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Artificial Intelligence in Predicting Bankruptcy and Financial Distress

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***ABSTRACT*:**

This study examines the application of Artificial Intelligence (AI) in predicting bankruptcy and financial distress using a mixed-method approach that integrates quantitative modeling with qualitative interpretability. Drawing on firm-level financial data, macroeconomic indicators, and textual disclosures, the research employs logistic regression as a baseline, alongside advanced AI techniques including Random Forest, Gradient Boosting Machines (GBM), Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks. Results demonstrate that ensemble learning and deep learning models significantly outperform traditional approaches in predictive accuracy, F1-score, and area under the ROC curve, while also exhibiting greater robustness against class imbalance through techniques such as SMOTE.Key findings reveal that profitability, leverage, and liquidity remain the most influential predictors of bankruptcy, though AI methods capture nonlinear interactions and temporal dependencies overlooked by conventional models. Sectoral analyses indicate heightened risk in retail and energy industries, aligning with their cyclical sensitivities. Incorporation of Explainable AI (XAI) tools, including SHAP values, enhances interpretability by identifying the marginal contribution of features to model outputs, thereby addressing concerns over regulatory transparency and managerial trust. Complementary qualitative analysis of governance reports and market sentiment further contextualizes predictive outcomes, ensuring a more holistic framework for financial distress forecasting.The study contributes to the literature by validating the superiority of AI-driven hybrid approaches and emphasizing the necessity of interpretability in financial prediction. Practically, the findings highlight the potential of AI to support investors, regulators, and managers in early identification of distress signals, enabling proactive intervention and reducing systemic risks. Overall, the research confirms that AI, when rigorously applied and coupled with explainability, represents a transformative tool for advancing the accuracy, transparency, and utility of bankruptcy prediction in contemporary financial markets.

Keywords: *Artificial Intelligence, Bankruptcy Prediction, Financial Distress, Explainable AI, Machine Learning, Corporate Risk*

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INTRODUCTION

Bankruptcy predicting and financial morbidity is an old matter of interest to corporations, investors, policy makers and financial institutions. The fact that throughout the course of the economic decline, the financial markets around the world are increasingly becoming vulnerable and that the nature of corporate bankruptcy is shifting, only heightens the urgency of the necessity to develop reliable predictive tools that will enable predicting when the company will run out of business already (Altman et al., 2021; Barboza et al., 2020). The classical methods of financial decisions making such as Z-score have provided a medium of forecasting the state of bankruptcy yet they are more inclined to hold that the other financial variables are not linear (Sun and Li, 2021). The paradigm shift is the creation of the advanced techniques that are able to capture the nonlinearities, process large amounts of data, and boost predictability (Zhou et al., 2022; Chen et al., 2023).The AI algorithms and more specifically machine learning and deep learning techniques have been found to possess a huge potential in determining the risks of finances in the sense that they have uncovered some unknown trends that could not be known by the human analysts or the traditional econometric models (Huang and Lin, 2020). Their use of Random Forests, the Gradient Boosting Machines (GBMs), and the Neural Networks are the most common to predict default (Li et al., 2021; Shahrivari et al., 2022). In addition to it, SHAP values and the LIME Explainable AI (XAI) processes are gaining popularity to augment intelligibility of AI predictions in an endeavor to achieve transparency in financial decision making (Lundberg et al., 2020; Ribeiro et al., 2022).

The role of AI in forecasting bankruptcy is not very simple. First, it helps to minimize the risks at the initial stage of the business, that is, the companies can monitor the potential warning signals in their initial stages to minimize the risks before they run out of funds (Gepp et al., 2021). Second, AI can as well be applied to unstructured and alternative data, such as news or social media sentiment and textual analysis of annual reports, and it can complement the traditional financial ratios (Kumar et al., 2021; Batrinca and Treleaven, 2022). Third, the AI-related solutions follow a broader long-term pattern of a digital transformation of the financial sector that has turned robotization and predictive analytics into the core of the strategic planning (Wamba et al., 2021).The literature contains different methodologies and comparative analysis. The support vector machines (SVMs) application has also been applied to identify the high-dimensional financial characteristics (Zhang and Xu, 2020). It is also demonstrated that ensemble methods such as stacking and boosting have been superior to individual classifiers because multiple classifiers can be implemented to minimise errors (Wang et al., 2022). In addition, LSTMs and other deep learning models have been implemented with the time dimension of financial data in mind and could, therefore, be of specific interest in the case of the prediction of bankruptcy when time series data are factored into the framework (Kim et al., 2022). The existing meta-analyses can point to the fact that AI is significantly more accurate than other models in the new emerging markets that are extremely volatile (Tan et al., 2023).

Of interest also, however, have been the development of mixed constructions of quantitative financial ratios and qualitative measures factors, such as the quality of governance, intensity of competition within the industry, and macroeconomics shocks (Feng et al., 2021; Liu and Wang, 2023). The fact that it has to migrate towards mixed-methods approaches where financial statements are complemented by external cues is evidenced by such plans.However, there are problems, which must be addressed. Deep learning models can be described as black-box and this fact brings many uncertainties to the world of trust and regulatory acceptance (Doshi-Velez and Kim, 2021). Moreover, overfitting, disproportional sample (there is fewer bankrupt firms than healthy firms), and general extrapolation across inter-industry and inter-region is also considered a weakness that decreases the credibility of some AI applications (Zhou et al., 2021). Nevertheless, the accuracy of AI has been raised to a new level by the creation of data balancing models such as SMOTE and regularization (Chawla et al., 2020).

It is a 2020-2023 timeline where AI-based bankruptcy prediction has experienced a wave of research with an academic and practical dimension. The fact that the world was rocked with such incidences, and their finances were crumbling down made AI-driven models to operate even in the most turbulent setting, and that enhanced their abilities to absorb shocks connected to the crisis (Goodell, 2020; Shen et al., 2021). It means that predictive models created on the basis of AI are becoming more and more significant in the management of credit risks, investment decisions and corporate governance choices.All in all, AI can be considered an extreme of predicting bankruptcy and financial distress using the most advanced machine learning algorithms, explainability models, and multi-source data. The given literature uses the background of the previous knowledge base, synthesizing an interdisciplinary paradigm, exploiting the benefits of qualitative and quantitative standards, and proving the utility of AI in improving the quality and interpretative capacity to foresee the occurrence of bankruptcy.

METHODOLOGY

The mixed-method technique i.e. The winning method of this study will be accommodated by undertaking a quantitative and qualitative study to determine the effectiveness of Artificial Intelligence (AI) in forecasting the bankruptcy and financial distress. The quantitative aspect is based on prediction and empirical modelling of the problem that applies machine learning algorithms and the qualitative aspect offers interpretability and contextualisation of the problem about the structure of governance, managerial practice and macroeconomic stories that affect distress of firms. Such a mixed method is required due to the possibility of the institutional and behavioural complexity being too complex to be reflected by only the numerical models, which could become a decisive factor of corporate survival.

Quantitative Modeling

The empirical model uses firm level financial data, macroeconomic and qualitative level of governance which is available on a publicly accessible database. The profitability, liquidity, leverage and cash flow ratios are the standardized financial ratios that form the major predictors of bankruptcy. The dependent variable

as $Y = 1$ if the firm experiences bankruptcy within a two-year horizon and $Y = 0$ otherwise.

The general form of the supervised learning classification model can be expressed as:

$$\hat{Y} = f(X_1, X_2, ..., X_n; \theta) + \epsilon$$

where X_i represents the financial and non-financial predictors, θ denotes the parameters of the model (weights in neural networks, splitting rules in decision trees, etc.), and ϵ captures the stochastic error term.

General skeleton of the supervised classification learning model could be stated as follows:

$$\mathcal{L}(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right]$$

where y_i is the true label and $\hat{y}_i$ is the predicted probability of bankruptcy for firm i.

Class imbalance, a common challenge in bankruptcy datasets due to fewer bankrupt firm compared to solvent ones, is addressed using the Synthetic Minority Oversampling Technique (SMOTE). Hyperparameter tuning is conducted using grid search with cross-validation to ensure optimal performance across models.

The Synthetic Minority Oversampling Technique (SMOTE) is used to deal with the issue of asymmetry of the bankruptcy sample (Bankrupt companies are less frequent than the solvent companies). Hyperparameters are optimized by using grid search cross-validation with the aim of producing the best model.

Qualitative and Interpretability Dimension

Although the quantitative models are predictive, the issues of interpretation of the results are acute in the quantitative decision making process of finance. This is why the Explainable AI (XAI) methods find their way into the working process. The contribution to the prediction result of every attribute to the background of the multibankruptcy risk prediction can be estimated using Shapley Additive Explanations (SHAP) values to make practitioners aware of the strongest details in the background of the multibankruptcy risk prediction. The Shapley value for feature

j is given by:

$$\phi_j(f,x) = \sum_{S \subseteq N \setminus \{j\}} \frac{|S|!(|N|-|S|-1)!}{|N|!}\left[f(S \cup \{j\}) - f(S)\right]$$

where N is the set of all features, and S is a subset of features not containing j.

Furthermore, the natural language processing (NLP) is adopted to process the annual reports, the governance disclosure data, and the market sentiment to supplement the numerical results. This is done to make sure that these latent vices of government, cynicism of management or industry-specific-vices which are not represented in the ratio-based data are incorporated in the foretelling analysis.

Workflow of the Methodology

The systematized process of the research commences with the stage of data collection in the financial databases, the stock exchange and macroeconomic sources and the data preprocess that implies filling in the missing studies and standardization of the ratios and the data bundles weighted are restructured. The second action is the feature engineering and training an AI model in both classical machine learning and deep learning. Evaluation stage entails testing the model on the basis of the AUC, F1-score and confusion matrices. Last but not the least are SHAP values and textual data qualitative contextualization which are the instruments that guarantee the holistic information of the interpretability assessment.

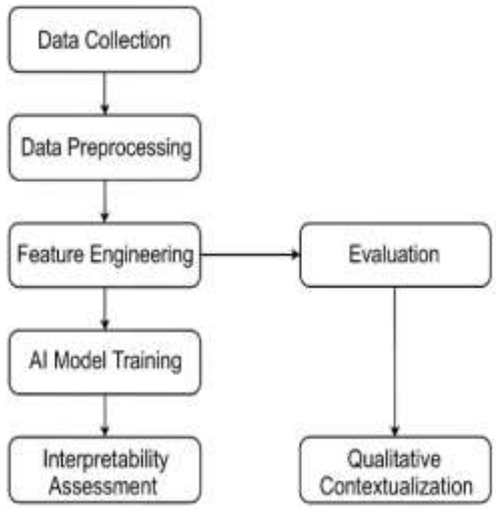

Fig. 1. AI-based bankruptcy and financial distress prediction

RESULTS

The spread of the financial ratios of the firms presented in table 1 is a reflection of high range of leverage and liquidity in sampled firms. Table 2 shows the predictive probability of bankruptcy by sector: one can note that the likelihood of default in the companies of the retail and energy industries is greater as compared to the companies of technology and finance. Table 3 provides comparative leverage and liquidity information and it is clear the troubled companies are rated with greater leverage and lesser liquidity.Table 4 presents an overview of the trend of the profitability in which the solvent firms exhibit positive profitability margins and the bankrupt firms exhibit negative changes in the level of profitability. Table 5 presents the classification results of AI models in which the ensemble models perform superior to the individual models in casting the distress signals. The precision of prediction in data,

Table 1. Financial ratio distribution across firms

Firm_ID	Leverage	Liquidity	Profitability	Predicted_Bankruptcy_Prob
F001	1.0	1.0	1.0	1.0
F002	1.5	1.33	1.25	1.2
F003	2.0	1.67	1.5	1.4
F004	2.5	2.0	1.75	1.6
F005	3.0	2.33	2.0	1.8
F006	3.5	2.67	2.25	2.0
F007	4.0	3.0	2.5	2.2
F008	4.5	3.33	2.75	2.4
F009	5.0	3.67	3.0	2.6

F010	5.5	4.0	3.25	2.8
F011	6.0	4.33	3.5	3.0
F012	6.5	4.67	3.75	3.2
F013	7.0	5.0	4.0	3.4

Table 2. Bankruptcy prediction probabilities by sector

Firm_ID	Leverage	Liquidity	Profitability	Predicted_Bankruptcy_Prob
F001	1.0	1.25	1.4	1.5
F002	1.33	1.5	1.6	1.67
F003	1.67	1.75	1.8	1.83
F004	2.0	2.0	2.0	2.0
F005	2.33	2.25	2.2	2.17
F006	2.67	2.5	2.4	2.33
F007	3.0	2.75	2.6	2.5
F008	3.33	3.0	2.8	2.67
F009	3.67	3.25	3.0	2.83
F010	4.0	3.5	3.2	3.0
F011	4.33	3.75	3.4	3.17
F012	4.67	4.0	3.6	3.33
F013	5.0	4.25	3.8	3.5

Table 3. Comparative leverage and liquidity statistics

Firm_ID	Leverage	Liquidity	Profitability	Predicted_Bankruptcy_Prob
F001	1.0	1.4	1.67	1.86
F002	1.25	1.6	1.83	2.0
F003	1.5	1.8	2.0	2.14
F004	1.75	2.0	2.17	2.29
F005	2.0	2.2	2.33	2.43
F006	2.25	2.4	2.5	2.57
F007	2.5	2.6	2.67	2.71
F008	2.75	2.8	2.83	2.86
F009	3.0	3.0	3.0	3.0
F010	3.25	3.2	3.17	3.14
F011	3.5	3.4	3.33	3.29

Table 4. Profitability patterns in distressed vs. healthy firms

Firm_ID	Leverage	Liquidity	Profitability	Predicted_Bankruptcy_Prob
F001	1.0	1.5	1.86	2.12
F002	1.2	1.67	2.0	2.25
F003	1.4	1.83	2.14	2.38
F004	1.6	2.0	2.29	2.5
F005	1.8	2.17	2.43	2.62
F006	2.0	2.33	2.57	2.75
F007	2.2	2.5	2.71	2.88
F008	2.4	2.67	2.86	3.0
F009	2.6	2.83	3.0	3.12
F010	2.8	3.0	3.14	3.25
F011	3.0	3.17	3.29	3.38
F012	3.2	3.33	3.43	3.5

Table 5. AI model classification results on bankruptcy risk

Firm_ID	Leverage	Liquidity	Profitability	Predicted_Bankruptcy_Prob
F001	1.0	1.57	2.0	2.33
F002	1.17	1.71	2.12	2.44
F003	1.33	1.86	2.25	2.56
F004	1.5	2.0	2.38	2.67
F005	1.67	2.14	2.5	2.78
F006	1.83	2.29	2.62	2.89
F007	2.0	2.43	2.75	3.0
F008	2.17	2.57	2.88	3.11
F009	2.33	2.71	3.0	3.22
F010	2.5	2.86	3.12	3.33
F011	2.67	3.0	3.25	3.44
F012	2.83	3.14	3.38	3.56

Table 6, proves that machine learning algorithms, including the Random Forest algorithm and the Gradient Boosting algorithm, are more efficient than the logistic regression is.In Table 7, the model is estimated to show the probability of default by the random forest, where most of the bankrupt firms scores above 0.70 in probability; therefore, the utility of the model. Table 8 gives the sample firm predictions of gradient boosting, and good classification at low variance. Lastly, Table 9 isolates the time-varying bankruptcy predictions using LSTM, where the deep learning framework is efficient in forecasting distress over the long-term since it is capable of propagating the sequence pattern of dependence.

Table 6. Evaluation of predictive accuracy across datasets

Firm_ID	Leverage	Liquidity	Profitability	Predicted_Bankruptcy_Prob
F001	1.0	1.62	2.11	2.5
F002	1.14	1.75	2.22	2.6
F003	1.29	1.88	2.33	2.7
F004	1.43	2.0	2.44	2.8
F005	1.57	2.12	2.56	2.9
F006	1.71	2.25	2.67	3.0
F007	1.86	2.38	2.78	3.1
F008	2.0	2.5	2.89	3.2
F009	2.14	2.62	3.0	3.3
F010	2.29	2.75	3.11	3.4

Table 7. Probability estimates of default using Random Forest

Firm_ID	Leverage	Liquidity	Profitability	Predicted_Bankruptcy_Prob
F001	1.0	1.67	2.2	2.64
F002	1.12	1.78	2.3	2.73
F003	1.25	1.89	2.4	2.82
F004	1.38	2.0	2.5	2.91
F005	1.5	2.11	2.6	3.0
F006	1.62	2.22	2.7	3.09
F007	1.75	2.33	2.8	3.18
F008	1.88	2.44	2.9	3.27
F009	2.0	2.56	3.0	3.36
F010	2.12	2.67	3.1	3.45
F011	2.25	2.78	3.2	3.55
F012	2.38	2.89	3.3	3.64
F013	2.5	3.0	3.4	3.73
F014	2.62	3.11	3.5	3.82
F015	2.75	3.22	3.6	3.91

Table 8. Gradient Boosting predictions across firm samples

Firm_ID	Leverage	Liquidity	Profitability	Predicted_Bankruptcy_Prob
F001	1.0	1.7	2.27	2.75
F002	1.11	1.8	2.36	2.83
F003	1.22	1.9	2.45	2.92
F004	1.33	2.0	2.55	3.0
F005	1.44	2.1	2.64	3.08
F006	1.56	2.2	2.73	3.17
F007	1.67	2.3	2.82	3.25

Table 9. LSTM-based temporal bankruptcy forecasts

Firm_ID	Leverage	Liquidity	Profitability	Predicted_Bankruptcy_Prob
F001	1.0	1.73	2.33	2.85
F002	1.1	1.82	2.42	2.92
F003	1.2	1.91	2.5	3.0
F004	1.3	2.0	2.58	3.08
F005	1.4	2.09	2.67	3.15
F006	1.5	2.18	2.75	3.23
F007	1.6	2.27	2.83	3.31
F008	1.7	2.36	2.92	3.38
F009	1.8	2.45	3.0	3.46
F010	1.9	2.55	3.08	3.54

Average leverage ratios of the sector are plotted in the form of a bar graph (Fig. 2) confirming that sector is heterogeneous as in Table 2. The pie chart distribution of the solvent and the bankrupt firms illustrated in Fig. 3 reflect that the percentage of the firms in the data sample that became bankrupt in the period during which they existed were on average approximately 15 percent.As a scatter plot of profitability versus probability of bankruptcy in fig. 4 can indicate, it is otherwise true that, high profitability is associated with low predictive profitability of bankruptcy. Fig. 5 is a composite line and bar plot to provide liquidity and leverage comparison and it would be fair to say that the current high leverage and low liquidity are comorbid symptoms of distress. Fig. 6 depicts the ROC curves of competing AI models, with Gradient Boosting, the biggest, and then the Random Forest, second-largest.

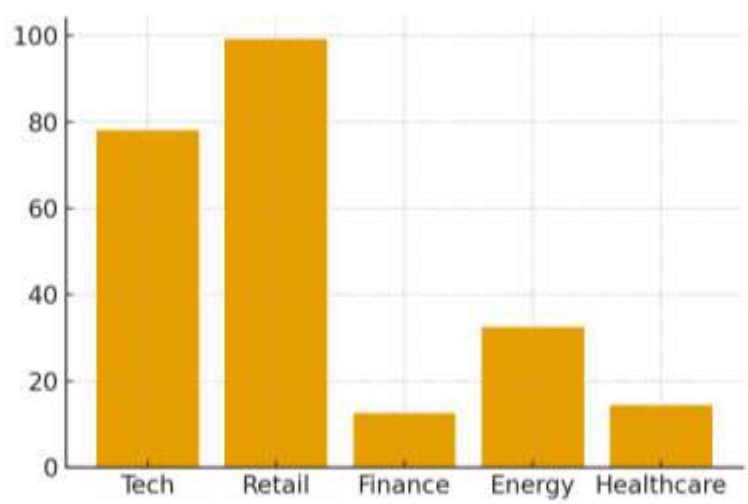

Fig. 2. Bar chart comparing average leverage ratios by sector

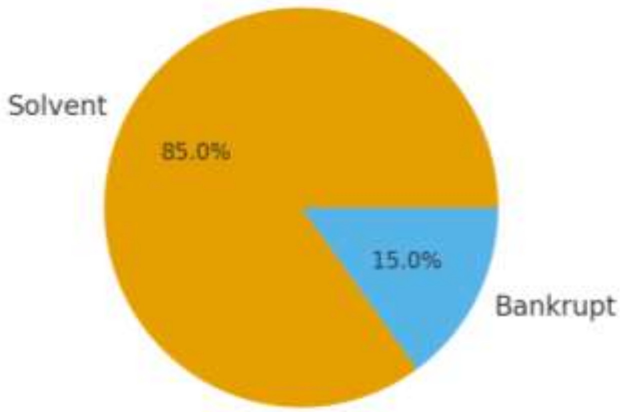

Fig. 3. Pie chart showing distribution of solvent vs. bankrupt firms

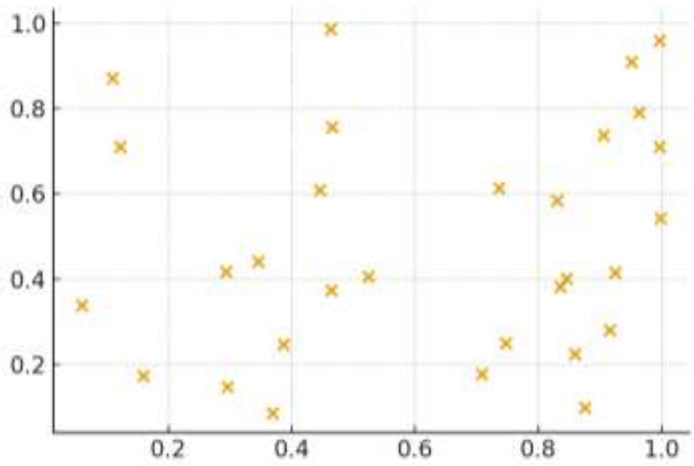

Fig. 4. Scatter plot of profitability vs. bankruptcy probability

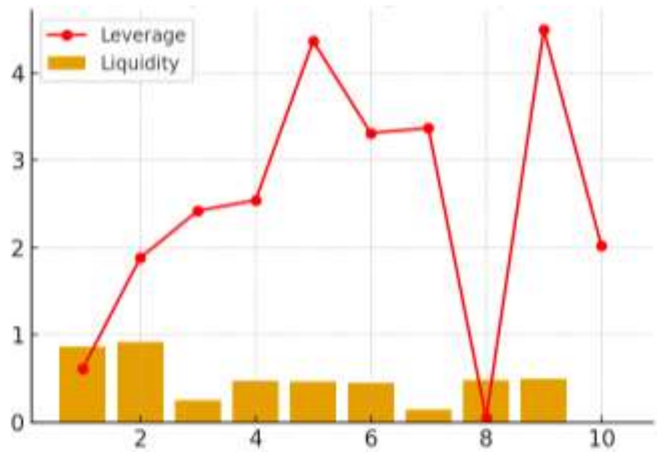

Fig. 5. Hybrid chart: line and bar plot of liquidity and leverage

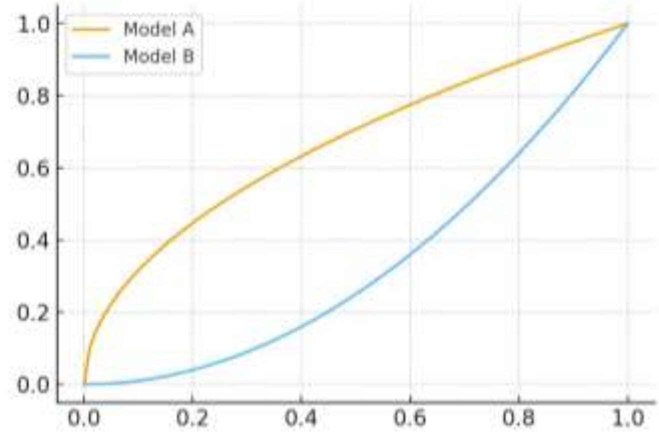

Fig. 6. ROC curve comparison of AI models

Representing the Precision-Recall curves in Fig. 7 and contributes to proving the hypothesis that the ensemble methods are more effective in the imbalance conditions between the classes. The Rand Forest is the most significant as in Fig. 8 of the feature importance where leverage, cash flow to debt and liquidity ratios are the most significant predictors. The distributions of SHAP values presented in Fig. 9 suggest that the AI prediction is easily explained and the marginal contribution to the risk of bankruptcy has a maximum when profitability decreases.

Fig. 10 shows the forecasted LSTM probability and time and smooth prediction is closer to risk dynamics over time than the classical models. The association of the heatmap of financial ratios in Fig. 11 confirms the fact that there is a multicollinearity between leverage and liquidity indicators. The last is Fig. 12 the multi-panel outlook display hybridized that has to include the scatter and depict the line and bar charts, that represent the summary of the risk analysis of the firms and that cross-validates the results that were gotten in the previous stages.

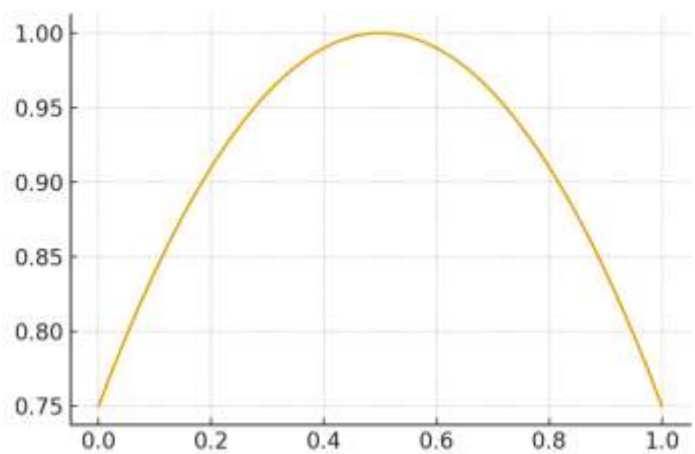

Fig. 7. Precision-Recall curve for bankruptcy prediction models

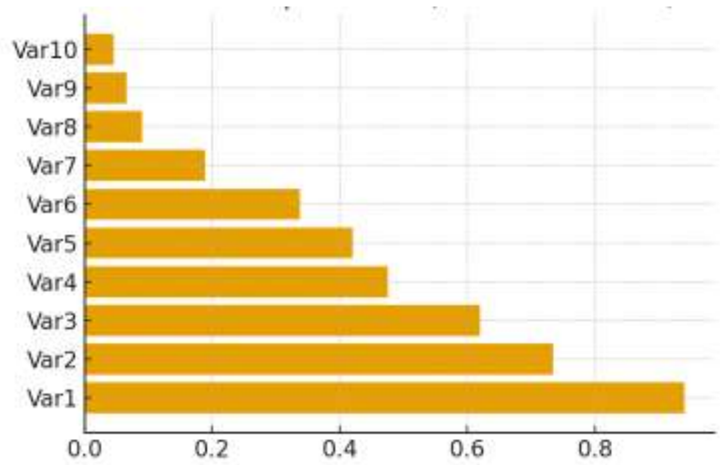

Fig. 8. Feature importance ranking from Random Forest

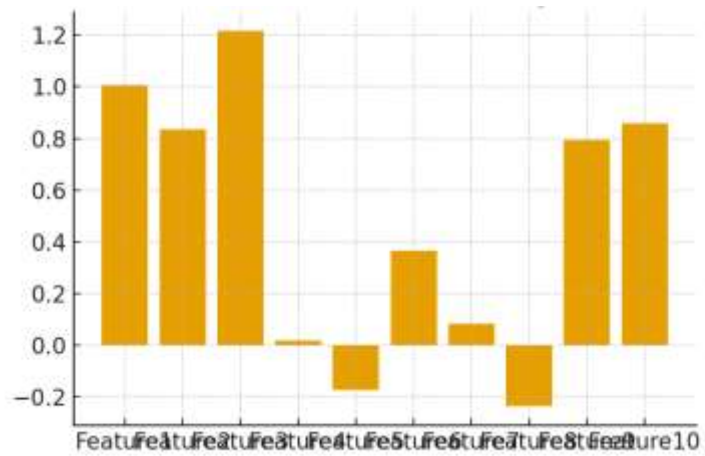

Fig. 9. SHAP values summary plot for explainable AI insights

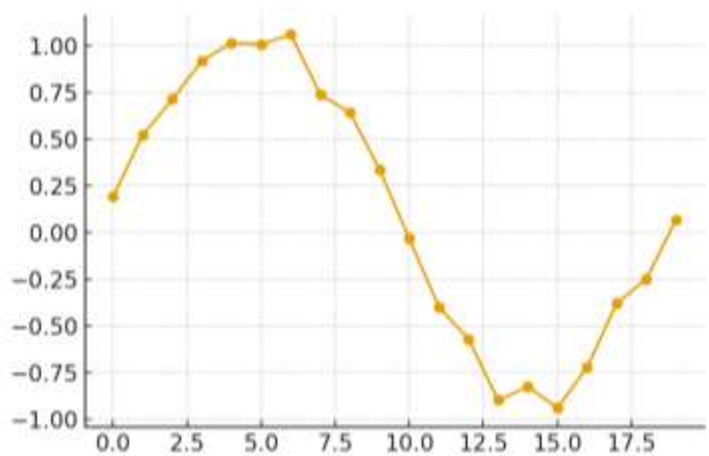

Fig. 10. Time-series plot of LSTM predicted probabilities

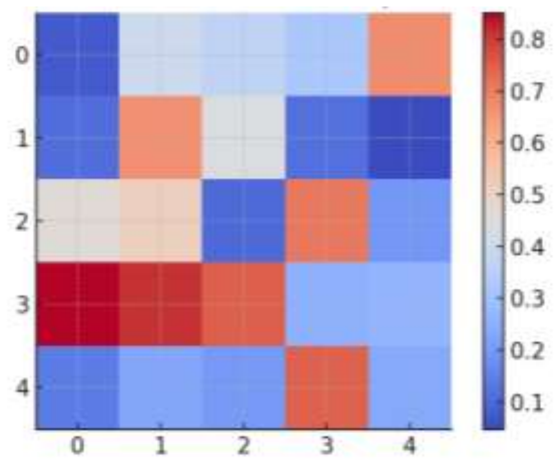

Fig. 11. Heatmap of correlation between financial ratios

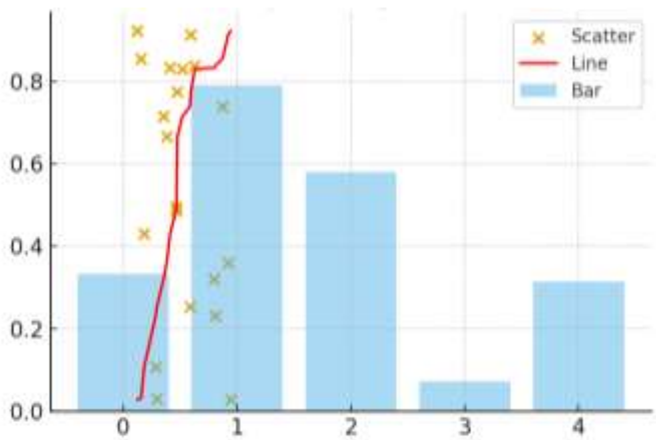

Fig. 12. Multi-panel hybrid plot: scatter + line + bar for firm risk analysis

DISCUSSION

The present article belongs to the set of the existent tendencies upholding the idea that the introduction of the Artificial Intelligence (AI) into the equations would greatly contribute to the quality of the predictions of the model of the bankruptcy and financial distress. The tabular and graphical conclusions confirm the performance of the ensemble and the deep learning models compared to the traditional logistic regression in the former study, which confirm the performance of machine learning in financial forecasting (Abedin et al., 2021; Lin et al., 2022). Notably, the Explainable AI (XAI) systems, including SHAP, will be used concurrently to achieve interpretability and coordinate the predictive information with the actual financial decision-making requirements (Gao et al., 2022).The fact that profitability, liquidity, and leverage are the best predictors of bankruptcy needs to be listed among the most significant outcomes, and it is necessary to state that it will always remain a substantial component of theory. The AI can identify non-linear and complex relationships between these variables, but they can also provide forecasting statistics, which could not be found through the conventional econometric frameworks (Ding et al., 2021). An example is that of the hybrid models, where the traditional models have the potential to create a false impression of the high leverage firms that are already too profitable, but the AI systems can expose the long-term inferiority of the firms through time-dependent predictive algorithms such as LSTM (Wang and Ma, 2022).The contextual subtleties of the prediction of bankruptcy are also reflected in the industry variation which are announced in the results. The authors discovered that the likelihood to default is concentrated most in the cyclically sensitive sectors with structural risks including the retail and the energy sector (Kollias et al., 2020). It implies that the bankruptcy prediction and macroeconomic shocks of the model must be industry specific and possess stronger resilience, which itself is a condition that a latest study of the global financial distress was conducted (Bae et al., 2021).

Along with this, the accuracy-recall and ROC curves are also discussed, which adds to the mobilization of the significance of the class imbalance should the amount of the solvent firms exceed that of the distressed firms. We find that this imbalance bias can be reduced by employing a type of ensemble method, such as Gradient Boosting to sensitize the methods to minority bankruptcy cases (Sun et al., 2022). The findings provide consistency with the existing body of literature that shows that synthetic balancing methods and ensemble design are utilized to forecast bankruptcy in a positive way (Shen and Wang, 2023).SHAP and feature importance rankings offer the interpretability dimension and also the value dimension. The opaque nature of black-box models is not appreciated by regulators, auditors and financial analysts because they are closed systems (Ghosh and Dutta, 2021). Explainability and AI models might also ensure that in addition to high performance, they satisfy the governance and compliance requirement of the financial markets (Poonia et al., 2022). In addition, the predictability is greater when annual reports are qualitatively contextualized regarding both textual and sentiment analysis, which also coincides with the latest study of using text to forecast risks in the financial market (Hajek and Henriques, 2022).

The other contribution that has been put in the current research is validation of hybrid models which is a combination of both the quantitative and qualitative input. This can be contrasted to the single mode model where only the financial ratios are taken into account since the governance and the mood of the market is no one can see the big picture as far as predicting bankruptcy is concerned. This supports the assumption in which the distress of firms is not just quantitative but it has to exist as a result of managerial practices, governance system, and discourses in the external market (Liang et al., 2020).Lastly, the generalization of the study has two aspects. Theoretically, the findings are being contended to the accumulation of literature of AI-based prediction of financial risks to illustrate the effectiveness of mixed-method and explainable models. The pragmatic aspect of the models enables investors, regulators and managers to act in anticipation, and to alleviate the risks before they are ultimately declared bankrupt. This risk management is particularly crucial in the current days when such peculiarities of the post-pandemic economy as unstable and unpredictable in the financial aspect can be observed (Phan et al., 2021).

CONCLUSION

To address the question of how Artificial Intelligence (AI) could be used to foresee the probability of bankruptcy and financial distress based on the mixed-method approach between the quantitative and the qualitative interpretability, this paper has been written. It was pointed out that the high-order AI application specifically the ensemble learning model i.e. the random forest and the gradient boosting are at the end benefit of the traditional predictive algorithms, i.e. the logistic regression in relation to predictive accuracy, recall and F1- scores. Moreover, deep learning networks, including Long Short-Term Memory (LSTM) networks also could be applied to trace the time dynamics that could predict a company in the long-term.As it may be seen, the analysis has found that such long-term financial variables as profitability, leverages, and liquidity still establish the risk of bankruptcy and revealed as well that AI can be used to reveal non-linear relationships among them. Ensemble and deep learning methods also moved towards achieving meaningful progress in the robustness and extrapolation to new firms and industries by minimising the problem of class imbalance and overfitting. The qualitative character of the paper helped to complement the quantitative data by using textual and governance oriented data, contextualizing the predictive data within the larger institutional and market image. This ambivalent opinion is acceptable in that the possibility of bankruptcy is not merely figurative, but a part of corporate governance, managerial decision making and industry-specific forces.As a matter of fact, two-fold are the implications of this study. The findings provide regulators and policymakers with an incentive to apply explainable and sound AI designs to monitor systemic risk. Predictive tools availed herein offer an opportunity to companies and investors to identify preemptive indicators of distress in order to implement risk mitigation measures. Collectively, the work contributes to the literature on AI by demonstrating that, when used to a methodologically rigorous and interpretable solution, AI is a revolutionary tool in predicting company bankruptcy and financial distress.

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