suitable.

Studies [3, 17-21] utilizing a neural network model with the CNN algorithm have demonstrated the capability to identify wood characteristics based on morphological aspects and specific variables within wood frames, achieving an average precision of 94.29% and an accuracy of 94.98%. Similar results were achieved with the application of the RNA algorithm [8], which aimed to obtain precise measurements of wood quality and prevent significant losses, resulting in an average precision of 66.00% and an accuracy of 72.00%. The RNN algorithm was also found to be effective for obtaining better metrics on wood quality, with an average precision of 93.60% and an accuracy of 93.50% [16]. Furthermore, the application of the ANN algorithm, which incorporated both internal and external wood-related variables, led to an average precision of 92.62% and an accuracy of 94.33% [13-15]. These results indicate that while improved models generally yield better outcomes, the choice of algorithm for data processing plays a crucial role in determining the success of the model.

The relevant factors were determined according to the recurring number of uses in the reviewed articles, which meant factors with significant influence in each model. For this reason, it was evident that resistance and durability are the most relevant and predominant factors in the models, which were identified in 28 articles and the density factor was identified in 25 articles. The authors specified that the identified factors significantly influence the determination of the quality of the wood in specific contexts and with consistent data. The study [48] specified that the resistance of the wood refers to the capacity to support different forms and types of load or force that prevents breakage, deformation or structural failure. Likewise, the type of wood (hard or soft), humidity and density are important. Regarding durability, the authors indicated it is the capacity to obtain resistance to degradation by various factors: environmental, chemical or biological. Other factors such as appearance, sustainability, hardness, humidity, sustainability and color are required between 3 to 8 items, but are part of variables that are required to enrich the model.

6. CONCLUSIONS

The wood industry requires knowing not only the defects of the wood but also promoting and determining quality aspects in order to avoid incurring significant costs in the medium and long term. Therefore, determining a useful and suitable model for prediction is very important.

Three (3) essential stages were identified for the treatment of the review, where the parameters, results of the formulas by model and determination of factors were specified. For the calculation of the average precision metric (APREC) and the average accuracy (AAUC), it was considered to classify the algorithms into groups of models, which were identified in the review together with the precision and accuracy metrics.

The articles reviewed correspond to specialized techniques in determining the defects of the wood and also the quality. In this context, the various techniques to determine the quality of the wood were part of previous studies to know the characteristics of the wood and the uses according to the context itself.

The 37 algorithms classified into 3 models that obtained the highest results were presented: machine learning, deep learning and alternative models, where precision and accuracy were identified as the study metrics. In this sense, the machine learning model with the decision tree algorithm was the one that obtained a better average precision (96.42%) and a higher average accuracy (91.12%). It is considered that the models with the highest results in the metrics improve the techniques carried out in the reviewed studies. Likewise, to obtain better results, precise details and data consistency are required. In order for the decision tree algorithm to adapt to a proposal as a scope and operability operation model, it is necessary to incorporate relevant variables such as the identified factors: Resistance, Durability, Appearance, Sustainability, Hardness, Humidity, Sustainability, Color, Odor and Density. The application of this algorithm focuses on initial conditions after the wood extraction stage without any type of work or loss of the input. Which would involve as a limiting factor (percentage of loss after extraction). It is ideal for models where quality needs to be known in a way based on prediction and forecasting.

It was identified that the factors to determine the quality of the wood respond to the knowledge of the characteristics of the context of the problem, where it was identified that the relevant factors were resistance and durability, followed by density. Likewise, other factors were specified to enrich the model such as: appearance, sustainability, hardness, humidity, sustainability and color.

The solid foundations of a review are determined by the studies that were the object of the compilation and analysis, where the incorporation of the relevant factors was specified to obtain a set of data with suitable variables to generate answers to the questions posed. Likewise, limitations were identified to obtain articles with other metrics that can potentially help improve the forecasts towards the prediction of the quality of the wood.

7. FUTURE WORK

The present systematic literature review allowed us to identify the most suitable algorithms and models to determine the quality of wood. It is necessary that the most relevant factors are incorporated into a more robust and solid model. It is also important that AI models in future work consider automation so that results are obtained more quickly.

It is important that in the next works relevant factors for the wood industry and the market in general are identified. This will lead to more dynamic studies and more disaggregated results.

Finally, upcoming studies are expected with the incorporation of new metrics such as f1-score, sensitivity, MAE, MSE and RMSE, which will generate a broader picture both at the level of the model and the results obtained to determine the quality of the wood. Model optimization is important to consider.

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