A Survey: Credit Sentiment Score Prediction

A. N. M. Sajedul Alam[1], Junaid Bin Kibria[1], Arnob Kumar Dey[1], Zawad Alam[1], Shifat Zaman[1], Motahar Mahtab[1], Mohammed Julfikar Ali Mahbub[1], Annajiat Alim Rasel[1]

[1] Department of Computer Science and Engineering, School of Data and Sciences (SDS), BRAC University, 66 Mohakhali, Dhaka 1212, Bangladesh
{a.n.m.sajedul.alam, junaid.bin.kibria, al.hasib.mahamud, arnob.kumar.dey, muhammed.zahidul.amin, md.sabbir.hossain1}@g.bracu.ac.bd, annajiat@bracu.ac.bd

Abstract. Manual approvals are still used by banks and other NGOs to approve loans. It takes time and is prone to mistakes because it is controlled by a bank employee. To improve different aspects of Credit Scoring prediction, numerous machine learning and data mining approaches have been used. The main goal of this survey is to look into current sentiment analysis models that have been used to generate credit scores.

Keywords: Credit Scoring, Sentiment Analysis, Fintech, Natural Language Processing, NGO, Credit Default

1 Introduction

Banks and other NGOs still use manual approvals to approve loans. In this way, the bank employee has to carefully monitor whether the client is eligible for the loan or how much loan should be given to him. Since it is managed by a bank employee, it is time consuming and prone to errors. If a client does not council their loan money then the bank suffers a loss. So loan prediction methods can be used to approve a loan in a short time and at low risk.

Credit scoring (CS) is an important and successful risk management tool used by banks as well as various financial organizations. It gives suitable recommendations on loan issuance and eliminates financial risks. As a result, businesses and banks are attempting to address the CS threat with unique automated solutions in order to secure their own funds and consumers. Different machine learning (ML) as well as data mining (DM) techniques have been utilized to enhance various elements of CS prediction in recent years.

Sentiment analysis, often known as opinion mining. It is a natural language processing (NLP) technique for determining the emotional tone of a written text. It is a common method for businesses to evaluate and classify customer views on a product, services, and concept. It entails analyzing text for sentiment and subjective information using data mining, machine learning (ML), and artificial intelligence (AI). Sentiment analysis tools assist businesses in extracting information from unstructured and disorganized language found online in places like blog posts, emails, web chats, social media channels, comments, support tickets and forums.

Predicting individual credit score using sentiment analysis is a fascinating technology by which we can predict the creditworthiness of individuals by analyzing their sentiment data using sentiment analysis. On the other hand, we can also classify the loan applications regarding the sentiment for taking the decision of granting them.

The current supremacy of machines having to learn natural language processing approaches has established a culture of exaggerating model precision rather than investigating the causes of their failures. However, for many downstream AI and NLP uses, such as banking, healthcare, and autonomous driving, interpretability is a must. Rather than providing a "new model," this paper examines the error patterns of certain well-known sentiment analysis approaches in the financial industry. They demonstrate that [1] techniques belonging to the same groups are susceptible to similar mistake patterns, and [2] frequent errors have six categories of language traits. These findings offer valuable insights and practical advice for enhancing sentiment analysis algorithms for financial services.

When it comes to commercial loans, credit risk evaluation is a crucial step for financial institutions to take. Manual investigation of a firm's general state via customer proper research reports, on the other hand, is time and labor intensive. The GMKL model is used in this research to present a revolutionary credit risk evaluation technique that automates the decision-making process. Sentiment indexes are created by mining client due diligence report text content for opinions, which are then utilized as information for model creation. The technique stands out by incorporating sentiment analysis into credit risk assessment in a novel way. The method's performance is tested using a dataset of real-life loan approvals.

Microfinance institutions primarily assist those who are unable to access traditional banking services due to a major absence of sufficient guarantees. Because of this, the institutions are at an extremely elevated danger. Financial firms use credit scoring to determine whether or not their customers are creditworthy. The author of this work provides a knowledge model which depicts the primary factors that might influence a credit score. A literature research was carried out to establish the many factors that influence credit scores. In the articles examined, a variety of models were discussed. The key dimensions of credit rating evaluation as well as their linkages have been identified using these models. Based on their research on current models for credit scoring in microfinance institutions, they developed a knowledge model for credit scoring. This paper proposed a generic model that is comprehensive in nature. It is possible to apply this model at the beginning stages of the rating model development process, as well.

Sentiment Analysis (SA) has gotten a lot of attention over the decades since it looked to be a huge advancement. Sentiment analysis (SA), often known as opinion mining.SA is often connected with customer-voice materials, such as reviews and research replies, as well as online and web-based life and social security resources for applications ranging from education to customer service to clinical treatment.Throughout this research, they lead a Sentiment Analysis of Client Surveys that has a significant impact on a business development strategy. They used Twitter data as an input variable in the form of a CSV file.They used SVM, NB, KNN, DECISION TREE, LOGISTIC REGRESSION, RANDOM FOREST. Researchers first gather data and group it into positive & negative data categories in order to begin this procedure. After the data has been grouped, they map out the various groups. After that Researchers use KNN and other algorithms to do a sentimental analysis.

Credit is the foundation of online store survival. When a transaction is completed, both parties can give praise, mid-level review or bad review to the other party. The second review is more representative of the actual credit rating of the store and can effectively improve the phenomenon of false brushing.

Peer-to-peer (P2P) lending is based on an electronic business platform and electronic commerce credit. In P2P lending, borrowers and lenders can use the internet platform to achieve online transactions. There is lower transaction cost, while the loan process is simple and easy to operate. Credit companies already use information from users from Facebook, LinkedIn and Twitter to evaluate credit risk of the consumers. Social data is most useful for people with little or no credit history. A person's social identity, online reputation and professional contacts should become a factor in the assessment of credit risk.

The sole purpose of this survey is to explore existing models of sentiment analysis which were used for generating credit scores and find out possible future implementations, limitations and extensions of those works. In this survey, we tried to get an overall idea of a total of eight research papers to bring out an overview of implemented sentiment analysis models for predicting individual credit defaults.

2 Survey Details

Xing et al. [3] in their paper, it has been seen that, given the same models, sentiment analysis results in the financial sector is much less accurate. MCC falls from over 74 to over 42 on average, F-score falls from 86 to 80.60, and accuracy falls from over 84 to over 71. The error frequencies reveal that lexicon-based systems create consistent errors, for example, SenticNet produces higher mistakes both for positively and negatively sampled data. In contrast, four out of five attempting to learn models (SVM, fastText, BERT and bi-LSTM) generate more false positives than false negative mistakes. This finding might imply that they are unable to address the problem of unbalanced data; yet, S-LSTM has learnt to make well-balanced mistakes. Because of its considerable expressive capacity, BERT has the top scores on all measures for something like the Yelp dataset.

Inside "model clusters," pairwise correlations are greater. They find the strongest correlation between SVM and fastText in the left matrix, and so build machine learning-based clustering. Similar to the deep learning system cluster (bi-LSTM, BERT, S-LSTM), the deep learning model cluster (bi-LSTM,BERT and S-LSTM) does have a darker shade. OpinionLex and L&M are likewise significantly associated (corr with a percent of 40%), however SenticNet loosens the lexicon-based cluster. This might be owing to the belief that SenticNet uses syntax to classify sentiment.

Zhang et al. [4] in this paper showed that the GMKL model is used in this work to propose a unique credit risk evaluation technique. This suggested technique is unique in that it incorporates sentiment analysis into credit risk analysis. The sentiment of over 950 analysis outcomes of the proper research report is regarded as a supplemental reference when compared to the standard credit evaluation approach. The sentiment score and indicators of finance are employed as input features in the GMKL model to automate the judgment process. The scientific experiment is conducted using a real-life loan-granting dataset, with over 1600 applicants serving as legitimate examples. The results suggest that integrating the emotion indicators improves classification performance significantly. Furthermore, the increase in the true negative variations that the sentiment results from the analysis of the proper research report improves the capacity to avoid fraud risk. When combining sentiment indices with financial indicators, GMKL has shown to be the best appropriate categorization model.

A novel approach has been developed by Raju K. D. and Dr. Jayasingh B. B. in order to provide accurate impressions of the restaurant or hotel. [5] Using audits, systems such SVM, KNN, NB, and so on may be set up to get results including "mad," "sad(bad)," and "glad". This is the most accurate technique to determine the survey's extreme. The feature pick has been based on the detected reviews of the specific eatery. The new data set was utilized to categorize the reviews in the Testing stage.

Authors Addi KB and Souissi N present a broad and comprehensive overview of credit scoring information in their paper. [6] With all of the existing data collecting techniques and the rate at which they are improving, financial organizations may be able to obtain substantially more useful information on customers and their environments. This study proposes a generic ontology model that may be used in any financial organization to create a generic credit scoring system.

The currently widely used evaluation system is compared with the evaluation system of this paper [7]. Through the comparison of pictures, we can clearly find that the scores of the analyzed comments are more detailed. After the improvement, specific words will be presented, and the label of the keyword language will be more completely supplemented. This avoids users who are threatened by praise or their own review habits.

In this paper [8], they used a public dataset from PPDai to study the loan default. Being different from datasets from America, their dataset is not detailed enough, without a FICO score. In order to solve the asymmetric information between borrowers and lenders, they added social behavior information into the variable sets to build the credit scoring model. The experimental result showed that although the dimension of the dataset is still not high, their model has good classification accuracy.

3 Analysis

We produced **Table 1** to help us analyze our survey findings by giving a brief summary of each article's core topics and classifying them into sub-domains and sub-disseminations within each domain.

Table 1. The following is a list of the articles that were considered for this Systematic Literature Review.

Articles	Major Domain	Sub-Domain	Key Concept
Financial Sentiment Analysis: An Investigation into Common Mistakes and Silver Bullets Introduction [3]	Financial	Banking	They compared the performance of some of the most well-known lexicon-based, machine learning-based, and deep models for financial sentiment analysis in this research. By displaying mistake patterns and undertaking language analysis, they went beyond merely comparing model metrics.
Can sentiment analysis help mimic the decision-making process of loan granting? A novel credit risk evaluation approach using GMKL model [4]	Financial	Banking	This paper approached the risk evaluation using a model named GMKL. By using sentiment analysis, they somehow mimicked the decision making system while granting the loan
Machine Learning for Sentiment Analysis for Twitter Restaurant Reviews [5]	Online Platform	Social Media	Throughout this research, they show how sentimental analysis was utilized to identify consumer reviews, including how those reviews were effectively identified using various classifier algorithoms.
An Ontology-Based Model for Credit Scoring Knowledge in Microfinance: Towards a Better Decision Making [6]	Financial	NGO	The research described in this study is based on an analysis of many models to determine characteristics of credit score in a microfinance environment, with the goal of developing an ontological model that depicts the dimensions that affect credit score including their interrelationships.The suggested

			methodology will aid such organizations in making decisions, particularly in evaluating loan applications
Research on Credit Evaluation Model of Online Store Based on SnowNLP [7]	Online Platform	Shops	The online store credit rating is a reflection of the seller's integrity and the quality of the product. The level of the credit rating directly affects the buyer's desire to purchase. Compared with the credit evaluation system commonly used in online stores, the evaluation results of this paper are more accurate, detailed and intuitive.
Research on Credit Scoring by fusing social media information in Online Peer-to-Peer Lending [8]	Online Platform	Social Media	Online Peer-to-Peer (P2P) lending market is rapidly expanding in China. We construct a credit scoring model by fusing social media information based on a decision tree. The experimental result shows that our model has good classification accuracy. However, the credit rating is not as important as the platform described.

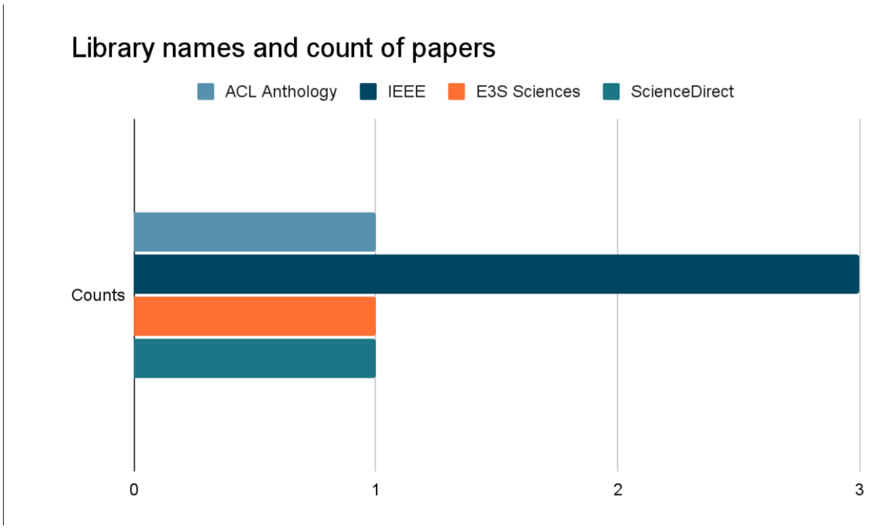

Fig. 1. Library names and count of papers from them.

The greatest counting number in **Fig. 1** indicates that the IEEE library holds the majority of the papers among the following papers. The number of publications in other libraries, such as ACL Anthology, E3S Sciences, and ScienceDirect, is the same.

Four libraries were used to uncover intriguing study topics for this project. This work selects conference papers from such publications' collections that are relevant to the research issues that are being investigated in a complete literature assessment of the acceptability of non-fungible token technology. Using the search capabilities of each publishing repository, this study critically analyses the publications related to our study goal. The libraries of all seven publishers are included in **Table 2**.

Table 2. List of the libraries that were searched.

No.	Library
1	ACL Anthology
2	IEEE
3	E3S Sciences
4	ScienceDirect

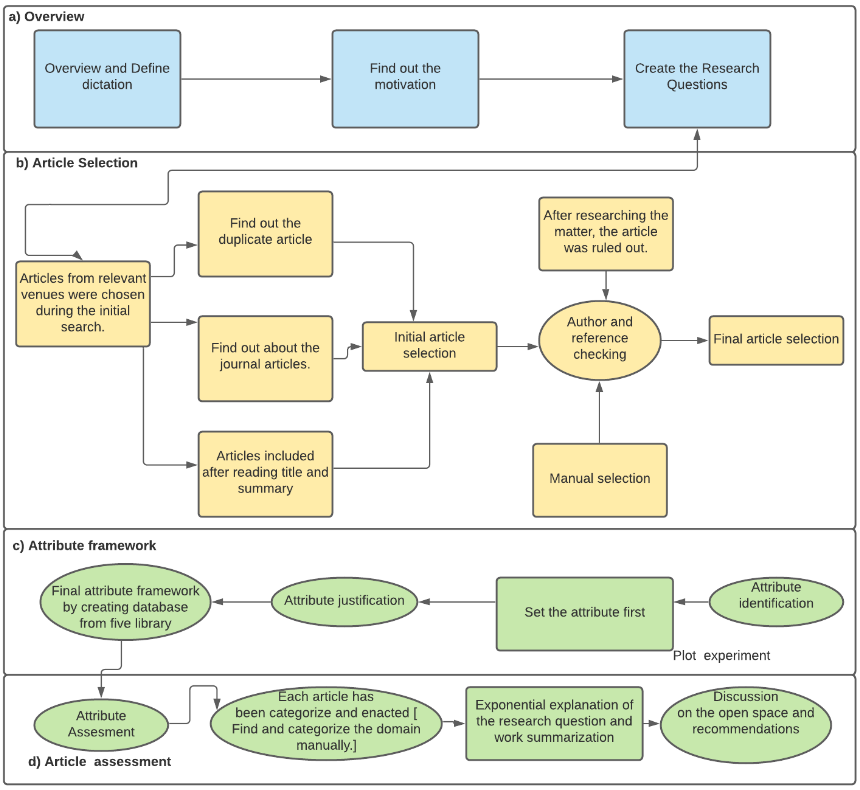

Fig. 2. Overview of Survey Details [2], [3], [4], [5]

The complete explanation of survey specifics is presented in **Fig. 2**, which depicts the beginning to finish section of the survey, that is, how the articles were selected, how the survey was conducted, and how the final suggestions were discovered. Kitchenham's approach, which comprises attribute selection, attribute framework, attribute assessment, and research questions, was used to create the whole procedure shown in **Fig. 2**. [9].

3.1 Sub Domain List:

I. Banking

II. Social Media
III. NGO
IV. Shops

3.2 Major Domain List:

I. Financial
II. Online Platform

We split the six articles into two primary domains based on two genres: **'Financial'** and **'Online Platform'**, based on the four subdomains we picked. **Table 3** shows which papers belong to which genres, and it can be seen from the table that all of the articles in this section may be allocated evenly.

Table 3. Genre distribution of selected papers.

Genres	Titles	Counts
Financial	a) Financial Sentiment Analysis: An Investigation into Common Mistakes and Silver Bullets Introduction b) Can sentiment analysis help mimic the decision-making process of loan granting? A novel credit risk evaluation approach using GMKL model c) An Ontology-Based Model for Credit Scoring Knowledge in Microfinance: Towards a Better Decision Making	3
Online Platforms	a) Machine Learning for Sentiment Analysis for Twitter Restaurant Reviews b) Research on Credit Evaluation Model of Online Store Based on SnowNLP c) Research on Credit Scoring by fusing social media information in Online Peer-to-Peer Lending	3

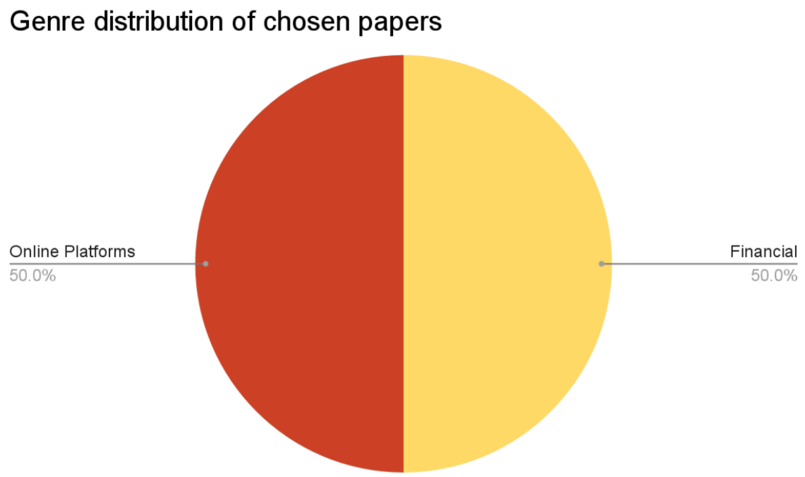
Genre distribution of chosen papers
Online Platforms
50.0%
Financial
50.0%

Fig. 3. Genre distribution of selected papers.

We have shown the categories into which we've split our works in **Fig. 3**. We discovered that half of our documents were financial and the other half were from online platforms throughout the categorizing process, resulting in a 50-50 ratio.

4 Conclusion

In this paper we surveyed six papers. We demonstrated the solutions that the surveyed papers produced to handle the problems of credit risk. We categorized the papers into two Domains including Financial and Online Platforms while further branching them into four subdomains. The findings we got from this survey are really distinguishing for the future implementations of sentiment analysis in credit scoring systems. To sum up this survey we can say that, in the banking sector, social media platforms, NGO, shops in these subdomains, there are already existing models of sentiment credit score system and in future more and more applications will be there to make decisions of credit worthiness of individuals by machines.

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