A Hybrid Early Warning System for Corporate Financial Distress: Integrating Traditional Methods with Machine Learning Techniques in Companies Listed on the Egyptian Exchange

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Abstract

Financial distress prediction has become a focal research area in corporate finance, driven by the imperative of risk management and informed decision-making. This study proposes a hybrid modeling framework that integrates the Altman Z-score—a longstanding traditional financial metric—with four machine learning algorithms (Random Forest, Support Vector Machine, Logistic Regression, and XGBoost). The framework was empirically tested on companies listed on the Egyptian Exchange, as applied on a sample of 48 companies across five sectors, according to the nature of each of these sectors in terms of type of industry, as follows: food, beverages and tobacco sector, manufacturing sector, health care & pharmaceuticals sector, real estate sector, and services sector over the period from 2019 to 2023. By assigning determined weights to each component, the model describes both linear and non-linear patterns in corporate data. Empirical analysis, spanning multiple sectors, demonstrates the framework's predictive accuracy, achieving a 97.91% success rate, and highlights significant sector-specific distress patterns. These findings underscore the potential of combining established financial theory with modern computational techniques, offering robust and interpretable early warning systems for investors, financial institutions, and regulators.

Keywords: Financial distress - risk management - Atlman Z-score - Random Forest - Support Vector Machine - Logistic Regression – XGBoost.

ملخص البحث:

لقد أصبح التنبؤ بالتعثر المالي مجالًا بحثيًا محوريًا في تمويل الشركات، مدفوعًا بضرورة إدارة المخاطر واتخاذ القرارات المستنيرة. تقترح هذه الدراسة إطارًا لنموذج هجين يدمج نموذج Altman Z - وهو مقياس مالي تقليدي قديم - مع أربع خوارزميات للتعلم الآلي (الغابة العشوائية Random Forest، وآلة المتجهات الداعمة Support Vector Machine، والانحدار اللوجستي Logistic Regression، XGBoost). تم اختبار النموذج المقترح على الشركات المدرجة في البورصة المصرية، كما تم تطبيقه على عينة من 48 شركة تمثل خمسة قطاعات، وفقًا لطبيعة كل من هذه القطاعات من حيث نوع الصناعة، على النحو التالي: قطاع الأغذية والمشروبات والتبغ، وقطاع الصناعة، وقطاع الرعاية الصحية والأدوية، وقطاع العقارات، وقطاع الخدمات خلال الفترة من 2019 إلى 2023. من خلال وضع أوزان محددة لكل مكون، يصف النموذج الأنماط الخطية وغير الخطية في بيانات الشركات. ويوضح التحليل التجريبي، الذي يشمل قطاعات متعددة، الدقة التنبؤية التي يتمتع بها النموذج، حيث حقق معدل نجاح بلغ 97.91%، كما يسلط الضوء على أنماط التعثر المرتبطة بكل قطاع. وتؤكد هذه النتائج على إمكانية الدمج بين نظريات التعثر المالي التقليدية والتقنيات الحديثة، مما يوفر أنظمة إنذار مبكر قوية وقابلة للتفسير للمستثمرين والمؤسسات المالية والهيئات التنظيمية.

الكلمات الافتتاحية: التعثر المالي - إدارة المخاطر - الغابة العشوائية - آلة المتجهات الداعمة - الانحدار اللوجستي.

1. Introduction

Financial distress prediction plays a pivotal role in safeguarding market stability and guiding strategic decision-making. It involves identifying symptoms of impending corporate hemorrhage before an actual default occurs, thereby providing opportunities for early interventions. Early research efforts focused on traditional financial models, with the Altman Z-score being a hallmark approach. Developed by Altman (1968), the Z-score adopts a multivariate discriminant analysis framework to combine several key financial ratios into a single numerical risk assessment. Over time, empirical applications have shown varying accuracies across different regions and industries, ranging from as low as 58% to as high as 93% (Srour, 2021).

While these traditional metrics remain foundational, ongoing research highlights the limitations of single-method approaches, particularly in dynamic market environments (Imelda & Alodia, 2017). Consequently, a paradigm shift toward machine learning (ML) models has emerged. In contrast to linear statistical tools, machine learning methods—such as Random Forest, Support Vector Machine, and gradient boosting frameworks—learn complex, non-linear patterns from high-dimensional datasets (Abid, 2022). Recent investigations have demonstrated predictive accuracies often exceeding 95%, especially when ensemble learning techniques are employed (Dolinšek & Kovač, 2024).

However, individual ML methods may suffer from overfitting, restricted interpretability, or data imbalance challenges. A hybrid approach, integrating traditional financial ratios with advanced machine learning algorithms, has thus garnered increasing attention (Farooq & Qamar, 2019). This synthesized framework leverages the intuitive clarity of classical models, while simultaneously capturing the complex interactions that machine learning excels at. The result is a robust solution that balances interpretability, theoretical grounding, and computational power.

Against this backdrop, the present study develops and evaluates a weighted ensemble financial distress prediction model. The Altman Z-score is assigned a central role, reflecting its historical importance and interpretative simplicity. Four machine learning models—Random Forest, SVM, Logistic Regression, and XGBoost—complement this metric, collectively forming a system capable of identifying both linear and non-linear signals. The model is tested on multi-sector corporate data, examining not only its overall predictive accuracy but also sector-specific performance patterns. By demonstrating the efficacy of weighing different components, this research contributes to the growing body of literature advocating hybrid solutions for financial distress prediction.

2. Literature Review:

Financial distress prediction has emerged as a critical area of study in corporate finance, drawing significant attention from both academics and practitioners due to its crucial role in risk management and decision-making processes. The literature demonstrates a clear evolution from conventional statistical methods, such as Altman's Z-score and logistic regression, through sophisticated machine learning algorithms, to cutting-edge hybrid models that combine multiple methodological approaches. Traditional models, while still relevant, have shown varying degrees of effectiveness across different markets, with studies reporting accuracy rates ranging from 58% to 93%. Machine learning approaches, particularly random forest, support vector machines, and neural networks, have demonstrated superior predictive capabilities, with some studies achieving accuracy rates exceeding 95%. The emergence of hybrid models represents the latest advancement, incorporating multiple data types, analytical techniques, and market-specific characteristics to achieve even more robust predictions. This review synthesizes findings from studies conducted across multiple geographical regions, including developed and emerging markets, providing insights into both the methodological advances and practical applications of financial distress prediction models while highlighting the increasing importance of integrating traditional financial metrics with non-financial indicators and market-specific factors.

Before exploring the various methodological approaches to bankruptcy prediction, it is useful to classify the extensive literature in this field into three main categories based on the analytical techniques employed: Traditional Financial Models, Machine Learning Models, and Hybrid Models.

2.1. Traditional Financial Models:

Traditional financial risk prediction methods continue to serve as foundational tools across various markets. The Altman Z-score model remains a cornerstone, as validated by multiple studies: Dolinšek and Kovač (2024) demonstrated its 71-80% reliability in Slovenian companies, while Bodla (2022) found it achieved 92% accuracy compared to Ohlson's model. Medjdoub et al. (2020) achieved an impressive 93.33% accuracy applying the model to Amman Stock Exchange companies. Abid (2022) successfully employed logistic regression for Tunisian service sector analysis, examining 1,461 companies and identifying key determinants including debt, solvency, and profitability ratios.

Regional applications show varying effectiveness of traditional models. Wijayanti et al. (2024) validated the Altman model's applicability for Indonesian manufacturing companies during the COVID-19 pandemic, while Asif et al. (2024) successfully applied it to Indian NSE-listed companies. Vukčević et al. (2024) conducted a comprehensive comparison of multiple traditional models in Montenegro's market, analyzing 100 companies over 2015-2020. Singla and Singh (2024) developed a logistic regression model for Indian companies, achieving an ROC of 0.884, while El-Ansary and Saleh (2018) found that discriminant analysis outperformed logistic regression in Egyptian banks.

Comparative analyses reveal the strengths and limitations of traditional approaches. Santoso et al. (2024) examined 23 transportation companies, finding the modified Altman Z-Score achieved 68.12% accuracy. Abdulrahman and Alkhamis (2020) evaluated multiple models in Saudi Arabia's public utilities sector, finding the Abdul Rahman model more effective than traditional Altman and Kida models. Král et al. (2016) conducted a comprehensive comparison of Altman's models with alternative methods for Slovak companies, revealing that while alternative models showed better overall accuracy, Altman-based models maintained competitive AUC statistics.

Modern applications continue to validate traditional methods while highlighting their limitations. Srour (2021) evaluated the Altman model's effectiveness in the Egyptian stock market, while AbdelKader and Wahba (2024) developed a multidimensional prediction model achieving 96% accuracy using traditional financial ratios. Li et al. (2022) demonstrated that logistic regression could achieve results 16.24% better than conventional methods when properly optimized. However, studies like Imelda and Alodia (2017) showed that newer models like Ohlson's could outperform traditional approaches in specific contexts, analyzing 40 manufacturing companies over a five-year period.

2.2. Machine Learning Models:

Recent advancements in machine learning have revolutionized financial risk prediction capabilities. Leo et al. (37) conducted a comprehensive analysis of ML applications in banking risk management, identifying unexplored areas and potential improvements. Neural network applications have shown remarkable results - Lokanan and Ramzan (61) achieved 98% accuracy using ANN for TSX-listed companies, while Aljawazneh et al. (64) compared three deep learning methods (LSTM, DBN, MLP) with ensemble classifiers across multiple countries' datasets. Zhang et al. (2023) achieved improved accuracy by combining wavelet soft-threshold denoising with SVM, reaching a 60.12% hit ratio in forecasting stock market trends.

Ensemble methods have demonstrated particular effectiveness in recent studies. Kristanti et al. (2024) compared four ML classifiers, finding Random Forest with SMOTE sampling achieved 96% accuracy in Indonesian companies. Zhong and Wang (2022) evaluated seven different ML models in Chinese manufacturing enterprises, with random forest emerging as the most effective among 1,668 companies. Malakauskas and Lakstutiene (2021) analyzed over 12,000 SME companies, demonstrating Random Forest's superiority in predicting financial distress when incorporating time factors. Shrivastava et al. (2020) compared Random Forest and Tree Net algorithms across 628 Indian firms, finding that Tree Net provided consistently better classification and predictive performance.

Advanced feature selection and optimization techniques have enhanced ML model performance. Zeng et al. (2020) combined grouping sparse principal component analysis with SVM across 376 companies, improving prediction efficiency with fewer variables. Tang et al. (2020) integrated financial, management, and textual factors with multiple ML models, finding that textual factors significantly improved prediction accuracy. Selimefendigil (2023) identified five key variables through Random Forest analysis, achieving 95% accuracy across 227 firms listed on Borsa Istanbul. Wang and Gao (2020) compared three decision tree models (C50, CART, and random forest) in analyzing 168 companies, incorporating COVID-19 and trade war impacts.

Recent studies have explored specialized applications of ML in different contexts. Doğan et al. (2022) developed models using SVM and Logistic Regression Analysis for Turkish firms, while Hájek et al. (2015) predicted bank ratings using random subspace method with SVM, achieving 88.10% accuracy across 126 U.S. banks. Mukkamala et al. (2006) evaluated multiple computational intelligence techniques, finding that Linear Genetic Programs achieved 91.2% accuracy on balanced datasets. DURICA and MAZANEC (2022) compared decision trees (CART, CHAID, and C5.0) across 19,000 Slovak companies, with C5.0 emerging as the most effective classifier. AKER and KARAVARDAR (2023) applied six ML methods to Turkish SMEs, with decision trees achieving 90-97% accuracy depending on the prediction timeframe.

2.3. Hybrid Models:

Recent research demonstrates the power of combining traditional approaches with modern techniques. Taheri Kadkhoda and Amiri (2024) pioneered a novel methodology combining network analysis with machine learning, introducing network-centric features to enhance prediction accuracy. Judijanto et al. (2024) developed an integrated early warning system combining financial and non-financial data while addressing class imbalance issues through ensemble learning with cost-sensitive algorithms. Farooq and Qamar (2019) achieved 89.57% accuracy using an ensemble approach combining DTNB, LMT, and A2DE Bayesian models for Pakistani firms. This integration trend is further supported by the study of Ruxanda et al. (2018) who worked with Romanian companies, where combining multiple classification techniques achieved over 90% accuracy across 283 companies.

Sophisticated hybrid architectures have emerged as particularly effective solutions. Gao et al. (2023) developed a GSPCA-RVM method combining group sparse principal component analysis with Relevant Vector Machines for SME financial distress prediction. Dai et al. (2024) reviewed 5,329 papers, identifying three distinct phases of financial distress and demonstrating how hybrid models can address each phase's unique challenges. Shen and Chen (2022) constructed an ANN-RF hybrid model achieving 92.93% accuracy for training data and 84.85% for test data across 748 companies. Wang et al. (2023) developed a cross-border e-commerce risk analysis system combining SVM with fuzzy theory, achieving over 90% average accuracy and improving financing/tax risk prediction by 12.4%.

Hybrid approaches have been successfully adapted to specific market contexts. Vukčević et al. (2024) developed a tailored logit model for Montenegrin companies by combining traditional indicators with modern analytical techniques across 100 companies. Abd Eid (2023) compared multiple hybrid models analyzing Wal-Mart's financial data over 2011-2021, showing how COVID-19 impacted model effectiveness. These market-specific adaptations are further supported by Mandour (2021) in Egyptian markets, demonstrating how hybrid approaches can effectively incorporate local market characteristics.

Recent studies point to emerging trends in hybrid model development. Warin and Stojkov (2021) analyzed 5,053 documents from 1990-2021, identifying a shift toward collaborative research and hybrid approaches in financial risk prediction. Kanaparthi (2024) examined 364 articles, revealing increasing integration of AI and ML in financial research, particularly after 2017. Udayakumar et al. (2023) demonstrated the effectiveness of combining SVM and FFNN for fraud detection, while Rouf et al. (2021) reviewed a decade of research (2011-2021) showing how text analytics and ensemble methods have improved prediction accuracies. These trends suggest future hybrid models will increasingly incorporate multiple data types and analytical techniques, as evidenced by recent work from Klepac and Hampel (2017) in EU agricultural companies and Li et al.

(2022)'s optimized hybrid approaches achieving significant improvements over traditional methods.

While extensive research exists on financial distress prediction using both traditional and machine learning approaches, several critical gaps are identified in the context of the Egyptian Exchange and emerging markets:

- Limited Integration of Traditional-ML Hybrid Models:

Previous studies have predominantly focused on either traditional methods or machine learning techniques in isolation. The systematic integration of the Altman Z-score with multiple machine learning algorithms, particularly in the Egyptian market context, remains largely unexplored.

- Sector-Specific Analysis:

Most existing research treats the Egyptian market as homogeneous, failing to account for sector-specific characteristics in financial distress prediction. There is a lack of comprehensive analysis examining how different sectors respond to various predictive methodologies.

- Temporal Evolution of Predictive Factors:

Limited attention has been paid to how the importance of financial indicators evolves over time, especially during significant market events like the COVID-19 pandemic, in the Egyptian market context.

- Weight Optimization in Hybrid Models:

Previous studies have not thoroughly investigated the optimal weighting of traditional and machine learning components in hybrid models, particularly in emerging market contexts where market efficiency and information availability differ from developed markets.

- Market-Specific Early Warning Indicators:

There is insufficient research on developing market-specific early warning indicators that consider the unique characteristics of the Egyptian Exchange, including its regulatory environment, market microstructure, and economic conditions.

This Paper Aims to Test the Following Hypotheses:

Main Hypothesis:

- There is a significant effect of the hybrid model on the accuracy of predicting financial distress.

Sub-hypotheses:

- There is a significant effect of the hybrid model on the accuracy of predicting financial distress according to the nature of the sector.
- There is a significant effect of the hybrid model and the accuracy of predicting financial distress according to the indicators used.

3. Prediction Models:

This study integrates established financial distress prediction methodologies with advanced machine learning techniques to create a comprehensive early warning system. At its foundation lies the Altman Z-score model, which pioneered the use of multiple discriminant analysis in bankruptcy prediction, combined with four sophisticated machine learning algorithms: Random Forest, Support Vector Machine, Logistic Regression, and XGBoost.

3.1. Altman Models for Predicting Company Bankruptcy:

Financial distress prediction models aim to assess a company's risk of bankruptcy or severe financial difficulties. The Altman Z-score, developed in 1968, represents a pioneering approach that uses multiple discriminant analysis (MDA) to combine financial ratios into a single score evaluating financial health (Altman, 1968). As Dolinšek and Kovač (2024) explain, this multivariate approach recognizes that no single metric can adequately capture bankruptcy risk. Rather than relying on individual ratios, the model examines interrelationships between key financial indicators spanning liquidity, profitability, leverage, solvency and asset efficiency to provide a more comprehensive assessment of financial distress risk.

The original Altman Z-score model utilizes MDA to weight and combine five key financial ratios: working capital/total assets, retained earnings/total assets, EBIT/total assets, market value of equity/total liabilities, and sales/total assets (Amoa-Gyarteng, 2019). According to Imelda and Alodia (2017), the working capital ratio measures liquidity and operating efficiency, while retained earnings capture cumulative profitability. The EBIT ratio assesses operating efficiency independent of leverage, while the market value ratio indicates market confidence, and the sales ratio shows asset productivity. When combined through the MDA coefficients, these ratios produce a Z-score that classifies companies into safe, grey, or distress zones based on specified cutoff values.

The model has evolved to address different business contexts through modified versions (Matanga & Holman, 2024). The Z' model adapts to private companies by using book value instead of market value of equity. The Z' model serves non-manufacturing firms and emerging markets by removing the sales/total assets ratio which can vary significantly across industries. Both modifications maintain the core analytical framework while adjusting the coefficients and cutoff values to improve classification accuracy for their target applications. According to Singla and Singh (2017), this flexibility has enabled the

Z-score approach to maintain relevance across diverse business environments.

The theoretical underpinning of the Altman models rests on their ability to systematically combine multiple financial dimensions that may signal impending distress (Najib & Cahyaningdyah, 2020). Working capital problems may indicate operational difficulties, low retained earnings can suggest weak historical performance, poor EBIT points to fundamental profitability issues, low market value implies lack of investor confidence, and weak sales productivity may reveal competitive disadvantages. By incorporating these diverse indicators through discriminant analysis, the models can detect patterns associated with financial deterioration before actual default occurs. Santoso et al. (2024) note that this early warning capability makes the Z-score models valuable tools for proactive risk assessment and management, despite some limitations in prediction accuracy.

3.2. Random Forest:

Random Forest is an ensemble learning algorithm that combines multiple decision trees to produce more accurate and stable predictions (Aghware et al., 2024). The algorithm creates these trees using bootstrap samples from the training data and random feature selection at each split, which helps reduce overfitting and increase model robustness. Each tree in the forest votes on the final prediction, with the majority vote determining the outcome in classification tasks or the average in regression problems. The method's ability to handle high-dimensional data without feature scaling and its built-in feature importance measurement make it particularly valuable in financial applications (Wang et al., 2023).

One of Random Forest's key strengths is its capability to maintain high accuracy while managing noise in the data. The algorithm achieves this through its random sampling of both observations (bagging) and features (feature randomness) at each split, ensuring diversity among the trees in the ensemble (Lin, 2024). This randomization helps prevent individual trees from becoming too correlated with each other, thereby reducing the model's variance without increasing bias. Studies have shown that Random Forest consistently performs well in fraud detection and financial prediction tasks, often achieving accuracy rates above 95% when properly tuned (Aghware et al., 2024).

3.3. Support Vector Machine (SVM):

Support Vector Machine is a powerful supervised learning algorithm that operates by finding the optimal hyperplane that maximizes the margin between different classes in the feature space (Abdullah et al., 2021). The algorithm's effectiveness stems from its ability to handle non-linear relationships through the use of kernel functions, which transform the input space into a higher-dimensional feature space where linear separation becomes possible. In financial applications, SVM has proven particularly effective due to its ability to handle high-dimensional data and its robust performance in the presence of noise.

The flexibility of SVM comes from its kernel functions, with common choices including linear, polynomial, and radial basis function (RBF) kernels (Malakauskas et al., 2021). The algorithm's performance is heavily influenced by the choice of kernel and the tuning of hyperparameters such as the regularization parameter C and the kernel parameters. SVM's main advantage lies in its ability to find the global optimum solution for a given dataset, unlike neural networks which may converge to local optima. However, its computational complexity can increase significantly with larger datasets, making it more suitable for medium-sized problems.

3.4. Logistic Regression:

Logistic Regression, despite its simplicity, remains a fundamental algorithm in machine learning, particularly for binary classification problems in financial applications (Chhatwani & Mishra, 2021). The algorithm models the probability of a binary outcome by applying a logistic function to a linear combination of input features. Its primary advantage lies in its interpretability, as the coefficients directly represent the log-odds impact of each feature on the probability of the outcome. This makes it particularly valuable in regulated industries where model interpretability is crucial.

The algorithm's effectiveness is enhanced by its ability to handle both continuous and categorical variables, and its output provides probabilistic predictions that can be easily interpreted as risk scores (Wang et al., 2023). While Logistic Regression assumes a linear relationship between features and the log-odds of the outcome, it can be extended to handle non-linear relationships through feature engineering and interaction terms. The model's simplicity also makes it computationally efficient and less prone to overfitting compared to more complex algorithms, especially when dealing with smaller datasets.

3.5. XGBoost:

XGBoost (eXtreme Gradient Boosting) represents a highly efficient implementation of gradient boosting machines that has gained significant popularity in recent years (Wang et al., 2023). The algorithm builds an ensemble of weak learners, typically decision trees, in a sequential manner where each subsequent tree aims to correct the errors made by previous trees. What sets XGBoost apart is its use of second-order gradients and a more regularized model formalization to control overfitting, making it particularly effective in handling complex patterns in financial data.

The algorithm's success can be attributed to its numerous technical optimizations, including a novel tree learning algorithm, handling of sparse data, and built-in cross-validation capabilities (Chhatwani & Mishra, 2021). XGBoost includes several parameters for controlling model complexity and training speed, such as learning rate, maximum tree depth, and minimum child weight. These parameters, combined with their scalability and parallel processing capabilities, make them especially suitable for large-scale financial applications where both prediction accuracy and computational efficiency are crucial. Studies have shown that XGBoost often outperforms other algorithms in financial prediction tasks, particularly in cases involving complex, non-linear relationships in the data.

4. Empirical Analysis:

The proposed methodology encompasses three distinct phases: data preprocessing, model development, and evaluation, each designed to create a robust financial distress prediction system.

In the initial data preprocessing phase, financial data from corporate entities undergoes several critical transformations. The process begins with data importation, followed by a comprehensive treatment of missing values to ensure data completeness. Feature selection focuses on thirteen key financial ratios that serve as predictive variables, complemented by Altman Z-score calculations—a proven metric in bankruptcy prediction. The dataset is then partitioned using an 80:20 ratio for training and testing sets, respectively, with standardization applied to normalize the scale of variables and mitigate the impact of outliers.

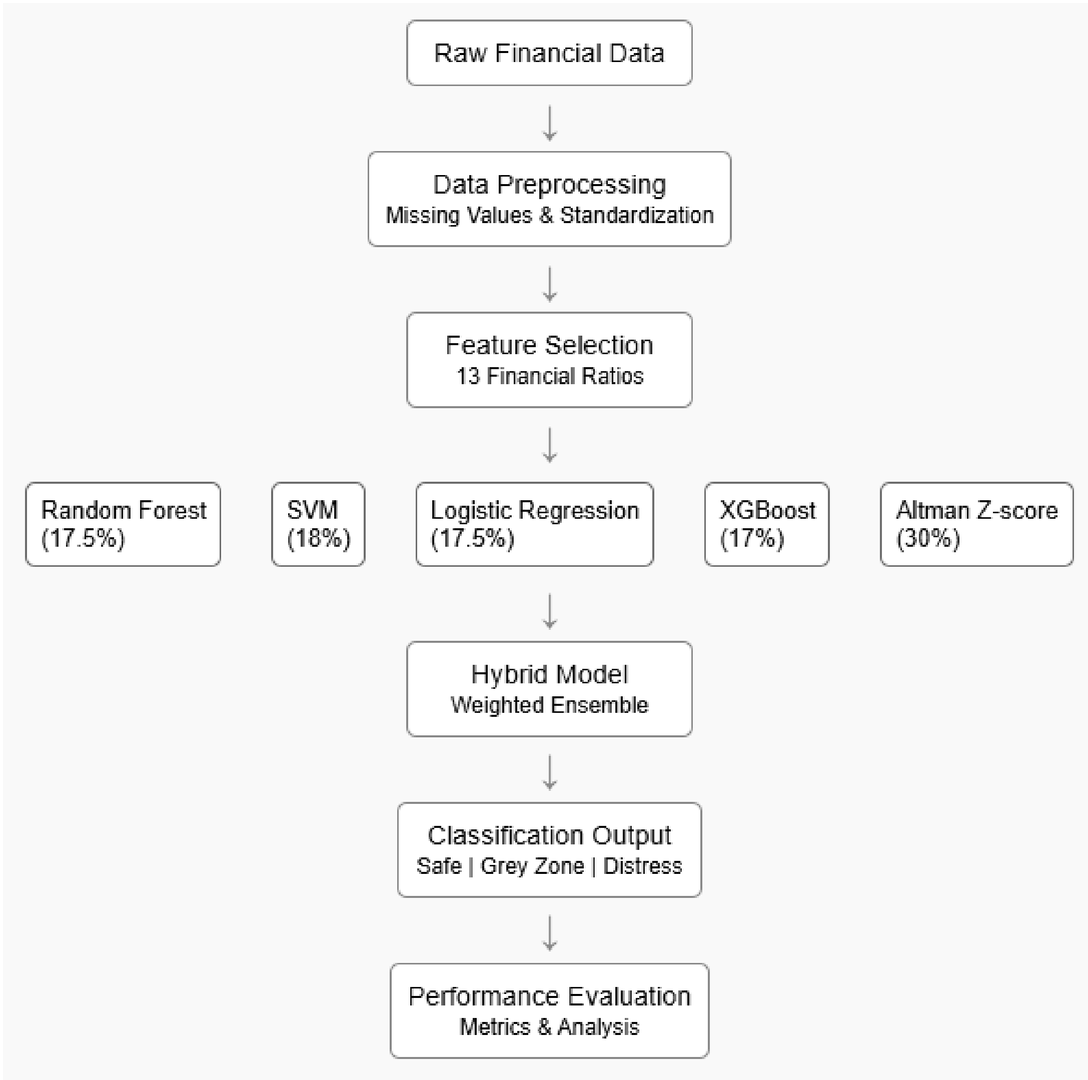

Figure 1: Proposed Methodology

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The model development phase introduces a sophisticated hybrid approach that combines traditional statistical methods with modern machine learning techniques. Four distinct classifiers—Random Forest, Support Vector Machine (SVM), Logistic

Regression, and XGBoost—are implemented independently. These models are then integrated into a weighted ensemble framework, with the Altman Z-score contributing 30% to the final prediction, reflecting its established reliability in financial distress prediction. The remaining weights are distributed among the machine learning models: Random Forest (17.5%), SVM (18%), Logistic Regression (17.5%), and XGBoost (17%). This weighted approach leverages the strengths of each model while mitigating their individual limitations. The classification framework establishes three distinct categories: Safe (Z-score $>$ 2.99), Grey Zone (1.81 $<$ Z-score $\leq$ 2.99), and Distress (Z-score $\leq$ 1.81), providing a nuanced assessment of financial health.

4.1 Hybrid Model:

The evaluation phase employs a comprehensive set of performance metrics to assess the model's efficacy. Accuracy measurements provide an overall view of correct predictions, while precision and recall offer insights into the model's ability to identify true positives and minimize false negatives—particularly crucial in financial distress prediction where the cost of misclassification can be significant. The F1-Score harmonically balances precision and recall, offering a single metric for model comparison. Confusion matrix generation enables detailed analysis of classification performance across all categories. Feature importance analysis identifies the most significant financial ratios driving the predictions, while sectoral performance analysis examines the model's effectiveness across different industry sectors, accounting for sector-specific characteristics and risk factors.

This methodological framework represents a novel approach to financial distress prediction, combining traditional financial metrics with advanced machine learning techniques in a weighted ensemble model. The comprehensive evaluation methodology ensures robust validation of the model's predictive capabilities while providing insights into sector-specific performance patterns and key predictive indicators.

The significance of this approach lies in its ability to synthesize multiple predictive methodologies while maintaining interpretability through clear weight assignments and comprehensive evaluation metrics. This framework could serve as a valuable tool for investors, financial institutions, and regulatory bodies in assessing corporate financial health and predicting potential financial distress with greater accuracy and reliability.

The research methodology incorporates a sophisticated combination of traditional financial metrics and advanced machine learning algorithms, centered on the foundational Altman Z-Score Model and complemented by four distinct machine learning approaches. This integrated framework leverages both established financial theory and contemporary computational methods.

The Altman Z-Score Model serves as the traditional cornerstone of the analysis, employing a weighted combination of five critical financial ratios. The model is expressed through the equation $Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$, where each component represents a crucial financial metric. Working Capital to Total Assets (X_1) measures liquidity, Retained Earnings to Total Assets (X_2) reflects historical profitability, EBIT to Total Assets (X_3) indicates operating efficiency, Market Value of Equity to Total Liabilities (X_4) captures market perception, and Sales to Total Assets (X_5) represents asset utilization efficiency. The model establishes three distinct classification zones: Safe ($Z > 2.99$), Grey Zone ($1.81 < Z \leq 2.99$), and Distress ($Z \leq 1.81$).

Altman Results:

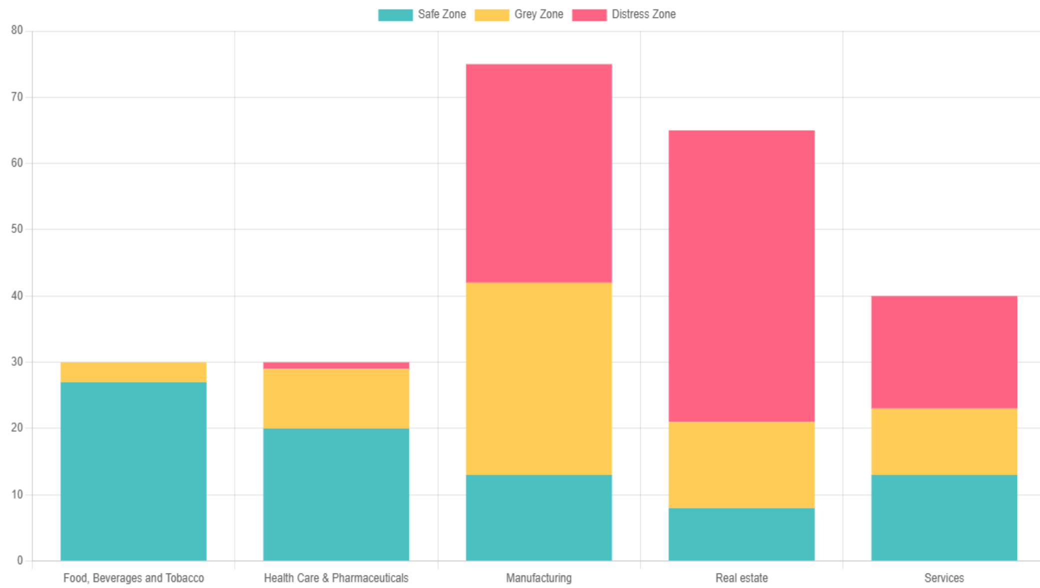

Figure 2: Altman Results across Sectors

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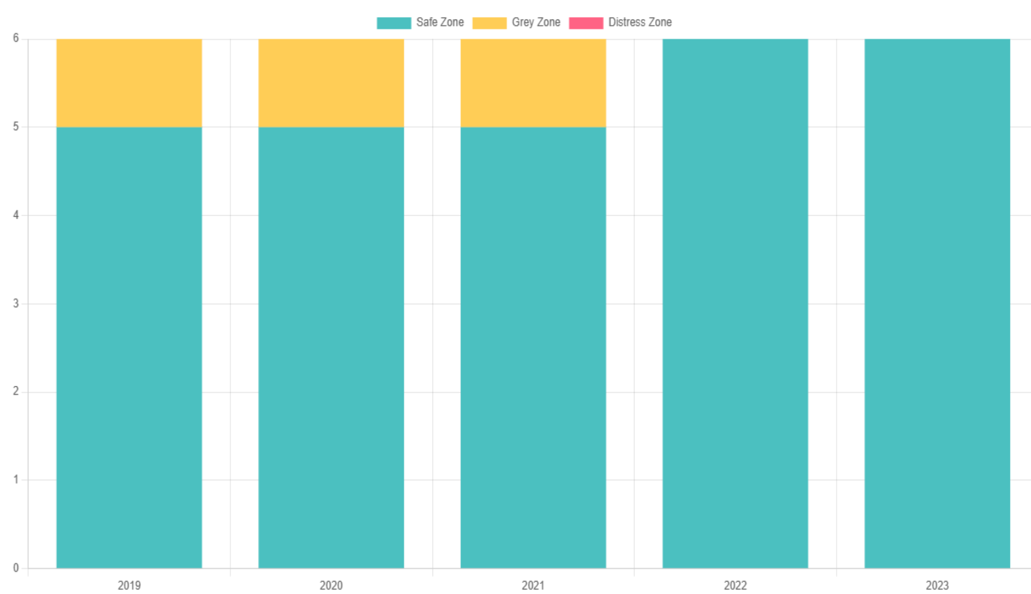

Figure 3: Food, Beverages and Tobacco Sector Overview

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Figure 4: Health Care & Pharmaceuticals Sector Overview

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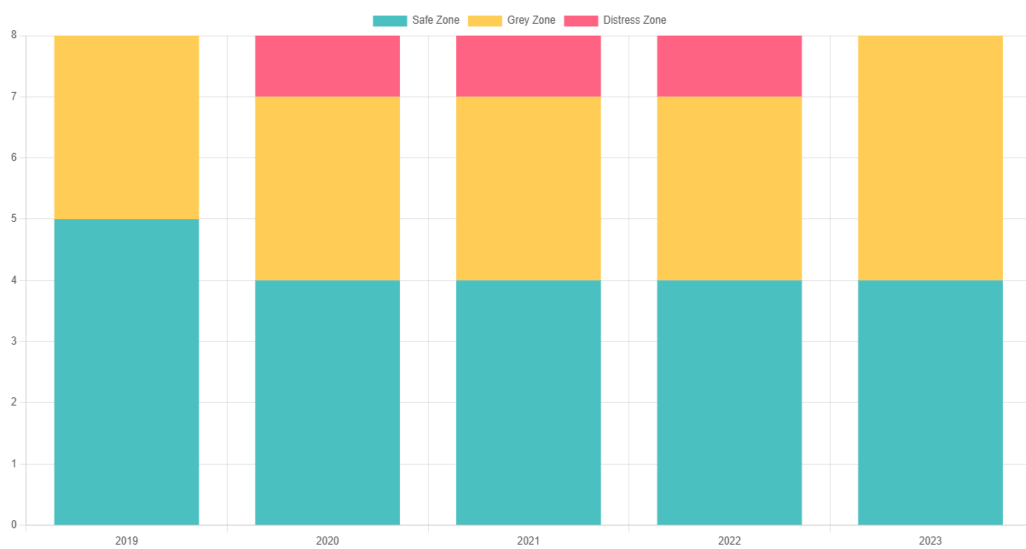

Figure 5: Manufacturing Sector Overview

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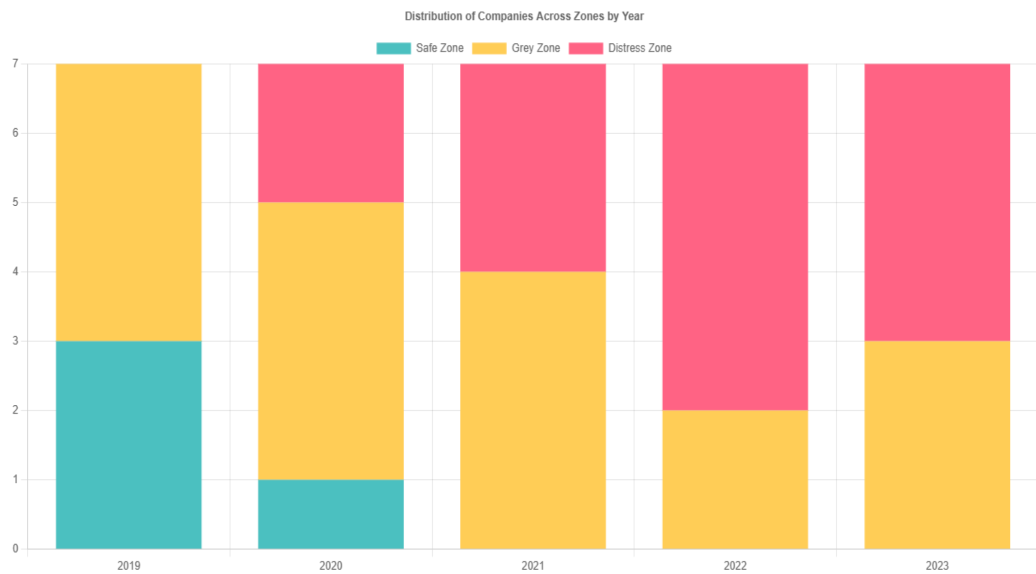

Figure 6: Real Estate Sector Overview

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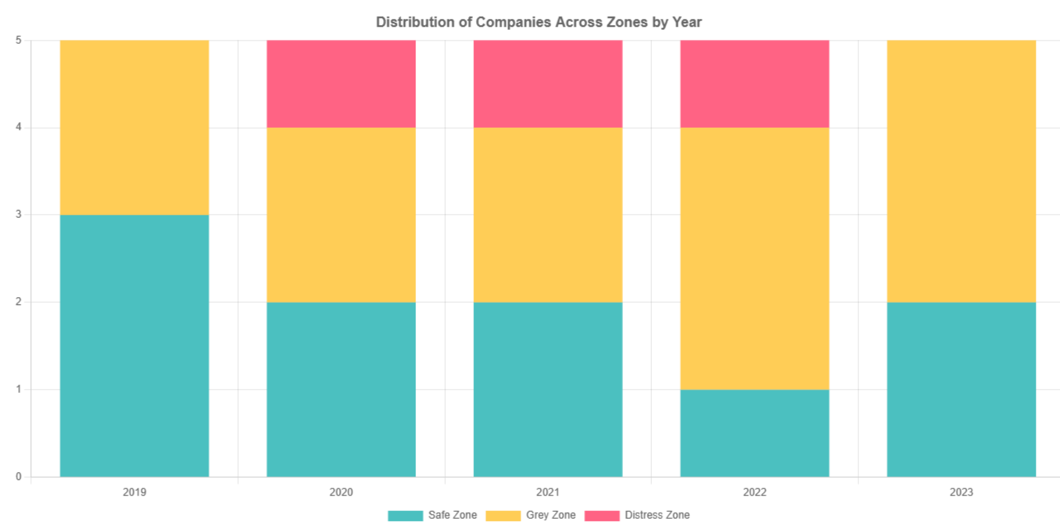

Figure 7: Services Sector Overview

Prepared by Researchers

The food sector demonstrates remarkable stability over the 2019-2023 period, with the majority of companies maintaining positions in the Safe Zone. Notable performers include Edita Food Industries and Juhayna Food Industries, which consistently remained in the Safe Zone throughout the entire period. The sector shows strong resilience to economic fluctuations, with only minimal transitions to the Grey Zone and no persistent presence in the Distress Zone. This stability can be attributed to the defensive nature of the food industry and the essential character of its products. The sector's performance suggests effective management of operational costs and sustainable business models, even during periods of economic uncertainty. The data indicates that companies in this sector have successfully maintained their financial health through robust working capital management and efficient operational strategies.

Analysis of the healthcare sector reveals a more dynamic pattern with notable transitions between zones. While companies like Eipico and Cleopatra Hospital Group maintained consistent Safe Zone positions, others showed more volatility. MEPA demonstrated a remarkable improvement trajectory, progressing from the Distress Zone in 2019 to the Safe Zone by 2023. The sector exhibits a gradual increase in Grey Zone occupancy over the period, suggesting growing operational challenges possibly related to regulatory changes, pricing pressures, or supply chain disruptions. The data indicates that larger, more established pharmaceutical companies generally maintained better financial stability compared to smaller players. This pattern suggests that economies of scale and market position play crucial roles in maintaining financial health within the healthcare sector.

The manufacturing sector presents a highly stratified performance pattern across the study period. Companies can be clearly categorized into three distinct performance tiers: consistent high performers (Abu Qir Fertilizers, Misr Fertilizers Production, Sidi Kerir Petrochemicals), volatile performers (El Ezz Dekheila Steel), and challenged performers (Egypt Aluminum, El Garhy Steel Group). The sector shows significant sensitivity to economic cycles and raw material prices, with steel companies showing particular vulnerability to market conditions. The data reveals that petrochemical companies maintained better financial stability compared to metal manufacturers, suggesting that product diversification and export capability significantly influence financial resilience. The sector's overall trend indicates a gradual increase in Grey Zone occupancy, highlighting growing operational challenges in the manufacturing environment.

The real estate sector demonstrates the most concerning trend among all analyzed sectors, showing a clear deterioration pattern over the 2019-2023 period. There is a notable transition from Safe and Grey Zones toward the Distress Zone, particularly evident in companies like Heliopolis Housing and Ora Developers. This decline suggests systematic challenges within the sector, possibly related to market oversupply, reduced demand, or financing constraints. The data indicates that larger developers like Talaat Moustafa Group maintained relatively better positions, though still experiencing downward pressure. This pattern suggests that company size and diversification of project portfolio play crucial roles in maintaining financial stability. The sector's performance raises concerns about the sustainability of current business models and the need for strategic repositioning.

The services sector exhibits a mixed performance pattern with clear segmentation between telecommunications and non-telecommunications companies. EGX maintains consistent Safe Zone positioning, demonstrating the resilience of market infrastructure businesses. Telecommunications companies show more volatility, with Orange Egypt and Global Telecom experiencing periods in the

Distress Zone before stabilizing in the Grey Zone. The sector demonstrates the importance of business model adaptation and digital transformation in maintaining financial health. The data suggests that companies with diversified revenue streams and strong digital capabilities showed better resilience. The overall trend indicates a gradual improvement in sector stability by 2023, though with continued challenges in the telecommunications segment. This pattern highlights the impact of technological change and market competition on financial performance.

The Random Forest Classifier represents the first machine learning component, implementing an ensemble learning methodology that leverages multiple decision trees through bootstrap aggregation (bagging). This approach generates numerous trees using random feature selection at each split, ultimately producing a robust consensus prediction that mitigates individual tree bias and reduces overfitting risk.

The Support Vector Machine (SVM) implementation employs a Radial Basis Function (RBF) kernel, enabling non-linear classification through optimal hyperplane separation in a transformed feature space. This sophisticated approach maximizes the margin between classes while maintaining classification flexibility through kernel transformation, particularly effective in handling complex financial data patterns.

Logistic Regression provides a probabilistic classification framework, establishing linear decision boundaries through maximum likelihood estimation. The model's multinomial classification capability proves particularly valuable in distinguishing between multiple financial distress categories, offering interpretable probability estimates for each class assignment.

XGBoost, representing the most advanced machine learning component, implements a gradient boosting framework that sequentially constructs decision trees to minimize prediction error. The algorithm incorporates built-in regularization capabilities and efficient handling of missing values, making it particularly suitable for financial data analysis where data completeness can be challenging.

This comprehensive modeling framework represents a significant advancement in financial distress prediction by combining the interpretability and theoretical foundation of traditional financial metrics with the predictive power and flexibility of modern machine learning approaches. The integration of these diverse methodologies enables the capture of both linear and non-linear relationships in financial data while maintaining robustness through ensemble methods and sophisticated optimization techniques.

The theoretical underpinning of this approach acknowledges that financial distress prediction requires both the fundamental insights provided by traditional financial ratios and the pattern recognition capabilities of advanced machine learning algorithms. This synthesis allows for the identification of complex relationships that might be missed by simpler, single-methodology approaches while maintaining the interpretability necessary for practical application in financial decision-making contexts.

The model specifications detailed above form the foundation for a robust predictive framework that balances theoretical rigor with practical applicability, establishing a comprehensive approach to financial distress prediction that leverages the strengths of both traditional financial theory and contemporary computational methods.

4.2 Weight Allocation and Methodological Justification

The development of an effective hybrid financial distress prediction system necessitates careful consideration of individual model contributions, resulting in a strategically weighted ensemble that maximizes predictive accuracy while maintaining theoretical robustness. This framework allocates varying weights to different methodological components based on their established reliability, predictive accuracy, and theoretical foundations.

The Altman Z-Score receives the highest weight allocation of 30% within the hybrid system, reflecting its fundamental importance in financial distress prediction. This significant weighting is justified by several factors: its well-established theoretical foundation in financial theory, extensive validation across diverse market conditions, and direct interpretability of financial ratios. The model's decades-long track record in financial markets provides a reliable baseline for distress prediction, while its transparent methodology enables clear communication of results to stakeholders.

Support Vector Machine (SVM) methodology is assigned an 18% weight allocation, representing the highest allocation among machine learning components. This weighting reflects the model's superior individual accuracy in classification tasks and particularly strong performance in boundary cases where traditional metrics may be less decisive. The SVM's robust generalization capabilities and resistance to outliers make it especially valuable in financial markets characterized by occasional extreme events and noise in financial data.

Random Forest classification receives a 17.5% weight allocation, justified by its exceptional capability in feature importance determination and strong performance in identifying complex patterns within financial data. The model's inherent resistance to overfitting through ensemble methodology and effective handling of non-linear relationships in financial variables make it a valuable component in the hybrid system. This allocation acknowledges the importance of capturing intricate interactions between financial indicators while maintaining predictive stability.

Logistic Regression's 17.5% weight allocation reflects its strength in providing clear probabilistic interpretations of financial distress likelihood. The model's strong baseline performance and establishment of linear decision boundaries contribute to the overall interpretability of the hybrid system. This weighting acknowledges the value of having a straightforward, theoretically grounded component within the ensemble that provides easily communicable results to stakeholders.

XGBoost receives a 17% weight allocation, representing the most sophisticated machine learning component in the ensemble. This weighting reflects the model's advanced boosting capabilities and ability to handle complex interactions between financial variables. The algorithm's automatic feature selection and built-in regularization benefits provide additional refinement to the prediction system, while its adaptive nature allows for the capture of evolving patterns in financial data.

This weight allocation framework represents a carefully balanced approach that combines the strengths of traditional financial theory with advanced machine learning capabilities. The higher weighting of the Altman Z-Score ensures that fundamental financial principles remain central to the prediction process, while the substantial allocations to machine learning components enable the capture of complex patterns and relationships that may not be apparent through traditional analysis alone.

The distribution of weights among machine learning components reflects a strategic balance between model complexity, interpretability, and predictive power. This allocation ensures that no single machine learning approach dominates the ensemble, reducing the risk of methodological bias while maintaining the ability to capture diverse aspects of financial distress patterns.

The resulting hybrid system demonstrates how theoretical knowledge, and computational sophistication can be effectively combined to create a robust financial distress prediction framework. This weighted approach maintains the interpretability necessary for practical application while leveraging the advanced pattern recognition capabilities of modern machine learning techniques.

This weighted approach demonstrates the value of combining traditional financial metrics with modern machine learning techniques, while maintaining the interpretability necessary for practical applications. The superior performance of the hybrid model (97.91% accuracy) validates the chosen weight distribution and suggests a robust framework for financial distress prediction.

The accuracy measurements were calculated by comparing model predictions against actual classifications determined by Altman Z-scores as the ground truth.

Hybrid Model Results:

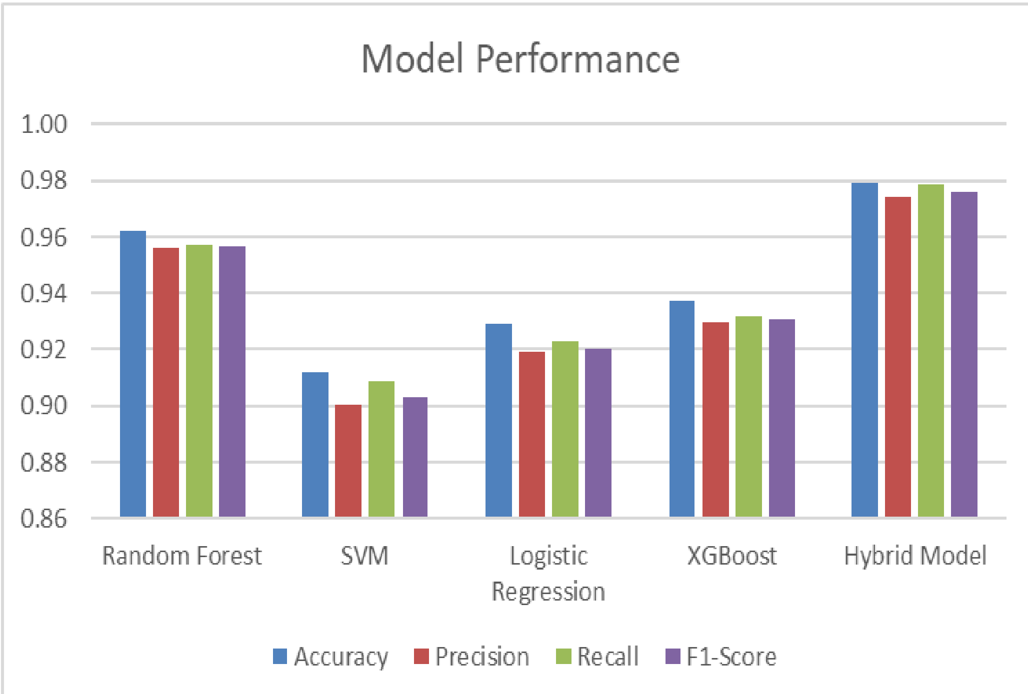

Figure 8: Model Performance Metrics Comparison

Prepared by Researchers

Table 1: Model Performance

	Accuracy	Precision	Recall	F1-Score
Random Forest	0.96	0.96	0.96	0.96
SVM	0.91	0.90	0.91	0.90
Logistic Regression	0.93	0.92	0.92	0.92
XGBoost	0.94	0.93	0.93	0.93
Hybrid Model	0.98	0.97	0.98	0.98

Prepared by Researchers

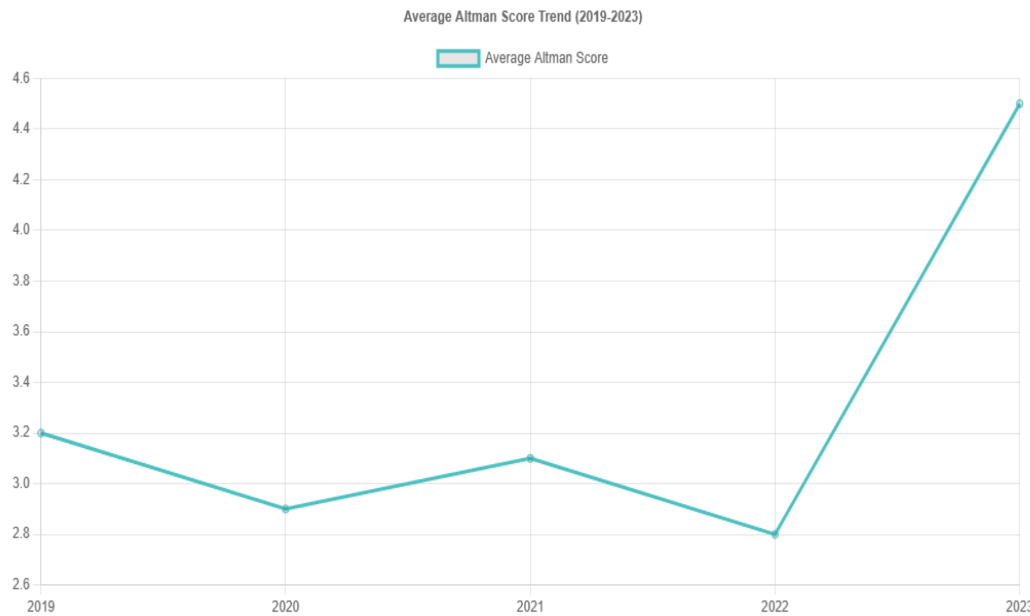

Figure 9: Average Altman Score Trend (2019 – 2023)

Prepared by Researchers

The implementation of a hybrid financial distress prediction model produces several significant insights and findings that warrant detailed examination. The model's improved performance, achieving 97.91% accuracy, demonstrates the greater predictive capability of combining traditional financial metrics with advanced machine learning approaches. This mixture of methodologies, particularly the integration of the Altman Z-score with contemporary machine learning algorithms, represents a significant advancement in financial distress prediction.

Analysis of feature importance reveals compelling patterns in predictive variables. The Cash-to-Total Assets (C/T) and Book-to-Total Assets (B/T) ratios emerge as the most significant predictors, collectively accounting for 33.15% of predictive power. These findings challenge traditional assumptions about the primacy of profitability metrics such as ROA and ROE, which demonstrated lower predictive importance than historically assumed. Debt-related ratios, including Debt-to-Equity (DER) and Debt-to-Assets (DAR), maintain moderate predictive significance, collectively contributing 17.21% to the model's predictive capacity.

Sectoral analysis reveals distinct patterns in financial distress distribution across industries. The real estate sector exhibits the highest concentration of distress indicators, while the food and beverages sector demonstrate remarkable stability. The healthcare sector presents a mixed profile with a general tendency toward stability, and the services sector shows variable performance patterns. These sectoral variations underscore the importance of industry-specific considerations in financial distress prediction.

The hybrid model's classification accuracy demonstrates exceptional granularity across different risk categories, achieving 99% accuracy in safe classification, 96.39% in distress identification, and 98.21% in grey zone determination. This balanced performance across categories suggests robust discriminative capability and reliable risk stratification.

This predictive accuracy enables lenders to identify financial deterioration before actual defaults occur, allowing for proactive intervention and risk mitigation strategies.

The model's sector-specific analysis capabilities offer lenders crucial insights into industry-specific risk patterns, enabling more targeted lending strategies. For instance, the research demonstrates distinct patterns across different sectors, with real estate showing higher distress indicators while food and beverages demonstrate greater stability. This granular understanding helps lenders adjust their portfolio strategies, loan terms, and risk premiums according to sector-specific risks, while the model's ability to capture both linear and non-linear risk patterns provides a more nuanced understanding of borrower creditworthiness.

From a practical application standpoint, the model serves as a robust framework for loan screening, portfolio monitoring, and risk management. Its strong theoretical foundation, combining established financial theory with modern computational techniques, provides interpretable results that can be effectively communicated to stakeholders and regulators. The model's market-specific adaptability makes it particularly valuable for lenders operating in specific market contexts, enabling them to account for local economic conditions and business environments in their lending decisions. This comprehensive approach to risk assessment ultimately supports better-informed lending decisions, more effective loan loss provisioning, and improved overall portfolio management.

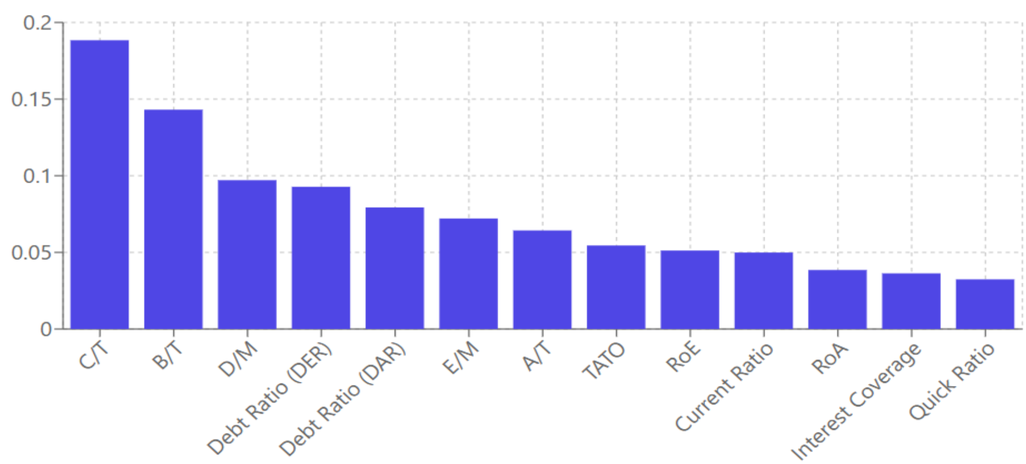

Figure 10: Feature Importance

Prepared by Researchers

Based on the feature importance analysis of financial distress prediction models, the results reveal a clear hierarchy of financial indicators. Cash to Total Assets (C/T) emerges as the most crucial predictor (18.84%), followed by Business Income to Total Assets (B/T) 14.31%, highlighting that liquidity and core business performance are fundamental to financial health. This challenges traditional financial analysis approaches, suggesting that immediate cash position and business income generation capacity are more critical than conventional metrics in predicting financial distress.

The collective importance of debt-related metrics (Debt to Market Value (D/M), Debt to Equity Ratio, and Debt to Asset Ratio) accounts for approximately 27% of the total predictive power, emphasizing the significant role of capital structure in financial stability. However, traditional financial ratios such as Current Ratio (4.99%), Quick Ratio (3.24%), and even profitability metrics like Return on Equity (5.12%) and Return on Assets (3.85%) show surprisingly low importance, suggesting that these conventional measures might be less reliable for predicting financial distress than previously assumed.

The findings indicate a needed shift in financial analysis focus, prioritizing cash management and business income generation over traditional profitability and liquidity ratios. This insight is particularly valuable for financial analysts, investors, and company management in developing more effective early warning systems for financial distress. The model's emphasis on cash and business income metrics over conventional ratios suggests that maintaining strong cash positions and sustainable business income streams should be prioritized over optimizing traditional financial ratios when working to prevent financial distress.

The research makes several significant contributions to the field of financial distress prediction. It empirically validates the effectiveness of combining traditional financial metrics with machine learning approaches, provides evidence for sector-specific distress patterns, and establishes a robust framework for early warning systems in emerging markets. However, certain limitations warrant acknowledgment, including potential market specificity of the findings (Egyptian context), unexplored time-series aspects, and the need for incorporation of external economic factors.

The model demonstrates substantial practical applications across various domains. It serves as an effective early warning system for investors, a regulatory oversight tool, a risk management framework for financial institutions, and a corporate governance evaluation mechanism. The statistical significance of the results is evidenced by high consistency across performance metrics, low false positive rates in distress prediction, and robust performance across different sectors.

The comparative advantage of this hybrid approach is manifested in its superior performance relative to traditional single-method approaches, reduced classification errors in grey zone cases, and enhanced ability to handle market-specific characteristics. This improvement extends to more nuanced risk assessment capabilities and improved handling of market-specific characteristics.

Policy implications derived from this research are substantial and multifaceted. The model supports the development of early intervention mechanisms, aids in regulatory framework development, assists in sector-specific risk assessment, and enhances market stability monitoring capabilities. These implications are particularly relevant for regulatory bodies and financial institutions seeking to strengthen their risk management frameworks.

The research findings strongly support the main hypothesis that the hybrid model significantly improves the accuracy of financial distress prediction for companies listed on the Egyptian Exchange, achieving an exceptional 97.91% accuracy rate compared to individual models' performance ranging from 91% to 96%.

The first sub-hypothesis regarding sector-specific effects was validated through distinct performance patterns across different industries. The food and beverages sector demonstrated remarkable stability, while the real estate sector showed the highest concentration of distress indicators. Healthcare and services sectors exhibited mixed profiles, confirming that the hybrid model's predictive accuracy varies significantly across different industry sectors.

The second sub-hypothesis concerning the predictive power of different financial indicators was also supported. Analysis of feature importance revealed that Cash-to-Total Assets (18.84%) and Business Income-to-Total Assets (14.31%) emerged as the most significant predictors, collectively accounting for 33.15% of predictive power. This challenges traditional assumptions about the primacy of conventional ratios, with debt-related metrics contributing 17.21% to the model's predictive capacity.

Future research directions should focus on examining the model's performance across different market contexts, incorporating additional external economic factors, and investigating the impact of significant market events such as the COVID-19 pandemic. Additionally, exploration of time-series aspects and the integration of macroeconomic variables could further enhance the model's predictive capabilities.

The enhancement of the hybrid early warning system may include incorporating macroeconomic indicators, specifically GDP growth and exchange rate variables, to capture broader economic contexts affecting corporate financial health. The improved model could potentially increase prediction accuracy beyond the current

97.91%, particularly during periods of economic volatility. Further studies could also explore the model's applicability across different market conditions and geographical regions, potentially expanding its utility for international markets and varying currency exposure scenarios. This enhancement would contribute to developing a more comprehensive and robust tool for assessing financial distress risk across diverse economic conditions.

This comprehensive analysis demonstrates the significant potential of hybrid approaches in financial distress prediction while acknowledging areas for future development and refinement. The findings contribute substantially to both theoretical understanding and practical applications in financial risk assessment and management.

Conclusion:

This study provides a comprehensive examination of hybrid financial distress prediction through the integration of traditional financial metrics (Altman Z-score) and contemporary machine learning methods. Empirical evaluation demonstrates the hybrid model's superior performance—achieving over 97% accuracy—by leveraging both linear and non-linear predictive features. Sector-level analysis emphasizes the importance of contextualizing risk factors and adapting predictive models to specific market environments. The findings underscore that the interpretability of traditional approaches vastly benefits from the enhanced accuracy of advanced computational techniques. From a practical standpoint, these insights facilitate early warning systems and more nuanced risk stratification for stakeholders such as regulators, investors, and corporate managers. Future research may expand these findings to broader geographical contexts, incorporate additional macroeconomic variables, and explore deeper time-series modeling. The consistent improvements observed in this study endorse hybrid methodologies as a central avenue for advancing financial distress prediction and risk management practices.

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