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A reference model for business intelligence to predict bankruptcy

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Abstract

Purpose – Bankruptcy is a financial failure of a business or an organization. Different kinds of bankruptcy prediction techniques are proposed to predict it. But, they are restricted as techniques in predicting the bankruptcy and not addressing the associated activities like acquiring the suitable data and delivering the results to the user after processing it. This situation demands to look for a comprehensive solution for predicting bankruptcy with intelligence. The paper aims to discuss these issues.

Design/methodology/approach – To model Business Intelligence (BI) solution for BP the concept of reference model is used. A Reference Model for Business Intelligence to Predict Bankruptcy (RMBIPB) is designed by applying unit operations as hierarchical structure with abstract components. The layers of RMBIPB are constructed from the hierarchical structure of the model and the components, which are part of the reference model. In this model, each layer is designed based on the functional requirements of the Business Intelligence System (BIS).

Findings – This reference model exhibits the non functional software qualities intended for the appropriate unit operations. It has flexible design in which techniques are selected with minimal effort to conduct the bankruptcy prediction. The same reference model for another domain can be implemented with different kinds of techniques for bankruptcy prediction.

Research limitations/implications – This model is designed using unit operations and the software qualities exhibited by RMBIPB are limited by unit operations. The data set which is applied in RMBIPB is limited to Indian banks.

Originality/value – A comprehensive bankruptcy prediction model using BI with customized reporting.

Keywords Genetic algorithm, Business intelligence reference model, Comprehensive bankruptcy model, Information delivery, Qualitative bankruptcy analysis, Quantitative bankruptcy analysis, Ant miner, Fuzzy AHP

Paper type Research paper

1. Introduction

Finance is essentially required for any business to extend its operations nationally and internationally. For an organization to enlarge its simple business plan to multinational business plan, finance is predominantly required. Businesses proportionally depend on the stability of the finance. Since, finance is a solid foundation of a business, financial stability is very essential for the survival of a business. A self-financial status prediction analysis may help an organization to plan its business activities for the smooth running of the business. The financial failure of a business is called bankruptcy.

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Bankruptcy has shown unexpected and distress outcomes to global economy. Its impact leads to financial failure, recession, unemployment and poor economic situations. It can produce substantial loss to banks, suppliers, shareholders and to the whole community (Sungbin *et al.*, 2010). Hence, it is very essential to conduct the Bankruptcy Prediction Analysis (BPA) to identify the financial stability of the organization. Bankruptcy prediction methods are classified into two type's quantitative and qualitative methods. The quantitative bankruptcy prediction methods find the bankruptcy prediction accuracy using financial ratios.

Qualitative bankruptcy methods are also developed and these methods predict the bankruptcy using business internal and external environmental factors (Myoung-Jong and Ingoo, 2003). From the literature, it has been found that in bankruptcy prediction methods, the focus has been limited to finding the bankruptcy prediction accuracy alone. These methods are not integrated with other techniques or methods to meet the requirements of the particular domain or an industry to conduct the bankruptcy prediction. Moreover, from the literature it is also evident that, in most of the bankruptcy methods, the results are not processed and delivered to the user according to their requirement. As bankruptcy prediction is a decision-making process it results should be processed, appropriate information should be identified and delivered to the respective user for decision making (Martin *et al.*, 2014a).

Hence, a comprehensive bankruptcy prediction model which considers both quantitative and qualitative bankruptcy prediction variables has been required to conduct the bankruptcy prediction analysis with customized reporting.

The rest of the section organized as follows, Section 2 describes about literature review on bankruptcy prediction methods, its constituents and business intelligence (BI) development towards bankruptcy prediction, Section 3 describes about design of reference model for BI to predict bankruptcy, Section 4 describes the experimental design which has been applied to the reference model and Section 5 discuss the experimental results, Section 6 discuss the implementation experience and Section 7 concludes the paper.

2. Literature review

In finance, one of the very important analysis is financial distress analysis. It is conducted in business to analyse the financial stability (Edward, 1995). The financial distress of a business is called bankruptcy. It has shown larger impact on global economy (Source: Bankruptcydata.com, 2011). Hence, it is very essential to conduct the bankruptcy prediction analysis for evaluating the financial health of a business.

2.1 Bankruptcy

Bankruptcy is described as legally declared impairment of ability of an organization to pay its creditors (Ohlson, 1980; Ariel and Marcela, 2007). It is a situation where operating cash flows are not sufficient to satisfy the current obligations of a firm and so the firm is forced to take corrective action (Altman, 1968; Deakin, 1972).

2.1.1 Bankruptcy resolution. Financial distress can be handled by asset restructuring and financial restructuring. Asset restructuring includes selling major assets, merging with another firm and reducing capital spending. Similarly, financial restructuring includes issuing of new securities, negotiating with banks and other creditors, exchanging debt for equity and filing for bankruptcy (Maria-del-Mar and Domenico, March 2014; Altman and Edith, 2006).

2.1.2 Impact of bankruptcy. The various examples of unforeseen side effects of bankruptcy are as follows:

- The largest bankruptcy in US history occurred on September 15, 2008, when Lehman Brothers Holdings Inc. filed for protection with more than USD$639 billion in assets (Source: Marketwatch.com, 2008).
- More than 20 largest corporate bankruptcies happened in between the years 1987 to 2009. Among these corporate distress 50 per cent of bankruptcies happened in financial services and banking holding companies. The asset worth of these companies is more than $327,913,000,000 (Source: Bankruptcydata.com, 2011).
- S&Ps downgraded the US credit rating from AAA to AA+ in the year 2011 (Source: Standardandpoors.com, 2011).

The impact of bankruptcy clearly states that there is a need for an efficient model to predict bankruptcy.

2.2 Bankruptcy prediction

Bankruptcy prediction is the art of predicting bankruptcy and various measures of financial distress of business (Edmister, 1972; Springate, 1978; Fulmer *et al.*, 1984). Bankruptcy is predicted using financial variables or ratios and non financial variables. These variables are applied in different techniques, e.g. artificial neural networks (Athanasios *et al.*, 2006), fuzzy support vector machines (Arindam and Kajal, 2011) and adaptive fuzzy *K*-nearest neighbour method (Hui-Ling *et al.*, 2011) from which bankruptcy is predicted. The key constituents of bankruptcy prediction methods are its variables which are described below.

2.2.1 Bankruptcy prediction variables. The prediction accuracy of bankruptcy methods depends upon its bankruptcy prediction variables which are described below.

2.2.1.1 Financial variables. Financial ratios reflect the characteristics of stability, profitability, growth, activity and cash flow of an organization (Xiaoyan and Yu, 2009). The commonly applied financial ratios for bankruptcy prediction are listed in Table I.

The most widely applied financial ratios are described in Table I. Many more ratios have been used to conduct the bankruptcy prediction analysis. The financial variables are also called as quantitative bankruptcy prediction variables.

Financial variables				
Working capital to total assets (Altman, 1968)	Retained earnings to total assets (Altman, 1968)	Earnings before interest and taxes to total assets (Altman, 1968)	Market value of equity to book value of total liabilities (Altman, 1968)	Sales to total assets (Altman, 1968)
Net income to total assets (Deakin, 1972)	Current assets to total assets (Deakin, 1972)	Cash to total assets (Deakin, 1972)	Current assets to current liabilities (Deakin, 1972)	Sales to current assets (Deakin, 1972)
Net profit before interest and taxes to total assets (Springate, 1978)	Sales to total assets (Springate, 1978)	Net profit before taxes to current liabilities (Springate, 1978)	Annual funds to current liabilities (Edmister, 1972)	Equity to sales (Edmister, 1972)

Table I.
List of financial ratios used for bankruptcy prediction analysis

2.2.1.2 Non financial variables. In addition to the financial variables, the bankruptcy can be predicted using internal and external business environment variables (Myoung-Jong and Ingoo, 2003). These business environmental variables are collectively called as non financial variables or qualitative bankruptcy prediction variables. Totally 14 inner risk factors and 68 outer risk factors have been considered as non financial variables identified from a business environment which are used for bankruptcy prediction analysis (Myoung-Jong and Ingoo, 2003; Kasirga and Ömür, 2009; Neşe *et al.*, 2009). These variables are described in Table II.

Table II shows the various qualitative bankruptcy prediction parameters which are used in business to analyze the bankruptcy prediction. However, bankruptcy prediction techniques have substantial improvement in prediction accuracy when it is operated with selected number of bankruptcy prediction variables (Philippe, 2010; Myoung-Jong, 2010; Atiya, 2001).

2.2.2 Bankruptcy prediction methods. Different kinds of bankruptcy prediction methods or techniques are developed from simple to complex techniques to find the bankruptcy prediction accuracy. Statistical methods are applied to predict bankruptcy which includes univariate analysis (Beaver, 1966), multivariate discriminant analysis (Altman, 1968), logistic regression approach (Ohlson, 1980) and factor analysis technique (West, 1985). To improve the prediction accuracy techniques such as genetic algorithm (Ning *et al.*, 2011), genetic programming (Hussein, 2009; Pedro *et al.*, 2010), case-based reasoning (CBR) (Sungbin *et al.*, 2010), neural networks (Chulwoo *et al.*, 2012), fuzzy classification (Fengyi *et al.*, 2011) and decision trees (David *et al.*, 2012) are widely applied for bankruptcy prediction.

Despite the availability of quantitative bankruptcy prediction methods very limited number of qualitative bankruptcy prediction methods has been developed. Genetic algorithm is applied to find the bankruptcy prediction accuracy using qualitative variables. In this method, the genetic operator mutation and cross-over are applied to generate the qualitative bankruptcy prediction rules. These rules are applied to find the prediction accuracy (Myoung-Jong and Ingoo, 2003).

2.2.3 Bankruptcy prediction reporting. Bankruptcy prediction analysis is the art of predicting bankruptcy and various measures of financial and non financial distress of business. Reporting is very important in the enterprise information processes and is very much essential to help in decision making (Shu-Jen *et al.*, 1992; Liu *et al.*, 2005). From the literature study it is evident that bankruptcy methods have not addressed about the reporting of prediction results (Sarath, 2013; Nigib *et al.*, 2013). After obtaining

Non financial variables			
Industry risk (IR)	Management risk (MR)	Financial flexibility (FF)	(Myoung-Jong and Ingoo, 2003)
Credibility (CR)	Competitiveness (CO)	Operating risk (OR)	
Pricing (PP) (Neşe *et al.*, 2009)	Differentiation parameters (DP) (Neşe *et al.*, 2009)	Marketing parameters (MP) (Neşe *et al.*, 2009)	(Neşe *et al.*, 2009)
Delivery parameters (DEP) (Neşe *et al.*, 2009)	Productivity (PRP) (Neşe *et al.*, 2009)	Reorganization parameters (RP)	
Common business performance analysis parameters (CBP) (Yi-Chung, 2009)		Firm default parameters (FD) (Kasirga and Ömür, 2009)	

Table II. List of non financial bankruptcy prediction parameters the results of bankruptcy prediction, it should be processed according to the stakeholder requirement and delivered at right time for decision making.

Based on the literature survey a number of techniques and influencing variables which can be used for bankruptcy prediction are available discretely. A comprehensive model which combines the above mentioned techniques and variables is the need of any business today. Generally BI offers business models that can combine various techniques and variables to provide a unified solution for better decision making. Hence, the next section lays its importance on discussing about BI, ongoing researches, its contribution in various domains specifically finance domain and different solutions offered for it.

2.3 BI

BI is an integrated set of tools used to support the transformation of data into information in order to support decision making. It analyses the performance of an organization and increases its revenue and competitiveness (Mahdi *et al.*, 2012; Kun-Lin, 2011; Tobias and David, 2011). It also helps in formulating new strategies in order to increase the profit of the business (Eran and Amir, 2013; Jalileh *et al.*, 2011). To make effective decisions in any business, BI derives information or knowledge from huge volumes of business data using a set of data mining and analytical techniques (Cheung and Li, 2012; Yoichi *et al.*, 2010; Sirawit *et al.*, 2010). The ongoing research works in BI are as follows.

2.3.1 Ongoing research in BI. In BI, the foremost research is applying it to different domains to take better decisions. It has been applied in Stock market (Eran and Amir, 2013), E-Commerce (Hao Wang and Wei, 2012), Education (Brian and Margie, 2012), Inventory Management (Tobias and David, 2011), Crime Fighting (John, 2010), Aircraft (Steven *et al.*, 2010) and many more domains. In most of the domains, BI has been applied either to take decisions or to provide input to the decision.

The strength of BI is integration of data at different levels and it provides right information for decision making at right time. The basic advantage of using BI is effective decision making and to further enhance its performance intelligent techniques have been applied (Li *et al.*, 2013; Jui-Yu, 2010; Alexander and Babis, 2010). In BI, information extraction techniques play a key role to find relevant information in order to arrive an effective decision making. Different kinds of data collection techniques (Thiagarajan *et al.*, 2012; Cvitas, 2010, 2011) and factors that influence BI data collection strategies (Wingyan and Tzu-Liang, 2012; Kaiquan *et al.*, 2011) have been addressed.

A BI system can be integrated with other techniques which lead to rapid development in business process. At present, it is integrated with SOA, CRM, ERP and Mobile BI (Tanko and Musiliudeen, 2012; Dien and Douglas, 2010; Long-Wen and Zhang, 2008). BI has been customized to integrate with social environmental indicators for the organizational sustainable development (Maria and Maribel, 2009). To model BI applications two design models such as frameworks and models have been proposed (Cheung and Li, 2012; Liyi and Xiaofan, 2009; Fereydoon and Mohammad, 2012). The contribution of each of these ongoing researches has been described in π-chart depicted in Figure 1.

From the literature review, it has been found that mostly BI has been applied in many domains to take better decision making (Martin *et al.*, 2014b). The next major contribution stands on BI information extraction techniques and frameworks. In addition to that, BI algorithms, BI architecture models, BI evaluation techniques and other developments in BI are having limited contribution. Among ongoing research

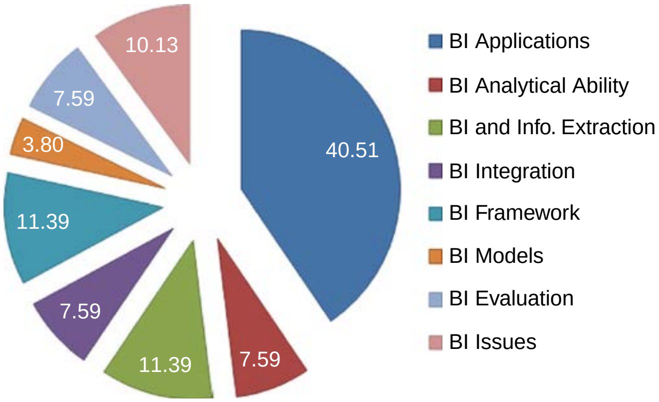


Figure 1.
Ongoing research contributions in BI

contributions, BI design has 15.19 per cent contribution in which BI model has shared 3.80 per cent contribution. The next section describes about BI domains and its contributions.

2.4 BI and its domain

The detailed understanding of BI applications and its domains paves a layout to know its contribution in each domain. BI and its contribution in various domains are represented in bar chart depicted in Figure 2.

From the graph it has been found that although BI has been applied in various in domains for better decision making, its contribution in finance is limited. Finance is very essential domain and it lays solid foundation for the business. It plays important role in the growth of the business. From these studies it has been found that the contribution of BI in finance is very limited (7.32 per cent). Moreover in finance the very critical part is financial distress analysis which indicates the success and failure status of the business. To apply BI in finance distress analysis, it offers various solutions.

2.5 BI solutions

BI offers three solutions such as algorithm-based solutions, architecture-based solutions and model-based solutions.

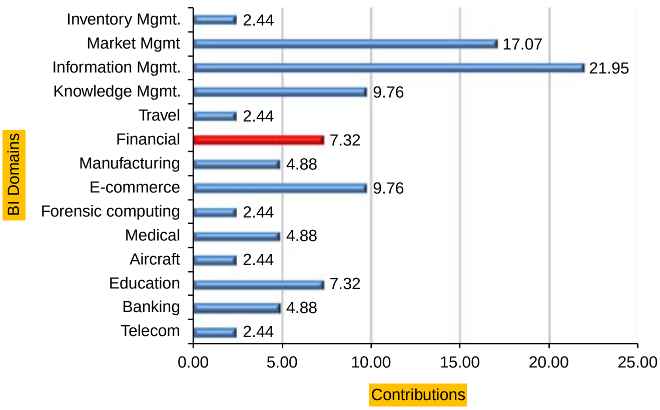


Figure 2.
BI applications and its domains

2.5.1 Algorithm-based BI solutions. In the process of analysis, various techniques and algorithm have been applied in BI to find the required information and knowledge. In BI, different kinds of algorithms and techniques have been applied to conduct analysis. According to the domain and application the appropriate algorithms has been chosen to conduct the analysis.

2.5.2 Architecture-based BI solutions. Successful BI system should translate the business requirement into high-level BI architecture (William and Andy, 2010). Organizations must consider two important aspects when constructing the BI architecture: integration of large heterogeneous data sources and provision of analytical capabilities to analyse that data (Aleš *et al.*, 2012). Generally BI architecture consists of data transformation, data warehouse, data analysis and reporting.

2.5.3 Model-based BI solutions. In BI, to design an application, models and framework have been applied. The frameworks and models which are applied in BI have been described in Table III.

From the literature, it has been found that BI applications have been designed using either frameworks or models. Three BI models have been developed and among the three BI models, two models are domain specific and one is generic in nature.

Domain	Requirement	Approach
Online product reviews (Wingyan and Bill, 2012)	Discovering BI from customer ratings and their reviews	Pattern recognition and information retrieval techniques
Procurement (Lee *et al.*, 2009)	To improve the existing procurement process using BI	Agent-based procurement system with BI module
Medical – liver disease (Ayman, 2013)	BI framework to treat the chronic liver disease	Architecture of multi-criteria BI approach
Manufacturing (Hans-Georg *et al.*, 2013)	To close the gap between IT support for management and production	Operational BI
Manufacturing (Zhang and Zhou *et al.*, 2008)	Sharing and exchanging of information	Based on the basic model of the manufacturing information system (MIS)
Market management (Mahdi *et al.*, 2012)	To acquire correct and well-timed understanding of marketing condition	Based on business, organizational and IT skills
Online product reviews (Wingyan and Bill, 2012)	Discovering BI from customer ratings and their reviews	Pattern recognition and information retrieval techniques
Domain independent (Liyi and Xiaofan, 2009)	Lack of prototype for BI for enterprises	Based on the analysis of enterprise data model structures
Domain independent (Yong *et al.*, 2010)	To reduce developmental cost of BI systems	Multi-agent technology
Domain independent (Yeoh *et al.*, 2013)	Relationships between BI competency, absorptive capacity and assimilation	Based on BI competency
Online retailers (Dien and Douglas, 2010)	To incorporate customer satisfaction and relationships	Integration of BI and CRM
Telecom (Tanko and Musiliudeen, 2012)	SOA approach to BI for customer satisfaction	From the review of existing models and architectures
Domain independent (Öyku *et al.*, 2013)	Role of decision environment in BI success	Based on technological BI, organizational BI and decision environment

Table III. List of BI models and framework

These three BI models have been matured to implementation level (Dien and Douglas, 2010; Tanko and Musiliudeen, 2012; Öyku *et al.*, 2013). Similarly there are totally nine BI frameworks, in which three are generic in nature and other six are domain specific (Wingyan and Bill, 2012; Lee *et al.*, 2009; Ayman, 2013; Yeoh *et al.*, 2013). Most of the BI frameworks are conceptual works which have not been implemented. Hence, a model-based BI solution is required for bankruptcy prediction analysis.

The findings of the reviews of different levels of research work on bankruptcy prediction and BI are gives a precise note that there are no works on reference model for BI to apply it on bankruptcy prediction analysis.

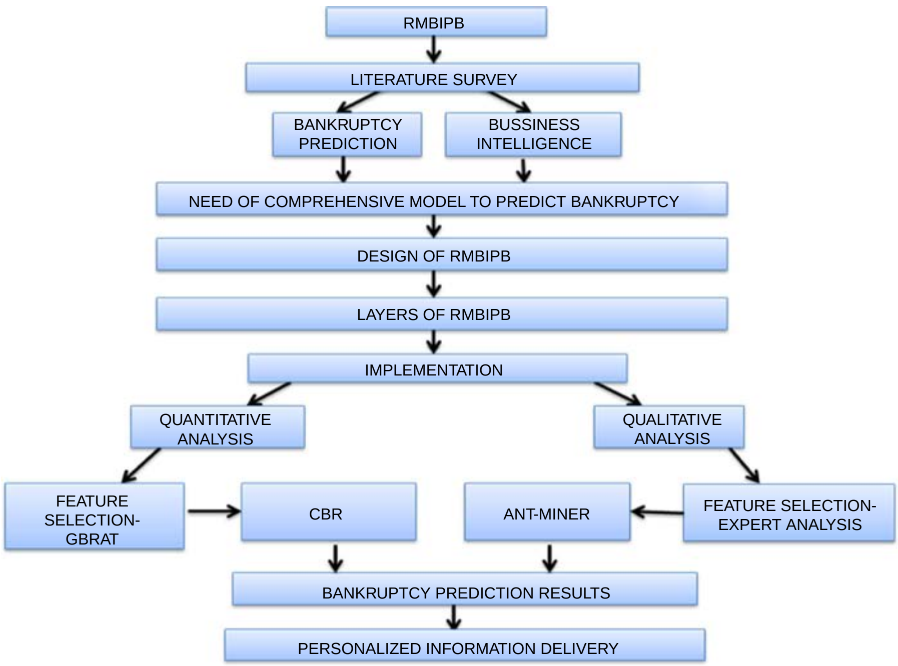
3. Design of Reference Model for Business Intelligence to Predict Bankruptcy(RMBIPB)

This section describes about the development of reference model by applying set of design operations called as unit operations. This section also compares this reference model with existing BI models. The whole process of reference model development, implementation and its results are represented in Figure 3 as shown below.

From the findings of the literature survey the need of reference model for BI to predict bankruptcy has been identified. In the next step, the reference model has been developed with its components. Finally the RMBIPB has been implemented and its results are revealed with research implications.

3.1 Reference models

A reference model is a representation of entities and their interrelationships of the intended software in abstract form. Abstraction in the reference model aids in



Notes: Genetic bankrupt ratio analysis technique (GBRAT); case based reasoning (CBR)

Figure 3. Workflow diagram for BPA using RMBIPB

achieving concrete models. Reference model also helps in explaining the software, prior to its development, to the stakeholders. To achieve a reference model a set of design operations has to be applied (Bass *et al.*, 2002). These design operations are called as unit operations which are commonly used in software architectures. The unit operations which are commonly applied in software architecture are compression, abstraction, resource sharing, decomposition and replication. To develop reference model for BI to predict bankruptcy the unit operations abstraction and separation has been applied.

Abstraction:

- It hides underlying implementation and simplifies the creation and maintenance of software components.

Separation:

(1) It segregates a part of a system's functionality and aids both modifiability and portability. It has two sub types such as decomposition and replication.
   - Decomposition – it decomposes large system components into two or more smaller components.
   - Replication – it duplicates a component within the architecture for reliability.

3.2 Design of RMBIPB

This reference model has been designed on the principle of functional decomposition of a system (Bass *et al.*, 2002; Peter *et al.*, 2005). Based on the functional requirements of the Business Intelligence System (BIS) this reference model has been decomposed. This model has four levels of decomposition and part – whole relationship has been applied to decompose the system. The functionalities of this reference model addressed in step-by-step and start from high-level abstraction the level of detail has been improved (Prasanna, 2009). The various notations used in this reference model have been described below:

Model (M)
Model nature
    Abstract model (a)
    Concrete model (c)
Model type
    Domain independent model (DI)
Model components
    Quantitative component (Q)
    Qualitative component (q)
Sub components
    Pre-processing process (PPP)
    Analysis process (AP)
    Reporting Process (RP)

Based on these notations, components of this reference model has been named, for example:

BI_{M} - BI model
BI^{a}_{MDI} - Domain Independent BI model and abstract in nature
BI^{a1}_{MQ} - BI Quantitative component and abstract in nature

BI^{a1}_{Mq} - BI qualitative component and abstract in nature

BIC^{c1}_{PPP} - BI pre processing process component and concrete in nature

Other notations which are applied to represent the design of reference model have been depicted in Figure 4.

The design of the reference model starts with a component called as BI model (BI_M). The unit operation abstraction is applied to this component, from which a component called domain independent abstract BI model (BI^a_{MDI}) has been derived represented in Figure 5.

The scope of the proposed reference model not limited to bankruptcy prediction analysis alone, it can be extended to other domains. To keep open this model for other domains the unit operation decomposition has been applied to the component – BI^a_{MDI}. When applying decomposition to this component then it is decomposed into N number of domain independent BI model component (abstract in nature) described in Figure 6.

The decomposition simplifies to extend this domain independent component into other domains. In the next step, the component BI^{a1}_{MDI} has been decomposed which yields two sub components called as quantitative component and qualitative component as described in Figure 7.

The decomposition divides the analysis process into quantitative and qualitative analysis process. To the quantitative component BI^{a1}_{MQ} decomposition operation is applied and it is divided into three sub components namely "pre-processing process", "analysis process" and "reporting process" to carry out feature selection, business analysis and reporting process which are represented in Figure 8.

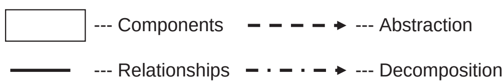


Figure 4. Notations used in the design of reference model

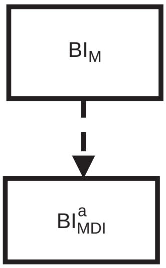


Figure 5. Design of a component - domain independent BI model abstract in nature

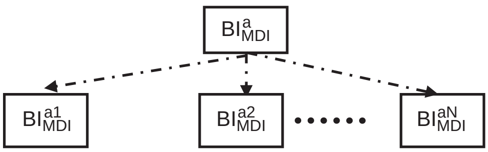


Figure 6. Deriving N - domain independent BI model components (abstract)

In a typical business process, a methodology or a process is required in different ways or many numbers of times to refine it. For example a business analysis may require feature selection one or more times in different ways. Similarly, different number of analysis and different number of reporting may be required for a business process. To accommodate the above said process, the proposed reference model has been designed to have *N* number of pre-processing, analysis and reporting process represented in Figure 9.

At the end of the design process abstraction is applied to each abstract component to implement it. By applying abstraction to pre-processing, analysis and reporting components, the software to be applied is realized/implemented and it performs the actual process. The same set of unit operations has been applied to qualitative component BI_{Mq}^{a1} to accommodate similar number of component to efficiently perform the bankruptcy prediction analysis. The design of reference model after applying the unit operations has been represented in Figure 10.

The evolution of reference model for bankruptcy prediction analysis has been represented with its components in Figure 10. The proposed reference model includes both quantitative factors and qualitative factors to perform the bankruptcy prediction analysis. The financial and non financial parameters with BI analysis definitely helps to take better decision in bankruptcy prediction analysis.

This model has greater flexibility in which any number of components can be added or removed for each process according to the stakeholders requirements. These kinds of models are very essentially required to address the different business domains to conduct the bankruptcy prediction analysis. The next section describes about the layers of the proposed reference model.

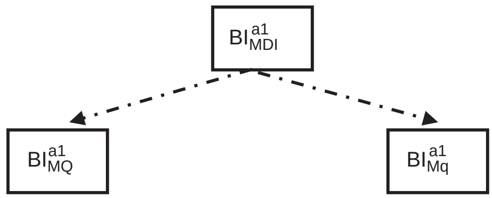


Figure 7.
Decomposition of BI_{MDI}^{a} into sub components

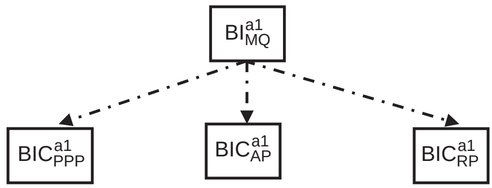


Figure 8.
Decomposition of BI_{MQ}^{a1} into sub components

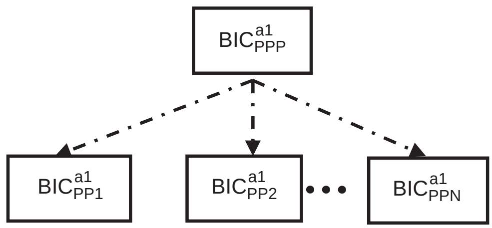


Figure 9.
Decomposition of BIC_{PPP}^{a1} into sub components

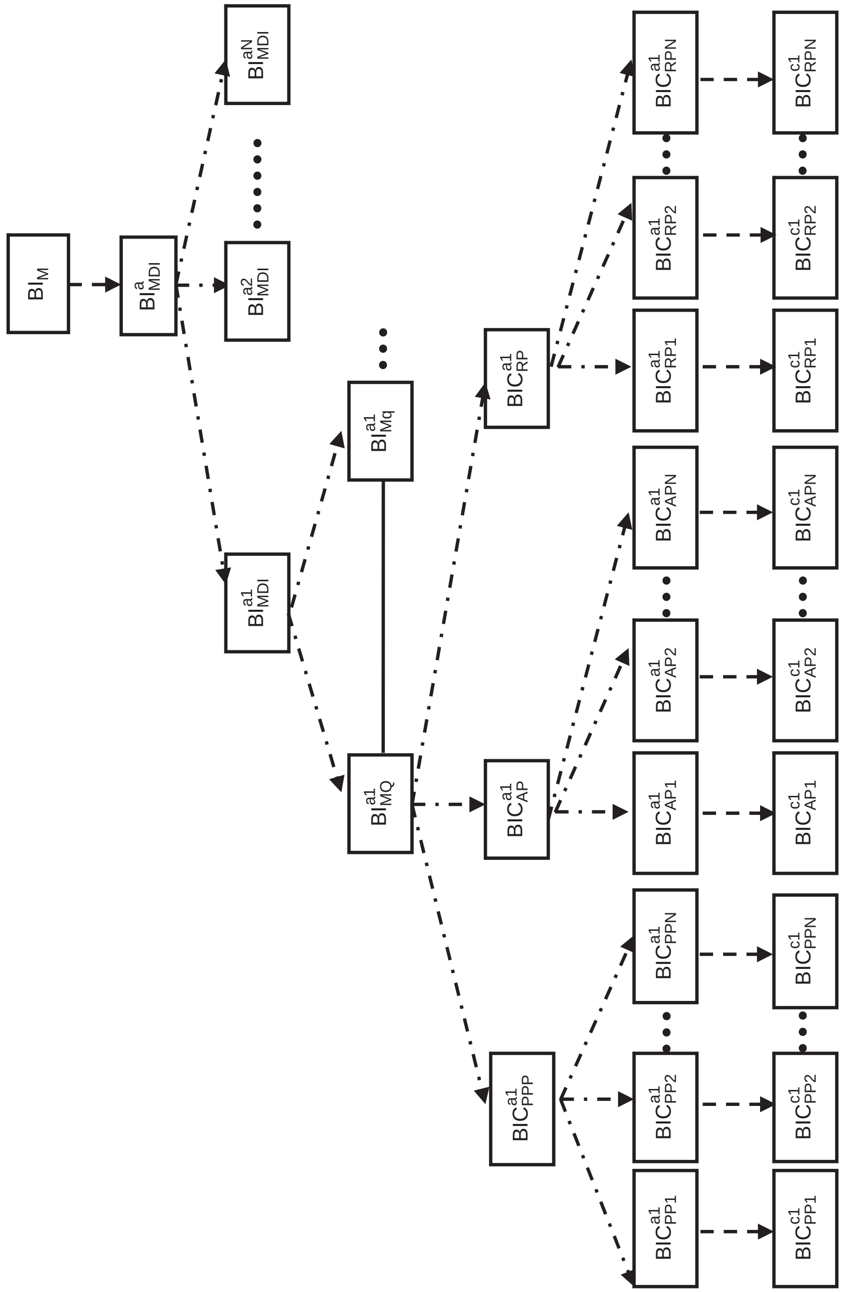


Figure 10.
Hierarchical tree
structure of the
reference model

3.3 Layers of RMBIPB

The layers of the RMBIPB are directly derived from the hierarchical tree structure of this reference model. The layers of RMBIPB with its components are given below:

- Business data layer – it is constructed using composition of quantitative data and qualitative data.
- Bankruptcy prediction analysis layer – it is constructed using composition of pre-processing component, quantitative bankruptcy prediction component and qualitative bankruptcy prediction component.
- Information delivery layer – information delivery layer is derived for customized reporting from the basics of the reporting process.

The diagrammatic representation of layers of this reference model is depicted in Figure 11.

This model has three layers in which the bottom layer address about data storage which includes quantitative data as well as qualitative data. The middle layer performs analysis process which includes layers such as influencing feature selection layer and bankruptcy prediction analysis layer. The bankruptcy prediction layer includes components such as quantitative and qualitative bankruptcy analysis. The top layer is information delivery layer. Information delivery layer delivers suitable information to right user according to the criteria and user preference (Stone, 2009; Jane *et al.*, 2001; Hinze *et al.*, 2009).

Normally in a business environment each stakeholder has different level information requirement and they might have different requirements to receive the information. For example in case of "mode of delivery" each user has different preference on delivery channels. One may like to receive information by e-mail and another user may like to

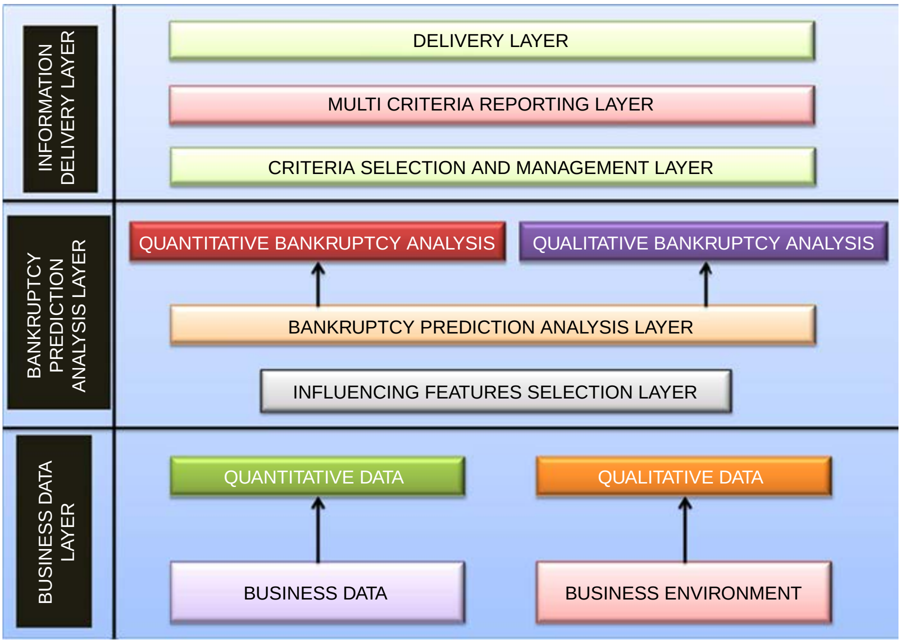


Figure 11.
Layers of RMBIPB

receive by hand-held device and some other user wants to receive information in person. The customization and delivering of information according to the user preference is called as information delivery. The sub layers of information delivery layer are as given below:

- Criteria selection and management layer – this layer finds, analyzes and selects the criteria.
- Multi-criteria reporting layer – finds best alternative among other alternatives. This layer develops a customized report and passes it to the next layer.
- Delivery layer – customized information delivered to respective user at respective channel.

The next section describes about the quality attributes of RMBIPB.

3.4 Quality attributes of RMBIPB

RMBIPB offers reusability at components level such as feature selection component, quantitative and qualitative bankruptcy analysis component and information delivery component. Moreover, this model encourages the design level reuse, by designing the components as domain neutral which can work with the other domains. This model also acts as a basis to find out the architectural and design patterns for bankruptcy prediction analysis software development.

RMBIPB offer modifiability by separating its components into various layers. In RMBIPB, the components are decomposed into different layers. Hence, the modification which takes place in one layer do not affect the components present in another layer. The component-level changes and layer-level changes are handled with the help of appropriate abstract models. Hence, size of RMBIPB can be enlarged according to the requirement of the stakeholder which makes RMBIPB to exhibit the scalability.

RMBIPB helps the designer to focus on the business domain to experiment it for comprehensive bankruptcy prediction. Since it is designed to be adoptable to any domain, the components are selected based on the requirements of stakeholders of the respective domain. This characteristic simplifies the ease of creation and facilitates to integrate the various components of RMBIPB to experiment it in various domains.

This reference model has been compared to existing BI models to find the software qualities which are exhibited by the design operations such as abstraction and separation. Table IV describes the comparative analysis of RMBIPB with other BI models.

BI models	Scalability	Modifiability	Integrability	Ease of creation	Reusability	Adaptability
BI+CRM (Dien and Douglas, 2010)	+−	++	++	+−	+−	+−
SOBI (Tanko and Musiliudeen, 2012)	++	++	−−	+−−	−−	+−
BI research model (Öyku *et al.*, 2013)	−−	+−	++	−−	+−	++
RMBIPB	++	++	++	++	++	++

Notes: Indicators used for the quality-wise comparison ++, +− and −− and these qualities are qualitative in nature, ++ presence of the specified quality in the particular model, +− partial presence, −− the quality is absent in the particular model

Table IV. Quality attributes of RMBIPB with existing BI models

The comparison stated in Table IV reveals that RMBIPB offers all the mentioned software qualities and stands to be better than other models. Hence, RMBIPB is useful to the stakeholders in various ways. The next section describes about the implementation of this reference model.

4. Implementation of RMBIPB

This section addresses about implementation of reference model and techniques which are applied for each of its components have been described. In quantitative bankruptcy analysis, for feature selection Genetic Bankrupt Ratio Analysis Technique (GBRAT) and for bankruptcy prediction CBR has been applied. In qualitative bankruptcy prediction, for influencing features selection expert analysis has been conducted and for prediction ant-miner algorithm has been applied. The results of both of the quantitative and qualitative analysis reported using information delivery component which is implemented using Fuzzy Multi-Criteria Decision Making (Fuzzy MCDM) technique. The implementation details of model with its layers are depicted in Figure 12.

The implementation details of each of the components have been described in the following section.

4.1 Business data layer

To conduct the quantitative and qualitative bankruptcy analysis both kind of data has been collected from the literature. Quantitative data: the financial ratios of various banks from year 2002 to 2011 have been collected from Centre for Monitoring Indian Economy (CMIE). Qualitative data: the qualitative data which is considered

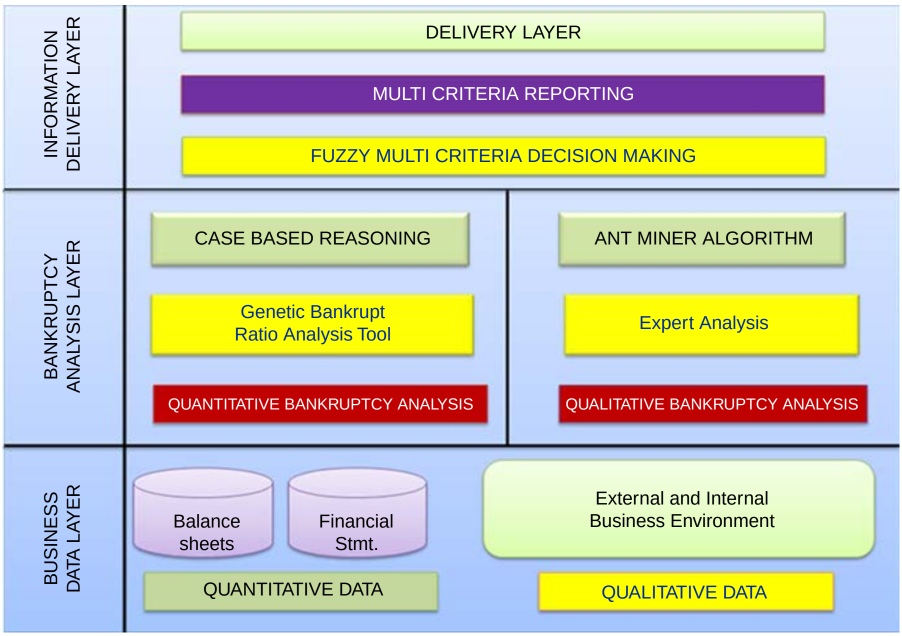


Figure 12.
Implementation of RMBIPB with its techniques

for qualitative bankruptcy analysis (Martin *et al.*, 2011f, g, h) has been described in Table II.

Qualitative parameters are subjective in nature and to evaluate qualitative parameters, we need help from experts. Experts will be evaluating the parameters based on their decision and this analysis depends on the history. Hence, the values will not be accurate but approximate. To evaluate these qualitative parameters three types of scores has been applied and they are high (100-66), medium (65-46) and low (45-0). The questionnaire which is applied to conduct expert analysis for industry risk has been depicted in Figure 13.

4.2 *Bankruptcy analysis layer*

In this layer, for quantitative bankruptcy analysis to select influencing financial features GBRAT has been applied and for quantitative bankruptcy prediction CBR has been applied. In qualitative bankruptcy analysis, for qualitative features selection expert analysis is conducted and for qualitative bankruptcy prediction ant-miner has been applied. The result of both of the analysis has been delivered as customized reporting to the respected user using information delivery component. Implementation of each of the component has described in the following sections.

4.2.1 GBRAT. In last 50 years, more than 200 scientific papers for Bankruptcy Prediction (BP) have been published (Hui and Jie, 2012; Zijiang *et al.*, 2011; Hui-Ling *et al.*, 2011; Udaya *et al.*, 2012). In all these BP methods, more than 500 different financial ratios are used (Philippe, 2010). When specific number of financial ratios is applied (Atiya, 2001; Khalid, 2008) the stability of the model performance increases and prediction accuracy of bankruptcy substantially increases.

In literature, selection of ratios has been carried out based on human expertise and different experts tend to have different opinions. It indicates the need of finding a

I. Industry Risk (IR)

IR is measured by the stability and the growth of the industry, the degree of competition over the industry, and the overall conditions of the industry.

1. Do Governmental Policies and International Agreements (GPI) affect the Bankruptcy?

☐ High ☐ Medium ☐ Low Score

2. Does Cyclicality (CY) Affect Bankruptcy?

Sensitivity towards worldwide economic fluctuations. These fluctuations occur around a long-term growth trend, and typically involve shifts over time between periods of relatively rapid economic growth.

☐ High ☐ Medium ☐ Low Score

3. Does Degree of Competition (DEG) affect Bankruptcy?

☐ High ☐ Medium ☐ Low Score

4. Does the Price and Stability of the Market Supply (PSM) affect Bankruptcy?

☐ High ☐ Medium ☐ Low Score

5. Does the Size and Growth of Market Demand (SGM) affect Bankruptcy?

☐ High ☐ Medium ☐ Low Score

Figure 13. Questionnaire for qualitative parameters – industry risk

systematic method to find the influencing ratios to predict the bankruptcy. The financial ratios which contribute more in predicting the bankruptcy called as influencing ratios. This GBRAT designed based on the concept of genetic algorithm. It analysis the non linear relationship among financial ratios of bankruptcy model and classifies the ratios into influencing and non influencing ratios (Martin and Prasanna, 2011c; Martin *et al.*, 2011d, e). The top five bankruptcy models with accuracy level of more than 80 per cent are chosen for genetic operation and the chosen models are given below:

- Altman Model (1968).
- Edmister Model (1972).
- Deakin Model (1972).
- Springate Model (1978).
- Fulmer Model (1984).

To analyse the influencing ratios experiment is conducted using GBRAT which takes parameters such as bankruptcy model name, financial ratios with its specified range of ratios, prediction accuracy of each of the bankruptcy model. In this experiment, GBRAT completes 1,000 trial for each ratio in the respective bankruptcy models. For Altman model, the total number of trials performed is 5,000 and for Deakin model, has 5,000 trials, Springate model has 4,000 trials, Edmister model has 7,000 trials and Fulmer model has 9,000 trials (Martin *et al.*, 2012c, d). The next section explains about quantitative bankruptcy prediction using influencing ratios.

4.2.2 CBR. Many bankruptcy prediction techniques are available to predict bankruptcy. CBR is a machine learning technique which solves a new problem based on the past experiences. It is more efficient since it provides prediction along with explanation. The CBR prediction performance depends on feature selection technique and case retrieval algorithm. In this experiment, the bankruptcy prediction accuracy using influencing features with CBR is obtained. For experimentation, protégé (3.4.7) with plug-in myCBR is applied to predict the bankruptcy (Martin *et al.*, 2012b).

4.2.3 Expert analysis. In the qualitative bankruptcy prediction analysis, to identify the influencing qualitative parameters expert analysis has been conducted. To conduct the expert analysis, questionnaire has been designed (Appendix 1) from the qualitative parameters identified from the literature.

4.2.4 Ant-miner. Qualitative bankruptcy prediction has been conducted using ant-miner technique. Ant-Miner is ant colony optimization (ACO)-based algorithm for the classification task of data mining. This technique has been applied for the discovery of classification rules. The first application of ACO for the classification task is conducted using medical data set obtained from University of California, Irvine (UCI) machine learning repository. The data set such as Wisconsin breast cancer, Cleveland heart disease and Hepatitis has been applied to obtain the classification rules using ant-miner algorithm (Parpinelli *et al.*, 2002).

Ant-miner induces – if rule antecedent then rule consequent,

If < Term1 and Term2 And Term3 […] > Then < Class >

Each term in the antecedent is a triple (a,o,v)

where,

a is the attribute of a domain, o is an operator and v the value belongs to the attribute.

It has been applied to qualitative data set which is obtained from various banks. From which qualitative bankruptcy prediction rules are generated (Martin *et al.*, 2013). The next section describes about experimental design of information delivery components.

4.3 *Information delivery layer*

Literature on prior research indicates the non availability of information delivery process for bankruptcy prediction analysis (Meimei, 2013). Designing of information delivery process for BP involves many factors such as:

- stakeholders;
- bankruptcy analysis information;
- various criteria; and
- delivery channels.

The various stakeholders considered in this information delivery process are share holders, regularities, banks, lenders, directors, employees, customers, bond holders, government, managers and community. The next element is bankruptcy prediction information or bankruptcy indicators. For quantitative bankruptcy, performance of various financial ratios has been considered and for qualitative bankruptcy, performance of various qualitative parameters which are described in Table II has been considered. The various delivery channels which are applied to deliver the customized bankruptcy information are e-mail, hand-held devices, bank premises, customer premises, phone calls and newsletters. The next element is criteria which are applied to find the suitable user and to customize the bankruptcy prediction analysis reporting. These criteria are grouped into two categories such as user and delivery channel. Based on these elements an information delivery process for bankruptcy analysis information has been designed (Martin *et al.*, 2014a). In this information delivery process, to prepare the customized report the criteria most valuable is applied and then level of information is applied.

While delivering information, same level of information cannot be given to all users which lead to inconsistency. The level of information depends on user responsibility and interest. However, user interest varies from time to time and it leads to uncertainty. These kinds of inconsistency and uncertainty problems in MCDM can be solved using Fuzzy MCDM techniques (Martin *et al.*, 2012a). In this information delivery process, Fuzzy Analytic Hierarchy Process (Fuzzy AHP) has been applied to find the suitable user to receive the customized information (Martin *et al.*, 2014a). In fuzzy AHP, weight has been assigned to criteria and alternatives (users). To assign a weight a survey has been conducted from various Indian banks (Appendix 2). Based on this survey weight has been assigned to criteria and alternatives which are described in Table V.

Criteria and its weight
Most valuable user
Level of information
Level of security
Speed of delivery

$$W^T = \begin{pmatrix} \bar{9} \\ \bar{6} \\ \bar{7} \\ \bar{5} \end{pmatrix}$$

Table V.
Assigning weight to criteria applied in information delivery layer

Table VI describes weight assigned to each BP indicators according to the criteria "most valuable user".

According to criteria each of the information assigned weight by the respective user. To every fuzzy number (*R*) the mean and standard deviation is calculated and the fuzzy number which has higher standard deviation considered as better performance than others fuzzy numbers. The mean of the final score is given by:

$$\overline{x}(\overline{r_i}) = \frac{\int x f_{\overline{r_i}}(x)dx}{\int f_{\overline{r_i}}(x)dx}$$

The spread of the final score is given by:

$$\overline{\sigma}(\overline{r_i}) = \left[\frac{\int x^2 f_{\overline{r_i}}(x)dx}{\int f_{\overline{r_i}}(x)dx} - (\overline{x}(\overline{r_i}))^2\right]^{1/2}$$

Based on the spread of the final score, suitable user to receive the information has been identified and the customized information has been delivered. The next section discusses the experimentation results of RMBIPB and its components.

5. Results and discussion

The results which are obtained from each of the components of RMBIPB have been described in this section. The details of the experimentation results of RMBIPB with its techniques are described in Table VII.

The experimentation results of RMBIPB starts with bankruptcy analysis. In the first phase, for quantitative bankruptcy prediction analysis, the influencing financial features are identified using GBRAT and the bankruptcy prediction result is obtained using CBR. The results of the both components are described with its research implications. In the next phase, for qualitative bankruptcy prediction analysis the effective qualitative features are selected using expert analysis and the prediction results are obtained using ant-miner. The results of the qualitative bankruptcy components are described. In the third phase, both of the prediction analysis results are passed to information delivery component. It finds the suitable user to receive the multi-criteria reporting through fuzzy AHP. The result of the information delivery component is described with its research implications. Finally RMBIPB implementation results are

Table VI. Weights of BP indicators under the criteria "most valuable user"

Alternatives/ information	Financial ratios	Industry risk	Management risk	Financial flexibility	Credibility	Competitiveness	Operating risk
Directors and managers	$\overline{9}$	$\overline{8}$	$\overline{8}$	$\overline{7}$	$\overline{8}$	$\overline{8}$	$\overline{6}$
Bond holders	$\overline{8}$	$\overline{8}$	$\overline{6}$	$\overline{6}$	$\overline{7}$	$\overline{8}$	$\overline{5}$
Shareholders	$\overline{4}$	$\overline{7}$	$\overline{6}$	$\overline{6}$	$\overline{7}$	$\overline{8}$	$\overline{7}$
Banks and other lenders	$\overline{5}$	$\overline{7}$	$\overline{6}$	$\overline{5}$	$\overline{6}$	$\overline{6}$	$\overline{5}$
Employees	$\overline{6}$	$\overline{5}$	$\overline{6}$	$\overline{4}$	$\overline{6}$	$\overline{5}$	$\overline{9}$
Customers	$\overline{3}$	$\overline{3}$	$\overline{2}$	$\overline{3}$	$\overline{6}$	$\overline{2}$	$\overline{2}$
Community	$\overline{2}$	$\overline{2}$	$\overline{2}$	$\overline{2}$	$\overline{2}$	$\overline{3}$	$\overline{1}$
Regularities	$\overline{1}$	$\overline{3}$	$\overline{3}$	$\overline{2}$	$\overline{2}$	$\overline{2}$	$\overline{1}$
Government	$\overline{2}$	$\overline{4}$	$\overline{3}$	$\overline{3}$	$\overline{5}$	$\overline{4}$	$\overline{4}$

RMBIPB components	Software/technique	Experimentation results		
Quantitative bankruptcy Analysis component	GBRAT	Bankruptcy models	Altman Deakin Springate Edmister Fulmer	Generation of offspring using cross-over and mutation Identification of influencing ratios from the bankruptcy models using fitness function – precision of offspring (±1) Accuracy level of influencing financial features
	CBR	Quantitative bankruptcy prediction with influencing financial features identified using GBRAT		
Qualitative bankruptcy analysis component	Expert analysis	Effective qualitative bankruptcy prediction features		
	Ant-miner	Generation of qualitative bankruptcy prediction rules Qualitative bankruptcy prediction accuracy		
	κ-test	Agreement between expert and classifier		
Information delivery component	Fuzzy AHP	Different level of information preference and multi-criteria reporting		

Table VII. RMBIPB experimentation results

revealed with its research implications. The experimentation results of components of RMBIPB are described below.

5.1 Quantitative bankruptcy prediction analysis

The quantitative bankruptcy analysis consists of two components such as GBRAT and CBR. The results obtained in both components are detailed in the following sections.

5.1.1 Influencing financial ratios – GBRAT. GBRAT has identified influencing ratios from the given five widely applied bankruptcy models. The list of identified influencing ratios from each of the bankruptcy has been described in Table VIII.

The accuracy of influencing ratios obtained using GBRAT has been found by comparing each of the ratios, average impacted threshold value with respective models bankrupt value (Martin *et al.*, 2012c,d). The accuracy of influencing ratios obtained using GBRAT have been described in Figure 14.

Influencing ratios which are obtained using GBRAT having accuracy of more 85 per cent expect the influencing ratio which is obtained using Altman model (X_5).

Sl. no.	Bankruptcy models	Most influencing ratios
1	Altman	X_1 = working capital/total assets X_2 = retained earnings/total assets X_3 = earnings before interest and taxes/total assets X_5 = sales/total assets
2	Deakin	X_3 = cash/total assets
3	Springate	A = working capital/total assets
4	Edmister	X_1 = annual funds/current liabilities X_2 = equity/sales X_4 = current liabilities/equity, divided by RMA average ratio
5	Fulmer	V_5 = debt/total Assets

Table VIII. Influencing ratios of bankruptcy models

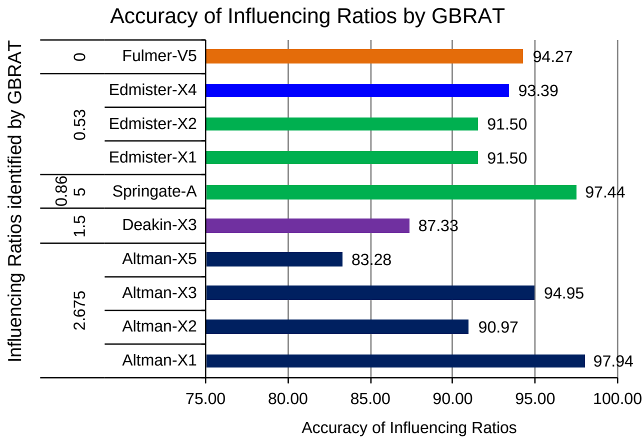


Figure 14.
Accuracy of influencing ratios obtained using GBRAT

In GBRAT, genetic operator's mutation and cross-over have been applied to generate the offspring and influencing ratios obtained in all the models only by using mutation process. The influencing ratios obtained using GBRAT in all the models are validated with the original threshold values of the respective bankruptcy model. These influencing ratios help to predict bankruptcy very efficiently and GBRAT can be applied to other bankruptcy models.

5.1.2 Quantitative bankruptcy prediction using CBR. The bankruptcy prediction accuracy obtained with influencing features using CBR has been compared with BP accuracy obtained using other feature selection techniques. In this comparative analysis, CBR with genetic algorithm have selected 15 financial features and its gives prediction accuracy of 86.73 per cent whereas CBR with decision trees have selected 15 financial features which give prediction accuracy of 87.20 per cent. GBRAT have selected nine financial features and it gives prediction accuracy 89.75 per cent which is higher in prediction accuracy compared to other feature selection techniques applied in simple CBR. The next describes about generation of bankruptcy prediction rules using ant-miner algorithm.

5.2 Qualitative bankruptcy prediction analysis

The qualitative bankruptcy analysis layer consists of two components such as effective feature selection using expert analysis and the qualitative bankruptcy prediction using ant-miner algorithm. The results obtained in both of the components are detailed in the following sections.

5.2.1 Expert analysis. From the Expert analysis the following qualitative parameters have been selected (Martin *et al.*, 2013) which are given below:

- industry risk (IR);
- management risk (MR);
- financial flexibility (FF);
- credibility (CR);
- competitiveness (CO); and
- operating risk (OR).

These parameters are applied in ant-miner to generate the qualitative bankruptcy prediction rules.

5.2.2 Qualitative bankruptcy prediction using ant-miner. Qualitative bankruptcy prediction rules are generated using ant-miner. It classifies the prediction rules into bankrupt and non bankrupt classes. The rules which are generated using ant-miner have been described below:

- Rule 1: if financial flexibility is negative and competitiveness is negative then bankrupt.
- Rule 2: if competitiveness is positive then non bankrupt.
- Rule 3: if credibility is negative then bankrupt.
- Rule 4: if management risk is negative then non bankrupt.
- Rule 5: if management risk is positive then non bankrupt.
- Rule 6: if financial flexibility is negative and credibility is negative then bankrupt.
- Rule 7: if industrial risk is positive and competitiveness is positive then non bankrupt.

From this experiment, different rules to predict the qualitative bankruptcy are generated. The qualitative bankruptcy prediction accuracy obtained using ant-miner is 96.29 per cent. The prediction accuracy obtained using ant-miner is relatively higher than other kinds of classification algorithms. These rules can be applied in various organizations and qualitative bankruptcy of a business can be predicted. The generated classified rules can reveal the qualitative bankruptcy state of the business. The next section describes about implementation of information delivery layer using fuzzy AHP.

5.3 Information delivery using fuzzy AHP

In information delivery layer, suitable user to receive the appropriate information has been identified. The customized reporting for bankruptcy prediction has been developed and delivered according to user preference. For each of the bankruptcy information considered in this experiment, fuzzy score is calculated using fuzzy AHP. The fuzzy score for the information "management risk" according to its stakeholders is described in Table IX.

Alternatives	Sum	Mean	SD
Directors and managers	551	183	939
Regularities	455	151	693
Banks and other lenders	403	134	762
Customers	403	134	618
Employees	414	138	900
Community	336	112	566
Bond holders	410	136	667
Share holders	391	130	697
Government	275	91	601

Table IX. Level of preference for management risk

Table IX describes the level of preference to receive the management risk information. The fuzzy score obtained using fuzzy AHP for different users have been described in Figure 15.

The best, least and intermediate users to receive the information "financial flexibility" is described in Figure 16.

Similarly, for other bankruptcy prediction indicators the suitable user to receive the appropriate information have been identified and delivered to respective user according to their preference. Thus the experiment conducted using Fuzzy AHP finds the relevant user for the given information. This information delivery layer is suitable to domains where the difference in preference of receiving the report. To develop the customized reporting, other Fuzzy MCDM techniques such as TOPSIS, ELECTRE and Grey theory can be applied.

In an organization, different levels of employees are designated to manage different positions and handles different level of information. Thus this information delivery component should be customized to find the suitable user according to the very specific type of user profile. This kind of customization reduces the information overload and paves a platform to make effective decision making.

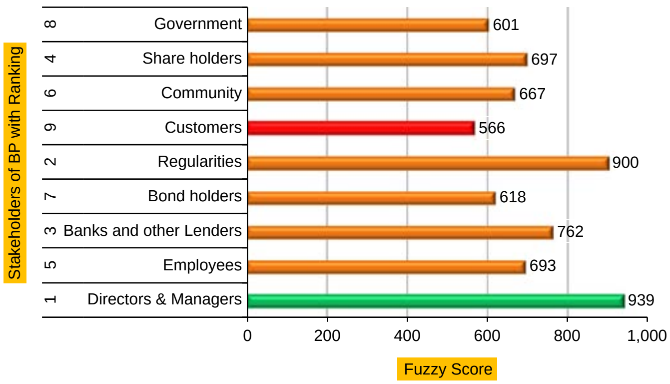


Figure 15.
Ranking of users to receive the information – "management risk"

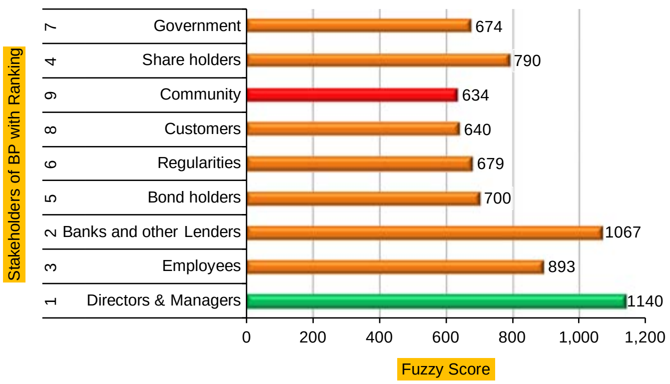


Figure 16.
Ranking of users to receive the information – "financial flexibility"

6. RMBIPB results – from the implementation experience

A Reference model for BI has been developed to conduct the comprehensive bankruptcy prediction. This reference model has been implemented with different kinds of techniques to conduct the comprehensive bankruptcy prediction. The implementation of RMBIPB is discussed in quantitative and qualitative aspects.

6.1 RMBIPB – from quantitative aspects

In RMBIPB, for quantitative bankruptcy prediction, influencing features are selected using GBRAT. The financial data sets which are collected from various Indian banks are represented in CBR and 89.75 per cent prediction accuracy is obtained using influencing financial features. CBR has given better prediction accuracy using influencing financial features when it is compared to other feature selection techniques.

To conduct the qualitative bankruptcy prediction effective features are selected from expert analysis. Ant-miner has been applied to classify the qualitative bankruptcy datasets into bankruptcy and non bankruptcy classes and obtained 96.29 per cent of prediction accuracy. Both of the results are passed to information delivery components for customized reporting. This component selects the required criteria and fuzzy AHP is applied to find the suitable user for customized reporting.

6.2 RMBIPB – from qualitative aspects

In this reference model, techniques are selected with minimal effort to conduct the bankruptcy prediction. The same reference model for another domain can be realized with different kinds of techniques for bankruptcy prediction.

According to the domain, problem and requirement of the stakeholders RMBIPB can be realized. For example RMBIPB has been realized to analyze the performance of the students in education domain (Miranda *et al.*, 2013a, b). In this realization the performance of students has been analyzed using quantitative parameters (academic performance) as well as qualitative parameters (family background, friends, relations support and other related factors). Similarly, RMBIPB would be realized in different domains for failure prediction. These effortless changes make this reference model as a flexible model to be applied in various domains according to the requirement.

RMBIPB is designed to accommodate any number of techniques for each of its components according to the requirement of a particular domain. The proposed model has not been bounded to any specific technique which reduces the implementation cost and development time. This model is designed using unit operations such as abstraction and decomposition. Software qualities like reusability, modifiability, integrability, scalability, understandability, adaptability and ease of creation are exhibited by this model.

6.3 Limitations

The limitations which are found in RMBIPB and its components are described below.

In this research, RMBIPB is developed specific to bankruptcy prediction. This model is designed using unit operations and the software qualities exhibited by RMBIPB are limited by unit operations. The software qualities which are observed from the implementation experience of RMBIPB have not been quantified.

The data set which are applied in RMBIPB is limited to Indian banks. In GBRAT, to generate offspring simple pair cross-over is applied. The performance of influencing ratios has to be analysed with classification methods like neural networks, decision trees, support vector machine and other methods in order to find the bankruptcy prediction accuracy. In RMBIPB, for customized reporting criteria selection is limited to four criteria and Fuzzy AHP is applied to find the suitable user for customized information delivery.

This section has described the experimentation results of RMBIPB. The experimentation results of its techniques such as GBRAT, CBR, expert analysis, ant-miner and fuzzy AHP are described with its research implications. Finally the outcome of the RMBIPB is described.

7. Conclusion

Financial stability is the essential characteristics of a business. The performance of the business irrespective of its size solely depends on wealth of the financial status. To analyze the financial stability bankruptcy prediction methods are applied. This research is an attempt to provide a comprehensive solution for bankruptcy prediction. To realize the comprehensive model, BI solution is applied and reference model is designed using unit operations to predict bankruptcy.

This model is flexible in design in which the number of components required for each of the layers can be decided according to the requirement. Thus the bankruptcy variables and components can be decided according to requirement to implement this model with lesser effort.

In this research, banking data has been applied to predict the bankruptcy. This reference model has been validated qualitatively. The results of components of this reference model have been validated quantitatively. In this reference model, GBRAT has been applied to select influencing financial ratios for quantitative bankruptcy analysis. These influencing ratios improve the prediction accuracy of bankruptcy and GBRAT can be applied to other bankruptcy models. The bankruptcy prediction accuracy using CBR with influencing ratios have shown higher accuracy compared to previous methodologies.

In qualitative bankruptcy prediction, the influencing qualitative parameters have been selected using expert analysis. These parameters are evaluated using expert analysis and qualitative bankruptcy prediction rules have been generated from these parameters using ant-miner. The κ-value of qualitative bankruptcy prediction rules is 0.9367 which is higher than previous studies to generate qualitative bankruptcy prediction rules. The results of quantitative and qualitative bankruptcy prediction analysis are passed to information delivery layer. In this information delivery layer, using fuzzy AHP suitable alternative to receive the customized reporting has been identified and reported to the respective user.

On maturity this model can be supported by a framework which will reduce the software developmental effort in building the applications. To this model knowledge-based systems can be added which could reason and use a knowledge base to apply smartness to the decisions-making process.

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