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Systematic literature review on insolvency avoidance instruments

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Abstract

The decision to select and study the selected machine learning algorithms was influenced by research after the economic crisis of 2008. The neural network approach is commonly explained and used for predicting insolvencies. Regression and decision tree were selected to supplement the neural network approach from a theoretical perspective and research those approaches further as they have not been investigated in such a volume. Therefore, this study will explain the current atmosphere regarding the state of research in machine learning algorithms and touch upon the trends that are being used in daily business. The situation in insolvency avoidance assisted by artificial intelligence is still in its beginnings. There is a massive amount of data that needs to be mined and acquired and calculated in order to produce a relevant prediction tool that would show the true state of a business. Small and medium-sized enterprises are focus of this thesis because there are only a few papers that were published on that topic. That is unusual as most of the business in the world are SMEs. Therefore, a spotlight was shined on the issues that researchers face when researching SMEs and the possibilities that could solve them.

The research questions of this thesis it what the trends of artificial intelligence machine learning methods in insolvency avoidance are and how do they work. With that in mind, the goal is to observe and produce a thesis that will answer that question and address the state of insolvency prevention in 2021. The goal will be achieved by researching scientific research articles (papers) on the topics of insolvency and bankruptcy prevention, machine learning methods, artificial intelligence and selected methods stated above. In order to produce a thesis that is correct and relevant to the time when it was written, great care was referred to the actuality of selected scientific papers and their relevance in the topic. The goal was achieved by following a systematic literature approach procedure which is the selected approach for this master's thesis. The biggest limitation of the work was the vast amount of data that had to be structured in a respectable manner to add valuable research on the topic of insolvency avoidance.

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List of abbreviations

Abbreviation	Meaning
NN	Neural Network
LR	Logistic Regression
DT	Decision Tree
GA	Generic Algorithm
SVM	Support Vector Machine
RF	Random Forest
PSO	Particle Swarm Optimization

1.Introduction

The decision to select and study the selected machine learning algorithms was influenced by research after the economic crisis of 2008. The neural network approach is commonly explained and used for predicting insolvencies. Regression and decision tree were selected to supplement the neural network approach from a theoretical perspective and research those approaches further as they have not been investigated in such a volume. Therefore, this study will explain the current atmosphere regarding the state of research in machine learning algorithms and touch upon the trends that are being used in daily business.

Over the past 20 years, the amount of data being observed is exponential rising. The reason for that is the growing need for information and optimization in every process known today. This paper will put a focus on corporate insolvency prediction and prevention using selected artificial intelligence algorithms. Insolvency is a state of not being able to pay the debts and is closely linked with bankruptcy as that is the next step after. In the research of (Jayasekera, 2018) a prediction of a company failure is being observed. However, it is focused mainly on large companies that already have safety nets issued by the government as they employ many employees.

This paper will look at the small and medium enterprises, mainly because the number of publications considering SMEs is still relatively new and not ultimately discovered. Small businesses have to consider many issues, from the inability to take the full effects of the economy of scale to a worse credit rating, which makes investments more difficult. One of the aims of this paper is to show the owners of SMEs that they should fight this problem together and improve and grow. As researched by (Camacho-Miñano, Segovia-Vargas and Pascual-Ezama, 2015), 94% of the business in the world are small, 5% are medium, and only 1% is significant, which is an essential factor to worry about as this is also a problem of favouring only the most prominent companies. In addition to that, the whole bankruptcy procedure is costly and has a very negative impact on the psyche of business owners.

The term failure is something that is often connected to insolvency and in that regard a definition. That is why a short overview and definition of failure will be given in the theoretical part of the paper.

That is why research by the likes of (Qu *et al.*, 2019) in the area of insolvency prediction is vital in preserving the small business by detecting troubling factors on time. By using real-time data combined with machine learning algorithms, we can prevent insolvency in its beginning and, in that way, improve the corporate ecosystem that fuels most of the population.

This paper is a systematic literature review, which means that it is an assessment of a body of research that addresses our research question. The question is what artificial intelligence corporate insolvency prediction algorithms are used the most and how interconnected. SLR aims to identify what is already know about this area of study and provide a case for further research.

The issue of insolvency transcends the walls of a single business that is fighting it. It has a much bigger reach. It becomes harder to receive legal compensations, shareholders, investors. Human capital suffers from a lack of perspective and the manufacturing capital has difficulties utilizing its full capacity. Sustainability is the backbone of a business and it allows for a working environment that negates insolvency. Predicting insolvent companies is a way to minimize the economic impact and to negate social losses that are imminent. Some of the reasons for business failure are failures in sales, financing, experience, financial management and a non-consistent research and development philosophy.

Collecting data from SMEs that have existed for less than three years poses a challenge because of the lack of financial data. The financial statements are usually collected once a year and that time period is just too broad. The data acquisition of one year is just not sufficient in an environment as complex and rapid changing. Also, the issues with SMEs do not stop there, the problem of precise information is due to the management that is vulnerable. A new way of thinking needs to be taken into consideration and evaluate SMEs according to their latest actions.

The action plan, according to (Lee, Choi and Yoo, 2020) is the following: firstly, the businesses are divided into new business and established business. Then LR, DT and NN are used to build prediction and prevention models. The models show the following classification regarding the wellbeing of business:

- Excellent
- Mature
- Development-stage
- Declining
- Restructuring
- Crisis

When banks decide to provide funds to business the data that is the determining factor are usually credit ratings. Because of that, business needs to have a good classification to secure their influence and to guide their future. The reliance on credit ratings is a philosophy that is normal from the perspective of the bank or a firm that is an investor in new ventures. And it is hard to calculate that credit risk due to factors mentioned before. The profit for banks is also low as the loans tend to be lower and handling cost higher and that leaves a little wiggle room for profitability. From the viewpoint of SMEs they see the credit ratings as unfavourable to them. They rely on government support in the way of funds and incentives to up their annual budget.

Altman's Z-score was one of the first models that were used for predicting the insolvency of researched companies. The ratios that were used were the following:

- Working capital / total assets
- Retained earnings / total assets
- Earnings before interest and tax / total assets
- Market value equity/book value of total debt
- Sales / total assets

The advantage of using financial information is that it is the most standardized type of data. The only limitations are the acquisition periods. Larger companies, especially the ones listed have records that are open to the public and easy to access. SMEs are not listed and therefore, there is a difficulty when reaching financial data as stated before. Nevertheless, the methods that are conventional are being supplemented by AI to develop even more accurate models of insolvency prevention. The overcoming of limitations that the usual approach has allows better data spreading and more complex methods that can calculate many important parameters.

The legal procedures around insolvent firms in many countries are outdated, long, costly and offer little or no assistance in bailing out the company. The economic crisis was the best showing that the system is inefficient. The effects are huge on a micro and macro level all over the world. But the phase of bankruptcy is the last straw in a caterpillar that is a business failure, more insight should be shifted towards the reorganization of businesses in distress. In order to resolve a quick fix from the government side, a reorganization agreement could save managers form facing insolvency and decrease the cost, delays and issues the happen on a macroeconomic scale (Camacho-Miñano, Segovia-Vargas and Pascual-Ezama, 2015).

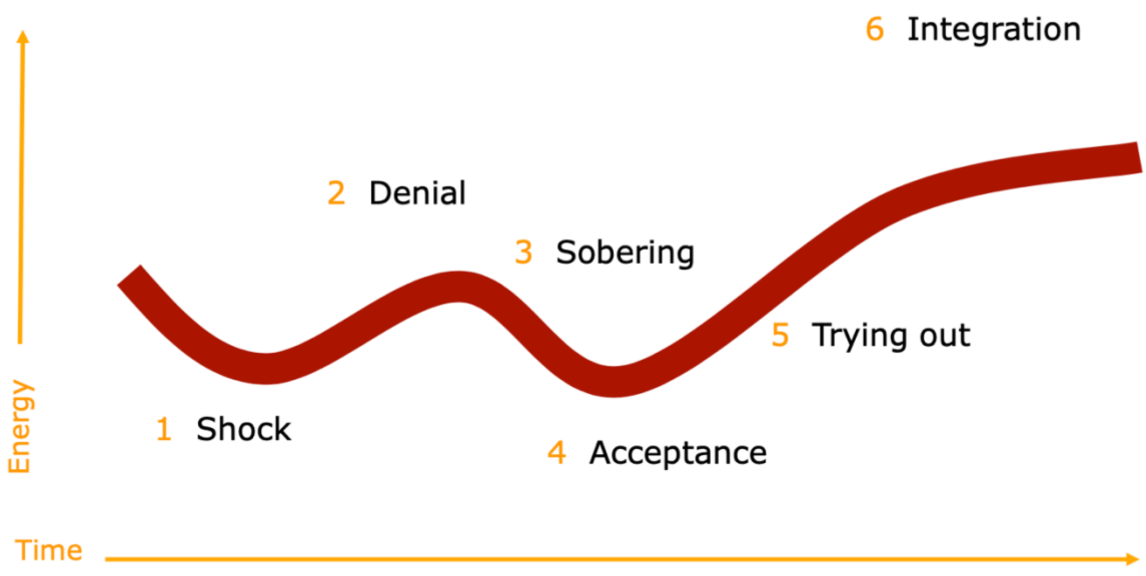

Figure 1. Mathematical change curve

As seen in Figure 1. the change curve represents a way of dealing with change. The initial stage is the shock phase which determines the way of change. The following one is denial which often causes that a change never happens as it blinds and is subjective. The third phase is sobering, in which the necessity for a change is understood and the true change starts to happen. The fourth stage is acceptance, the lowest on the energy scale as it takes a psychological toll on the makers of change. After that it is easier and the trying out and integration stages come. In tying out different hypothesis are tried out and the best are taken for optimisation.

As previously stated, the issues of change cannot be understated. That is something that will be researched later in this thesis. One interesting research is the one connected to managers that produce false data in order to show something that is not there. It can be said that that is an issue of pain of losing respect and losing perspective of their job. But pain is a product of change, and in that way everything that is done in order to stop the advances is something that will eventually lead to business failure and a situation form which it is very difficult to exit.

The problems that will be researched in this thesis are problems connected to the theoretical and practical limitations of the current trends in insolvency avoidance method and the research that was influenced by those issues. If a look is taken at the situation in the world and the countries that have the biggest difficulties with insolvency prevention is will be seen that all countries that are from a wealthier part of the world have developed systems to fight insolvency that it never happens.

The following sections of this paper will discuss the following. Section 2 is a literature review of the systematic literature review. Section 3 defines the research methodology and the article election process. Section 4 addresses the theory behind selected machine learning algorithms. In section 5, a review of the findings with the corresponding visualization is shown. While in section 6, a conclusion is presented.

2. Algorithms in Artificial Intelligence

There are many algorithms used for predicting and preventing corporate insolvencies. Each one has its advantages and drawbacks. To keep this article easy to read and straight to the point, the algorithms that will be reviewed here will be Neural Networks, Logistic Regression and Decision tree methods. During the research, those methods were the ones that popped out the most. As this is a study considering articles after 2008, these methods are also one of the main ones used to understand and implement the Artificial Intelligence approach.

Information and Communication Technology (ICT) tools and techniques are first applied in accounting, area that has most of matter for every company. At first, ICT applications was used in the elementary financial systems. Later, the economic modelling schemes showed that it is crucial in the analytical aspect of accounting. Barras and Swan thought that ICT implementation in accounting is slow and that it has conservative approach. Until the end of 1990, this works was computerised to promote its efficiency, reduce expenses and to be more competitive.

Artificial intelligence was something that made an impact in accounting efficiency, so most of the big companies decided to implement it. Electronic Data Interchange, Electronic File Transfer and Image processing were some of the ICD devices that are progressively replacing traditional methods and changing the entire audit process.

There were major advances in auditing in the last hundred years. The idea of auditing is to give and insight in the true state of financial situation of a company by using the neutral approach that a third-party expert has. It is understood that the information is intensive and all the processes that implement data mining and organising and evaluating the data are presenting data in order to produce a relevant option in the process of auditing. The final audit is most commonly a mix of the grades of the auditors that have been grading the company on all aspects of financial data that was considered relevant. A relevant audit option is important in order to have everything right and organised in the right way.

Auditing and AI systems are a part of the methods that involve data acquisition, the identification of random objects, the diagnostics of issues that are used in structuring, designing which is an incorporation of the manipulation of data, quantifying of objects, and the alternatives of the process of risk and the coherent values of risk. It also incorporates the statistical approach in order to generate alternatives that are used in the simulations of data and after that the explanations which offer the possibility of explaining the choices. Artificial intelligence is one of the major influencers in producing results which have been researched and developed in a technical way, but also, all the operations that have a leadership focus and the business that are the focus of auditors (Omoteso, 2012).

Previous researches have shown that bankruptcy prediction is a big issue even though there are methods like multivariate discriminant analysis and logistic regression.
A system that asserted the trustworthiness of credit data analysis of companies is better with companies that have a low revenue which made difficult to secure funds.
Project of observation in this experiment was using credit card sales of small sellers because of the limitation of financial data. They do not have information's about other credit card sales since they use only its own cards. Credit card processor is responsible for storing the data of every financial card transaction at thermal unit of all member stores and then sending that data to the banks that have issued those credit cards. It also provides information in order to give an insight at any time with the credit card provider because that was the pact between the holders and the sellers and the banks. Delicate information has been collected from Korea Federation of Banks and among the 412,773 merchants, some data has been deleted that did not match on sellers on the data model that was used by the banks that have issued the cards. There was a low amount of insolvency cases and in order to avoid the issue of overfitting a lot of samples were taken for a random data point. The data was taken from seller that had a business failure and from the ones that did not have it.
It is not easy to collect those information's on small businesses (small businesses often do not give the true statements of the data of business failure.

To understand the business failure of SMEs the data of the credit card transactions have been used in order to provide an insight that would allow for a data gathering model which could increase the chance of prediction of insolvency. Cases that had suspended credit card transactions within few months, were described as bankruptcy.

Various inputs variables are being used in order to create the model. Firstly, there are many variables, twenty-four to be exact that are related to credit card information which have the parameters that are needed to produce a result. Those are all the variables connected to the amount of transactions and the sum of transactions. On the other side there are the variables that show the suspension of the months, the average of the sales, the total amount of sales, the statistic of sold goods, the strength and frequency of transactions for a given period of half a year. The figures for half a year are higher than the ones for the period of the first three months. In the end, about thirteen variables were selected for the experiment. After the definition of the task, nine were concluded to be the best in that scenario. After that the direction of the small business were defined to produce a model which would understand the sales.

The concept of prediction of a potential financial disruption has become one of the most important and challenging tasks a quality management system has to implement and set up for a company to work efficiently. Problems connected with financial health of the company such as illiquidity, insolvency or in the worst scenario bankruptcy have been the main cause of many financial distresses and are seen as something that a quality prediction plan could definitely minimize or prevent.

The topic of financial prediction or forecasting has been put under a lot of research and further development from the moment that has predicted serious financial distress.

Financial misleads and failures can occur because of the two main reasons and those are internal factors such as the corporate culture, corporate governance and management itself and on the other hand there are external factors such as auditing and due diligence process. Audit itself has a big role when talking about financial distress predictions. The person auditing is obligated to inform the supervisor about the client's insufficiency and key failures so that the opinion of auditor can be analysed, assessed and put under the supervision of external body (Hsieh, Hsiao and Yeh, 2012).

The papers that are being reviewed are here to give the reader an insight into the theory behind the selected methods.

2.1 Neural Networks

Neural Networks is arguably one of the most popular methods in machine learning and a likely role model on which other machine learning methods were developed. It is concluded that the method is similar to a human brain in the way of its processing and functioning. There are layers upon layers similar to neurons in a human brain. Those layers are influenced by input factors that guide the method (Qu *et al.*, 2019). The philosophy behind a NN can be explained simply as a system that mimics a human brain and, in that regard, processes information. It is an inspiration for other computational models is merely its resemblance with our brain. Therefore, it is easy to adapt to other computational models according to NN.

Neural Networks use the imitation of the processing of a human brain and its neurons to function. The AI implementation of neural networks are called Artificial neural networks. They work on two models which guide the reasoning that is similar to human reasoning. The first model examines the neural networks from a biological standpoint that mimics a human brain to experiment and further understand the functions of the brain. The second method sees neural networks as data handling method which has a special structure that allows a neater data processing (Alrammahi and Radif, 2019).

Learning is the basic process of every machine learning method. It symbolizes the calculations of the power of neurons in a neural network approach. The power is calculated as the value of the neuron which affects the output of the method. There are two learning varieties. Supervised and unsupervised. Supervised learning is learning where each variable is influenced by an operator and is controlled in every way. Unsupervised learning is learning where the AI takes over and the operator sees the results but not the iterations that happen inbetween (Alrammahi and Radif, 2019).

In most of the literature reviews on the topic on insolvency and bankruptcy prediction one method offers better accuracy across the whole range compared to other statistical models. That method is the Neural networks (NN). This model is special because of its way of operating in such a manner that it can understand the uncertainty of the data and that there is not always a need to be most efficient but most accurate. Learning and experience is something that develops over time, and as neural networks work on a brain like modus of operating, they offer better and better results every time they do a new research. Because of that reason, there are the most studies that focus solely on neural networks than any other machine learning method. Because of that reason it is safe to say that neural networks have been proved to be an effective tool in fighting bankruptcy. The possibilities of optimization of NN does not come from changing the way the method works but from changing the input variables that guide the initial steps of research. One other way to further increase the accuracy of NN is to try experiments with larger databases and distribute the data differently, in that way if from two or more different perspectives show the same result, that it is safe to assume that NN are currently the best tool in prediction corporate insolvency (Callejón *et al.*, 2013).

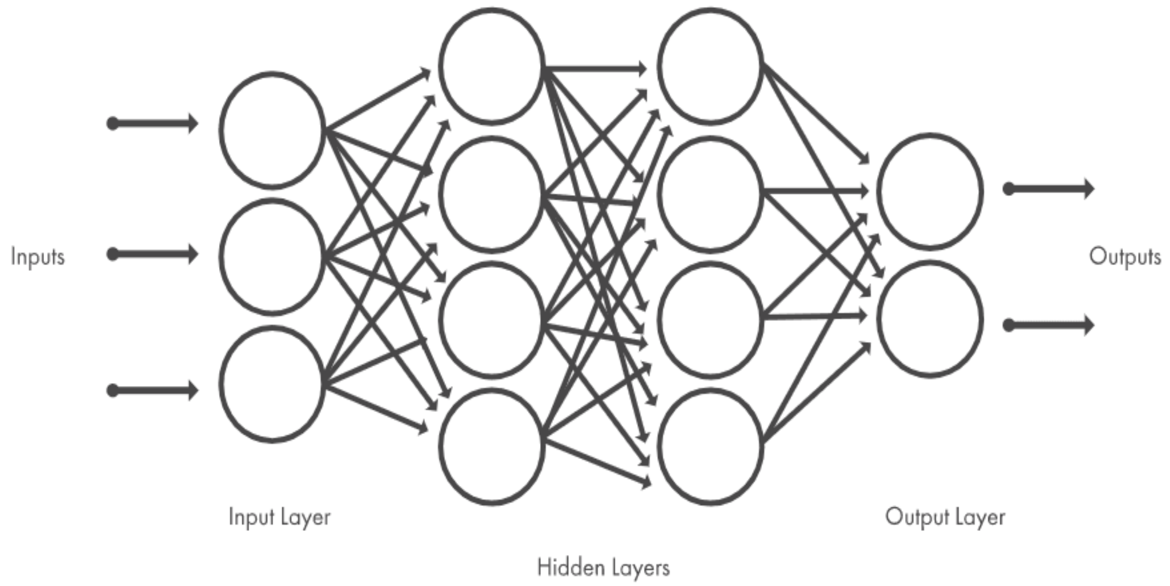

Figure 2. Neural network structure

Ass seen in Figure 2. the structure of a neural network is shown. The principle is as stated above. There are inputs that are the data of the machine learning method acquired by the researchers. That data takes the path through input layers which detects the classification and parameters of the data. The next step is the hidden layers phase where data is structured, and the principles of neural networks are on work. When the data has been structured, it goes through the output layer where it is elaborated in order to be understood. The finished output is the result of the method that the researchers see and that is the fuel of their research.

Other statistical models have a linear and independent way of reaching the result which makes them inflexible in some researches that need a method that can disentangle the web that is unstructured data that is a common problem in data acquisition. NN are suitable for even that kind of data because they are a non-linear and non-parametric method. There are other advantages to a non-linear model in comparison to the linear model. The financial ratios that predict an insolvency have a degree of saturation which is non-linear.

It is a series of algorithms/computing systems that are interconnected and work much like neurons in the human brain. They can recognize hidden patterns and correlations, classify and improve it. NN can solve many problems such as sales problems, market analysis, customer reach, the validation of data. They are very effective in producing accurate predictions when there are data of similar situations that already happened. The decisions of auditing are based on previous data, so implementation of NN in assessing trends and patterns are helping it not to be over-emphasised (Omoteso, 2012).

2.2. Logistic Regression

Logistic regression is fundamentally a linear model, which means it has and output of either a 0 or 1 (Qu *et al.*, 2019). Logistic regression is a model that is mostly used for producing classification systems of businesses. The first usage of the method was the prediction of insolvency using data that was available in the public. Logistic Regression is a method that regulates the significance of variables of credit risk in two categories.

The idea is that there are only good debtors or bad debtors (Petropoulos *et al.*, 2020). The simplicity of the model comes from the fact that there are only two possibilities to assign data.

“In the first step of the proposed approach, we transform the multiclass task into few simple binary models of classification (similar to decision tree) and then, in the second stage, apply the additional classifier responsible for undertaking the final decision of the classification”.(Swiderski, Kurek and Osowski, 2012) The parameters are estimated based on maximum similarity. This process does not need independent variables to have multivariate normal distribution. In order to achieve a needed predictivity and reasonable results interdepended variables are used because they provide information that is needed for the results. (Nyitrai, 2019)

According to (Shi and Li, 2019b) regression is the most frequently used statistical model because it gives reliable data which can be analysed further using other machine learning methods. In other words, logistic regression has a black and white approach that researchers can easily understand.

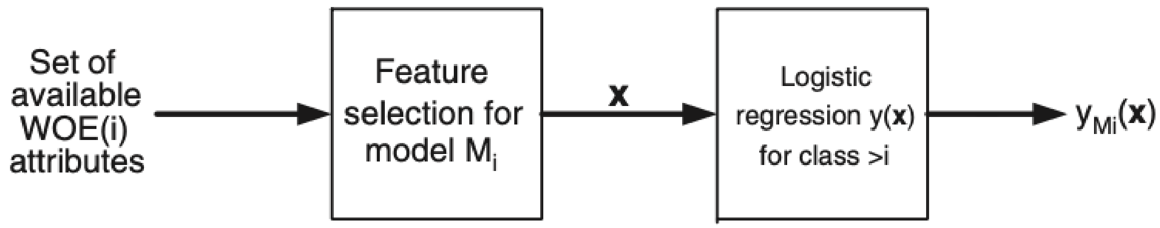

Figure 3. Logistic regression scheme

In Figure 3. the scheme of a logistic regression method is being visually described. Firstly, a set of attributes is incorporated and inputted. A feature selection follows for the classifiers and their determination. And in the end the logistic regression for each of the classes is performed.

The first step of the method is to transform tasks in simple binary models od classification. After that a classifier is added in order to influence the final result. There are two steps of classification which lead to an accuracy and a prediction model for insolvency. There are only two labels, it is a zero or it is a one. The input parameters are data in form of a vector, and they represent all financial data with their corresponding weights. An assumption is made that the data has a binomial distribution with the number of tries and the probability of success. The result is achieved by estimating the probability.

The beginning is to separate a big problem in a binary ony. That is done by adding subclasses to each input data. This part looks like a decision tree. There are seven models of classesification. M1 shows the case when the data represented by class 1 belongs to the class one of a class higher then 1. M2 shows the case when the data represented by class 2 belongs to the class one of a class higher then 2. M3 shows the case when the data represented by class 3 belongs to the class one of a class higher then 3. M4 shows the case when the data represented by class 4 belongs to the class one of a class higher then 4. The next three classes M5, M6 and M7 work in a similar way but M5 has chance of being in a class, M6 to class 3 and M7 to a class 4.

Each model is made independently from other models. Each model has different parameters and features. The last step is to give each class a data. That data will form probabilities (Swiderski, Kurek and Osowski, 2012).

Credit report data:

- Identification of a business
- Registry data
- Legal fillings
- Management and workers
- Board of directors
- Share capital
- Shareholders
- Corporate affiliation
- Financial accounts
    - Age of the account

  - Consolidation
  - Sales income
  - Gross interest
  - Operating income
  - Profit before tax
  - Profit after tax
  - Present assets
  - Total assets
  - Current liabilities
  - Long-term liabilities
  - Total liabilities
  - Shareholders' equity
- Payment behaviour

2.3. Decision Tree

"Decision tree (DT) techniques generate tree-based classification rules to construct a DT (also known as a classification tree). DTs assign data to predefined classification groups: a DT usually gives each business to a successful or failing group. In general, DTs are binary trees, consisting of a root node, non-leaf nodes and leaf nodes connected by branches, whereby each non-leaf node has two branches leading to two distinct nodes" (Gepp, Kumar and Bhattacharya, 2010).

One of the main bonuses of decision trees is their non-parametricity, meaning that there is no need to include transforming variables. The downside is that previously researched data is needed for this method to achieve its goal. If there is no data available, the DT will not be precise, giving conflicting results.

These results are pretty easy to understand, and analysts or managers can understand how classes function (Obermann and Waack, 2015). As with every method, the goal is to gather the data that will predict and prevent insolvency from happening in the first place. Because of that reason, great attention must be dedicated to methods that offer a structure that is understandable to anyone that observes it.

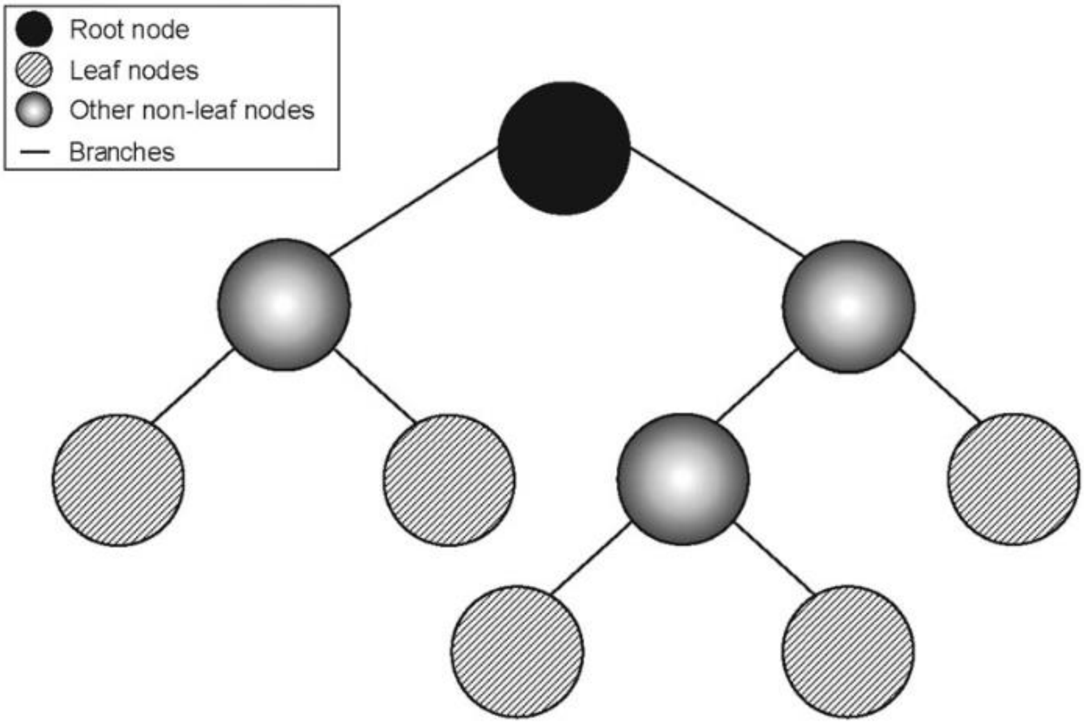

Figure 4. The basic structure of a decision tree

Figure 4. shows a visual interpretation of the nodes of the decision tree machine learning method. The scheme is structured in such a way to mimic the functions of a decision tree. The initial node or the so-called root node is the main node from which leaf nodes are distributed. Each node carries a specific information which offers a way to the result of the research. The branches are the waypoints that the data takes when the iteration process of branching the nodes happen.

Decision trees use the principle of entropy to measure the strength of samples and variables. They are the reason we have the so-called decision rules. Heuristics are the determining factor in the issue of the position of rules. They place the researched factors according to their importance in the method. For example, if quality is more important than profitability then it will be placed and measured before profitability. There are many factors that are necessary to have an effective bankruptcy prediction method. The factors are reliant to many influences. But to put it simply, the prediction model needs to predict if the firm is healthy and solvent in order to have a possibility of getting a loan or contact. The other part is the knowledge of the business owner. The owner needs to have the best accuracy and transparency in order to know where the business went wrong and what are the possibilities to return to the prosperous way. The focus of the rescue of a business needs to be well interpreted so that the rescue is successful. There are many factors that are influencing the decision regarding bankruptcy prediction models, but they can be narrowed down to 13 most important ones. (Alaka *et al.*, 2018)

1. Accuracy
2. Results Transparency
3. Non-deterministic
4. Size of sample
5. Dispersion of data
6. Selection of variables
7. Variable types
8. Variable relationship
9. Assumptions imposed by tools
10. Overfitting of sample
11. Updatability
12. Capability of integration
13. Multicollinearity

Decision trees are a non-parametric method and that is their biggest advantage over other methods. DTs have no assumptions regarding distribution and no need to use transforming parameters. DT are interesting because of their ability to handle data that is missing and that they are represented by a user-friendly graphic. Errors play a huge part in producing an accurate result and decision trees can classify Type I and Type II errors as inputs which are then incorporated in the machine learning method.

In interpreting results DTs also pose a simple challenge. They allow for an easy constatation of parameters and variables. And the interaction between the nodes is simple to calculate as they always connect to the root node. Only the relevant significant variables are identified unlike other methods that have a quantified statistical approach (Gepp, Kumar and Bhattacharya, 2010).

It is common to use DT with NN to have a hybrid model that has a great accuracy and simple handling.

DTs are superior classifiers and great indicator of insolvency. There is a trouble regarding continuous data and no paper has given a finite answer if DT are able to handle the data worse than other methods as many specify.

2.4. Other algorithms

Financial institutions, managers, government all need to know the stat of the firm they are in contact with. The capital market is open and because of that a predictive method is needed to minimize the possibility of working with an insolvent firm. Credit risk rises not only because of insolvency but also because of decreasing the debt rating and credit assets. Insolvency was always studied but after the crisis of 2008 all financial institutions made credit risk management a focus point in their researches. But no global standard has been achieved, the trial-and-error method still has to much movement. Credit risk analysis can be compared to pattern recognition problems, algorithms used by AI can grade the creditworthiness of firms. That is why the incorporation of these methods is important (Barboza, Kimura and Altman, 2017).

Machine learning methods have proved to be one of the biggest advances of applied mathematics in recent times. They have not only been present in the financial industry but also in medicine, engineering and computing.

The major spots in a credit reports are the evaluation of financials business. This information can be found online but they can also be untrustworthy. That is why the best information is found on other places such as the suppliers, affiliates, customers etc. The information is usually non structured and hard to read even for experts with year of experience in the field, not only to machine learning methods which demand structured data which is a key for an effective result. That is why information needs to be coded and tailored to a specific method to maximize effect (Swiderski, Kurek and Osowski, 2012).

The continuing and thriving change in the IT industry is making companies in the constant growth to benefit from this positive, upcoming and challenging trend by demonstrating their key competitiveness.

Nowadays, there are large volumes of the data stored in databases that are somehow hard to be accessed which complicates the entire process of the decision making. Therefore, the effectiveness of the science-based process of data mining can have positive effects on resolving such an issue and contribute to the efficiency of various business processes in a way that it makes access to the large scale of poorly known information easier. Furthermore, key information that were unknown to the point prior to data mining can now easily reach people obliged to make serious and key business decisions that affect the wellbeing of the business itself. Information is the key, so the most important part of the mentioned IT process is to extract precisely chosen information, which is needed in the given moment, in various automatically or non-automatically set up ways, and make significant relations among the huge amount of information offered.

The data mining can also be process interpreted as the discovering many new unspecified relations and connections among the presented information which leads to beneficial and easier ways of decision making and business planning.

Many sciences agree that the explained process of “data mining” can be extremely useful in a way that it enables getting relevant and new knowledge by using various techniques and ways to uncover information from the enormous sea of data hidden in the databanks.

One of the most important business segments of using data mining is definitely the banking industry which stores huge amount of information in its data warehouse. Credit analyses, credit card departments and other key sections of a bank mark the sea of information and data which are needed to be carefully analysed, subtracted and implemented in the process of key decision making such as the credit allowance. This paper will take certain credit data that collects 310 individuals and analyses their financial health and its contribution to the bank's general health. Precisely determined income of a certain loan borrower decides the solvency of a borrower and the factor that highly affects its good financial state, e.g., solvency and liquidity is the amount of bank deposit.

Nevertheless, clients who have private houses used as mortgages get better credit results and on the other hand a bank has a strong guarantee to cover its loss from a certain credit by using this type of collateral which can also be put in auction. Not having that kind of collateral to offer means a client will have to face a credit limit.

What also affects to one's high or low credit score is definitely the profession of a person asking for a credit which makes the entire process easier or it complicates the process itself. Highly paid jobs above the range of a manager get a high chance of gaining excellent results in credit scores while on the other hand, clients with jobs that are poorly paid or do not enjoy the stable income are characterised as high-risk client groups and have minor chances of getting a wanted credit line. Furthermore, two major factors of getting high credit scores are definitely the age of a person asking for a credit and a marital status itself. Groups of people such as students and young people on entry level positions are expected not to get a credit or getting one seems harder. On the other hand, being married and having children implies that a person has its finances under bigger control and pays attention to the consumption and his or her own expenses.

From the bank's point of view, it is certainly important to track record of clients having multiple credit cards especially when the debt occurs on every of them.

To sum up, credit lines being high or low imply to also high or low credit risks for the banks which are mostly determined by the factors discussed above. Crucial process of data mining plays an empowering role in the abstract of key information in all the segments mentioned above so that the credit analysis can be as precise as possible.

Going on, the so-called ANN is the data processing system stimulating the structural and functional parts of the bio neutral network using a whole range of simply connected artificial neutrons. Simple explanation is that the information is taken from the external environment and then put through a process of computing from which it provides the information to external environment or another type of ANN. Decision tree is as an excellent problem-solving system which makes the analysis and decision making in various business segment, especially the bank industry, more efficient (Chen and Huang, 2011).

Another, lightly said just useful, tool for noticing all the incorectiveness and mistakes in the analytical and predicament systems is by far the most beneficial the confusion matrix which lowers the percentage of any errors in general.

2.4.1. Generic Algorithms

According to (Gordini, 2014) to develop and produce a relevant machine learning algorithm some generic algorithms need to be used. This is a short overview how do they work. Generic algorithms are different to other non-linear optimization methods because they keep the database provided and optimize it rather than changing in each and every iteration. The basic is a population of stings that have in them a "hidden" solution to the problem which needs to be found. When the best results in a generation are found the iteration stops and takes those results in consideration for the next optimization. This process is done over and over until the target result is accomplished. The iteration starts by taking random data and in generations a result is achieved. The evolution begins from a population of random date and resolves in generations. Each entity is graded utilizing a before defined fitness function. For realistic applications in the real world choosing the correct function is the most important step. In every iteration the fitness functions are graded and some of the initial data is selected regarding their quality. Then they are modified and they for the next step in the iteration process. New data that is produces is the backbone of the new iteration step. The algorithm is over when a final result is found or when the number of processes have been maxed.

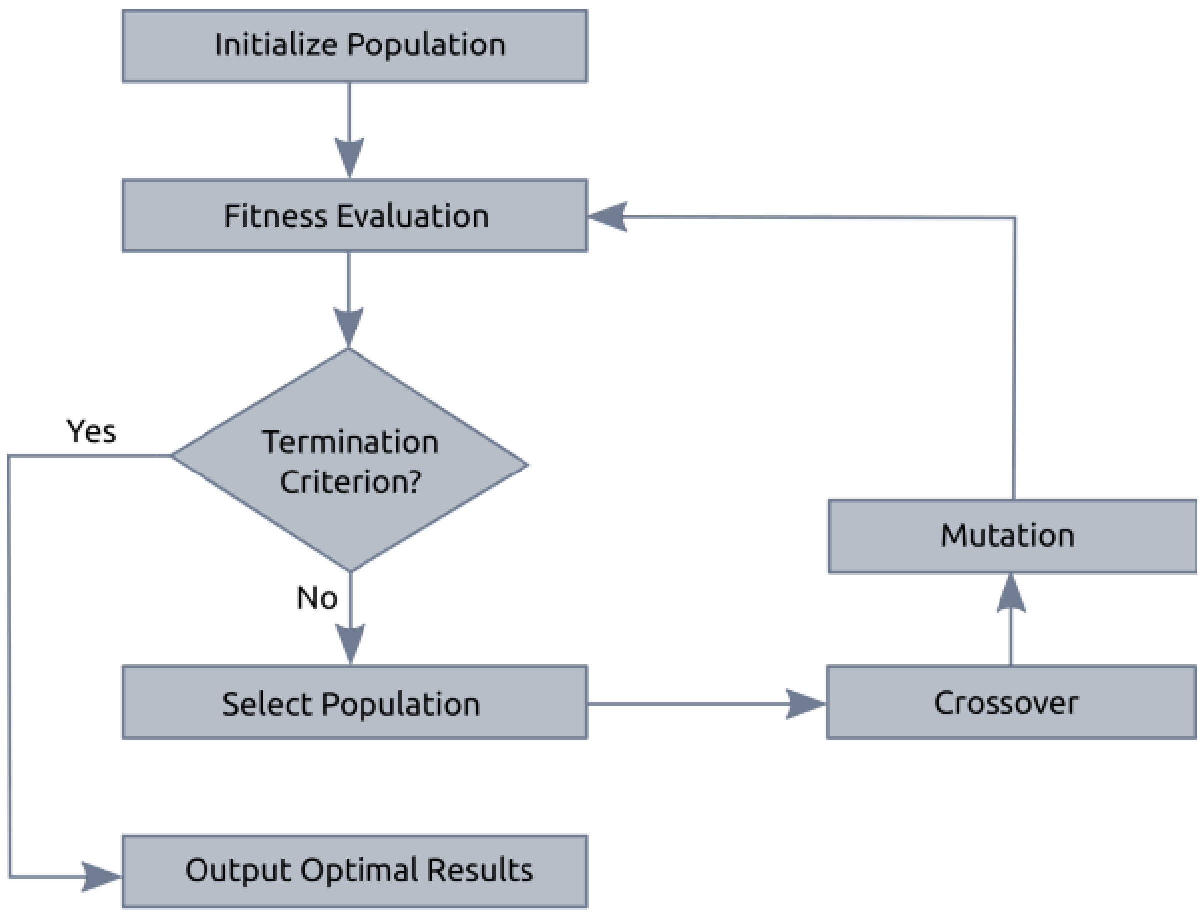

Figure 5. Generic Algorithm scheme

In figure 5.the scheme of the generic algorithm is shown. It starts with the initialization of population I which the fitness of the population is being inputted to the method. After the data has been entered the step of fitness evaluation happens in which the fitness of every individual is evaluated. When the fitness has been evaluated the termination criterion determines if the necessity for further steps is needed. If the answer is no, the selection of population happens again, and the crossover is being produced. In the crossover step the data is being manipulated in such a way that the best result happens. After that the mutation takes only the best data and the fitness evaluation takes place again. The process is completed when either the method is stopped or when the goal has been reached.

The principle behind the mutations is the following. Firstly, each individual is given a grade. Those grades are the determining factor of that individual in the mutations. Some individuals are selected from the first pool and they are mutated. In order to produce a new mutation which has all the good sides of the initial mutation but less defects that could influence the result in a negative matter. That new mutation is then used for the next iteration. The method is over when the target is reached, or the necessities have been fulfilled.

There are four main steps that are mostly used in genetic algorithms:

- Initialization
    - The starting point of the iteration process and the random data is selected. In this point the data is unstructured and in a dire need for a structuring.
- Selection of better individuals
    - In this step the relationship between the selected data and the realistic scenario is defined. The grading factor of the fitness functions is added. This step can be connected to the Darwinian philosophy, it is only the fittest who survive the selection process. The data that has the best grades is selected and passes onto the next iteration of the algorithm. The point is to have only the data of the best quality that occurs more and more in the search population.
- Crossover
    - The crossover step is the step in which the data merges in such a way that the best outcome happens. The goal is to have consistent grades thought the iteration process, so the best overall result is achieved. The crossover is successful when the grades are similar and reproduceable over generations to come.

- Mutation
    - The last main step that can be best explained with the biological mutation. Mutation allows that the data is always changing and adapting in such a way to extract the best quality possible. In theory It should prevent downgrades and only focus on the upwards trajectory of the algorithm.

The definition of the problem of optimization needs to be encoded in order to have a possibility of grading the data and defining the fitness functions. The parameters encoded are financial ratios, test signs and the data performance evaluation. According to these parameters the algorithms search the entire array of results and they usually favour the best solution. There is always an issue of deciding how big of a database is needed regarding a specific research. The usual rule is simple, the bigger the problem the bigger he need for a vaster amount of data. But the idea is that there is never a need for a too large data population, an optimum is also equally effective if the data is completely randomized.
In order to understand the fitness functions, they need to be understood as they always have a specific function to them.

The fitness function measures the performance of an individual entity of a data. One of the main objectives of a system is to find rules that have the highest possibility of producing a result that is effective. The final part is to find the optimal solutions, optimal crossovers and optimal mutations. The converging rate is also one important factor. The decision of stopping the algorithm is important, the dilemma is always if there should be a fixed number of iterations or to allow the iterations to run until they are finished, to increase the probability of success.

2.4.2. Support Vector Machine

This model is a model based on transforming a mathematical function by another mathematical function. That function is here to calculate the distance in between similar parameter that have a different class. This model could be 100% accurate as the parameter groups can be completely separate but in finance there is a subjective overtone that causes data that is biased and subjective. That is the reason why SVM allows to implement a margin of error to the research. Each optimisation via SVM will have a different number of parameters. A classification scheme is produced in order to keep track of all parameters going into the research (Barboza, Kimura and Altman, 2017).

2.4.3. Bagging

Bagging is a method that is also called bootstrap aggregating. The goal of this method is to classify the portion of data and use model averaging to produce a result. Sampling is quite important to ensure an accurate prediction. The mail goal of bagging is to reduce the chance of overfitting by recombining the training set in order to provide better and more accurate results (Barboza, Kimura and Altman, 2017).

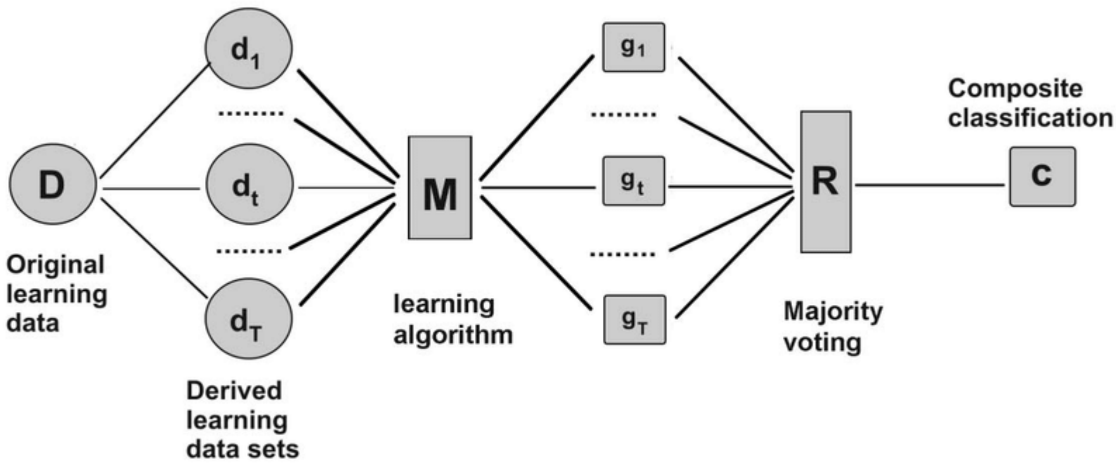

Figure 6. Bagging scheme

Figure 6. shows the scheme of a bagging method. As stated above, the goal is to classify the data in order to produce a result. In this scheme the principle behind that function can be observed. The original or input data is firstly derived using data sets that were previously entered. The derived data then transfers to the learning algorithm

which segregates it according to model averaging. As the goal is to reduce overfitting the data has to be structured and recombined the provide accurate results. One big advantage of bagging is that multiple bagging processes can be active at the same time and tin that way achieve results faster. The downside is that it can be computationally expensive as it requires strong computational background.

2.4.4. Boosting

Boosting is a method that repeats the usage of a first prediction rule or functions on different initial sets. It builds on other classification models to weight them in training. The data is then implemented in the model. Boosting allows for a better classification and lowering the error rate (Barboza, Kimura and Altman, 2017).

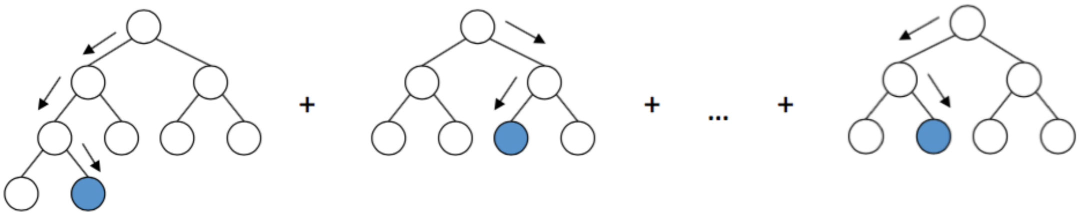

Figure 7. Boosting scheme

Boosting scheme can be seen in Figure 7. where the training of the model can be visualized. The function of the model is to reduce bias and to reduce the variability of supervised learning. It also makes weaker machine learning algorithms stronger by training them. In order to train them, a classification needs to be made in order to separate them into weaker and stronger learners. The difference between weak learners and strong learners is that strong learners have a great corelation with the method while weak learners have a slight corelation with the method. The process of transforming weak learners into strong learners is introducing strong learners into the weak learners' branch. In that way the strong learner "shows" the weak learner how to learn better and in that way influences that the whole system is strong and adaptive to provide even better results. The problem with boosting is to decide which classifiers are needed to be improved and trained to determine which ones are strong and which ones are weak.

2.4.5. Random Forest

Random forest method has a similar principle to the decision tree model. It is robust and allows for a better result than boosting. Random forest identifies each parameter in the results of the classification. It works on a similar principle as bagging in that regard that it also repeatably produces classifications. The difference is that it randomly selects parameters form each node of a tree and in that way prevents bootstrapping (Barboza, Kimura and Altman, 2017).

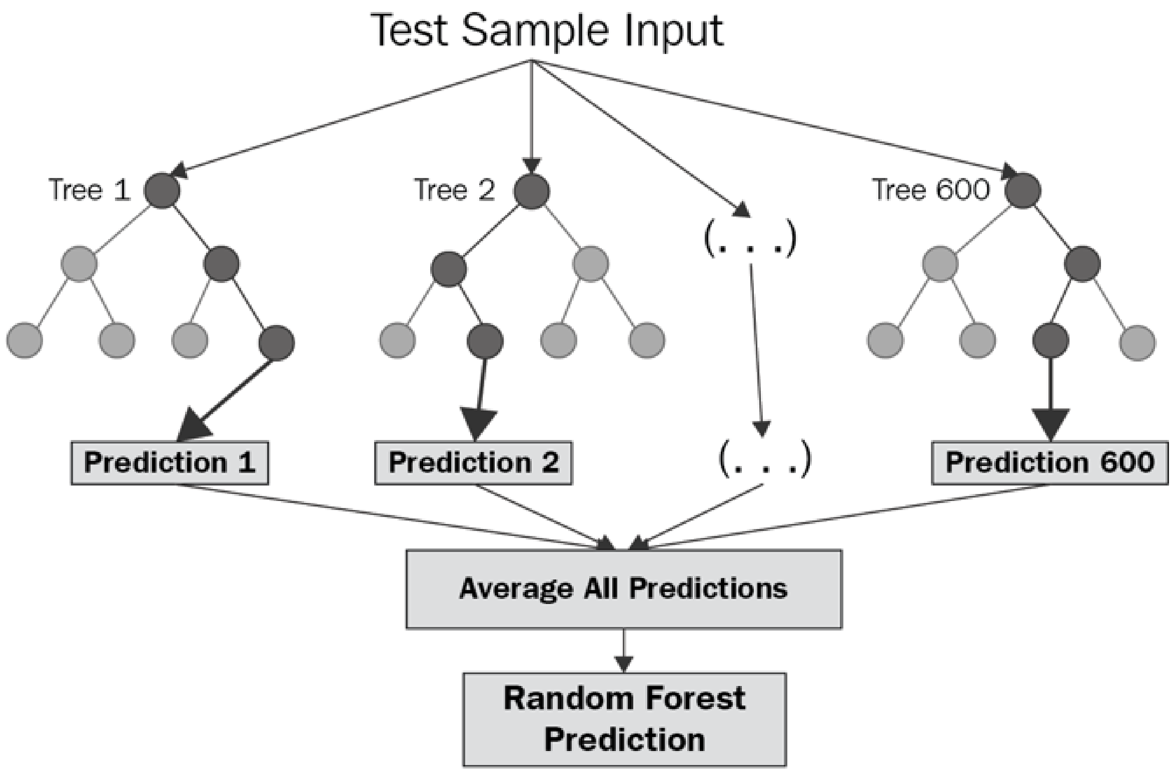

Figure 8. Random forest scheme

The random forest scheme can be seen in figure 8. It works in such a way that it produces multiple decision trees that are trained at the same time to provide a prediction. It corrects the issue of overfitting to the training sets that usually happens during a decision tree method. The disadvantage of the random forest method is the lack of interpretability that a single tree decision tree has.

2.4.6. Particle Swarm Optimization

The group of birds with the plan to reach an unknown destination inspired scientists to develop a model called PSO (Particle swarm optimization) where every solution is represented by a “bird” in the group and is called a “particle” The birds somehow evolve their movements and entire behaviour and therefore move following their past paths. Communication of the birds during the flying is inevitable.

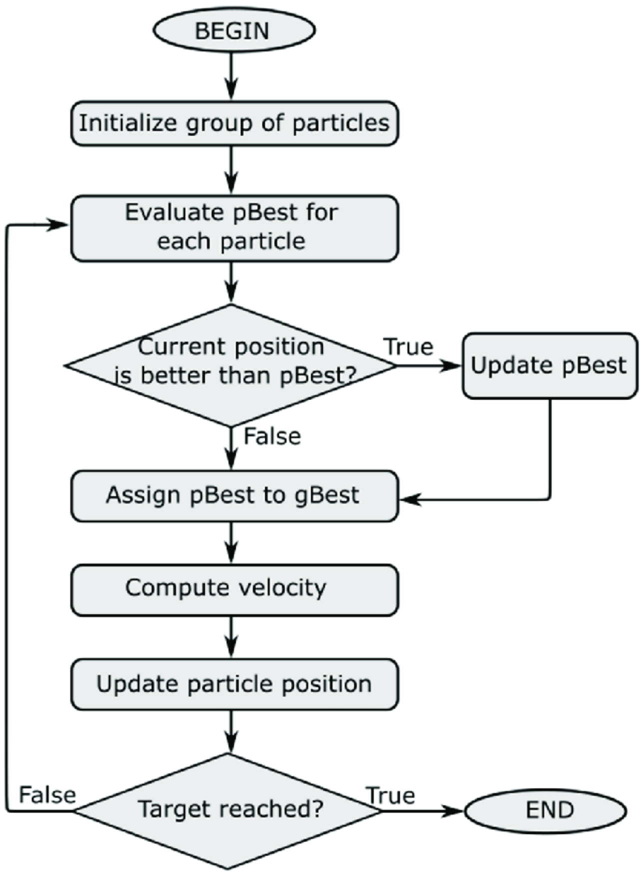

Figure 9. Particle swarm optimization scheme

For example, each bird has its own specific movement and it first identifies the location of the best bird flying while also investigating about its best-known position. Finding a new direction is the union of the local and global circumstances and according to those, that is by far the most optimal solution. The mentioned process is repeated until a wanted result has been produced (Hsieh, Hsiao and Yeh, 2012).

Figure 9. shows the particle swarm optimization scheme. This method was firstly developed for the simulation of social behaviour because of its representation of a flock of birds or school of fish. Because of its simplicity, particle swarm optimization is great for researching vast amounts of data. As seen in the scheme the first process is the initialization of a group of particles. These particles are the data that is being optimized. The second phase is the evaluation of each particle and determination of the best position for every particle in regard to their current position. If the particle is in the right position the method updates the position and calculates the velocity of the particle. If it is not in the right position it updates that position to a better one. The PSO is finished when the final target has been reached. If not, the process is repeated until the target is reached.

2.5. Literature review on insolvency avoidance instruments

Financial difficulties are something that many companies face on a daily basis. The terms that are usually used for describing those situations are “bankruptcy”, “insolvency” and “company failure”. As financial difficulties happen daily, there is a discrepancy between the data that a company receives and the actual financial state of a company. Small and medium-sized businesses are more exposed because their insolvency prevention systems are usually not as highly monitored as their bigger equivalents.

In that regard, this paper was influenced by the works such as (Antunes, Ribeiro and Pereira, 2017) that have researched the idea of probabilistic modelling and visualization to predict bankruptcy sooner. The problem of identifying a problem early is the task of preventive diagnostics, which guides the fight against insolvency. (Kim, 2005; Camacho-Miñano, Segovia-Vargas and Pascual-Ezama, 2015) researched the principle of using artificial intelligence methods to analyse a sample of companies and determine which characteristics predict the survival of insolvent companies. The usage of machine learning techniques is essential to segregate the needed data and provide an easy gateway for the researchers such as (Qu *et al.*, 2019) to review and analyse. The sorting of information presents a significant challenge, and relation between researched firms dramatically increases the performance of research, like in the case of (Tobback *et al.*, 2017) where the relation shared are high-level managers. A multistage classification developed by (Swiderski, Kurek and Osowski, 2012) is a necessity to predict the risk of insolvency. Objective results provide the much-needed accuracy of data acquisition (Obermann and Waack, 2015). However, every company has a slightly different mindset, and therefore a standardized approach to insolvency prevention is a good base but a skilled researcher needs to have the right information about the past, present and the future of a business (Jayasekera, 2018) The keyword and part of the focus in this article are SMEs and, in that regard, a slightly different approach to insolvency prediction is take due to the nature of SMEs (Lee, Choi and Yoo, 2020).

2.5.1. Research Methodology

This systematic literature review (SLR) has been accomplished out by sourcing academic databases Scopus, Science Direct and Web of Science published from 2008 to 2021. The first search for finding papers that are important to the topic of corporate insolvency have been produced with the usage of specific keywords and implemented in the search algorithms. The algorithms are based on previous systematic literature reviews conducted by the following authors (Shi and Li, 2019a) in their two SLR that cover a similar topic but from another angle.

The SLR methodology is an very important attribute of every academic project. It is crucial to give researchers insight into the current state of academic documentation on their respected topic. The advantage is that reliable information will be provided by critically evaluating and integrating all relevant, high-quality papers.

A high-quality research methodology allows for a great insight in the minds of the researchers that are devoting their lives to provide valuable research. The quality is achieved by having an open mindset and exploring multiple similar papers to achieve the desired goal. In this SLR the start of the research was firstly deciding the research question that will guide the flow of the research. The idea was firstly to study and see what machine learning is and what are the principles that allow for their implementation in the spectrum of insolvency and bankruptcy.

After an initial study was done and the machine learning algorithms were found a decision was made to choose only the ones that are applicable to the topic of this paper. The second part was to decide which of the proposed machine learning algorithms were already researched and how are they relevant to the topic of insolvency prevention. The choice was narrowed to the following machine learning principles: Neural Network, Regression and Decision tree. Each one uses a different perspective to achieve the same goal of allowing the accumulation of data that allows the possibility of prevention of insolvency.

In that regard the article selection process was guided, and the best related papers were selected. The sum of the papers is a great overview of the current trends as well as problems that are present in insolvency prevention.

The addition of the artificial intelligence approach broadens the selection process and puts a spotlight on the future and the possibilities of a real time insight in the observed business functions.

2.5.2. Article selection process

This study will take a focused and structured approach when selecting which papers will be a part of this SLR. The studies collected were analysed concerning keywords and logics to discuss the issues and advances in insolvency prediction and prevention. All the articles were collected from the following three academic databases: Scopus, Science Direct, Web of Science.

As seen in Figure.10, the first part of the searching process was to select the keywords needed for this study and to make a search string that would incorporate the terms of Insolvency, AI, Neural Network, Regression and Decision Tree. All of the databases have a slightly different way of searching, so minimal adjustments had to be made. The first part produced 1635 articles. The second part was to determine which papers will be included and excluded from the search. As this paper aims to make a Master Thesis, only the most trusted sources were included, articles and reviews. Book chapters, notes, conference papers and such were excluded as they do not fit the parameters. The second part produced 1171 articles. The third part of the search was a refinement by the year. As this is a modern paper with AI and machine learning techniques, a decision was made to consider only papers released from 2008.

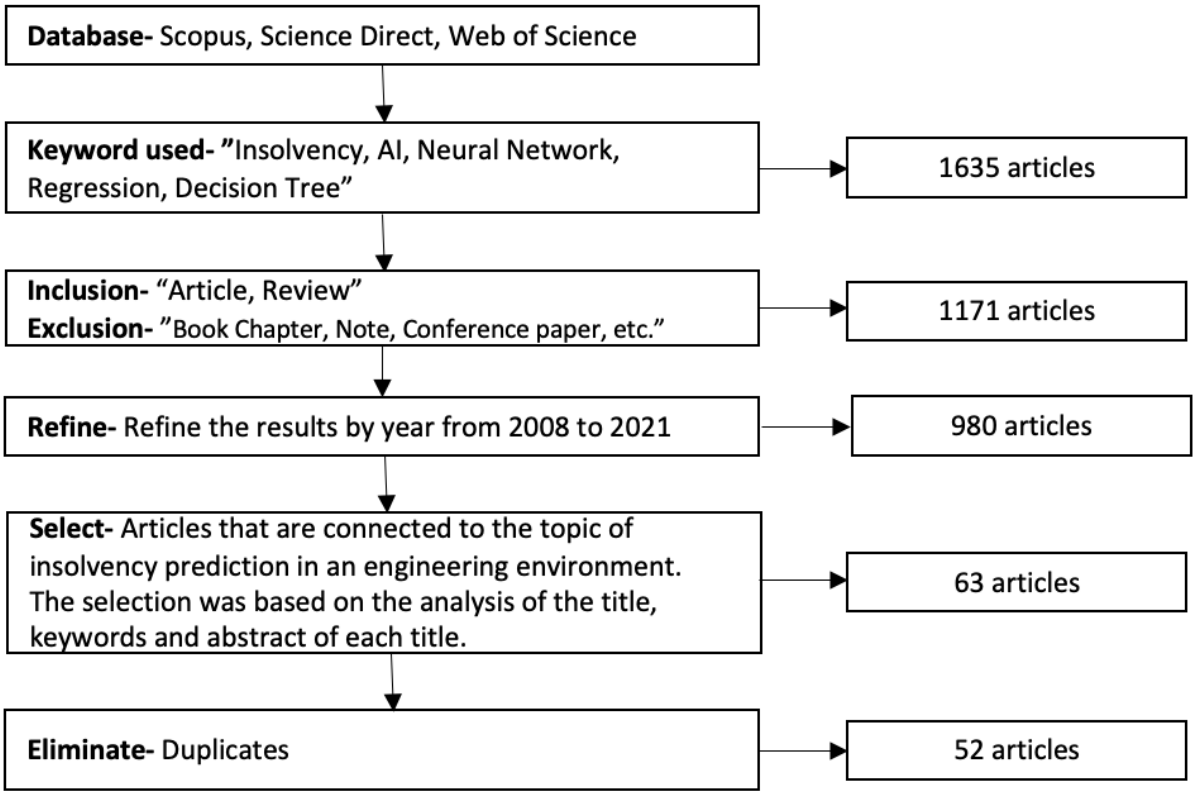

Figure 10. Process for selecting research papers

Another reason to take that specific year was the economic crisis that happened that year. After the refinement, the number of articles dropped to 980. The fourth part was the most interesting one. All the papers were reviewed, and only the ones connected to insolvency prevention in an engineering environment were selected. The selection was based on the analysis of the title, keywords and abstract of each title. This selection dropped the number of articles to 63. The fifth and last part was a duplicate elimination activity which narrowed the number of reports to 52.

After the search was over, each of those 52 articles was researched, and the most important topics will be reviewed in this SLR.

3. A systematic literature review on insolvency avoidance instruments and findings

The results show a descriptive result from 52 articles obtained from Scopus, Science Direct and Web of Science. The number of publications is on the rise since the economic crisis of 2008. That shows the relevance of the topic in the eyes of researchers. During the search for the SLR articles on the points of insolvency, a large number of reports were produced (15242), but with the implementation of keywords such as neural networks, regression, decision tree, and AI drops the amount to a staggering 52. That shows that the topic could be researched even more in the grand scheme of insolvency prevention and prediction. The most relevant database was Scopus, followed by ScienceDirect and Web of Science. In the results, the complete overview of the researched data is shown.

Artificial intelligence approach to insolvency and bankruptcy prevention is the new trend in solving tis major financial problem. AI is here only as a supplement to the conventional statistical methods that have shown good results in the past, the goal is only to make them more accurate and faster. But AI also makes some of the more traditional methods obsolete.

There are two ways to design an intelligent system.

- Expert systems approach
    - Consists of knowledge that experts accumulated in a real-life scenario and programmed into a computer program. The major issue and limitation are that the data gathering process is slow as it relies on interaction with experts.
- Machine learning approach
    - A computer method that generates all its knowledge through data analysis. Some methods are easy to understand and produce while others have a more complicated approach that is hard to master.

Both methods are successful in analysing data and have many pros, the choice is on the researcher and his subjective stance. The objective is to find which characteristic insolvent firms show and how to prevent it and if the worst scenario happens and bankruptcy happened then the objective is to have all the relevant data in order to do a quick reorganization to mitigate the costs.

Some countries such as Spain have something called a prebankruptcy which allows businesses that are facing insolvency to have another lifeline that should, in theory, stop them from going bankrupt. Incentives such as prebankruptcy allow for business to have a guiding hand in a reorganization procedure that is hard to achieve. This should be a joint venture of the public and private sector that would allow for a good climate in which business that are honest and hardworking can find their way out of the jaws of bankruptcy. To put it in a realistic perspective, a set of rules should be produced that allow managers to focus on the right issues and have a warning system that uses the data form previously insolvent firms and how to manage the situation they face (Camacho-Miñano, Segovia-Vargas and Pascual-Ezama, 2015)
The recent financial crisis put a spotlight on prediction of insolvency. The strength of a result is guided by predictive accuracy that was achieved by machine learning models. Some restrictions have been applied. The use of raw data without adaptation suggest that the methods can easy be used in a realistic scenario (Barboza, Kimura and Altman, 2017).

There are two main streams in the current state of the financial distress: accounting-based models and structural models. Structural model is considered superior by many, but his application requires data from digital markets which limits its application on a sample of private companies or in an environment with an underdeveloped capital market. The study aimed to contribute to research in a specific way: analysing the usefulness of cashflow-based indicators as predictors of distress, which is a novel approach. Authors of accounting-based analyses often rely on traditional financial ratios which are easy to manipulate by distressed businesses (such businesses have tendency to cover up their unviable situation). There is a strong link between cashflow insufficiency and business distress which shows the importance of those kind of analysis. Also, cashflow approach is recognised in a way of estimating the business value in which businesses are able to satisfy the ongoing concern assumption.

There is not always enough attention paid to the assumptions of the applied classification algorithms. Focus of this study was a specific group of variables. Therefore, there is a high probability of the presence of multicollinearity in the initial sample. To deal with this problem, they modify a previously published approach of hybrid distress modelling.

Various methods have been applied to many financial distress methods that have been proposed to date. Exploring the possibilities of creating the hybrid model is a current trend. Hybrid model can benefit from the features of the incorporated methods. Many authors said that those methods are often hard to interpret. In this study, it was used a modelling approach by Brezingar-Masten and Masten but with few modifications. Focus was not on a number of areas of financial ratios (such as solvency, profitability and asset management) because that approach was a paradigm in financial distress studies since the pioneer paper by Altman. Cash-flow-component ratios represent an area of potential predictors and was neglected by the mainstream of research.

Since there was inability to generate such inflows, there comes an inability to meet short-term obligations which is one of the most common reasons of bankruptcy. Also, cash-flow-based indicators are less vulnerable to earning management because cash flow is not accrual-based like for instance profit. The increase of net accruals is a possible way of earning manipulations and this phenomenon occurs often in cases of distressed businesses. Situation is complicated because the profit-based indicators are considered the most significant predictors of distress.

To sum up, accounting-based financial ratios are often used to predict the financial distress of a business. Those kinds of businesses have tendency to manipulate to

cover their situation from stakeholders. Cash-flow-based ratios are less vulnerable, and they do not employ accruals of any kind.
In this study, it was worked on a hybrid model which connects best out of both. It was worked with cash-flow components such as free cash flow and operating cash flow. Previous study concluded that there is a need for a new model and approach. Hybrid model was chosen because that kind of approach shows current trends in this area of research. In here there was only one type of ratio, so they had to deal with potentially severe multicollinearity. This was one of the main reasons why this model was modified in the first place.

Even though the research was successful, there are some limitations to the results. The analysed period was pretty much stable period of economic growth which means there was not a lot of bankruptcies. Focus was on manufacturing SMEs and there is no guarantee that these results could be applied to other industries. On the other hand, method that was presented can be useful for applications analysing businesses from other branches of the economy (Karas and Reznakova, 2020).

Researched deep learning methods that simulate the behaviour of investors in the market, was also researched. It provides evidence for characteristic features od DL that generalizes structured data sets.
The deep neural network has specific modus of operations. It has layers that have inputs from former layers that are used for learning the information which is relevant to the method. That information is then used to influence the next layer and help in the adaptation process. The interesting information is that the deep neural networks have such a strong learning curve that they are able to predict something as complicated as a human face from a picture that is incredibly dim and unrecognisable.

Deeper layers have more complex concept like for instance particles like polygons that could form an image. This is a great support in corporate credit risk modelling. Insolvency prevention and prediction models show a probability on the backbone of financial ratios. In DL that framework represents a low-level representation. Sheet figures are the inputs in the first layers that use the variables to produce information.

By using data from the spread-trading market, the predictions of usefulness of traders are made. The idea of this method is to find the individuals that pose a significant risk and recommend it a hedging policy that maximizes the markers maker's profit. Trader risk prediction are functions that represent challenges that are sometimes encounters in ML-based decision support. They deduct the representatives of the beginning data and ML suffers from reduced representativeness.

Also, this DL method is not new, but it uses ideas such as distributed representations that are not that often used in business. If understanding DL concepts, company owners can use it and understand its business better. DL is a learning method whose higher levels are the more advanced ideas that represent something innovative and new that could influence the method in a great way. It provides many bonuses over standard machine learning methods.

The deep architecture of a deep learning method is something that is considered new, but in truth it has been present in some regard in history. They are the factor that connects the relationship of the initial observation and the prediction. ML approach is versatile, and this function can complicate its results and lead into poor judgment. It includes outside influences that disturb the method and its operations. If representing functional relationship, it is better to use a learning method with a known profundity that is in need of other machine learning methods to supplement it. Deep learning is also interesting to give an impact on the methods that have the tendency to learn themselves and in that way produce a new way of thinking of machine learning models and their implementation in the current business enviroment. The idea of profundity is best understood by empirical data that the methods use to learn and implicate better results and further learning. Each other level is something new that uses the generally known data from the initial training set. The learning method can understand more variations of the result because it houses a greater capacity of data storage and computational power. The number of methods used is influenced by the initial number of training sets. The more training sets there are the more methods can be used. The results are extremely complex when various interest of the target exist.

Many elements of transformations of linear and non-linear nature are needed to build a deep neural network. When training a deep learning method an optimization solving procedure required. That makes it difficult due to vanishing gradient problem. Connection between lower levels sometimes cannot be adapted if errors show up in upper layer back or lower layers in network. Result of it is that often the optimization will delete in the lower part of the minimal spectre. The result to the solving of that problem will include multiple training parameters and normalization.

When speaking of DNN, it generates prediction in the last layer. The last layer has the information of all the previous layers. DNN predictions are compared to results from normal LR that has original features. Logistic model is representing an approach which sustains only the last layer. This can be useful if approaching the distributed information of hidden layers that have raw features.

Training that is not supervised is used for information gathering and the acquisition of data. It is crucial to understand each neuron in the training stage so that the merit of pre-training can be confirmed. Checking which data is in the DNN is a process of information redistribution. (Kim *et al.*, 2020).

The effectiveness of deep learning in support was tested. Some applications sometimes consist of the models form the data that comes from a structured perspective. The focus in on risk taking as a risk management system are also one of the focus points of deep learning principles. The evidence of some of the characteristic of the features show that deep learning can structure the data differently, especially in SME-s. There is also a probability of using methods that have patterns with specific individuals and in that way producing results and negating risk that is an issue in every business.

The credit scoring models and the process of data mining which guarantees them to be even more precise are widely used in highly ranked banks all over the world more and more every day. Credit analyses based on calculations and analyses made by humans are also present in the banking systems but take less space and importance in getting good results and credit scores in comparison to the automatized credit scoring models which are designed to completely take over the entire process of credit analyses (Chen and Huang, 2011).

The financial ratios used for calculating and predicting insolvency:

- Gross Margin
- Operating Margin
- Net profit margin
- Return on equity
- Return on assets
- Equity slope
- Current ratio
- Debt ratio
- Long term ratio

Establishing of a forecast model for managing, minimizing and in the best-case scenario preventing financial disabilities is of a great importance for future business planning and development. To do so it is important to use certain variables for corporate management estimation and also the opinions of a professional accountants. Furthermore, indicator as the earnings management indicator with the two mentioned above is also the key to a well-constructed forecasting model.

There are some key differences between the companies that face a financial failure and the ones that do not. The first one is some evident financial manipulation concerning the earnings that ware characteristic for companies who were facing financial failure. On the other hand, companies with evident financial stability did not demonstrate any kind of financial manipulation which evidently indicates a stable and reliable management policy and people in charge of it.

The main act that characterizes impacted companies involved in some kind of manipulation is that the acts of fraud have been carried out to hide the real malignant condition from the public and make them believe the financial picture of the company is rather clear. Going on, the reason for doing so is also to blur the eyes of the stakeholders or other investors involved in the company's business. One of the most common ways to do that is the use of ministerial accounts and inventory received to improve the company's financial picture or the use of overvalued assets in order to better up the book earnings (Hsieh, Hsiao and Yeh, 2012).

In conclusion there are three variables that differ the impacted companies from the financially stable ones. Management policy, opinions of internal and external audit and earnings management are the key ones that lead to establishing a healthy company that does not lead into a financial malversation and manipulation.

3.1. Descriptive description of the papers

To observe and assess the trends of publications in this field of research, a systematic literature review regarding insolvency prevention and the prediction was performed. VOSviewer software was applied to analyse the papers and produce a visual representation of the co-occurrence of keywords, bibliographic coupling of countries and the overview of when specific keywords were researched. The visualization is a creative way to understand the connections between specific keyword and their frequency in research. The need for a visualization such as these is to bring the researchers to the right solution because the work of researcher is often monotonous and visual simulation offers some new insights that could aid the result.

3.1.1. Network visualization of keyword co-occurrence

In the network visualization, keywords are represented by their label and, by default, also by a circle. The weight of the item determines the size of the label and the circle of an item. The higher the importance of an item, the larger the label and the circle of the item. For some items, the label may not be displayed. This is done to avoid overlapping labels. The colour of an item is determined by the cluster to which the item belongs. Lines between items represent links.

The distance between two journals in the visualization indicates the relatedness of the journals in terms of co-citation links. In general, the closer the two journals are located to each other, the stronger their relatedness. Lines also represent the strongest co-citation links between journals.

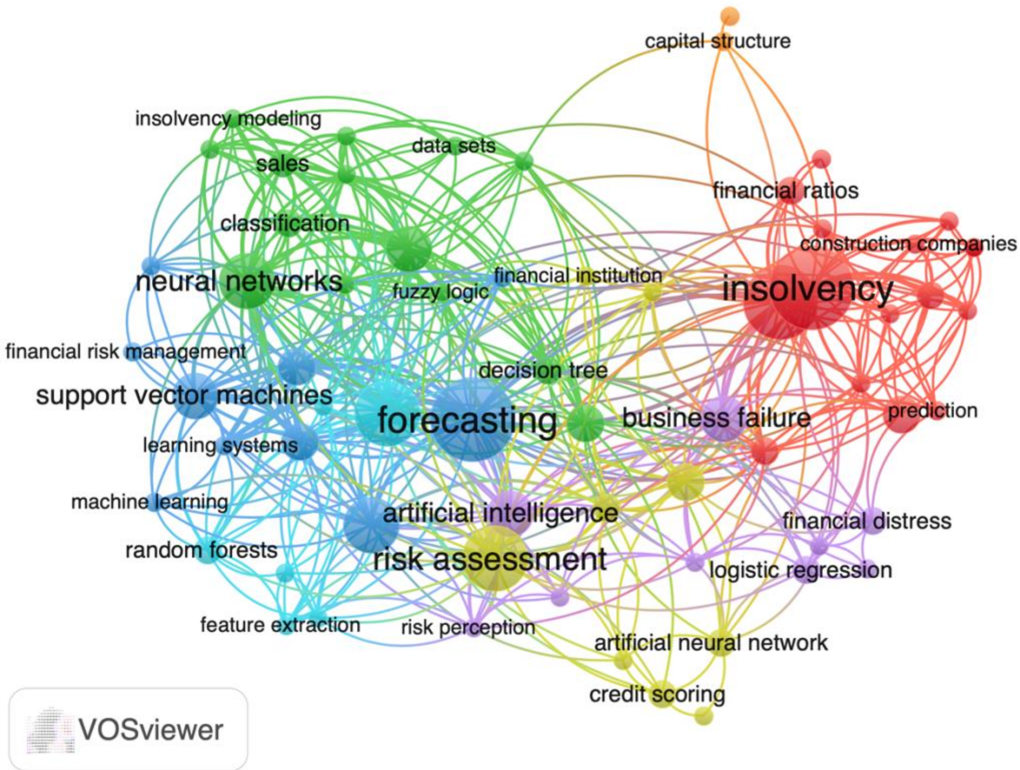

Figure 11. Co-occurrence keyword network visualization

In this paper, it is evident that insolvency was the main keyword driver with the most substantial link strength. Other keywords such as neural network, AI and decision tree are hardly seen. That shows that there is still a low amount of papers that touch upon those keywords. But, to understand the purpose of the co-occurrence of keyword, we need to take a more detailed look at the links between the keywords. This network visualization is a good showing of the following principle. Insolvency itself is an economic term that has the strongest connection to business failure and financial ratio.

The exciting part is that the relationship with forecasting methods opens up the links with the keywords researched in this paper, especially the artificial intelligence approach, one of the main drivers for research of machine learning technologies. The left part of the visualization network is denser, which shows that the link strength regarding prediction and prevention is getting stronger. We are experiencing a switch that will surely favour machine learning methods in the future.

3.1.2. Network visualization of the bibliographic coupling of countries

A bibliographic coupling is a measure that uses citation analysis to determine similarities between documents. The strength is calculated regarding a reference to a shared document that they share. The link is stronger the more citations the papers share. In the case of countries bibliographic coupling analysis, we can see and understand which countries are the drivers in this research.

The data shows that the main drivers are European countries Spain, Germany and Poland, but it is easy to spot that the effort to fight insolvency is global, a concern in many different cultures. As stated by (Szetela, Mentel and Brożyna, 2016) there is a growing trend of going bankrupt because of their inability to fight insolvency. And it is a problem that even the most robust economies have to fight. In the case of (Grdić, Nižić and Mamula, 2017) where they observed a small European country Croatia, it is shown that smaller countries often lack measures that can combat the growing concern of insolvency. That is why AI and machine learning methods could significantly impact lending a helping hand to countries in that regard.

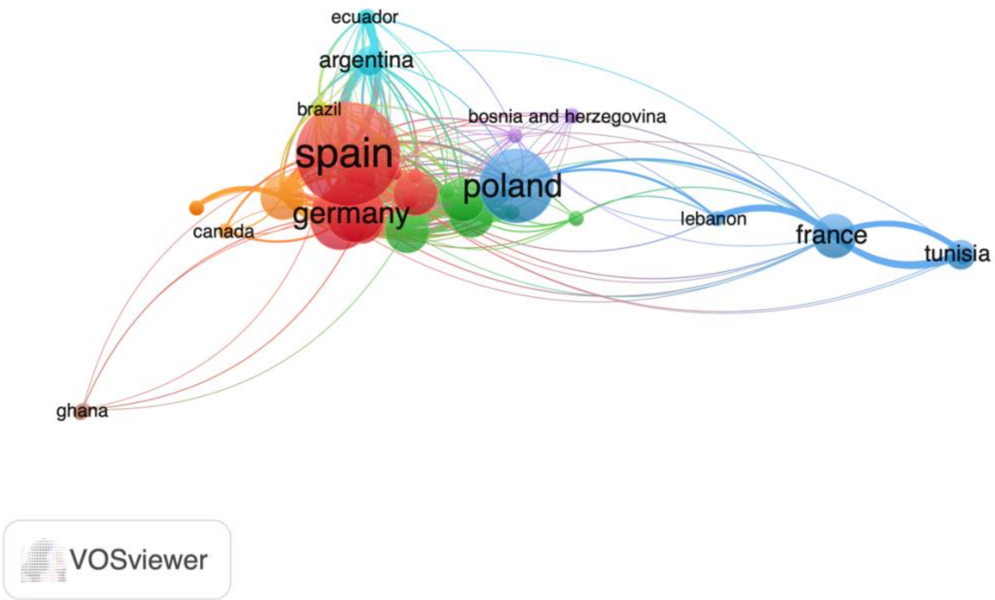

Figure 12. Bibliographic coupling countries network visualization

3.1.3. Overlay visualization of specific keywords

The overlay visualisation is similar to the network visualization but it has visual aids in different colours. There are two ways in which things can be coloured in the overlay visualization. If items have scores, the colour of an object is determined by the item's score, whereby default, colours range from blue (lowest score) to green to yellow (highest score).

This overlay visualization focuses on the timeliness of specific keywords and the number of papers published in the last 13 years. The keywords included in the search algorithm have started to make a more significant impact from 2014, shown in this visualization. As stated before, decision trees are a simple method that is easy to implement, and it is no wonder that it is one of the first ones to gain the attention of researchers.

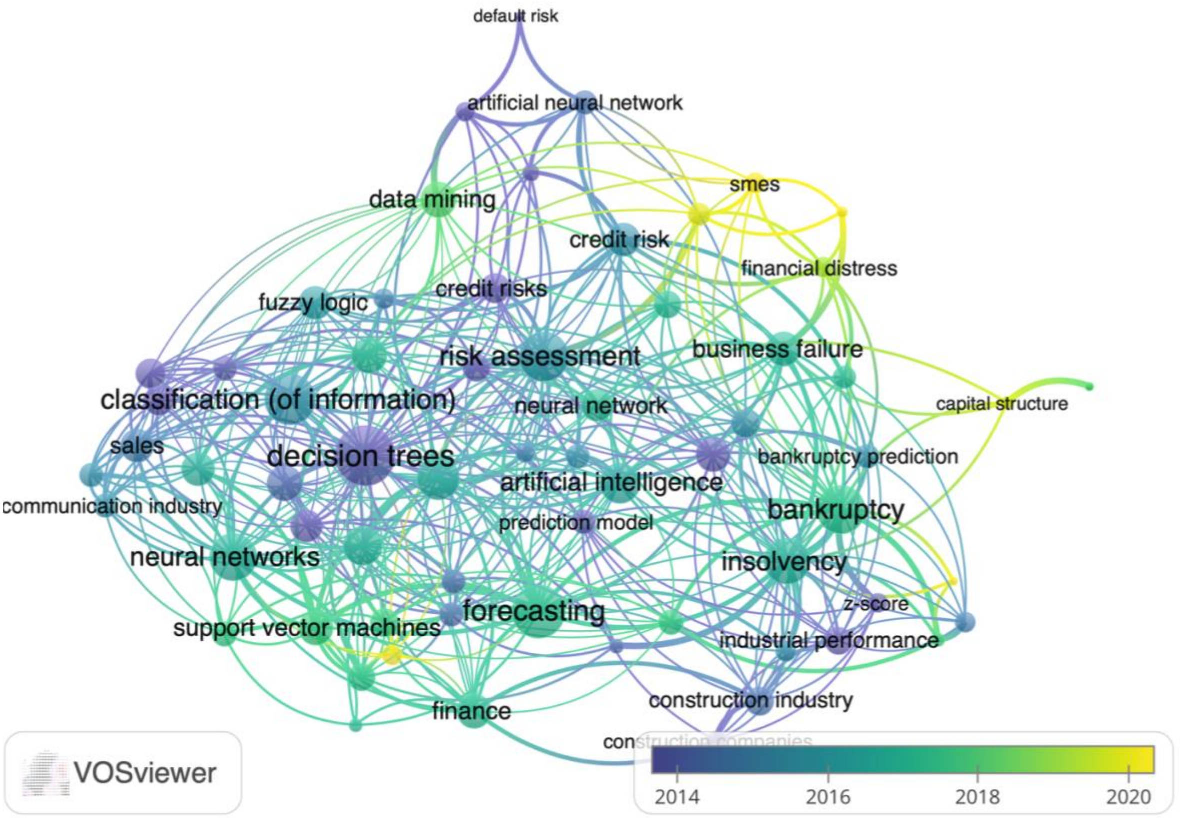

Figure 13. Overlay visualization keywords

In the last few years, there is a growing trend of observing and researching small and medium enterprises as they have always been hard to audit because of their dynamic structure. In the researches of (Camacho-Miñano, Segovia-Vargas and Pascual-Ezama, 2015; Tobback *et al.*, 2017; Lee, Choi and Yoo, 2020) a lot of care is focused on the issues concerning SMEs. This is mainly because many surveyed enterprises are younger than three years, and no relevant data can be collected in that timeframe. But that is where AI takes over a fair portion of the assignment, and new methods are being discovered that can collect the data daily and not yearly as it was done in the past.

The point of overlay visualization is to visualize the data in order to see when which keyword was used and, in that way, see the relevance of that particular keyword. From figure 13. it is visible that the biggest hits were bankruptcy, insolvency and forecasting starting from 2016 which show a tendency of research towards those topics.

3.1.4. Network visualization of author keyword co-occurrence

The co-occurrence author keyword visualization shows the focus of the researched perceived by the authors. As seen in Figure 12. The main points of this visualization are insolvency and bankruptcy which would be expected as that was the search keyword. But the interesting part is the branching from those keywords and their interaction. It is visible that the main branches of insolvency are business failure and machine learning methods which proves the point that firstly, insolvency leads to a possible business failure and that machine learning methods are a way to negate that possibility. It is also visualized that the tools like financial ratios are currently the main way of receiving the required data to fuel the machine learning methods and therefore preventing business failure all together.

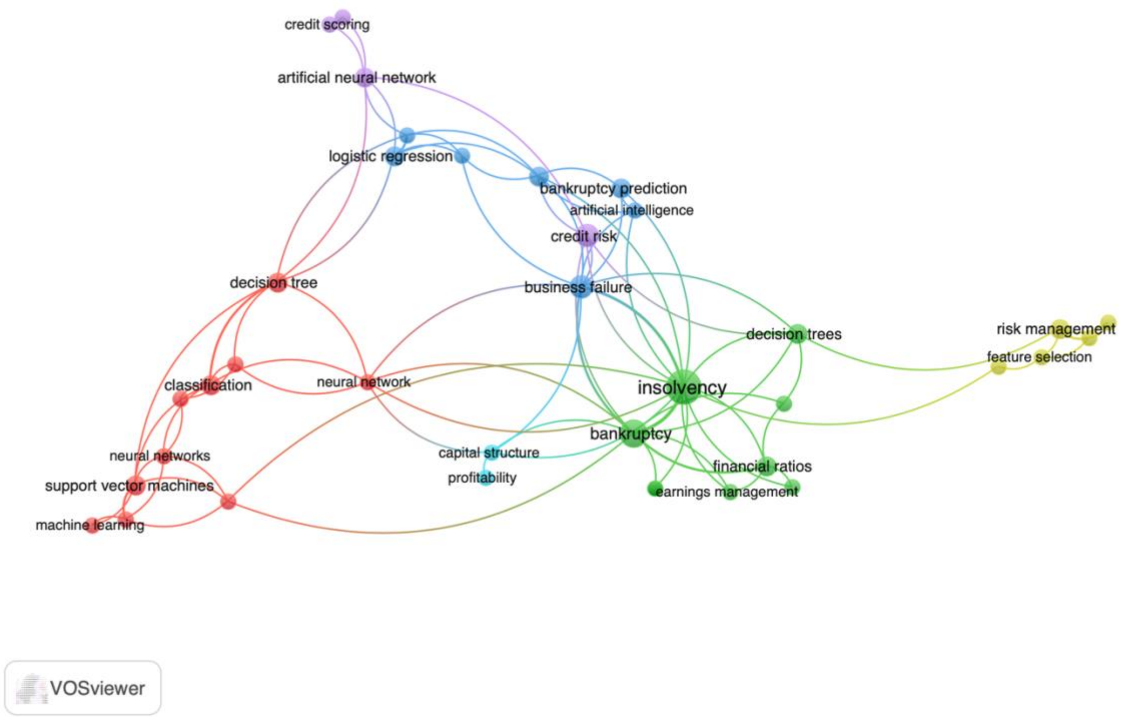

Figure 12. Co-occurrence index keyword visualization

3.2. Results of the research

The results were measured by testing the accuracy of the algorithms for SMEs regarding the selected financial ratios and their correlation to the size of the business a few years before the failure. The general goal of an optimization is to develop and produce the best possible result for a goal. The solution should be one but that is in a situation that happens rarely. In reality there is always an element of a decision that is needed to understand the issue. If there are a lot of alternative good results the optimization is also effective. As the fitness functions measure quality of an individual data result the ones with the best grades need to be selected.

The strength of the algorithm in not only the result of a good prediction accuracy but also the handling of the errors. The algorithm that handles errors the best is the one that can predict most successfully. The results of the errors can have the following consequences. They can lead to a loss of interest and capital for businesses. That is something that affects the shareholders and in that way the leadership of a business. The second way is that the algorithm can claim that the business will become insolvent when in reality it is solvent. Because of that reason the business can lose backers and customers and have more difficult times when working with loans from banks. All that just because it was predicted that it will become bankrupt. Results such as those have a several implications for SMEs. As they are always searching for better funding and better credit score. Outside supplements of cash are crucial for some SMEs to function on a daily basis.

A good algorithm can allow that, but it can also complicate it. Because of that the managers need to change operations and the structure of the business to adapt to the algorithm and in that way have the best results. But the issue is always the quality of data and the quality of parameters. The weaker results have also been connected to a weaker attitude to risk from the managers and owners of SMEs (Gordini, 2014)

As the focus of this thesis are SME-s a lot of research went into understanding the reasons of why insolvency happens and what are the evidence that have already researched that topic. According to (Gordini, 2014) who researched the topic of SME insolvency in Italy a following conclusion was taken. A lot of financial data and financial ratios are contaminated with some degree of error because SME-s mostly show a weak financial stability. Because of that reason a purge is a good idea in which the top

1% and the bottom 1% of data is erased to preserve a realistic overview of the SME-s in question. In order to get a good accuracy of the date a training set of firms and a holdout set of firms needs to be separated. The training set is used for learning the rules of a machine learning algorithm while the holding set is used for testing and estimation of the accuracy of the algorithms. Another issue is the quantity of the data gathered. A larger data sample is always better because it is less prone to overfitting.

3.2.1 Errors of insolvency prediction

The results of a bankruptcy prediction model are always presented regarding to each individual factor. The outcomes are used to judge the tools based on the research. As with every method, cost of errors is one very important factor as it influences the accuracy greatly. As errors are something that is hard to judge, usually a statistical approach is taken. Therefore, sometimes the answer are varying tools which are a bit more flexible and, in that regard, usually produce a more reliable dataset. The comparison between LR, DT and NN shows that NN are the most accurate, followed by LR and DT.

Two types of errors are present in bankruptcy and insolvency prediction. Type I and Type II. Type I errors are errors of tools when they fail to produce a result that shows that a firm that is really in bankruptcy is healthy. The cost of type I errors can stretch outside the business in the way of allowed loans that do not have the backing needed to pay them off. They could also take the guard of a business down when it should be fighting to prevent a possible insolvency. Type II errors is the other way around, a business is said to be bankrupt but in reality, it works normally and without a pending insolvency in the future. Type II errors are not so costly, but they can prolong the timeframe in which a firm will receive its needed loan.

The logics behind is that the method that produces a smaller amount of Type I errors is better and more accurate. In the eyes of backers and potential customer, it is enough to provide and predict as two scenarios: Healthy and bankrupt. For owners it needs to show the way forward and how to resolve the failure because only in that way a way forward can be found and errors can be resolved. (Alaka *et al.*, 2018)

3.2.2. Overfitting and underfitting

The equivalent of having a specificity of samples in artificial intelligence is known as overfitting and it is something well documented. The other problem is underfitting. The avoidance of this problems in now something that is a norm in the industry, and it is done by observing and testing the methods on samples. Over 30% of reviewed methods have this issue. It is connected to AI in such a way that if a longer research is needed there is a bigger chance of overfitting and if it is shorter underfitting. The possibility to reduce the chance of such issues comes from the structural risk minimization (Alaka *et al.*, 2018).

Overfitting is an issue that happens when the data fits the training parameters really well and because of that the errors of the approach cannot be seen. In theory, it is better to have an odd one out to know that the selected method is working the way it should work. To negate overfitting data is divided in two parts. One part is divided for the use of training and the second part is divided specifically to counteract overfitting.

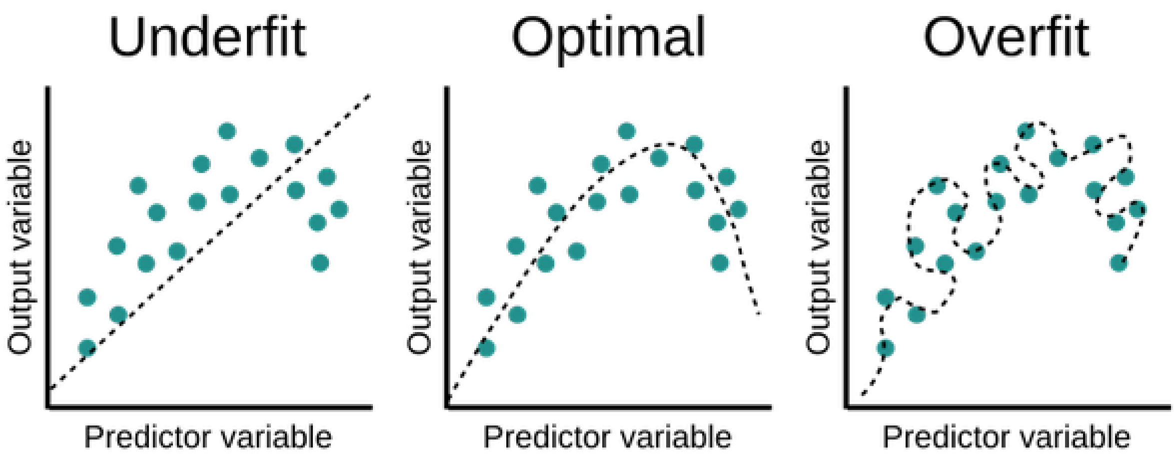

Figure 14. Overfitting and underfitting scheme

The scheme of overfitting and underfitting can be seen in figure 14. The principle behind it is that the output variable and the predictor variable need to have a predictable result that will supplement the method in the best possible way. The issue of underfitting is when the output variables are not corelated with the predictor variable and therefore produce an issue that may cause structural risk to the method.

Overfitting happens when a corelation exists but is overcomplicated and in that regard the method has a false function. The optimal curve is the curve which allows for an optimal functioning of the methods and therefore results that are relevant and predictable.

3.2.3. Under-sampling and over-sampling

The mitigation of a problem that occurs via the imbalance is resolved by using the whole population and over or under-sampling it. Under-sampling means that the learning data thought the system without balancing. The idea is to find a major focus point and work from there.

The advantage is a lower learning time hence faster result. On the other hand, over-sampling is a method of complication of the whole system and producing more data then needed. Over-sampling is done according to a strict set of rules that allow for a realist realization of the sampling (Lee, Choi and Yoo, 2020)

Insolvency can be graded by observing the technological feasibility.

- Technological feasibility
    - Management ability
        - Business promotion
        - CEO reliability / expertise
        - Business management
            - Financing ability
            - Adequacy
            - Financing plan

                - Management stability
    - Business feasibility
        - Market environment
        - Future profitability
            - Market competitiveness
            - Market capability
            - Future growth
    - Technical ability
        - Development and production factors
        - Core technology
        - Production technology
        - Technology development environment

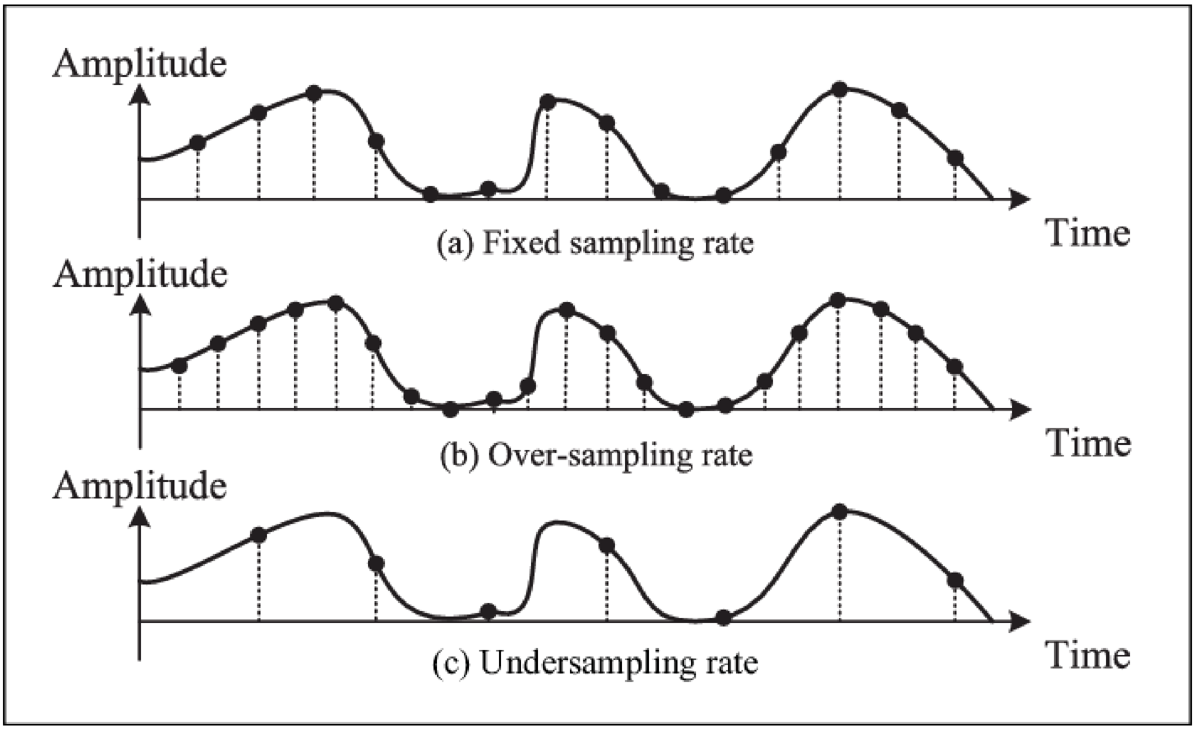

Figure 15. Under-sampling and over-sampling scheme

Sampling is an important issue that needs to be takes wisely. As seen in figure 15 the following issues can happen. Firstly, the observation is made to understand the fixed sampling rate which is the standard that shows the true form of sampling. Fixed sampling has standardized intervals that allow for best data acquisition and optimal performance to the selected method. The reason why an optimal sampling rate is needed is to allow the data acquisition program time to calculate the data as in insolvency avoidance there is an abundance of data that needs to be mined. Oversampling is an issue that happens when the sampling rate is too high, and the result is a complication that overstains the method and produces unreliable results. Under sampling is an issue that the sampling rate is too low and in that regard the results are unreliable and not accurate as most of the relevant data is not sampled and the method does not have all the information it needs to make a trustworthy result.

3.2.4. Neural networks limitations

Neural Networks have the ability to approximate non-parametric functions, and because of that they can simulate the behaviour of complex functions with high degrees of accuracy. Artificial neural networks try to simulate a biological system. They typically consist of layers and layers of computational elements neurons. The base of each neuron is perceptron, which hold a specific input and a specific weight. The sum of all neurons is the activation function.
The structure of a NN is made of three layers of neurons:

- Input layer
- Hidden layer
- Output layer

The input layer consists of as many neurons as the system has. The hidden layer is a layer that is possible to optimize, but with experimentation the number is about twenty to fifty NN in each neuron. The output layer is related to the number of outputs. Sensitivity, specificity and the Matthews' coefficient are the training parameters of NN. Sensitivity is a parameter that predicts the systems correctness in finding out which businesses are insolvent. High sensitivity would communicate that the method has identified a company as insolvent. But it does not show which business it classified as insolvent but in reality, they are solvent (Callejón *et al.*, 2013).

The results show that solvency is biased to the set of financial variables. The main ones being the possibility of repaying the debt and the level of profit that a business earned.

There is a neural network classification model that is using specific financial data in order to evaluate the analytics of the method. Model was designed so that audit can recognize any fraudulent financial statement. To sum up, NN can be very helpful to reduce the risk of any financial statement fraud, and also to reduce control. Auditors role in corporate governance is enhanced which is the effect of it (Omoteso, 2012).

3.2.5. Insolvency in the World

Theme here was trying to prove, by using the logistic regression machine learning method that the insolvency procedure in many countries is directly corelated to the standard of that country and the economic strength of that country. The better the security of business failure the better the living standard which is logical in some way. Of course, there is a second theory that is considered to be closer to reality. It is also important to determine that only with strong financial institutions that are adhering to the law are the factors that allow for growth and prosperity in a country. The result of that is that the countries that give their attention to the problem of business failure truly have a better security, life satisfaction and overall a more prosperous business environment that produces work for everyone in need.

Three parameters are chosen; “recovery rate” (return on investment in percent in case insolvency proceedings take place), “time” or the duration of insolvency proceedings and, lastly, “costs” of proceedings that is observed.

“Since higher costs are accompanied by a lower rate, there is a proportion between recovery rate and costs. When the yields from insolvency proceedings do not reach the total sum of claims plus costs incurred by the insolvency proceedings, costs of enforcement are borne by the creditor.” (Szetela, Mentel and Brożyna, 2016)

Funds that ate given out to the ones in need are comparable to the need of monetization od the debtor’s property minus costs of insolvency proceedings. The recovery rate gets smaller when as the costs increase which means that bigger cost directly devalues a possibility of a possible insolvency and the reduction of yield for the business that are giving the money.

Indicator of gross domestic product per inhabitant is chosen for measurement of efficiency of an economy. GDP is a monetary measure of the market value of all the final goods and services produced in a specific time period. In some economies, GDP is a great measure but is lacking the power to show the efficiency of the economy of a country. A good example are countries that have great reserves of mineral wealth which is hard to implement in that equation.

Many data give a lot of space for comparative analysis. The wealthier the country the faster the business failure process is. That means that the wealthier countries know the fact that insolvency proceedings take a lot of time and money and want to speed up the process to allow for the healing period and growth if the insolvency is predicted successfully. 25 poorest countries take double the time as the 25 wealthiest countries. Some of the top wealthiest countries are on the top only on their continents and not in global because there is a significant difference between the length of insolvency proceedings in the world’s wealthiest countries and in the 25 wealthy countries.

Therefore, there is also a huge difference between the 25 poorest countries and that is the product of the fact that there is a huge difference between a poor country in Africa and a poor country in Europe. There is also a very big difference in the cost and handling of the cost of insolvency. In some countries the creditors just have no economic calculation to be influenced by insolvency proceedings. The life standard in some countries is just so low that any expense seems incredibly high which produces a mindset that just does not care about insolvency prevention. This does not mean that proceedings in wealthy countries are cheaper; this means that the level of creditors satisfaction reflects reality in how assets in a given region can be sold.

Hypothesis that institutional quality expressed in GDP per inhabitant should remain in relation to the selected insolvency proceeding parameters is confirmed by this research.

“In wealthy countries there is a stronger relationship between individual insolvency proceedings parameters which can be find surprising. Even though wealthy countries very different in their limit data, they are internally more compact than the identically composed group of poor countries. Also, its economic environment is more compact too.” (Szetela, Mentel and Brożyna, 2016)

The main relation is the one that puts in direct proportion GDP per inhabitant and recovery rate. An economy that has a higher efficiency will have a higher efficiency of the insolvency prediction system. That is due to the fact that an economy that is strong, has the ability to separate the funds in order to help prevent business failure. Also, recovery rates, costs and time are significant, and they indicate the internal logic of the system and the better or poorer actual functionality.
It is important to create a system that is ensuring the enforceability of law and that enables the emergence of an efficient economy, and especially in the world’s more populated countries. It is interesting that countries like China or India, who have a population unmatched by no one have the quality of insolvency proceedings like the wealthy countries in the United Arab Emirates. That shows that if it is possible to organise a country with a billion people and still have room to improve, it should be possible for every other country to invest the time and funds in producing systems that would guide the process of business failure and prevent it from happening.

With all that said, it is important to state that it comes down to the focus points of each country. Every country should decide if it is for a long-term approach that could improve the economy in the long run or focus on other things that may not have such an impact.
These are not statically proved yet, but they are frequently discussed. Further research will show the direction of institutional and legal framework impacts on efficiency of insolvency proceedings in the national conditions (Arltová *et al.*, 2016).
When thinking about an entire country going bankruptcy it is extremely hard just to even imagine a scenario like such. However, the events over the past decades and in recent years have shown that this scenario might be much more real than people could

have ever imagined. To explain this situation, this study takes Iceland as an example. The mentioned country has declared bankruptcy in 2008 which was quite a shock for the local and global society, since Iceland was one of the wealthiest and most stable among European countries. The Iceland scenario was just the beginning of the similar scenarios to occur and begin so called “Domino effect” among other countries.

The predictions of financial disability have become one of the most important tools with who the scenario above could be prevented. Besides that, a new common insolvency law was something the European Union has started developing effectively along with the so-called MIP or Macroeconomic Imbalance Procedure which included 11 early warning indicators that have a role of the so-called security buffer with the role of protection and prevention of the entire EU community and each country individually. How does the system work? It uses data gathered form every member of the EU and makes a statistical evaluation of the country that is being reviewed. That review is the data that was researched on the topic of insolvencies in history. The whole goal is to reduce the chance of an economic meltdown of a country.

The methodology of an Early Warning System (EWS) and the sovereign risk default have all been published with quite various assumptions and therefore conclusions, and although a large number of papers concerning the theme has been published, the topic is even today not examined fully.

Since there were not so many cases of bankruptcy of the European countries and was not possible to analyse every case on its own, countries facing bankruptcy scenario were all put into one data sample which allowed scientists to analyse them together. This procedure led to gaining the most reliable and valuable results and conclusions (Szetela, Mentel and Brożyna, 2016).

When does a sovereign calls a bankruptcy? The distress itself happens when a country suffers a severe debt crisis, directly announces the bankruptcy or receives restructuring, financial support or strategic rescheduling. The numbers of countries announcing bankruptcy may seem small, but it has to be emphasized that those were mainly emerging economies going through major transformations in economic and political system during the last 30 years which has definitely been a period of constant change, major investments and the European golden age in general. On the other hand, countries as Spain, Iceland and Greece faced financial difficulties quite in recent times whereas countries from West Europe that were influenced by those difficulties but did not apply for any financial aid were not classified as insolvent.

3.2.6. Insolvency in Croatia

“Solvency is the ability of a company to meet its long-term debts and financial obligations. It is an important measure of financial health because it is one way of demonstrating a company’s ability to manage its operations into the foreseeable future.” (Grdić, Nižić and Mamula, 2017)

When company’s liabilities exceed its assets, it is called insolvency. When company’s total assets are in form of money, then it can be said that the business is a condition of full solvency. Risk of deviations from full solvency is higher when company’s property is further from the form of cash.
Great consequences are expected for the Croatian economy because of the negative macroeconomic trends that are set in Croatia which is one of the things that many authors are warning. It is thought that the insolvency in Croatia was escalated by the crisis of 2008. “Others think that most of the actions that were taken to, in terms of legislation and financial incentives, such as Bankruptcy Act, Act on Financial Operations and Pre-Bankruptcy Settlement, Adoption of Regulations with the Rules of European Insolvency Law, Law on Securing Worker’s Claims in the Event of an Employer’s Bankruptcy, The Value Added Tax law, Act on the special measure for collecting the tax debt, were ineffective.” (Grdić, Nižić and Mamula, 2017)

“Croatian economy has a big problem with insolvency increasing and this can be proved based on the purpose of the proposed research. According to this research, most of the actions taken by Republic of Croatia, were ineffective. This research has

shown that the increase in current assets to liabilities ratio has resulted with decreasing in the total debt. It is obvious that the implementation of Croatian economic policies was not effective for companies and its solvency.
Croatia needs to grow economic activities, production, services and employment to decrease the insolvency and get out of the crisis." (Grdić, Nižić and Mamula, 2017) There is a need for active and healthy enterprise.

To achieve the long-term economic growth, Government needs to make deep structural changes. Some of the following steps are suggested to make a change in negative macroeconomic situation; the introduction of legal instruments (it should reduce insolvency), the Croatian National Bank should focus on increasing the overall insolvency through the system, entrepreneurs should be more active in increasing their cash receipts and thew should increase their sources of financing (Grdić, Nižić and Mamula, 2017).

3.2.7. Insolvency in the manufacturing business

Last decade was a period that created a new wave of scientific and technological progress had huge impact on the manufacturing industry, it defined and influenced it. Therefore, that period is called "the fourth industrial revolution". In addition to numerous benefits, this wave also brought a lot of risks. The method that has the best accuracy and prediction possibility of credit risk is very necessary to ensure the continuous program of manufacturing. Those methods help the manufacturing company to attract investor as they show that their business is conservative and maintainable. There are many factors that influence if a company will receive funding or not and, in that regard, all the instruments that can help influence that decision in a positive way are welcome and are something that is being invested in. Stakeholders use those methods to see if their stake is at risk by controlling and monitoring the quality of the process and of the financial data which gives them an insight in the true state of the business.
Most common measure of creditworthiness is public credit ratings (PCRs). PCRs are assigned by domestic and international rating agencies (such as Moody's investors

Service, Fitch Ratings, Standard Poor's Financial Services). They provide a consistent global framework for accurate assessment and comparison of countries' and companies' credit quality. However, PCRs have a lot of limitations such as high cost of the rating, large amount of information that need to be provided to agencies, low ratings in small companies, long update intervals, as well as errors and inefficiencies of rating agencies. To solve these issues, investors developed an internal credit rating model (ICRs) which has proven to be objective and low-cost.

The idea is to find the predictive strength of empirical methods in reproducing Moody's ratings (especially for manufacturing firms) and to identify what is the optimum in data acquisition and data mining, what is the ability of the business to forecast the possible insolvency and how the outcomes are calculated. There are several ways that this is a contribution for literature for manufacturing companies. Manufacture is a process that needs to be constant and uninterrupted. Insolvency poses a risk of interruption. If that risk is minimized and the manufacturing process is allowed to be uninterrupted it will have a great economic impact. The results of insolvency prevention in manufacturing firms is a great insight in industrial firms' insolvency and creditworthiness.

To conclude, ML techniques are effective in reproducing manufacturing companies' PCRs. There is a need for future studies that should show how the addition of non-financial metrics can improve models' predictive power. Indicators of market, operational performance, corporate governance, quality management, companies' intellectual capital are some of the metrics included. There is a possibility to make insolvency prevention in manufacturing even better and that is what should be researched further. The determination and comparison of those factors that influence credit risk are a necessity for companies in the fast growing and fast acting industries like oil and gas, automotive, chemical, etc. New studies should help improve the predictive power of the methods and in that way increase the productivity and the feasibility of the industrial business in regard to the prevention of business failure and insolvency prevention. (Grishunin *et al.*, 2020).

3.2.8. Anomalies that predict business failure

Assumption is that accounts, that have a goal of predicting a failure of a business, are providing a truthful information about the financial state of a business. Sometimes, the centre of attention is the selection of the best machine learning method. Most recurring machine learning methods inputs used for prediction purposes are profitability, solvency and liquidity. Some studies included the implementation of the stock market details which are a good indicator of changes on a macroeconomic scale. Stock market is interesting because it is dynamic and can give a great insight in the current trends. Those trends can be researched and then applied in order to make the process of business failure less frequent and easier to outflank. These models are not always aware that there are many managers that purposely feed information that is incorrect to better their position on the market and to try to hide the fact that the business that they are managing is in a bad state of affairs which will lead to business failure. That misinformation of, better said, falsification of information leads to annual statements that are incorrect and are the reason why the business will most likely fail. The irony is that by doing that the help themselves in the short term but in the medium to long term they ensure that the business fails. The idea behind this paper was to study and research different accounting methods of detecting fraud and anomalies and analyse them in order to produce an insolvency prevention model that incorporates the risk of fraud and fights a business failure in that way.

“Annual accounts are not always a reflection of a true situation of a company; there is a presence of creative accounting practices, earnings management, profits smoothing and accounting fraud. Since companies are often in difficult situations, things above can distort accounting figures. Still, most of the models which predict bankruptcy do not incorporate indicators to detect accounting frauds. Those indicators are directing, and they measure distortions in depreciation, they detect exaggerated receivables and abnormal accruals. Some of the other indicators are indirect and they measure variations in debt, salesy or profits because companies that have financial problems tend to cover them. Because of those things, it is discovered paper that detect distortions in accounting that is built from several financial ratios that try to measure accounting anomalies. This index is effective cause of its application to private firm sample that provides main contribution of the paper." (Serrano-Cinca, Gutiérrez-Nieto and Bernate-Valbuena, 2019)

The results usually give a better prediction accuracy to firms that have given a good and trustworthy sample. That is a great action from the private firms that decide to help themselves and others by giving real data which can be used for calculations. To conclude, bankruptcy prediction is always easier to resolve in private firms as they have a better control of the whole business, in the issue of public firms the problem is harder to understand and harder to fight as public companies usually have a political impact and are financed in a different way which allow for a less risky outcome of an insolvency procedure. In practice, it is never safe to assume that the data is correct, but the data needs to be checked before an insolvency prediction method. The anomalies that may be present will be the reason that will determine if the prediction is a success or fail.

As conclusion, predicting bankruptcy for small businesses is a great challenge and problem. One of the biggest issues is the fact that the documentation that the business needs to fill in is unstructured and not standardized in any way which mean that the data will take a longer time to be implemented and there is a high chance that the person in charge of producing such documents will make a mistake and provide information that is false. Because of the uncertainty of data acquired in that way a new method needs to be developed which will allow for a data mining process which is not influenced by people in any way. That is where artificial intelligence and AI take over. For the case of small business, the bas way to produce such information are credit sales information. If credit sales information is used the insolvency is done quicker in small businesses. The time period is usually three years but with sales information the time period is six month and even three months which is a time period that is much faster than the traditional models. Credit card sales are also a good input variable and a trustworthy indicator because they cannot be influenced in any way. They come straight from the bank which is guaranteed by law to have information that is accurate and structured. (Yoon and Kwon, 2010).

3.2.9. Performance of bankruptcy models

Models for predicting bankruptcy were set up by the use of decision trees in various examinations and analyses along with the logistic regression and linear discriminant analysis. When there are outliers present, the last two show quite the sensitivity and the statistical financial ratios range were categorized by the process of developing a so-called univariate tree for each variable which is able to be explained. Ordinal variables on the other hand are shown as the terminal node numbers.
More than two percent was the hit rate of stable companies increased in case of the logistic regression, whereas when talking about the unhealthy companies the increase was not more than one percent. That are interesting information that show the true state of bankruptcy models in the world and the situation that is currently active in the process of insolvency avoidance.

If the models for predicting a bankruptcy were designed of a linear model, outliers and its values must be taken with caution. It can easily be concluded that a bankruptcy expectation can be predicted much better by using the mentioned models rather than the statistically - financial ratios. The number of researches concluded, and articles published considering bankruptcy prediction has grown sharply in the previous years, while on the other hand such studies are never complete because of the different approach in each of them. Using qualitative factors as independent variables is definitely a smart approach. Moreover, the use of financial ratios can also be improved by increasing the information core of the financial ratios. Classical measures used in accounting can be seen as the explanatory variables but also be considered mainstream. The use of classical methods allows for a method that is easy to understand and produce as it was produced many times through history.
The answer to the question what a financial performance is quite simple. It is the obvious result of a prior period where the first one is used as a base to the second one. Furthermore, this can be explained by developing an indicator variable that

reflects the value of the given financial ratio explaining if the given financial ratio is higher, lower or identical to the values from the previous period.

To sum up, subjective categorization is far more suitable for a dynamic type of variable than the objective one. The dynamic of the financial ratios must be taken into consideration when talking about the bankruptcy prediction. Furthermore, two simple and sufficient methods are suitable for being used in any kind of classification methods and its framework. (Yoon and Kwon, 2010).

3.2.10. Terminal failure process

Numerous studies have been focused on improving the machine learning models predictability. These methods are used by banks and institutions to find out their risks. One of the components used for that purpose is to have a system of borrowing of one year called a horizon. The prediction precision is a very important issue for credit giving companies in order to know the amount of a possible loss. The precision of an estimation is quite important in order to calculate the debt of clients to the credit institutions in the midterm for the knowledge factor in planning next steps in the crediting process. Most often traditional statistical models are used but their quality is questionable as they fail when there is a lot of data that needs to be predicted.

However, every company has its own path, which is the reason why some business will manage to find a way out of business failure, some will simply fail as they do not have the ill and the data in order to save themselves and the ones in the middle that are either slowly stopping or slowly rising.

“Some companies use traditional modelling methods such as discriminant analysis, logistic regression, survival analysis and a neural network. For each and every situation there is different type of solution and method. Models are used with test data to assess their prediction ability over 1-, 2- or 3-years period. Results are being compared to the results of the companies that uses traditional models. Some companies rely on instantaneous measures of their financial health (like financial ratios which are measured once). They tend to give up the ideas developed by all disciplines that are rooted in organizational theory. That can be dangerous and most of the time it leads companies into the bankruptcy." (du Jardin, 2015)

Also, lack of reference model and a lack of a theoretical infrastructure will lead to insolvency, bankruptcy and business failure. The issue with most machine learning methods is that they are strictly theoretical and allow no influence from the real sector which has the relevant data which would improve the data mining models. The positive part is that there are data mining techniques that can find specific patterns which are the beginning of the design of a company.

"All of the factors above, lead to models that have a lack of ability to assess stable forecasts over time. That is why some authors try to improve the model ability to correctly forecast the fate companies beyond a 1-year horizon. They use variables that are likely to provide a time dimension to a mode. It is idea that the model relies on a static conclusion." (du Jardin, 2015)

"In this study, two types of models were designed. First model is made out of the models that are designed for a given sector of activity. Chosen sectors were failed companies in France between 2003 and 2012. Second set is made out of models designed for the companies that belong to any sector of activity. " (du Jardin, 2015)

Discriminant analysis is a statistical model that produces finding the linear combination of these variables. The variables are binary and are represented in two classes. This method is used for calculations of variables and their comparison to failed and non-failed companies. First method used instead of discriminant analysis was logistic regression. It calculates the score of a company and the possibility of a bankruptcy.

Neural model network shows if company will go bankrupt or not. The calculation of scores is compared to a specific database. The is then used in a network of hidden layers and outputs that have no bias. The variables are characterized by a sample of observations by a set of measures that have a specific occurrence that needs to be forecasted. The research is processed is such a way that the network is assigned to each individual observation and adds the value to the status, if it is failed or not. That value is as near to the referenced value as necessary.

Not only one model was designed but a few of them so that companies can be quantified by different terminal failure processes. Some companies go through an insolvency period of a few years and another business will manage to survive even though they have similar financial profile. It is important how the company goes into the space of risk over time and it is shown in a self-organizing map that represents all financial profiles that some companies can embody over the time.

There is a right model for each and every situation; general model (traditional) and submodules. Different test samples were used to calculate companies' ability to survive. Firstly, all of the individual failure processes needed to be calculated. After that, it is needed to estimate the prototype failure process. Everything above was calculated using data that characterized each company over 3 years and it shows its financial health. Three maps were used to calculate failure process but if data are not available then it is not possible to estimate it. The businesses where classified according to their functions and the best possible alternative was produced to ensure that the best method is used for each specific business in order to ensure better results overall.

The result was the situation that a timeframe of one year is not enough time to produce relevant data and information which will produce an insolvency prediction. If a company is in a bankrupt mode, no additional information is will help its cause in fighting bankruptcy from a prediction standpoint. It is hard to calculate the reasons of bankruptcy and what is the right way out of that critical situation. Maybe the maybe the company is very liquid because its customers pay faster but on the other hand maybe it is on a verge of collapse as it can no longer pay the supplier and because of that they cannot produce goods that they are selling and that is providing the firm with income. The stabilization is seen in the three year period because that is enough time to produce all the information to fuel further insolvency avoidance models. (du Jardin, 2015)

Financial failure model that takes into account companies that go into business fail mode in a brief time period was the product of this paper. Those results are a work of over a year of calculating and the idea was to have a model that is as precise as a traditionally accepted model. This method is here to allow for an easier identification of liabilities or the ability to survive, they achieve better forecasts if some economic changes occur. It attempts to account the history of companies and finds best option for survival fighting. Failure-based models impersonate a different way of thinking when producing methods that are used for insolvency prevention proceedings in the business environment. The importance of failure-based models will be seen when the possibility to influence the credit data will be negated and the manager will have to provide data that is true and relevant in every way. Until that happens the models described here will allow for a seamless function of the insolvency models.

3.2.11. AI in calculating the risks of insolvency

Precise identification of what to assess is from the extreme importance in order to the result and business decisions be analysed so that its importance and added value to the company can be precisely examined.

Certain management aspects such as financial segments, customers and internal business processes are closely linked to the precise criteria of assessment because they offer an important and detailed overview of the health of the company. System accepted widely among the corporates is definitely the risk adjusted balance scorecard which makes the entire assessment process be implemented more easily and give sufficient results.

Along with the assessment model, a forecasting one makes also very important role in highly important managerial processes and making key business decisions. Above mentioned, ANN has proven to be one of the most important forecasting models, which is made through BP learning algorithm which easily notices problems of high criticism.

The RVFLN (random vector functional link networks) has been made to improve obstacles and problems like those and whose original idea is that there is no need for the hidden nodes and its coefficients to be implemented and adjusted by traditional learning approaches.

The problem with some certain measurements of company's operating performances is that they only include monetary factors which do not give the entire picture of the financial health of the company and can negatively affect on someone's judgement concerning the company's overall picture. One of the solutions to this problem can definitely be the BSC which in that case has to be incorporated into the risk management systems so that the output could be an extensive comprehension of company's profile and the goal of increased profit and risk relevance.

A global economic crisis starting in 2008 has made a huge shock on the global economic system revealing that the lack of efficient management and risk management systems had made the problem even bigger causing the negative effects to be spread even more faster and widely. It can easily be concluded that the poorly developed management systems can make the financial distress make more harm than it can be predicted.

The quality of the company's management can easily be represented through the operating performance of the company by extending the BSC with the returns that are risk adjusted and are therefore way more reliable in presenting the entire picture of the company's situation (Lin and Hsu, 2017).

3.2.12. Probabilistic modelling

Big economic crisis that has impacted the world's economy in 2008 has made small and medium enterprises (SMEs) to announce zero profit and losses. Insolvency, illiquidity and bankruptcy had become the main terms when talking about corporate health at that time. A great number of companies involved in various kind of industries have faced insolvency, not only in national but in global terms also and those problems have vastly spread from the financial system into the real economy. The main solution among the banking systems all over the globe was to implement an efficacious credit risk assessment into the rescue plans.

Mainly, the classification of the company's health has two different points of view. For example, looking from the investors point of view, the potential error of company being classified as bankrupted has a completely diverse consequence than the appearance of false alarm, or better to say a situation when a financially stable and a good health company is being classified as distressed.
Classification itself is a perfectly good toll for any kind of financial distress prediction, especially for investors with conservative views whose main goal is to put the risk of investment to minimum levels and put the control of the insecurity of their investment into their own hands (Antunes, Ribeiro and Pereira, 2017).

It can freely be stated that a certain degree of uncertainty is involved in steps of generalization and in a business environment that is prone to strong changes and dynamic movements and volatility each prediction is transient in a form that is probabilistic. And that is what makes the uncertainty quantified which is in some ways connected with the process of generalization and in other ways with the complexity of market behaviour. Generalization itself can be from big importance when it comes to decision making and developing processes because stakeholders are protected from unwanted situations such as bankruptcy or credit losses.

3.2.13. Non-inferiority of easy interpretable methods

Credit ratings and financial distress predictions discussed above are the most significant for evaluation of the economic health of the company. Predictions are also quite sensitive area since they need to be taken with major caution because inaccurate predictions may cause enormous financial losses. In connection to this, IT development, data mining and development of various financial models have an important role in preserving the good and stable financial picture of the enterprise. The knowledge of the mechanism learning is highly efficient and among the very best procedure that means process of algorithm which derives hypothesis out of the base of information with the aim of generalizing and not remembering samples for the unknown data evaluation. These programmes become a crucial part of computers and therefore serve for far better objective analysis and evaluation than the one made by humans. However, the subjectivity of humans can on the other hand have a positive impact to a certain percent on making business decisions.

The so-called DTs are conceptual processes in which the certain variables represent factors or the nodes of the decision tree where labels are known as its leaves.
In further development DT classifiers were made and used for training a classification that involves some bankrupt and some healthy companies. The input space in a decision tree is split by the nodes and the classification is determined by the leaves. Commonly used algorithm that built DTs is so called C4.5. which represents the enhancement of the ID3 algorithm. The main idea is that they both split data in accordance with the information gain. After the tree calculation, C4.5 removes branches not necessary and therefore reduces the size of the hypothesis. The amount of pruning is controlled by the confidence factor C and the leaf M contains the minimum of instances. Speaking of the so called ANNs which are made to stimulate the connection between the basic neurons that lead to general information characterized with high complexity, the discussed process was used for prediction of failure of more than 50 bankrupt and non-bankrupt banks in Texas that were connected by main measurable variables. Some other hypotheses called the white box, grey box and black box were also included in some studies. When talking about the hypothesis size the white box is limited to secure a quality interpretation which shows an excellent goal because of the great importance of interpretation and mostly non error percentage. All of the mentioned models either lose their precision or have problems giving the interpretation level able to compare. Applying these models will either lead to lowering performance or yield an even lower interpretability with the existing low performance. Strong decision supporters such as computing ratings and the forecast of insolvency are effective tools to rely on in making crucial business decisions.

To sum up, quite simple DT model shows better results than the black box models which shows it is possible to make the result best possible which is also easy to explain. Two models mentioned above have the ability to become each other but on the cost of losing ability to be interpreted. In conclusion, the best method is a completely personal decision according to one's preferences. What is also interesting is now knowing that the asymmetrical bagging works to tackle the loss of balance of information for various learning algorithms. To conclude, it can be said that the interpretable models involving thresholds are of great choice for classifying financial problems and are popular for using.
Even though the quality of the discussed models are almost the same, the hypothesis themselves are on the other hand different, the models both should be used to interpret the prediction results the best way possible (Obermann and Waack, 2015).

3.2.14. Dynamization of bankruptcy models

Because of practical relevance it is not easy to predict future insolvency or bankruptcy of companies so that makes a long-standing problem in financial and accounting areas. For the creditors, it is well known, that direct and indirect costs of those events are substantial for the whole economy. On this note, it is created a topic called "bankruptcy prediction" or "business failure prediction". Back in the 1960s pioneer researchers supposed that there is an information with the great predicting potential regarding the future bankruptcy of companies. First study identified that financial statements of companies can be used for calculation of potential explanatory variables. They build set a mandatory series of substantive elements for making prediction models of bankruptcy. It is empirical task to select variables for this model cause of lack of theoretical framework.

Firstly, a modeler must find correlation between bankruptcy occurrence and chosen the series of explanatory variables. If the correlation exists using the data from the previous period and if it is valid also for the future cases, then it is reasonable to assume that it will be valid for the prediction models. Multivariate classification methods are used to find the link between the two.

This is probably the main reason why this topic is applicable also for scientists dealing with mathematical approach of the bankruptcy prediction. Due to the fact that this could be find as multidisciplinary but also an empirical topic, it is able to find diverse od approaches and methods.

In bankruptcy predicting, application of static financial ratios is a “mainstream”. Majority of studies try to improve model’s capabilities by implementing a new classification method or combining them.

Using proposed indicator gives an efficient way for implementing the time trends of financial variables into cross-sectional classification method. This method is widely used in the literature and practice.

From the empirical point of view, predictive performance can be enhanced by applying the proposed dynamic indicator variables in combination with static financial ratios. Very important thing that was found during the study was that proposed indicator variables are more effective in the case of linear models. “The best result for bankrupt firms was obtained in the case of logistic regression where (hit rate increased from 81.8 to 83.0 percent by the inclusion of the proposed indicator variables). In the case of discriminant analysis, the inclusion of the suggested variables increased the hit rate of healthy firms and only marginally increased that of bankrupt firms.” (Nyitrai, 2019)

3.2.15. Financial ratios

These are the formulas that are used for calculating financial ratios:

- Gross margin (GM)
    - $GM = \frac{Gross\ profit}{Sales\ turnover}$

A net sales revenue that a company retains after incurring the direct costs connected with the production of the good it sells, together with the services it provides, is called the gross margin. Simply stated it is the revenue of the net sales minus the cost of goods sold, e.g. COGS.

Higher gross margin means better financial results for the company because the higher gross margin is connected with the higher capital a company retains on each dollar, which can be used to pay off existing debts or other costs.

- Operating margin (OM)
    - $OM = \frac{Operating\ profit}{Sales\ turnover}$

Operating margin shows how much of a profit company makes on a dollar of sales after it had paid for costs of production and other variable costs, but prior to paying interest or tax. Higher operating margin is better than the lower operating margins, so it can easily be concluded that the only good operating margin is the positive one or the one increasing over time.

- Net profit margin (NPM)
    - $NPM = \frac{Profit\ after\ tax}{Sales\ turnover}$

The net profit margin is a percentage of profit left after all the sales turnover have been deducted. The measurement shows how much profit a business can extract from its sales. It is supposed to measure the successfulness of the business. A high net profit margin that a business is pricing its products or services correctly and that the cost control is good.

- Return on equity (ROE)
    - $ROE = \frac{Profit\ after\ tax}{Shareholdes'\ equity}$

The return on equity ratio reveals the profit earned regarding shareholders' equity that is invested in a business. This measurement is mostly used by investors to calculate their perspective of a potential business investment. The return can be better when a business buys its own stocks from investors or by being more in debt and having less equity for its operations.

- Return on assets (ROA)
    - $ROA = \frac{Profit\ after\ tax}{Total\ assets}$

The return on assets is a comparison of profits in regard to the assets that the business has. It is an estimation of efficiency of management in using assets to develop profit. It is one of the tools that evaluate management performance. The limitations are that ROA is different for every industry and cannot be compared in that way. If a business is asset heavy like production, it cannot be compared to a business such as auditing which is asset light.

- Equity slope (ES)
    - $ES = \frac{Equity\ (t+\Delta t) - Equity\ (t)}{\Delta t}$

An equity slope is the change in value of a business account over a time period. If the slope is positive, it indicates that the business is profitable. If the slope is negative, it shows that the return that a business is achieving is negative and therefore it is losing money.

- Current ratio (CR)
    - $CR = \frac{Total\ assets}{Total\ liabilities}$

The current ratio is a ratio that measures a business's ability to execute short-term obligations. It incorporates all obligations up to one year. The purpose of CR is to show the investors how can a business maximize its current assets on the balance sheets to pay off debt and other necessities. A CR that is in line with the average of a specific industry is acceptable. A lower CR indicates a higher risk of default. A too high CR shows that the assets are not used efficiently.

- Debt ratio (DR)
    - $DR = \frac{Total\ liabilities}{Total\ assets}$

Debt ratio measures the leverage extent that a business has. This is the ratio of total liabilities to total assets, expressed in percentages or decimals. It is the proportion of assets that are financed by debt. A ratio greater then 1 show a considerable portion of debt is being funded by assets. High ratio indicates a high risk on not being able to pay interest rates. A ratio under 1 shows that a greater portion of the assets are funded by equity.

- Long term ratio (LTR)
    - $OM = \frac{Long\ term\ liabilities}{Shareholders'\ equity}$

The long-term ratio is a measurement that represents the long-term liabilities over shareholder's equity. This ratio provides a measure of the long-term financial position of the business. Business capability to reach its financial obligations it included in LTR.

4. Conclusion and Discussion

The current state of usage of machine learning algorithms is reassuring. The idea of digitalization is advancing rapidly, and a switch from traditional models is coming online. The most significant conventional insolvency downside models are the long waiting period of one year to have the relevant financial data. With the implementation of financial instruments, real-time insight is possible. The purity of the gathered data is the main factor that ensures the quality of insolvency prediction machine learning algorithms. We live in an age where information is global, where there are no limits regarding the ideas that change our perception of the economy, business and thinking.

Only changing the way we think and how we operate will negate the effects of insolvency. Real-time data gathering and proper usage of machine learning methods allow us to find the missing links that prolongate optimization and complicate day to day business. But, as with every relatively new technology, some adapt it quickly and feel the consequences of their boldness speedily and some wait until it is too late and jump to the trend when a new one is already emerging. That is why research is essential. Without studying the matters that genuinely regress the present, we as a collective will never reach the goal in front of us.

In this paper, helped by visual aids such as the VOSviewer software, the relationship between researchers and their research can be seen.

That is the issue of change, it is hard, and it is difficult to achieve as it incorporates something that is emotional. And because of feelings that get in the way a lot of data is simply oversighted by managers that are following their gut feeling that is totally different to the actual state of things in the business. The curve of a change procedure is a mathematical one and because of that it is easy to understand but challenging to implement. Nonetheless, change is a must, especially in the issue of an insolvent firm that still has the possibility to save the business and adapt. There is no right answer and no right path, but if no path is taken the only way forward is the path of bankruptcy.

Therefore, one must try to be better than it is and then, only then, will the road ahead be a bit brighter and hopefully prosperous again in the near future. Change is a process that inflicts pain and, in that way, prevents change from even happening. In order of it to happen there must be issued a directive which will influence the change disregarding the pain that it causes. But one very important information is that when a change process starts it never ends, it just spirals around and around in order to get more and more optimized.

The conclusion of this thesis is that the is no right way to do an insolvency prediction method. There are just too many variables, parameters, classifications, methods, inputs, outputs, calculations, reviews, data (structured and unstructured). The right way is researching the principles that are in line with the business (or country) they are researching.

In the matter of SME-s the following is concluded. A real time data acquisition method is need in order to get the data instantly to calculate the risks of insolvency much before it happens. The state of affairs in the current times if just too slow and outdated. The data collected is still often written on papers and the data that is online and available is often unstructured and hard to read as it is not standardized and every business develops its own way of providing information.

4.1. Theoretical and practical limitation

The limitations of this study are based on the technology limitations of artificial intelligence. The state of AI is currently still in development, but a 100% trustworthy option is still not available. On the other hand, all of the methods rely on data. And data is easily manipulated, especially financial data which can make or break a business. In that regard, the trustworthiness of data acquisition plays a huge role in the accuracy of the final result. A switch to a system of data mining that has no human interreference is a necessity that will allow for a process that can truly predict insolvency in its beginnings. Another limitation is the fact that each insolvency avoidance method consumes a vast amount of energy, data and time. This limitation could be improved through time when the technology finds a solution to the problem of manipulation unstructured data. The speed of calculation will be most definitely improved in the next few years as it is faster and faster in each iteration of every method.

One other limitation is the frequency of financial data that is the fuel of every bankruptcy prediction method. In the case of SMEs a data acquisition frequency of half year or in most cases one year is just to slow and in most cases the process of helping is to complex. With such business, that operate on a day-to-day basis, at least a weekly, or monthly frequency is a must in order to provide a solution in a timely manner. That means that a new standard needs to be developed which will allow researchers and business owners a possibility of having the information when it truly matters.

The theoretical limitations are limitations that affect the machine learning methods themselves. Each method has a different approach and function in a different way which limits the data that is inputted in each method. That also complicates the procedure of checking one method with another method and in that way producing a system that uses multiple ways of quality control.

4.2. Future research needs

For future and future studies, a deeper insight into data collection methods is needed to detect insolvency in its beginning. The current situation in insolvency avoidance is a major step up from the financial crisis of 2008 and the tools needed to prevent an event such as that have been developed. Optimization is the way how these methods will made advances that will make insolvency obsolete. Artificial intelligence approach and its further implementation will most definitely be the future. The most important factor that is worth the time researching is also one of the biggest limitations, so a breakthrough in its research should be one of the biggest advances in insolvency avoidance and prevention of critical business failure. This factor is real time data which will provide researchers with all the relevant information every time and any time it will be needed.

But every other advancement that will supplement the goal that is prevention of business failure because of insolvency will be a valuable contribution to society and will be a huge help to all struggling business that have that service or product quality but lack the financial knowledge that in the end bring profit or demise.

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