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Developing an Artificial Intelligence-Based Financial Distress Prediction Model for Sustainable Industrial Development: Evidence from the Electrical Engineering Sector

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Abstract - Electrical engineering is especially vulnerable to macroeconomic instability and misaligned flow because of its high capital investment and complexity of the supply chain. Linear bankruptcy analysis techniques, such as the Altman Z score, are likely to fail in the event of quick deterioration and non-linear asset shock, which in turn would affect the continuity of business and economic viability of the industry. To address this deficiency, the current paper proposes an AI methodology that is based on a longitudinal panel data sample of 50 electrical engineering companies in the period 2018-2025. To resolve the problem of class imbalance, the preprocessing stage utilises the Synthetic Minority Over-sampling Technique (SMOTE) algorithm and winsorizes the data on outliers. The benchmarking results demonstrate the superiority of the Extreme Gradient Boosting (XGBoost) algorithm relative to conventional methods and neural network-based architectures, with the highest predictive accuracy reaching 93.5% and the global Area Under the Receiver Operating Characteristic (ROC-AUC) metric equaling 0.96. Relative Gini importance matrices point to the interest coverage capacity (0.224) and inventory turnover (0.186) as the main indicators of the onset of problems in business operations. Reducing false negatives ensures optimal allocation of capital from outside the firm and helps to preserve jobs in high-tech manufacturing.

Keywords: Artificial intelligence, economic resilience, electrical engineering sector, financial distress prediction, supply chain risk management, sustainable development, XGBoost.

I. INTRODUCTION

The Electrical Engineering Sector is a structural pillar in the modern Industrial Transition. It serves as an infrastructure to the automation and smart grids, and to the hardware involved in the distribution of renewable energy, which are capital-intensive processes [1]. The entire technological chain is threatened by the instability of micro-economic factors in this sector. Maintaining manufacturing jobs and high-tech capabilities is directly sustained through corporate sustainability in this field [1]. The reason for these operational disruptions is very fast, as it affected not only industrial production locally, but also renewable energy targets [2]. Thus, structural stability in the field of electrical engineering allows for sustainable macroeconomic growth.

Electrical engineering companies are in a very vulnerable situation when it comes to system dangers [3]. Structurally mismatched cash flows result from the length of the research and development (R&D) period [4]. Meanwhile, the pressure comes to the balance sheet from serious semiconductor shortages and fluctuations in raw material prices. The current risk measurement is based on traditional lagging measures and is not able to identify companies in trouble in time [1]. Detection systems have to change their approach, moving from lagging to leading indicators [5].

Legacy frameworks for analysing company failure are strongly anchored in the use of linear discriminant models and static financial disclosures [2]. Z-scores by Altman and binary logistic regressions assess company performance through fixed weightings [6]. These methods assume stable multicollinearity of relationships and do not take into account the high dynamics of the corporate environment. Moreover, mathematical models are unable to deal with the complexity of non-linear shocks occurring in various industries [7]. As a result, academic literature reveals a dramatic decrease in classification accuracy of the old framework during macroeconomic turmoil [8].

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Moreover, artificial intelligence (AI) provides a new framework for assessing corporate vulnerability [9]. Machine learning models analyse huge nonlinear accounting datasets without the use of rigid parametric assumptions. The use of ensemble models, including Random Forest and XGBoost, helps to assess the dynamics of complicated interactions between different features [9]. Neural networks identify hidden indicators of distress occurring in the multi-year corporate panel dataset [10]. The usage of computational analysis transforms the entire framework of corporate monitoring.

Despite advances in algorithms, modern financial machine learning literature still lacks considerable contextual aspects. Existing studies on distress tend to aggregate heterogeneous business activities into one general sample [11]. Such generalisation leads to the loss of unique financial features of specific industries, causing mispredictions [11, 12]. Moreover, different asset compositions of the electrical engineering sector are under-researched using any AI algorithms [13]. In most empirical approaches, the focus is on absolute error and ignores other social consequences of sustainability [10]. So, it is important to overcome such a gap to have a stable industrial ecosystem.

This study directly deals with these theoretical and practical limitations. First, a custom financial distress model using granular-level firm data is created. This analysis compares state-of-the-art machine learning (ML) execution with diagnosis baselines that have been with us for a long time, second. Furthermore, the study is a clear mapping of the predictions of the algorithms to specific corporate sustainability goals. Finally, this structure inquiry offers managers and business decision makers a very actionable systemic risk oversight indicator.

II. METHODOLOGY

This research employed a very scientific and data-driven methodology to design a highly resilient, scalable and detailed early warning indicator to anticipate financial distress in the electrical engineering industry. Since electrical engineering companies are highly capital-intensive in nature, their products usually require long research & development cycles, and their suppliers are highly dependent on each other, the use of conventional financial indicators does not always succeed in capturing their inherent weaknesses prior to their failure. The purpose of this section is to give a methodological design for filling this gap by employing machine learning.

A. Data Collection and Sampling

The present study has relied primarily on empirical data gathered from multi-national databases of companies, with particular emphasis on the publicly traded and large-sized privately held manufacturing companies in the field of electrical engineering. The criteria for structuring the sample are given below:

Classification by Sector: Companies, whose main activity is the manufacturing of electrical machines, electronics, power distribution systems, industrial automation equipment, etc., and are classified in the internationally accepted industry codes (SIC Code 3600-3699 or NACE Rev. 2 Section C27).

Horizon of Time: The panel data is collected over a well-documented period of time (2018 – 2025). The time frame was also selected with care as it included many of the critical macroeconomic events, including the impact of the global pandemic on supply chains, the semiconductor crisis and inflationary pressures on the local market, which was an ideal test for the model.

Financial Audit: The companies that did not supply the necessary information regarding their important accounting statements (Income Statement, Balance Sheet and Cash Flow) for two or more periods were eliminated from the sample. Adjustments for inflation were made to the data.

Operational Definition of Financial Distress

The one crucial shortcoming in the context of contemporary bankruptcy prediction research is an excessive dependence upon conventional dichotomous definitions of financial insolvency, which are usually post hoc statements rather than predictive signs [14]. The present research uses a complex operational indicator that identifies a company as financially distressed (Target Y = 1): Firms are considered financially distressed if they have negative operating net income (EBIT) for two consecutive years [15]; the market value declined by more than 70% from the 36-months moving median [16]; or measures were taken because of non-compliance, such as debt restructuring, bankruptcy and de-listing [17]. Conversely, Herman and Zsido [18] and Owusu et al. [19] pointed out that companies with positive economic value added and adequate debt capacity are healthy (Target Y = 0).

B. Feature Engineering and Variable Selection

Current data sets that contain unstructured accounting information are too sparse in signals to be used by modern machine learning algorithms. Thus, a set of twenty-four (24) distinct financial ratios is developed and then translated into five different structural dimensions that are important in capital-intensive manufacturing. These are the factors along which microeconomic distress appears.

TABLE I. Feature Engineering and Variable Selection

Dimension	Financial Ratio / Feature Name	Economic Justification for Sector Resilience
Liquidity	• Current Ratio • Quick Ratio • Cash to Total Assets	Reflects the immediate protection of the short-term buffer against a sudden disruption of components and debt calls from component suppliers.
Leverage	• Debt-to-Equity Ratio • Interest Coverage	Evaluates the insolvency of the structure, which is very important for electrical engineering

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	Ratio • Debt Service Coverage Ratio	companies, having a large number of capital expenditures.
Profitability	• Return on Assets (ROA) • Operating Profit Margin • EBITDA Margin	Records the long-term economic viability, pricing advantages over raw materials and inherent cost efficiencies.
Solvency	• Retained Earnings to Total Assets • Working Capital to Total Assets	Shows long-term historical stability and its ability to finance internally to withstand extended periods of macro-economic shocks.
Efficiency	• Inventory Turnover Period • Asset Turnover Ratio • Days Sales Outstanding (DSO)	Traces operational optimisation; vital for evaluating working capital lockup in raw materials and finished engineering hardware.

Data Preprocessing and Managing Class Imbalance

Databases used in corporations for identification of financial distress are inevitably affected by severe problems of class imbalance since defaulting firms constitute a tiny fraction of all market participants (usually 3% to 7% of the active segment). To avoid bias towards the major class, the data preprocessing included a three-phase procedure:

Extreme Outliers Winsorization: To provide computational stability, all financial ratios are winsorized at 1% and 99% levels, avoiding distortion from anomalous reports or macroeconomic restructuring changes.

Missing Values Treatment: Single missing values were processed through the K-Nearest Neighbours (K=5) approach, utilising intra-industry peers' metrics instead of simply replacing with the average value, thus keeping the original local distribution intact.

Class Balancing through Synthesis (SMOTE): The training set was artificially balanced through the Synthetic Minority Over-sampling Technique (SMOTE). Through generating new synthetic distressed vectors between actual distressed nearest neighbours, the minor class distribution was reinforced, and any artificial increase in accuracy measures was avoided.

C. Model Construction and Algorithmic Expressions

Four different classification models were developed for a thorough performance range. They included the conventional multivariate diagnostic model and three contemporary and sophisticated non-linear machine learning models.

1. Conventional Reference Model: Modified Altman Z-Score for Manufacturers. As an empirical reference model, a modification of the classic Altman Z-Score of manufacturers is considered. The linear equation included five ratios and produced one solvency ratio as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 0.999X_5 \quad (1)$$

where X_1 is the Working Capital/Total Assets ratio, X_2 is the Retained Earnings/Total Assets ratio, X_3 is the EBIT/Total Assets ratio, X_4 is the Market Value of Equity/Total Liabilities ratio, and X_5 is the Sales/Total Assets ratio. The model served as a starting point for evaluating the added value of complex non-linear machine learning algorithms.

2. Random Forest (RF) Classifier

The Random Forest classifier is an ensemble of the bagging class, which seeks the best stability to minimise overfitting and achieve that through an unweighted voting scheme over a large forest of decorrelated decision trees [19]. Every tree in the collection was learned using a different bootstrap sample taken from the initial learning sample. The predictor for the entire ensemble was defined mathematically as:

$$H_{(x)} = argmax_y \sum_{b=1}^{B} I(h_b(x) = y) \quad (2)$$

Where $Hb_{(x)}$ is the classification result of the b-th decision tree when fed with an input feature vector x, $I(\cdot)$ is the indicator function, and B is the number of independent estimators. In our framework, the parameters are selected using the randomised grid search approach to set B = 500 trees, with the max depth parameter being limited to 15.

3. Extreme Gradient Boosting (XGBoost)

Unlike the bagging methods, XGBoost employed a highly sophisticated technique of sequential boosting. Specifically, it minimises a complex objective function involving a chosen loss function and penalties on the complexity of the model. The function minimised at step t is the one described below:

$$L^{(t)} \approx \sum_{i=1}^{n} \left[l(y_i, y_i^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \quad (3)$$

Where g_i and h_i are the first-order and second-order gradient statistics of the loss function, respectively, while $\Omega(f_t)$ manages complexity through penalties on the number of leaves and weights. For our task, we have limited the maximum tree depth to 6, the learning rate (eta) to 0.05, and sampling to 0.8 to protect from the effects of localised data noise.

4. Artificial Neural Networks (ANN)

To reveal deeper structural relationships between financial variables, a multi-layer perceptron (MLP) is developed. MLP network has the following structure: It has an input layer that corresponds to the 24 designed features, two hidden layers with ReLU activation function, and one neuron on the output layer powered by the Sigmoid function to calculate probabilities of bankruptcy explicitly:

$$P(Y = 1|x) = \sigma(W_2 \cdot max(0, W_1 x + b_1) + b_2) \quad (4)$$

where W_1, W_2 and b_1, b_2, are the weight matrix and bias vector for each layer, respectively. Optimising is done using the Adam optimiser and minimising the cross-entropy loss function on the stratified 80/20 training/test set partition.

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D. Framework for Model Evaluation

Assessment of the early warning systems solely based on accuracy in risk management could be very deceptive. For example, classifying a firm which is actually in distress as healthy (False Negative) is much worse than the other mistake. That is why models are validated along five different aspects with a stratified 10-fold cross-validation design:

Sensitivity / Recall: It is used to determine whether the model is capable of detecting all firms that are truly in distress and preventing any unexpected structural collapse.

Precision: This measure helps to ensure that distress signals are precise and capital allocation is not affected by false positive results.

F1-Score: It is the harmonic mean of Precision and Recall and represents a useful single measure of imbalanced model validation.

ROC-AUC: This measure shows the area under the curve and determines the model's global discriminatory power regardless of any sample prior.

With such a complex assessment of the model's performance within the technical framework, the obtained predictive models could offer valuable operational safety from any industrial destabilisation.

III. RESULTS

This section presents the results that have been observed through analysing the panel dataset used for electrical engineering. The analysis process involves a number of steps, starting with descriptive statistics. This is followed by model benchmarking. Lastly, the financial drivers are identified through feature importance analysis.

A. Descriptive Statistics and Sample Stratification

The unstructured sample data contains exactly 400 unique observation periods across a multi-year layout. This represents 50 distinct corporate entities tracked continuously between 2018 and 2025. Through examining the raw sample, there is an identification of distinct baseline changes in the financial structure variables.

TABLE II. Summary of Descriptive Statistics and Sample Stratification

Financial Metric Area	Healthy Cohort (Mean)	Distressed Cohort (Mean)	Statistical Variance Level
Current Ratio (X)	1.92	0.78	High Variance ($p < 0.01$)
Debt-to-Equity Ratio (X)	1.10	4.25	High Variance ($p < 0.01$)
Return on Assets (ROA)	6.5%	-6.8%	High Variance ($p < 0.01$)
Inventory Turnover Period (Days)	64.2 Days	134.8 Days	Moderate Variance ($p < 0.05$)
Days Sales Outstanding (DSO)	54.7 Days	102.3 Days	High Variance ($p < 0.01$)

Source: Field Data (2026)

Based on the descriptive analysis as evinced in Table II above, the capital structure is highly stressed within the troubled manufacturing industry. The healthy companies have a current ratio of 1.92, which shows the existence of a significant level of short-term liquidity capacity. On the other hand, the troubled engineering industry has low liquidity capacity, accompanied by a higher leverage ratio of 4.25. Operation turnover ratios show that there are inefficiencies due to a doubled inventory turnover period of 134.8 days.

B. Predictive Model Performance Comparison

After balancing the dataset through the Synthetic Minority Over-sampling Technique (SMOTE), all the models were evaluated through the stratified 10-fold cross-validation method. This will help in obtaining generalisation measures and detecting any form of overfitting issues. Table III gives a comparison of all the performance measures.

TABLE III. Summary comparison of the performance measures

Classification Model	Accuracy	Precision	Recall (Sensitivity)	F1-Score	ROC-AUC
Altman Z-Score Baseline	74.1%	69.3%	66.2%	67.7%	0.75
Random Forest (RF)	89.4%	87.1%	88.5%	87.8%	0.92
Extreme Gradient Boosting (XGBoost)	93.5%	91.8%	94.1%	92.9%	0.96
Artificial Neural Network (ANN)	91.2%	89.5%	90.3%	89.9%	0.94

From the above results, it can be seen that the sophisticated machine learning methods are way better compared to the traditional baseline multivariate method. The Altman Z-Score method was able to only obtain 67.7% of the F1-score due to its very strict linear framework. In the AI algorithms employed, Extreme Gradient Boosting (XGBoost) showed better precision and recall. Also, the highest accuracy and overall ROC-AUC scores that were obtained by XGBoost were 93.5% and 0.96, respectively. Importantly, the high recall rate of XGBoost (94.1%) is indicative of a few dangerous false negatives.

C. Feature Contribution and Structural Risk Drivers

To avoid the 'black box' challenge associated with machine learning systems, the feature contribution weights have been obtained from the ensemble model. This helps to highlight the major warning signals in the asset structure of electrical engineering.

TABLE IV. Summary of featured contribution weights

Rank	Financial Feature Variable	Relative Gini Importance	Primary Operational Vector

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1	Interest Coverage Ratio (ICR)	0.224	Leverage / Debt Service Margin
2	Inventory Turnover Period	0.186	Efficiency / Working Capital Lockup
3	Return on Assets (ROA)	0.151	Profitability / Economic Viability
4	Days Sales Outstanding (DSO)	0.128	Efficiency / Collection Latency
5	Current Ratio	0.109	Liquidity / Short-term Buffer

In the context of the relative Gini values, interest coverage ability (0.224) turns out to be the most important leading signal for health monitoring. The second most important indicator is the inventory turnover time (0.186), highlighting the specific exposure to shortages in the industry. Discovering such weights makes it possible to convert raw predictive signals into meaningful indicators of risks in the industry.

IV. DISCUSSION

A. Evaluation of Algorithmic Paradigms

Empirical evidence shows the superiority of non-linear machine learning algorithms compared to the old accounting system. The adapted Altman Z-Score algorithm shows a constrained linear structure, which is ineffective in cases of extreme volatility in macroeconomic conditions. Classical diagnostic systems rely on stable multicollinear relationships, which are incapable of identifying quick microeconomic events. Due to this, the model achieves an F1-score of 67.7% while analysing complex industrial structures. In contrast, the optimised Extreme Gradient Boosting achieves remarkable accuracy with a maximum value of 93.5% [8]. Improved classification is due to the sequential boosting, which minimises objective loss.

Ensemble learning models handle large data configurations without considering rigid parametric and historical continuity assumptions. Random Forest and XGBoost analyse complex company parameters to minimise potential false negative predictions. Reducing false negatives will prevent external capital investors from structural defaults in high-tech industries. Empirical findings indicate that neural networks can trace concealed non-linear information from company panel datasets [10]. Nevertheless, XGBoost is better than the neural network algorithm to study the property of data structure through localised tree weight adjustment for data noise. It achieves an ROC-AUC score of 0.96.

B. Risk Drivers and Sector Characteristics

Gini coefficients reveal the particular operational risks associated with the contemporary electrical engineering industry. Interest coverage ratio works as the leading predictor with a weight of 0.224. Firms operating in this sector operate capital-intensive automated infrastructure construction projects, which involve significant amounts of borrowing. Long research and development periods create structural cash flow problems and put at stake the short-term debt repayment ability of the firms. Therefore, tight interest coverage ratios reveal early signs of vulnerability prior to bankruptcy declaration [5]. The statistical data support high capital structure distress among the distressed manufacturers.

Moreover, operational efficiency variables also play an important role in prediction through the machine learning process. Inventory days represent the second key driver of risk, with the Gini coefficient of 0.186. Electrical engineering firms have high systemic vulnerability related to the semiconductor crunch and supply chain disruptions [19]. In the case of the distressed group of firms, there is an extreme working capital constraint problem, which leads to a doubling of inventory days to 134.8 days. On the other hand, long collection delays lead to an increase in days' sales outstanding to 102.3 days among failing manufacturing businesses [10].

C. Implications for Sustainable Industrial Policy

Incorporation of machine learning computational models in structural surveillance frameworks leads to the transformation of corporate risk management strategies. Mitigation of early distress contributes to the protection of jobs in manufacturing sectors, green energy objectives, and regional supply networks [20]. Corporate shocks spread quickly, leading to severe localised economic crises and quick disruption of supply networks [2]. The lack of consideration of overall socioeconomic resilience aspects, in addition to the need for perfect predictability, forms the most significant weakness in existing empirical research literature. This framework makes up for such an analytical void through alignment of technical information with industrial surveillance criteria.

V. CONCLUSION

In conclusion, this research has demonstrated success in developing an advanced, non-linear artificial intelligence model designed for the electrical engineering industry. Analytical results show that linear bankruptcy indicators will fail to reflect rapid changes in company operations amidst supply shocks. Using the sequential ensembles technique, the final pipeline delivered an impressive level of prediction accuracy of 93.5%. Most importantly, interest coverage capability and inventory turnover duration have proven to be the main indicators of microeconomic instability. By avoiding false negative classifications, companies are protected from sudden failure, guaranteeing the safety of regional technological labour market indicators.

Moving on, this paper provided practical recommendations for sector stakeholders. It states that managers should employ advanced machine learning monitoring in their ongoing internal audit systems. Using only lagging factors will result in high susceptibility to rapid working capital shortages. Operational

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teams need to track inventory days and accounts receivable lateness indicators to identify vulnerabilities and avoid total depletion of the company's capital. Moreover, commercial banks are to switch from static risk evaluation methods to dynamic non-linear scoring models. Transitioning to automated risk management systems allows one to minimise default risks and sustain proper capital distribution.

Also, sector-wide early warning monitoring registries should be constructed by industrial policymakers through machine learning (ML) models. Localised corporate failure can be avoided from affecting wider technology supply and installation networks. These high-precision predictive indicators are suitable for the allocation of stabilisation funds and restructuring subsidies by state agencies. The financial strength of engineering companies is vital to the protection of critical regional infrastructure and clean energy deployment goals. Sustainable macroeconomic transition strategies of emerging industrial corridors depend on the resilience at the microeconomic level. Thus, the economic sustainability of the long-term will be guaranteed by including AI in regulations.

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