# CHAPTER – III

# REVIEW OF LITERATURE

# 3. REVIEW OF LITERATURE

## 3.1. Introduction

Like other business entities, profit is the primary objective for commercial banks also. Contrary to normal accounting practice, the deposits in the banks are considered to be its liabilities and the loans given are accounted as asset. The profitability of a bank is then a function of efficient asset management (Kohlscheen, Murcia, & Contreras, 2018).

Lending is a function of deposits, more the deposits, the greater shall be the capacity of banks to lend money (Nations, 2005) (Walsh, 2003). In case of weak lending control mechanism banks may end up lending to sub-prime applicants and it may fall in the fatal trap of default. Such defaults put immense pressure on banks deposits. Thus, it becomes extremely pertinent to balance the function of borrowing and lending with thorough due diligence (Rouse, 2002).

With an objective to safeguard depositors' money, central bank supervises all the functions of commercial banks (Mankiw, 2013). The loans issued by commercial banks has an intrinsic element of risks; the risk of interest or principal amount not being regularly paid by the borrower (Peterson, 2012) (Boyd, Nicolo, & Jalal, 2009). Bad loans, non-performing loans, problem loans, non-performing assets are synonymous expressions to the Non-payment of principal and interest of disbursed loan. Basically if the borrower is not meeting the debt obligation, it may result is in Non-Performing Asset (NPA). The nuances of NPA are discussed further; it includes NPA at international level followed by the dynamics and causes in reference to India. The study provides insights on wilful default specifically of the companies which had IPO, borrowed loans from the banks and subsequently defaulting intentionally. This serious issue is then discussed further with reference to usage of Bankruptcy Models; various types of models and evaluated models based on transparency, accuracy, etc.

## 3.2. Non-Performing Assets - An International Overview

By and large, an NPL (Non-performing Loan) or NPA are those loans in which interest (or principal) is overdue by 90 days (RBI, Master Circulars, 2001).The NPA qualifying definition may vary in US, UK, Japan, Korea, Taiwan, China or any other country (Golin & Delhaise, 2013) (Khan, 2009) (Bloem & Freeman, 2005) (Inaba, Kozu, & Sekine, 2017) (Bank C. C., 2004) (Bank

H. S., 2015) (Taiwan, 2014) (Bholat, Lastra, Markose, Miglionico, & Sen, 2016).The world is facing an unpleasant condition, the aggregate rate of NPLs exhibits large disparities on a cross-country basis, particularly between developed and developing countries. As per Global Stability Report published by International Monetary Fund in 2007, few countries like Egypt, Nigeria, Philippines, Morocco, Algeria, and Tunisia suffer 15 percent of total loans as bad loans, other countries like Sweden, Norway, Finland, Australia, and Spain less exposed to weak assets quality, having less than 1 percent exposure to bad loans. The report states that better infrastructure and banking mechanism enables the system to work efficiently (Allen, 2004) (IMF, 2007). Strategically, for developing countries like India, China, Brazil, etc. it is extremely important to keep low NPA else it will pull the brakes on the growth engine (Mishkin, 1996).

The natural course and progression guides to study the nature and causes of NPA as it is an important Key Performance Indicator of the banking system, especially related to safety and soundness (Throsten & Cull, 2005) (Lin & Zhang, 2009) (Siraj & Pillai, 2013). A significant branch of research stresses central role of assets quality as a predictor of bank failures and; apart from endogenous and exogenous factors impact of banking regulation and poor supervision can be one of the causes of NPA (Abdelkader , Boulila Taktak, & Jellouli, 2009) (Barth, Caprio, & Levine, 2004) (Abdelkader , Boulila Taktak, & Jellouli, 2009) (Berger, 1997). By using different nomenclature, the factors are categorized as Internal and External; political, economic, social and technological (Gopalkrishnan T. V., 2004).

### 3.2.1. Internal Factors

Several studies on Internal factors of NPA have concluded that operational inefficiency can lead to NPA (Kwan & Eisenbeis, 1997). Increased competition in the banking sector coupled with agency problem can bring down credit standards and leads to bad loans (Salas & Saurina, 2002). Diversion of borrowed funds was found to be the major reason for NPA in Tanzania and the reason concluded is poor monitoring and appraisal system (Richard, 2010). In Indian context, one of the internal reasons attributed to NPA is diversion of funds, funds are utilized for other reason than originally granted. (Vemula & Mahalingam, 2012). There is a very strong direct correlation between quality of asset and efficiency of bank (Siraj & Pillai, 2013) (Naveenan, 2016). In addition, time overrun, business failure, stalled projects, poor monitoring by banks, improper selection of technology amongst others has also significantly lead to higher NPA (Joseph &

Prakash, 2014).In context to internal controls related to market discipline was found to be lesser significant for better economic outcomes and emphasis is made on legal system, democracy and strong institution building (Abdelkader , Boulila Taktak, & Jellouli, 2009).The effective management of credit risk is an important aspect of risk management and essential to the long-term success of any banking organization (Spuchľáková, Valašková, & Adamko, 2015).

Inthe study on 50 commercial banks in District of Columbia of the USA, it was revealed that the banks should take into consideration the 'Micro' and State-Level Macroeconomic condition to control NPL. The study was based on micro variables including capitalization, liquidity risks, poor credit quality, greater cost inefficiency and banking industry size; it also included macro variables like real GDP, real personal income growth rates, changes in state housing price index, inflation, state unemployment rates, and US public debt (Ghosh, 2015).

### 3.2.2. External Factor

Study on impact of legal, political, sociological, economic, and banking institutions on NPA was reviewed, and the same concluded that conflict of interest lead to mismanagement of funds and culminates in NPA (Breuer, 2006).A research conducted on 70 countries with focus on multiple supervisor in banks raised a question that should the control mechanism be centralized or decentralized? The research found that countries with one supervisory body tends to have more NPL in comparison to those countries with multiple supervisory bodies. It also highlighted countries with multiple supervisor have lower capital ratios and higher liquidity risk. (Barth, Dopico, Nolle, & Wilcox, 2002). In another research related to legal system covered 59 countries for the period 2002-06 highlighted that the higher Capital Adequacy Ratio and judicious provisioning policy can help in reducing the losses through better legal system, increasing transparency and democracy rather than focusing on regulatory aspects. A study of Financial Soundness Indicators (FSI) for 96 countries for the period between 1998 and 2005 drawn conclusion as capital adequacy, profitability, and asset quality with macroeconomic indicator finds that FSIs fluctuate strongly with both the business cycle and the inflation rate. (Babihuga, 2007). A study covered 85 banks in sensitive countries like Greece, Italy and Spain from the period 2004-2008 revealed the problem loans varies negatively with the growth rate of GDP and the profitability of banks' assets, while positively with the unemployment rate, the loan loss reserves to total loans and the real interest rate (Messai & Jouini, 2013).In Latvia, the banks were depending heavily on foreign currency loans till 2010and followed pegged-Foreign Exchange method. Due to global recession the banks had to foreclose many loans. This was one of the major reasons for debacle of Latvia economy which was also the case with Azerbaijan (Bank W. , 2018).

### 3.3. Non-Performing Assets in India

The highlighting of the problem of NPA in India starting in 2014. According to the Financial Stability Report, 2014 published by RBI categorically stated the problem of Wilful Default is to be segregated and ensuring equity participation of the promoters in the losses leading to defaults. RBI extended its concerns over the need for bringing in greater transparency in the process to find net economic value of large corporate debt restructuring. Another point highlighted in the report was related to the problem of corporate leverage and its impact on banks' balance sheet, especially, 'double leveraging' through holding company structures and shares pledged by the promoters (RBI, 2014).

In India, the problem of NPA including causes and remedial measures have been studied in detail since last few years. One of the findings includes NPA is influenced by major sets of factors; terms of credit, bank specific indicators relating to asset size, credit orientation, financial innovations (non-interest income), and regulatory capital requirement and the business cycle shocks (Mishra & Dhal, 2003). NPA causes adverse economic and market factors, ranging from recessionary conditions, regulatory changes and resource shortages to inefficient management and strained labor relations (Vemula & Mahalingam, 2012) (Pharate, 2014). Price escalation of inputs, unanticipated short of inputs, exchange rate fluctuations, and change in government policies (Joseph & Prakash, 2014). The impact of NPA on profitability and soundness of the banks has been researched in India, it is found to be a negative on the performance of banks with respect to sustainability, economic deterioration, financial viability and Domino's effect on interconnected sectors. (Ahmed, 2009) (Vadivalgan & Selvraljan, 2013) (Zafar, Maqbool, & Khalid, 2013) (Onkareppa & Vanaki, 2013)

Managers with poor credit assessment skills lead to significant damage to the asset quality of the bank, further it may also lead to unlawful activities in order to achieve professional targets; all this has a significant influence on NPA. Also, seizure and disposal of mortgaged assets is a major challenge while other challenges include government and political influences (Sanjeev, 2007)

(Vasuki, Sravanan, & M, 2008). A study on NPA focusing on PSU bank by using Sample Panel reveals the inefficiency is the main reason for NPA at PSU banks. The finding corroborated the view of the Varma committee that recapitalization is not the solution to two PSU banks; Indian Bank and United Bank of India (Vasishtha & Rajaraman, 2002).

In order to control NPA, several measures were undertaken in the history, as privatization of public sector banks, consolidation of banks, creation of separate entity for social sector lending, restructuring of operations, strategy, role and purpose, strong penalty for compromised work ethics, rotation of staff, transparency in the market, better audit system, market intelligence, extensive use of technology for data mining, comprehensive credit appraisal and monitoring. (Roy, Subramaniam, & Ravi, 2018).

At international level, the problem of default is addressed by Bank for International Settlements (BIS) which was established in 1930. The main objective of incorporation was to address the issue on reparation payment imposed for Germany after World War I. Subsequently, it worked for financial stability post Great Depression and World War II. Later on, it worked for coordinating G10 countries for economic stability and foreign exchange mechanisms erstwhile system of foreign exchange fixation based on Gold, Fixed and market driven. The importance of BIS has been of significance after introduction of Basel Norms for stabilizing the banking system (BIS-History). In 1988, Basel Accord was floated to internationally active banks in G10 countries to hold capital equal to at least 8 per cent of a basket of assets based on their risk profiles. It introduced capital bifurcation as Tier 1 for Shareholders' equity and retained earnings and Tier 2 being the additional internal and external sources available to the bank. The measurement of risk was under 4 distinct baskets; 10, 20, 50 and 100 per cent based on the quality of assets. The norm focused mainly on the credit risk, however, the regulatory measures 8 percent adequacy ratio was found to be insufficient and mere considering credit risk was not enough. Thereafter, Basel Accord II was introduced to encompass many more aspects of risks in banking. It consists of 3 pillars; Minimum Capital Requirement considering Credit Risk, Market Risk and Operational Risk, Supervisory Review Process and Market Discipline and Disclosure. After the shocks of Sub-Prime Crisis, banking system required a robust bulwark to provide safety against the risk of default. Basel Norm III increased the capital adequacy ratio to 10.5% and redefine capital and hence the incorporation of Capital conservation Buffer, Countercyclical buffer required for Systematically Important

Financial Institutions (SIFI) and leverage ratio was made (Balthazar, 2006), (BIS, 2006) (Taurllo, 2008) (Merwe, 2015), (Ramirez, 2017) (Suresh & Paul, 2018).

A study from 1998 to 2014 reveals public sector banks are more sensitive towards internal-bank specific factors, while private and foreign banks were affected by macroeconomic and industry related factors significantly in determining credit risk. By using different panel data estimation models and sub-samples of ownership groups it provided an insight into the formation of default risks (Gulati, Goswami, & Kumar, 2019).

### 3.4. Credit Appraisal Techniques

The most important aspect of Credit Appraisal lies in the recognition of Credit Risk. The bank contemplates the entire risk exposure at international and national level through central bank and Basel Norms. The comprehensive set of risk includes Operational, Currency, Interest Rate, Market and Credit Risks. A bank is exposed to multiple risks just in one profile of the prospective borrower (Rousse, 2002). Public Sector Banks are lagging behind the NBFC and Private Banks in terms of MSME lending mainly due to credit risk underscoring (RBI, Financial Stablility and Progress Report, 2018).

Reserve Bank of India has issued guidelines on Loan and Advances as the part of credit appraisal system. It encompasses the statutes and other restrictions which includes banks cannot take loan against its own shares, loan to Director is prohibited or on behalf of the Director where they have connections with other entities, loans to the relatives of the Director should provide a disclaimer from the concerned Director as well as Senior Managers, restricted to provide loans to the Industries Producing / Consuming Ozone Depleting Substances and Sensitive Commodities under Selective Credit Control. The guideline restricts financing Initial Public Offerings (IPO), assisting employees to buy their companies' shares, other parties to purchase shares, debentures or bonds. A set of definite regulations have been made by RBI for financing overseas entities like brokers, MSMEs, Real Estate Sector, Infrastructure Sector, Gold loans, Working Capital for IT sector, Bridge Loans, etc. It has also chalked down the precise process of credit appraisal emphasizing fair practices of the lender with trust, honesty, integrity and balanced approach to the applicant. (RBI, Master Circular- Loans and Advances – Statutory and Other Restrictions, 2015).

The tussle of credit assessment being art or science is perennial. Since, it is based on human interaction verbal and non-verbal cues, financials results and other economic aspects create a tussle for bankers. Evaluation of the quantitative information with the help of statistical techniques and tools has evolved over decades. Short listing of loans for evaluation and evaluation of the shortlisted loans is tricky. With the use of linear programming techniques, a model derived which was a useful tool for bank auditors, loan officers, and examiners with a meaningful measure of the loan portfolio's quality (Orgler, 1969).

In India credit appraisal process was formally introduced in 1975 where RBI constituted Tandon committee; the major focus on credit appraisal techniques has been deliberated and discussed. It suggested need-based credit, ensuring end-use of credit, improving financial discipline that is, achieving a healthy bank-borrower relationship in short. In 1980, the Chore Committee made additional recommendations apart from the recommendations from Tandon Committee focused on working capital. It suggested strict adherence to submission of quarterly financial statements to ensure close monitoring (Bhattacharya, 2011).

Traditionally, a bank would undertake a two-stage appraisal process, when the evaluation cost drops below the threshold cost which can permit to conduct the second-stage loan appraisal. It concluded that banks have fewer tendencies to conduct stage two evaluations for good borrowers (Chen, Guo, & Huang, 2009).

### 3.5. Wilful Default

Globally, different terminology is used to identify wilful default. In the US, bankruptcy is of two types; voluntary and involuntary. However, the fraud cases leading to bankruptcy is called as Wilful Default in India. Wilful Default concept was firstly introduced in the budget speech by Finance Minister on 28$^{th}$ February 1994 (Gist of RBI Schemes of Defaulter Lists, 1994). RBI thereafter introduced the framework in 1999 where list of wilful default should be disseminated and guidelines for the banks (RBI, Notification-DBOD. No..DL(W).BC ./110 /20.16.003(1)/2001-02 , 2002) (RBI, Collection And Dissemination Of Information Oncases Of Wilful Default Of Rs.25 Lakhs And Above, 1999). There were many refinements in definition of wilful default from time to time. RBI has provided guidelines to deal with wilful default starting from identifying, recording and treatment in terms of penalty and judicial procedure (Master Circular on Wilful

Defaulters, 2015). The evolution in space of wilful default has been discussed at length in the following chapter on legal aspects of wilful default.

Research on Wilful Default in India has drawn attention of regulators, banks, academician, policy makers and lawyers. In the quest to find the solution to the problem of Wilful Default the Insolvency and Bankruptcy Code was introduced in India in 2016; in anticipation to the faster dissolution of bad assets. In India, the infrastructure for faster disposal has been introduced recently; such mechanism is present in the US, the UK, Canada, Singapore and Australia (EY Financial Services, Restructuring & Turnaround Services, 2017).However, IBC can help to resolve the case by bringing in liquidity but the problem of wilful default is overarching in banking industry.

### 3.6. International Voluntary Bankruptcy of Public Limited Companies

In 1801, the United States of America's constitution, Clause 4 of section 8 under Article 1 uniform laws on the subject of bankruptcies throughout the United States was introduced. Subsequently, Bankruptcy Reforms Act, 1978, Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA) were enacted. In 1705, the right to individual and/or firm to petition for bankruptcy was first granted in England, then USA in 1805, Canada in 1869, Switzerland in 1889, Australia in 1966, the United Kingdom in 1986, China in 2006, Ireland in 2011, and India in 2016.

After Sub-Prime Crisis, a major number of individuals amounting to more than a million individual and 300 companies are bankrupt in the US under chapter 7 and 11. While nearly one lakh cases in England and Wales of individual and an average of 13000 firms filed for bankruptcy (The insolvency Service, 2017).

In India voluntary bankruptcy was earlier linked with winding up of the company under Companies Act, 2013, later on the laws related to Bankruptcy and Insolvency was codified as Insolvency and Bankruptcy Code, 2016. Bankruptcy and Insolvency Code empowers firms (Sole Proprietor, Partnership, Limited Liability Partnership, Private Limited Companies and Public Limited Company) to undergo liquidation through legal and organized medium. By the end of December 2017, 30 cases of bankruptcy have been filed with Insolvency and Bankruptcy Board of India ( Insolvency and Bankruptcy Board of India, 2017).

### 3.7. IPO Performance and Leverage

Initial Public Offering (IPO), Seasoned Equity Offering or Secondary Equity 0ffering (SEO) is the fresh equity share being offered to general public and subsequently getting listed on equity stock market. The performance of IPOs has been studied extensively in most of the countries considering its pricing, timing, size, etc. In 1602, first IPO was brought by Dutch East India Company (Goetzman & Rouwerhost, 2005). Worldwide the study on IPO strives to find whether IPO helps to generate wealth in long term or it's a short term investment. It is a pertinent question for investors across the globe to know whether IPOs are overpriced or under-priced in long and short run.

Under-pricing was reported to the in 11 cases from the study of IPOs in the US between 1963 and 1965 (Reilly & Hatfield, 1969). Subsequently from 1963,the IPO market in the US has been under-priced in short run, this has been found in various researches (Ibbotson, 1975), (Reilly F. , New Issues Re-visited, 1977) (Aggarwal & Rivoli, 1977), (Ritter J. R., 1991) (Loughran & Ritter, 1995) (Ljungqvist & Wilhelm, 2002).

Similar results were shown in Canadian market, German market and Australian market. (Jog & Riding, 1987) , (Ljungqvist A. , 1997) (Gong & Chander, 2001). Also, for Singapore, Chinese market and Malaysian market reported underpricing of IPOs in the Asian markets (Wong & Chiang, 1986) (Yong & Isa, 2006). 'Anomalies' of under-pricing in the short run and under performance of IPOs in long run is due to the presence of few irrationally exuberant investors. Such investment coupled with short-sale restriction leads to long run underperformance (Ljungqvist & Singh, 2006).

Pricing Model used by company plays a vital role in IPO performance. Ina research of 49 IPOs on Euronext Brussels with respect to valuation method used by investment banker found that most of them used Discounted Cash Flow Method as it was considered more accurate than Dividend Discount Model (Deloof, Maeseneire, & Brecht, 2009).

Since 2000 when revised SEBI guidelines for IPOs were published, a large number of IPOs have hit Indian equity market through book-building process. Ostensibly, SEBI guidelines have been prepared with an objective to help investors as well as promoters by striking a proper balance. IPO from 2010 to 2015 was not found significantly under-priced for both graded and non-graded IPOs while under-pricing found with higher grading (Tripathy & Pandey, 2018). In a comparative study among Australia, Canada, China, Germany, India, Japan, U.K., and U.S., a positive relationship between the IPO pricing and Net Income was in all eight countries; the economic impact has been maximum in China and lowest in Australia (Bhagat, Lu, & Rangan, 2018).

Flotation of new shares in India had so far seen four distinct regimes starting with a tightly controlled regime that existed prior to 1992, fixed price regime after 1992, Book Building process after 1995, and refined guidelines for Book Building Process after 1998. Before 1992, companies needed to take approval from the office of Controller of Capital Issues (CCI) for raising funds, which was at par for new companies and at a premium for existing companies with substantial reserves where premium was calculated in accordance with CCI norms. Since 1992, after CCI guidelines were abolished and Security Exchange Board of India (SEBI) was formed under the SEBI Act, eligible companies have the freedom to issue shares at a premium decided in consultation with lead managers of the issue (Murthy, 2009) (Chakrabarti, 2018). Information is required to be provided to investors justifying the premium being charged. This helped companies in raising funds and also gave good returns to investors (Kothari & Mehta, 2014). In a technical report by CMIE bearing a study of 2056 new listings during January 1991 to May 1995, a phenomenal 105.6 excess return over the offer price was found (Shah A. , 1995). A study of IPOs offered on Bombay Stock Exchange during the period 1992 to 1995 shows that underpricing was higher than the international experience in the short run and also in the long run as IPOs yielded higher returns compared to the negative long-run returns recorded from the international markets (Madhusoonan & Thiripalraju M, 1997). Performance of IPOs were studied with a sample of 500 issues which entered market during January 1993 to March 1996 and it was found that the short run underpricing was to the extent of 36.6%of the total samples and the long-run overpricing was 40.8%of the total samples (Kakati, 1999). IPOs study between 1992 and 1994 demonstrated the under-pricing to the extent of 72.34%of the total samples with respect to returns (Chandrasekhar & Kumar, 2002). For the period between 1999 and 2006, a study on 156 companies found that the IPOs on an average offered positive returns to investors (Chandrasekhar & Kumar, 2002). While, in the long run the IPOs offered positive returns up to twenty four months, they subsequently underperform the market (Kumar, 2006).

The point of reference of IPO lies in the fact that NPA cases are from listed entities also, it is vital to study to what extent wilful default are listed companies. Since these companies have to first come with an IPO, raise funds from general public and then going for leverage. When listed companies raise money from general public, bank and go bankrupt wilfully it certainly a matter of concern. This indicates the intentions are malicious from the beginning and there has to be an attempt to predict such type of bankruptcy. Further, several Credit Risk models are discussed and evaluated to find out if any model can be proposed to be used professionally by the banks in future.

### 3.8. Credit Risk Models

After World War I, America had to tighten up its banking policy and passed Glass-Steagall Act, 1933. It distinguished banking, investment banking services, and insurance and further restricted banks to buy securities other than government (Rothbard, 2002). The idea was to differentiate lending and investing activity. However, decades later, the provision of banning banks to own companies, commercial banks, was repealed by Gramm-Leach-Bilely Act, 1999. Earlier, in 1982 Garn-St. Germain Depositories Institution Act had deregulated savings and loan associations (Chaudhari, 2014). Financial innovation leads the banking system to provide bundled services and provide them with an opportunity to earn more (Mullineaux, 1987). In UK, a major reform in the financial sector had taken place commonly known as Big Bang, lead to deregulation of banks in 1986. After the reform the UK attracted many US practice bearing the Wall Street imprint; in a piquant remark by Rowan Bosworth, a Financial Criminologist and former detective for Financial Fraud criticized the people involved in Financial advisory as “a tidal wave of fraudsters, con men, financial snake-oil salesmen and masquerading people under the title of ‘Financial advisors’” (Shaxson, 2018).

After considering the global scenario of banking deregulation, it is imperative to study the side effects of deregulations; excess liquidity with the banks lead to higher lending at lower interest rates (Saxegaard, 2006) (ECB, 2017). This can be a bigger problem and hence the further study shows the forward path on the loan appraisal processes of the banks. The lending has become very complex and bankers need to consider domestic and international markets in depth. The focus has been shifting from Balance Sheet to Cash Flow analysis for lending. Securitization of loans by banks and investment banks has standardize approach for evaluating credit risk. Also, with the increase in geographical reach, bank need to have objective and adopt standardize approach for evaluation. With the introduction of technology, modern lending techniques adopt sophisticated methodology to evaluate the probability of repayment and quantifying the risk. The major development has been in the field of credit rating, portfolio management, neural network and neural and intelligent knowledge-bases system. Two governing factors for lending are credit culture and credit standard. (Rouse, 2002). There has been a tremendous growth in the area of Credit Risk Evaluation; tools are broadly based from Statistics, Operations Research and Financial Market Based models. Statistics and Operations Research includes Survival Analysis, Neural Networks, Mathematical Programming, Deterministic and Probabilistic Simulation, Stochastic Calculus and Game Theory while Financial Markets based model includes Arbitrage Pricing Theory, Option Pricing Theory and Capital Asset Pricing Model.

All of these were extensively studied, refined and tested under various conditions to be found if effective and profitable. These models need to undergo various constructs/variables; identify the variable and derive the relationship by using mathematics and statistics, simulation and other relevant technique to authenticate the relationship. Lastly, the models need to be tested upon and verified for outcome. In case of Credit Risk, models undergoes the process which verifies the relationship through classification of tools or techniques employed, the sector or the domain of application, and last the products on which the models shall be applicable (Caouette, Altman, Narayanan, & Nimmo, 2008).

The most commonly used technique is from Econometrics, then Neural Networks, Optimization Models, Rule-Based or Expert and Hybrid systems.

### 3.8.1. Econometrics Technique

Econometrics is an application of statistical tools and techniques to economic data in order to find some relationship between two or more than two variables. It is widely used technique in the area of economics and financial research. It includes multiple regressions, logit analysis, linear and multiple discriminant analysis, and probit analysis taking probability of default or default premium as dependent variable and a set of independent variables. The credit scoring is a technique which translates the risk factors in the form of scores. The credit scoring valuation technique can be classified as conventional methods and advanced statistical techniques. The former includes weight of evidence, genetic algorithms, multiple linear regression, discriminant analysis, probit analysis and logistic regression. The latter comprises fuzzy algorithms, expert systems and neural networks (Hand & Hendly, 1997) (Abdou & Pointon, 2011).

In 1928, Wall and Duning created the first example of real linear multivariate discriminant analysis through a ratio index, a weighted combination of several different ratios with the weights being randomly selected to predict bankruptcy (Wall & Dunning, 1928). Later in 1932, Fitzpatrick investigated the differences between ratios of successful industrial enterprises with those of failed firms (Fitzpatrick, 1932). Smith and Winakor investigated the trends of twenty-one accounting ratios, analyzed the mean of each ratio up to ten years prior to the occurrence of the financial difficulty and concluded that the ratio of net working capital to total assets was the most accurate predictor of failure (Smith & Winakor, 1935). In 1942, nearly 1000 companies were analyzed spanning the period 1926-1936 by using ratios, namely, Current ratio, net worth to total debt, and net working capital to total assets (Merwin, 1942). Hickman found net profit to sales and the times-interest-earned ratios were the best predictors of default. In 1966, Beaver analyzed 79 failed companies between 1954 and 1964 by using 30 variables tested across 6 groups of financial ratios. A year before the bankruptcy was predicated 87% accurately and five year before at 78% by using Multivariate Discriminate Analysis (MDA) concluded single ratio known as best performing ratio Cash Flow/Total Debt Best Value (Beaver, 1966). From 1968 to 1980 was the era of multivariate discriminant analysis. In 1968, Edward Altman had come up with the now famous bankruptcy model known as Z-Score model. Altman’s Z-Score method was introduced to incorporate the quality of ratio analysis as an analytical technique wherein a multiple discriminant statistical methodology was employed and set 5 ratios were introduced. The data of 66 companies equally distributed amongst bankrupt and non-bankrupt in the year 1964 were selected. With the use of Multivariate Discriminant Analysis (MDA) the accuracy results were 95% (Altman, 1968). With the use of linear programming technique, a model was derived which was a useful tool for bank auditors, loan officers, and examiners with a meaningful measure of the loan portfolio's quality (Orgler, 1969) (Gissel, Giacomino, & Akers, 2007).

Working further on Beaver’s predictable model; in 1972, Deakin extended by attaching probability and could produce better results. Total14 Financial Ratios were selected for MDA technique to predict bankruptcy improved to 90% before 2 years of bankruptcy claimed to be better than Beavers model accuracy rate 78% (Deakin, 1972). In the same year, research focusing on the small business failure prediction used a dataset of 42 bankrupt companies which borrowed from Small Business Association and Robert Morris Associates reduced the ratios to 7 through MDA technique. It could predict 39 out of 42 bankrupt firms with accuracy rate of 93% (Edmister, 1972).Total 230 companies both failed and non-failed used Failing Company Model (FCM) developed through MDA technique that quantify probability with an accuracy rate of 93-95%, (Blum, 1974). In 1977, Altman's model was criticized in terms of predictability and accuracy was presented by Professor of the University of New Mexico (Moyer, 1977). Dependability of these techniques lies in correct predictability of good and bad applicants accurately. All these techniques are well researched in West, it finds Discriminant Analysis, Linear Regression, Probit Analysis, Poisson distribution techniques produced reliable results with the following percentages respectively: 65.4%, 55.1%, 71.9% and 62.4% respectively (Guillen & Artis, 1992) (Dionne, Manuel, & Guillen, 1996) .

The valuation of an asset is also a yardstick to predict the failure, a major breakthrough in the option valuation was presented in the public domain in 1973. One of the parameter of valuation lies in the discount of bonds based on the probability of default. In such a framework the default process of a company is driven by the value of the company's assets, and the risk of a firm's default is therefore explicitly linked to the variability of the firm's asset value (Black & Scholes, 1973), (Merton, 1974), (Altman, Resti, & Sironi, 2004). Zavgren and Friedman used Logistic Regression for US based companies extracted from COMPUSTAT predicted bankruptcy using 7 financial variables. Prediction rate before 5 years of bankruptcy was just 12% while just before a year it was 98% (Zavgren & Friedman, 1988). The Hazard Model is preferred over static model theoretically; it corrects for period at risk and allows for time-varying covariates. It used financial ratios and converted to natural log, the results showed 95% accuracy in prediction (Shumway, 2001). By using 8 Financial Ratios of Bankrupt companies in Belgium used Logistic Regression Model resulted with 67% for business termination category and 91% for audit report model (Gaeremynck & Willekens, 2012). In an interesting study on comparison between sector focused and general prediction models, it was found that the Spanish companies general or unfocused prediction models are superior to focused (sector specific) models (Fernández, Laguillo, Castillo, & Becerra, 2018).

#### 3.8.1.1. Logistic Regression (LR)

The objective of logistic regression lies in understanding the binary or dichotomous results based on one or more variables. It has been widely used in the area of medical science, social science and machine learning (Hosmer, Lemeshow, & Sturdivant, 2013). Logistic Regression considers multiple variables and provides the results whether the borrower will default or not. It fits in well and many researches are based on LR and it has been extensively used to develop the prediction model. The biggest advantage over other techniques lies in the transparency of the model. It provides total transparency to the users and provides the weight of variable which is required to be considered for the predictions.

In a study based on 3200 companies in Finland which used logistic and linear regression prediction model, the outcome was prediction of bankruptcy above 90% accuracy (Laitinen, 1999). A study on financial distress and stock prices computed abnormal returns; Average Abnormal Returns and Cumulative Average Abnormal Returns resulted in negative at or before the announcement concluded there was a leakage of information or market expected the default. The study was conducted on with the use of regression parameter of the market model estimation period of 15 months before the announcement of default was studied (Devji & Suprabha, 2016). More research work using Logistic Regression is discussed and compared with other models in Evaluation of Models section below.

#### 3.8.1.2. Z-Score

Z-Score and Zeta Score are one of the most used models to test whether it hold true in various countries, industries and context. They have been widely used by most of the countries involved in research for bankruptcy prediction. One of the most prominent models is Altman's Z-Score conceived by Edward Altman in 1968. The model is a widely accepted measure for predicting bankruptcy even today. There is a plethora of research done using the model and it has been easier to compute and provides reliable results. Altman Z-Score

$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5$

X1 = working capital / total assets (WCTA) (%),

X2 = retained earnings / total assets (RETA) (%),

X3 = earnings before interest and tax / total assets (EBITTA) (%),

X4 = market value of equity / book value of total liabilities (VETL) (%),

X5 = sales / total assets (STA) (number of times), and

Z = the overall index or "Z-score".

The result is divided into three categories; first, more than 3.00 score implies default chances are very less, second, between 1.81 and 2.99 implies cautious lending and default chances are higher, thirds, less than 1.8 implies default chances are very high and no lending to be made. Few studies based in Italy, Oman, Taiwan and Ghana on Z Score is discussed further.

In Italy, a study based on the usage of Z-Score provided a critical view on administration of the companies. (Altman, Danovi, & Falini, 2013). A case study on cement industry in Oman by using Z-Score concluded the companies are sound financially and chances of bankruptcy are very low (Mohammed, 2016). In a recent study by using Z score for Taiwan based Solar Energy companies disclosed the distress and a decline in profit efficiency of the select companies. (Ko, Fujita, & Li, 2017). The Z Score of ITI Ltd. showed high chance of bankruptcy before it was declared insolvent (Nandini, Zachariah, & Rao, 2018). A cluster based study on Ghana Stock Exchange made a comparison of Hierarchical agglomerative clustering against Z-score resulting in tri-dimensional analysis of the companies (Bunyaminu, Mohammed, & Issah,, 2019).

#### 3.8.1.3. O-Score

O-score is one of the widely used models for bankruptcy prediction; it not only considers financial performance but also the overall economic condition in the economy. It takes Gross National Product (GNP) as one of the variables of the model. O-Score evaluate the probability of company's failure, then exp (O-Score) is divided by 1 + exp (O-score). With the use of11 variables; financial and macroeconomics variables MDA technique is used to predict bankruptcy. The accuracy of the correct prediction stands 96.3%. It was then widely used to predict bankruptcy in various countries (Ohlson, Financial Ratios and the Probabilistic Prediction of Bankruptcy, 1980).

O-score is one of the widely used models for bankruptcy prediction; it not only considers financial performance but also the overall economic condition in the economy. It takes Gross National Product (GNP) as one of the variables of the model. The calculation for Ohlson's O-Score is given below:

$$T=-1.32-0.407\log(TA_t/GNP)+6.03TL_t/TA_t+0.0757CL_t/CA_t-1.72X-2.37NI_t/TA_t-1.83FFO/TL_t+0.285Y-0.521\ (NI_t-NI_{t-1})/\ |NI_t|+|NI_{t-1}|$$

1. TA = total assets
2. GNP = Gross National Product price index level
3. TL = total liabilities
4. WC = working capital
5. CL = current liabilities
6. CA = current assets

7. X = 1 if TL > TA, 0 otherwise
8. NI = net income
9. FFO = funds from operations
10. Y = 1 if a net loss for the last two years, 0 otherwise

Highest weight is to Total Liabilities followed by the Ratio Net Income, Ratio of Total Assets to GNP and so forth. It considers net income, working capital, funds from operations, current assets and current liabilities. Also, Total Assets and Total Liabilities are integral part of the formula. It interprets data as more than 0.5 as probability of default is low while less than 0.5 indicates the chances of default increases. For Thailand, a sample of 120 of which 60 were bankrupt were predicted accurately 90% before one and two years of bankruptcy (Lawrence, Pongsatat, & Lawerence, 2015).

### 3.8.2. Neural Networks (NN)

Neural Network computer programming based models work on the same lines as a human brain (Bishop, 1995). They are interconnected with many algorithms set up through econometric models. It provides flexibility in building non-linear association between the dependent and independent variables. One of the types of NN, namely, Multilayer Perceptron (MLP), consists of 3 layers; inner, hidden and outer. Each layer is connected to the other and the interconnection is very strong; it works like a wire mesh to transmit the information and calculate it further (Brown, 2014). This technology helps in higher iterations and minimal error in the outcome. Accuracy comparison with various Bankruptcy Prediction Models in traditional techniques; Linear and Logistic Regression finds Neural Network and Genetic Programming as far more Advance tool with consistent accurate results in prediction. The Multi-Layer Perceptron technique of Neural Network is one of the most appropriate NN model, a mixer of expert and redials basis function of NN can be considered for credit risk models. Logistic Regression is found to be the most accurate of traditional method (West, 2000). “Early warning system” with probability-based neural networks using Bayes’ classification theory was developed (Yang, 2001). A set of data was tested on small Italian business by using NN showed positive results in prediction, two NN models were developed in the research; one with Standard Feed forward Network and other with special Architecture (Angelini, Tollo, & Roli, 2008). Another interesting research based on experimental method suggested both emotional and neural network can be used effectively for evaluating credit risk. But emotional models outperformed in terms of speed and accuracy of decision making (Khashman, 2011).

An innovative mixed logit methodology attempted to classify firms into three failure groups; non-failure, outright failure defined as entering administration, receivership, or liquidation, and insolvency defined as failure to pay listing fees, loan default, restructuring in order to meet debt payments, and capital raising to finance continuing operations. The firm classification by their model boasted an impressive 99.16% accuracy (Jones & Hensher, 2008).For Polish companies, a synthetic featured prediction model was created by using Extreme Gradient Boosting for learning an ensemble of decision trees and high order statistics (Zięba, Tomczak, & Tomczak, 2016).

### 3.8.3. Optimization Models

The technique uses concept from the Operation Research branch, it strives to minimize the loss and maximize the returns. The models used for credit risk workswith the objective of giving optimum weight to borrower where loan can garner maximum returns at minimum error. Technique includes Vector and functions, Matrices, Symmetric Matrices, Linear Equation and Least Square Methods, Geometric Models, and others (Calafiore & Ghaoui, 2014). The modern Portfolio Theory was propounded by Harry Markowitz in 1954 and the extension to it was made by William Sharpe in 1964; both of them were awarded with Nobel Prize in Economics. Markowitz Model was worked out on the basis of Optimization Technique to increase the profit at least risk and the graphical representation of Risk and Return is known as Efficient Frontier. The risk is measured as Standard Deviation and the returns as Mean, however, Standard Deviation has an inherent limitation that the results viewed as negative while it can be positive too (Markowitz & Blay, 2014). Sharpe Model used the principle of covariance and proposed a theory that Expected Returns should be higher in case of higher risk. The relationship between Market and the stock is a measurement of risk called Beta; it is the covariance or the co-movement between market and respective stock.

The Institutional Investors wanted to overcome the problems of previous models, hence a new model was constructed called Black Litterman Model. This model is divided into two; Unconstrained Black Litterman Model (UBL) and Black Litterman Model (BL); UBL consider the Bayesian approach for identifying investor's view on expected return of asset class; it does not prohibit constraints. While BL model is a reverse optimization, the implicit expectation of returns in a diversified portfolio along with investors' views on expected returns. The personal view is then adjusted with expected return forecast and then used in mean-variance optimization framework (Litterman & Et, 2003).

For Fixed Income Securities, a portfolio optimization model considers new and the existing portfolio construction. It takes into account the dynamic nature of debt market through detailed scenario analysis (Adamidou, Ben-Dov, Pendergast, & Pica, 1995). In an advanced study of three layers for construction of portfolio in the bond market, a successful simulation of the best hedging position of individual securities, minimizing the error in portfolio and credit risk return efficient frontier is constructed using parametric programming (Mausser & Rosen, 2001).

### 3.8.4. Rule-Based or Expert Systems

Credit decisions rely a lot on human interventions; the evaluation about the personality of the borrower, intentions, etc. are judged by the expert in credit evaluation. The usual approach is to consider 4Cs; Character, Collateral, Capacity and Capital of the borrower. The Central Bank guides the banks to have both the channels of evaluations; judgmental decision based and Statistical Score Technique. The experts have varied knowledge of various sectors and industry; they are in touch with the suppliers, customers and various stakeholders of the industry. The informal channel of information helps them in making decision better. The real time challenges address only by a human being in this scenario (Baesens, Roesch, & Scheule, 2016), (Bandhopadhyay, 2016). Expert helps in quantifying various risks in the business, like political, social, technological, environmental, internal, etc., this helps the banks to evaluate and make a decision whether to lend and how much to lend in case it gives a positive signal (Cunningham, Herzog, & London, 2008), (Vose, 2008), (Wehn, Hoppe, & Gregoriou, 2010).

### 3.8.5. Hybrid systems

A combination of direct simulation, estimation and computation is known as Hybrid System. It uses various estimation techniques and the underlying premise is generally driven by direct causal relationship. The process identifies all the stakeholders in the lending process, a detailed discussion take place and points are noted through score card system. It takes into account the primary and secondary source of information; the process is divided into many phases and various key persons are held responsible for the overall functioning (Caouette, Altman, Narayanan, & Nimmo, 2008) (Huang & Kahraman, 2013) (Bandhopadhyay, 2016). Hybrid models are very adaptive; it can keep on changing and upgrading continuously over the life. This helps in better prediction and can be augmented as and when required (Huang & Kahraman, 2013). Fuzzy Control, Qualitative analysis, Statistical models and Neural Network has been clubbed together to make a comprehensive Hybrid model for decision making (Ling, 2009) (Taremian & Neini, 2011) (Pourdarab, Nadali, & Nosratabadi, 2011) (Chan, Xiang, Lui, & Wang, 2012) (Walusala, Rimiru, & Otieno, 2017). Based on a construct of 11,827 US public companies resulted in predicting bankruptcy accurately by using Textual content for the first time. It was developed with the help of Deep Learning Models for Predicting Bankruptcy. However, results showed averaging embedded method is more effective than convolutional method of neural networks (Feng, Shaonan, Chihoon, & Ling, 2019).

The primary and the simplest method of Bankruptcy prediction model is through Econometric Techniques for credit risk management. It includes probability based Linear and multiple discriminant analysis, multiple regression, logit analysis, and probit analysis. These are based on independent and dependent variables; independent being financial ratios and dependent the default risk. Many Econometric Models has gained recognition worldwide for its accuracy includes Merton Model, Z Score, O Score and the Shumway Model.

### 3.9. Evaluation of Bankruptcy Models

There is a plethora of prediction models used across the globe; which are developed considering various factors highly sensitive under different context. The model construction is based on the data selection, tools/techniques, country, sector, etc. In an interesting interaction narrated in the article by Ajit Balakrishnan, founder Rediff.com quoted as "*If you reject a consumer loan application and the consumer asks why her loan was rejected, you will get into regulatory trouble if you say, 'I don't know, the algorithm did it*". His expression brings a strong conviction on the requirement of transparency in the method of loan evaluation for the customer. It is highly desirable to include the transparency trait in selecting the right model (Balakrishnan, 2018).

The quest to find a universal bankruptcy model will be really difficult due to variety of complications and factors involved in the data. Bankruptcy Prediction Models caters to different stakeholder considering their perspectives; lender will be interested in the accuracy of prediction while the company owner will be interested in knowing the transparency of the model. Total 13 criteria have been short listed for the evaluation; broadly divided as Results, Data and Tools Property (Alaka, et al., 2018). The list of criteria is as follows:

1. Accuracy: prediction classification with minimum error, Type I and II.

2. Result transparency: Tool should be interpretable.
3. Deterministic: Tools must be able to classify the companies.
4. Sample size: The approximate sample size suitable to the tools to function optimally.
5. Data Dispersion: Tools ability to compute equally or unequally dispersed data.
6. Variable selection: Variable selection method required for optimum results.
7. Multi-collinearity : It checks the sensitivity of the tool to deal with collinearity
8. Variable types: The tools capability to differentiate Quantitative and Qualitative variables.
9. Variable relationship: The tools capability to analyse linear and non-linear relationship.
10. Assumptions imposed by tools: Sample data has to satisfy for a tool to perform optimally.
11. Sample specificity/over-fitting: This is essential when the model is created by using one of the tools and it performs well on the sample but badly on validation data.
12. Updatability: Tool should be easy to update in case of any dynamic changes.
13. Integration capability: the ease with which the tool can be integrated with others for making it hybrid.

Approximate 50 research papers on Bankruptcy prediction were reviewed and the analysis of various models resulted in weighing the models on the prescribed variables mentioned above. The variables or the characteristics are further presented in Table 3-1 Evaluation of Bankruptcy Prediction Models-Multivariate Discriminant Analysis (MDA), Logistic Regression (LR), Artificial Neural Network(ANN) and Decision Tree (DT). Accuracy of each model is categorized from low to very high; MDA has the lowest while DT and LR are moderate and ANN has the highest accuracy. Transparency of results is high with LR and DT since LR explicitly shows the variables and its weight in the prediction model and DT diagrammatically shows the weight of variables. ANN, LR and MDA are deterministic while DT is non-deterministic; it means classification of companies is done with former models and not with DT. The quantum of data for prediction has to be generally large in size; it increases the probability of prediction since it considers variety of scenarios. None of the tools work well with small sizes. MDA and ANN have high ability to handle dispersed data while LR has normal but the same is not applicable to DT. The process of suitable variable selection is stepwise in MDA and LR while ANN and DT adopt case based method. Co-linearity amongst the variable is computed best in LR, then MDA followed by ANN and DT. The extreme cases/data where dispersion difference is too high is handled better by LR than MDA, ANN and DT. MDA requires quantitative data only while LR, ANN and DT can use both qualitative as well as quantitative data. MDA requires linear relationship amongst the variables; LR requires Logistic which means the results are dichotomous, ANN and DT can work on any kind of relationships the user wants to program. Liberty to incorporate assumptions in order to function optimally is well accommodated with MDA, lesser with LR and none with ANN and DT. If the model is developed on sample it should give desirable results on other data also, all the tools have been able to function properly on other data. This is most important of all since the model will be then replicated by the banking industry for lending decisions. The ease in updating the data with additional samples can be done with only ANN while rest does not support this function effectively. For creating hybrid model, ANN and DT can work effectively but not MDA and LR. The decision or the results reflected by some cut-off points or probabilities in MDA, LR and ANN are in binary while DT provides the Decision Rule. As discussed above the following

**Table 3-1 Evaluation of Bankruptcy Prediction Models-Multivariate Discriminant Analysis (MDA), Logistic Regression (LR), Artificial Neural Network(ANN) and Decision Tree (DT)**

| | **Important criteria** | **Tools** | | | |
|---|---|---|---|---|---|
| | | *MDA* | *LR* | *ANN* | *DT* |
| 1 | Accuracy | Low | Mod. | V. High | Mod. |
| 2 | Result transparency | Low | High | Low | High |
| 3 | Can be Non-deterministic | No | No | No | Yes |
| 4 | Ability to use small Samples size | Low | Low | Low | low |
| 5 | Data dispersion sensitivity | High | Normal | High | NR |
| 6 | Suitable variable selection | SW | SW | Any | Any |
| 7 | Multi-collinearity Sensitivity | High | V. High | Low | Low |
| 8 | Sensitivity to outlier | Mod. | High | Mod. | Mod. |
| 9 | Variable type used | QN | Both | QN (both) | (both) |
| 10 | Variable relationship required | Linear | Logistic | Any | Any |
| 11 | Other Assumptions to be satisfied | Many | Some | None | None |
| 12 | Over-fitting possibility | Yes | Yes | Yes | Yes |
| 13 | Updatability | Poor | Poor | OK | Poor |
| 14 | Ways to integrate to give hybrid | Few | Few | Many | Many |
| 15 | Output Mode | Cut-off | Binary | Binary | DR |

NR: Not Reported SW: Stepwise V.: Very Mod: moderate QN: Quantitative QL: Qualitative DR: Decision rules.

Source: Adapted version (Alaka, et al., 2018)

The combination of all the four would overcome the weakness of each other; based on various factors evaluated Accuracy and Transparency are most diverse and critical from the view point of the end user, hence model selection must stress upon these factors.

The following discussion is based on using various techniques to find better method in various countries and industries. Z-Score method has been very popular across the world, to test the accuracy of model, parameters of Z-Score were used Artificial Neural Network techniques resulted in better accuracy than MDA; ANN resulted 90% and MDA with 85% accuracy rate for US companies (Wilson & Sharda, 1994). Similarly, an attempt to find the bankruptcy risk for Greek banks used a hybrid method of Rough Sets to predict the risk of insolvency used many financial ratios and qualitative data like years of experience of the bank managers, errors of management, firm's market position, and special competitive advantage claimed to be functioning well with Greek Banks (Slowinski & Zopounidis, 1995).In a comparative study of various bankruptcy prediction models for Korean companies, viz., Case Based Reasoning, MDA and ANN, 51 financial ratios across 6 industries were used resulting in accuracy ranging between 81 and 83% in all the methods; ANN with 82.98%, MDA at 82.43% and Case Based Reasoning at 81.88% (Jot, Han, & Lee, 1997). A study on model comparison of 1139 banks in all the regions of the USA used ANN, Logit and MDA for 3 years prior to the bankruptcy resulting in ANN with better accuracy and lesser cost in comparison to other methods (Etheridge & Sriram, 1997). Various branches of computer programming based methods became famous amongst the financial fraternity and grabbed the attention of Computer Science, Financial and Banking sectors. Support Vector Machine method was used for 1160 bankrupt and non-bankrupt Korean companies each with 10 financial ratios as the variables. The method of optimizing was used to discover where SVM has the highest level of accuracies and better generalization performance than BPN as the training set size was getting smaller sets. Overall accuracy was more than 73% at the optimum level (Shin, Lee, & Kim, 2005). As discussed above, prediction models, in a study covering all non-finance industry UK firms fully listed on the London Stock Exchange (LSE) at any time during the period 1985-2001 with a sample size of 2,006 firms, a total of 15,384 firm years, and 103 failures, used prominent models, viz., Z-Score, Hillegeist Models and Bharat Schumway Model. Z-Score had the best result with 89% accuracy followed by Bharat Schumway with 87%

and Hillegeist with 84% (Agarwal & Taffler, 2008). For bankruptcy prediction with respect to Turkish Banks, a sample of 65 failed banks and 130 non failed entities was selected with 20 variables including that of CAMEL analysis, capital adequacy, asset quality, management quality, earnings, liquidity and sensitivity to market risk.

The study used 2 methods to predict the failure: Neural Network and Multivariate Statistical methods; in the case of neural networks, four different architectures namely multi-layer perceptron, competitive learning, self-organizing map and learning vector quantization are employed while multivariate statistical methods; multivariate discriminant analysis, cluster analysis and logistic regression analysis tested. Learning vector quantization (LVQ) resulted in a phenomenal result of 100% accuracy followed by Multi-Layer Perceptron with 95% and Support Vector Machines (SVM) with 91% accuracy (Boyacioglu, Kara, & Bayken, 2009).

In another attempt to find the better technique for bankruptcy prediction, 32 bankrupt and 45 non-bankrupt companies in England comprised the sample. Variables selected are ratios regarding Management Inefficiency, Capital Structure, Insolvency, Adverse Economic conditions and Income Volatility for the Logit model and the quadratic interval logit model, Multi Layered Perceptron and Radial basis Function Network resulted in the accuracy ranging from 91.5% to 77.05% where the best method is Radial Basis Function Network (Tseng & Hu, 2010). Considering the Decision Tree models for bankruptcy predictions, 200 US companies with 142 non-bankrupt and 58 bankrupt companies were selected to fit in Recursive Partitioning Analysis (RPA), Multivariate Discriminant Analysis and CART. RPA and CART has provided best results of accuracy as compared to other methods (Gepp, Kumar, & Bhattacharya, 2010).In an exhaustive study on Neural Network techniques for bankruptcy prediction, more than 200 researches on bankruptcy prediction were analyzed since 1964. It was found that the most predominant techniques are discriminant analysis, logistic regression and multi-layer perceptron neural network. The research data consisted of 260 bankrupt and healthy French companies respectively. The idea was to shortlist the variable to be used for the bankruptcy prediction model; 41 variables in total were considered the important variables. NN is the best of all with an accuracy of 92.32% while MDA with 84% and Logistic Regression with 89% (Jardin P. d., 2010). For 887 bankrupt companies in the US from 1980-2006,compared Altman, Ohlson, Zmijewiski, Shumway and Hillegeist models resultedas Ohlson being the best followed by Zmijewski, Hillegeist, Shumway and lastly Altman. In a new proposed model, most of the variables from the above mentioned model were used comprehensively provided best results with accuracy of 89% (Wu, Gaunt, & Gray, 2010).

A total of 562 bankrupt Slovenian companies were studied on 64 financial variables by using the Decision Tree technique, CART. For estimation, 75% of the variables were used and the remaining for the test. The accuracy rate stood at 94.6% (Masten & Masten, 2012). In Iranian companies, logistic regression model provided 88.8% accuracy (Ahmadi A. P., Soleimani, Vaghfi, & Salimi, 2012). A study on bankruptcy models for UK companies used 18589 company-years and selected 12 variables covering accounting, market and macro economy. Three methods were tested upon; NN, Altman's Z Score and Logistic Regression. NN had the maximum accuracy of 84.7%, Altman's with only 65% and Logistic Regression with 84% (Tinoco & Wilson, 2013).

A study on bankruptcy prediction involving Russian companies were worked upon for Bankruptcy prediction on the data size of 3505 company years Bankrupt and 3104 Non Bankrupt company year. It used 98 unique ratios across various parameters including Cash Flow, Liquidity, Profitability, Turnover, Balance Structure, indicators from previously constructed models and Russian Legislations to compute by using LR, MDA, ANN and Classification and Regression Tree (CRT). A unique method of combining various models was decided on the basis of significance, intersection and CRT+LR. The basis of intersection by using ANN provided best results with an accuracy of 88.8% while MDA, CRT and LR resulted in accuracies of 74.5%, 86.7% and 87.8% respectively (Fedorova, Gilenko, & Dovzhenko, 2013). In an extension to the study on bankruptcy prediction models by Phillippe Jardin, further focuses on retail, construction and service sectors in France from 2005-2010 with 50 financial ratios. The failure prediction 1, 2 and 3 years prior to default computed by using a new failure based model to compute LR, Cox model, MDA and ANN techniques. Accuracy rate was ranging from 75 to 85 % across the period. Failure based model provided best results in predicting accuracy 3 years before the default for all the years for all the techniques. However, average accuracy rate for all the methods was 80% (Jardin P. d., 2014).Around A study on 250 companies, including 107 bankrupt ones, for which data were obtained from a Korean bank with 107 Bankrupt companies, used 6 major heads of financial ratios to decide how MDA, SVM and LR methods can predict accurately. With 94.55 accuracy, SVM was the best and MDA at around 93% and LR with 92% predictions (García, Marqués, Sánchez, & Ochoa-Domínguez, 2019).For the bankrupt companies in Pakistan, a sample pool of 422 bankrupt companies used Altman's Z-score, Ohlson's O-score, Zmijewski Model, Shumway

Model and Blums model resulted in overall accuracy of 66%, 68%, 70%, 73% and 42.8% respectively (Ashraf, Felix, & Serrasqueiro, 2019).
For India, 1460 listed companies were taken as sample to test Altman's, Zmijemski's, Springate's and IN05 models. It was further computed using Decision Tree model where the accuracy rate was a meager54.6% and ANN was just 43% (Kapil & Agarwal, 2019).Prior to this, from 2002-2016 a research study focusing on wilful default used total 558 sample companies with equal number of bankrupt and non-bankrupt, 279 in each category used logistic regression and resulted in overall 87.5% accuracy (Karthik, Subramanyam, Shrivastava, & Joshi, 2018).In the quest to develop a bankruptcy model for Cyprus based companies, 318 companies out of which 73 were bankrupt used financial ratios of the non-financial listed companies with the help of Logistic Regression resulted in 91.2% accuracy in the results (Nouri & Soltani, Designing a bankruptcy prediction model based on account, market and macroeconomic variables (Case Study: Cyprus Stock Exchange, 2016).

A summary is presented in Table 3-2 Compilation of Bankruptcy Prediction Models based on Accuracy rate (%) prepared after going through various research sources. It is the summary of various bankruptcy prediction models used in various countries accuracy rate. Total 33 various research papers were studied from 1966 till 2019 across US, UK, France, Spain, India, Pakistan, Thailand, Greece, Korea, Finland, Belgium, Cyprus and Turkey. Logistic Regression was present in 15, Decision Tree in 5, Multivariate Discriminant Analysis in 11, Artificial Neural Network in 10, Z-Score in 4, Support Vector Machine, Schumway and Ohlson in 3, Zmijewski and Heilgeist in 2 and Case Based Reasoning in 1 research paper.

**Table 3-2 Compilation of Bankruptcy Prediction Models based on Accuracy rate (%)**

| | | | | Method/Accuracy | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | **Author** | **Variables** | **Country** | **LR** | **DT** | **MDA** | **ANN** | **Z Score** | **CBR** | **SVM** | **Schu mway** | **Heilleg iest** | **Ohl son** | **Zmij ewski** |
| 1966 | Beaver | Financial Ratio-30 | US | | | 87 | | | | | | | | |
| 1968 | Altman | Financial Ratio-5 | US | | | 95 | | | | | | | | |
| 1972 | Deakin | Financial Ratio-14 | US | | | 90 | | | | | | | | |
| 1972 | Edmister | Financial Ratio-7 | US | | | 93 | | | | | | | | |
| 1974 | Blum | Financial Ratio -12 | US | | | 93-95 | | | | | | | | |
| 1980 | Ohlson, James | FinancialRatio-10, Macroeconomic-1 | US | | 96.3 | | | | | | | | | |
| 1988 | Zavgren, Freidman | Financial Ratio-7 | US | 98 | | | | | | | | | | |
| 1994 | Rick L. Wilson and Ramesh Sharda | Altman-5 Variables | US | | | 85 | 90 | | | | | | | |
| 1995 | R. Slowinski and C. Zopounidis | | Greece | | | | | | | | | | | |
| 1996 | Dionne, Manuel, & Guillen | Questionnairre | Spain | 65 | 55 | | | | | | | | | |
| 1997 | Hongkyu Jot And Ingoo Han Hoonyoung Lee | | Korea | | | 82.43 | 82.98 | | 81.88 | | | | | |

| | | | | Method/Accuracy | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | **Author** | **Variables** | **Country** | **LR** | **DT** | **MDA** | **ANN** | **Z Score** | **CBR** | **SVM** | **Schu mway** | **Heilleg iest** | **Ohl son** | **Zmij ewsk i** |
| 1997 | Harlan L. Etheridge1 and Ram S. Sriram | | USA | | | | Be- tter | | | | | | | |
| 1997 | Hand and Hendley | Model Evaluation | | | | | | | | | | | | |
| 1999 | Laitinen | Questionnair re | Finland | 96.75 | | | | | | | | | | |
| 2001 | Shumway | Financial Ratio-5 | US | 95 | | | | | | | | | | |
| 2005 | Kyung-Shik Shin*, TaikSoo Lee1 , Hyun-jung Kim2 | 10 financial ratios | Korea | | | | | | | 73 | | | | |
| 2006 | Vineet Agarwala and Richard Tafflerb* | | UK | | | | | 89 | | | 87 | 84 | | |
| 2009 | Melek Acar Boyacioglua Yakup Karab Ömer Kaan Baykanc | CAMEL Analysis Variables | Turkey | | | | 100 | | | 91 | | | | |
| 2010 | Fang-Mei Tsenga Yi-Chung Hub | Financial, macro economic | UK | 77.05 | | | 91.5 | | | | | | | |
| 2010 | Adrian Gepp, Kuldeep Kumar, Sukanto Bhattacharya | | USA | | | | | | | | | | | |

| | | | | Method/Accuracy | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | **Author** | **Variables** | **Country** | **LR** | **DT** | **MDA** | **ANN** | **Z Score** | **CBR** | **SVM** | **Schumway** | **Heilleg iest** | **Ohlson** | **Zmijewski** |
| 2010 | Philippe du Jardin | Financial Ratio-41 | France | 89 | | 84 | 92.32 | | | | | | | |
| 2010 | Wu, Gaunt, & Gray | Models-Altman, Ohlson Zmijewski, Shumway, Hillegiest | US | 89 | | | | 28 | | | 73.96 | 75.24 | 79.7 | 78.54 |
| 2012 | Arjana Brezigar-Masten, Igor Masten | Financial Ratio-64 | US | | 94.6 - CART | | | | | | | | | |
| 2012 | Akbar Pourreza Soltan Ahmadi, Behzad Soleimani, Seyed HesamVaghfi and Mohammad Baradar Salimi | Financial ratios | Iran | 88.8 | | | | | | | | | | |
| 2012 | Gaeremynck & Willekens | Financial Ratio-7 | Belgium | 90 | | | | | | | | | | |
| 2013 | Bagher Asgarnezhad Nouri1 , Milad Soltani2 | Financial Ratio | Cyprus | 91.2 | | | | | | | | | | |
| 2013 | Mario Hernandez Tinoco, Nick Wilson | Financial Ratio, market and macro economy-12 | UK | 84 | | | 84.7 | 65 | | | | | | |

| | | | | Method/Accuracy | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | **Author** | **Variables** | **Country** | **LR** | **DT** | **MDA** | **ANN** | **Z Score** | **CBR** | **SVM** | **Schumway** | **Heillegiest** | **Ohlson** | **Zmijewski** |
| 2013 | Elena Fedorova, Evgenii Gilenko, Sergey Dovzhenko | Financial Ratio -98 | Russia | 87.8 | 86.7 | 74.5 | 88.8 | | | | | | | |
| 2014 | Philippe du Jardin | Financial Ratio -50 | France | 80.5 | | 80.15 | 80.9 | | | | | | | |
| 2015 | Lawrence, Pongsatat, & Lawerence | Financial Ratio-Macroeconomics | Thailand | | | | | | | | | | <90 | |
| 2017 | Hafiz A. Alakaa , Lukumon O. Oyedele, Hakeem A. Owolabi , Vikas Kumar, Saheed O. Ajayi, Olugbenga O. Akinadef, Muhammad Bilal | NA | | | | | | | | | | | | |
| 2017 | Vicente García, Ana I. Marqués, J. Salvador Sánchez, Humberto J. Ochoa-Domínguez | 6 Category of Financial Ratio | Korea | 92 | | 93 | | | | 94.5 | | | | |
| 2018 | Karthik, Lakshmi; | Financial Ratio -9 | India | 87.5 | | | | | | | | | | |

| | | | | **Method/Accuracy** | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | **Author** | **Variables** | **Country** | **LR** | **DT** | **MDA** | **ANN** | **Z Score** | **CBR** | **SVM** | **Schu mway** | **Heilleg iest** | **Ohl son** | **Zmij ewsk i** |
| | Subramanyam, M.; Shrivastava, Arvind; Joshi, A. R. | | | | | | | | | | | | | |
| 2019 | SheebaKapil, Shrey Agarwal | Models-Altman, Zmijewski,Springate | India | | 54.6 | | 43 | | | | | | | |
| 2019 | Ashraf, Felix, &Serrasqueiro | Models-Altman, Zmijewski, Ohlson, Shumway, Blum | Pakistan | | | | | 66 | | | 73 | | 68 | 70 |
| | Total | | | 15 | 5 | 11 | 10 | 4 | 1 | 3 | 3 | 2 | 3 | 2 |

| | Abbreviation |
|---|---|
| LR | Logistic Regression |
| DT | Decision Tree |
| MDA | Multivariate Discriminate Analysis |
| ANN | Artificial Neural Network |
| Z Score | Altman Z Score |
| CBR | Case Based Reasoning |
| SVM | Support Vector Machine |

Further analysis of the models evaluated is present in Table 3-3 it shows total 70 models were evaluated across 35 research papers studied in 15 different countries. Maximum research is in the US with 18 followed by UK with 8 and Korea with 7, France based studies were 6 while Pakistan was 4. India was studied on 3 models while Spain and Turkey were 2 followed by Belgium, Cyprus, Finland, Iran and Thailand with one each. Out of all techniques LR was used in 16 research papers in all countries except Greece, Thailand and Turkey.

**Table 3-3 Country-wise Bankruptcy Model Evaluations**

| Country | LR | Heillegiest | SVM | Schumway | DT | Z-Score | Zmijewski | CBR | Ohlson | MDA | ANN | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Belgium | 1 | | | | | | | | | | | 1 |
| Cyprus | 1 | | | | | | | | | | | 1 |
| Finland | 1 | | | | | | | | | | | 1 |
| France | 2 | | | | | | | | | 2 | 2 | 6 |
| Greece | | | | | | | | | | | | 0 |
| India | 1 | | | | 1 | | | | | | 1 | 3 |
| Iran | 1 | | | | | | | | | | | 1 |
| Korea | 1 | | 2 | | | | | 1 | | 2 | 1 | 7 |
| Pakistan | | | | 1 | | 1 | 1 | | 1 | | | 4 |
| Russia | 1 | | | | 1 | | | | | 1 | 1 | 4 |
| Spain | 1 | | | | 1 | | | | | | | 2 |
| Thailand | | | | | | | | | 1 | | | 1 |
| Turkey | | | 1 | | | | | | | | 1 | 2 |
| UK | 2 | 1 | | 1 | | 2 | | | | | 2 | 8 |
| US | 3 | 1 | | 1 | 2 | 1 | 1 | | 1 | 6 | 2 | 18 |
| Grand Total | 16 | 3 | 4 | 4 | 6 | 5 | 3 | 2 | 4 | 12 | 11 | 70 |

With the use of data related to research on various bankruptcy prediction models further analysis on the basis of variables usage has been presented in Table 3-4 where only Financial Ratios are used in 49 models,7 models used Financial Ratios as well as Macroeconomic indicator and only 3 researches had questionnaire.

**Table 3-4 Variable wise Bankruptcy Prediction Model Evaluation**

| | LR | Heillegiest | SVM | Schumway | DT | Z Score | Zmijewski | CBR | Ohlson | MDA | ANN | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Financial Ratio | 11 | 2 | 3 | 3 | 3 | 5 | 2 | 1 | 2 | 11 | 8 | 49 |
| Financial Ratio and Macroeconomic | 2 | | | | 1 | | | | 1 | | 2 | 6 |
| Questionnairre | 2 | | | | 1 | | | | | | | 3 |
| **Grand Total** | **16** | **3** | **4** | **4** | **6** | **5** | **3** | **2** | **4** | **12** | **11** | 70 |

The accuracy rate across the models ranges from 100 per cent to as low as 45 per cent. However, the following

Table 3-5 shows the research paper with highest accuracy amongst various Bankruptcy Prediction Models. Description is as follows:

1. Logistic Regression gave best result at 98% accuracy in 1988 for the US companies.
2. Decision Tree with 94 % in 2012 for the US companies.
3. Multivariate Discriminant Analysis with 95 % also for the US companies.
4. Artificial Neural network with 100% in 2009 for Turkish companies.
5. Z Score in 2009 with 89% accuracy for the UK.
6. Case Based Reasoning in 1997 for Korean companies with 81.2% accuracy.
7. Support Vector Machine in 2017 for Korean companies with 94.5% accuracy.
8. Schumway Model and Hiellgeist Model for the UK in 2006 with 89% and 84% respectively.
9. Ohlson model by using financial and macroeconomic factor was best found in Thailand at 90%.
10. Zmijewski with just 78% accuracy in 2010 for the US companies.

**Table 3-5 Most Accuracy in various Bankruptcy Prediction models**

| Technique | Year | Author | Variables | Country | Accuracy Rate (Per Cent) |
|---|---|---|---|---|---|
| LR | 1988 | Zavgren, Freidman | Financial Ratio | US | 98 |
| DT | 2012 | ArjanaBrezigar-Masten, Igor Masten | Financial Ratio | US | 94 |
| MDA | 1968 | Altman | Financial Ratio | US | 95 |
| ANN | 2009 | MelekAcarBoyaciogluaYakupKarabÖmerKaanBaykanc | Financial Ratio | Turkey | 100 |
| Z Score | 2006 | VineetAgarwala and Richard Tafflerb | Financial Ratio | UK | 89 |
| CBR | 1997 | Hongkyu Jot And Ingoo Han Hoonyoung Lee | Financial Ratio | Korea | 81.2 |
| SVM | 2017 | Vicente García, Ana I. Marqués, J. Salvador Sánchez, Humberto J. Ochoa-Domínguez | Financial Ratio | Korea | 94.5 |
| Schumway | 2006 | VineetAgarwala and Richard Tafflerb | Financial Ratio | UK | 89 |
| Hiellgeist | 2006 | VineetAgarwala and Richard Tafflerb | Financial Ratio | UK | 84 |
| Ohlson | 2015 | Lawrence, Pongsatat, &Lawerence | Financial Ratio and Macroeconomic-1 | Thailand | 90 |
| Zmijewski | 2010 | Wu, Gaunt, & Gray | Financial Ratio | US | 78 |

Based on the data from Table 3-1, Table 3-2, Table 3-3, Table 3-4 and Table 3-5 it indicates various models produces distinct results in variety of situation. The situation changes because of period, nature of companies, techniques and ultimately ratios. This clearly indicates the model construction is very dynamic in nature and it always strives to bring better results. This is a good piece of learning for the academia and corporate to continuously strive for making better and better prediction models. The review of literature is thus concluded covering the aspects of NPA, Wilful Default, IPO and leverage, Bankruptcy Models and its evaluations.

### 3.10. Conclusion

The problem of NPA has been well documented across the countries; India's burgeoning problem of NPA has drawn attention with the country and outside too. The reason for NPA in India has been categorically divided considering internal and external factors; internal factors are related to the borrower and the bank while external factors are beyond of either party's control. Few peculiar reasons included the political pressure of lending coupled with weak appraisal and monitoring system in Indian banking system (Sanjeev, 2007) (Richard, 2010), (Spuchľáková, Valašková, & Adamko, 2015) (Roy, Subramaniam, & Ravi, 2018) . However, the share of wilful default in the total NPA has been increasing drastically in the recent NPA saga. The literature available is limited; however, few researchers have documented the problem of wilful default with the intention of presenting a bankruptcy model (Karthik, Subramanyam, Shrivastava, & Joshi, 2018).

The malicious intentions to not repay loans are the problem areas for the economy; it works out to be double whammy for the listed companies. The intention of fraud leading to IPOs and then going for leverage is dangerous is not only the banks' money but also the direct investment by the general public in IPO. Over-pricing in the long run has been concluded in many research study across the countries (Aggarwal & Rivoli, 1977) (Bhagat, Lu, & Rangan, 2018) (Chandrasekhar & Kumar, 2002) (Kakati, 1999) (Ibbotson, 1975) (Ljungqvist & Singh, 2006) (Loughran & Ritter, 1995) (Madhusoonan & Thiripalraju M, 1997) (Shah A. , 1995) (Ritter J. R., 1991) (Reilly F. , 1977). The literature review indicates that a thorough study on wilful default listed companies should be attempted, in context of technical and legal perspectives, so that to highlight the problem and suggest feasible solutions to the problem of wilful default.

The problem of wilful default appears to be systemic as the share of wilful default is more than 44% of the total NPA of the commercial banks in India. A systemic problem requires a structural or an objective solution. For such problems it would be absolutely essential to consider strong prediction bankruptcy models, to have a systemic monitoring and approval mechanism. Therefore, it is imperative to study this category of default considering the model which can help in providing early warning signals to the banks.

From 1928 onwards till date Bankruptcy Prediction Models across the world were studied and was found to be very dynamic in nature. Multiple factors are considered in selecting models and its applicability. The techniques like accounting ratio, econometric techniques, Expert systems, hybrid systems and Artificial Intelligence have been used so far for different countries like the US, UK, Spain, Belgium, France, Greece, Korea, India, etc. by using50 different bankruptcy models across 15 countries were studied and following points were observed.

1. Notably, major 4 techniques are widely used; Logistic Regression since it brings out dichotomous results whether the company will default or not, Multivariate Discriminant Analysis which includes all major affecting variables and provides a binary answer, Decision Tree provides a pictorial presentation of the weight of variables and Artificial Neural Network which has been predominantly used in many cases with best results compared to others.
2. Variables used are mostly Financial Ratios of the companies and few were macro-economic variables to factor in the impact of business cycle (Boyacioglu, Kara, & Bayken, 2009) (Feng, Shaonan, Chihoon, & Ling, 2019) (Ohlson, Financial Ratios and the Probabilistic Prediction of Bankruptcy, 1980).
3. Initially LR was used while later in 1960 MDA became more popular and few prominent models like Altman's Z Score Model, Ohlson's O Score Model, Zavgren Model, Zmisjewski Model, etc. were constructed. After 1990, ANN technique was widely used with various versions and models like Support Vector Machines, Rough Sets, Case Based Reasoning, Decision Tree and Genetic Algorithm.
4. The tools are evaluated mainly on the basis of transparency in the process and most importantly; accuracy of the models. LR and MDA have the maximum transparency of the process as compared to other like ANN, DT, SVM, etc. However, in terms of accuracy; ANN and related techniques provides the best results as compared to LR and MDA.
5. Results of various bankruptcy models can be categorized in terms of accuracy. When one wants to deal with the systemic problem; accuracy of the models is of vital importance. Based on the survey of literature it concludes the ANN has an average accuracy rate of almost 90% ranging from 80 to 100% in different set ups followed by LR with around 87% and MDA with 86% average accuracy rates.
6. Total 49 models used financial ratios and 6 used financial ratios with macroeconomic indicator for the respective country to predict bankruptcy.
7. Maximum studies are based in the US followed by the UK.

8. In terms of best accuracy rate; ANN has proved to be 100 per cent accuracy for Turkish companies followed by Logistic Regression with 98 per cent, MDA with 94 per cent and Decision Tree with 95 per cent as best in the class in the US context.
9. In India, the best results were with Logistic Regression at 89% accuracy while MDA and DT was barely 50 percent accurate.
10. Thereis ample literature available based on existing models like Altman, Ohlson, Zmijewski, Schumway, Heillgeist, etc. have been incorporated to test the accuracy of these models in various conditions like time period, country and the sample size. Testing has been done for US, UK, Iran, India, Thailand and Pakistan results in accuracy ranging from 60% to 80%. It would be a good forward path to consider these models in Indian condition with special reference to wilful default.
11. The Ohlson and Z Score methods from the existing models used under different scenario bring about 90 per cent accuracy.

After an extensive survey of literature, few areas are identified which requires attention, there has been limited research in the field of Wilful Default in India. The use of existing models under Indian circumstances with reference to Wilful Default requires an examination to verify the accuracy of the models. Further, new models should be constructed that can suit the condition of Indian Wilful Default companies. On the basis of survey, Econometric Techniques should be considered as it has an advantage of maximum transparency as well as ANN with maximum accuracy rate. It is being an interesting proposal to study LR, MDA, DT and ANN models as it overcomes the weakness of each other.