A Systematic Review of the Literature on the Use of Artificial Intelligence in Forecasting the Demand for Products and Services in Various Sectors

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***Abstract*—This systematic review, carried out under the PRISMA methodology, aims to identify the recently proposed artificial intelligence models for demand forecasting, distinguishing the problems they try to overcome, recognizing the artificial intelligence methods used, detailing the performance metrics used, recognizing the performance achieved by these models and identifying what is new in them. Studies in the manufacturing, retail trade, tourism and electric energy sectors were considered in order to facilitate the transfer of knowledge from different sectors. 33 articles were analyzed, with the main results being that the proposed models are generally ensembles of various artificial intelligence methods; that the complexity of data and its scarcity are the main problems addressed; that combinations of simple machine learning, "bagging", "boosting" and deep neural networks, are the most used methods; that the performance of the proposed models surpasses the classic statistical methods and other reference models; and that, finally, the proposed novelties cover aspects such as the type of data used, the pattern extraction techniques used, the assembly forms of the applied models and the use of algorithms for automating the adjustment of the models. Finally, a forecast model is proposed that includes the most innovative aspects found in this research.**

Keywords*—Demand; agglomeration algorithm; services; PRISMA methodology; artificial intelligence

I. Introduction

Accurate demand forecasting is essential for the efficiency and normal development of companies' activities. Forecasts are vital in both operations and supply chain planning: in operations they are essential to design production processes, manage bottlenecks, schedule production and determine long-term capacity; in the supply chain, forecasts are the basis for determining purchasing and inventory levels and for coordinating with suppliers and customers. Finance requires adequate forecasting to project cash flow and capital needs; while Human Resources needs them to anticipate hiring and training needs [1]. Even more, having advanced demand forecasting capabilities, by allowing you to minimize costs, time, and optimize resources, can be an important source of competitive advantage; while inaccurate forecasts can cause damage such as excess inventories, lack of supplies for production, high labor costs and loss of reputation [2]. The strategic importance of having adequate forecasts is clear, then. In the words of Krajevsky and Malhotra [1]*[1]*"managers at all levels need to forecast future demand so that they are able to plan the company's activities in accordance with its competitive priorities*"* (p. 315).

Due to its importance, demand forecasting has become an extremely complex and challenging activity due to the uncertainty and volatility of modern markets, structural and technological changes in various sectors and the emergence of unpredictable crises. Spiliotis et al. [3] pointed out, for example, that the daily demand for products in a large part of industrial and retail companies is erratic and intermittent, which makes the forecast very complicated. Similarly, Quiñones-Rivera et al. [4] found that, in the context of the manufacturing of electrical products in Colombia, it is difficult for companies to adequately forecast demand due to its volatility and its dependence on various non-linear exogenous factors. Fildes et al. [5] found that due to the rise of electronic commerce, demand forecasting in the retail sector faces, on the one hand, the need to model the complex competition and complementarity of online sales in an increasingly omni-channel context and, on the other hand, the challenge of foreseeing the impact of sectoral and global crises such as those experienced, for example, with the COVID 19 pandemic. Along the same lines, Viverit et al. [6], points out that the aforementioned pandemic has had short and long-term consequences on the hotel industry, plunging it into an unprecedented situation where its historical demand has lost its value, making forecasting activities very complex. Finally, Sun et al. [7] pointed out that the rise of online activities has opened the possibility of forecasting the demand of the tourism sector using a large amount of data related to customer behavior on web search engines and social networks, however, the Exploitation of this possibility represents enormous challenges in terms of managing an infinite number of independent variables and the consequent increase in the complexity of the models.

To address these challenges, with the rise of artificial intelligence, a variety of innovative forecasting models based on machine learning have been proposed with the idea of surpassing the accuracy of classical models established in various industries [8], [9], [10]. Given the situation described, this study seeks to describe the state of the art of the use of artificial intelligence in the vital field of demand forecasting, clarifying the main challenges addressed and the most important innovations. To have a broad multi-sector vision but at the same time not be unnecessarily exhaustive, this study has been limited to the manufacturing and retail sectors (hereinafter retail), the tourism sector and the electric energy sector.

This research arises from the need to know the most recent advances in the field of demand forecasting. The main motivation is to improve, with the advances of artificial intelligence, the forecasting methods that companies use as a basis for their operational plans. The main contribution of this study is to have clarified the nature and scope of the contributions of artificial intelligence in the field of demand forecasting. In doing so, we also aspire to contribute to academic debate and decision-making based on evidence, and rigorously examined and updated information.

Finally, the findings of this study have important implications for both academia and decision makers in operations management. Firstly, they suggest the need to replace, or at least complement, classical forecasting methods with methods based on artificial intelligence. Furthermore, the results point to the importance of incorporating techniques such as image-based forecasting, dynamic ensembles and deep learning. Finally, this research provides evidence that could be used by companies to gain efficiency in their operational planning.

The order of this investigation is structured as follows. In Section II is the development of the research using the PRISMA methodology, whose choice was because it fits the work; Next, in Section III we will see the results obtained from the analysis of the articles found and a proposed model for the evaluation of readers.

Subsequently, in Section IV, the discussion of the research was carried out with the proposals made by the authors and a conclusion of the findings found in the work.

Finally, the references used in this research are listed.

II. Methodology

This systematic review of the literature was carried out under the PRISMA methodology, which was created to guarantee the rigor of this type of studies, avoiding possible biases [11]. Additionally, the selected documents were classified using automatic grouping algorithms, in order to provide an objective panoramic view of the different uses and methods of artificial intelligence in the field of demand forecasting.

A. Research Questions

As part of the research process, five research questions have been posed to serve as a guide throughout the investigation and to allow the knowledge contained in the documents examined to be extracted and synthesized. These questions are shown in Table I.

B. Search Strategy

To construct the search chain, the PICOC methodology, population, intervention, comparison, objective, and context were taken into account. Table II TABLE IIshows the search terms related to each of these factors.

TABLE I. Research Questions

Code	Questions
Principal	What novel artificial intelligence models for forecasting demand have been proposed in recent years?
P	What demand forecasting issues or challenges have been addressed with artificial intelligence?
I	What artificial intelligence methods have been used for this purpose?
C	What metrics have been used to measure the performance of the proposed models?
O	What is the performance of the new proposed models in relation to the established models?
C	What are the new features or innovations introduced by these models?

TABLE II. Search Terms

Factor	Description	Search terms	Synonymy
Problem	Demand forecasts for business products and services	"demand forecasting"	"demand prediction" "demand prognostic" "demand prognosis" "product forecasting"
Intervention	Forecasting using artificial intelligence	"artificial intelligence"	"machine leargning" "deep learning" "reinforcement learning" "generative models"
Comparison	Forecast Accuracy	"accuracy"	"performance" "error" "effectiveness" "precision"
Objetive	Accuracy improvement	"improve"	"outperform" "better" "superior" "enhance"
Context	Proposal for a novel model	"new"	"original" "unprecedent" "novel" "innovative"

The search terms were combined with Boolean operators to construct the following search string with which the search is carried out:

("demand forecasting" OR "demand prediction" OR "demand prognostic" OR "demand prognosis" OR "product forecasting") AND ("artificial intelligence" OR "machine learning" OR "deep learning" OR "reinforcement learning" OR "generative models") AND ("accuracy" OR "performance" OR "error" OR "effectiveness" OR "precision") AND ("improve" OR "outperform" OR "better" OR "superior" OR "enhance") AND ("new" OR "original" OR "unprecedent" OR "novel" OR "innovative")

C. Eligibility Criteria

For this research, some criteria were considered that fit the field of activities of the sector linked to product demand and management using artificial intelligence algorithms.

TABLE III. INCLUSION CRITERIA

Code	Description
I1	Articles that propose a novel quantitative method for demand forecasting
I2	Articles that apply artificial intelligence in the forecast model they propose
I3	Empirical articles with models validated with real data from companies
I4	Scientific articles and conference papers

The inclusion criteria established for this study are shown in Table III TABLE IIIand the exclusion criteria in Table IV. , taking into account the relevance and impact factor of the journals.

TABLE IV. EXCLUSION CRITERIA

Code	Description
E1	Articles published in languages other than Spanish or English.
E2	Articles published before 2019
E3	Articles that study demand forecasts outside the retail, manufacturing, hospitality, tourism and electric energy sectors.
E4	Articles with full text not available

D. Information Sources

The scientific database Scopus was chosen to be used as a source of information, as it is recognized for its reliability among the academic community (see Fig. 1).

E. Article Selection Process

The research process was carried out in four stages. In the identification stage, the search string was applied and the total number of articles in the database that contained all the specified conditions was found. In the pre-selection stage, exclusion criteria were applied at the title and abstract level. In the selection stage, the inclusion criteria were also applied at the title and abstract level. Finally, in the inclusion stage, the introduction, methodology and conclusions sections of the articles were reviewed and, applying the inclusion criteria, it was decided whether or not to integrate them into the qualitative synthesis.

The application of the search string in the Scopus database yielded a total of 204 documents as can be seen in Fig. 2.

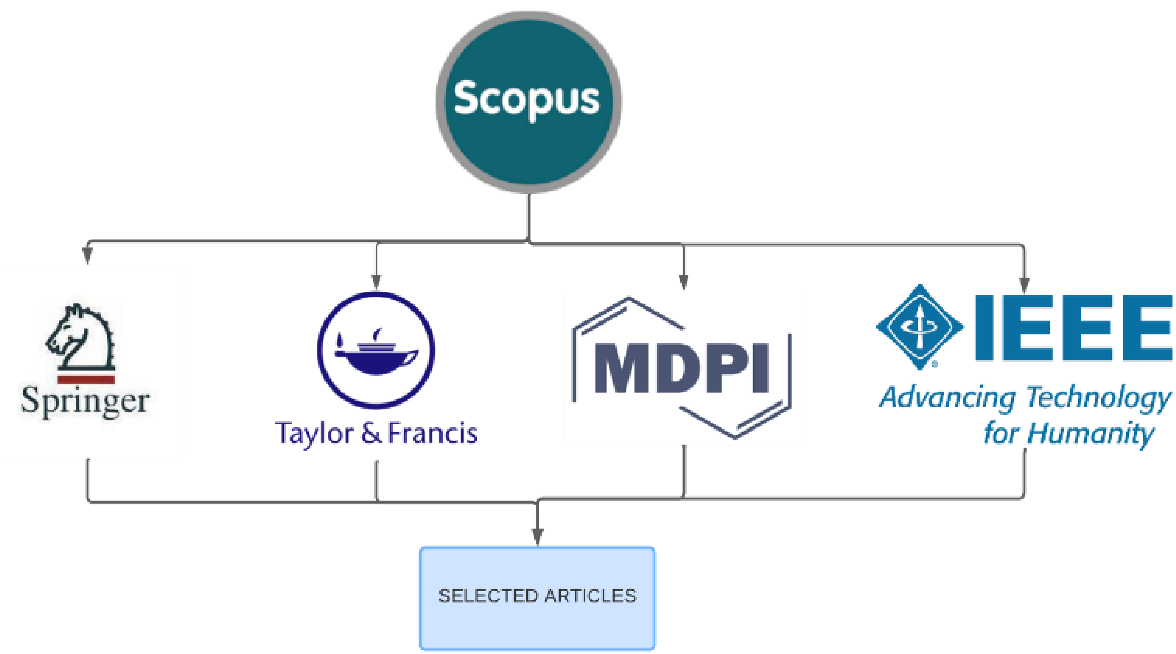

Fig. 1. Source of information used in the research.

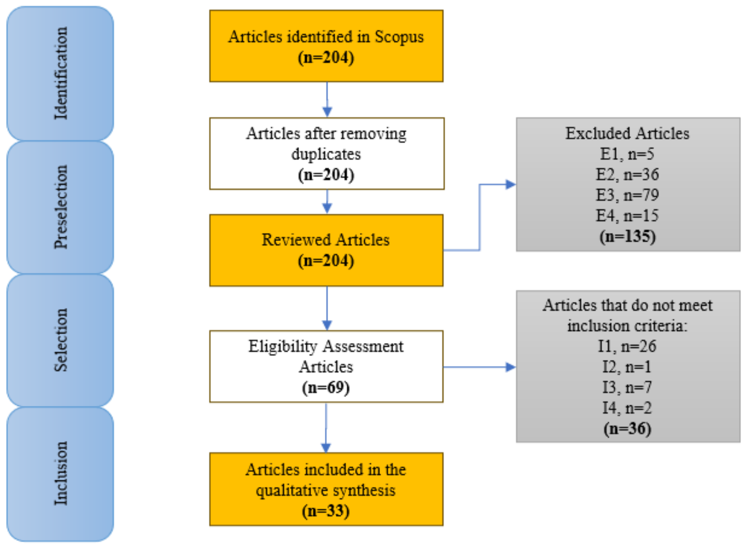

Fig. 2. Results of article selection.

No duplicates were found among the 204 articles found; after applying the exclusion criteria, 135 articles were eliminated and 69 remained for the evaluation of the inclusion criteria. After this last evaluation, 36 articles that did not meet at least one criterion were eliminated, leaving a total of 33 articles for inclusion in the qualitative synthesis.

F. Automatic Grouping of Articles

After the selection process and to support the analysis process, each article was labeled according to the type of data used, the type of feature engineering used, the type of forecasting methods used, the form of training and adjustment. of hyperparameters of the models, to the assembly form of the applied methods and to the business sector in which it is applied. Likewise, to classify the articles according to their similarity using these labels, it was decided to use an automatic grouping algorithm in order to ensure objectivity in carrying out this task and avoid classifications biased by the authors' preferences. An agglomerative hierarchical clustering algorithm with Euclidean distance was then used to measure the similarity between the documents and construct a dendrogram. This method was chosen since it allows an objective, visual and detailed representation of the articles under study, which facilitates their interpretation. Another advantage of this method is that it does not require specifying a priori, and therefore subjectively, the number of clusters into which the documents will be divided. The silhouette method was then used to identify the optimal number of clusters since it also offers a visual and objective interpretation of the number of convenient clusters.

The agglomerative hierarchical grouping of the documents generated five clearly differentiated groups that we will describe below (see Fig. 3 and Fig. 4).

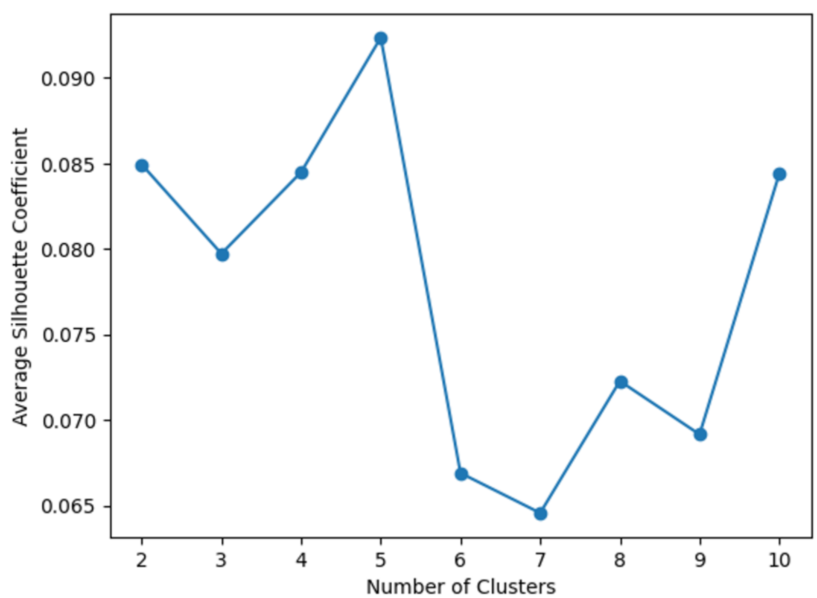

Fig. 3. Silhouette method.

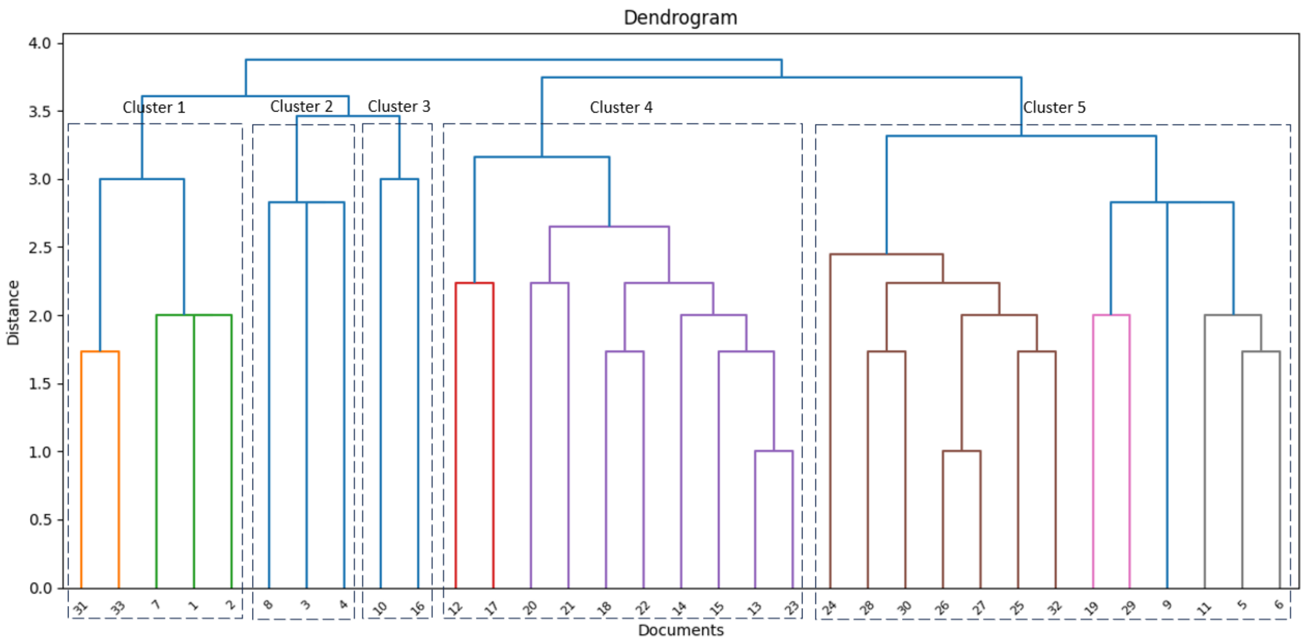

Fig. 4. Agglomerative hierarchical grouping of articles.

1) Group 1: Consisting of five documents from the energy and retail sectors whose common characteristic is the use of “bagging” methods and data derived from the calendar such as holidays, weekends, weekdays, etc. The models proposed by these documents assemble the “bagging” methods with “boosting” methods, since the former are capable of compensating for the “overfitting” problems of the latter, while the latter correct the bias errors typical of the former [12], [13]. Other novel models from this group also propose the use of a “Generative adversarial network” to create “synthetic” data [14] and “transfer learning” [15], in both cases, to overcome the limited volume of data available for training.

A special case within this group is the study [16] which assembles a bagging, Random Forrest (RF) with a deep neural network, “Long-short term memory” (LSTM). The LSTM models the temporal patterns of the time series while the RF relates the forecast errors produced by the LSTM with variables “external” to the time series itself such as special calendar days, characteristics of the products and the point of sale. . The final prediction results from the addition of the LSTM forecasts plus the RF forecasts.

2) Group 2: Made up of three articles from the retail sector that propose the use of simple machine learning methods in conjunction with clustering methods as a way to extract useful patterns for forecasting. First, it processes the time series with RF, and then models the errors produced by it with a multiple linear regression (MLR) using Internet search intensity indices as independent variables [17]. The second document [18] uses k-means to separate the data into different clusters, to then identify which “Suport Vector Regression” (SVR) or “Extreme Learning Machine” (ELM) method is the best predictor for each cluster. Finally, [19] proposes a forecast model consisting of a base of predictors composed of statistical methods, simple machine learning and a deep neural network, the “Multi-Layer Feed Forward Artificial Neural Network” (MLFFANN); that are combined dynamically, using weighted weights calculated in inverse proportion to the errors they generate.

3) Group 3: Consisting of two documents, one from the retail sector and the other from the tourism sector, which propose models that use a base of predictors formed by simple methods, bagging methods and boosting methods, and that make use of decomposition as a way to extract important patterns to improve forecast accuracy. The first document [20], focuses on the optimization using various algorithms of the input variables of the model, while the second [21], in a similar way to the last document of the previous group, proposes a dynamic assembly of the predictors through of an exponential function that decreases with the error produced by each of them.

4) Group 4: This group is made up of ten documents from the tourism sector, whose main characteristic is the predominant use of neural networks in their forecast models. A striking subset of papers in this group makes use of several neural networks of the same type forming a “stacking” configuration: [22] stacks LSTM networks, while [23] and [24] use multiple deep belief networks (DBN).) and kernel extreme learning machines (KELM) respectively to generate the stacks. These three documents also have in common the use of predictor variables based on Internet search intensity indices and the use of some type of dimensionality reduction, due to the large number of variables, to select the most significant ones, [23] uses an algorithm called “double boosting” for this purpose, while [22] and [24] use neural networks called "autoencoders" to do the dimensionality reduction.

Without the "stacking" figure, the documents [25], [26], [27] use deep neural networks (RNN the second and LSTM the other two) but add as a novelty the use of some automatic dimensionality reduction method (elimination of superfluous input variables) also based on neural networks; [25] and [27] use the so-called "attention mechanism" which consists of a neural network with only one hidden layer that assigns weighted weights to the input variables, thus selecting the most relevant ones for the forecast. The paper in [26] uses a Recursive Neural Network (RNN) for sequential pattern learning and a single hidden layer MLP for extracting low-level features in addition to a multi-layer MLP for high-level feature extraction.

Another important model within this group is the one proposed by the document [28] which converts time series into images and then uses special convolutional networks for processing. Finally, two papers from the group [29] and [30] focus their models on the decomposition of the original time series into several component series to then find the best forecasting methods for each of them. Notable in this sense is the document [30] that proposes using statistical or simple machine learning methods, such as ARIMA or SVR, for low complexity components and using neural networks with bidirectional GRU for the forecast of high complexity components.

5) Group 5: Finally, we have that this group is made up of 13 documents belonging mainly to the energy and retail sectors, whose main characteristic is the use of deep learning in their forecast models. The models proposed by this group are aimed at improving the performance of deep learning algorithms through various resources, among which are: the use of hyper-parameter optimization algorithms, such as the "firefly algorithm" [31] or the " Improved Giza pyramids construction algorithm" [32]; the use of dimensionality reduction techniques such as "Encoders" [33], [34] and "Principal Component Analysis" (PCA) to optimize the model inputs; the use of "cross or transfer learning", that is, the use of data from similar products or services when the data of the product under study is very limited [35], [36], [37]; the use of "clustering" to divide the data into groups of similar behavior and train a neural network for each cluster [38]; the transformation of the data into images and their decomposition to then use a CNN for feature extraction and an LSTM for prediction [39]; the use of complex time series decomposition algorithms using neural networks [40]; the use of parallel computing [41]; and the use of special architectures of convolutional networks [42].

III. RESULTS

This section answers the research questions in light of the analysis of the selected documents.

Main question: What novel artificial intelligence models for forecasting demand have been proposed in recent years?

The artificial intelligence models proposed in recent years for demand forecasting were described in the previous section. Below we will deepen our understanding of them by answering the specific research questions.

A. *Q1: What Demand Forecasting Issues or Challenges Have Been Addressed with Artificial Intelligence?*

The analyzed documents address various challenges and problems related to demand forecasting. Below, we detail the main ones (see Table V).TABLE VII

B. *Q2: What Artificial Intelligence Methods Have Been Used for this Purpose?*

The machine learning methods used to solve the problems raised in the previous section can be classified into five groups, which we describe below (see Table VI).

TABLE V. RESULTS OF THE KEYWORDS CORRESPONDING TO Q1

Keyword	Input
Complex and non – linear data	Fourteen of the 33 documents analyzed indicate that the main problem that the proposed "machine learning" models are intended to solve is the complexity and non-linearity of the patterns generated by the variables that affect the forecast. [12], [18], [20], [21], [22], [28], [23], [25], [26], [31], [43], [40], [41], [42].
Numerous casual factors	Nine documents also raise the difficulties caused by the fact that the factors that affect demand are very diverse and numerous, such as calendar factors, climatic factors, economic factors, market factors, etc. Which makes the construction of adequate models extremely challenging [12], [13], [17], [29], [30], [26], [34], [37], [41].
Low volumen of training data	Machine learning models that are capable of capturing the complexities of the relationships between variables also require large amounts of data for training. However, many times the historical data available is scarce, not only because the products or services of interest have little history, but because as markets change, old data loses relevance or explanatory power. This leads to the need to build models that can perform well in these types of situations. [14], [15], [18], [28], [27], [35], [36], [40].
Temporal patterns and external factors	The demand for many products exhibits temporal patterns, such as trend and seasonality, however, other patterns are superimposed on these temporal patterns due to external factors such as the economy, climate, competition, etc. Simultaneously modeling both types of patterns can be a very complex task and a great challenge for forecasting models [16], [20], [29], [28], [30], [26], [40], [41].
Complexity of internet search intensity factors	Internet search patterns have proven to be very effective in forecasting demand for various products and services. However, the use of these indices poses several problems in the design of forecasting models based on them, the main of which is the existence of an infinite number of search terms candidates for predictor variables. This fact poses the enormous challenge of selecting the most appropriate predictors for demand forecasting. [22], [23], [44], [24], [27], [35]. This problem becomes more acute even when spatiotemporal data are necessary to feed the models [28], [25].
Overfitting	Closely related to the problem of numerous causal factors and the large number of predictive search indices is the problem of overfitting, that is, models generating very little error with the training data, but large errors with the test data. One of the causes of this problem is the use of too many predictor variables. Documents [28][23][44][26][24][36] present models that address this problem.
Disruption	Another problem that significantly affects forecasts is disruptive events, such as calendar events or COVID 19. The robustness of

	forecast models with respect to these types of events is highly desirable and is addressed by documents [13], [30], [37] and [41].
Complexity of supply chains	The demand forecast within the context of the problems inherent to supply chains such as excess or insufficient inventories, the bullwhip effect or the complexities imposed by omnichannel, are addressed by documents [16], [19], [20] and [38].
Management of large volume of data	The problem of processing large amounts of data to make forecasts is addressed by documents [22][39].
Model optimization	Optimizing a forecast model of increasing complexity entails several challenges, such as selecting the most appropriate hyperparameters [31], [32], identifying the appropriate amount of historical data to introduce [27], limiting the complexity of the model [36], preserving its explanatory power [33] and avoid model degradation [42]

TABLE VI. RESULTS OF THE KEYWORDS CORRESPONDING TO Q2

Keyword	Input
Simple Machine Learning Methods	Within this group are the traditional machine learning methods multiple linear regression (MLR) and support vector machine (SVM). Twelve documents propose the use of these methods, however they are proposed in combination with other more complex methods [12], [15], [18]-[21], [29], [30], [35], [40] or with classical statistical methods [17].
Bagging Methods	This method builds models by training them a large number of times with various random subsets of the training data. Within these methods we find the Bagging Decision Tree, or simply Bagging [13], and the Random Forrest (RF). As in the previous case, these models are not proposed alone but in combination with other models of different types[12], [14], [16], [13], [15], [20], [21], [35].
Boosting Methods	Within these methods we find Extreme Gradient Boosting (XGB), Light Gradient Boosting (LGB), AdaBoost and Categorical Boosting. Six studies propose the use of these algorithms and, similarly to the previous ones, they are proposed in combination with other methods. [12], [14], [13], [15], [20], [21].
Simple Neural Netwotks	These methods generate models that use single hidden layer neural networks such as the Multi Layer Perceptron (MLP), the Extreme Learning Machine (ELM), or the so-called Autoencoders. Seven documents propose the use of these networks, however, only in three of them are they proposed as the main predictor [41], [24], [44], in the others they are proposed as part of a base of predictors [18][20][29], or as mechanisms for pattern extraction before applying the main predictor [26], [24].
Deep Learning	This machine learning method uses at least one deep neural network, that is, a network with several hidden layers, to build the forecast model. Twenty-three of the thirty-three documents analyzed propose some type of deep learning. Three of them propose the deep neural network as part of a base of predictors of different types [19][29][35]]; fifteen of them propose it in combination with other simpler methods [14], [16], [22], [23], [25], [27], [43], [36], [40], [34] or in combination with other deep neural networks [28], [26], [39], [33] and, finally, five papers propose a single type of neural network as the main predictor [31], [38], [32], [37], [42]. Of note are the studies that propose the use of multiple neural networks of the same type as “stacking” [22], [23], [31], [42]. Therefore, the tendency to use deep neural networks when proposing innovative forecasting models is evident.

C. Q3: What Metric Have Been Used to Measure the Performance of the Proposed Models?

All of the proposed models measure their performance with at least one of the classic error metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). or its standardized versions NMAE, NMSE, NRMSE and NMAPE. Some studies also include among their metrics the coefficient of determination (R^2) [12][14][22][31]. Two studies also propose the “Directional statistics” metric [29][24]. Finally, only one study additionally uses the “Theil coefficient” (TC) metric.

D. Q4: What is the Performance of the New Proposed Models in Relation to the Established Models?

All the proposed models report at least the same performance as the models they take as reference [12], [21]. Some report slight improvements of the order of one or two percent [33], [32], but the vast majority report significant improvements that can be of the order of 60 or 70 percent [31], [27]. However, these results must be taken very carefully since many proposed models are compared with models very similar to them, with only slight improvements, while other models are compared with diametrically different models with very different logics and methodologies, which make it more likely large performance differences. Finally, in the documents where the proposed machine learning models have been compared with classical statistical methods, the former have been clearly superior [16], [17], [21], [29], [23], [30], [44], [25], [24], [27], [43], [36], [41], [42]

E. Q5: What are the New Features or Innovations Introduced by these Models?

The analyzed documents propose various novelties that we then classify according to the stage of model development in which they occur (see Table VII).

F. About the Bibliometric Analysis

1) Publication analysis by keywords: The bibliometric analysis carried out with the help of the VosWiever and Bibliometrix software, which have good performance in these types of research. The search string was used from which 204 articles related to our research topic were obtained.

The Fig. 5 shows the publications by keywords in the different articles reviewed we can see that the word forecasting has greater acceptance in the different researches, followed by deep learning, machine learning, learning systems, etc.

Fig. 6 shows the thematic research groups, which are related to specific research areas forecasting (yellow), demand forecasting (blue), machine learning (green) and to a lesser extent forecasting method (violet).

In Fig. 7, you can see the publication trend according to the authors' interest in the keywords, with the research using machine learning algorithms to evaluate the forecast of product and service demands, followed by deep learning. , forecasting, among others.

2) Publication trend in different countries: In Fig. 8, it is observed that there is great interest in different countries in investigating the chosen topic. Firstly, we see that in Asia there are more articles published, followed by Australia and the United States.

TABLE VII. RESULTS OF THE KEYWORDS CORRESPONDING TO Q5

Keyword	Input
New related to the variables used	The analyzed documents propose the use of various variables for demand forecasting, such as: calendar event variables [12], [14], [16], variables related to product or service characteristics [16], [35] related variables with the characteristics of the supply chain [20], [35], [38], variables related to the point of sale [12], [14], [16], variables related to the climate [14], [15], [18], and economic and financial variables [30], [24]. However, the most striking novelty in this regard is the successful use of Internet search intensity indices as predictors of demand, mainly in the tourism sector [22], [23], [44], [24], although it has also been applied successfully in the B2B manufacturing sector [17]. Another important novelty is the inclusion of spatio-temporal data, mainly from mobile devices, among the predictor variables of demand in the tourism sector [28], [25].
New in feature extraction	Feature engineering is the phase in building a model in which relevant patterns are extracted from the data to feed forecasting algorithms. The analyzed documents propose various feature extraction techniques, one of the main ones is dimensionality reduction, through this procedure, it is identified which of the multiple variables have the greatest impact on the precision of the model and the influence of the rest is discarded or reduced. . Novel algorithms are proposed for this purpose such as “particle swarm optimization” (PSO), “recursive feature elimination”, “extra three” [20] among others [34], simple neural networks are also proposed for this purpose. such as autoencoders [33], [22] and attention mechanisms [27], [25] and even more complex neural networks [26], [24]. Another important technique proposed by the models studied is decomposition. This consists of dividing the original time series into simpler time series. The classic decomposition generates three components called trend, seasonality and noise. However, the documents studied propose more advanced decomposition techniques such as “Noise-assisted multivariate empirical mode decomposition” (NA-MEMD), which divides the time series into a greater number of components according to their behavior on various time scales. [29], or the “Improved Complete Ensemble Empirical Mode Decomposition With Adaptive Noise” (ICEEMDAN) that allows the choice of a different predictor for each decomposed series according to its degree of complexity [30]. Clustering, which is the automatic grouping of similar data, is another proposed technique. Through this procedure, the heterogeneity of the data within each cluster is reduced, allowing suitable predictors to be found for each of them [18], [38], [36]]. One of the most innovative feature extraction techniques is the conversion of time series to equivalent images, in this way, with the use of convolutional image processing networks, patterns that would not otherwise be possible can be detected. The importance and effectiveness of this technique can be seen in the documents [28], [39]. Finally, a useful technique in cases where training data is scarce is “transfer learning”. The documents studied propose several of these techniques to take advantage of the similarity of the product or service of interest with other products and services that do have abundant data [15], [25], [36], [27].
New regarding the adjustment of the model	The number of historical data that is introduced into the model and the adjustment of its hyper parameters are two aspects with a great impact on the accuracy of the forecast and that are usually done manually by the authors. The documents studied propose, in relation to this aspect, novel algorithms that automate and optimize these tasks. For the number of historical entries, algorithms such as PSO [20], Principal component analysis (PCA), Effective time lags, and autoenconders [34] have been proposed. For the automatic adjustment of hyper parameters, the Bayesian optimization algorithm [25], Firefly algorithm [31] and the Giza pyramids construction algorithm [32] are proposed.
New regarding the assembly of the models	Finally, the documents studied propose various ways to assemble the various machine learning methods used. One of the most striking is the dynamic ensemble, in which a base of predictors are combined with each other in a diverse way according to their recent performance. [19], [21]

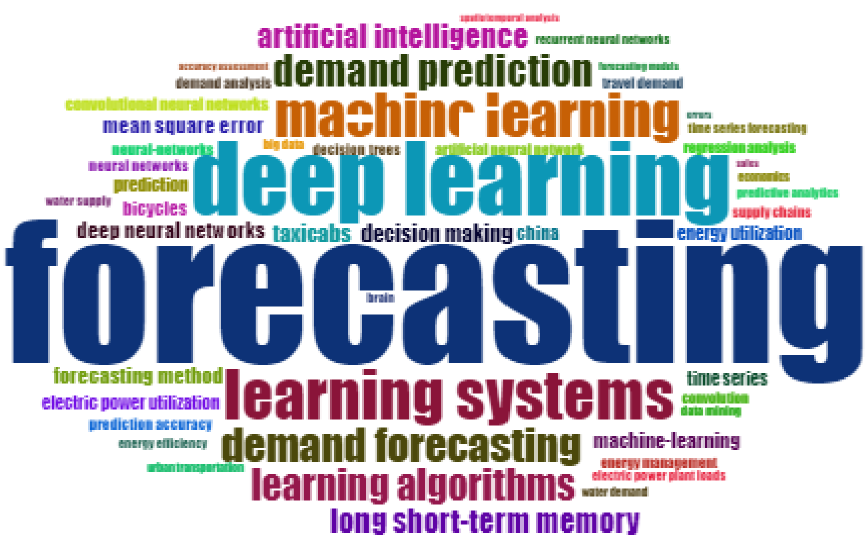

Fig. 5. Keywords.

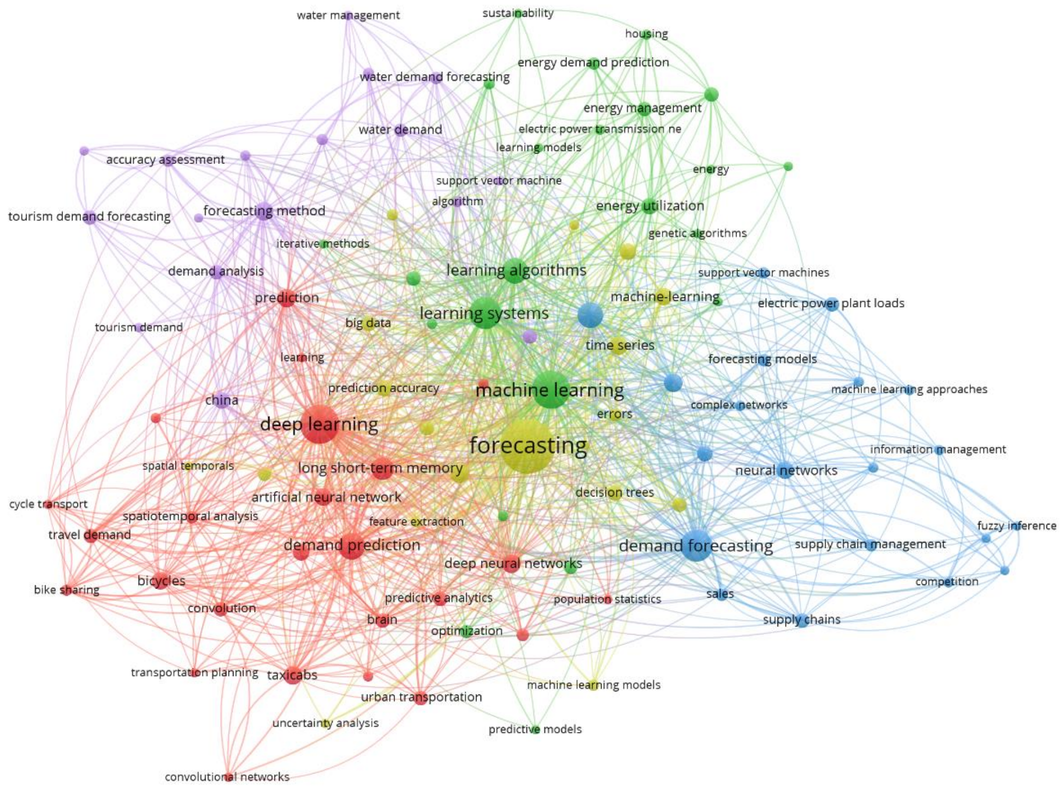

Fig. 6. Network visualization.

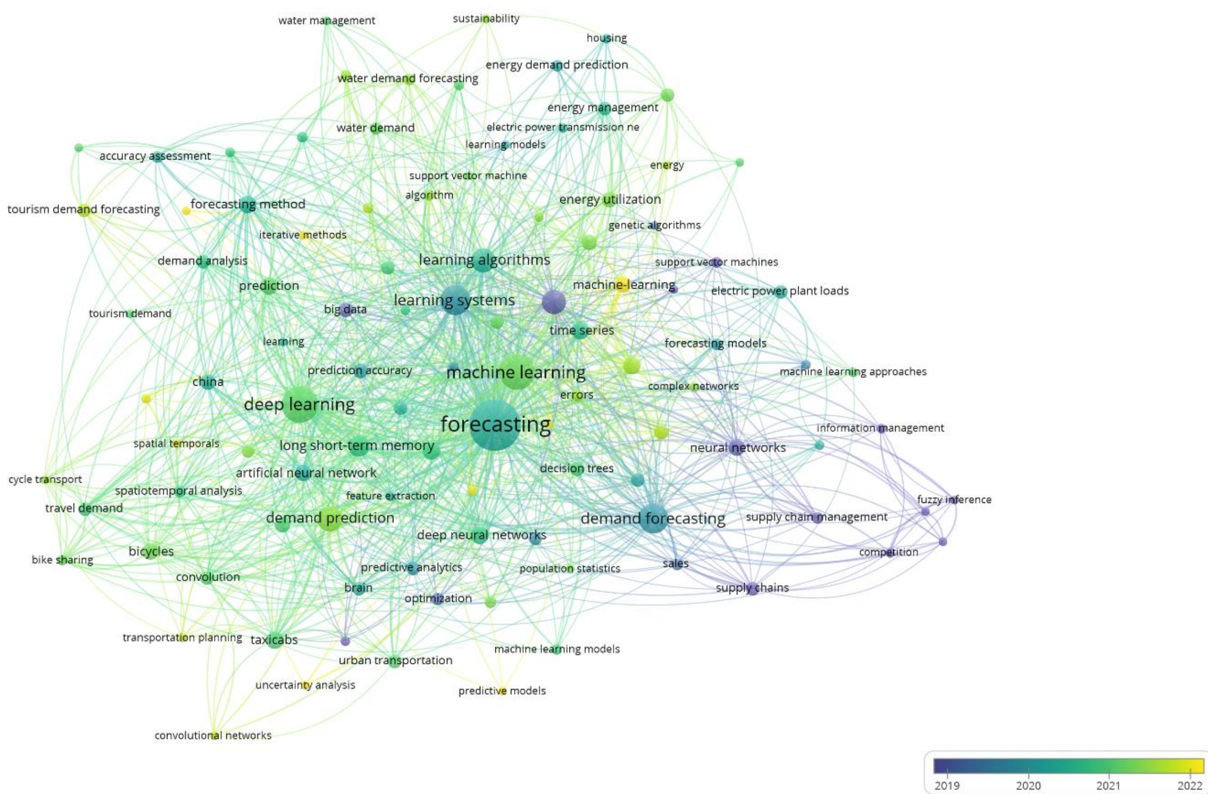

Fig. 7. Overlay visualization.

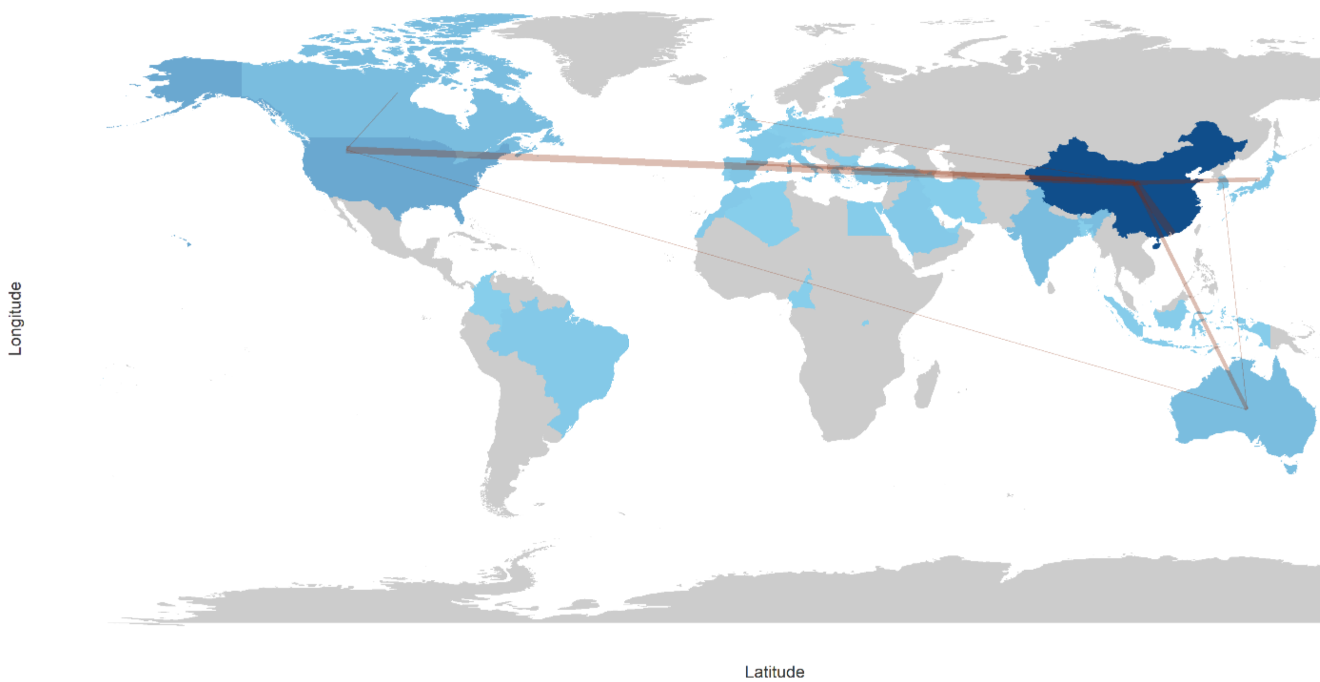

Fig. 8. Country collaborations maps.

G. Proposed Model

As a synthesis of the research findings, a demand forecasting model is proposed below that takes the most innovative techniques from the various studies and sectors and integrates it into a new proposal (see Fig. 9).

The proposed model, in addition to the historical data represented by the time series, is capable of using other internal variables, such as data from the point of sale (store location, promotions, etc.), or external variables such as special calendar days, economic variables, financial and even internet search intensity indices (SII). To determine the appropriate number of historical data to consider in the forecast, optimization algorithms would be used, after which the time series would be converted into images for the extraction of features contained in them. In relation to the other variables, they would be subjected to dimensionality reduction with coders and attention mechanisms. Regarding the artificial intelligence methods to be used, deep neural networks would be used: CNN to extract patterns from the images and LSTM to make a first forecast based only on the time series. The error produced by this first forecast would be used to train a base of ML predictors, both simple and bagging and boosting, which would have the mission of relating the internal and external variables from the encoders with the error produced by the neural networks. The predictors from this base would finally be dynamically assembled according to the performance they show, to finally produce the final forecast. Regarding the adjustment of hyper parameters of the neural networks, these would also be found with optimization algorithms.

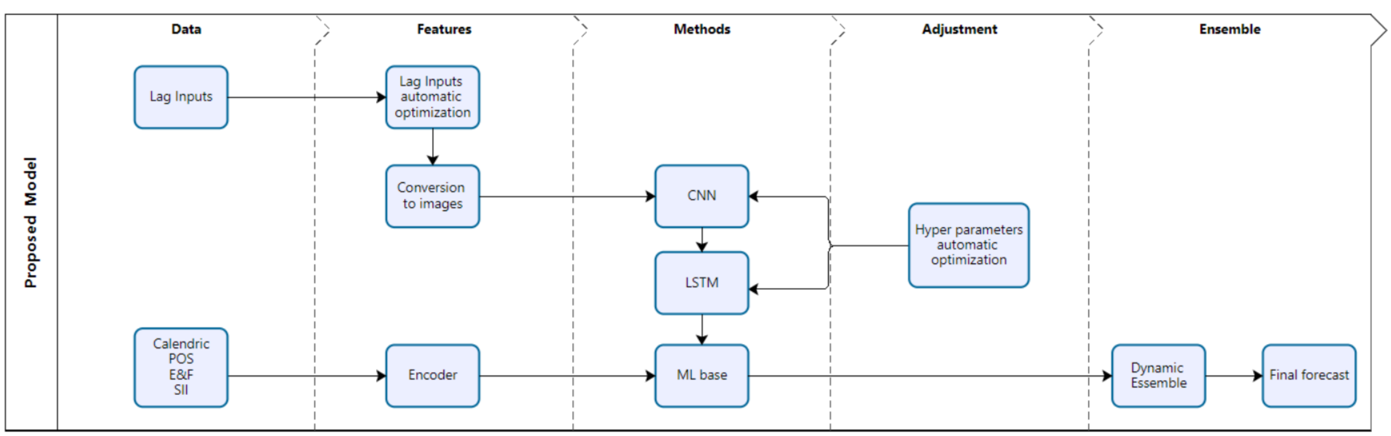

Fig. 9. Proposed model.

IV. Discussion and Conclusions

A. *Discussion*

Regarding the importance of using “explanatory” variables in addition to time series, [17] established that the inclusion of these leads to significant improvements in forecast accuracy. They proposed a model that adjusts the forecasts obtained initially by a base predictor, through multiple regressions that relates this result with external indices related to Internet search intensity. In agreement with these authors, in [16] a similar effect of “exogenous” variables was found; the authors proposed an LSTM network as a base predictor on the historical data and then adjusted the residuals of this forecast using RF and variable indices exogenous” such as calendar events, product characteristics, information about the point of sale, etc. The model proposed in this study takes advantage of these findings and follows the scheme: base predictor on historical data and subsequent adjustment against external variables. In this way, the predictive power of various external variables is taken advantage of.

The importance of appropriately selecting the amount of past data to be considered in the forecast was established by [20]. These authors indicate that this is not only important to avoid variable redundancy, but also improves the precision of the model. Given this, they propose the use of the “particle swarm optimization” (PSO) algorithm for this task. Similarly, [34] points out that selecting useful inputs effectively results in improved forecasting, but they recommend using the “effective time lags” method for this purpose. In study [21] the authors propose instead the use of the “False Nearest Neighbors” method, while in study [27] the authors propose incorporating the self-selection of historical data into the same architecture of the deep neural network by adding attention mechanisms. Within this same line, the model proposed in this study proposes the use of some of these algorithms, especially the PSO or the attention mechanisms, to determine the optimal input of historical data.

Regarding the effectiveness of the conversion to images of the time series in [45] the authors point out that by converting to images not only can the patterns between the input data and the target variable be studied, but this technique allows reveal the complex relationships of the input variables with each other, enriching learning. Along these lines, in study [28] the use of this technique is proposed to extract the patterns of the spatiotemporal data used, while in [39] the authors go one step further and not only propose the conversion to images of the series temporal, but rather they propose the decomposition of these images for better processing. In accordance with these studies, the model proposed by this research uses the conversion of the time series to images to fully exploit the information contained therein.

The use of the enormous amount of data obtained from the Internet, such as SII, complicates the task of selecting the most relevant variables. To address this, in study [22] the authors propose the use of autoencoders to automate this task. In study [7] the authors add that the use of a large number of independent variables not only makes the model more complex, but also frequently causes “overfitting” problems and they propose the use of “stacking autoencoders” to reduce dimensionality. Finally, in study [27] they add that multiple variables require large amounts of data and that the scarcity of these leads to poor performance models, which is why they propose implementing attention mechanisms to identify the most important variables. To avoid these drawbacks generated by the proliferation of explanatory variables, the model of this study includes the use of autoencoders for their selection.

The determination of the hyper parameters of the neural networks is an aspect that significantly affects the accuracy of the forecast models, however, the choice of these values is usually done with techniques that are far from being exhaustive, which is why in [31] The authors propose the automatic selection of hyper parameters using the “firefly” algorithm; the precision gained by the model was very noticeable. The authors of [32] agree that the performance of deep neural networks is greatly affected by the choice of hyper parameters, but they propose the “Giza pyramids construction” algorithm to determine them. Along the same lines [25] finally proposes a “Bayesian optimization”. The model proposed in this study, by using two deep neural networks, proposes the optimization of hyper parameters using one of these algorithms.

Finally, in study [46] the authors established the importance of a heterogeneous base of predictors and the effectiveness of dynamic ensembles of these according to their performance. The model proposed in that study was compared with others in [21], managing to surpass all of them in performance. A similar model, respecting the heterogeneity of the predictors and the dynamic ensemble, was proposed by study [19] with similar results. Along the same lines, the model proposed in this research proposes a heterogeneous base of machine learning predictors that relate the forecast errors produced by the neural networks, with the “exogenous” variables selected by the autoencoder. The heterogeneity of the predictors and their dynamic assembly ensure superior performance.

In short, the innovations introduced by artificial intelligence in the construction of demand forecasting models are broad and varied and impact all phases of the development of a model. Some of the most striking innovations, such as the use of images and dynamic assemblies, are part of the model proposed in this research; however, it is possible to conceive multiple alternative models with the innovations left aside by the latter. Future work should explore the effectiveness of the model proposed in this study and propose new models with the other innovations identified in the research.

This study provides a broad view on the contributions of artificial intelligence in the field of demand forecasting in various sectors. However, it is important to recognize certain limitations. The articles were restricted to the retail, manufacturing, tourism and energy sectors, which may have left out important innovations in other sectors such as the transportation, logistics and services sectors to name a few. Furthermore, the collection of studies was based only on a single, although very recognized and extensive, database: Scopus, other significant studies on the subject could be found in other prestigious scientific databases such as Web of Science. Future research could expand the sectors considered and the databases used to corroborate and expand our findings.

B. Conclusions

In this systematic review of the literature, after reviewing and analyzing the 33 selected articles, the six research questions were answered. In relation to the first question about what artificial intelligence models have been proposed in recent years for demand forecasting, this study determined that the models proposed have been diverse, highlighting the strong tendency to propose ensembles of heterogeneous methods, to use Internet search intensity indices, to use various feature extraction techniques and to employ deep neural networks ("deep learning") in the construction of the models. Regarding the second question about what problems or challenges of demand forecasting these proposals try to solve, it was found that the problem is also diverse, highlighting the complexity of the data, the scarcity of training data, and the deterioration of the forecasting models due to the large number of variables used. Regarding the third question related to the machine learning methods used, it was found that they are used from the simplest statistical methods to the most complex deep learning methods, predominating the use of the latter and the assembly between heterogeneous methods. In relation to the fourth question about performance measurement metrics, it was found that the vast majority of models almost exclusively use various forecast error metrics. Regarding the fifth question about the performance of the proposed models, it was found that almost all documents reported performance equal to or better than the models taken as reference, and that in all cases the proposed models had better performance than the statistical methods, considered classics. Finally, in relation to the innovations introduced by these models, it was found that this is very varied, with contributions on the type of data used, the extraction of characteristics, the type of machine learning method used, the automation and improvement of the adjustment of the models and the way to assemble the predictors. Future studies could focus their attention on recognized machine learning techniques that do not appear in the present selection of articles, such as reinforcement learning and genetic programming, or on sectors not considered in the present research.

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