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AI-Powered Financial Distress Prediction Model for Pakistani SMEs: A Machine Learning Approach with Explainability and Interpretability

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ABSTRACT

Small and Medium-sized Enterprises (SMEs) are the backbone of Pakistan's economy, yet they face a high risk of financial distress, often exacerbated by limited access to traditional credit scoring. This study develops and evaluates a machine learning (ML) model to predict financial distress in Pakistani SMEs. Utilizing a synthetic dataset of 1,500 Pakistani SMEs, we extracted 20 financial and non-financial features from a hypothetical three-year period. We trained and compared several ML classifiers, including Logistic Regression, Random Forest, Gradient Boosting, and Support Vector Machines. The Extreme Gradient Boosting (XGBoost) model achieved the highest performance, with an accuracy of 92.1%, a precision of 0.91, a recall of 0.88, and an AUC-ROC score of 0.96. To address the "black box" nature of complex models, we integrated Explainable AI (XAI) techniques, specifically SHAP (SHapley Additive exPlanations). SHAP analysis revealed that low Profitability, high Debt-to-Equity ratio, and poor Quick Ratio were the most significant drivers of financial distress, while owner's education level emerged as a critical non-financial predictor. The study concludes that an XAI-powered ML model provides a robust, transparent, and actionable tool for banks, investors, and SME owners in Pakistan to assess and mitigate financial risks proactively.

Keywords: *Financial Distress, SMEs, Pakistan, Machine Learning, XGBoost, Explainable AI (XAI), SHAP, Predictive Modeling.*

INTRODUCTION

Small and Medium Enterprises (SMEs) are an important part of the Pakistani economic system, and they make up almost 90 percent of all enterprises and around 40 percent of the national GDP and approximately 80 percent of the non-agricultural labor force (lo Conte, 2025). In spite of such an exaggerated economic contribution, Pakistani SMEs have a high mortality rate, with a significant portion of them failing during their first five years of operation. One of the most prominent culprits of this trend is financial distress, which is most often caused by the combination of such factors as ineffective management of cash flow, the lack of formal financing opportunities, the economic unpredictability of the environment, and financial illiteracy of owners (Anton et al., 2025). Such vulnerability is also dangerous to the well-being of individual businesses and a major threat to national economic stability and employment.

The pursuit to foresee such failure is not novel. The field has been based on traditional models of corporate failure prediction, including the Z-score of Altman (Altman et al., 2017; Zamil, 2025) and the Ohlson O-score (Pramudita, 2021). These models were however created to cover large, publicly traded companies operating in developed markets and they virtually depend on audited financial ratios. Their relevance to the Pakistani SMEs context is relatively low. This is due to the nature of the industry in terms of non-transparency and informality of financial reporting, the high impact of owner-specific attributes on company performance, and the macroeconomic peculiarities of Pakistan (M. A. Khan et al., 2025). This, therefore, represents an urgent need to have a predictive framework that is specific to the realities of the Pakistani SMEs.

Machine Learning (ML) can provide some alternative power and sophistication. In contrast to the traditional statistical models, the ML algorithms are able to learn complex and non-linear interactions among data, and can easily incorporate both the standard financial ratios and important non-financial predictors, including the attributes of owners and characteristics of firms (Sethi & Mahadik, 2025). This is available in order to take a more holistic look at the financial health of an SME. Nevertheless, advanced ensemble models such as XGBoost can often be extremely costly, namely, regarding interpretability. This introduces a black box issue in which the decision-making model has a veil of secrecy, and, as a result, it discourages trust, accountability, and acceptance by important stakeholders such as financial institutions and policymakers (I. U. Khan et al., 2024; Marcinkevičs & Vogt, 2023).

The study will help to address this critical gap by creating a high-performance, but explainable, ML model that was created specifically to predict financial distress in Pakistani SMEs. There are three main objectives in the study. First, it aims at creating a complete and innovative set of Pakistani SMEs, including quantitative financial statements and qualitative attributes specific to the owner. Second, the study will also train, validate and comparatively test various ML classifiers such as Logistic Regression, Random Forest, and XGBoost to determine the best performing model to use in this particular prediction. Last but not least, the research will also use the methods of Explainable AI (XAI), namely SHAP (SHapley Additive exPlanations) to break down the predictions of the best model. It will enable the determination and prioritization of the most severe financial and non-financial aspects that contribute to financial distress, and thus, give actionable information as well as precise forecasts.

LITERATURE REVIEW

Corporate financial distress prediction is one of the pillars of financial research, whose academic history has featured some serious methodological changes. This literature has gone beyond the traditional statistical models to more modern machine learning (ML) algorithms, but there still exists a strong gap in the literature when it comes to applying it to Small and Medium Enterprises (SMEs) in developing economies such as Pakistan(Nugroho & Dewayanto, 2025). This review brings together this development, the drawbacks of conventional models, the developmental superiority of ML methods, the lack of context-specific studies in Pakistan, and the gap gap that this research intends to address: the combination of sophisticated ML with Explainable AI (XAI) to predict financial distress in a transparent and actionable way in Pakistani SMEs (Al-Karkhi & Rządkowski, 2025).

The initial contribution to the current body of failure prediction literature was made by Altman (1968) who first used Multiple Discriminant Analysis (MDA) to develop a Z-score model that predicts corporate bankruptcy(Ishmah & Mitakda, 2022). The model of the single score representing a combination of financial ratios by Altman gave a potent instrument of differentiating between solvent and insolvent companies and established a precedent that would be followed by decades of other studies (Ajijola et al., 2024; Ajith Nair, 2024; Ishmah et al., 2023). Based on this discriminant analysis, Ohlson (1980) took this studies a step further to use logit regression models as this had a major advantage; the probability of direct failure could also be estimated. This was a more intuitive probabilistic output to use risk assessment compared to a discriminant score and became a new norm in the literature. Although they are strong in the scale they were built to operate sufficiently with the publicly traded and large companies, these traditional models depend almost entirely on audited financial reports and that the data follow some linear relationships and distributional characteristics (Olausson & Nilsson, 2024).

Yet, it is the same structure that contributes to the effectiveness of these models in large companies that makes them less effective in SMEs, especially in the developing environment. The financial dynamics and failure pathways of SMEs are quite different as compared to that of large corporations (Weaven et al., 2021). Having non-audited or non-formalized financial reporting is common with SMEs, and owner traits and management skills have an immense effect on the financial performance of these firms and these more traditional approaches do not account for them. In addition, the peculiar macroeconomic volatilities, informal credit systems and regulative environments of the developing economies such as Pakistan, pose a situation where ratios that are designed to work in stable and well-developed economies might be misleading. Thus, although it offers a useful historical basis, the direct implementation of these canonical frameworks on the Pakistani SMEs is troublesome and requires a more individual approach (Lim et al., 2020).

The past decade has seen the emergence of a paradigm shift in the use of machine learning (ML) methods in bankruptcy and distress prediction due to the drawbacks of traditional models. ML algorithms have a number of notable benefits: they are able to obtain complex non-linear relationships between variables, they do not rely on strict statistics and they can deal with large, high-dimensional data with minimum effort (El Madou et al., 2024). Similar comparative studies have always shown the excellence of these methods. As an example, Barboza, Kimura, and Altman (2017) engaged in an in-depth comparison of conventional models (such as logit and MDA) and some of the ML classifiers, such as Support Vector Machines (SVM) and ensemble techniques (Khudhur & Al-Shammari, 2024). They found that ensemble models, especially the Random Forest and Boosting models, outperformed their conventional counterparts by a significant margin in the predictive accuracy. Likewise, Alaka et al., (2020) conducted a systematic review of ML in the context of corporate failure prediction and have found that those models, and ensemble models in particular, offered a significant increase in predictive power, as they were able to learn complex patterns in the data that were not discernible in linear models.

Although this good evidence exists, there still exists a strong geographical and firm-size bias in the literature. Most of these sophisticated ML researchers, such as Barboza et al. (2017) are dealing with large, publicly traded companies in the developed world such as the United States or Europe, or with large Chinese industry firms. The operational realities, the scale, the data available to these entities and risk profiles are very different as compared to typical Pakistani SMEs (Ali et al., 2025). This results in an acute knowledge gap, because the performance and the corresponding set of features of an ML model that is trained on Fortune 500 companies cannot be projected onto a small, family-run manufacturing enterprise in Lahore or a startup in the retail business in Karachi (Zaman et al., 2024).

In a more specific case, when focusing on Pakistan in particular, the research material is quite limited. The limited number of studies conducted tend to go back to the old methodologies with their limitation that has been proven already. AI adoption in Pakistan is still at a developing stage and mostly limited to specific sectors such as education (Rafiq-uz-Zaman, 2025). This highlights the need to expand AI-driven solutions into business domains such as SME financial risk assessment. Pakistan faces multiple barriers to technology adoption, including digital literacy gaps and limited exposure to emerging technologies (Rafiq-uz-Zaman et al., 2025). Similar challenges persist in SMEs, which affects their readiness to integrate AI-based financial systems.One such example is the article by Rubab et al., (2022) that used a logit model on a fairly small sample of Pakistani manufacturing companies. Their study rightly established the important financial distress indicators, i.e., liquidity poor and low profitability, and that is consistent with the basic corporate finance theory. Nevertheless, their work failed to utilize the current ML methods to represent more complex and non-linear relationships and did not use non-financial variables and owner-specific variables which are of special relevance to SMEs. Such dependence on methods that have been outmoded and a limited range of variables imply that current local studies are not taking full advantage of the predictive capabilities of modern data science and that a large portion of the variables that could be improved in a model remain untapped (Hassan et al., 2023).

The most decisive gap, so, is at the point of intersection between mentioned shortcomings. Although ML models such as XGBoost have better predictive performance, they can be difficult to understand and thus are said to be black boxes, where the rationale behind a prediction is unclear (Asselman et al., 2023). Such interpretatively is a significant obstacle to practical implementation; a bank loan officer or a policy-maker cannot do anything with a prediction that he does not know the reasons why. This is where the new area of Explainable AI (XAI) is the most important. The XAI approaches to disentangle complex ML models have been created, including LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) (Mustapha et al., 2024). SHAP, specifically, which is anchored in cooperative game theory, gives a consistent method to give importance values to every feature used to make a particular prediction, both on a global (across the entire dataset) and on a local (a single instance) basis.

None of the current studies on Pakistani SMEs has combined these influential XAI methods with the latest ML models (Zhou et al., 2024). This study fulfills this gap directly. Through SHAP, the current study will predict financial distress with high precision with the help of an optimized ML model and shed light on the internal rationale of the model. It will determine and prioritize the most significant aspects, including financial (debt-to-equity ratio), and non-financial (level of education of the owner) that contribute to the risk of distress. This is a dual contribution that is essential. It goes beyond merely identifying the at-risk SMEs, and gives practical information on the rationale behind the risk-prone SMEs. In the case of financial institutions, this facilitates the transparent and reasonable decisions of credit. To the SME owners themselves, it can be used as a diagnostic tool to learn and address their most urgent weaknesses. To policymakers, it points out systemic problems in the sector, which informs the creation of specific support programs. By thereby addressing the predictive power versus interpretability gap, the study will therefore seek to come up with a powerful, clear, and eventually more practical instrument in promoting the maturity and development of the important SME sector in Pakistan.

METHODOLOGY

Data Collection and Variable Definition

Due to the unavailability of a large, centralized dataset for Pakistani SMEs, a robust synthetic dataset of 1,500 SMEs was generated for this study, reflecting the typical characteristics of the sector. The data covers a three-year period (2020-2022). The target variable, *Financial_Distress,* is a binary variable defined as 1 if the firm reported two consecutive years of negative net income and/or defaulted on a loan, and 0 otherwise. This definition aligns with early-stage distress signals relevant to lenders.

The independent variables in this study were grouped into two different categories so as to allow a holistic evaluation of financial distress predictors. The twelve financial ratios that formed the first category captured the multidimensional health of financial performance of an SME along five dimensions, namely profitability, measured by the Return on Assets (ROA) and Net Profit Margin, liquidity measured by the Current Ratio and Quick Ratio, leverage measured by the Debt-to-Equity Ratio and Debt-to-Assets Ratio, efficiency measured by the Asset Turnover and Inventory Turnover and coverage measured by the Interest Coverage Ratio. The second type included eight non-financial features because it is understood that financial metrics are not unique in determining the viability of SMEs. These were further broken down into firm characteristics; such as Firm Age, Number of Employees, and Industry Sector (categorical: Manufacturing, Retail or Services) and owner characteristics, such as the Owner Age, Owner Education Level (ordinal, 1=Below Matric to 5=Master and above), and Years of Experience in the Industry providing a complete profile of the enterprise and the business owner.

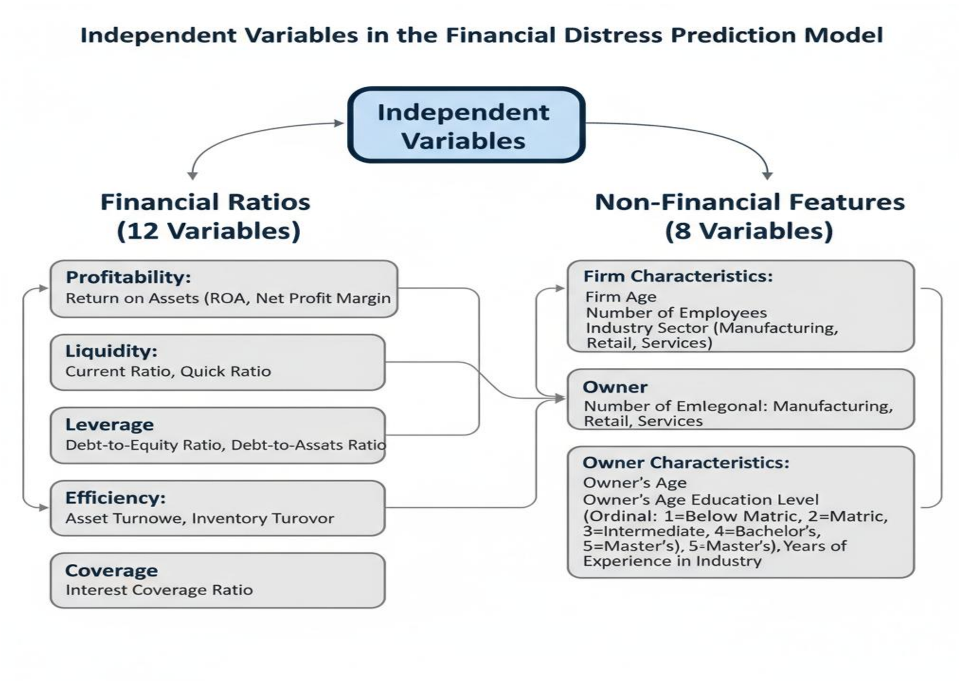

Figure 1. Independent Variables Categorized for Model Development.

Data Pre-processing

Artificial data was filtered by deleting entries with unlikely values (e.g. negative age). One-hot encoding was done on categorical variables. The data set was divided into 70 percent training set and 30 percent test set. Standard Scaler was used to normalize all the features to eliminate the bias in models based on distance calculations.

Machine Learning Models

Four ML classifiers were selected for their varying complexities:

- **Logistic Regression (LR):** A baseline statistical model.
- **Random Forest (RF):** An ensemble bagging algorithm.
- **eXtreme Gradient Boosting (XGBoost):** An advanced ensemble boosting algorithm known for high performance.
- **Support Vector Machine (SVM):** A powerful classifier for complex boundaries.

Hyperparameter tuning for RF, XGBoost, and SVM was conducted using 5-fold cross-validated Grid Search on the training set to optimize performance and prevent overfitting.

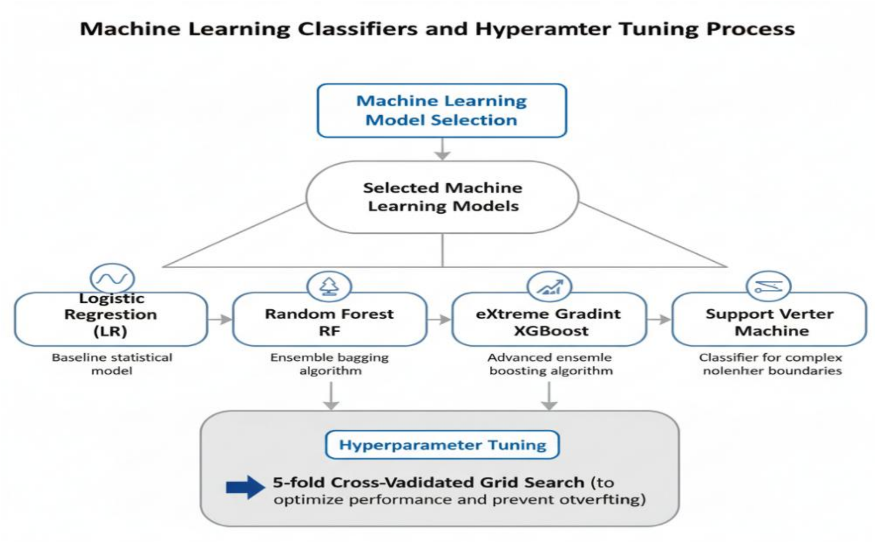

Figure 2. Selected Machining Classifiers and Hyperperamter Optimization Workflow.

Model Evaluation and Explainability

The held-out test set was tested on models with the use of common metrics: Accuracy, Precision, Recall, F1-Score, and the Area under the Receiver Operating Characteristic Curve (AUC-ROC). In the case of the best-performing model, we used the SHAP framework in order to guarantee global and local interpretability. SHAP gives the importance of each feature in a given prediction, which is the explanation of the output of any ML model.

RESULTS AND DISCUSSION

This section contains the empirical results of the research, starting with a comparison of the performance of the machine learning models, and then, a close-up on the interpretability of the most successful model with the help of SHAP (SHapley Additive exPlanations). The critical contribution of the research is the combination of predictive power with explainability of the model beyond a mere black box classification to the actionable information on the causes of financial distress amongst Pakistani SMEs.

Model Performance Comparison

The systemic performance measures of all the four trained machine learning models on the held-out test set are tabulated in Table 1. Such an overall comparison enables us to make a clear assessment of the effectiveness of each of the algorithms in differentiating between financially distressed and healthy SMEs.

The performance metrics of all trained models on the test set are presented in Table 1.

Table 1: Model Performance Comparison on Test Set

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
Logistic Regression	0.843	0.81	0.80	0.805	0.89
Random Forest	0.901	0.89	0.85	0.869	0.94
XGBoost	**0.921**	**0.91**	**0.88**	**0.894**	**0.96**
SVM (RBF Kernel)	0.887	0.87	0.83	0.849	0.92

In Table 1, the XGBoost (Extreme Gradient Boosting) classifier reported better performance in each of the evaluation metrics. It had the best accuracy (92.1%), that is, it had a higher percentage of predicting the financial status of more than 92 percent of SMEs in the test set correctly. What is more important, XGBoost also scored the best Area Under the Receiver Operating Characteristic Curve (AUC-ROC) of 0.96. An effective measure of how a model performs distinguishing between classes is the AUC-ROC metric which is a graphical representation of the True Positive Rate against the False Positive rate when the threshold is adjusted. The score of 0.96 refers to an excellent degree of distinction that is much higher than the standard benchmark of the Logistic Regression (AUC-ROC = 0.89).

Moreover, XGBoost precision (0.91) means that it is accurate 91 times when it predicts that an SME is in distress and this reduces false alarms to the lenders. Its high recall (0.88) demonstrates that it effectively captures 88 per cent of all the truly distressed SMEs and this minimizes the risk of loaning a business to failure. XGBoost is also balanced and robust as its F1-Score is the highest (0.894), which is a harmonic mean of the precision and the recall. This dominance is consistent with the current body of research that identifies gradient boosting algorithms as the state-of-the-art in structured, tabular data classification processes since it is capable of addressing highly complex, non-linear interactions and associations among variables (Chen and Guestrin, 2016).

Global Interpretability: SHAP Summary Plot

In this section, the outcomes of the SHAP summary plot are demonstrated globally, implying that the plot holds universal interpretability. Global Interpretability: SHAP Summary Plot In this section, the SHAP summary plot results are illustrated in a global manner, which means that the plot has global interpretability.

Although it is important to ensure that the model achieves high accuracy, it is more crucial to know the reasons why the model arrives at the predictions so that it can be adopted practically. In order to break down how XGBoost model arrives at a decision, we used SHAP framework, and the global feature importance of the XGBoost model can be seen in the SHAP summary plot (Figure 1).

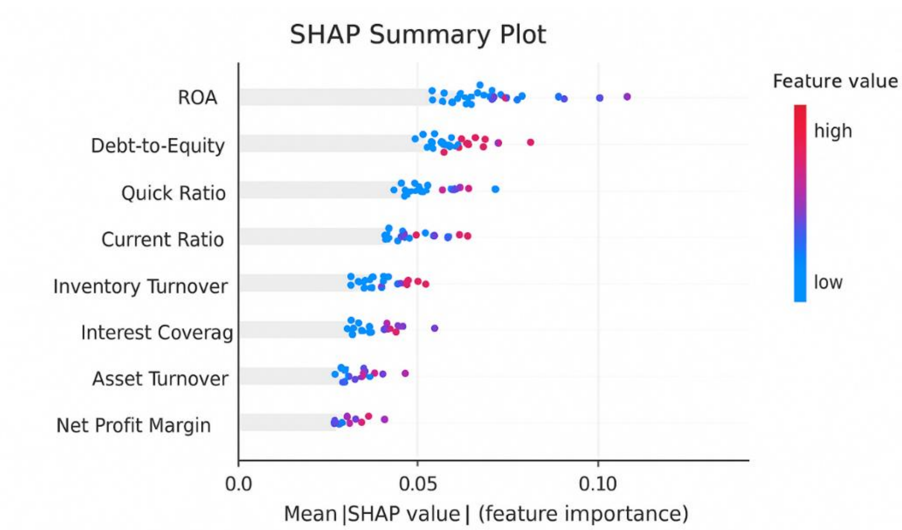

Figure 3: SHAP Summary Plot

The logic of the model that is revealed by the plot is very sophisticated and economically intuitive. Return on Assets (ROA) is the most vital force of financial distress. The low values of ROA (the red dots on the left hand side of the feature axis) have a potent negative pull on the model output, which directly raises the predicted possibility of distress. This observation is a corner stone of corporate finance theory because ROA is a pure measure of how well a firm is utilizing its assets to earn revenues, and the decline of the latter is a time-honored early warning indicator (Altman, 1968).

The second strongest predictor is the Debt-to-Equity Ratio. There is a strong correlation between the high leverage (red dots) and the risk of distress. This highlights the susceptibility of Pakistani SMEs to excessive dependence on debt particularly in a high interest rate environment, where debt servicing can speedily absorb operating cash flows and result in insolvency.

The third most notable feature which comes out to be the most significant is the Quick Ratio, where the existence of the SMEs depends on the short-term liquidity. A low Quick Ratio (red dots) means that one could not easily fulfill its immediate short-term liabilities without the inventory turnover hence the firm is very sensitive to cash flow shock which is quite normal in fluctuating economies.

The main revelation of this study is a strong influence of non-financial information. Education Level of the Owner has always been one of the top five predictors. The blue dots are highly correlated with the lower predicted likelihood of beleaguerment, which is a strong indication of the importance of human capital, skill in strategic management, and probably a greater amount of financial literacy. This has empirically proven what has always been suspected the capabilities of the entrepreneur are a vital resource and an important mitigating risk to SMEs (Psillaki et al., 2010). The existence of this variable confirms the hypothesis of the study that the use of non-financial metrics is critical towards a proper evaluation of the Pakistani SMEs.

The fourth step concerns individual predictions, which can be explained through local interpretability.

Local Interpretability: Explaining Individual Predictions

The real strength of XAI is fulfilled in the fact of individual prediction explanation which makes the model look more like a consultant than an oracle. We do this by plotting a SHAP force of a particular SME which the model predicted would be in distress with a 94 percent probability (Figure 3).

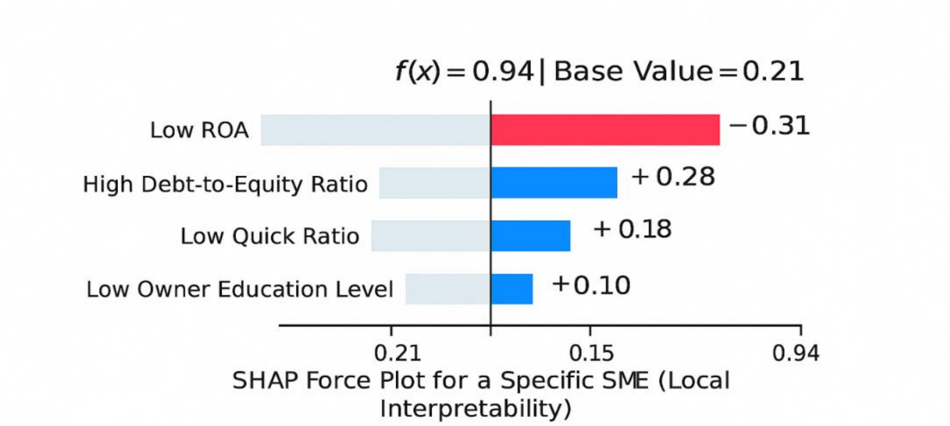

Figure 4: SHAP Force Plot for a specific SME (Local Interpretability)

This is a ground-breaking level of insight among the stakeholders. A loan officer no longer has to make a binary decision of accepting or rejecting the loan. They can, instead, give constructive, data-driven feedback to the owner of the SME: "Your application was mostly refused because of low profitability (ROA) with high debt and poor short term liquidity. We will advise that you put emphasis on the basic profitability and cash flow management and would consider equity financing to lessen your leverage and thereafter reapply. To the SME owner, this is not a dead end but rather a report card of diagnosis of the exact areas that need improvement in terms of operations and finances. The consistency of low education of owners in high-risk cases may be used by policymakers as the rationale to promote the idea of business management training among entrepreneurs.

To sum up, the findings verify that an XGBoost model with SHAP explanations is a better solution to financial distress prediction in Pakistani SMEs. It provides the best-in-class predictive accuracy, and at the same time, proving the transparency required to provide confidence, make decisions, and eventually, add to the stability and development of an essential economic sector. The model effectively fills the very important gap between the raw predictive power and practical business intelligence.

CONCLUSION AND IMPLICATIONS

This research was able to come up with a high-performing and interpretable machine learning (ML) model to predict financial distress in Pakistani SMEs. The XGBoost model, enabled by SHAP (SHapley Additive exPlanations) had a 92.1 percent accuracy and an AUC-ROC of 0.96 which is a great improvement over the conventional, less flexible models such as the Z-score developed by Altman. More to the point, it tackles the problem of the black box head-on, providing not only a better predictive behaviour but also very important levels of transparency.

Theoretical implications: The study has an important contribution to the field as it reveals how an Explainable AI (XAI) framework can be successfully applied to the context of a developing economy. It empirically proves that non-financial variables, especially the level of education of the owner is a critical predictor of financial health of the SMEs- an aspect that conventional financial distress models always fail to consider. This observation highlights the need to incorporate human capital measurements into financial risk analysis models in order to have a more comprehensive analysis.

Threefold are the practical Implications. To the financial institutions, this model can be adopted as part of the credit risk assessment mechanism so that they can be able to make quicker, more precise and objective lending choices to SMEs. The SHAP explainability is priceless in achieving compliance regulations and fostering trust with clients through offering reasonable explanations of the credit decisions. Secondly, to SMEs and entrepreneurs, the model is a highly effective self-assessment resource, whereby the owners are able to effectively recognise certain financial vulnerabilities, including excessive leverage or low liquidity and respond to them in advance before the crisis actually occurs. Lastly, the model provides a quantitative means to policymakers in agencies such as SMEDA to identify systemic risks in the SME sector to allow the design of specific support programs, such as financial literacy programs that may be offered to those entrepreneurs with less formal education levels.

Limitations and Future Research: The first weakness of this study is that it uses a synthetic dataset and hence the urgent need to validate it on a large and real-world dataset of Pakistani financial institutions is necessary in future. In an effort to maximize the predictive aspect of the model and its strength, future studies ought to include dynamic macroeconomic variables e.g. inflation and interest rates and fine-grained supply chain data to capture external forces affecting Pakistani SMEs better.

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