Bankruptcy Prediction through Soft Computing based Deep Learning Technique

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To our families and teachers

Preface

Bankruptcy prediction has been actively studied in industrial and financial institutions in the recent past. The problem has been investigated through statistical and machine intelligence prediction techniques. Here, complex hierarchical deep architectures (HDA) are proposed for predicting bankruptcy. HDA are formed through fuzzy rough tensor deep stacking networks (FRTDSN) with structured hierarchical rough Bayesian (HRB) models. FRTDSN is formalized through TDSN and fuzzy rough sets. HRB is formed by incorporating probabilistic rough sets in structured hierarchical Bayesian model. Then FRTDSN is integrated with HRB to form the compound FRTDSN-HRB model. HRB enhances the prediction accuracy of the FRTDSN-HRB model. The experimental datasets are adopted from the Korean construction companies, American and European nonfinancial companies and UCI Machine Learning Repository bankruptcy database. The research revolves around the impact of choice toward cut-off points, sampling procedures, and business cycle accuracy for bankruptcy prediction techniques. Misclassification can often lead to incorrect predictions resulting in prohibitive costs to both investors and the economy. The selection of cut-off points and sampling procedures affects the model rankings. The results lead to the fact that empirical cut-off points derived from training samples result in minimum misclassification costs for all the techniques. FRTDSN-HRB achieves superior performance as compared to other statistical and soft computing models. The experimental results are given in terms of several standard statistical parameters revolving different business cycles and mid-cycles for the datasets considered.

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