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Data mining based framework for organisational financial management

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Abstract: An organizational financial management framework based on data mining utilizes data mining (DM) techniques to uncover latent and valuable insights within unstructured risk data. This empowers informed risk management decision-making. By utilizing business intelligence and data mining techniques to identify, assess, and mitigate various types of supply chain risks, and to develop a comprehensive supply chain risk management (SCRM) framework, it seeks to address the increasing complexity and variety of risks in supply chains. The framework's validity is established via a case study conducted in the heavy machinery sector, thereby making a valuable contribution to the domains of supply chain risk management research and practice. An exhaustive examination of the intelligent financial management system's design is conducted initially, followed by the construction of a support system based on data mining. The second section defines and organizes data mining and data warehouses, as well as the financial management applications of data mining strategy and technology. Further research is being conducted on intelligent data mining and data mining algorithms for technology.

Keywords: Risk management; data mining; data analytics; and decision support systems.

I.INTRODUCTION

In the rapidly evolving landscape of organizational financial management, the need for efficient and effective decision-making has become paramount.Data mining is the discovery of patterns and trends in huge databases, has established itself as a potent instrument for extracting insightful information from financial data. By leveraging advanced algorithms and statistical techniques, organizations can gain a competitive edge by making informed decisions, mitigating risks, and identifying new opportunities.This framework seeks to investigate the role of data mining in improving organizational financial management. It will go over many areas of data mining, such as its applications in financial analysis, risk assessment, and predictive modeling. Furthermore, the framework will address the challenges and considerations associated with implementing data mining techniques in financial management, emphasizing the importance of ethical and responsible data usage.

Through this framework, organizations can harness the power of data mining to optimize their financial strategies, streamline operations, and drive sustainable growth.

The ongoing advancement of artificial intelligence technology, computer technology, and financial knowledge models has made it easier to implement Complex financial models, analyses, and forecast procedures. This advancement provides powerful technical support for enterprise financial management innovation, transforming accounting information systems are being incorporated into managerial decision-making models. Furthermore, employing modern computer technology to develop effective smart financial management support systems is not only a viable option, but also an unavoidable trend in financial informatization.

This integration highlights the significance of data mining, financial management is being revolutionized by artificial intelligence and technology [1].The advancement development of an intelligent financial management support system based on data mining is critical for the growth and strength of businesses. Utilizing data mining technology to analyze financial data aids in informed decision-making in business finance management [1]. Integration of large amounts of data technology in enterprise management analysis frameworks is pivotal for the development of a comprehensive business management model.This technology presents opportunities for improved decision-making and operational optimization, as evidenced by the effectiveness of the improved C4.5 algorithm in reducing fuel consumption costs for a shipping company [2]. Incorporating artificial intelligence technology into financial analysis and accounting information systems provides robust technical support for intelligent operation and financial management analysis, ultimately transforming accounting systems into decision-making support systems [3].

In this research paper we are discussing Data warehousing and data mining technology are utilized in developing an advanced system to provide intelligent help for financial management. This entails the examination and application of pivotal technologies such as Clustering technology, decision tree technology, and association rule mining technologies are all available. Additionally, you are working on improving the efficiency of the association rule mining algorithm and suggesting a better data mining algorithm for financial management. The purpose of this paper is to improve the functionality and efficacy of intelligent financial managementsystems through advanced data mining techniques.

II.RELATED WORKS

The field of AI and data science has witnessed numerous technological advances over the past decade, leading to significant developments in research and applications. The keyword for this era of AI research is "learn," with big data technologies and improved computing power playing pivotal roles in driving advancements in AI [1][2].In the realm of healthcare data mining techniques have been used to forecast the length of stay (LOS) for heart patients in hospitals.

A research analyzing the medical information of 4,948 people with coronary artery disease (CAD) utilized classification algorithms such as to forecast LOS, Decision trees, support vector machines (SVM), and artificial neural networks (ANN) were utilized. The research found that these algorithms were effective to varying degrees, with SVM demonstrating the highest accuracy. Additionally, factors like comorbidities, ejection fraction, smoking status, and insurance type were identified as impacting LOS, highlighting the significance of predicting and managing LOS for efficient hospital resource utilization [3].

Data mining technology is used in other countries has undergone significant development, leading to the maturation of algorithms and the establishment of commonly used data mining software. These tools are classified as follows traditional management software and those utilizing newer decision tree algorithms, genetic algorithms, artificial neural networks, and expert system technology are examples of such technologies. Influential mining methods, such as the concept tree promotion algorithm, classification algorithm, and association algorithm.

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Furthermore, Data mining technology has piqued the interest of well-known research institutions, leading to the development of intelligent decision analysis algorithms for financial management, as well as business-based concepts such as document warehouses, are proposedintelligence. Moreover, in the telecom sector, to help telecom operators with intelligent data analysis, a service-oriented business intelligence architecture based on the decision tree algorithm has been developed[4].

Conventional accounting methodology and examination of financial data approaches have failed to suit people's multifaceted needs in terms of form, timeliness, and effectiveness for analyzing and making decisions on complex problems. The emergence of artificial intelligence and expertise systems has provided excellent solutions to such difficulties, propelling the evolution of contemporary accounting systems has progressed from information and network-based systems to intelligent systems[4].   The tripartite theory, which serves as the foundational theory of Decision Support Systems (DSS) and has significantly influenced the subsequent advancement of DSS, has contributed to this transition towards intelligent financial management systems. [5].

The three-system structure, comprising the language system, problem processing system, and knowledge system, possesses distinct attributes when it comes to problem processing,creating a solid The establishment of intelligent financial management systems.   Considerable advancements have been achieved in both the theoretical and practical investigation of intelligent financial management systems, leading to the creation of systems such as the IFPS (conversational financial planning system) and the AAIMS system, which support planning, decision-making, finance, plan optimizations, benefit analysis, and forecasting[5]. FDSS's data analysis and decision support capabilities have also been increased by the combination of data warehouse technology with online analytical processing functions.

A data mining framework for organizational finance management entails research into data warehouses, data mining theory, and data mining technology [6]. The objective of this framework is to provide a sophisticated system for financial management support that relies on data mining techniques with an emphasis on the architecture and technologies involved. It also addresses problems in the intelligent data mining method and provides a new approach, emphasizing its benefits through associated mining experiments. The framework also highlights the use of data mining in decision support systems and intelligent forecasting in financial management, notably in the context of enterprise financial management.

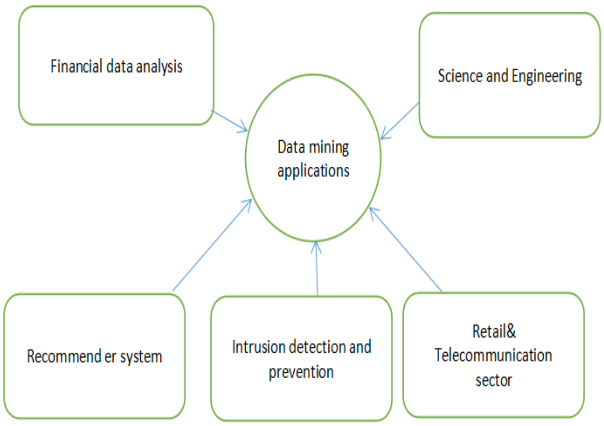

Fig.1.1 denotes framework for the proposed research.

A data mining-based framework for organizational financial management can be expressed in a flow chart using information from the search results. Financial data analysis, recommended ER system, science and engineering, intrusion detection and prevention, and other data mining methods can all be included in the flow chart. These components can be linked together to show how data is collected, evaluated, and used for financial management. The flow chart can also demonstrate the use of Data mining technology is utilized in financial analysis, cost control, and business model management to showcase the potential advantages and influence of data mining in the process of managing an organization's finances.

III.RESEARCHMETHODOLOGY

Data mining is a very strong field for looking at big volumes of complex data since it uses methods and techniques from both statistics and machine learning. Advanced analytics and business intelligence technologies employ the data they analyze to generate insight. Financial data analysis is an important aspect of determining whether a business is steady and profitable enough to justify investing in new equipment. The major goals of financial experts are to analyze the balance sheet, cash flow statement, and income statement. Data mining has been employed in the financial markets to reveal concealed patterns and predict future human behavior and actions. In order to extract information from this specific kind of data, especially high-frequency financial data, it is occasionally necessary to employ sophisticated statistical, mathematical, and artificial intelligence techniques.

Data mining techniques pertaining to finance can be applied to the following categories:

- Gross Profit on Peak Sales
- Stockpile of Net Sales

Data mining is beneficial in the subsequent domains:

Money laundering is a criminal activity in which unlawful finances and assets are disguised as legitimate. It entails turning "black money" into "white money" in order to make it appear legitimate. The approach allows people or groups to profit from unlawful operations while keeping the source of the funds hidden. Data mining approaches have been developed to discover and detect questionable behaviors in the fight against money laundering. Furthermore, financial organizations use data mining to estimate loan payments and analyze client credit policies, since it helps manage critical data and big databases for loan distribution. Data mining also aids focused marketing by classifying and clustering clients based on their habits and interests, allowing for better marketing decisions and profit retention. Furthermore,

The research aims to create a framework for supply chain risk management (SCRM) based on data mining (DM) by The process involves various tasks, including detecting risk indicators, collecting and storing risk data, converting risk management issues into data mining problems, evaluating the data using data mining algorithms, and interpreting the results to determine effective risk mitigation methods [6].

The research places an emphasis on the growing complication and diversity.The supply chain is exposed to many risks due to factors such as globalization, increasing customer expectations, and advancements in technology [6]. Furthermore, it emphasizes the importance of employing data-driven decision-making methodologies, such as Business Intelligence (BI) and Data Mining (DM) in order to successfully manage supply chain risks, and it blends DM and risk management methodologies in order to detect, assess, and mitigate various types of supply chain risks.

Creation of a system that utilizes data mining techniques

The first step in the process of developing the framework for DM-based SCRM (Social Customer Relationship Management) is to conduct an overall model overview. This overview prepares the reader to comprehend the components and ideas that underpin the design and implementation of the framework by providing context and background information. In the following sections, we will go into the exact elements and intricacies of the model, revealing insights into its structure, functionality, and prospective impact on customer relationshipmanagement in this era of digital technology.

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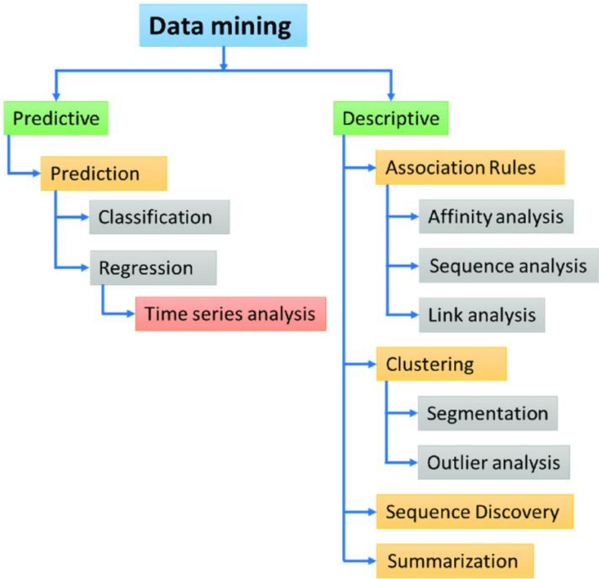

Fig.1.2 Flowchart denotes Predictive and descriptive data mining tasks.

Since the late 1970s, researchers have been studying performance measurement and management, with an emphasis on numerous topics such as performance indicators, evaluation, and quality implementation [7]. Efforts have been made to build appropriate frameworks and models for performance evaluation and management, such as the balanced scorecard and other methodologies. For efficient utilization of performance measurement findings, businesses must migrate from measurement to management, a notion known as performance management in organizational performance research.

Performance assessment is regarded as a complex and difficult undertaking, with aspects such as information technology, empowerment, global competition, partnerships, culture, and performance appraisal methods determined to have an impact on organizational performance. The adoption of a diverse collection of financial and non-financial indicators has been linked to improved measurement system satisfaction and stock market returns, highlighting the significance of diversity in performance assessment methodologies.

Additionally, the use of accountability measures based on performance, such as performance indicators has been a common method for demonstrating performance.

	With the entire training set	With 34% of the training set	With 5-folds cross validation
Naïve Bayes	0.09	0.09	0.10
J48	0.04	0.13	0.1
IBK K=1	0.004	0.15	0.14
MLP	0.01	0.11	0.13

Table.1: Shows Classification of transparency levels based on absolute average inaccuracy.

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Transparency level classification can be determined using the concept of absolute average error (AAE). AAE is a metric that quantifies the average disparity between predicted and actual values[8]. In relation to transparency level classification, AAE can be used to measure the accuracy of a model's predictions.

To classify transparency levels using AAE, follow these steps:

1. **Gather a dataset:** Collect a dataset that consists of instances with known transparency levels. Each instance should have corresponding predicted values and actual values.
2. **Train a model:** Use the dataset To develop a machine learning model capable of making predictions, transparency levels based on given features. Decision trees, random forests, and neural networks are popular methods for this task.
3. **Evaluate the model:** Once the model is trained, evaluate its performance using AAE. Calculate the absolute difference between predicted and observed transparency levels for each instance in the dataset[9]. Then, compute the average of these absolute differences to obtain the AAE.
4. **Define transparency levels:** Determine the transparency levels you want to classify. For example, you might have three levels: high transparency, medium transparency, and low transparency.
5. **Set thresholds:** Set AAE thresholds for each transparency level. These thresholds will help classify instances based on their AAE values. For example, you might set a threshold of 0.2 for high transparency, 0.4 for medium transparency, and anything above 0.4 for low transparency.
6. **Classify instances:** Compare the AAE of each instance to the defined thresholds. If an instance's AAE falls below the threshold for a specific transparency level, classify it accordingly. Repeat this process for all instances in the dataset.By following these steps, you can classify transparency levels based on the absolute average error[10]. Remember to choose an appropriate threshold for each transparency level, as it will affect the accuracy of the classification.

IV.RESULTS AND DISCUSSION

The research suggests a data mining paradigm for financial markets that focuses on interpretability, appropriate prediction measures, and reporting mechanisms. The framework was applied to real-world financial prediction problems and achieved an 84% prediction performance. It also provided additional insight through hierarchical information. The framework aims to support active agents in making quick and accurate data-driven decisions in the real world. Establishing a defined procedure for obtaining data-driven insights directly related to financial market performance is crucial. Additionally, for the classification of data, a data mining paradigm based on rough set theory existshas been presentedorganizational performance.

The analytic hierarchy process (AHP) is a frequently used decision-making procedure that allows for the evaluation of both objective and subjective elements. The procedure involves decomposing a problem into a hierarchy, consisting of a goal level, a criterion level, and a measure level. The next step is to construct a contrast matrix, which involves comparing elements in the hierarchy to determine their importance and quantify them. Once the matrix is constructed, predictions can be made based on current data and trend models. Lastly, association analysis can be performed to identify relationships and rules between objects, which can be useful in various decision-making processes, such as analyzing commodity transaction data.

The data mining-based enterprise financial analysis system is intended to meet the needs of enterprise executives, Managers in the finance department, financial analysts, and professionals engaged in intelligent enterprise financial management analysis. Constructing a coherent conceptual framework and establishing effective interaction among potential entities inside each functional module of the system is achievable by performing thorough investigations and assessing the requirements of these stakeholders. This provides a solid foundation for the database's logical and physical structural design.

Illustrative Verification

This page makes use of information from the Library's CSMAR, which is based on the Company's up-to-date database and covers stock, bond, fund, foreign currency, and other markets. We selected 36 publicly traded companies at random

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Retrieve data from the database for the time period spanning from May 1, 2010 to May 9, 2011. Initially, we conducted data preprocessing and identified specific stocks that had incomplete transaction data. The inception of these stocks occurred in 2011. Upon removing any unfinished inventory, proceed to process the field.

As a result of the restricted availability of the daily opening price, the data is subjected to preprocessing and the daily rate of increase is computed using a specific formula. In order to eradicate the increase data, first determine if the increase is more than zero in the programming implementation. There were 6,100 data points in the last 25 stocks. Figure 1.3 depicts the data format. Today's growth is negative if it is less than zero.

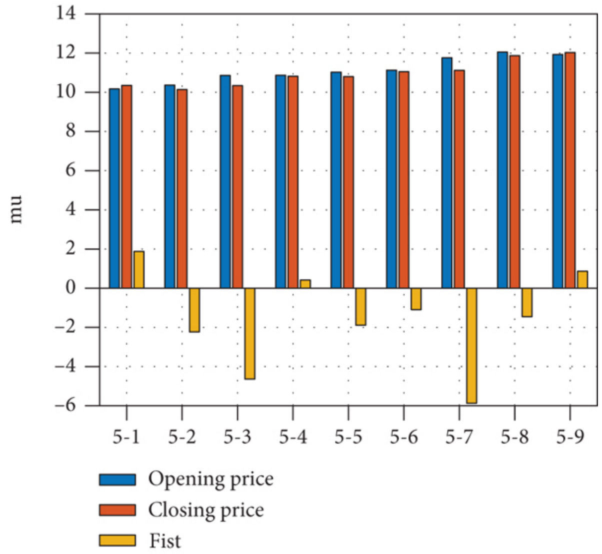

Fig.1.3 denotes Data format of intelligent financial management system.

V.CONCLUSIONS AND FUTURE DIRECTIONS

A conclusion regarding a data mining-based framework for organizational financial management can be drawn from the information garnered from the search results:Financial management can utilize the potent technique of data mining to extract significant patterns and trends from massive quantities of information.Secondly, data mining algorithms can be employed to create a sophisticated financial management support system. Using intelligent data mining algorithms, their defects can be identified, allowing for the development of improved algorithms.To assure its efficacy, Data mining's application in financial decision-making should be exhaustively investigated.The intelligent financial management support system could use critical technologies including clustering, association rule mining, and decision tree.

Foreign countries have made greater strides in data mining technology is evolving, and renowned research institutions and devices are now available for data mining. The data mining-based approach can aid in the execution of intelligent risk management choices by facilitating the identification of hidden and relevant information in unstructured risk data. In conclusion, a data mining-based organizational finance management framework can leverage the capabilities of data mining algorithms to draw substantial insights, improve decision-making processes, and enable informed risk management.

A framework for organizational finance management based on data mining can provide valuable insights and support in making informed decisions for future directions. By utilizing data mining techniques, organizations can analyze large volumes of financial data to find patterns, trends, and connections that typical analysis approaches may miss. This framework can help in forecasting financial outcomes, identifying potential risks and opportunities, optimizing resource allocation, and improving overall financial performance. It can also assist in monitoring financial indicators, detecting anomalies, and providing early warning signals for potential financial problems. By leveraging data mining, organizations can gain a competitive advantage and make more informed strategic decisions for their future financial direction.

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