The survival of businesses: a new approach using a mix of explainable AI techniques to predict bankruptcy and financial distress

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Abstract

In today's highly dynamic and hypercompetitive markets, firms do not have any more buffer of inefficiency allowed, and wrong decisions can silently compromise corporate equilibrium undermining survivorship! Since Altman's 1968 contribution, researchers have been striving for decades to implement new models and techniques for predicting corporate crisis, but no superior model has emerged among the others. In this context, our work joins the stream of research that leverages Artificial Intelligence for corporate default prediction with a novel approach based on a mix of techniques, enabling to achieve a higher accuracy in anticipating crises compared to all previous contributions. We investigated models with sequence lengths that were both fixed and variable and we chose a variable sequence length model that boasted an Accuracy of 0.85 and a ROC-AUC score of 0.927, which is the most optimal predictor, superior to existing tools of bankruptcy prediction. Our results provide significant implications as they offer a noteworthy instrument for preventing business crisis. Moreover, it opens the possibility of introducing non-financial variables to maximize the potential of this model, further enhancing the accuracy in forecasting.

Keywords: Bankruptcy Prediction, Corporate Failure, Generative Artificial Intelligence, Financial Distress, Business Crisis.

1. Introduction

The topic of predicting corporate crises is very hot nowadays. The statistics revealing the number of businesses that cease to exist every year worldwide, especially startups, as well as the average lifespan of companies, are impressive (Fuertes-Callén et al., 2022). Over the past decades, millions of companies have filed for bankruptcy[1] with detrimental consequences on society and the economy as a whole (Carruthers, 2015). Many papers investigated the financial and non-financial causes of failure, as it represents a multidimensional phenomenon (Ooghe &

De Sofie, 2008), while others focused the attention on the process that brings firms to bankruptcy (Levratto, 2013). Bankruptcy has a negative impacts on firm, but also on personal life of entrepreneurs (Kliestik et al., 2018) and employees (Ellul & Pagano, 2019; Graham et al., 2023), on the efficiency of the supply chain (Yang et al., 2015), and on the society (Bower & Gilson, 2003), and the global economy (Tung, 2005).Thus, bankruptcy prediction represents a highly significant corporate activity with a growing awareness among businesses[2]. No firm can reduce the risk of bankruptcy to zero, but efforts can be made to minimize it as much as possible. Firms need to manage very well the crisis risk and choose the best model of bankruptcy prediction to discern the nature of the decisions and anticipate any negative consequences of crises.

In this context, the research community contributed on predicting business crises and several models and techniques have been developed for this purpose. Academics paid attention to this topic since the 1960s and some models for predicting corporate crises stand as milestones in this field of research (Altman, 1968; Deakin, 1972; Ohlson, 1980; Zmijweski, 1984). In particular, the noteworthy contribution of Altman (1968) laid the groundwork and has been an inspiration for numerous subsequent research on the topic. Following Altman, over the time researchers and practitioners have developed crisis prediction methods and techniques that go beyond the traditional mathematical and statistical models, with the purpose of predicting the bankruptcy of firms quickly and more accurately (Barboza et al., 2017). In addition to traditional methods, since the 1990s, machine learning models, such as decision trees, neural networks, and Support Vector Machine, have been extensively applied in this field of research as tools to predict the bankruptcy of firms (Lin et al., 2012). Recently, deep learning has emerged and gradually developed into a powerful technique for a wide range of applications, and in bankruptcy prediction. Indeed, a neural network can learn from data automatically, so it can be trained to recognize patterns, classify data, and forecast future events (Atiya, 2001; Charalambous et al., 2023; du Jardin, 2023; Dube et al., 2023; Jabeur et al., 2020; Kim et al., 2022; Mai et al., 2019; Tsai & Wu, 2008). A particular Neural Network architecture, called Recurrent Neural Network (RNN), can process information with a temporal dimension in the form of time series. Such RNNs can identify data patterns that evolve, by considering a set of features measured at subsequent time steps (Kim et al., 2022). Some authors used the machine learning algorithm to predict the bankruptcy (Barboza et al., 2017; Nanni & Lumini, 2009; Shin et al., 2005), and more in general, there is a very huge literature investigating bankruptcy prediction using Artificial Intelligence (AI) techniques (Bell, 1997; Charitou et al., 2004; Heo & Yang, 2014; Hosaka, 2019; Huang et al., 2004; Jackson & Wood, 2013; Jang et al., 2019; Kim et al., 2022; Lin et al., 2012; Mai et al., 2019; Narvekar & Guha, 2021; Perboli & Arabnezhad, 2021; Shin et al., 2005; Tsai & Wu, 2008; Zhao et al., 2015).

All these approaches demonstrated that bankruptcy prediction models based on AI techniques outperform classic mathematical and statistical models, even considering different industries, and both in cross-country and single-country studies.

The importance of these models based on computational solutions is additionally demonstrated by the fact that since their first use in this area of investigation, researchers have never stopped developing new and more accurate ones. In a context where many models of bankruptcy forecasting have been developed (Lundberg & Lee, 2017) we questioned what drove researchers in this ongoing pursuit, reaching a point where, to date, it is difficult to find a universally accepted and standard model to prevent corporate crisis. Certainly, one of the reasons is linked to the fact that previous models utilizing this research approach employ various AI techniques, each of which naturally yields different results. Furthermore, prior works have certain limitations, such as using short-term temporal sequences or a limited number of observations.

Within this strand of research, our innovative work employs a mix of explainable AI techniques, focusing particularly on the most recent and advanced ones applied in the last two years. This is because artificial intelligence techniques used in practice are evolving at an impressive pace, for which the development of a very accurate corporate crisis prediction model compared to previous ones should be grounded on cutting-edge techniques. Moreover, as the accuracy of a model depends on the length of the time series, sample size, and quality of input data, this work stands out by utilising a large sample (4,172,046 observations) over a broad time span (from 2012 to 2021) sourced from the Orbis database by Bureau Van Dijk. Orbis, which is a Moody's analytics company, represents the most extensive database of financial and business information across Europe, as it contains detailed and well-harmonised accounting, financial and business information for firms. Moreover, it is the world's most powerful comparable data resource on private companies[3].

Our sample also consists of small and medium sized enterprises (SMEs). This is important because SMEs have a key role in economic growth as they represent 99% of businesses in Europe[4]. Hence, their bankruptcy prediction could be very relevant both for local and global economies. Additionally, SMEs are businesses that are particularly affected by asymmetric information problems within financial markets (Fasano & La Rocca, 2023), hence suffering more during difficult periods such as the recent COVID-19 crisis (La Rocca et al., 2022). The coronavirus emergency amplified the attention of the media and business community to the precarious situation for businesses, highlighting once more the negative consequences of the financial crisis.

Our findings demonstrate that the artificial techniques implemented lead to greater accuracy in predicting business crises compared to all previous research efforts, even those utilizing long time sequences or a high volume of observations. Furthermore, our results highlight the key variables that need monitoring to prevent business crises. Finally, with this contribution, we aim to open a new avenue of research that, starting from the use of these techniques, can implement models incorporating non-accounting variables such as governance, ESG, and information from companies' social media to prevent business crises.

The paper is structured as follows: the second paragraph presents the theoretical framework and research gap, while the third paragraph outlines the materials and methods used. The fourth paragraph provides results with a focus on explainability in the fifth paragraph. The sixth paragraph offers conclusions, discussions, and the managerial contribution of the work.

2. Theoretical framework and research gap

Bankruptcy prediction in the business community is a field of growing interest, particularly since the financial scandals at the beginning of the 2000 and even more the global financial crisis of 2008, after which the number of studies on the topic has greatly increased becoming a significant area of study within the field of management and corporate finance (Shi & Li, 2019). However, investigations into predicting corporate crises date back a long time. Indeed, a significant amount of research has focused on the prediction of corporate financial distress since Altman's influential introduction of his bankruptcy prediction model in 1968[5]. Altman found that predicting bankruptcy can be done by using discriminant analysis and liquidity, profitability, productivity, leverage, and asset turnover ratios to establish the so-called Z-score. The Z-score, is calculated using five financial ratios assessing a company's liquidity, profitability, efficiency, solvency, and turnover, thereby providing a comprehensive view of its financial health. A higher Z-score indicates better financial strength and stability, while a lower score suggests higher bankruptcy risk. Altman pioneered a field of studies that aim to describe the financial variables that lead to the default of companies during different years. After Altman, other models have been particularly influential. Ohlson (1980) for instance investigated the bankruptcy prediction for American firm from 1970 to 1976 using the logistic regression model and nine financial ratios (Ohlson, 1980). Begley et al. (1996) investigated the bankruptcy in three of the major stock markets in the U.S. (NYSE, AMEX, and NASDAQ), observing that the Altman model performed better than the Ohlson model for data from 1980 to 1989 (Begley et al., 1996). Some other papers went beyond the use of financial variables. Hu and Sathye (2015) for instance observed financial distress in the Hong Kong Growth Enterprise Market from 2000–2010 and found that a logistic model that used financial, non-financial, and macroeconomic variables over-performed the other models (Hu & Sathye, 2015). Liang et al. (2016) used the combination of financial ratios and corporate governance indicators for bankruptcy prediction, finding that combining such rations rand indicators is more efficient than using only financial data (Liang et al., 2016).

The main techniques employed following the seminal contribution of Altman and the subsequent influential contribution mainly aim to distinguish firms into bankrupt or non-bankrupt and include multivariate discriminant analysis, logit, probit, and neural networks (Bellovary et al., 2007). However, analysis of the most recent literature on anticipating business failure reveals a wide array of models employed that extend far beyond the ones observed by the review of Bellovary. This diversity stems from advancements in statistical techniques and information technology over time that have tried to establish more accurate bankruptcy prediction models compared to earlier ones.

In particular, information technology-based techniques have been developed since the 1990s, after which neural networks have been the most widely used methods to predict corporate crisis. Obviously, in the initial stages of using this technology, the adopted models were less complex than the more recent ones. Indeed, in the 1990s, some artificial intelligence models were developed (Tam & Kiang, 1992; Wilson & Sharda, 1994), followed by subsequent models in the succeeding decade. For instance, in the twenties Atiya (2001) shows that neural network (NN) models performed well in the predicting of bankruptcy prediction for Credit Risk. Shin et al. (2005) investigated bankruptcy prediction in Korea by using support vector machines (SVM) and back-propagation neural network (BPN). They found that the SVM performed better than BPN when the training set size got smaller. Tsai and Wu (2008), in another study, shows that single neural networks perform better than multiple neural networks. Nanni and Lumini (2009), in their paper, reported that the machine learning models outperformed the traditional statistical analysis methods in predicting bankruptcy in three credit markets (Australian, German, and Japanese). In the following decade, there was an increase of studies on the prediction of corporate crises, particularly considering that the negative effects on businesses caused by the global financial crisis exacerbated and underscored the gravity of this phenomenon. Barboza et al. (2017) shows that machine learning models have a higher capacity for predicting Bankruptcy compared to ANN, LR, and MDA models for data from 1985-2013. Also Mai et al., (2019) used machine learning models with non-financial variables to predict bankruptcy (Mai et al., 2019). Jabeur et al. (2020) studied Bankruptcy prediction of French companies from 2014-2016 using fuzzy convolutional neural networks (FCNN). They concluded that FCNN performs better than neural networks, logistic regression, partial least square discriminant analysis, support vector machines, or discriminant analysis.

As a matter of fact, the use of Artificial Intelligence provided a higher explanatory power in crisis prediction in comparison to deterministic model based on financial rations. A fight for the best technology-based approach started. The vast amount of research has led in recent years to the utilization of highly advanced artificial intelligence techniques to predict corporate crises, leading up to the models characterizing this research trend in the last two years. In a recent study, Kim et al. (2022) used textual sentiment analysis (BERT) to predict bankruptcy. They found that BERT-based analysis performed better than dictionary-based analysis and Word2Vec-based analysis combined with a convolutional neural network for data from 1995-2020. Yang et al. (2023) shows that the HDNN algorithm was a good solution for higher dimensional corporate credit risk during the entire sample period (from 1 January 2009 to 31 December 2019). Chen et al. (2023) investigated the corporate bankruptcy prediction of U.S firms in the period from 1994 to 2018, by including the text-based communicative value of annual reports in four machine learning models. They reported improvements in the performance of XGBoost and Random Forest models. They confirmed the importance of annual report text-based for bank's corporate loan underwriting decisions. Charalambous et al. (2023) observed the U.S. public firms for data from 1990–2015 and found that structural models, like the Black-Scholes-Merton and the Down-and-Out option models, perform better than a standard neural network. They reported that the neuro-structural model performed better than a sample neural network. Dube et al. (2023) used Artificial Neural Networks (ANN) to investigate the financial distress models on the Johannesburg Stock Exchange (JSE) between 2000–2019. They found that ANN had good accuracy, and predicted financial distress for up to five years for the financial services and manufacturing companies. Kim et al. (2022) found that from January 2007 to December 2019, the recurrent neural network (RNN) and long short-term memory (LSTM) increased the performance of bankruptcy prediction compared to the use of logistic regression, support vector machine, and random forest methods. They concluded that the RNN and LSTM methodologies cannot detect the importance of each explanatory variable for bankruptcy prediction. Elhoseny et al. (2022) in another study found that combining the deep learning and Whale optimization algorithm (AWOA-DL) overperformed the TLBO-DL, DNN, LR, and RBF Network models in predicting bankruptcies and assessing credit risk. du Jardin (2023), in his study, found that the convolutional neural networks CNN performed better at corporate bankruptcy and financial failure compared to the traditional model.

Despite the attention on crisis prediction from both academics and the community in general, no superior model has emerged among the others to forecast corporate crisis. Researchers every year develop models that aim to be more capable to predict corporate failure better than others, but these efforts have not led to the development of a universal model used by all companies nowadays. Veganzones and Severin (2021) highlight that the way researchers design experiments is a crucial factor since it can have a big impact on the outcomes (Veganzones & Severin, 2021). They believe that differences among the key elements (definition of failure, sample approach, prediction methods, variables, evaluation metrics, and performance) of such kinds of analysis are at the core of different outcomes.

Thus, here comes into play the need to develop a model that can encompass as much information as possible to predict corporate crises more accurately than prior contributions. With this in mind, we try to fulfil this research gap by investigating bankruptcy prediction using a mix of explainable artificial intelligence techniques among the most recent and advanced ones. Indeed, we use machine learning and deep learning models at the same time, while other papers use just one technique. In doing so, we pay a lot of attention to variable selection and data characteristics, using the Orbis database provided by Bureau Van Dijk. Moreover, Italian studies on the topic are very few and use a shorter timespan or a lower sample size. The Italian context is a suitable context for this analysis as in Italy there are significant differences among provinces in terms of institutional development. Moreover, our work differs from previous studies by using data about firms that include the Covid-19 period.

Artificial intelligence

Neural networks

Neural Network(NN) is one of the most popular machine learning methods. NN is inspired by the human brain function and structure, by using interconnect nodes called neurons in a layered structure that resembles a graph. In each layer, several neurons use the outputs of all neurons in the previous layer as inputs, such that all neurons interconnect with each other through the different layers. Each neuron typically is assigned a weight that is adjusted during the learning process by a decrease or an increase. A neural network can learn from data so it can be trained to recognize patterns, classify data, and forecast future events. It breaks down the input into layers of abstraction and defines a wide range of models characterized by an extremely high number of parameters, especially in the so-called deep models, which can be based on supervised or unsupervised learning paradigms. In the supervised learning approach, a neural network employs a sample of data consisting of corresponding inputs to outputs. By manipulating input parameters, the neural network finds the best non-linear predictive model that generates output consistent with the sample. This model has generalization properties, which means that it can be used to predict an output when we add a new set of inputs that the model has never seen. This approach is typically used to solve regression and data classification problems. Instead, the unsupervised learning approach provides the computational model with a sample that does not include output information. In this case, it identifies statistical structures within the sample, such as correlations or associations, producing an output that describes such relationships. The unsupervised strategy is typically applied to solve clustering problems and it is a useful tool to assess industry similarities and data analysis in the financial field. There exist different types of Neural Networks.

Recurrent neural networks

A Recurrent Neural Network (RNN) is a neural network that adopts the following principle: it processes sequences by iterating through the sequence elements and maintaining a state containing information relative to what it has seen so far. In effect, an RNN is a type of neural network that has an internal loop. Unlike traditional neural network algorithms which are limited in their ability to handle ordered data, such as time-series data, music, or sentences, RNNs can manage such data by exploiting these loops in their structure.

The state of the RNN is reset between processing two different, independent sequences, so you still consider one sequence a single data point: a single input to the network. What

changes is that this data point is no longer processed in a single step; rather, the network internally loops over sequence elements. There exist different ways to implement a Recurrent Neural Network. The simplest one is SimpleRNN, but in practice, it's never used because it suffers from the vanishing gradient problem, as you keep adding layers to a network, the network will struggle to remember information seen many timesteps before, so long-term dependencies are impossible to learn. The LSTM and GRU layers are designed to solve this problem. Indeed, they work similarly: they save information for later, thus preventing older signals from gradually vanishing during processing.

SHapley additive explanation

We employed SHAP to elucidate the interpretability of neural network models. SHAP values, derived from cooperative game theory, were used to quantify the contribution of individual features to the model's predictions. By calculating Shapley values for each input feature, we discerned their impact on the neural network's output, thereby enhancing the interpretability of complex model decisions. This approach facilitated a comprehensive understanding of the neural network's behavior, offering insights into the relative importance of features in driving predictions, thereby contributing to the transparency and interpretability of our model.

3. Materials and Methods

Data and variables

The data used in this study was collected from the Orbis European database by Bureau Van Dijk (BVD). We collected annual accounting data from 2012 to 2021. The dataset counts about 4’172’046 Italian firm-year observations, 66,226 of which experienced bankruptcy. In this dataset, each financial index is collected for 10 years from 2012 to 2021. From such a dataset we extracted sequences of annual accounting data for different periods, considering period length from 2 to 9 years. The dataset consists of 24 indexes of financial performance: intangible assets, non-current plant, and equipment, Inventories, Current Assets, Receivables from customers, Cash, and cash equivalents, Total Assets, Equity, Share capital, Long-term indebtedness, Non-current liabilities, Current liabilities, Debts, Payables vs Suppliers, Total value of production, Revenue, sales and services, Operating profit [EBIT], Financial income, Financial charges, Total taxes, Profit/loss for the year [net profit], Inventory Rotation, Cash-out times (days), Payment times (days). In this dataset, we distinguish between two classes: *Class 0* is the set of firms for which bankruptcy occurred (66,226 firms); *Class 1* is, conversely, the set of firms in good health (4,105,820 firms). This dataset is characterized by unbalanced classes, meaning that the number of firms in Class 1 is significantly lower than the number of healthy ones.

Preprocessing

Along with the need for large amounts of data, machine learning models and, in particular, neural networks, need to work with data values distributed in a well-defined range and with data balanced among the classes. For this reason, we first normalized each variable in the range [0, 1] and then re-balanced the classes by generating synthetic data samples (firms). We indeed augmented the Class 0 by using the Synthetic Minority Over-sampling Technique (SMOTE) Bowyer et al. (2011). Thanks to this technique, new synthetic instances are created starting from existing ones that are in the minority class, and small perturbations are added to the new data points.

Experiments and Models

In this section we discuss the development of optimization of an RNN model for predicting bankruptcy. We conducted experiments on 4 RNNs architectures by considering different numbers and types of recurrent layers. We selected the best performing model over these ones in terms of accuracy and subsequently, performed an automated model selection process with Cross-Validation to ensure the robustness and generalization capabilities of the selected model across different data partitions. Finally, we used an Explainable AI method called SHAP (Shapley Additive explanations) to explain the contribution of each financial index to the prediction.

Training and Hyperparameters Optimization
In the development of bankruptcy prediction models, we implemented and evaluated a set of four models, each characterized by a distinct set of hyperparameters. Our dataset comprised 84,000 actual data instances, augmented by 26,000 synthetically generated samples using SMOTE. The dataset was partitioned into training (80%) and test (20%) sets, with the test set being exclusively constituted of real (non-synthetic) samples. All the models shared the following configuration, First, as a loss function we used Binary Cross-Entropy, suited to the binary classification nature of the bankruptcy prediction task. Second, the Metric Accuracy is defined as the proportion of correct predictions out of the total predictions made. Finally, we used Adam as an optimizer.

The architectural details about the used models follow:

Model 1: 2 subsequent Long Short-Term Memory (LSTM) layers of 128 and 64 blocks respectively, followed by 3 fully connected layers of 64,128,64 neurons with dropout.

Model 2: 3 subsequent Conv1D layers of 64 blocks respectively, followed by 3 BatchNormalization of 64 blocks, and finally GlobalAveragePooling1D of 64 blocks.

Model 3: 2 subsequent LSTM layers of 256 and 128 blocks respectively, followed by 2 fully connected layers of 256 and 128 neurons with dropout.

Model 4 : 2 subsequent of Gated Recurrent Units (GRU) of 128, followed by 2 fully connected layers of 128 and 128 neurons with dropout

Model 1 resulted in the best one, with the best accuracy in each test. We trained it several times by varying the input data, exploring models with fixed sequence's length (from length 2 to 9) as well as models with variable sequence's length. To properly evaluate its performance, we used K-fold Cross Validation technique with K=10.

Metrics
In this work, different models were created by varying the input data. As evaluation metrics, we used Accuracy which is the ratio between the number of correct predictions and the total number of observations and ROC-AUC.

4. Results

This section reports the performance of Model 1 in two cases: 1. When the model is trained and tested on fixed sequence's lengths; 2. When the model is trained and tested on sequences of variable lengths.

Fixed Sequence's length models
As the first report, we want to compare results between models in which input data are only data with fixed lengths. It means that each of these models is specialized for input sequences of fixed length, so a model whose input data length is 2 (2012-2013) learns from data with complete information only for 2012 and 2013. For the tests reported in the table 1 we split the sampled dataset as follows: 80% training set, 20% validation set, and 20% test set.

Number of Firms	Input Len	Acc. on test	95% conf. int.	ROC-AUC
15k	2 (2012-2013)	0.800	[0.778, 0.794]	0.880
15k	3 (2012-2014)	0.826	[0.792, 0.816]	0.897
15k	4 (2012-2015)	0.836	[0.799, 0.821]	0.910
15k	5 (2012-2016)	0.862	[0.831, 0.846]	0.926
15k	6 (2012-2017)	0.859	[0.844, 0.853]	0.924
15k	7 (2012-2018)	0.851	[0.823, 0.838]	0.924
15k	8 (2012-2019)	0.850	[0.832, 0.845]	0.924
15k	9 (2012-2020)	0.844	[0.826, 0.841]	0.914

Table 1

The points out an important trend: as the length of the sequence increases (i.e. the information becomes more complete), the network performs better. This difference is more apparent between "low length model" and "high length model". Indeed, the histograms below show the difference between predictions of the length-2 model (Figure 1) and predictions of the length-9 model (Figure 2).

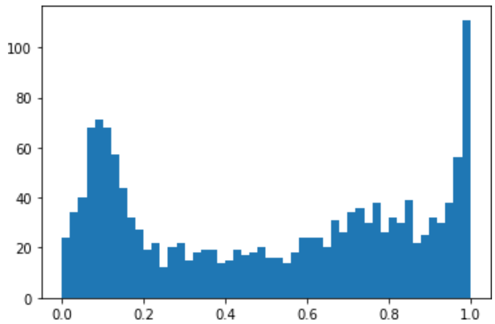

Figure 1

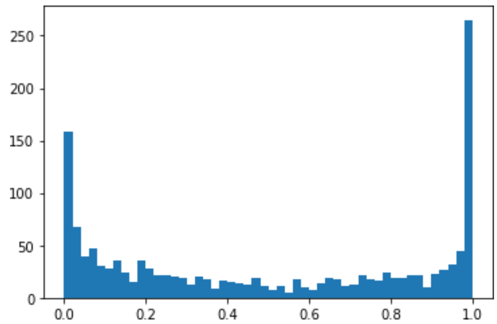

Figure 2

It is possible to notice how the length-9 model (Figure 3) is way too accurate concerning the length-2 one. Another comparison can be made with confusion matrices. A confusion matrix (Figure 4) is a technique for summarizing the performance of a classification algorithm.

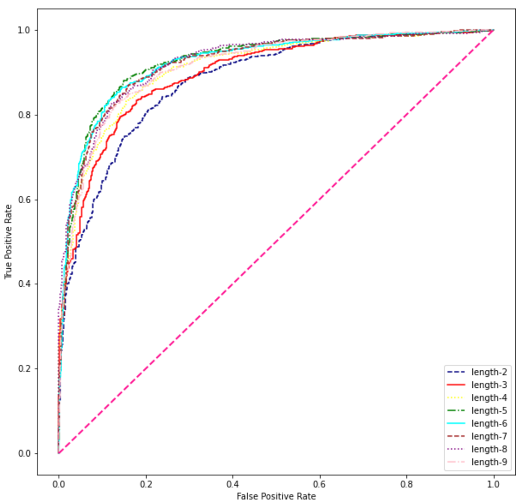

Figure 3

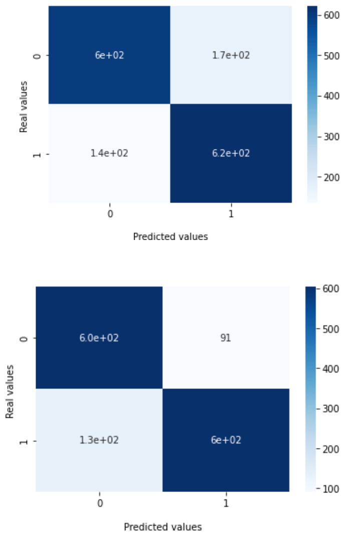

Figure 4

Also here it's possible to conclude that the length-9 model is more accurate because it makes fewer mistakes. We can also compare ROC curves of all models, to remark the difference between models.

The Area Under the Curve (AUC) of the *length-2* model is lower than the other areas. Moreover, for length greater than 5, the difference in terms of ROC-AUC score and Accuracy is minimal.

Variable Sequence's length models

Now we want to compare results between models whose input data are mixed this it means to have more flexible models that can perform with sequences of different lengths. So, each model is no longer specialized for input sequences of fixed length. For the tests reported in the table 2 below we split the sampled dataset as following: 80% training set, 20% validation set and 20% test set.

Number of Firms	**Input Len**	**Acc. on test**	**Loss on test**	**95% conf. int.**	**ROC-AUC**
110k	all length	0.835	0.403	[0.829, 0.832]	0.912
55k	6-7-8-9	0.850	0.349	[0.828, 0.842]	0.927
43k	3-4-5	0.834	0.392	[0.816, 0.828]	0.908
54k	3-5-7-9	0.836	0.415	[0.812, 0.827]	0.910

Table 2

The model that performs better with a considerable difference concerning others is highlighted in green. It is the model that has been trained on sequences with complete information from 2012 to 2017, 2013 to 2018, 2012 to 2019, and 2012 to 2020.

The ROC curves in figure 5(a), show the superior performance of the first model.

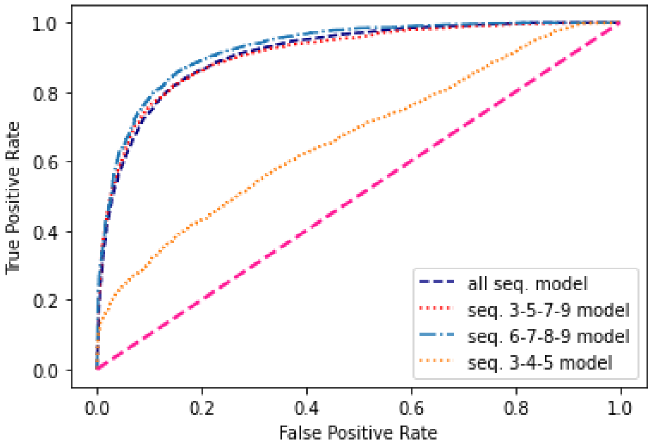

Figure 5 (a)

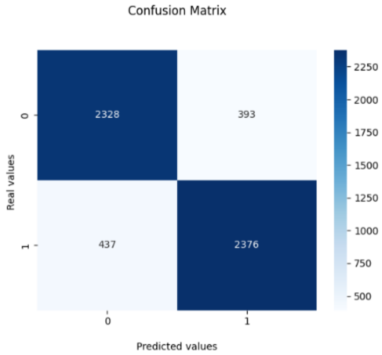

Figure 5 (b)

It's possible to notice how the model trained with sequences of length 3, 4, and 5 is the worse model in this case, and this can be explained by the fact that it's the model with less complete information across all other models, so it's more likely to be wrong with predictions. Figure 5 (b) shows the confusion matrix for the best model in Table 2 (seq. length 6-7-8-9).

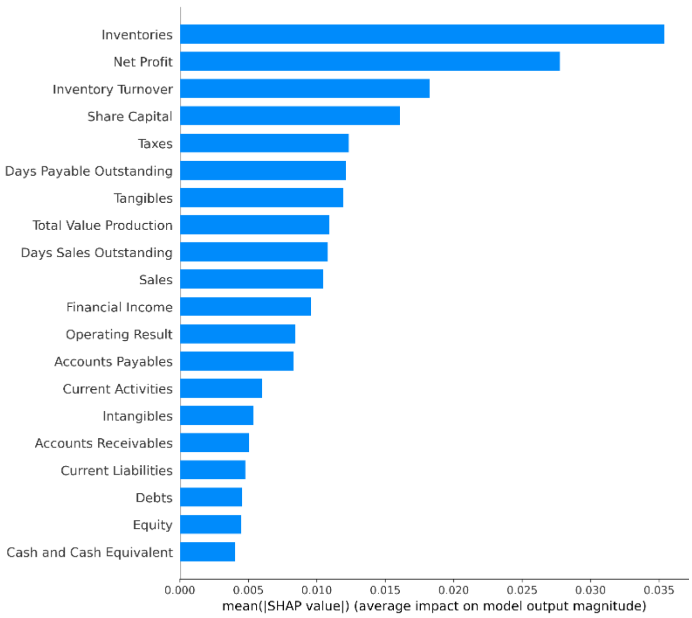

Figure 6: global feature importance

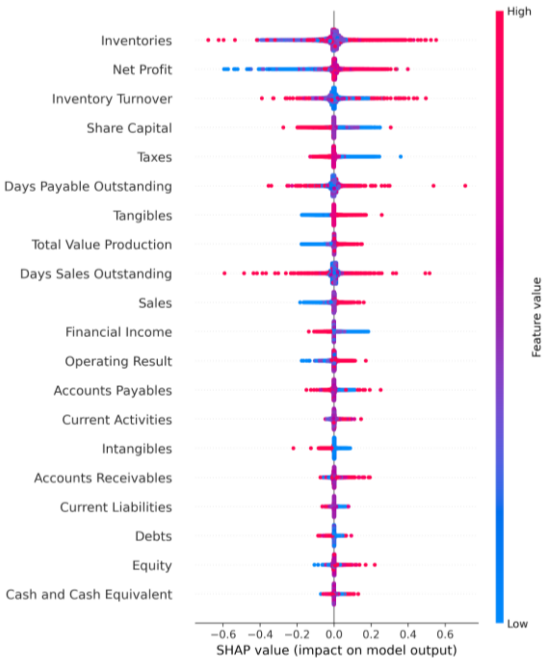

Figure 7: *global summary plot*

5. Explainability

In this section, SHAP results will be reported and interpreted. SHAP has been used to interpret the output of the best model with variable sequence's length. For each SHAP plot in this section, we show the top 20 variables which most affected the prediction of the model.

Global Feature Importance

Figure 6 shows a waterfall plot of absolute mean SHAP values, reporting the average importance of each financial index in the model, and hence the contribution of each one on the predictions, evaluated by using SHAP. Indexes are reported in order of importance. For example, the model was strongly influenced by "Inventories" e "Net Profit", moderately influenced by "Tangibles" and poorly influenced by the others below.

The feature importance plot is useful, but contains no information beyond global importances. For a more informative plot, you can look at the global summary plot, reported in figure 7.

Moreover, as shown in (right), higher values of Utile/Perdita Inventories are associated with positive SHAP values, meaning that they will increase the prediction towards 1 (healthy firms). Moreover, lower values of the variable are associated with negative SHAP values, meaning that they will decrease the prediction towards 0 (bankruptcy). Conversely, for the Taxes lower values are associated with positive SHAP values, increasing the prediction towards the 1. Higher values of the latter index, instead, are associated with negative SHAP values, meaning they will decrease the forecast towards 0, which means bankruptcy.

Summary plot for each time step

We analyzed the impact of variables at each different timestep. As you can notice, each time step has its features rank. Indeed, as we said before, “Inventories” is the most impacting feature at a global level, and this is confirmed by data of time steps 2017-2018 (Figure 8, 9). As you can notice from the time step 7 (Figure 10), the feature “Net Profit” is the most impacting one. This feature indicates the net profit of the company, and its contribution is directly related to the output of the model: it means that as the value of the feature increases, the Firm is pushed towards a status of health. In other words, a company whose net profit assumes a high value tends to be in financial health and vice versa. In time step 8 (Figure 11), instead, the feature “Taxes” occupies the first position. As we said before, it refers to Taxes, and in this case, its contribution is inversely related to the value of the prediction: as the value of the feature increases, the output tends to be negative. In other words, a company with a lot of taxes to pay is more likely to fail. An interesting thing to discuss is that the feature “Taxes”(Taxes) is the most impacting in the last time step(2020) see Figure 10. Indeed in 2020, the first year of the COVID-19 pandemic, the amount of debts (for most companies) drastically increased due to a lack of income and heavier taxes, resulting in a large number of bankruptcies.

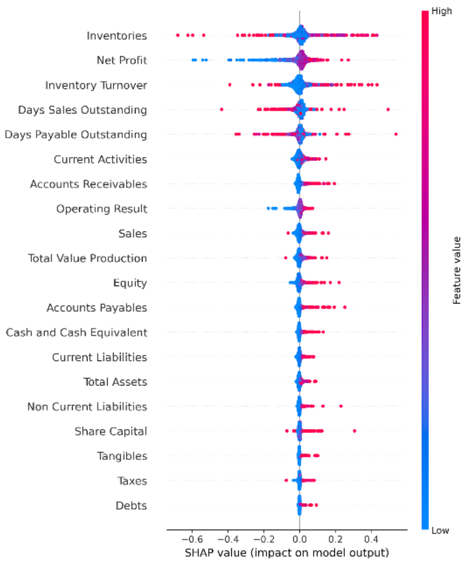

Figure 8: time step 5 (2017)

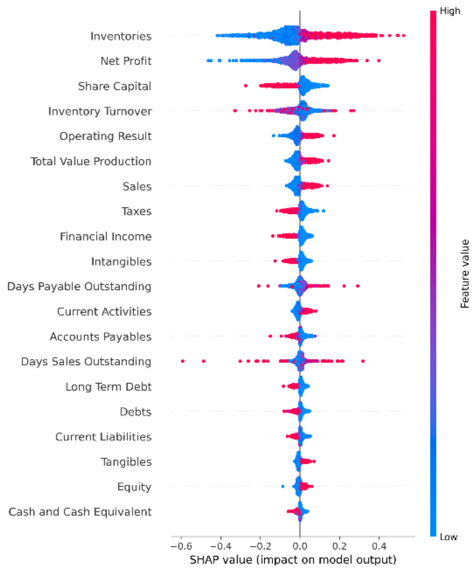

Figure 9: time step 6 (2018)

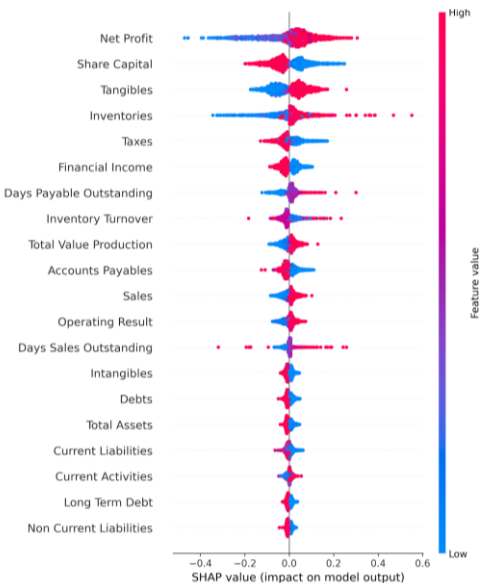

Figure 10: time step 7 (2019)

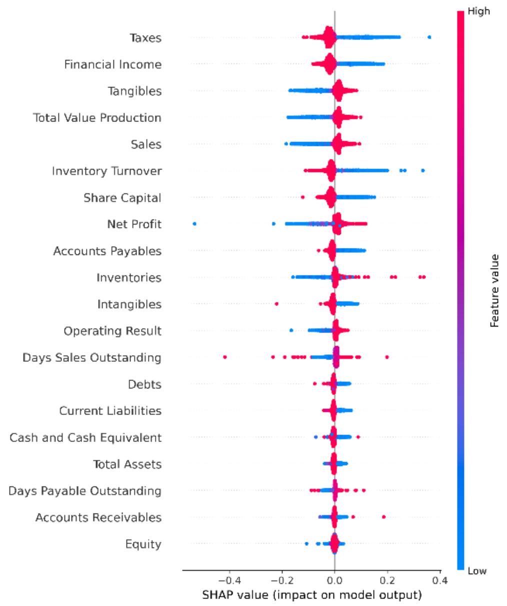

Figure 11: time step 8 (2020)

As you can notice, each time step has its features rank. Indeed, as we said before, “Inventories” is the most impacting feature at a global level, and this is confirmed by data of time steps 5-6 (2017-2018). Different story for time step 7-8(2019-2020), in which other features are more influential. As you can notice from the time step 7 plot (Figure 10), the feature “Net Profit” is the most impacting one. This feature indicates the net profit of the company, and its contribution is directly related to the output of the model: it means that as the value of the feature increases, the contribution becomes positive. In other words, a company whose net profit assumes a high value tends to be in financial health and vice versa. In time step 8, instead, the feature “Taxes” occupies the first position. As we said before, it refers to Taxes, and in this case, its contribution is inversely related to the value of the prediction: as the value of the feature increases, the output tends to be negative. In other words, a company with a lot of taxes to pay is more likely to fail. An interesting thing to discuss is that the feature “Taxes” is the most impacting in the last time step(2020). Indeed in 2020, the first year of the COVID-19 pandemic, the amount of debts (for most companies) drastically increased due to a lack of income and heavier taxes, resulting in a large number of bankruptcies. These results open new research prospects as they suggest investigating business crisis situations before, during, and after the COVID-19 crisis using the techniques we have employed. Surprisingly, in the last two time steps the feature “Inventories” is not even in the top five impacting features. This proves the fact that SHAP is also useful at the local level to understand better what happens time step after time step.

6. Discussion, Managerial contribution, and Conclusions

In this work, we presented a Deep Learning approach to address the Bankruptcy Prediction problem, utilizing Recurrent Neural Networks. Extensive experimentation and literature review on Machine Learning and Deep Learning models underscored the significance of our chosen methodology. Notably, our best model outperformed other architectures, and we explored fixed and variable sequence length models, ultimately selecting a variable sequence length model with an Accuracy of 0.85 and an ROC-AUC score of 0.927 as the optimal predictor. Leveraging the SHapley Additive exPlanations method, we elucidated the impact of each feature on model predictions, enhancing interpretability of the results.

Our findings demonstrate the viability of RNNs in bankruptcy prediction, offering a valuable tool for decision-making in financial contexts. We have identified potentially variables with a higher predictive power so as to prevent corporate financial crisis. The use a of a long time-series also allows to understand how many years before the crisis there are signals of possible financial distress. Concerning potential practical implication, the first important implication of the research is to provide a model/tool that assesses in advance a possible business crisis through a monitoring and alert system. In this way, it is possible to provide indications on the critical business areas and exploit an easy-to-use management support tool. Another important application is for policy-makers, who can use our research's output as a tool to combine with current credit-scoring systems and to assess the effectiveness of the new corporate crisis reform that are upcoming in many European countries. This would favour public and private collaboration. In addition, it would support the current control system on the business crisis, reducing and making the assessments more efficient. In particular, in Italy, such a model would make it possible to improve the "assisted settlement of the crisis", a system introduced in Italy through the Legislative Decree 14/2019. More generally, the model can more effectively support the entire Italian control system, with regard to managers and the Corporate Crisis Settlement Organization (the Italian OCRI). The timeliness of the alerts could even reduce the crisis reports sent to the OCRI, which, occur in the presence of ex-post financial data or events that reveal a status of insolvency. Moreover, our model can be used by the Italian financial institutions to elaborate the existing Indices of Reliability for companies, going beyond the techniques currently. A further social impact of the model is due to its greater simplicity and effectiveness in forecasting the crisis. In fact, through this model it is possible to avoid/mitigate the negative consequences of socio-economic effects from business failure, such as less commitment for the courts on insolvency proceedings, lower unemployment, fewer social consequences for entrepreneurs whose project fails, fewer psycho-emotional reactions and personal traumas that often characterize "failed" entrepreneurs. Therefore, the potential practical/technological applications are considerable and the tool can be available to companies in order to reduce corporate crises with important socio-economic benefits. The tool can be also made available to banks, public entities and consulting firms that interact with companies and are interested in the evaluation of firm's financial health. Our results also provide implications with strong impact on the scientific/technological community at the international level. The output of the research has an important impact on the scientific community as it represents the starting point of new challenges on technological innovation aimed at applying AI techniques to predictive models of business strategies, such as investments, financial decisions, marketing choices and so on. It is possible to start a new a line of scientific and technological research that would lead to the use of AI in various areas of management, exploiting machine learning techniques for applications that guide the entrepreneur not only towards the correct quantitative

choices, but which also provide support for strategic/qualitative decisions, with a consequent strong impact on business activity and economic growth. used.
Future research prospects involve the integration of governance, ESG and social media information into our RNN model which could provide real-time insights, overcoming the limitations of delayed financial reporting and improving predictive accuracy. Utilizing LSTM for processing unstructured text from governance indicators, ESG and social media and news articles holds promise for capturing economic trends, thus enhancing the overall predictive capabilities of neural networks in identifying risky business situations and signalling potential financial distress. This research opens avenues for more accurate and timely bankruptcy prediction methodologies, crucial in today's dynamic economic landscape.

[1] Failure, insolvency, default, and bankruptcy are essentially the four terms used to characterise those unsuccessful businesses (Altman & Hotchkiss, 2011).

[2] For example, the recent Italian reform of Bankruptcy Law by the Business Crisis and Insolvency Code (Legislative Decree # 14 – 12th January 2019), effective since the 15th June 2022, corroborates the attention for this phenomena. This reform is in line with the EU Directive 2019/1023 on Preventive Restructuring Frameworks, on Discharge of Debt and Disqualifications, and on Measures to Increase the Efficiency of Procedures Concerning Restructuring, Insolvency and Discharge of Debt.

[3] https://www.bvdinfo.com/en-gb/

[4] https://single-market-economy.ec.europa.eu/smes/sme-definition_en

[5] Before Altman, Beaver in 1966 was the first to investigate corporate bankruptcy using financial ratios to predict the default (Beaver, 1966)

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