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Deep Recurrent Convolutional Neural Network for Bankruptcy Prediction: A Case of the Restaurant Industry

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Abstract: Using logistic regression technique and Deep Recurrent Convolutional Neural Network, this study seeks to improve the capacity of existing bankruptcy prediction models for the restaurant industry. In addition, we have verified, in the review of existing literature, the gap in the research of restaurant bankruptcy models with sufficient time in advance and that only companies in the restaurant sector in the same country are considered. Our goal is to build a restaurant bankruptcy prediction model that provides high accuracy, using information distant from the bankruptcy situation. We had a sample of Spanish restaurants corresponding to the 2008–2017 period, composed of 460 solvent and bankrupt companies, for which a total of 28 variables were analyzed, including some of a non-financial nature, such as age of restaurant, quality, and belonging to a chain. The results indicate that the best bankruptcy predictors are financial variables related to profitability and indebtedness and that Deep Recurrent Convolutional Neural Network exceeds logistic regression in predictive capacity.

Keywords: bankruptcy prediction; deep recurrent convolutional neural network; economic sustainability; logistic regression; restaurants

1. Introduction

The objective of this study is to estimate bankruptcy prediction models for companies belonging to the restaurant industry. The fact of focusing on this industry derives from two essential reasons: First, because of the importance of this branch of activity, both in the field of the Spanish economy, in which the service sector has special weight and in participation of the same in the international level. Second is due to the notable increase in bankruptcy situations of companies belonging to this sector, with a significant impact, even in the first year of activity. These circumstances have motivated interest in analyzing the causes that lead to bankruptcy in the restaurant industry and trying to provide tools or strategies to their managers, with a view to avoiding it and ensuring the permanence of their companies.

The previous studies done so far have focused on American companies, analyzing bankruptcy 1 or 2 years before bankruptcy [1]. Consequently, the absence of empirical work with samples of Spanish companies in this sector of activity makes it especially interesting that we analyze the causes that cause it. This paper contributes to the literature on bankruptcy prediction in the sector: (1) provides new models with high classification accuracy, (2) uses an exclusive sample of restaurants, (3) with a horizon of up to three years for bankruptcy. In addition, we apply a novel deep learning method,

Deep Recurrent Convolutional Neural Networks, which has obtained high accuracy levels in previous works [2,3].

On the other hand, and in order to have a greater margin to carry out strategies that avoid the bankruptcy of these companies, we intend to obtain models that have the objective of predicting it 1, 2, and 3 years before it occurs, comparing the similarities and differences of these models as we move away from the moment of bankruptcy. Likewise, and in order to obtain robust models, a total analysis period of 10 years has been considered, between the year 2008 and 2017, a period that would cover several economic cycles and, consequently, avoids the risk of obtaining models only valid for times of growth or economic decline.

From a professional point of view, the results obtained and the high predictive capacity of the model are useful for decision-making by managers of companies in the sector and other stakeholders such as financial institutions, investors, or regulators.

To achieve our objectives, the structure of the document includes an introduction and review of the published literature on insolvency prediction models in the tourism sector in general and in the restaurant sector in particular, describing the different methodologies that have traditionally been used to establish insolvency prediction models and the different variables that the authors have considered decisive when predicting bankruptcy in restaurants. The second part of the document is dedicated to presenting the methodology used, the results obtained, and their discussion. The final part deals with the main conclusions and implications of our study and future lines of research on the subject.

2. Literature Review

Although there are numerous studies on the prediction of bankruptcy [4–8], those carried out specifically for the hospitality sector are scarce, despite the recognition of the high vulnerability to the bankruptcy of companies belonging to the said sector. Another relevant issue is the ability of models to predict bankruptcy well in advance since in most cases, there are indications of financial problems several years before the bankruptcy [9]. Gu [10] carried out the first empirical study focused exclusively on the prediction of bankruptcy in the restaurant sector using American companies in its sample. In the following works, more advanced statistical methods began to be used. Such has been the case of logistic regression (LOGIT) and artificial neural networks (NN) and currently, newer methods based on the detection of atypical companies and the analysis of their financial indicators using the test of equality of means or the chi-square [11]. The first to use a LOGIT model were Kim and Gu [12], which used LOGIT applied to 32 companies in the hospitality sector (16 in bankruptcy and another 16 not bankrupt). In addition, Kim and Gu [13] estimated a LOGIT model using the same sample of restaurants used by Gu [10], in order to compare the predictive capacity of a LOGIT model against the model estimated by Gu [10]. Their results showed greater precision, although not with a high difference, of the LOGIT model. Park and Hancer [14] made a statistical prediction of bankruptcy using a sample of 80 companies (40 bankrupts and 40 solvents), which combined hotel companies, restaurant and entertainment services companies. They compared the predictive capacity of a LOGIT model and an NN, concluding that the NNs predict better within the sample, but that the predictive capacity of both models is similar in the external sample used to check the accuracy of the models. Recently, Gregova et al. [15] used logistic regression, random forest, and neural network models in order to identify a model with the highest predictive accuracy of financial distress to industrial enterprises. Neural network models yielded the best results.

Another question much discussed by numerous authors in the insolvency prediction literature deals with the variables that are the best predictors of corporate insolvency. Many variables are used, highlighting those that refer to debt and profit margin [16,17], or regardless of income [12,16,18]. Besides, the existence of dependency between the explanatory variables of economic sustainability and the country of origin of the models has recently been verified [19].

Of the empirical bankruptcy prediction studies discussed above, only three of them have used data from restaurant companies exclusively, and three others included restaurant companies in a mixed

manner (including companies from other industries). The first of the works carried out in this area was that of Gu and Gao [20], who estimated a multidiscriminant analysis model (MDA) of bankruptcy prediction based on a sample of 14 bankrupt companies, including 4 hotels and 10 restaurants, and a similar number of solvent companies. The model was able to classify the companies within the sample with an accuracy of 93%. However, since the model was derived from a mixed sample of hotels and restaurants and was not tested with restaurants outside the sample, its applicability to restaurant bankruptcy prediction is limited. Gu [10] used a sample of somewhat larger size, considering 18 bankrupt restaurants, paired with as many unbroken restaurants, with data from the 1986–1998 period. The estimated model obtained a prediction level outside the sample of 80%. Later Kim and Gu [13] estimated a LOGIT model using the same data from Gu's MDA model (2002) [10]. The LOGIT model, resulting from a more advanced statistical sophistication, correctly predicted 94% of the companies that had gone bankrupt one year before bankruptcy, as well as 93% of the companies used in the external sample to verify the ability to predict. With these results, it was demonstrated that the LOGIT model provided a somewhat higher predictive capacity (94% compared to 92% of the MDA of Gu [10]), without considering on the other hand that the LOGIT model has greater theoretical strength.

For their part, Kim and Gu [12] estimated two LOGIT models to predict bankruptcy with 1 and 2 years prior, to companies belonging to the hospitality sector. The predictive capacity of the model amounted to 91% for 1 year before bankruptcy and 84% for 2 years before. The authors concluded, based on the estimated models, that companies in this sector are closer to bankruptcy if they have a lower cash flow and greater indebtedness. Youn and Gu [21] was the subsequent empirical study that focused on the restaurant industry using information from publicly traded or publicly traded companies. These authors were the pioneers in applying NN in prediction for this industry. Together they estimated a LOGIT model in order to compare the predictive capacity of both statistical techniques, estimating models to predict bankruptcy 1 and 2 years before it. They determined that, although NNs predict well, they do not provide better prediction than LOGIT, especially in the external sample. Park and Hancer [14] estimated LOGIT and NN models as bankruptcy predictors of this sector, estimating both types of models for 1 year before bankruptcy. Based on the empirical results of two methodologies, NN obtained a higher level of prediction than the LOGIT model within the sample (97.5% versus 90% of the LOGIT model). However, when the test is carried out for verification in the external sample (formed by 8 solvent companies and 8 insolvent companies that had not been included in the initial model), both models predict 100%. Recently, Kim and Upneja [18] estimated the financial difficulties of American restaurants with the AdaBoost Decision Tree model, showing an accuracy close to 97%. Kim [16] examined the financial difficulties of the hospitality sector in the US concluding that for the restaurant-stacking model, debt-to-equity ratio and the net profit margin, in line with Kim (2018) and Valaskova et al., (2018), and also the growth in owners' equity and the stock price trend were significant predictors. Finally, Brito et al. [22] applied different variations of Support Vector Machine, LOGIT, Decision Trees, Random Forest, AdaBoost and Neural Network to predict business failure in hospitality sector, showing as Random Forest and AdaBoost are most accurate techniques, after obtaining 96% of accuracy.

Regarding the methodological aspect, within statistical techniques, logistic regression (Logit) has been the one that has shown the best predictive capacity and reliability compared to other techniques such as Multivariate Discriminant Analysis (MDA). Over the past decades, Logit has shown precision with out-of-sample data in a median range of 71–77% [23,24]. For its part, MDA has shown an average precision of 68–76% [25,26]. Prediction techniques have evolved, emerging new techniques such as neural networks that have shown their predictive superiority both with Logit and other computational classifiers, such as decision trees and genetic algorithms, among others [27]. In this line, neural networks have been the most widely used technique in studies of financial distress prediction and bankruptcy, with an average precision of close to 85%, obtaining greater precision than statistical techniques and even showing an average precision higher than that of other computational classifiers [28–31]. To provide greater methodological innovation, this work uses the combination of neural networks

with the Deep Learning type design, which has shown in recent years to be a type of methodology that improves the prediction results achieved so far as well as improves the reliability of the results of the models built since their design hidden layers (or also called ‘black box’) are better specified than previous individual computational methods [32]. For this reason, the Deep Recurrent Neural Network is chosen as a computational technique, to improve the precision results of financial distress in the restaurant sector and that it can become a new tool for the analysis of this problem.

3. Methods

In the present study, we use two different methodologies to predict bankruptcy: logistic regression model (LOGIT) and Deep Recurrent Convolutional Neural Network (DRCNN). Although the LOGIT models have had and continue to maintain special relevance in the studies carried out in this area in the last 30 years, the deep learning models correspond to more advanced methodologies, which have shown to have significant potential in the field of prediction. The main advantage of LOGIT models lies not only in the ability to predict previously if a company is expected to be solvent and insolvent, but also to provide information regarding the variables that are significantly explanatory of bankruptcy, and consequently, allow deduct appropriate strategies in the management of the company in order to ensure its solvency. On the other hand, the deep learning models have great classification potential, surpassing LOGIT in many cases, although they do not have the explanatory utility of the latter. In this paper, we compare the usefulness of both methodologies in the prediction of bankruptcy in the restaurant industry in Spain, contrasting their results with those obtained in previous work.

3.1. Logistic Regression

The LOGIT model is a non-linear model, although it contains a linear combination of parameters and observations of the explanatory variables. The logistic function is bounded between 0 and 1, thus providing the probability that an element is in one of the two established groups. From a dichotomous event, the LOGIT model predicts the probability that the event will or will not take place. If the probability estimate is greater than 0.5, then the prediction is that it does belong to that group, and otherwise, it would assume that it belongs to the other group considered.

To estimate the model, we start from the quotient between the probability that an event will occur and the probability that it will not occur. The probability of an event occurring will be determined by Expression (1):

$$P\left(Y_i = \frac{1}{x_i}\right) = \frac{e^{(\beta_0 + \beta_1 X_1 + \dots + \beta_k X_k)}}{1 + e^{(\beta_0 + \beta_1 X_1 + \dots + \beta_k X_k)}} = \frac{1}{1 + e^{(\beta_0 + \beta_1 X_1 + \dots + \beta_k X_k)}} \quad (1)$$

where β_0 is the constant term of the model and $\beta_1, \dots, \beta_k$ are the coefficients of the variables. If logarithms are finally applied in (1), the linear expression of the model is obtained Y_i^* , as follows:

$$Y_i^* = \ln \frac{P(Y_i = 1)}{1 - P(Y_i = 1)} = \ln e^{(\beta_0 + \beta_1 X_1 + \dots + \beta_k X_k)} = \beta_0 + \beta_1 X_1 + \dots + \beta_k X_k \quad (2)$$

The coefficients of the model ($\beta_0, \beta_1, \dots, \beta_k$) are estimated by applying the maximum likelihood method, which would entail a series of steps: first, specify the maximum likelihood function, the model that collects the joint probability for the independent observations considered; secondly calculate the Neperian logarithm of the function of likelihood; thirdly, the calculation of the derivative of the Neperian logarithm of the said function with respect to the parameters that are to be estimated, and finally, to obtain the solutions to the system of k-equations posed or plausible estimators [33].

In this study, stepwise regression is used, where the choice of predictive variables is carried out by an automatic procedure. In each step, a variable is added to add or subtract from the set of explanatory variables based on some pre-specified criteria [34,35]. In our case, the backward approach is applied. All the initial explanatory variables are introduced, and the method expels those non-significant variables considering the R-square result obtained by the model.

3.2. Deep Recurrent Convolution Neural Network

Recurrent neural networks (RNN) have been successfully used in many fields for time-series prediction due to this huge prediction performance. For a simple neural network, the inputs are assumed to be independent of each other. The common structure of RNN is organized by the output of which is dependent on its previous computations [36]. Given an input sequence vector x , the hidden states of a recurrent layer s , and the output of a single hidden layer y , can be calculated as follows:

$$s_t = \sigma(W_{xs}x_t + W_{ss}s_{t-1} + b_s) \quad (3)$$

$$y_t = o(W_{so}s_t + b_y) \quad (4)$$

where W_{xs} , W_{ss} , and W_{so} denote the weights from the input layer x to the hidden layer s , the hidden layer to itself and the hidden layer to its output layer, respectively. b_y are the biases of hidden layer and output layer. σ and o are the activation functions.

$$STFT\{z(t)\}(\tau, \omega) \equiv T(\tau, \omega) = \int_{-\infty}^{+\infty} z(t)\omega(t - \tau)e^{-j\omega t} dt \quad (5)$$

where $z(t)$ is the vibration signals, $\omega(t)$ is the Gaussian window function focused around 0. $T(\tau, \omega)$ is a complex function that describes the vibration signals over time and frequency.

When time-frequency features $\{T_i\}$ are used for bankruptcy prediction with RNN, the convolutional operation is conducted in the state transition. To calculate the hidden layers with a convolutional operation, the following equation is applied:

$$S_t = \sigma(W_{TS} * T_t + W_{ss} * S_{t-1} + B_s) \quad (6)$$

$$Y_t = o(W_{YS} * S_t + B_y) \quad (7)$$

where W term indicates the convolution kernels. The convolutional operation has been determined by local connections, weight sharing, and local grouping, which allow every unit to integrate time-frequency data in the current layer. The convolution is operated between weights and inputs and is performed in the transition of inputs to the hidden layers.

Recurrent Convolutional Neural Network (RCNN) can be heaped to establish a deep architecture, named deep recurrent convolutional neural network [37]. With DRCNN for bankruptcy prediction, the last part of the model is a supervised learning layer for bankruptcy, which is determined as:

$$\hat{r} = \sigma(W_h * h + b_h) \quad (8)$$

where W_h is the weight and b_h is the bias, respectively. The error between predicted observations and actual ones in the training data for bankruptcy prediction can be calculated and backpropagated to train the model [38]. Considering that the actual data at time t is r , the loss function is determined as shown in the next equation:

$$L(r, \hat{r}) = \frac{1}{2} \|r - \hat{r}\|_2^2 \quad (9)$$

The stochastic gradient descent is applied for optimization in order to learn the parameters. The gradient of loss function regarding parameters W_h and b_h are determined as follows:

$$\frac{\partial L}{\partial W_h} = -(r - \hat{r})\sigma'(\cdot)h \quad (10)$$

$$\frac{\partial L}{\partial b_h} = -(r - \hat{r})\sigma'(\cdot) \quad (11)$$

In addition, and in order that the DRCNN model can report the importance of each variable in the results of the built model, a sensitivity analysis was applied [39]. This analysis consists of taking 100% of the data and dividing them into groups, and each group of data is processed in the network constructed as many times as there are variables of the model. The value of one of the variables is modified each time, placing it with zero value. The answers of the network are evaluated in relation to the objective values or classification values already known, by means of Expression (12).

$$S_{x_i} = \sum_{j=1}^n (\Phi x_{ij}(0) - \Phi x_{ij})^2 \quad (12)$$

where $\Phi x_{ij}(0)$ is the value of the network output when the variable X_{ij} is zero, Φx_{ij} is the known classification value, X_i is the variable whose importance you want to establish, S_{x_i} is the sensitivity value of the variable.

4. Data and Variables

The database used in this work is formed by 460 companies, both solvent and insolvent, belonging to the restaurant industry and whose activity is developed or has been developed in Spanish territory. An insolvent company is one that is legally declared as a legal situation of a bankruptcy situation. These data have been obtained from the SABI database (Iberian Balance Analysis System), which is defined as an economic-financial database that includes more than 1,250,000 Spanish companies and more than 400,000 Portuguese companies. In order to validate the models to be estimated and check their predictive capacity, test samples are also used, different, and outside those used in the estimation of the models. The sample is divided into data within the sample (training), which is used to build the model. This step has 70% of the total sample data. And the remaining 30% of data is dedicated to data outside the sample (testing). This step is used to quantify the precision capability of the built model.

Specifically, the present study has considered three different samples in order to analyze the bankruptcy prediction of companies in the restaurant industry in Spain, for 1, 2, and 3 years before the bankruptcy. In the three samples carried out, the same number of solvent companies as of insolvent companies has been considered, a general rule carried out in all bankruptcy prediction studies, as well as that maintained in the specific case of the restaurant industry. Likewise, and since DRCNN properly requires another sub-sample, a partition will be made, using a part of the data as a validation sample. This sample differs totally in concept and utility with respect to the test sample, since the validation sample is required only for the correct estimation of the DRCNN, avoiding its over-training. The test sample, on the other hand, is the one used to verify the capacity of generalization of the models with data other than those used properly to obtain them. Table 1 gives details of the number of companies in the sample and the percentages of which belong to the chain and hold a quality certificate.

Table 1. Sample size.

Sample	M.I		M.II		M.III	
	Solv	Bankr	Solv	Bankr	Solv	Bankr
Companies	230	230	224	224	192	192
Age (Log)	0.91	0.76	0.94	0.78	0.97	0.79
Belonging to chain (%)	20.81	13.90	17.65	13.87	19.09	13.84
Quality Certificate (%)	26.23	20.62	25.64	17.83	26.54	19.21

In the study, a total of 28 financial variables or ratios have been considered, obtained from the review of the literature of previous research papers on the prediction of bankruptcy in the restaurant industry [1]. All the variables that have been considered are quantitative, corresponding to different economic ratios obtained from the accounting information of the companies used in the different samples. These ratios have been classified, in turn, in the categories of size, efficiency, liquidity,

cash flow, profitability, solvency, and non-financial (Table 2). In addition to the financial ratios under analysis, a dummy variable of the binomial type has been used, which is the dependent variable to identify the company as solvent or insolvent.

Table 2. Description of the independent variables.

SIZE	CODE	Expected Sign
Total Assets (Log)	VZ1	-
EFFICIENCY		
Income/Non-Current Assets	VE1	-
Income/Total Assets	VE2	-
Cost of Sales/Average Inventory	VE3	+
LIQUIDITY & CASH-FLOW		
(Treasury + Short-term financial investments + debtors)/Current Liabilities	VL1	-
Current Assets/Current Liabilities	VL2	-
EBIT/Current Liabilities	VL3	-
EBITDA/Current Liabilities	VL4	-
Working Capital/Total Assets	VL5	-
(Free cash flow + financial expenses)/Total Liabilities	VC1	-
(Free cash flow + dividends)/Total Liabilities	VC2	-
Cash-flow operating/Total Liabilities	VC3	-
PROFITABILITY		
Net Profit/Income	VR1	-
Net Profit/Net Equity (ROE)	VR2	-
Net Profit/Total Assets (ROA)	VR3	-
EBIT/Total Assets	VR4	-
Gross profit margin	VR5	-
SOLVENCY		
Long-term debts/Total Assets	VS1	+
EBIT/Financial expenses	VS2	-
EBIT/Total Liabilities	VS3	-
EBITDA/Total Liabilities	VS4	-
Net Equity/Non-Current Liabilities	VS5	-
Total Assets/Net Equity	VS6	-
Total Liabilities/Net Equity	VS7	+
Total Liabilities/Total Assets	VS8	+
NON-FINANCIAL		
Age (Log)	VN1	-
Belonging to chain	VN2	-
Quality (Quality Certificate 'Q')	VN3	-

Regarding non-financial variables, we have considered the age of the restaurant (VN1), which is calculated by applying a logarithm to age. The variable of belonging to a chain (VN2) is a dummy variable, in which it is denoted with 1 if the restaurant belongs to a chain and 0 otherwise. Finally, the variable of quality (VN3) is also a dummy variable in which it is denoted with 1 if the restaurant holds the quality certificate 'Q' and 0 otherwise. This quality certificate is granted by the Institute for Spanish Tourist Quality of Spanish Ministry of Industry. Establishments endorsed by the "Quality Q" have passed strict audits that ensure that their service provision is a guarantee of quality, safety, and professionalism. All of this is to ensure customers the best possible tourist experience.

5. Results and Discussion

5.1. Exploratory Analysis

The exploratory analysis proposed in this study includes a descriptive analysis of the variables, which is presented in a differentiated way for the solvent and insolvent companies of each of the three samples, in order to compare the parameters obtained, depending on whether the companies are solvent or insolvent (Tables 3–5). Observing the means obtained for each of the variables, differentiating the solvent companies from the insolvent companies, it is deduced that in the M.I sample, 62.5% of the selected variables have a different signed average, depending on whether they are solvent companies or of the insolvent companies and that among them would be all the variables considered of profitability and most of the variables classified as liquidity and cash flow, as well as half of the solvency variables. Although it is necessary to highlight that, generally, there are variables that never show a negative sign (such is the case of the variable VE2 representative of Income/Total Assets). When analyzing the means of the M.II sample, it was observed that only 46% of the variables have a different sign depending on whether they are solvent and insolvent companies, this proportion being even lower in the M.III sample, in which so it only occurs in 25% of the variables. These results make us deduce that as we move away from the moment of bankruptcy, the differences between the variables of the solvent and insolvent companies are attenuated, and consequently, it is foreseeable that it will be more complicated to be able to make a prediction of the solvency with greater accuracy.

Table 3. Descriptive statistics; M.I.

		MEAN		MEDIAN		S.D.		MINIMUM		MAXIMUM		M-W TEST	
		Solv	Bankr	Solv	Bankr	Solv	Bankr	Solv	Bankr	Solv	Bankr	M-W	Sig.
SIZE	VZ1	5.54	5.17	5.12	5.06	2.73	2.81	4.12	4.01	6.44	6.22	2.147	0.000
EFFICIENCY	VE1	5.64	6.75	3.89	3.78	5.76	12.94	0.31	0.01	41.15	98.81	1.462	0.000
	VE2	2.06	1.20	1.67	0.87	1.55	1.16	0.15	0.00	6.96	7.65	2.489	0.000
	VE3	17.70	26.21	5.79	4.24	35.51	112.37	0.00	0.00	289.82	1.192.94	1.953	0.017
LIQUIDITY & CASH-FLOW	VC1	0.16	−0.03	0.06	−0.02	1.26	0.35	−1.55	−1.35	15.29	1.87	8.962	0.000
	VC2	0.13	−0.05	0.03	−0.03	1.18	0.34	−1.55	−1.35	14.18	1.87	7.164	0.000
	VC3	0.14	−0.02	0.06	0.02	1.32	0.28	−1.66	−1.12	16.17	0.80	5.452	0.000
	VL1	2.42	0.67	1.12	0.35	3.73	0.90	0.00	0.00	25.97	6.10	4.947	0.024
	VL2	2.29	0.75	1.21	0.44	2.99	0.88	0.00	0.01	24.15	5.21	6.264	0.000
	VL3	0.26	−0.23	0.13	−0.16	0.48	0.49	−1.56	−2.82	3.16	1.66	4.416	0.000
	VL4	0.52	−0.13	0.32	−0.09	0.76	0.51	−0.08	−2.82	5.95	2.00	3.842	0.007
	VL5	0.13	−0.48	0.09	−0.29	0.35	0.91	−0.68	−7.36	0.89	0.69	4.613	0.000
PROFITABILITY	VR1	0.02	−0.56	0.01	−0.15	0.04	1.78	−0.03	−12.17	0.23	1.02	6.345	0.000
	VR2	0.13	−0.41	0.07	0.24	0.26	3.86	−1.35	−28.69	1.72	4.01	4.963	0.000
	VR3	0.03	−0.21	0.02	−0.11	0.04	0.33	−0.07	−2.02	0.23	0.36	8.162	0.000
	VR4	0.05	−0.20	0.04	−0.10	0.06	0.36	−0.09	−2.69	0.30	0.51	6.492	0.000
	VR5	0.04	−0.47	0.03	−0.12	0.05	1.55	−0.04	−11.92	0.32	1.65	3.169	0.000
SOLVENCY	VS1	0.25	0.46	0.17	0.39	0.26	0.39	0.00	0.00	0.85	2.11	2.345	0.000
	VS2	14.34	−11.36	2.27	−3.02	51.84	33.21	−5.23	−316.36	554.97	51.14	9.165	0.028
	VS3	0.15	−0.12	0.07	−0.09	0.30	0.20	−0.10	−0.91	2.71	0.82	10.756	0.000
	VS4	0.26	−0.07	0.15	−0.05	0.35	0.21	−0.08	−0.91	2.78	0.99	2.627	0.000
	VS5	2.62	−0.07	0.36	0.00	7.12	3.26	0.00	−19.73	63.83	15.23	3.489	0.000
	VS6	6.26	2.93	2.88	−0.56	7.95	28.38	1.07	−143.01	45.32	187.76	6.538	0.000
	VS7	5.26	1.93	1.88	−1.56	7.95	28.38	0.07	−144.01	44.32	186.76	2.782	0.000
	VS8	0.62	1.29	0.65	1.05	0.27	0.91	0.06	0.30	0.98	8.36	2.396	0.000

Note: M-W: Mann-Whitney test; S.D.: Standard Deviation.

Table 4. Descriptive statistics; M.II.

		MEAN		MEDIAN		S.D.		MINIMUM		MAXIMUM		M-W TEST	
		Solv	Bankr	Solv	Bankr	Solv	Bankr	Solv	Bankr	Solv	Bankr	M-W	Sig.
SIZE	VZ1	5.47	5.23	5.14	5.02	2.79	2.86	4.08	4.02	6.41	6.25	2.238	0.000
EFFICIENCY	VE1	5.10	4.95	3.86	3.18	4.31	5.71	0.31	0.00	24.19	33.88	2.418	0.000
	VE2	2.02	1.21	1.64	0.88	1.53	1.11	0.15	0.00	6.96	6.39	3.942	0.000
	VE3	17.04	14.10	4.60	4.56	36.32	24.67	0.00	0.00	289.82	140.23	3.675	0.011
	VC1	0.17	−0.04	0.06	0.00	1.32	0.34	−1.55	−1.12	15.29	1.66	1.762	0.000
	VC2	0.14	−0.07	0.03	−0.02	1.23	0.34	−1.55	−1.16	14.18	1.61	2.895	0.000
	VC3	0.15	0.06	0.06	0.05	1.39	0.27	−1.66	−0.83	16.17	1.62	8.346	0.000
LIQUIDITY & CASH-FLOW	VL1	2.07	0.72	1.19	0.47	2.52	0.71	0.00	0.01	14.18	3.43	2.862	0.000
	VL2	2.02	0.85	1.24	0.58	2.01	0.81	0.00	0.03	10.88	4.20	3.451	0.031
	VL3	0.22	−0.09	0.13	−0.05	0.31	0.27	−0.34	−1.02	1.84	0.66	1.623	0.000
	VL4	0.44	0.02	0.31	0.02	0.44	0.29	−0.03	−0.82	2.28	0.81	7.482	0.000
	VL5	0.13	−0.27	0.09	−0.19	0.33	0.52	−0.63	−2.87	0.89	0.71	5.627	0.000
PROFITABILITY	VR1	0.02	−0.18	0.01	−0.05	0.04	0.34	−0.02	−1.76	0.23	0.37	2.191	0.000
	VR2	0.13	0.22	0.07	0.12	0.20	2.20	−0.22	−17.68	1.11	11.22	3.858	0.000
	VR3	0.03	−0.10	0.02	−0.04	0.04	0.19	−0.06	−0.98	0.18	0.27	2.687	0.000
	VR4	0.05	−0.08	0.04	−0.03	0.05	0.21	−0.06	−1.32	0.26	0.41	1.063	0.000
	VR5	0.04	−0.13	0.03	−0.02	0.05	0.34	−0.02	−1.66	0.32	0.83	0.415	0.000
SOLVENCY	VS1	0.25	0.44	0.17	0.44	0.26	0.33	0.00	0.00	0.85	1.53	1.408	0.000
	VS2	10.12	−2.40	2.25	−1.06	26.71	14.45	−5.23	−84.70	250.60	91.70	0.958	0.000
	VS3	0.13	−0.05	0.06	−0.02	0.22	0.15	−0.08	−0.71	1.84	0.42	0.419	0.027
	VS4	0.25	0.00	0.15	0.01	0.30	0.15	−0.03	−0.69	2.28	0.45	1.941	0.000
	VS5	2.83	0.12	0.35	0.00	7.45	5.91	0.00	−57.23	63.83	32.05	8.196	0.000
	VS6	6.02	8.13	2.83	2.13	7.38	36.00	1.07	−144.24	45.32	176.21	3.114	0.000
	VS7	5.02	7.13	1.83	1.13	7.38	36.00	0.07	−145.24	44.32	175.21	2.562	0.000
	VS8	0.62	1.07	0.65	0.98	0.27	0.51	0.06	0.29	0.98	4.97	2.972	0.000

Note: M-W: Mann-Whitney test; S.D.: Standard Deviation.

Table 5. Descriptive statistics; M.III.

		MEAN		MEDIAN		S.D.		MINIMUM		MAXIMUM		M-W TEST	
		Solv	Bankr	Solv	Bankr	Solv	Bankr	Solv	Bankr	Solv	Bankr	M-W	Sig.
SIZE	VZ1	5.44	5.29	5.17	5.01	2.84	2.92	4	3.98	6.38	6.27	2.342	0.000
EFFICIENCY	VE1	5.58	5.03	3.92	3.56	5.31	4.97	0.58	0.00	35.92	25.15	2.082	0.000
	VE2	1.86	1.42	1.58	1.14	1.37	1.13	0.15	0.00	6.47	5.43	0.544	0.000
	VE3	17.64	14.78	5.70	4.76	37.31	23.14	0.00	0.00	289.82	120.84	1.592	0.019
	VC1	0.21	0.00	0.07	0.01	1.46	0.58	−1.55	−1.57	15.29	4.74	2.194	0.000
	VC2	0.18	−0.03	0.06	−0.03	1.36	0.58	−1.55	−1.60	14.18	4.74	3.497	0.000
	VC3	0.16	0.08	0.05	0.07	1.53	0.31	−1.66	−1.41	16.17	1.23	3.965	0.000
LIQUIDITY & CASH-FLOW	VL1	1.71	0.80	1.02	0.63	1.82	0.72	0.00	0.01	9.66	4.11	2.195	0.000
	VL2	1.76	0.88	1.10	0.66	1.70	0.75	0.00	0.06	7.89	3.97	3.379	0.000
	VL3	0.20	0.00	0.13	0.01	0.24	0.27	−0.05	−0.95	1.39	0.86	2.104	0.034
	VL4	0.44	0.13	0.32	0.06	0.41	0.30	−0.03	−0.55	2.23	1.22	2.324	0.000
	VL5	0.08	−0.20	0.06	−0.12	0.30	0.43	−0.63	−1.53	0.81	0.69	1.069	0.009
PROFITABILITY	VR1	0.02	−0.09	0.01	0.00	0.04	0.30	−0.02	−2.29	0.23	0.20	1.314	0.000
	VR2	0.13	0.16	0.06	0.17	0.18	1.48	−0.03	−9.54	1.04	6.20	2.415	0.000
	VR3	0.03	−0.05	0.02	−0.01	0.04	0.14	−0.02	−0.54	0.18	0.31	1.263	0.000
	VR4	0.05	−0.02	0.04	0.00	0.05	0.16	−0.02	−0.50	0.26	0.47	2.457	0.000
	VR5	0.04	−0.06	0.03	0.00	0.05	0.31	−0.02	−2.09	0.32	1.00	2.364	0.000
SOLVENCY	VS1	0.25	0.39	0.18	0.33	0.25	0.30	0.00	0.00	0.85	1.21	1.606	0.000
	VS2	11.42	1.24	2.30	0.00	29.29	16.14	−5.23	−41.39	250.60	92.06	4.175	0.000
	VS3	0.12	0.01	0.06	0.00	0.17	0.18	−0.05	−0.43	0.99	0.68	6.318	0.000
	VS4	0.24	0.07	0.15	0.05	0.25	0.19	−0.03	−0.34	1.11	0.79	4.562	0.022
	VS5	3.37	0.79	0.60	0.08	8.18	4.50	0.00	−18.70	63.83	30.97	6.584	0.000
	VS6	5.39	9.24	2.69	3.52	5.50	25.08	1.08	−77.81	30.27	107.85	1.126	0.000
	VS7	4.39	8.24	1.69	2.52	5.50	25.08	0.08	−78.81	29.27	106.85	3.177	0.000
	VS8	0.62	0.98	0.63	0.94	0.26	0.37	0.07	0.17	0.97	2.42	1.941	0.000

Note: M-W: Mann-Whitney test; S.D.: Standard Deviation.

With respect to the Mann-Whitney test, it was analysed if two populations are independent of each other, where the null hypothesis is to check if the two populations are distributed in the same way. If the null hypothesis is not accepted, this would imply a central displacement of one of the distributions with respect to the other, which I would suggest a difference in the shape of dispersion of a population with respect to the other [40]. This test would be analogous to the t-test used in the tests parametric. In this study, most variables reject the null hypothesis at a level of significance of 5%. Therefore, given the high percentage of significance of almost all the variables, it seems possible to obtain adequate prediction models, since they are a priori variables that are appropriate to assess insolvency.

Although this descriptive analysis has shown evidence of which variables may be relevant in the bankruptcy study, it is not yet possible to conclude whether these variables are really significant, while this first analysis would be insufficient to assess whether the differences presented are precisely because of their significance or because of their own variability that the economic variables present. This leads to the need for a confirmatory analysis to assess the significance of such variables in the bankruptcy analysis.

5.2. Confirmatory Analysis

In this section, a confirmatory analysis of the results obtained in the exploratory analysis will be carried out. In this sense, two models will be estimated for each of the selected samples in order to predict 1, 2, and 3 years of bankruptcy. Once the different models have been obtained for each of the three samples, and for the purpose of comparison, a summary of their results is presented below (Tables 6–8).

DRCNN architecture is composed of 24 input nodes, 14 hidden nodes, and 2 output nodes for the model M.I. In the case of the model M.II, the specific architecture is composed of 24 input nodes, 11 hidden nodes, and 2 output nodes. Finally, for the model M.III, the architecture is composed of 24 input nodes, 15 hidden nodes, and 2 output nodes. In all cases, the activation function of the hidden layer used was a hyperbolic tangent, and Softmax was the applied activation function of the output layer.

In conclusion, it is possible to highlight the relevance of the VR3, VR1, and VS8 variables as explanatory variables in the bankruptcy prediction models. The higher the values of the VR3 and VR1 variables, the more solvent the company expects, while the higher the value of the VS8 variable, the more likely it is that the company will be insolvent. In addition, other variables, such as VE2 and VS1, although they have not been so relevant, have been necessary to obtain robust models. Variables VE2 and VS8 have been significant in all estimated LOGIT models. Likewise, the VR3 variable was also significant in more than one model (M.I and M.II), the VS1 and VR1 variables being significant only in the M.II and M.III models, respectively. On the other hand, in DRCNN models, these variables have been significant, but other VZ1 has been significant in two models (M.I and M.II). Other variables appear as explanatory variables in the DRCNN models, such as VN3 and VR4 (in M.I), and VS4 (in M.II).

Comparing the prediction levels of the chosen models (LOGIT and DRCNN), it can be verified that in all cases, the level of DRCNN success is higher than that of LOGIT, both inside and outside the sample (test sample). Likewise, if we compare the level of adjustment measured by the area under the COR curve of each model, it was also found that the adjustment in the case of the DRCNN model would exceed that of LOGIT for M.I and M.II, although it is lower in the case of M.III. The prediction capacity, as we move away from bankruptcy, decreases, and this capacity of the model obtained for M.III is, therefore, lower than that of the other models. This fact would show that the prediction of bankruptcy is more accurate as we approach the time of bankruptcy, while the economic variables used would show more differences between solvent and insolvent companies.

Table 6. Results of the estimated models; M.I.

LOGIT				DRCNN		
VARIABLES	β	Odds Ratio	Sig. (Wald)	VARIABLES	Normalized Importance (%)	Expected Sign
VE2	−0.477	0.628	−0.002	VZ1	47	-
VR3	−13.128	0	0	VE2	62	-
VS8	4.115	61.674	0	VR4	43	-
Constant	−2.954	0.059	0	VS8	71	+
				VN3	39	-
CLASSIFICATION MATRIX						
In-sample (Training)		84.10%		95.00%		
Out-sample (Testing)		80.40%		93.50%		
MODEL SET						
RV coefficient		0		-		
Hosmer-Lemeshow		0.195		-		
−2 log likelihood		218.440		-		
R ² Cox-Snell		0.515		-		
R ² Nagelkerke		0.68		-		
ROC Curve		0.927		0.975		

Table 7. Results of the estimated models; M.II.

LOGIT				DRCNN		
VARIABLES	β	Odds Ratio	Sig. (Wald)	VARIABLES	Normalized Importance (%)	Expected Sign
VE2	−0.378	0.681	−0.007	VZ1	38	-
VR3	−17.077	0	0	VE2	77	-
VS1	−1.731	0.172	−0.022	VR3	52	-
VS8	4.786	119.814	0	VS1	63	+
Constant	−2.694	0.066	0	VS4	45	-
CLASSIFICATION MATRIX						
In-sample (Training)		81.00%		92.70%		
Out-sample (Testing)		78.60%		89.60%		
MODEL SET						
RV coefficient		0		-		
Hosmer-Lemeshow		−0.063		-		
−2 log likelihood		226.372		-		
R ² Cox-Snell		0.445		-		
R ² Nagelkerke		0.572		-		
ROC Curve		0.895		0.967		

Table 8. Results of the estimated models; M.III.

LOGIT				DRCNN		
VARIABLES	β	Odds Ratio	Sig. (Wald)	VARIABLES	Normalized Importance (%)	Expected Sign
VE2	−0.245	0.781	−0.073	VE2	83	-
VR1	−6.492	0.002	−0.025	VR1	74	-
VS8	3.834	463.432	0	VR4	52	-
Constant	−2.658	0.072	0	VS1	34	+
				VS8	41	+
CLASSIFICATION MATRIX						
In-sample (Training)		71.30%		88.80%		
Out-sample (Testing)		74.20%		85.60%		
MODEL SET						
RV coefficient		0		-		
Hosmer-Lemeshow		−0.238		-		
−2 log likelihood		224.285		-		
R ² Cox-Snell		0.324		-		
R ² Nagelkerke		0.426		-		
ROC Curve		0.829		0.895		

The present study makes prediction models for horizons more than one year prior to the bankruptcy, while the rest of the previous work only considers one year prior to bankruptcy [16,18]. The most relevant significant variable that our models have yielded—Net Profit/Income— was also proven as a meaningful variable in other previous works [16]. However, other meaningful variables shown in our study, such as Net Profit/Total Assets and Total Liabilities/Total Assets, are different from the most significant variables shown by previous bankruptcy literature for restaurants, such as the proportion of debt over equity, equity growth, income margin, or EBITDA over total liabilities [13,16,18].

5.3. Discussion

This paper analyzed the causes that can lead to bankruptcy for a company in the restaurant sector, trying to determine a set of financial and non-financial variables that explain sufficiently in advance that a company in the sector is in danger of bankruptcy and provide tools for managers to avoid this situation. Initially, the most significant antecedents in the generic bankruptcy literature were analyzed, as well as works related exclusively to bankruptcy prediction in companies in the tourism sector in general, as well as insolvency prediction research focused exclusively on the restaurant sector.

The results obtained in our work indicate a high predictive capacity, mainly in the M. III model, in the same sense indicated by Youn and Gu (2010) and Park and Hancer (2012), who obtained NN models with a high level of prediction, although these last authors found that, although the NN models predict well, they do not provide a better prediction than LOGIT, especially in the external sample.

Regarding the best predictors of bankruptcy in restaurants, our study suggests variables related to liquidity, solvency, and profitability. In this sense, Kim (2018), in her study on the hospitality sector for the USA, partially coincides. Specifically, this author points out the debt/capital ratio like our indicator VS7 Liabilities/Net Equity. There is also agreement with this author regarding the high predictive capacity of the Net Profit Margin indicator similar in predictive capacity to VR1, used in our study. The importance of VR1 was also considered in other studies such as that of Kim and Gu (2006) and Kim and Upneja (2014).

Non-financial variables considered in our study as VN3, related to quality and significant in some of our models (M.I), were not considered in the previous literature.

Our models confirm that the prediction of bankruptcy is more accurate when we approach the moment in which it occurs in the same sense as that contributed by Kim and Gu (2006).

Finally, the relationship between the country of origin and the significant variables in bankruptcy prediction observed in previous studies (Kovacova et al., 2019) is confirmed by our study when different variables were found than in other studies for the same sector but a different country.

6. Conclusions

The objective of this paper is to develop bankruptcy prediction models for companies in the restaurant industry. For this, a sample of 460 companies with activity developed in Spain was used, from which financial and non-financial information was obtained. Subsequently, statistical and computational techniques were applied, which showed robust results.

The results obtained indicate that the best predictors of bankruptcy are the variables related to liquidity, profitability, and solvency. In addition, other non-financial variables, such as quality, are significant in predicting the bankruptcy of results. The results also suggest that the DRCNN computational technique shows a high level of classification, with an accuracy of 93.50% for one year before bankruptcy, 89.60% for two years prior, and 85.60% for three years prior to bankruptcy.

The main limitation of our research is that we did not had access to internal information from the companies studied, which would have allowed us to have qualitative information that could have been significant, such as business model, level of market presence, CEO financial education, or corporate social responsibility policies.

As a future line of research, it would be interesting to analyze whether the conclusions obtained in this work can apply to the three types of differentiated activities within the sector: restaurants,

restaurant services, and beverage establishments, that is, to check the results of the complete sample with the results obtained by analyzing each of these activities in detail. Likewise, it is also proposed as a future line of research to analyze this economic sector in different European countries and compare the results obtained between the different countries, to analyse if the conclusions obtained would be generalizable or not.

In this way, it could also be verified whether the conclusions obtained by the previous studies and that have focused on samples of American companies may or may not be extrapolated to these countries, or as they have occurred in the present work with the sample of Spanish companies, it is verified that the conclusions obtained in American companies would not be extrapolated for the rest of the European countries.

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