Cognitive Modelling of Bankruptcy Risk: A Comparative Analysis of Machine Learning Models to Predict the Bankruptcy

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***Abstract*— Machine learning models can assess the financial health of companies and predict the likelihood of them going bankrupt. Early detection gives companies and stakeholders more time to implement strategies to mitigate financial risks or take corrective actions to avoid bankruptcy. This can be particularly useful for companies as it helps them avoid potential financial difficulties, for example, the recent bankruptcy of Silicon Valley Bank (SVB) has led to market volatility, liquidity disruption, and economic instability. This paper compares machine learning models to determine which model predicts bankruptcy better. The dataset of 20 years of US company bankruptcy was obtained from Kaggle.com and consists of 78682 instances and 21 attributes. In this study, we applied robust preprocessing to increase the accuracy of bankruptcy prediction. It aids in determining significant factors contributing to operation uncertainty and helps regulators and investors forecast the probability of default for better risk management. We applied an 80:20 split for training and validation respectively in our dataset and followed proper tuning of parameters using cross-validation in the training set. We compared several performance matrices, including accuracy and ROC-AUC in various machine learning models such as logistic regression, KNN, decision tree, support vector machine, neural network, and random forest to demonstrate the validity of our study findings. The KNN Classifier has come up champion model with an accuracy of 94.41% and an ROC AUC of 80.45% among all machine learning models as better predictors for bankruptcy.**

Keywords*— *bankruptcy, machine learning, predictive analysis, svm, nn, logistic regression

I. INTRODUCTION

Understanding and predicting financial risk is one of the critical tasks carried out by regulatory agencies and private credit assessment companies across the financial sector everywhere. Bankruptcy is the event that happens when an entity (people or corporations) is unable to pay their debts and becomes insolvent. Bankruptcy is a grave concern for the overall economy. Hence, regulatory bodies and investors are always looking for early warning signs regarding the financial health of corporations to protect their investments and, in the case of banks, the deposits of customers [1]. For corporations, bankruptcy could lead to liquidation of assets to pay off the debt and stockholders, or they could go through a reorganization plan to try and get back on their feet based on the local laws and regulations. Possible reasons for bankruptcy include a weak business model, poor management practices, heavy reliance on debt, and conflict of interest with the audit process [2]. However, in many cases, bankrupt companies do not see profit nor manage to become solvent [3] and regular investors and depositors end up losing money.

Consumer trust is a very fickle yet decisive factor that the regulators and the corporations are trying to navigate around. Bankruptcy points out the negative sentiment, especially the weak financial scenario of the company, and puts more stress on the economy as consumers become wary. The bankruptcy of a corporation, whether a publicly traded company or a big company, is usually evident for a while before the actual bankruptcy occurs. Banks are particularly vulnerable in this case due to their business models inherently having the risk of running into a liquidity crisis, and rumors of poor financial health could lead to a bank run that could lead to bankruptcy rapidly [4]. That is why regulatory authorities must monitor the financial performance of the companies to detect signs of bankruptcy so they can intervene promptly since bankruptcy not only leads to the loss of investors and creditors but also to the loss of jobs and other business opportunities.

Predicting bankruptcy has been a topic that has been discussed since the 1960s. Before data availability and advanced machine learning algorithms came into the fold, financial ratios [5] and z-score models using financial ratios [6] were used to predict corporate bankruptcy. Many other researchers incorporated Altman's Multiple Discriminant Analysis (MDA) model in their approach. This philosophy began to change with better computing power, data availability, and machine learning algorithms that could employ better algorithms to produce meaningful results in the late '90s and early '00s. Models using machine learning algorithms like genetic algorithms [7], neural networks [8], and duration analysis using hazard models [8] opened the doorway for Artificial Intelligence (AI) use for predicting bankruptcies. With the progress of AI technology, models with more complex algorithms are now being used to predict bankruptcies, such as recurrent neural networks and long short-term memory algorithms [10]; extreme gradient boosting (XGBoost), support vector machine (SVM), deep neural network [11] and random Forest and neural network algorithms [12], etc. With more data and computational power, machine learning is expected to become more prominent in this field, and the models will become more efficient.

This paper aims to do a comparative analysis of machine learning models to find out which model performs better in predicting bankruptcies. A dataset of 20 years of bankruptcy data with 78,682 records is used in this paper with an 80:20 split for training and validation. After data processing and feature engineering, 7 different machine learning models are built to find out which algorithm shows better predictability for bankruptcy. The models compare 5 metrics: recall, precision, F1 score, accuracy, and area under the curve (AUC), and their results are analyzed. KNN and Random Forest were found to be the best-suited models to predict bankruptcy based on the results.

II. Literature Review

Barboza et al [13] tested several machine learning models such as support vector machines, bagging, boosting, and random forests to predict bankruptcy one year before the event. They compared the performance of these models with traditional models such as discriminant analysis, logistic regression, and neural networks. The researchers used data from 1985 to 2013 on North American firms, integrating information from the Salomon Center database and Compustat, analyzing more than 10,000 firm-year observations. The results showed that machine learning models were more accurate, on average, by approximately 10% compared to traditional models. The best models, with all predictive variables, showed that the machine learning technique related to random forest led to 87% accuracy.

Jabeur [14] created a predictive model for bankruptcy using a sample of 800 French firms from various sectors. The model was constructed using the DIANE database, which provides instant access to French business data for economic analysis. The sample was divided into two groups, with 50% used for training and 50% used for testing. Sami's motivation for this research was to improve upon traditional forecasting models. Partial Least Squares Logistic Regression (PLS-LR) was utilized to integrate a large number of ratios into the model, resulting in a coherent model at the coefficient level while retaining all ratios even with low weight in the analysis. The accuracy of this PLS-LR bankruptcy prediction was reported to be 94.5%.

According to Bredart's [15] study, which used a sample of 3,728 Belgian small and medium enterprises (SMEs), including 1,864 businesses declared bankrupt between 2002 and 2012, the Belfirst database (Bureau Van Dijk) was used to collect all the information regarding this sample of businesses. The total sample of businesses was split into three parts: 70 percent of the observations were part of the training group, 10 percent of the data was from the validation group, and 20 percent of the observations were used for the test. Bredart adopted a neural network for three explanatory variables: the businesses' solvency, liquidity, and profitability. The neural network showed a reasonable classification rate of 81.50% on test data.

Zelenkov et al [16] proposed a two-step classification method called TSCM to predict bankruptcy. This method uses genetic algorithms to select relevant factors and adapt the model to the application. In the first step, classifiers of various models are trained and combined into a voting ensemble in the second step. The authors used random sampling and feature selection techniques to ensure the necessary diversity level of classifiers. Genetic algorithms were used in the feature selection step and then in the ensemble's weight determination step. The proposed method was tested on a balanced data set of 456 bankrupts and 456 successful companies and 55 financial ratios and macro or micro business environment features. The results showed that the proposed method had the best accuracy value 93.4% among the tested models.

Keya et al [17] conducted a study on bankruptcy prediction using bankruptcy data from the Polish association over a period of five years. The study involved using various machine learning techniques to predict bankruptcy, with 80% of the data used for training and 20% used for testing. The authors utilized RFE to eliminate unsuitable features and SMOTE to rectify any inequality. SMOTE involves sampling a select few examples and replicating them to increase the number of minority category examples, thus balancing the distribution within the segment. The models used in this study include AdaBoost, Decision tree, J48, Bagging, Random Forest, and K fold cross-validation(k=10). The bagging accuracy range over the five years was found to be highest at 97%.

Zhang [18] utilized a combination of neural network, K Nearest Neighbor, and Random Forest techniques. However, the author did mention that neural networks can become prone to overfitting when dealing with large datasets. The study focused on predicting bankruptcy and relied on data from Sebastian Tomczak, a researcher at the University of Science and Technology, Poland. The training, testing, and validation data were divided into 80%, 10%, and 10%, respectively. Through experimentation, KNN with a K value of 3 and a truncate of 50 was found to be the most effective given the relatively small dataset. In conclusion, the author suggests that a smaller K value can lead to a more accurate prediction rate of nearly 99%.

Erodgan [19] conducted a study in 2012 that aimed to predict bankruptcy using a support vector machine. According to the author, difficulties encountered in implementing NNs led to deploying SVMs for predicting classification. The study included 18 failed banks between 1997 and 2003 and 24 successful commercial banks, and the banks were categorized based on 19 variables such as capital ratio, asset quality, quality, profitability, and income expenditure. Failed banks were assigned code 1, and non-failed banks were assigned code -1. The authors used different gamma and cost parameters to overcome any problem in generalization and reduce overfitting. The best accuracy was predicted at 98% when gamma was set to 2.

Shetty et al. [11] conducted a study on predicting bankruptcy using financial data of 3728 Belgian Small and Medium Enterprises (SME's) from 2002 to 2012. They used advanced machine learning techniques, including extreme gradient boosting (XGBoost), support vector machine (SVM), and a deep neural network. The dataset was divided into three batches: training, development, and testing. XGBoost was found to be one of the most successful methods for large-scale data classification and was used for predicting the categories of new inputs as bankrupt or otherwise. The accuracy of the XGBoost classification algorithm on the testing dataset was found to be 82%.

III. METHODOLOGY

According to the suggested methodology, pre-processing begins after data gathering is completed. The classifiers chosen for the study are Logistic Regression, KNN, SVM (linear kernel), SVM (RBF Kernel), Neural Network, and Random Forest. Hold-out validation processes were employed to train and evaluate the obtained data set on bankruptcy. Then we analyzed the results of each model to identify the best approach for forecasting bankruptcy. The proposed plan's general structure is shown in the figure.

A. Dataset collection

The dataset used in this study, "US Company Bankruptcy Prediction Dataset," was obtained from the Kaggle online domain. The dataset consists of 78682 instances and 21 attributes, including 18 predictive attributes and 1 class attribute. To predict bankruptcy, relevant attributes were used to identify bankruptcy, such as current assets, cost of goods sold, depreciation and amortization EBITDA (earnings before interest, taxes, depreciation, and amortization), inventory, net income, total receivables, market value, net sales, Total assets, total long-term debt EBITA, gross profit, total current liabilities, retained earnings, total revenue, total liabilities, and total operating expenses are being considered as predictive factors. The status-label class attribute was utilized in this process as the target value.

B. Dataset pre-process

Clean up the information that is previously available online from public sources. Since the attributes were absent from the data retrieved from the internet, the names of the attributes were initially assigned to the data (Uddin et. al, 2023). To remove missing values from the dataset, such as NAs or blank values, use the WEKA function "Replace Missing Values," which replaces NAs with the mean values of that attribute. Pre-processing of the dataset comprised handling missing values, data cleaning, feature extraction, and transformation of categorical variables.

C. Validation Process

Selecting an appropriate validation method is essential when working with a particular dataset. Hold-out validation is typically the best option for large datasets, as it yields accurate results. In this study, we employed the hold-out validation technique to test 20% of the dataset and train the remaining 80%. Using this validation process, we calculated performance metrics such as precision, recall, and F1-Score for each ML approach. The result analysis section provides a detailed demonstration of the performance metrics and output graphs. We have depicted the overall research process in a step-by-step flowchart.

D. Machine Learning Model

Machine learning algorithms are essential in predicting bankruptcy as they can analyze large datasets and identify complex patterns that may be difficult for human experts to detect. These algorithms play a crucial role in evaluating the financial well-being of both organizations and individuals, assisting in the detection of possible bankruptcy threats using sophisticated data analysis methods. Here we used five different machine-learning algorithms to predict bankruptcy.

1. Logistic Regression

Logistic regression is a statistical technique used to estimate the probability of a categorical outcome based on one or more input variables. Logistic regression is commonly used to predict a binary outcome, which refers to a situation where there are only two possible values, such as true/false or yes/no. Multinomial logistic regression is a statistical technique that can be used to analyze situations in which there are multiple discrete outcomes, beyond two possibilities. Logistic regression is a valuable analytical technique for solving classification problems, where the objective is to select the most appropriate category for a new sample. Given that several areas of cyber security include classification difficulties, such as detecting attacks, logistic regression proves to be a valuable analytical approach.

2. KNN

The K Nearest Neighbor (KNN) method is a simple, comprehensible, and adaptable machine learning technique. It is used in various domains, including handwriting analysis, image identification, and video detection. K-Nearest Neighbors (KNN) is particularly advantageous in situations where acquiring labeled data is prohibitively costly or unattainable, and it has the capability to attain a remarkable level of precision across a diverse range of prediction-oriented challenges.

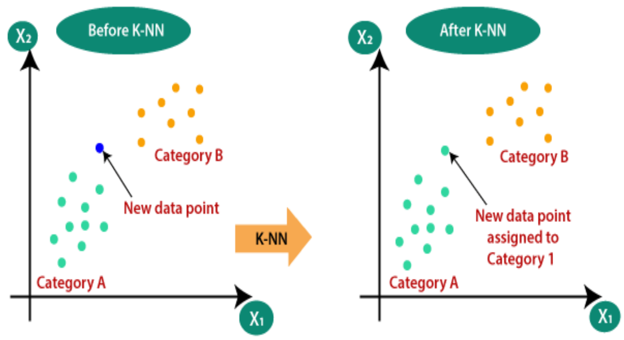

Fig 1. Diagram shows application of KNN algorithm before and after [20].

3. SVM

The Support Vector Machine (SVM) is a highly popular method in Supervised Learning. It is commonly employed for both Classification and Regression tasks. However, its primary use is in the realm of Classification problems within the field of Machine Learning. The objective of the SVM method is to construct an optimal line or decision boundary that may effectively divide an n-dimensional space into distinct classes, enabling accurate categorization of fresh data points in the future. The decision boundary that optimally separates the data points is referred to as a hyperplane. SVM selects the most significant points that contribute to the construction of the hyperplane. These exceptional instances are referred to as support vectors, so the approach is known as Support Vector Machine.

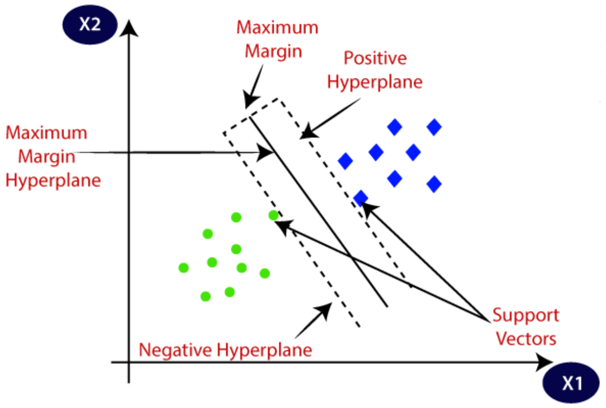

Fig 2. There are two different categories of SVM [21].

4. Neural Network

A neural network is an artificial intelligence technique that enables computers to interpret data by emulating the cognitive processes of the human brain. Deep learning is a machine learning technique that employs interconnected nodes or neurons arranged in a layered structure, similar to the structure of the human brain. It establishes an adaptable structure that enables computers to learn from errors and enhance themselves consistently. Artificial neural networks

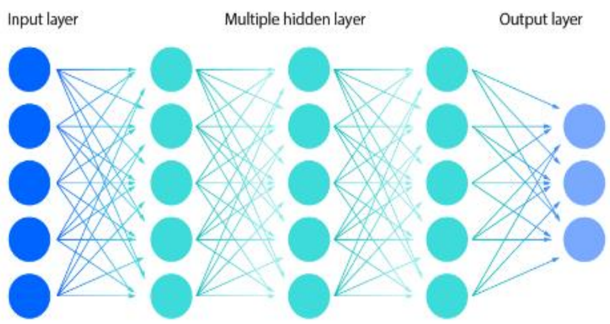

Fig. 3. Three different layers of Neural Network [22].

aim to address complex tasks, such as document summarization or facial recognition, with enhanced precision.

In general, the neural network consists of three following layers:

- The input layers.
- The hidden layer
- The output layers.

5. Random Forest

Random forest works by building multiple decision trees at training time and aggregating their results to make a final prediction. Each decision tree in the forest is constructed using a different random subset of the input features, which helps to reduce overfitting and improve accuracy [23]. The Random Forest algorithm is a widely used supervised machine learning algorithm that is specifically designed for solving Classification and Regression problems in the field of Machine Learning. As the name suggests, "Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset" [24],[28].

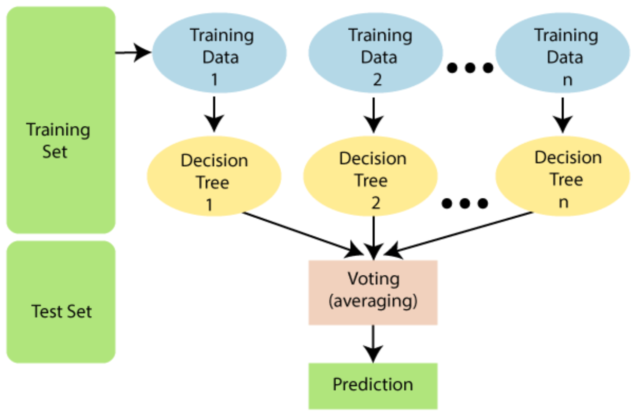

Fig. 4. Diagram explains the working of the Random Forest algorithm [24].

IV. RESULTS

Table 1 presents a comparison of seven ML algorithms, which were evaluated based on several performance metrics, including recall, precision, F1 score, accuracy, and area under the curve (AUC). Although accuracy is one of the commonly used performance indicators, it is insufficient to assess a model's effectiveness. A model's ability to distinguish between classes is evaluated by the AUC value, which becomes a crucial matrix for measuring its performance. The AUC value is analyzed to assess the True Positive Rate and False Positive Rate at different thresholds along a probability curve.

TABLE I. COMPARISON OF SEVEN MACHINE LEARNING ALGORITHMS

Models	**Accuracy**	**Precision**	**Recall**	**F1 Score**	**ROC-AUC**
Logistic Regression	0.936011	0.936641	0.999253	0.966935	0.667623
KNN	0.944144	0.95069	0.991788	0.970804	0.804537
Decision Tree	0.899028	0.950452	0.941228	0.945818	0.609836
SVM (Linear Kernel)	0.936328	0.936328	1.0	0.967117	0.591862
SVM (RBF Kernel)	0.936583	0.936622	0.999932	0.967242	0.599162
Neural Network	0.936519	0.937787	0.998439	0.967163	0.733672
Random Forest	0.941158	0.94121	0.999593	0.969523	0.853076

Figure 5 shows that K-Nearest Neighbors (KNN) and Random Forest exhibited the highest overall performance, achieving accuracies of 94.41% and 94.12%, respectively. These models also demonstrated high precision, recall, and F1 scores, indicating their effectiveness in correctly classifying bankrupt and non-bankrupt instances.

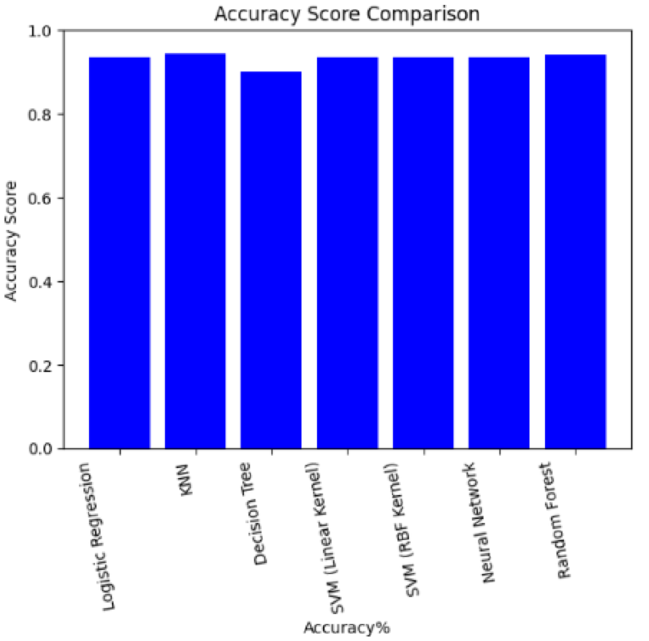

Fig 5. Accuracy analysis for predicting the Bankruptcy using machine learning models.

While Support Vector Machine (SVM) models showed better predictive performance in terms of accuracy and F1 score, they exhibited relatively lower ROC-AUC values compared to KNN and Random Forest. This suggests that SVM models may not perform as well in distinguishing between bankrupt and non-bankrupt instances at different classification thresholds.

Neural Network achieved a relatively high ROC-AUC value of 73.37%, indicating its capability to produce well-calibrated probabilities for bankruptcy prediction. However, its overall accuracy and F1 score performance were slightly lower than KNN and Random Forest.

Despite its simplicity, the Decision Tree demonstrated respectable performance with an accuracy of 89.90% and an F1 score of 94.58%. However, it exhibited a lower ROC-AUC value than other models, indicating potential limitations in capturing subtle patterns in the data.

The AUC measures how well the models can differentiate between positive and negative classes. A higher AUC indicates better results, with values ranging from 0 to 1. Having an AUC score 0.5 indicates that the test is incorrect, while a score of 1 represents perfect accuracy. In practical terms, an AUC score of 0.7 or higher is often considered acceptable for many classification tasks, including bankruptcy prediction. Performance between 0.8 and 0.9 is considered excellent, and scores above 0.9 are considered exemplary [18].

We used a hold-out validation process to train 80% of the dataset and test 20% to generate AUC curves and average results. Although Logistic Regression, SVM (Linear Kernel), and SVM (RBF Kernel) demonstrate high precision and recall values, their ROC-AUC scores are relatively lower than those of KNN and Random Forest. This suggests that while these models may perform well in specific evaluation metrics, they might need to be more effective in distinguishing between bankrupt and non-bankrupt instances at different classification thresholds.

Furthermore, Neural Network shows competitive performance with an accuracy of 93.65% and a precision of 93.78%, along with a relatively higher ROC-AUC score of 73.37%. However, it falls slightly short compared to KNN and Random Forest regarding overall accuracy and precision.

V. CONCLUSION AND FUTURE WORKS

Bankruptcy prediction is a critical aspect of financial risk management, aiming to identify companies at risk of financial distress before it escalates. The dataset utilized in this study comprises financial indicators collected over a period, enabling the investigation of bankruptcy prediction [25]. With an accuracy of up to 94.41% and precision of up to 95.07%, our research contributes to the early detection of bankruptcy, allowing for proactive measures to mitigate financial losses and potential economic repercussions [26]. Employing machine learning algorithms such as K-Nearest Neighbors (KNN) and Random Forest, our findings indicate promising results in accurately predicting bankruptcy. KNN demonstrates strong performance across various metrics, including precision, recall, and F1 score, while Random Forest achieves high accuracy and ROC-AUC scores. These results underscore the efficacy of machine learning-based approaches in augmenting financial risk assessment strategies [27]. Future research endeavors may incorporate additional datasets spanning diverse industries and explore advanced classification techniques to enhance predictive capabilities in bankruptcy prediction further.

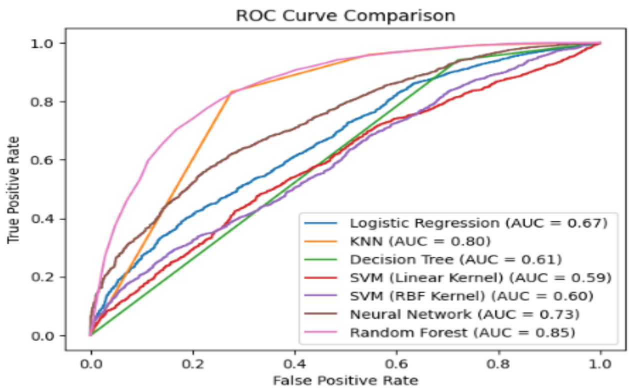

Fig. 6. ROC Curve Comparison

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