**Machine Learning Applications for Predicting Bank Insolvencies**

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**Abstract**

This paper looks to expand on the current literature regarding predicting bank failures using an early warning system. In comparison to other methodologies on this subject very little attention has been given until recently regarding the use of Random Forest. Along with that there is an even bigger gap in the current literature regarding the potential of using sampling methods in conjunction with early warning systems. In this paper I propose using sampling methods in combination with Random Forest to create a 2 year early warning system. **Continue with Results of Paper**

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**Introduction**

Since the global financial Crisis (GFC) in 2008, there was 511 bank failures in the United States with the majority resulting from the crisis (FDIC). The GFC prompted governments across the world to enact new legislation and regulations aimed at promoting better stability for the financial system. As a result, Basel III was developed which are international supervisory guidelines meant to mitigate the risks financial institutions can pose due to lack of proper safe guards. In an effort to improve supervision there has been a resurgence in research regarding early warning systems (EWS) following the work of Beaver (1966) who originally used financial ratios to predict bank failures. These are statistical models used by regulatory agencies to identify institutions that are potentially at risk of default. EWS allow regulators to proactively take action for at risk institutions minimizing the impact on consumers. These actions range from regulatory restrictions to assuming conservatorship of an institution.

Many statistical methods have been used over the years in an attempt to quantify the likelihood of an institution failing. One popular method has been a Multivariate Logistic Regression (Martin, 1977; Ohlson, 1980). This method was found to not be reliable due to the linear assumptions made by logistic regression. It prevents the model from potentially capturing non-linear patterns. Due to this researcher’s began applying machine learning algorithms such as support vector machines (Erdogan, 2013; Gogas et al.,2018), Neural Networks (López-Iturriaga et al., 2010; . Constantin et al. 2018),

The remainder of the paper is as follows: Section 2: literature review. Section 3: is a discussion of the data. Section 4: explains the choice of models and configurations. Section 5: Examines the validation results of the model’s performance, Section 6: Discussion about the methodologies and results. Additionally, limitations and the potential for further research will be touched upon.

**2. Literature Review**

Predicting bank failures has been an extensive area of research for academics and regulatory bodies. Early research focused on inferential understanding of the causes which has evolved over the decades to be primarily concerned with the ability to construct accurate EWS. Most research on predicting bank failures has been based on using financial ratios instead of nominal values as they do not capture the potential impact based on size constraints (Beaver 1966). The ratios used primarily focus on the international regulatory structure CAMELS which stands for ***C*** Capital adequacy ***A*** Asset quality ***M*** Management ***E*** Earnings ***L*** Liquidity ***S***Sensitivity capturing idiosyncratic risk. Some studies add macroeconomic indicators attempting to capture the potential systemic risk  (Betz, Oprica, Peltonen, & Sarlin, 2014; Mayes & Stremmel). There is still a division as to the significance of macroeconomic variables with (Halling & Hayden, 2006;  Vuono 2019) finding lack of significance in prediction ability.

**3. Data**

The financial data which are to be used as predictor variables were collected from the FDIC’s Statistics of Depository Institutions database which contains all reported bank financial data received by their member institutions. The data used in this paper is quarterly based covering Q1 2006 - Q4 2012. The FDIC keeps a list of banks which have failed or have been in need of assistance. Due to the small sample size of failing banks, it had been decided to predict bank failures as well as banks in need of intervention and/or support. This collection of banks will all be referred to as insolvent throughout the rest of the paper. These banks have been encoded as a binary variable with 1 being an insolvent bank or bank requiring intervention and 0 being a solvent bank representing the dependent variable. The bank failures data was comprised of banks who were insolvent between the years of Q1 2008 – Q1 2014.

To obtain the training and testing sets, data from Q1 2008 - Q4 2012 were used while the observations from Q1 2013 - Q4 2014 were reserved for the out of time group. The train-test data had a 80/20 split stratified along the solvency indicator due to the highly imbalanced nature of the data.

**4. Model & Model Development**

**5. Validation**

**6. Conclusion & Discussion**

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# Original Random Forest Paper

# Macro Economic Approach to bank Failure

https://pdfs.semanticscholar.org/28f0/39c903741b393c3631dc501871add6741aad.pdf?\_ga=2.247283463.267459489.1637302820-284921495.1637302820

# Smote approach to balancing data for RF on multiclass which they made into binary classes

R. C. Bhagat and S. S. Patil, "Enhanced SMOTE algorithm for classification of imbalanced big-data using Random Forest," *2015 IEEE International Advance Computing Conference (IACC)*, 2015, pp. 403-408, doi: 10.1109/IADCC.2015.7154739.

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#  Our study clearly demonstrates the need to apply at least some sampling to big data with class imbalance and suggests the 50:50 class distribution does not produce the best Medicare fraud detection results.

R. Bauder and T. Khoshgoftaar, "Medicare Fraud Detection Using Random Forest with Class Imbalanced Big Data," *2018 IEEE International Conference on Information Reuse and Integration (IRI)*, 2018, pp. 80-87, doi: 10.1109/IRI.2018.00019.

#Experimental results demonstrated that the proposed approach considerably increases the detection rate for rarely encountered intrusions.

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