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Utilizing Business Intelligence Tools in Fintech: Visualizing Risky Credit Categories With K-Means Clustering Using Rapidminer

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ABSTRACT

In the field of financial risk assessment, understanding and categorizing credit risk is critical for effective decision making. This study explores the use of KMeans Clustering, implemented via RapidMiner, to visualize and describe risky credit categories. Leverage a rich data set of related financial attributes, including total income, education, family status, residence type, ownership, and more. K-Means clustering facilitates customer segmentation into different risk groups based on similar credit profiles. Through the application of this grouping technique, financial institutions can gain insight into potential credit defaults, thereby enabling proactive risk management strategies. The visualization aspect enhances interpretability, enabling stakeholders to understand and navigate the complex credit risk landscape more intuitively. By leveraging the capabilities of RapidMiner, this research contributes to the advancement of data-driven methodologies in financial risk assessment, offering a practical approach to visualizing and understanding credit risk categories. These findings provide valuable insights to financial analysts, policy makers and decision makers, empowering them to make informed decisions and mitigate credit risks effectively.

Keywords*: Credit Risk Assessment, Financial Data Analysis, K-Means Clustering, RapidMiner Visualization, Risk Management Strategies*

ABSTRAK

Dalam bidang penilaian risiko keuangan, memahami dan mengategorikan risiko kredit sangat penting untuk pengambilan keputusan yang efektif. Studi ini mengeksplorasi penggunaan KMeans *Clustering*, yang diimplementasikan melalui RapidMiner, untuk memvisualisasikan dan mendeskripsikan kategori kredit berisiko. Manfaatkan kumpulan data yang kaya dengan atribut keuangan terkait, termasuk total pendapatan, pendidikan, status keluarga, jenis tempat tinggal, kepemilikan, dan banyak lagi. K-Means *clustering* memfasilitasi segmentasi pelanggan ke dalam kelompok risiko yang berbeda berdasarkan profil kredit yang serupa. Melalui penerapan teknik pengelompokan ini, lembaga keuangan dapat memperoleh wawasan tentang potensi gagal bayar kredit, sehingga memungkinkan strategi manajemen risiko yang proaktif. Aspek visualisasi meningkatkan interpretabilitas, memungkinkan pemangku kepentingan untuk memahami dan menavigasi lanskap risiko kredit yang kompleks dengan lebih intuitif. Dengan memanfaatkan kemampuan RapidMiner, penelitian ini berkontribusi pada kemajuan metodologi berbasis data dalam penilaian risiko keuangan, menawarkan pendekatan praktis untuk memvisualisasikan dan memahami kategori risiko kredit. Temuan ini memberikan wawasan berharga bagi analis keuangan,

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pembuat kebijakan, dan pembuat keputusan, memberdayakan mereka untuk membuat keputusan yang tepat dan mengurangi risiko kredit secara efektif.

Kata kunci: Penilaian Risiko Kredit, Analisis Data Keuangan, K-Means *Clustering*, Visualisasi RapidMiner, Strategi Manajemen Risiko

INTRODUCTION

Fintech refers to the combination of finance and technology, where Fintech uses technology to develop activities in the financial industry, including the banking sector [1]. Examples of Fintech banks in Indonesia are FinAccel (Kredivo), M Cash Integration, KoinWorks, Amartha, Modalku, Komunal, and others, which have mainstay products in the form of peer-to-peer (P2P) lending financial technology platforms. P2P, according to Bank Indonesia, is the provision of financial services to bring together lenders/borrowers with loan recipients/borrowers to enter into rupiah currency lending and borrowing agreements directly via an electronic system, also known as Information Technology-Based Joint Funding Services (LPBBTI) [2].

Credit risk assessment is becoming an important integral part of financial risk management, a major concern for financial institutions and lenders. In a dynamic financial ecosystem, a deep understanding of credit risk helps financial institutions make the right decisions in providing credit to customers [3]. By identifying and assessing the potential risks associated with each borrower, financial institutions can reduce the likelihood of losses due to bad credit [4]. Therefore, the development of effective methods for assessing credit risk is a must. Data analysis methods, such as clustering, have become important in helping financial institutions better manage and understand credit risk. By applying advanced data analysis techniques, financial institutions can increase precision in identifying different credit risk categories and formulate more effective risk management strategies [5].

The use of data analysis techniques, in this context, such as clustering becomes important to identify potential credit risk categories. Clustering allows financial institutions to group customer data into similar groups based on certain characteristics, such as income, education, type of residence, ownership assets, and other risk factors [6]. By using this approach, financial institutions can gain a deeper understanding of their customers' credit risk profiles and differentiate between those with low, medium, and high credit risk. This information is invaluable in making credit decisions, as it allows financial institutions to enact policies appropriate to the risks associated with each customer [7]. Additionally, by using clustering, financial institutions can identify patterns of credit behavior that may be indicative of potential future credit risks. Thus, clustering techniques become a powerful tool in credit risk management, helping financial institutions to reduce losses due to bad loans and increase the success of their credit portfolios [8].

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K-Means clustering is a method commonly used to group data into different clusters based on feature similarity. In this method, the cluster center point, called the centroid, is chosen randomly for each cluster initially. Then, each data point is assigned to the nearest cluster based on the Euclidean distance between the data point and the centroid. Next, the centroid for each cluster is updated by calculating the average of all data points in that cluster. This process is repeated iteratively until there is no change in the assignment of data points to a particular cluster or until the iteration reaches a predetermined maximum number. K-Means clustering is effective in handling data with a large number of features and can be used to identify hidden patterns in complex credit data. By applying this method, financial institutions can gain better insight into the credit risk structure within their portfolios and take appropriate actions to manage those risks [9].

RapidMiner is a powerful data analysis platform that allows users to perform a variety of data analysis tasks, including data processing, predictive modeling, and data visualization. It provides an intuitive user interface and a variety of analytical tools that data practitioners from various backgrounds can use to explore and analyze data more effectively. The use of RapidMiner facilitates practitioners to quickly and efficiently visualize complex credit data.

With a variety of features and operators, including the K-Means Clustering algorithm, RapidMiner supports in-depth analysis of credit data and presents the results in easy-to understand graphs [10]. Practitioners can easily identify high-risk patterns, such as delayed payment trends or unusual spending patterns, that may not be immediately apparent from raw data. With this visualization, financial institutions can take proactive steps in managing credit risk, including carrying out tighter monitoring of risky credit segmentation or making timely adjustments to credit granting policies [11]. Thus, the use of RapidMiner helps financial institutions to increase effectiveness and efficiency in credit risk management, as well as strengthen their position in facing challenges related to financing [12].

LITERATURE REVIEW

In the context of Fintech, the use of Business Intelligence (BI) includes not only data analysis, but also the importance of data visualization [13]. Data visualization allows Fintech companies to present information graphically, which makes it easier for stakeholders to understand and interpret the data. With data visualization, Fintechs can clearly see patterns, trends, and anomalies that may be hidden in their datasets [14]. For example, visualization can help in the identification of potential credit risk categories through techniques such as K-Means Clustering. By understanding identified credit risk patterns, Fintech companies can optimize the lending process and manage their credit portfolio more effectively, in accordance with the bank lending concept. Thus, data visualization plays a key role in converting data

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into insights that can be used to make better decisions and improve operational efficiency in the Fintech industry [15].

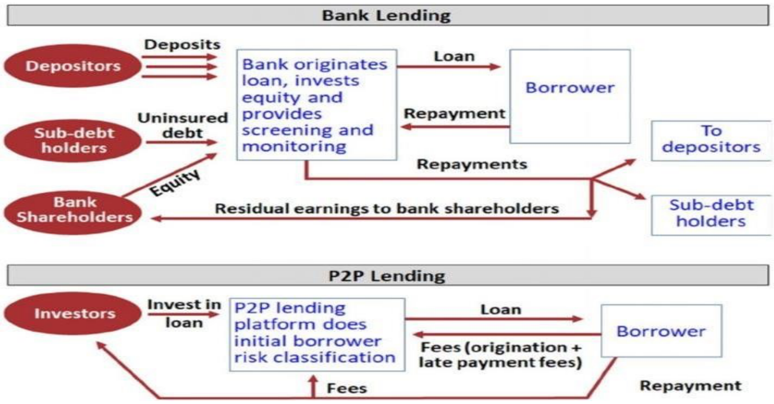

Figure 1. Bank Lending Concept (readkong.com)

The K-Means Clustering algorithm is one of the most commonly used clustering methods in data analysis. This algorithm works by grouping data into a number of clusters based on feature similarities. In the context of credit analysis, K-Means Clustering is used to identify and group credit data into different risk categories based on existing patterns. Literature studies show that K-Means Clustering has been successfully applied in credit analysis to identify borrowers with similar credit risks. By analyzing factors such as payment history, credit amounts, and other characteristics, these algorithms can help financial institutions better understand their credit risk profile. Thus, the use of the K-Means Clustering algorithm in credit analysis makes an important contribution to making more accurate and effective decisions in credit risk management [16].

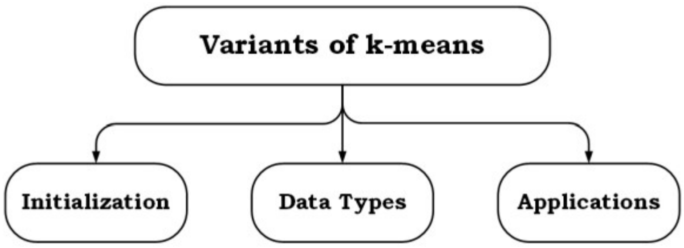

Figure 2. A Simple Taxonomy of Variants of K-Means Algorithm

RapidMiner is a popular data analysis platform and is often used by data science and business analysis practitioners. The platform offers a variety of powerful features and functionalities to assist users in performing complex data analysis. In the context of Fintech, RapidMiner has particular relevance due to its ability to process and analyze credit data quickly and efficiently. RapidMiner provides the tools necessary to import, clean, and visualize credit data, as well as to apply various analysis techniques such as K-Means Clustering [17]. These features enable Fintech practitioners to gain deep insight into patterns and trends in credit data, so they can

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make more informed and proactive decisions in credit risk management. Thus, RapidMiner becomes an invaluable platform in helping financial institutions optimize the use of their credit data for business purposes and decision making [18].

Data visualization plays a key role in credit risk management, as it helps practitioners understand and communicate the information contained in credit data in a clearer and easier to understand manner. With effective visualization, complex information about credit risk can be presented in the form of intuitive graphs or diagrams, enabling decision makers to quickly identify patterns or trends that may be hidden in the data. Research literature has investigated a variety of effective visualization techniques for credit risk, including heatmaps, scatter plots, and dendrograms. Heatmaps can be used to depict the level of risk in various credit categories with different colors, while scatter plots make it possible to see the relationship between various risk variables. Dendrograms, on the other hand, can help identify clusters representing different risk categories in credit data. By applying appropriate visualization techniques, practitioners can gain deeper insight into their credit risk structure and make better decisions in risk management [19].

Accuracy of predictions and visualization plays a central role in the Fintech industry, especially in the context of decision making related to providing credit. As part of the technology-based financial industry, Fintech relies on sophisticated data analysis to assess credit risk precisely and efficiently. By using predictive techniques and machine learning, Fintech companies can create accurate prediction models to evaluate the possible credit risk of borrowers. However, to optimize decision making, data visualization is also key. Through intuitive visualization, Fintechs can interpret prediction results more easily, gain deeper insight into credit risk profiles, and take necessary actions more quickly. Thus, the combination of predictive accuracy and effective visualization allows Fintech companies to improve the quality of their services, reduce credit risks and strengthen their position in competitive financial markets [20].

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METHODOLOGY

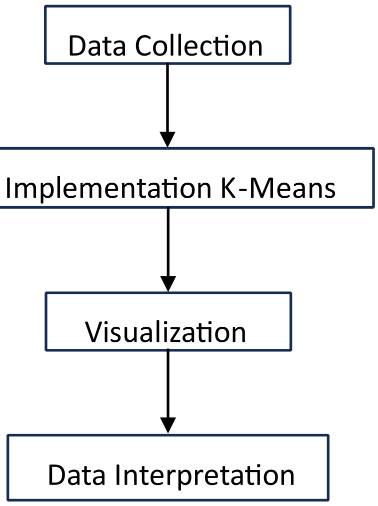

Figure 3. Research analysis flowchart

a. Data collection:

- Data testing for point **4.2** was taken from the Kaggle platform which provides a total of 527,709 datasets related to credit approval in a format that suits research needs.
- Select a dataset that contains relevant information, such as the borrower's income, status, family responsibilities, and other variables that are important for credit risk analysis.

b. Implementation of K-Means Clustering using RapidMiner:

- Loading the processed dataset into the RapidMiner platform.
- Using the K-Means Clustering operator to group data into clusters based on feature similarity.

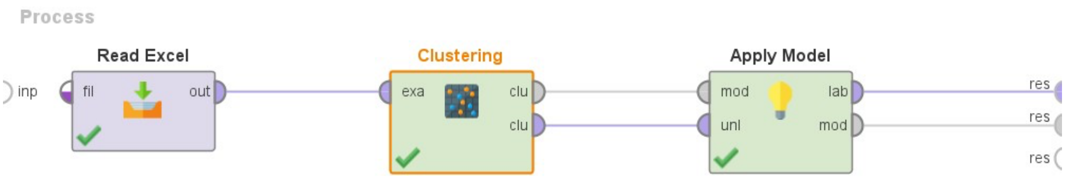

Figure 4. Implementation of K-Means Algorithm in RapidMiner

c. Visualization of Clustering Results:

- Using the visualization features provided by RapidMiner to depict clustering divisions in graphic form that is easy to understand.
- Analyze patterns that emerge from visualizations to gain insight into different credit risk profiles based on characteristics.

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d. Data Interpretation:

- Interpret clustering results to identify potential credit risk categories and factors that influence the determination of these categories.
- Draw conclusions and provide recommendations based on analysis results to support decision making regarding credit risk management in the context of the Fintech industry.

RESULTS AND DISCUSSION

Example of Data without a Pattern

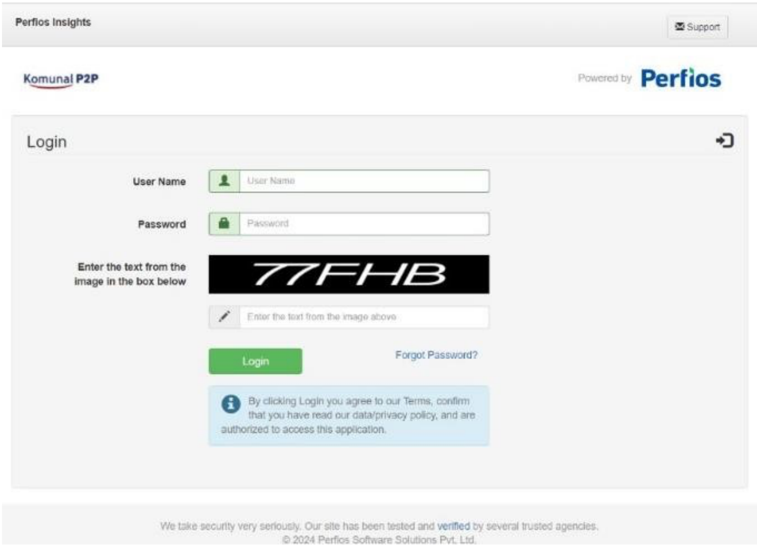

Figure 5. Display of The Perfios System in Komunal Fintech
(https://komunal.powercred.io)

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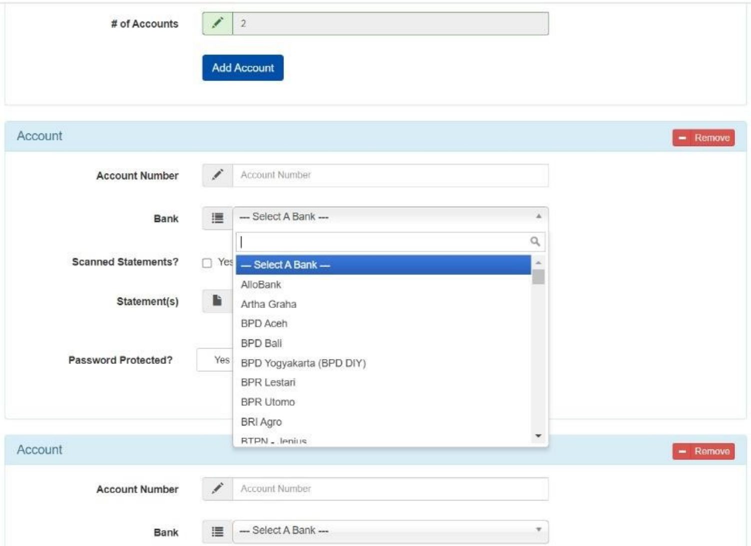

Figure 6. Dashboard Display in Komunal Fintech
(https://komunal.powercred.io)

Figure 6 shows the initial appearance of Perfios where in Perfios there are 5 main menus, namely Account (assignment). In this menu, a credit analyst will fill in the account number of bank statement, and then choose the name of the bank of the borrower's account. After that, we have to choose yes or no in the fill of scanned statements. This is to provide information to the system to be more aware. Some borrowers provide bank statements in the form of scanned documents, of course this makes the system work more difficult, but it is still possible. The credit analyst will upload the account mutation documents on a monthly basis. There is a fifth column, namely the code to open the document if you need a password. The results of this process will be grouped into several sections in the Microsoft Excel. And this process will only take 1-2 hours.

Possible Fraud Indicators	Tamper check	Identified	Count of Triggers	Remarks	Tamper Tag
0	PDF E-Statement Verification	Not Verified	6	;ustus 23.pdf* des 23-1.p	Early Warning
1	Font-Check	Verified	0	All files are verified.	Fraud

Figure 7. Display of Results of Performance in Microsoft Excel.

Figure 7 illustrates the outcomes of the verification process, offering crucial insights into the validity of bank account transactions. The data reveals that transactions conducted in August 2023 and December 2023 failed to pass verification, indicating uncertainty regarding the authenticity of the account during those periods. Conversely, transactions from other months received verification clearance by Perfios, affirming their credibility.

=This verification process plays a pivotal role for credit analysts in scrutinizing the legitimacy of the data and documentation provided by loan applicants. By highlighting discrepancies or potential issues with certain transactions, it serves as an

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invaluable tool for assessing the borrower's trustworthiness. Specifically, it acts as an early warning system, alerting analysts to possible fraudulent behavior or dubious intentions on the part of the borrower, particularly if there's a pattern of suspicious activity.

This capability greatly enhances the efficiency and reliability of decision-making for analysts, enabling them to swiftly identify and respond to red flags while evaluating loan applications. Ultimately, it empowers them to make more informed and prudent lending decisions, safeguarding the interests of the financial institution and minimizing potential risks associated with fraudulent activities.

File Name	Institution	Account No	Transaction Start Date	Transaction End Date	Statement Status	Perfios Transaction Id
sep23.pdf	Bank Rakyat Indonesia (BRI), Indonesia	012801001972309	1/Sep/23	30/Sep/23	REFER	FAF41709102469666
oktober23.pdf	Bank Rakyat Indonesia (BRI), Indonesia	012801001972309	1/Oct/23	31/Oct/23	REFER	FAF41709102469666
agustus23.pdf	Bank Rakyat Indonesia (BRI), Indonesia	012801001972309	1/Aug/23	31/Aug/23	REFER	FAF41709102469666
JAN24.pdf	Bank Rakyat Indonesia (BRI), Indonesia	012801001972309	5/Jan/24	31/Jan/24	REFER	FAF41709102469666
nov23.pdf	Bank Rakyat Indonesia (BRI), Indonesia	012801001972309	1/Nov/23	30/Nov/23	REFER	FAF41709102469666
des231.pdf	Bank Rakyat Indonesia (BRI), Indonesia	012801001972309	1/Dec/23	31/Dec/23	REFER	FAF41709102469666

REMARKS

All considered statements are identified as **REFER**, due to insufficient data for fraud check

File Name	Institution	Account No	Transaction Start Date	Transaction End Date	Name as in Statement	Statement Status	Perfios Transaction Id
OCBCHKDOKT2023.pdf	Bank OCBC NISP, Indonesia	642800003195	11/Oct/23	17/Oct/23	PT. HUSEIN ALAM INDAH	VERIFIED	M4LK1712229503683
OCBCHKDDES2023.pdf	Bank OCBC NISP, Indonesia	642800003195	1/Dec/23	1/Dec/23	PT. HUSEIN ALAM INDAH	VERIFIED	M4LK1712229503683
OCBCHKDNOVEMBER2023.pdf	Bank OCBC NISP, Indonesia	642800003195	29/Nov/23	29/Nov/23	PT. HUSEIN ALAM INDAH	VERIFIED	M4LK1712229503683

Figure 8. Display of List of Bank Statements Every Month on Perfios

(https://komunal.powercred.io)

Perfios provides information about the statement status for each month of the referenced bank account. From this information, credit analysts can analyze data that indicates potential fraud checks. However, on the other hand, we can see that Perfios will provide "Verified" status for the bank statements they process if the data is proven to be correct and valid. As such, Perfios plays an important role in validating and providing confidence in the data used in the credit analysis process.

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Jan-24	
Description	**Amount**
Transfer To Self	1,115,000,000.00
Transfer to DONI SURYANA	75,000,000.00
Transfer to BPR INTIDANA SUKSES MAKM	52,356,000.00
Transfer to EEP SUHERMAN	50,000,000.00
Transfer to RINI ANDINI	50,000,000.00
Feb-24	
Description	**Amount**
Transfer To Self	707,000,000.00
Transfer to EEP SUHERMAN	55,000,000.00
Transfer to BPR INTIDANA SUKSES MAKM	52,356,000.00
Transfer to ASEP ASNAWI AZIS	50,000,000.00
Transfer to MUHAMAD IKBAL	50,000,000.00
Mar-24	
Description	**Amount**
Transfer To Self	216,500,000.00
Transfer to EEP SUHERMAN	140,000,000.00
Transfer to BPR INTIDANA SUKSES MAKM	48,980,000.00
Transfer to SURYANA	28,600,000.00
Transfer to OPTIMA PERKASA NUSANTARA PT	25,000,000.00

Jan-24	
Description	**Amount**
Interest	286,979.19
Feb-24	
Description	**Amount**
Transfer from ASEP ASNAWI AZIS	637,000,000.00
Transfer from MITRA PRIMA INVESTAMA PT PEMBAYARAN TERMIN	480,196,094.00
Interest	109,593.85
Mar-24	
Description	**Amount**
Transfer from ASEP SYAIFUL MALIK LAINNYA	150,000,000.00
Transfer from Self	140,000,000.00
Interest	13,473.38

Figure 9. Display of Result which Shows Top 5 Funds Remittance and Top 5 Funds Received

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Figure 9 offers a detailed breakdown of transaction verification outcomes, aiding analysts in distinguishing between credit (sales) and debit (purchases) transactions. This helps track the borrower's cash flow and validates key data points like top buyer and supplier information. Verified transaction data forms the basis for assessing repayment capacity, allowing analysts to evaluate revenue consistency and overall financial health. In summary, Figure 9 is vital for conducting precise repayment capacity analyses, improving the accuracy of credit risk assessments and lending decisions.

When delving into data stored in Excel files, it's frequently a daunting task to uncover patterns or trends embedded within. This challenge arises from the intricate nature of the data and the sheer abundance of information present, which can overwhelm traditional methods of analysis such as simple tables or graphs. For instance, financial datasets are notorious for their complexity, often encompassing myriad variables and entries. In such cases, attempting to discern relationships or correlations among the various factors manually can become an arduous and time-consuming endeavor. This complexity is further compounded by the potential interplay between different variables, making it even more challenging to extract meaningful insights from the data using conventional approaches.

Excel, as a commonly used data management tool, has limitations in its ability to process and analyze data with high complexity [21]. Meanwhile, more advanced data analysis tools such as RapidMiner offer more effective solutions [22]. By using techniques such as K-Means Clustering, RapidMiner can automatically identify hidden patterns in the data [23]. This allows users to explore data in greater depth, uncover new insights, and make better decisions in a business or financial context. Thus, the use of more advanced data analysis tools such as RapidMiner can unlock new potential in understanding and utilizing the information available in financial and business data [24].

See Patterns with Visualization

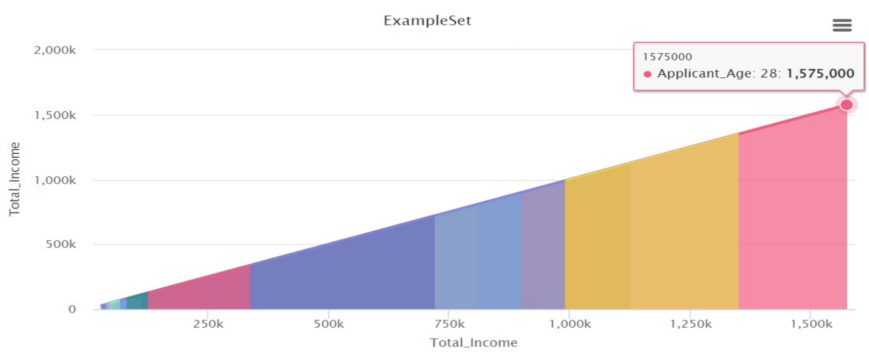

Figure 10. Visualization of Total Income Based on Age

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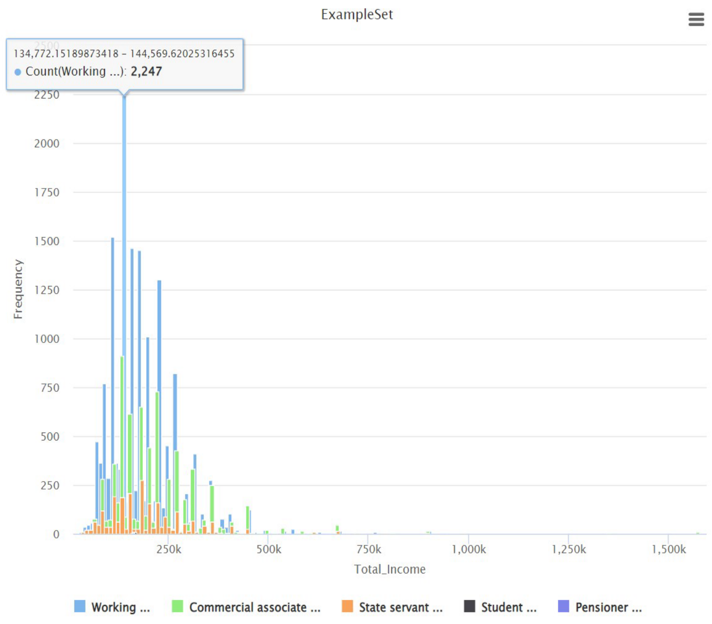

Figure 11. Visualization of Total Income Based on Type of Income Seen from Frequency

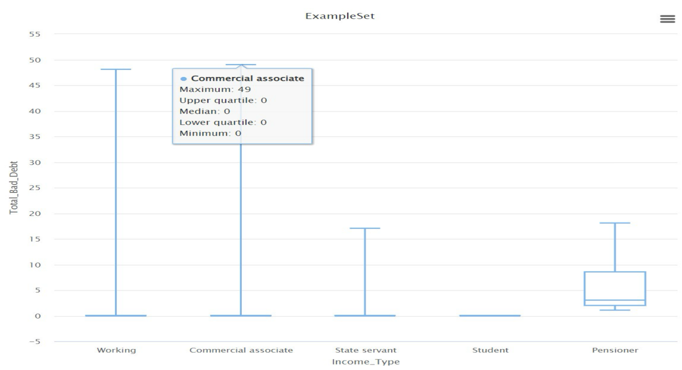

Figure 12. Visualization of Bad Debts by Income Type

Discussion

Figure 10 portrays significant income patterns, emphasizing that the peak income occurs within the 28-year-old age group within the application cohort. Shifting focus to employment categories, Figure 11 indicates that the highest total income is concentrated within the "working" category. Meanwhile, Figure 12 provides insights into the categories contributing to the highest bad debt, revealing that the highest bad debt emanates from the "commercial associate" group. Lastly, Figure 13 highlights the pattern of the highest frequency of bad debt, once again showcasing dominance from the "working" category. Through this series of visualizations, key information regarding income, employment types, and bad debt patterns is gleaned, offering a deeper understanding of financial dynamics within the context of credit

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analysis. Leveraging this data, decision-makers are equipped with a stronger foundation to design more effective risk strategies and respond to changes in credit profiles more responsively.

The visualizations presented in Figures 10 through 13 offer valuable insights into various aspects of income distribution, employment categories, and bad debt patterns within the context of credit analysis. Figure 10 highlights a noteworthy trend where the highest income peaks among individuals aged 28 within the applicant cohort, suggesting potential correlations between age and income levels. Moving on, Figure 11 shifts the focus to employment categories, revealing that the "working" category exhibits the highest total income. This underscores the significance of employment status in determining income levels and subsequent creditworthiness. Conversely, Figure 12 sheds light on the categories contributing to the highest bad debt, pinpointing the "commercial associate" group as the primary source. This emphasizes the importance of understanding the risk profiles associated with different employment categories. Additionally, Figure 13 underscores the prevalence of bad debt within the "working" category, indicating a recurring pattern that decision-makers need to address in risk mitigation strategies. By synthesizing these visualizations, stakeholders gain deeper insights into income dynamics, employment trends, and bad debt occurrences, empowering them to make more informed decisions in credit risk assessment and management [25]. Armed with this comprehensive understanding, decision-makers can develop more effective risk strategies tailored to address specific challenges and fluctuations within credit profiles, ultimately enhancing the overall risk management framework.

CONCLUSION

Visualization using RapidMiner provides important information about income patterns, job categories, and bad credit patterns in credit analysis. From figures 10 to 13, we see that age 28 is the peak income, the "working" category has the highest total income, the highest bad debt comes from the "commercial associate" group, and the highest frequency of bad debt also comes from the "working" category. RapidMiner's advantage is its ability to process complex data quickly and present it intuitively, enabling fintech decision makers to design more responsive and precise risk strategies.

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