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A SURVEY ON BIG DATA METHODOLOGY: LARGE-SCALE DATA-DRIVEN FINANCIAL RISK DEVELOPMENT

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Abstract: Big data has a significant impact on Internet credit service providers as well. Initial results show that even people with bad financial status may be assessed, as well as those who have good credit. Credit rating agencies also rely heavily on big data. China's two official credit agencies, financial information of just 0.3 billion individuals, for instance. Others only have their name, date of birth, and address, therefore standard models are unlikely to provide good credit risk forecasts. This scenario makes it difficult for financial institutions to reach out to new customers.In this situation, big data is advantageous since it allows for infinite data access. Financial systems make use of transparent information methods to efficiently deal with credit risk. By combining the benefits of cloud computing and information technology, Market-based credit systems for both firms and individuals may be impacted by big data. With the use of mobile internet technology and cloud computing, non-internet-based traditional financial transactions may now use crystal pricing generation processes in cloud computing and big data.It establishes a good interaction between the regulatory authorities of the banking and securities sectors, in addition to providing information to both borrowers and lenders. Multi-dimensional variables arise when a firm has a huge data collection from many sources. However, maintaining large datasets is challenging; in certain cases, if huge datasets are not properly handled, They can appear to be a hindrance rather than a help. Data mining technology, which employs decision trees, neural networks, and Association regulations for managing a large volume of financial market data can help alleviate these issues. FinTech companies are more equipped than conventional financial institutions to handle large amounts of data because they can do it more consistently, efficiently, effectively, and at a lower cost. They can analyse and provide a greater number of customers with more in-depth services because of this. They can also benefit from systemic financial risk research and predictions. Individuals and small enterprises, on the other hand, may be unable to afford direct access to big data. Various information organisations, including professional consultancy businesses, relevant commercial agencies, and
so on can use big data in this circumstance. In this paper, a survey is taken in An Effective Big Data Methodology for Large-Scale Data-Driven, Financial Risk Developing using Logical Regression and various methods.

Keywords-Market-based credit systems, cloud computing, Big Data Methodology, Financial Risk, Logical Regression

I. INTRODUCTION

Both real estate and financial enterprises involve a significant amount of risk. Individual and institutional investors alike weigh the potential return and risk of an investment when making investment decisions. Individual investors' financial risk tolerance appears to be a critical determinant of their asset selection and use of savings in financial markets in this context. As a result, this element is crucial for both personal financial planning and portfolio optimization for investors.As a result, financial service providers must determine an individual's financial risk tolerance to be able to offer their clients the services they require. Financial risk tolerance is a personal characteristic that defines how much uncertainty a person can accept while making financial decisions. Risk aversion is commonly used instead of financial risk tolerance, despite the fact that it implies the reverse. When someone avoids risks, their degree of financial uncertainty and comfort diminishes. The linked study has sought to explain risk tolerance in the context of behavioural finance utilising normative models given by classical finance (such as anticipated utility theory and descriptive models based on behavioural and/or psychological variables)[1].

Providing credit is a vital activity for banks all around the globe, and it is a key driver of economic growth. An organisation called the Hong Kong Institute of Bankers says that a company's ability to manage credit risk and credit management systems affects whether it will be successful or not. Credit risk is the most serious threat to the banking system since it represents the majority of the sector's assets. Credit risk is, in fact, one of the most pressing issues facing banks today, and much research is being conducted to reduce risk. Risk management is an essential component of most big businesses' and financial institutions' business strategy, therefore it is vital to assure the sustainability of their activities. We have no way of knowing if file fraud or bank fraud has occurred, since we only have data on defaults. Customers are also concerned about loan repayment. Using the bank's customer data, the credit score algorithm can properly assess the applicant's credit risk. To anticipate the credit of the client, the income of the user, and the family situation of the user, the logistic regression hybrid technique is employed [2].Financial firms rely heavily on analytics and the outcomes of big data management. Despite the fact that all data mining and data categorization operations are taking place for financial decision making, analytics prefer data visualisation. When forecasting financial risks, the accuracy of data analytics is always a major problem [3].

Data, not oil, is widely regarded as the world's most precious resource. Massive amounts of organised and unstructured data dispersed over several platforms, including multimedia data, are referred to as "Big Data," and they are practically hard to handle with standard databases and software tools. The exponential growth in processing power and storage capacity has made it possible to capture massive volumes of data of many different sorts with relative ease. As a result, both commercial and public sector organisations, as well as society at large, stand to benefit significantly from this sort of data[4].

Because of big data technology, finding relevant insights for data-driven decision-making and taking advantage of reduced financial market risk have never been more crucial. Previously, analysing stock return volatility was a typical empirical indicator of a company's instability and risk, based on previous stock prices. To forecast stock prices, several financial data analysts used time series modelling approaches. These studies were primarily concerned with parameter estimation and the testing of the fitted model's economic assumptions. They believed that well-defined market phenomena might capture stock price movements.Financial reporting has recently been described as the collection and presentation of historical overall performance and company shares. In financial reports, managers must disclose a variety of financial risks connected with operations, among them are risks associated with loans, interest rates, and currency fluctuations. Linking financial report textual information to volatility in stock returns is an appealing information economics approach for evaluating the notion of market efficiency [5].

Algorithms are employed in a variety of fields to achieve a variety of goals. For example, they are used in businesses to hire people who are a good fit for the job. Algorithms can help to simplify the process, make it faster and more fluid, and so on. Algorithms, on the other hand, are a collection of programmes with specific goals in mind. For example, during the recruiting process, it may inject prejudice or a certain profile, and then "shape" the individuals working in the business. It's the same with loan provisions from a bank to a company, where the choice is determined by the algorithm. As a result, it is critical to comprehend these types of abuses and devise methods to restrict the usage of algorithms [6]. Logistic Regression (abbreviated as LR) is a technique that use the whole data set to train a single classifier [7]. Logistic regression is the best fit, and it is a numerical demonstration approach. The area must depict the relationship between many autonomous explanatory variables and the variable response. In many applications, the response to repeating interest or ward variables must be constant, and hence carry an infinite number of characteristics with no top or lower bound. Scientists have determined to forecast each element in predicting response variables in response to diverse difficulties and consumer confused behaviour [8]. Using the bank's customer data, the credit score algorithm can properly assess the applicant's credit risk. Using logistic regression and other algorithms, they can tell if a consumer has good credit, how much money they make, and whether they have children. This article will primarily cover An Effective Big Data Methodology for Large-Scale Data-Driven Financial Risk Development Using Logical Regression and Other Methods.

II. LITERATURE SURVEY

Arun Bansal et al. [9] Following the stock market crash of October 1987, Wall Street investment banking and brokerage businesses are adopting more effective risk management strategies. Financial institutions are creating innovative techniques to employ sophisticated technological applications in risk management genuinely in order to protect themselves as they have a better knowledge of them.There have been recent advances in risk management technologies including the invention of algorithms as well as software and hardware, and market data (RMT). Progress in risk management has affected the identification, measurement, and design of financial risk reduction strategies at all three stages. Five areas of RMT progress are examined in this article: Communication software includes things like object-oriented programming, parallel computing, neural networks, and artificial intelligence. You can utilise any of these for the development of systems that increase the value of an organization's operation. A business value linkage study illustrates how to analyse and justify the utility of complex technologies in order to justify their costs.

LianDuan et al. [10] People produce data more quicker and gather data much larger than ever before in business, research, engineering, education, and other fields because to the development of automatic identification, data collection, and storage technologies during the last few decades. Big data has developed as a critical field of study for practitioners and scholars alike. It has a significant influence on data-related issues. In this article, we highlight the major challenges surrounding big data analytics and then examine its applicability to business concerns.

Tsun-Siou Lee et al. [11] In addition to accounting variables, binary logistic regression models were applied to a variety of corporate governance indicators. One aspect of corporate governance that was investigated was the percentage of board and management shares pledged as collateral for loans, the separation of control rights from cash flow rights, and the number of board (supervisory) seats held by the largest shareholder. Research shows that the more a company's largest shareholder has power over its board members and supervisors, the more likely it is to face financial difficulties the following year. This is reflected in its stock pledge ratio. The counter-argument that controlling owners may want to extend the expropriation honeymoon and so keep the businesses out of financial trouble is unsupported.

Tsan-Ming Choi et al. [12] Many industrial systems engineering and cybernetics specialists and practitioners are fascinated by the term "big data." It's clear that firms might benefit from big data analytics. Because connected industrial systems have many data collection routes, business operations and risk management can benefit. Big data research, on the other hand, is still in its infancy. Its emphasis is rather hazy, and related research are not effectively integrated. They demonstrated how big data analytics may be utilised to address problems in a specific application sector. The development and improvement of technology for industrial-based business systems, as well as industrial system dependability and security, and operational risk management are all examined. Future research directions are also explored and identified.

Hussein A. Hassan Al-Tamimi et al. [13] The goal of this study is to look at the relationship between financial risk and the performance of Islamic banks in the Gulf Cooperation Council, as well as the relative importance of the most common types of risk. From 2000 to 2012, the study examined 11 of the Gulf Cooperation Council's 47 Islamic banks, based on data that was readily available. It was possible to find this information by searching the Bankscope database. A bank's performance was measured using a variety of metrics, including return on average assets (ROA), return on equity (ROE), and risk measures. Credit risk, liquidity risk, operational risk, and capital risk were the four categories of financial risk considered. Regression analysis has revealed a substantial connection between Islamic banks in the Gulf Cooperation Council's performance, capital risk, and operational risk. The findings show reveal a strong negative link between the performance of Gulf Cooperation Council Islamic banks.

Sulin Pang et al. [14] This research looked into the commercial bank. We look into the big data systems used by Chinese commercial banks, the unified risk management chain, and the implementation of commercial bank risk control under conditions of an intelligent system control model. Commercial bank data systems are discussed, as well as the influence of dynamic stability on commercial bank business models. The financial indicators utilised in this study are the fourth net profit, the average rate of return on total assets, non-performing loans, and the capital adequacy ratio data analysis system, with the industrial and commercial bank system emerging as a dynamic reference. The money in commercial banks is handled securely.

Wei-Yuan Huang et al. [15] Given that there are so many variables at play in the financial market, predicting price movements may be extremely difficult, particularly during market falls. Low-risk entry points are critical for investors looking to make money. Market Profile Theory is used to discover the greatest short-term entry and exit opportunities in financial big data research by dispersing the point of control (POC) on multiple trading days. We expect to find market insights and behaviour that will help traders make money in the very short term. Finally, the Taiwan Index Futures Market disproves the flimsy efficiency market hypothesis. A prior trading day's POC can be utilised as a guide and recommendation for an entry point, according to the findings of this study. The highest profit return is obtained by joining the trial with a 5-day historical POC. It also shows that POC possesses the feature that the majority of merchants accept its price.

Yan Zhang et al. [16] Enterprises face financial risks because of the ambiguity surrounding financial operations and dealing with financial relationships. According to information from the corporate finance system, association rules and a Bayesian network were used to identify financial risk factors and risk transmission channels. Risk factors are found using association rules, and then a Bayesian network is used to build a risk transmission channel. The most recent case is investigated.

Yang Ruobinget al. [17] This paper proposes a unique big data-based supervisory approach to address the possible hazards connected involves the financial sector large data. There is a new technique based on big data, and it entails building a financial big data application platform and using real-time mining to analyse huge volumes of big data from the financial sector. Results demonstrate that this technique can deal with the problem of the data island, and improve the security of personal private data, and promote big data standardisation in addition to solving the data island problem.

Zhang Tingting et al. [18] New big data financial systemic risk prevention technologies presented in this article will help to lessen future financial systemic risk severity and frequency. With the use of big data analysis and Internet and cloud computing, they monitor the financial market in real time and weed out misleading information. Research demonstrates that this technology identifies the significant relationship between big data and the financial market, lowers the cross-infection of financial systemic risk and enhances the controllability of financial systemic risk.

XU Rong-zhenet al. [19] This article offers an online supply chain credit risk assessment technique based on deep belief networks in the context of "Internet Plus" to cope with the challenge of completely mining credit risk behind huge financial online supply chain data (DBN). RBM and classifier SOFTMAX are used to construct a deep belief network assessment model, which is then put through its paces on three distinct types of data sets for performance evaluation testing and evaluation evaluation testing. Factor analysis is used to choose eight indications from a total of twenty-one, and these indicators are then translated to RBM to generate a more scientific assessment index.The results show that this method's assessment accuracy is 96.04 percent, which is greater than the SVM method and Logistic method and has superior logic.

Chuan-Hsiang Su et al. [20] The goal of this study is to build a risk assessment system for global financial markets using data science approaches to extract meaningful information from massive data sets using fuzzy theory. To begin, incomplete and erroneous data, such as missing values and wide time gaps, have been removed and simplified in order to improve the integration of global financial market data. Statistical approaches are then used to analyse daily signal changes to determine causation and worldwide financial market investment risks. Finally, there are several inputs and outputs in the fuzzy inference system.

Abdullah Salamai et al. [21] Building Decision Support Systems (DSS) capable of anticipating different operational risks, such as financial and quality concerns, is currently proving difficult for organisations. There are a lot of financial losses and damage to a company's market reputation associated with operational hazards. An organization's huge volume of data combined with fuzzy inference methods form the basis of the Fuzzy Inference DSS (FIDSS). With the Emerging Association Patterns method, it is possible to pinpoint the key characteristics of each risk event. A number of membership functions and the Mamdani fuzzy inference approach are then assessed using data from the firm's sources. By categorising risks as low, medium, or high, the FIDSS approach aids in the improvement of an organization's decision-making processes. For medium and high severity forecasts, it aids organisations in taking further measures to lessen the severity.

XIUMEI LYU et al. [22] Supply chain finance and associated risk have been the subject of much qualitative and statistical research. However, there is a scarcity of literature on Internet supply chain financing (ISCF), notably quantitative studies on its risk. An intelligent risk assessment technique for ISCF is developed after analysing data from partners' panoramas as well as data from the internet supply chain upstream and downstream. With the help of analytical hierarchy process grey assessment theory, ISCF risk assessment model is developed. ISCF risk may be analysed in real time by utilising an assessment model based on big data, surveillance and monitoring of partners' panorama data and upstream and downstream supply chain data, so the investor can decide whether or not to lend before and dynamically monitor the lender after the loan. An example, this article looks at the risk of lending to a certain financing company and provides an exact risk value which describes the level of risk. As a consequence, the model may be applied in certain scenarios.

Abduh Sayid Albanaet al. [23] An investment's viability may be evaluated by doing a financial analysis. Investors frequently utilise methodologies in order to evaluate if a financial investment is successful or not. On the other side, there are many people that work in financial analysis, exclusively employ a deterministic method when doing a feasibility assessment for investment. In reality, numerous unknown variables, such as the exchange rate, are included in the financial analysis of the feasibility study. These unpredictability elements might be viewed as hazards.

Ka Yee et al. [24] To prepare for this, we've developed a model that utilises commercial-grade machine learning techniques. Using an international data quality standard from the banking sector, we first use the model to detect data disturbances in a risk dataset, and then we employ Gaussian and Bayesian techniques to assess the effect of those noises. Second, we use an attention method to promote sequential learning in several deep neural networks for prediction. The model is verified using data to illustrate the model's usefulness, and it is evaluated using different network ways to demonstrate the predictive capability of machine learning techniques. Other than the banking business, the methodology is scalable and may be used to any industry that uses big data.

HANGJUN ZHOU et al. [25] Big data mining using PSO-based Back propagation (BP) neural networks is proposed for financial risk management in commercial banks with IoT deployment, which builds a nonlinear parallel optimization model with Apache Spark and Hadoop HDFS techniques on the dataset of on-balance-sheet and off-balance sheet item. This parallel risk management approach has a rapid convergence rate, high predictive capacity, and is effective in screening default behaviours, according to experiments. Meanwhile, distributed implementation on huge data clusters decreases significantly the processing time for model training and testing.

Dong-Her Shih et al. [26] Most investors have been drawn to the stock market due to its high compensation. However, there are several factors that influence stock market trading price variations. Many measurement techniques are available to investors in order to decrease investment risk. One of the most significant subjects in the financial industry is the forecast of stock trading prices. Machine learning algorithms are widely used in financial time series forecasting. According to previous studies, sophisticated forecasting algorithms can reliably predict trade price fluctuations in financial markets. The project will use the big data Spark framework's real-time stream data processing architecture to analyse real-time stock trading volume using the bursting comprehensive trading volume index and to provide risk alerts based on various levels of trading volume. Investing may be done at the investor's convenience, whenever they have the time to do so. This study's findings suggest that investors who desire to operate in a high-risk environment might enhance their earnings by utilising stock trading volume risk assessment criteria.

Ning Li et al. [27] To address the issue of inadequate dependability of existing financial risk assessment models, a rural financial risk assessment model is created against a backdrop of supply-side structural change. The rural financial risk detection detector is built using an assessment model structure based on neural networks and an upgraded negative selection strategy. Rural finance risk assessment model is created by mapping detection results from an identification detector to the nodes in a decision tree that assesses risk.

Logistic regression: Statistics uses logistic regression to estimate the probability of distinct outcomes in response to a certain variable. It presupposes that the log probability is a linear combination of independent variables (predictors). Using logistic regression to predict a categorically scattered, unordered response variable is a smart strategy. Unordered variables are those that can fall into any of the possible outcomes but can't be meaningfully ordered. Unordered answer variables include things like health plans, commute options, and occupational options.

The status of one's health is such an ambiguous concept. Clinical medicine, engineering, social science, and economics all employ logistic regression to make predictions.

DBN: The deep neural network optimization problem is addressed by the Deep Belief Network (DBN), which employs a layer-by-layer training technique. The limited Boltzmann machine is beneficial in the training process since it resolves the label sample number issue as well as the training process sliding into the local optimum area. The Deep Belief Network (DBN) is made up of several restricted Boltzmann machines (RBMs), with the RBM acting as its basic fundamental model. For the first time, Hinton et al. put out the RBM theory. Theoretically, while learning a multilayer neural network, it may be divided into multiple RBMs ahead of time and then taught layer by layer, which significantly increases neural network training efficiency and dramatically improves training outcomes.

TABLE 1. Accuracy of Financial risk assessment using various models

Ref. No.	Author Name	Year	Technology	Accuracy
[4]	VishanthWeerakkody	2020	Logistic Regression	59.46 %
[7]	Xiaohan Zhang	2021	Logistic Regression	92.20 %
[15]	Wei-Yuan Huang	2016	Efficient Market Hypothesis	80.78%
[19]	XU Rong-zhen	2020	DBN	87.91%
[20]	Chuan-Hsiang Su	2018	Fuzzy Risk Assessment	70.7 %
[21]	Abdullah Salamai	2019	Fuzzy Inference DSS (FIDSS) Mechanism	97.6%
[24]	Ka Yee	2020	Prediction and Machine Learning	86.05%

FIDSS: Fuzzy Logic (FL) is used to analyse risk occurrences by utilising an inference model based on qualitative choices. They assert that FL can correctly anticipate risk events' likelihood and occurrence, allowing them to take preventive measures.The FIDSS framework is made up of three major components: a large data gathering system, an EAP method, and a fuzzy inference system. Recognizing risk occurrences necessitates gathering appropriate characteristics based on expert knowledge because each sector of the supply chain has its unique collection of data. With the use of the EAP technique, many datasets acquired from an aluminium company are analysed for key traits that might indicate risk occurrences.

III. COMPARISION OF VARIOUS TECHNIQUES

The accuracy of financial risk assessmentusing various techniques are explained in the table given below.

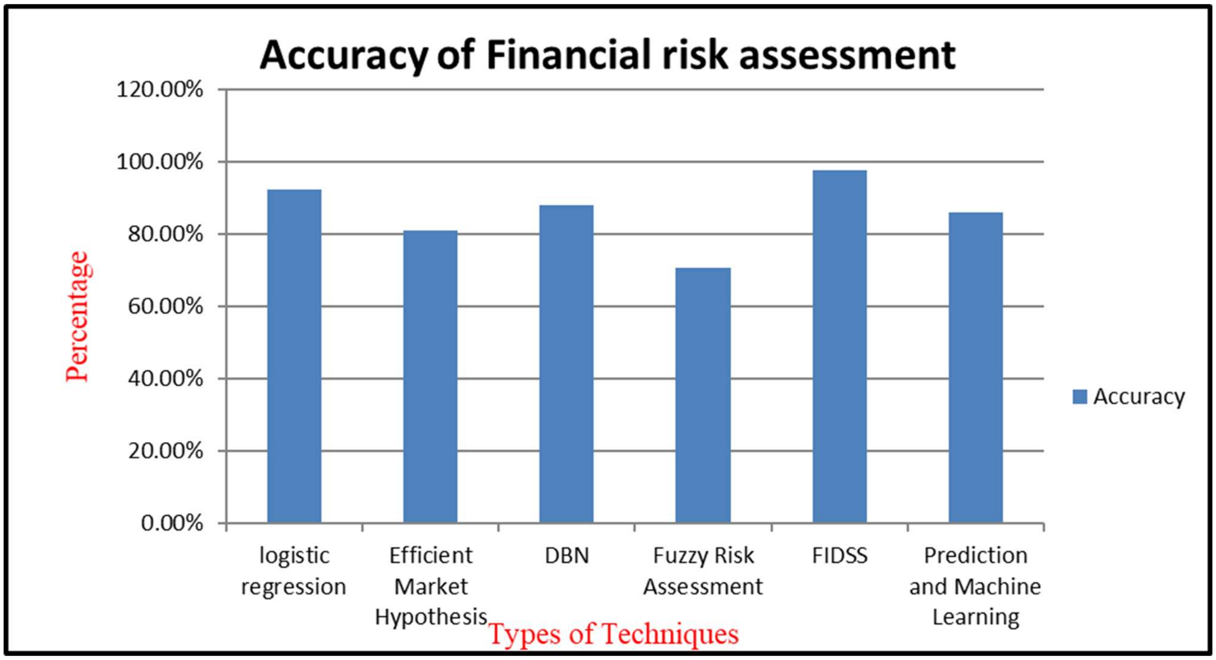

Fig. 1. Accuracy of Financial risk assessment using various models

From TABLE 1 and Fig. 1, we get the highest accuracy in logistic regression and Fuzzy Inference DSS (FIDSS) mechanism model. Even though Fuzzy Inference DSS (FIDSS) mechanism model has higher accuracy of 97.6% than logistic regression with 92.20 %. The logistic regression is the best method for Large-Scale Data-Driven Financial Risk Developing model.

IV. CONCLUSION

The hazards associated with the rapid increase of personal financial demands should not be overlooked in

the context of this rapid expansion. Currently, credit risk exists mostly because financial institutions cannot objectively access all of an individual's information because of information asymmetry, resulting in such information asymmetry being incomplete. Personal credit risk is used as the study aim in this work, and each credit scoring model is compared. We conclude that the logistic regression is the best method for Large-Scale Data-Driven Financial Risk Developing models when surveying the existing methods.

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