# Using Artificial Intelligence in Predicting Financial Distress:
# Comparative Analysis under the Context of IFRS 9 versus Basel III Accord

**Abstract**

The ability to predict business failure accurately is very important in financial decision making for both corporations and financial institutions. We propose using artificial intelligence to construct financial distress prediction models using various datasets of companies from several countries. The goal of this paper is to compare conventional techniques with this highly advanced machine learning application and to document significantly enhanced predictive performance. This study contributes to existing empirical financial distress research in at least two important ways. First, we use a machine learning application that has not been used in financial distress, credit risk or bankruptcy prediction literature. Second, we identify and test additional macro-economic classifiers as proxy for business cycles, to reflect the major changes in accounting standard and guidance that went into effect recently, specifically IFRS 9 and Basel III Accord. Our empirical results would suggest that artificial intelligence is an effective way to predict corporate financial distress.

## 1. Introduction

*Both financialists and economists were blamed during the most recent financial crisis;*

*the former group for creating it, and the latter group for failing to predict it*

*(~ collected, unknown ~).*

The financial (and emotional) consequences of financial crises and distress are quite often immeasurable in full. Therefore, it is important to develop financial distress prediction model with high predictive power. In the past, statistical approaches (parametric models) are commonly used, most notably logistic regression and regression analysis. More recently, however, researchers have reported that machine learning techniques are superior to the traditional methods.

The literature on financial distress using machine learning is still thin. Most focus on binary outputs such as bankruptcy, frauds, or credit rating changes and using U.S.-based data (Olson, Delen & Meng, *Decision Support Systems* 2012, Yu, Miche, Severin & Lendasse, *Neurocomputing* 2014, Jones, Johnstone & Wilson 2015, Barboza, Kimura & Altman, *Expert Systems with Applications* 2017). Several studies examine financial distress but applying machine learning tools (Tsai, *Information Fusion* 2014, Gepp & Kumar, *Procedia Computer Science* 2015); or using Chinese sample (Geng, Bose & Chen, *European Journal of Operational Research* 2015), or both (Sun & Li, *Applied Soft Computing* 2012). To the best of our knowledge, artificial intelligence (AI) or deep learning application in financial distress has not been used in peer-reviewed published journals.

## 2. Literature review

### 2.1. Artificial intelligence

AI or deep learning is a type of machine learning, but not all machine learning is deep learning. AI is built upon machine learning which is trained to learn constantly over time, with lower chance of making mistakes, and the ability to analyze vast volumes of data. Besides some weak to semi-strong AI such as automation, voice recognition, chat bots, or cognitive computing, the more developed AI has transformed the finance industry in some major ways, including personal credit risk assessment, fraud detection and management, financial advisory services, trading, managing personal finance, and lending. Many believe that AI will transform financial industry in the next few years.

### 2.2. Financial distress

Companies sometimes are considered financial constrained or financial distressed if they take on higher leverage or increased ratio of debt in capital structure, and maintain that operational setting for a long time, typically years. In worst case scenario, that could result in bankruptcy. In other conditions, these companies might be unable to finance their activities or they have to do so in a costly way. Occasionally, a major fraud would happen first, leading to highly distressing situation and eventually bankruptcy. As a result, being able to accurately predict the financial distress or financial quality of the companies is critically important to financial institutions. Financial distress could be “bankruptcy” in legal definition, or just some financial difficulty.

### 2.3. IRFS 9 versus Basel III Accord

IFRS 9[1] is an International Financial Reporting Standard (effective January 01, 2018) that addresses the accounting for financial instruments and covers three major topics: classification and measurement of financial instruments; impairment of financial assets; and hedge accounting. Basel III Accord is a global, *voluntary* regulatory capital and liquidity rules mutually agreed upon by Basel Committee members, with the implementation date extended till March 31, 2019. Basel III was developed after the financial crisis of 2007-2008 during which the deficiencies of financial regulation were exposed, to promote global stability.

The most critical difference (and change) in IFRS 9 is arguably the way probability of default (PD) is calculated. IFRS 9 allows for flexible "*point-in-time*" probabilities depending on economic conditions, compared to the "*through-the-cycle*" probabilities that have normally been used for regulatory purposes (or, cycle-neutral). Under IFRS 9, the PD behavior will show more of short-term fluctuation as opposed to long-term trend, and therefore raising the need of including time-series of macro-economic factors, hence credit environment, into assessment.

## 3. Methodology

We will use mainly MatLab and Python to conduct artificial analysis on our large datasets. Deep learning hierarchical models are well accepted as being able to produce more useful results than other conventional methods in finance, such as pricing securities, constructing portfolios, and risk management. Particularly, artificial intelligence can learn deeper and therefore detecting and exploiting interactions unexplored to existing financial economic theories. Some major advantages of AI are the ability to include all relevant items of input data, the increased in-sample fit since non-linearities and complex interactions are both accounted for, and, the ease of avoiding over-fitting problem (Heaton, Polson & Witte, *working paper* 2016)).

The overall construction of deep learning includes several steps. First, the input dataset is split into three subsets, namely training, validation, and testing. In step 1, the training set is used to adjust the weights of the network. In step 2, the validation set is used to minimize overfitting. In step 3 which is the last step, testing is used to confirm the actual predictive power of the deep learner. In Finance, deep learning is a great application for deep factor models in asset pricing or indexing, default probabilities, and event studies.

AI certainly has not been widely accepted as a conventional application in finance, including market efficiency. Until that happens, deep learning models have the potential to significantly improve the predictive power of certain decision models, where prediction is critically important.

## 4. Data collection

The phrase "Big Data" emphasizes a large and continuously growing amount of data. In this work, we do not focus on new sources of unconventional data that is equally important in nature such as satellite images, formal and informal language information, sentiments in textual messages or emoticons, etc. (Mullainathan & Spiess, *Journal of Economic Perspectives* 2017). We propose using AI with traditional datasets to enhance the whole process.

In this study, we will use several datasets for both corporations and banks. Accounting and stock return data comes from Compustat Global under the WRDS platform. Bankruptcy data comes from multiple resources such as the Federal Deposit Insurance Corporation (FDIC)[2] for the U.S., NYU Salomon Center Database[3] (with subscription fee), Professor Panayiotis Theodossiou for Cyprus and Professor Phillippe du Jardin for France (hopefully generously shared), and the Australian[4], German[5], Japanese[6], and Polish[7] Credit datasets from various resources. We also have access to global credit ratings data from S&P Capital IQ and Bloomberg Data Terminal, and other international data from Datastream. For country-level factors, we use World Bank[8], IMF, and various resources for legal system, shareholders right protection, cultural factors, etc.

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[1] https://www.ifrs.org/issued-standards/list-of-standards/ifrs-9-financial-instruments/
[2] https://banks.data.fdic.gov/docs/
[3] http://pages.stern.nyu.edu/~ealtman/Credit%20&%20Debt%20Markets%20Databases.htm
[4] http://www.liacc.up.pt/ML/statlog/datasets/australian/australian.doc.html
[5] http://www.liacc.up.pl/ML/statlog/datasets/german/german.doc.html
[6] http://www.ics.uci.edu/~mlean/MLRepository.html
[7] http://mill.ucsd.edu/index.php?page=Datasets&subpage=Classification
[8] https://data.worldbank.org/indicator/ic.bus.ease.xq