**LITERATURE REVIEW**

The prediction of financial failure is a matter of utmost importance and has been a focal point for numerous researchers. An incorrect assessment of a company's financial health can lead to significant financial losses. Traditionally, predicting a company's financial status has been accomplished through statistical techniques such as Linear Discriminant Analysis (LDA), Multi-Discriminant Analysis (MDA), and Logistic Regression (LR or Logit). Alternatively, Machine Learning (ML) algorithms have also been employed as shown in *Devi and Radhika (2018)*. In the 1960s, *Altman (1968)* utilized MDA to forecast the financial status of companies based on their financial statements. Subsequently, *Ohlson (1980)* adopted the Logit model to predict corporate financial distress. *Brozyna, Mentel, and Pisula (2016)* applied LDA and LR to forecast the financial condition of Polish and Slovak companies. *Jones and Hensher (2004)* introduced a mixed Logit model and compared it with a standard Logit model for predicting financial distress, demonstrating that the mixed Logit model yielded superior results. More recently, several researchers have conducted comparative studies between statistical techniques and ML methods for predicting corporate financial failure. For example, *Pompe and Feelders (1997)* compared the performance of LDA with classification trees and neural networks in this context, concluding that neural networks outperformed other methods. *Min and Lee (2005)* assessed the effectiveness of SVM, MDA, Logit, and three-layer fully connected back-propagation neural networks in bankruptcy prediction, with SVM delivering the best results. Nevertheless, recent studies have indicated that ML algorithms tend to outperform statistical models in the realm of bankruptcy prediction. Consequently, many researchers have approached it as a classification problem and applied standard ML classification or regression methods for prediction.

Furthermore, some researchers have integrated multiple ML algorithms to enhance the effectiveness of forecasting financial failure in companies. For example, *Fedorova, Gilenko, and Dovzhenko (2013)* experimented with various combinations of RBF (Radial Basis Function) networks and MLP to predict the bankruptcy of Russian companies, employing a balanced dataset containing 2906 samples selected from the entire available dataset. *Iturriaga and Sanz (2015)* merged MLP and SOM (Self-Organized Maps) to forecast the financial failure of US banks up to three years in advance. They worked with a balanced dataset comprising 754 samples. Similarly, *Lanbouri and Achchab (2015)* introduced a hybrid model consisting of DBN and SVM to predict financial distress in French companies, using a balanced dataset with 966 samples. Nevertheless, it's worth noting that these studies assessed the performance of their algorithm combinations using just a relatively small dataset.

Bankruptcy prediction datasets typically exhibit an imbalanced distribution, reflecting the fact that only a small fraction of companies experience bankruptcy in real-world scenarios. Consequently, it becomes essential to employ data-balancing techniques. SMOTE and its variations have been widely utilized in various studies. For example, *M.-J. Kim, D.-K. Kang and H. B. Kim (2015)* incorporated SMOTE in conjunction with their Geometric Mean-based Boosting (GMBoost) algorithm, yielding highly favorable outcomes. Authors *Islam, Eberle, Ghafoor, Bundy, Talbert, and Siraj (2019)* also applied SMOTE to rebalance an extremely imbalanced dataset during preprocessing, resulting in performance improvements across 13 classification and regression algorithms. In another study by author *Zhou (2013)*, SMOTE was combined with various traditional classification methods. The author examined the optimal scenarios for using different balancing techniques and highlighted the benefits of considering diverse datasets, such as Japanese and American companies, to gain insights into how these methods perform in such contexts. In light of this, we have also incorporated multiple datasets to enhance our understanding of the problem.

Different variations of SMOTE have also been subject to comparison. In the study by *Le, Lee, Park, and Baik (2018)*, the impact of various balancing techniques, including SMOTE variants, was explored in the context of predicting the bankruptcy of Korean companies. Four classification models (RF, Decision tree, MLP, and SVM) were employed to forecast financial status. The dataset in question exhibited extreme imbalance, prompting the evaluation of five balancing techniques: the SMOTE variants (SMOTE, BL-SMOTE, SMOTE-ENN, SMOTE-Tomek), and ADASYN. Additionally, the classification models were tested on both the original and balanced datasets. RF consistently outperformed the other models in both scenarios, with the best results achieved when RF was paired with SMOTE-ENN. Consequently, given RF's superior performance in that study, we have also incorporated RF into our framework for predicting corporate financial failure, alongside other DL and ensemble methods, as mentioned earlier.

One of the driving factors behind our research is the utilization of DL algorithms as potent tools for forecasting corporate financial failure. In fact, there is a scarcity of studies that employ DL techniques with actual company data to predict financial distress.

*Jang, Jeong, Cho, and Y. Ahn (2019)* conducted a comparative analysis involving LSTM, Feed-forward neural network, and SVM for the prediction of business failure among listed US construction contractors. In a subsequent work by *Jang, Jeong, and Cho (2020)*, the same authors introduced a model based on LSTM to estimate the probability of business failure within a one-to-three-year timeframe, utilizing accounting data, construction market information, and macroeconomic variables. Notably, both studies incorporated the SMOTE-Tomek balancing technique during data preprocessing, which yielded superior results compared to using only accounting variables. Consequently, given the success of LSTM and SMOTE-Tomek in these two prior studies, we opted to integrate these methods into our research and assess their performance relative to other DL techniques and balancing approaches.

Taking a unique approach, certain researchers have leveraged financial data in the form of graphical representations. For instance, *Yeh, Wang, and Tsai (2015)* predicted the financial status of companies by employing Deep Belief Networks (DBN). They transformed the stock market returns of solvent and bankrupt companies into binary images, using these as training data for their models. Their findings demonstrated that DBN outperformed the traditional SVM classification method. In a similar vein, *Hosaka (2019)* introduced a method based on Convolutional Neural Networks (CNN) to forecast bankruptcy using grayscale representations of Japanese stock market data. Remarkably, this novel approach yielded superior results compared to classical methods and other DL classification techniques.

With the advancements in computational power and data availability, researchers have turned to new machine-learning techniques. Artificial Neural Networks (ANNs) were among the early methods applied to bankruptcy prediction due to their ability to learn complex patterns from the data provided. Subsequent studies incorporated decision trees, support vector machines, and random forests, all of which demonstrated improved predictive performances compared to traditional methods. These methods have demonstrated better performance than gradient-based algorithms as shown in *Ansari*, Ahmad, Bakar & Yaakub *(2020)*. Additionally, the effects of MOA on imbalanced datasets were discussed by authors *Al-Badarneh, Habib, Aljarah & Faris (2020)*, where a PSO algorithm was used as an optimizer for predicting bankruptcy in a neural network architecture. Authors *Mahendru, Garg, Sharma & Srivastava (2021)* describe in detail the effects of neural network architecture on bankruptcy predictions.

We have examined a dataset comprising Taiwanese companies, encompassing 6819 entries collected over a decade from 1999 to 2009. Among these entries, 6599 companies (approximately 97%) are non-bankrupt, while 220 companies (roughly 3%) are labeled as bankrupt. Clearly, the dataset exhibits significant class imbalance. It includes 95 financial health indicators and a single-class label indicating the bankruptcy status of each company. Detailed information about our dataset can be found in *Liang, Lu, Tsai & Shih (2016)*.

Bankruptcy prediction remains a critical task in financial analysis and decision-making. This literature review highlights the different bankruptcy prediction models and their approaches. The incorporation of non-financial data and the utilization of ensemble techniques have further advanced the predictive capabilities of these models. However, despite this significant progress, challenges persist, including imbalanced data and the interpretability of complex models. Our research efforts are focused on addressing these challenges to create more robust and practical bankruptcy prediction models that can better serve owners, investors, creditors, and stakeholders in the financial industry.

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