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Implementation of Business Intelligence and Data Mining in Money Changer Transaction Analysis (Case Study of PT. Gemilang Artha Valindo)

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ABSTRACT

This study aimed to implement Business Intelligence (BI) and Data Mining for analyzing currency exchange transactions at PT. Gemilang Artha Valindo to support data-driven decision-making. Transaction data was analyzed using Power BI to generate visualizations, including a pie chart for transaction frequency by currency type, a bar chart for the number of buy and sell transactions per currency, and a line chart for monthly average exchange rate fluctuations. The pie chart indicated that the AUD currency dominated transactions, contributing 51.95% of the total. The bar chart revealed that AUD buy transactions accounted for 63.22% of total AUD transactions, while the line chart showed that GBP and EUR had the highest average exchange rates, reaching Rp20,835 and Rp17,700, respectively. The exchange rate prediction process utilized three algorithms: Linear Regression, K-Nearest Neighbors (KNN), and Random Forest. Their performances were evaluated using Root Mean Squared Error (RMSE). The Random Forest algorithm produced the most accurate predictions with the lowest RMSE value of 134.63, followed by KNN and Linear Regression. These findings highlight the importance of leveraging BI and Data Mining to transform transaction data into valuable insights, enabling more informed business decisions.

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1. INTRODUCTION

The currency exchange business (money changer) is one of the financial sectors that is heavily influenced by fluctuations in exchange rates and global market dynamics [1]. Exchange rate changes, influenced by various economic factors such as interest rates, inflation, and economic growth, often introduce uncertainty that can affect the stability of the business and strategic decision-making. Additionally, exchange rate fluctuations, which are not easily predictable, often add complexity to a company's ability to plan and manage its operations. This is especially true in the money changer industry, where precise decisions regarding currency buying and selling prices highly depend on the constantly changing market conditions. PT. Gemilang Artha Valindo, as a player in the money changer industry, must also be able to anticipate these changes with the right strategies. Therefore, the company needs to have a structured and data-driven approach to manage risks and maximize profits, while considering external factors that influence the foreign exchange market [2][3].

In today's digital era, data-driven analysis has become a key factor in addressing these challenges. The advancement of information technology allows companies to collect and analyze large volumes of data to gain deeper insights. Business Intelligence (BI) and Data Mining are two approaches that can be used to analyze transaction data more effectively and efficiently. BI enables data processing into more structured, easily understood, and quickly accessible information for decision-makers [4][3][5]. With BI, companies can visualize data clearly and in-depth, making it easier to identify trends and patterns. On the other hand, Data Mining focuses on uncovering hidden patterns or information in data that may not be immediately visible [6][7]. This technique allows companies to discover patterns that can be used for predictions, such as future exchange rate trends [8]. The combination of these two approaches provides opportunities for companies to better understand market behavior, improve operational efficiency, and optimize business strategies based on more accurate and detailed data [9].

This study uses the ETL (Extract, Transform, Load) approach to prepare currency exchange transaction data collected from internal company sources, such as daily transaction data, as well as external data, including exchange rates from Bank Indonesia and macroeconomic indicators from the Central Statistics Agency (BPS). The ETL process aims to ensure that the data used is clean, consistent, and ready for analysis [10]. The first step, Extract, involves gathering data from relevant sources, while the Transform step changes the raw data into a more suitable and analysable format. The Transform process also includes data cleaning to eliminate errors or duplicates that could affect the analysis results. In the final stage, Load, the processed data is then loaded into the system for further analysis. By using the proper ETL approach, the company ensures that the data used in this study is of high quality and ready to generate valid and reliable insights. Once the data is prepared, Business Intelligence is used to generate visualizations that provide an overview of transaction patterns, while Data Mining algorithms are used to predict future exchange rates.

Data prediction in this study is conducted using three main algorithms: Linear Regression, K-Nearest Neighbors (KNN), and Random Forest. These three algorithms were chosen based on their ability to capture the relationship between predictor variables, such as interest rates and inflation, and the target prediction, which is the exchange rate. Each algorithm has its strengths and weaknesses, making them suitable for different types of data and prediction goals. For instance, Linear Regression is a simple method used for linear models between inputs and outputs. K-Nearest Neighbors (KNN) is an algorithm based on proximity or similarity between data points, while Random Forest is a decision tree-based algorithm that can handle more complex data with multiple variables. To evaluate the model performance, the Root Mean Squared Error (RMSE) metric is used, which is a common method for measuring prediction accuracy in data analysis. The evaluation results show that the Random Forest model provides the most accurate predictions with the lowest RMSE value, followed by KNN and Linear Regression, indicating how each method affects the accuracy of exchange rate predictions.

Furthermore, this study builds upon previous research that has demonstrated the value of BI and Data Mining in various domains, such as enhancing health services [11], identifying disasterprone regions [12], and optimizing business strategies [4]. These studies have highlighted how analytical technologies can transform raw data into actionable insights, enabling more effective decision-making across different sectors. Building on these findings, this study explores the potential of BI and Data Mining in a distinct and relatively underexamined domain: the financial sector, specifically within the money changer industry. By focusing on PT. Gemilang Artha Valindo as a case study, this research aims to showcase how these technologies can be adapted to address the unique challenges of fluctuating foreign exchange markets, offering a new perspective on their applicability and impact. The integration of BI and Data Mining in this study goes beyond simplifying data visualization and uncovering hidden patterns, it provides a framework for combining descriptive and predictive analytics tailored to the money changer context.

This study aims to provide a data-driven solution for PT. Gemilang Artha Valindo to support more precise and efficient strategic decision-making. By using BI and Data Mining, the company can gain deeper insights into transaction patterns and market trends that can be relied upon to plan future business steps [13][14]. Moreover, this study demonstrates how analytical technology can be used to predict exchange rate fluctuations based on relevant economic factors. With more accurate information, the company can develop more effective and competitive business strategies while managing the risks associated with exchange rate fluctuations. This study is also expected to contribute significantly to the development of knowledge in the field of analytical technology implementation in the financial sector, particularly in the management of increasingly complex foreign exchange transactions. It is hoped that the results of this research will not only benefit PT. Gemilang Artha Valindo but also the financial industry in general, by enhancing the understanding of how data technology can be used to improve competitiveness and data-driven decision-making.

2. RESEARCH METHOD

Figure 1. illustrates the research flow conducted in the implementation of Business Intelligence and Data Mining in the analysis of currency exchange transactions at PT. Gemilang Artha Valindo. Starting with the process of identification, this flow involves problem identification to understand the research needs, followed by literature review and data collection. The collected data then undergoes the ETL (Extract, Transform, Load) stages to ensure the data is clean and ready for analysis. After that, two main processes are carried out: data visualization using Power BI to provide initial insights into transaction patterns, and data prediction using the Orange software with specific algorithms. The prediction results are compared using RMSE to evaluate the accuracy of each algorithm. The final stages include presenting the results in the results and discussion section, followed by conclusions that provide strategic recommendations for the company. The process concludes with the end stage to close the entire research cycle.

2.1. Problem Identification

The research begins with the problem identification process, where the researcher thoroughly examines and identifies the specific issues or challenges faced by the company. This step is crucial as it helps define the scope of the study and ensures that the research focuses on solving the most relevant problems. By understanding the challenges faced by the company, the researcher can establish clear objectives and determine the appropriate methods and tools needed to address these issues effectively. This stage sets the foundation for the subsequent phases of the research, ensuring that the analysis and solutions developed are aligned with the company's needs and goals.

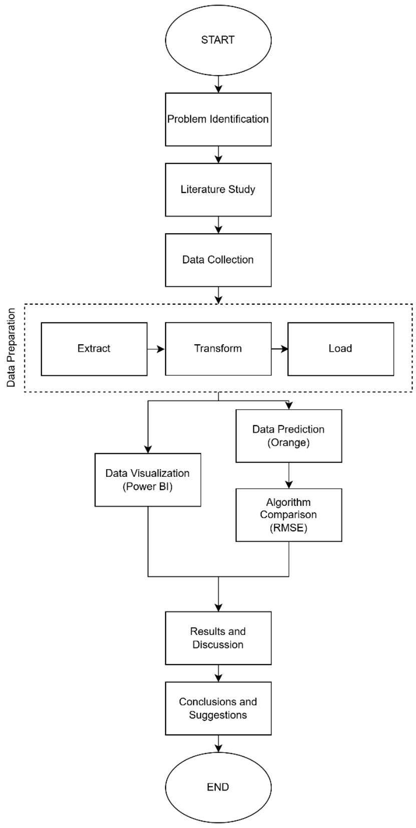

Figure 1. Research Flow

2.2. Literature Study

The researcher conducts an extensive search and analysis of previous studies, books, and scientific journal articles relevant to the research topic. This literature review serves as a critical step to deepen the researcher's understanding of the context surrounding the identified problems. By examining prior research, the researcher can identify existing gaps in knowledge, methodologies that have been previously employed, and insights into factors influencing similar challenges. Additionally, this process helps the researcher to build a theoretical framework and establish a solid foundation for the study. The literature review not only ensures that the current research is grounded in existing knowledge but also provides valuable references that can guide the selection of methods and tools. Furthermore, it allows the researcher to justify the significance of the study and position it within the broader academic and practical landscape, ensuring its contribution to both scholarly discourse and industry practices.

2.3. Data Collection

The data collection stage involves a systematic process of gathering information relevant to the identified problem [15]. This stage is crucial as it provides the foundational data necessary for analysis and decision-making. Researchers employ various methods to ensure the completeness and accuracy of the information collected. One of the primary methods used is interviews, which allow for in-depth insights directly from stakeholders involved in the company. Through interviews, researchers can explore the perspectives, experiences, and expectations of stakeholders, uncovering valuable qualitative data that may not be apparent through quantitative measures alone [16].

In addition to interviews, other techniques such as reviewing company records, analyzing historical transaction data, and consulting external data sources, such as industry reports or regulatory guidelines, may also be employed. These methods aim to provide a comprehensive understanding of the factors influencing the problem. By combining multiple data sources, researchers can ensure the robustness and reliability of the collected data. Furthermore, the data collection process is designed to be iterative, allowing for adjustments based on initial findings to capture all relevant variables comprehensively. This meticulous approach ensures that the subsequent analysis is well-informed and aligned with the research objectives.

2.4. Data Preparation

After the data is collected, the next step is to process the data by performing the ETL (extract, transform, load) process. The following is part of the ETL process [17]:

a) Extract

Data collection in this study was carried out by directly taking currency exchange transaction data owned by PT Gemilang Artha Valindo as in table 1. The data includes important information about daily transactions, such as transaction date, type of currency exchanged, type of transaction (buy or sell), amount of currency exchanged, exchange rate at the time of the transaction, and the amount of rupiah received or paid. The transaction data used covers the period January 2023 to June 2024, and is the main data used for visualization and prediction in this study.

Table 1. Transaction

	No Nota	Nama Nasabah	UKA	Jenis Transaksi	Jml UKA	Kurs Transaksi	Jml Rupiah
02/01/2023		#####	AUD	Beli	100	10.325,00	1.032.500,00
02/01/2023		#####	AUD	Beli	300	10.325,00	3.097.500,00
02/01/2023		#####	AUD	Beli	325	10.325,00	3.355.625,00
02/01/2023		#####	AUD	Beli	50	10.325,00	516.250,00
02/01/2023		#####	AUD	Beli	200	10.325,00	2.065.000,00
02/01/2023		#####	AUD	Beli	450	10.325,00	4.646.250,00
…	…	…	…	…	…	…	…
31/12/2023		#####	AUD	Beli	100	10.025,00	1.002.500,00
31/12/2023		#####	AUD	Beli	160	10.025,00	1.604.000,00
31/12/2023		#####	AUD	Beli	50	10.025,00	501.250,00

In addition to internal data from PT Gemilang Artha Valindo, this research also relies on external data from various trusted sources to complete the analysis. One of the external sources used is the official website of Bank Indonesia, to obtain data related to rupiah interest rates against foreign currencies. This interest rate is considered because it can affect exchange rate fluctuations which are an important part of analyzing future exchange rate predictions. This data can be seen in table 2.

Table 2. Interest Rate

Bulan	Suku Bunga
Januari 2023	5,75
Februari 2023	5,75
Maret 2023	5,75
April 2023	5,75
Mei 2023	5,75
Juni 2023	5,75
Juli 2023	5,75
Agustus 2023	5,75
September 2023	5,75
Oktober 2023	6,00
November 2023	6,00
Desember 2023	6,00
Januari 2024	6,00
Februari 2024	6,00
Maret 2024	6,00
April 2024	6,25
Mei 2024	6,25
Juni 2024	6,25

In addition, other macroeconomic data such as inflation and economic growth were obtained from the Badan Pusat Statistik (BPS) as shown in table 3. Inflation and economic growth data are used to provide a broader context for the analysis, helping researchers see how larger economic factors can impact transaction volumes and exchange rate trends at PT Gemilang Artha Valindo.

Table 3. Inflation and GDP

Bulan	Inflasi	Pertumbuhan Ekonomi
Januari 2023	5,28	5,04
Februari 2023	5,47	5,04
Maret 2023	4,97	5,04
April 2023	4,33	5,17
Mei 2023	4,00	5,17
Juni 2023	3,52	5,17
Juli 2023	3,08	4,94
Agustus 2023	3,27	4,94
September 2023	2,28	4,94
Oktober 2023	2,56	5,04
November 2023	2,86	5,04
Desember 2023	2,61	5,04
Januari 2024	2,57	5,11
Februari 2024	2,75	5,11
Maret 2024	3,05	5,11
April 2024	3,00	5,05
Mei 2024	2,84	5,05
Juni 2024	2,51	5,05

b) Transform

Transformation is the process of changing the data that has been collected to suit the desired business and technical needs. This process involves various steps, such as changing the format or type of data, performing certain calculations, filtering out irrelevant data, and summarizing information to make it easier to understand and use.

Table 4. Raw Data

	No Nota	Nama Nasabah	UKA	Jenis Transaksi	Jml UKA	Kurs Transaksi	Jml Rupiah
02/01/2023		#####	AUD	Beli	100	10.325,00	1.032.500,00
02/01/2023		#####	AUD	Beli	300	10.325,00	3.097.500,00
02/01/2023		#####	AUD	Beli	325	10.325,00	3.355.625,00
02/01/2023		#####	AUD	Beli	50	10.325,00	516.250,00
02/01/2023		#####	AUD	Beli	200	10.325,00	2.065.000,00
02/01/2023		#####	AUD	Beli	450	10.325,00	4.646.250,00
…	…	…	…	…	…	…	…
31/12/2023		#####	AUD	Beli	100	10.025,00	1.002.500,00
31/12/2023		#####	AUD	Beli	160	10.025,00	1.604.000,00
31/12/2023		#####	AUD	Beli	50	10.025,00	501.250,00

Based on Table 4, it seen that there are some data columns that have no values or are empty, so they do not contribute meaningfully to the analysis. In addition, there are also columns that contain sensitive information such as customer names, which are not relevant to use in this study due to privacy and data protection considerations. Therefore, empty columns and columns containing privacy data will be removed to ensure the data used is cleaner, more relevant and suitable for the analysis needs, while complying with data security standards.

Table 5. Data After Transformation

	UKA	Jenis Transaksi	Jml UKA	Kurs Transaksi	Jml Rupiah
02/01/2023	AUD	Beli	100	10.325,00	1.032.500,00
02/01/2023	AUD	Beli	300	10.325,00	3.097.500,00
02/01/2023	AUD	Beli	325	10.325,00	3.355.625,00
02/01/2023	AUD	Beli	50	10.325,00	516.250,00
02/01/2023	AUD	Beli	200	10.325,00	2.065.000,00
02/01/2023	AUD	Beli	450	10.325,00	4.646.250,00
02/01/2023	AUD	Beli	350	10.325,00	3.613.750,00
…	…	…	…	…	…
30/06/2024	AUD	Beli	200	10.375,00	2.075.000,00
30/06/2024	AUD	Beli	50	10.375,00	518.750,00
30/06/2024	AUD	Beli	200	10.375,00	2.075.000,00

In Figure 5, it seen the transaction data after the data cleaning process. This transaction data will be the main material in the visualization process that will be carried out using Power BI. By utilizing Power BI, transaction data will be processed and visualized in various forms, such as graphs and diagrams, which allow a deeper understanding of transaction patterns. Furthermore, data that has been obtained from data collection such as interest rate data and inflation and economic growth data will be combined with transaction data used as training data in the process of making predictions later. This merging is done to create a richer and more in-depth data set, which will be used as training data in the prediction process.

Table 6. Prediction Data

Tanggal	UKA	Jenis Transaksi	Jml UKA	Inflasi	Suku Bunga	Pertumbuhan ekonomi	Kurs Transaksi	Jml Rupiah
02/01/2023	AUD	Beli	100	5,28	5,75	5,04	Rp10.325,00	Rp1.032.500,00
02/01/2023	AUD	Beli	300	5,28	5,75	5,04	Rp10.325,00	Rp3.097.500,00
02/01/2023	AUD	Beli	325	5,28	5,75	5,04	Rp10.325,00	Rp3.355.625,00
02/01/2023	AUD	Beli	50	5,28	5,75	5,04	Rp10.325,00	Rp516.250,00
02/01/2023	AUD	Beli	200	5,28	5,75	5,04	Rp10.325,00	Rp2.065.000,00
02/01/2023	AUD	Beli	450	5,28	5,75	5,04	Rp10.325,00	Rp4.646.250,00
…	…	…	…	…	…	…	…	…
30/06/2024	AUD	Beli	200	2,51	6,25	5,05	10.375,00	2.075.000,00
30/06/2024	AUD	Beli	50	2,51	6,25	5,05	10.375,00	518.750,00
30/06/2024	AUD	Beli	200	2,51	6,25	5,05	10.375,00	2.075.000,00

In this prediction process, only transaction data for the Australian currency (AUD) will be used as shown in Table 6. The main reason for choosing AUD as the focus is the most significant transaction volume compared to other currencies.

c) Load

The Load process is the last stage in the Extract, Transform, Load (ETL) series. In this phase, the data that has been extracted and transformed is stored for further use. The data will be saved in .xlsx format, which will then be uploaded into the Power BI and Orange applications. This aims to facilitate better visualization and prediction, so that the information generated can provide deeper and more useful insights for the transaction analysis performed.

2.5. Data Visualization

The processed data is then visualized using Power BI to provide deeper insights and a clearer understanding of the information. Power BI, as a robust Business Intelligence tool, enables the creation of dynamic and interactive visualizations that present data in an intuitive and accessible format [11][18]. The visualizations can take various forms, including graphs, charts, and dashboards, depending on the type of data and the insights targeted. This visualization process is not merely about representing data but also about transforming raw information into actionable insights [12]. Through the use of Power BI, researchers and decision makers can identify key patterns and trends that might otherwise remain hidden in raw datasets. For instance, visualizations can highlight the most frequently exchanged currencies, providing a clear picture of market preferences and demand . Similarly, bar charts or pie charts can be used to illustrate the distribution of buy and sell transactions for each currency, offering valuable information about transaction dynamics. Furthermore, line graphs or trend charts can be employed to display the fluctuations in exchange rates over time for each currency. This enables stakeholders to analyze historical trends and anticipate potential future movements, aiding in strategic planning.

2.6. Data Prediction

The processed data will then be utilized for prediction using data mining techniques implemented via the Orange application. Three algorithms Linear Regression, Random Forest, and K-Nearest Neighbors (KNN) are employed to perform predictive analysis. These algorithms are carefully selected for their ability to model relationships between predictors and the target variable effectively, ensuring a comprehensive evaluation of their performance in the context of currency exchange transactions. The primary focus of this prediction task is to forecast the transaction exchange rate for the currency with the highest transaction volume, which, at PT. Gemilang Artha Valindo, is the Australian Dollar (AUD). This focus on AUD is driven by its dominance in the company's transaction portfolio, accounting for a significant proportion of total transactions. Predicting the exchange rate of AUD provides critical insights for the company to optimize pricing strategies, manage risk, and enhance customer satisfaction.

The prediction process begins by training each of the selected algorithms on historical data, which includes variables such as past exchange rates, transaction volumes, and relevant economic indicators like interest rates and inflation. Linear Regression is utilized for its simplicity and effectiveness in capturing linear relationships, while Random Forest is chosen for its robustness and ability to model complex, non-linear patterns in data [19][20]. KNN complements these methods by providing a proximity-based approach that can capture local variations in the dataset [21] [22]. Once the models are trained and validated, predictions are made for specific time periods, enabling the company to anticipate future trends in AUD exchange rates. The performance of each model is assessed using the Root Mean Squared Error (RMSE) metric, a standard evaluation criterion that quantifies the accuracy of predictions. The algorithm with the lowest RMSE will be identified as the most reliable for future forecasting tasks [23].

2.7. Algorithm Comparison

The algorithm used to predict will be compared with the Root Mean Squared Error (RMSE). By comparing RMSE values, this research can determine which algorithm is more effective and accurate in predicting transaction rates based on the data used. The RMSE formula is as follows [24][25]:

$$\text{RMSE}=\sqrt{\frac{\sum_{t=1}^{n}\left(A_t-Y_t\right)^2}{n}}$$

Where:

- At = Value of actual data
- Yt = Value of the prediction result
- n = Number of data
- t = Order of data

3. RESULTS AND DISCUSSION

3.1. Data Visualization Result

In the visualization stage, the author uses Power BI software to produce various visual analyses that facilitate data interpretation. This visualization includes the average transaction rate of each currency every month, the number of buy and sell transactions in each currency, as well as a comparison of the average transaction rates for various currencies in a certain period.

a) Transaction Frequency by Currency Type

This visualization is done to show the frequency distribution of transactions by currency type. Figure 2 shows a pie chart depicting the number of transactions of the various currencies used in the dataset. This diagram helps in understanding the proportion of transactions made with a particular currency in the analyzed period.

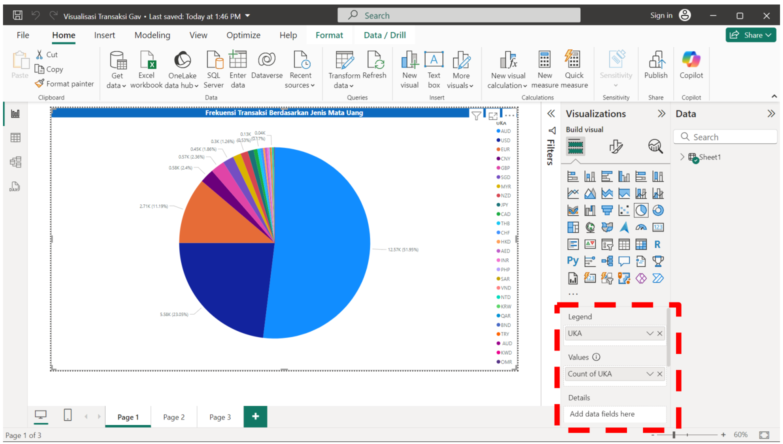

Figure 2. Pie Chart

To produce the visualization shown in Figure 2, the UKA column is used to represent the type of currency as Legend, while the number of transactions, represented by Count of UKA, is used as Values. The Legend function is to distinguish the type of currency in the graph, so that each color in the graph indicates a different currency. Meanwhile, Values serves to display the frequency or number of transactions for each currency displayed on the chart.

Values are used to show the size or total of each category to be visualized. Legend is used to explain the colors or symbols in the chart that represent different groups or categories. The legend is important to understand how the data is broken down or grouped based on certain variables. With this configuration, Power BI automatically calculates the frequency of each type of currency and displays it in the form of an easy to understand pie chart as shown in figure 3.

Based on this visualization, it can be concluded that AUD (Australian Dollar) dominates significantly in the frequency of transactions at money changers, accounting for more than half of all transactions that occur. USD (US Dollar) follows in second place with a significant proportion of transactions, but still far below AUD. Other currencies such as EUR, SGD and JPY recorded smaller contributions. Overall, transactions at this money changer are heavily centered on the two main currencies, AUD and USD, with the remainder split across several other currencies with much lower frequencies.

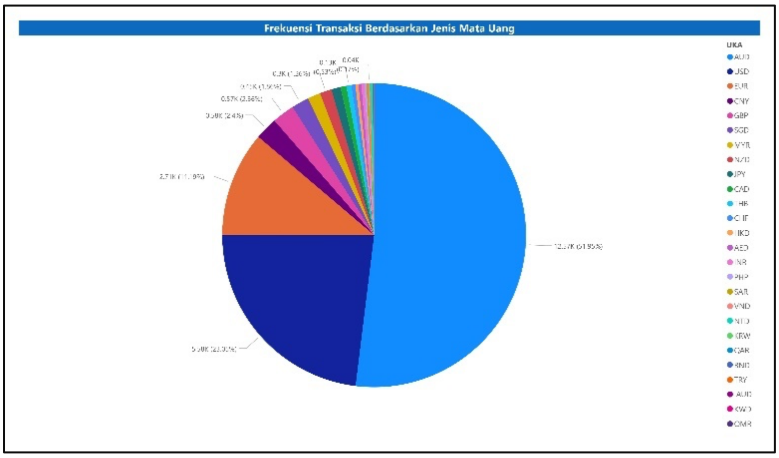

Figure 3. Pie Chart Result

b) Number of Buy and Sell Transactions in Each Currency

This visualization displays the number of buy and sell transactions of various currencies, with the aim of providing an overview of the differences in the number of transactions based on the type of transaction (buy or sell). This bar chart illustrates the frequency of transactions of each currency within a certain time frame.

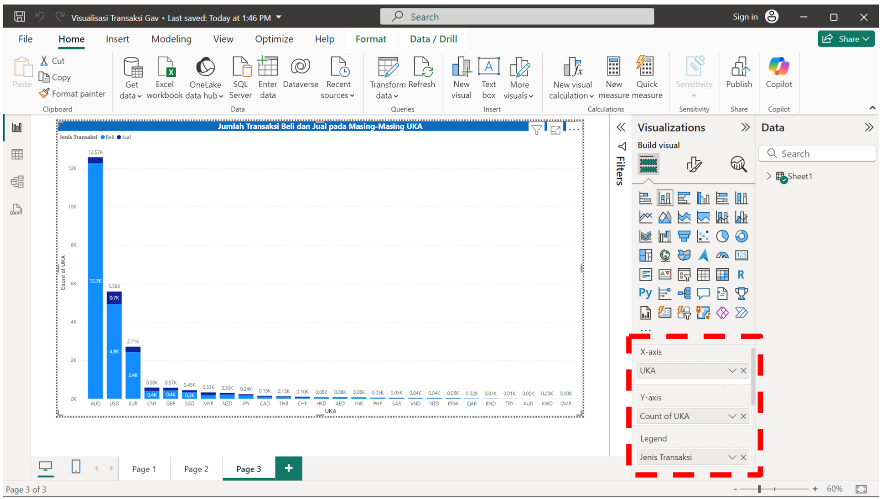

Figure 4. Bar Chart

To produce the visualization shown in Figure 4, the UKA Column is placed on the X-Axis to represent the type of currency used in transactions, such as AUD, USD, EUR, CNY, GBP, and others. Count of UKA is placed on the Y-Axis for the frequency or number of transactions that occur for each currency in a certain unit. The transaction type column is plotted on Legend which consists of two main categories, namely Buy and Sell.

The X-Axis function is the horizontal axis used to indicate the independent variable or category being measured. It is usually used to display discrete data such as category or time. Meanwhile, the Y-Axis function is the vertical axis that shows the dependent variable or the measured value in the visualization. With this configuration, Power BI automatically calculates the types of buy and sell transactions of each type of currency and displays them in the form of an easy-to-understand bar chart as shown in Figure 5.

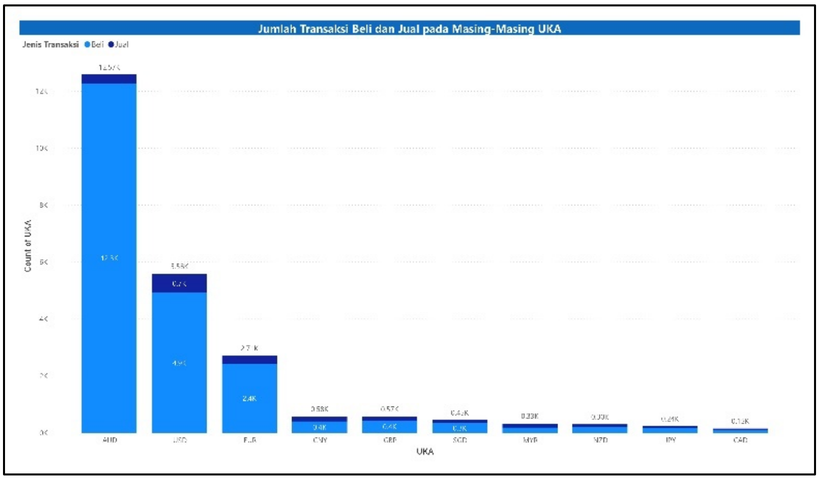

Figure 5. Bar Chart Result

Based on the visualization results, it can be concluded that the AUD (Australian Dollar) currency dominates the transaction at the money changer, especially in the purchase transaction which is much higher than the sale transaction. AUD recorded the largest number of transactions compared to other currencies, with USD (American Dollar) coming in second for total buy and sell transactions. This shows that these two currencies are the most popular among customers. Meanwhile, other currencies such as EUR (Euro), SGD (Singapore Dollar), MYR (Malaysian Ringgit), and JPY (Japanese Yen) recorded a significant amount of transactions, although still far below AUD and USD. Overall, the difference between buy and sell transactions was quite pronounced in some currencies, with currencies such as AUD having significantly more buy transactions than sell. This indicates a higher demand for the purchase of certain foreign currencies, especially AUD and USD.

c) Average Transaction Rate of Each Currency Each Month

This visualization displays monthly transaction rate fluctuations for the 10 most used currencies in transactions during the study period. The line chart presented provides an overview of the changes in the average value of transaction rates in each currency from month to month. The currencies shown are the main currencies that are frequently used in international transactions by users, namely: Australian Dollars (Aud), United States Dollars (Usd), Euro (Eur), Chinese Yuan (Cny), Pound sterling (Gbp), Singapore Dollars (Sgd), Malaysian Ringgit (Myr), New Zealand Dollars (Nzd), Japanese Yen (Jpy), and Canadian Dollars (Cad).

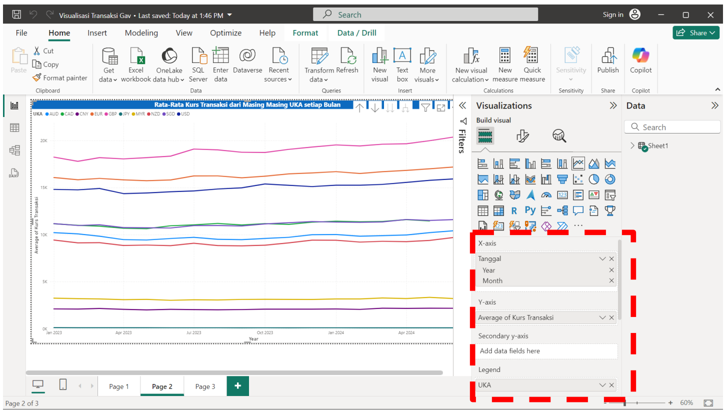

Figure 6. Line Chart

To get the visualization as shown in Figure 6, the Date column containing year and month is placed on the X-Axis to represent the time of the transaction. Average of Transaction Rates is placed on the Y-Axis to display the average transaction rate for each month. The UKA column is placed on Legend which consists of 10 UKAs with the most transactions. With this configuration, Power BI automatically calculates the average transaction rate of the currency and displays it in the form of an easy-to-understand line chart as shown in Figure 7.

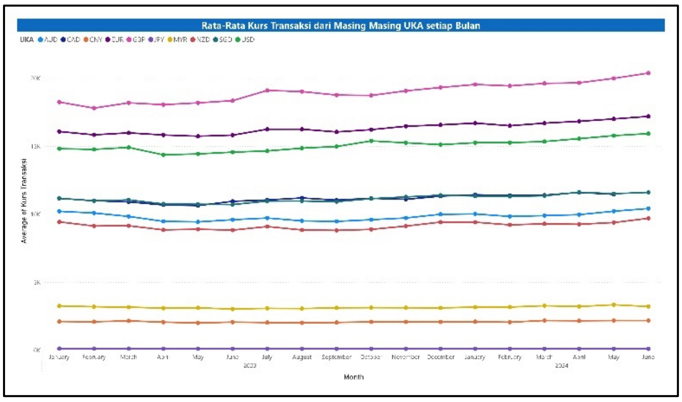

Figure 7. Line Chart Result

From this visualization it can be concluded that the average transaction rates of each currency have different levels and show varying trends of movement over the one-year time period. GBP (British Pound) and EUR (Euro) are consistently the currencies with the highest average rates, indicating that these two currencies are traded at higher prices than other currencies. Currencies such as AUD (Australian Dollar), SGD (Singapore Dollar), and JPY (Japanese Yen) experienced more stable exchange rate movements with minimal fluctuations. This shows that although there are changes from month to month, in general the transaction rates for the majority of currencies show stability with an upward trend in certain currencies such as GBP.

3.2. Data Prediction Result

In the prediction stage, the author uses Orange software as the main tool in the data mining process to predict currency exchange rates. Through the use of Orange, algorithms such as Linear Regression, k-Nearest Neighbors (k-NN), and Random Forest are applied to analyze the collected currency exchange transaction data. For this model in the Orange application can be seen in figure 8.

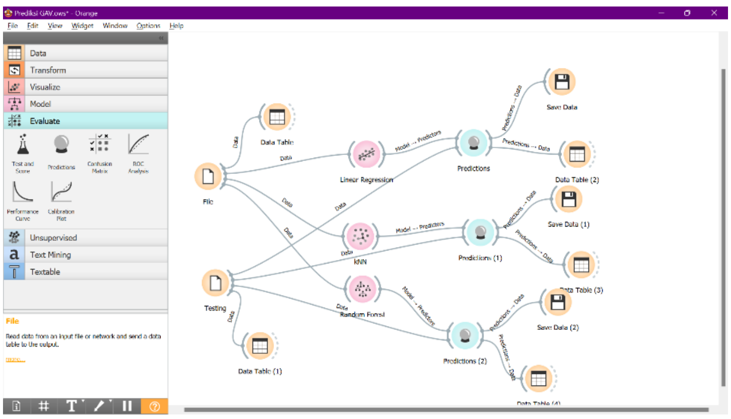

Figure 8. Prediction using orange

The first step in this data mining process is to enter data through the File node, where the two types of files entered are training data files and testing data.

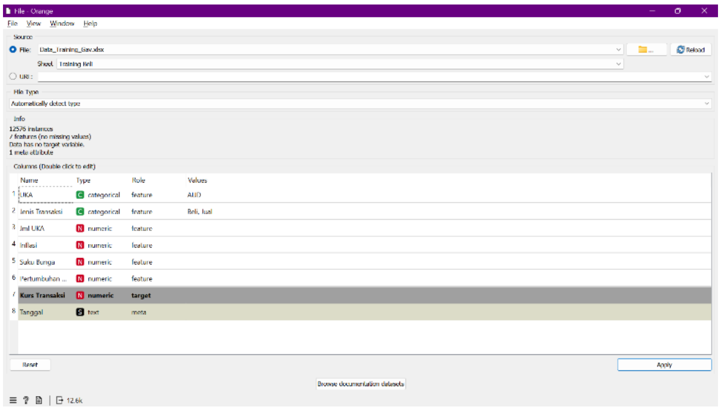

Figure 9. Input Data Training

In the training data file, there are several columns that contain important information divided into several categories, namely meta, feature, and target as shown in figure 9. The Date column is a meta column, which serves as supporting information but is not used directly in the prediction process. It helps provide additional context to the data, such as when the transaction occurred. Furthermore, columns such as UKA (AUD currency category), Transaction Type (Buy or Sell), UKA Amount, Inflation, Interest Rate, and Economic Growth are features. Features are variables or factors used by the model to learn and form patterns from the data. In this case, the features provide information related to economic conditions and transactions that affect currency rates. Finally, the Transaction Rates column is the target, which is the variable that we want to predict based on the features. This target acts as the expected output of the model, so the model will learn the relationship between the features and the target to produce predictions of future transaction rates.

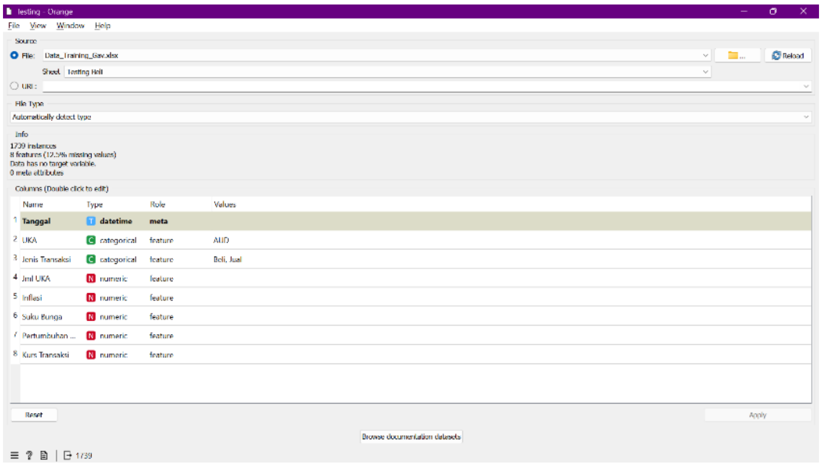

Figure 10. Input Data Testing

As for the testing data file, the data structure is similar, with some of the same columns, such as UKA, Transaction Type, Total UKA, Inflation, Interest Rate, and Economic Growth as shown in figure 10. However, the difference is that this file does not have the Transaction Rate column as the target, because this file is used to test the trained model, where the prediction of the transaction rate will be calculated based on the existing features. The data from these two files will be further processed to train the model and predict the results based on the testing data. The data entered through the File will then be displayed using the Data Table. This node is useful for visually displaying data so that researchers can verify that all required variables have been loaded correctly, as well as ensuring that there are no errors or discrepancies in the imported data.

After the data is displayed on the Data Table, the next step is to add the algorithms that will be used to build the prediction model. In this workflow visualization, there are three main algorithms used, namely Linear Regression, K-Nearest Neighbors (k-NN), and Random Forest. These three algorithms are directly linked to the node file that contains the training data, so that they can train their models based on the patterns contained in the data. These algorithms each work with different methods, but all aim to predict currency rates based on variables in the data.

After the model of each algorithm has been formed, a Prediction node is added which is tasked with making predictions using the model that has been trained. This Prediction will be connected to each algorithm (Linear Regression, KNN, and Random Forest) to retrieve the results of the model that has been formed. In addition, Prediction is also connected to the testing data file node that was previously entered. The testing data contains new information that has never been used by the model, so that the prediction results of the algorithm will be tested based on completely new and realistic data. After the prediction process is complete, the next step is to display the prediction results into a table for further analysis. For that, the next step is to draw a line from each Prediction node to the new Data Table node. This allows researchers to see the prediction results of the three algorithms in detail and compare the results of each model.

Table 7. KNN algorithm prediction results

Tanggal	UKA	Jenis Transaksi	Jml UKA	Inflasi	Suku Bunga	Pertumbuhan ekonomi	Hasil KNN	Data True
01/04/2024	AUD	Beli	220	3	6,25	5,05	9915,00	9.875,00
01/04/2024	AUD	Beli	400	3	6,25	5,05	10005,00	9.875,00
01/04/2024	AUD	Beli	500	3	6,25	5,05	9935,00	9.875,00
01/04/2024	AUD	Beli	50	3	6,25	5,05	10015,00	9.875,00
01/04/2024	AUD	Beli	100	3	6,25	5,05	10070,00	10.100,00
01/04/2024	AUD	Beli	100	3	6,25	5,05	10070,00	10.100,00
01/04/2024	AUD	Beli	300	3	6,25	5,05	10040,00	10.100,00
…	…	…	…	…	…	…	…	…
30/06/2024	AUD	Beli	50	2,51	6,25	5,05	10400,00	10.375,00
30/06/2024	AUD	Beli	200	2,51	6,25	5,05	10320,00	10.375,00

The results of the K-Nearest Neighbors (KNN) algorithm can be seen in table 7. Where the KNN algorithm produces consistent and stable predictions. As early as April 2024, the prediction shows a value that does not change much, even though the number of transactions on the same date varies. This prediction continues to experience a slight gradual increase until the end of June 2024. This shows that KNN is not sensitive to variations in the number of transactions, so changes in the data do not have a major impact on the prediction results.

Table 8. Linear Regression algorithm prediction results

Tanggal	UKA	Jenis Transaksi	Jml UKA	Inflasi	Suku Bunga	Pertumbuhan ekonomi	Hasil Linear Regression	Data True
01/04/2024	AUD	Beli	220	3	6,25	5,05	10290,41	9.875,00
01/04/2024	AUD	Beli	400	3	6,25	5,05	10289,73	9.875,00
01/04/2024	AUD	Beli	500	3	6,25	5,05	10289,35	9.875,00
01/04/2024	AUD	Beli	50	3	6,25	5,05	10291,05	9.875,00
01/04/2024	AUD	Beli	100	3	6,25	5,05	10290,86	10.100,00
01/04/2024	AUD	Beli	100	3	6,25	5,05	10290,86	10.100,00
01/04/2024	AUD	Beli	300	3	6,25	5,05	10290,10	10.100,00
…	…	…	…	…	…	…	…	…
30/06/2024	AUD	Beli	50	2,51	6,25	5,05	10193,53	10.375,00
30/06/2024	AUD	Beli	200	2,51	6,25	5,05	10192,97	10.375,00

The prediction results with the Linear Regression algorithm show a very uniform pattern on each date as shown in table 8. Although the number of transactions varies, this model produces almost the same prediction for transactions that occur on the same day.

Table 9. KNN algorithm prediction results

Tanggal	UKA	Jenis Transaksi	Jml UKA	Inflasi	Suku Bunga	Pertumbuhan ekonomi	Hasil Random Forest	Data True
01/04/2024	AUD	Beli	220	3	6,25	5,05	9833,73	9.875,00
01/04/2024	AUD	Beli	400	3	6,25	5,05	9977,26	9.875,00
01/04/2024	AUD	Beli	500	3	6,25	5,05	9980,55	9.875,00
01/04/2024	AUD	Beli	50	3	6,25	5,05	9965,89	9.875,00
01/04/2024	AUD	Beli	100	3	6,25	5,05	9987,15	10.100,00
01/04/2024	AUD	Beli	100	3	6,25	5,05	9987,15	10.100,00
01/04/2024	AUD	Beli	300	3	6,25	5,05	9928,82	10.100,00
...	...	...	...	...	...	...	...	...
30/06/2024	AUD	Beli	50	2,51	6,25	5,05	10392,85	10.375,00
30/06/2024	AUD	Beli	200	2,51	6,25	5,05	10415,36	10.375,00

The Random Forest algorithm produces more variable predictions than KNN and Linear Regression as shown in table 9. These predictions show significant variation between transactions on the same date, which suggests that the model is more responsive to changes in the data, including variations in the number of transactions.

3.2. Algorithm comparison results

In the comparison of prediction methods, the author uses three different algorithms, namely Linear Regression, K-Nearest Neighbors (KNN), and Random Forest. The purpose of this comparison is to determine which model is most accurate in predicting currency transaction rates based on several economic variables. The evaluation is done using the Root Mean Square Error (RMSE) metric, which gives an indication of how far the model's prediction is from the true value. For visualization of the comparison, two types of graphs are performed, namely bar charts to compare the RMSE values of each model, and line charts to show the comparison of predictions with true data. In this comparison, the data used comes from the prediction results stored in .xlsx format and has been categorized as table 10.

Table 10. Comparison with RMSE

Tanggal	Data True	Linear	KNN	Random Forest
01/04/2024	9.875,00	10.290,41	9.915,00	9.833,73
01/04/2024	9.875,00	10.289,73	10.005,00	9.977,26
01/04/2024	9.875,00	10.289,35	9.935,00	9.980,55
01/04/2024	9.875,00	10.291,05	10.015,00	9.965,89
01/04/2024	10.100,00	10.290,86	10.070,00	9.987,15
01/04/2024	10.100,00	10.290,86	10.070,00	9.987,15
01/04/2024	10.100,00	10.290,10	10.040,00	9.928,82
...	...	...	...	...
30/06/2024	10.375,00	10.193,53	10.400,00	10.392,85
30/06/2024	10.375,00	10.192,97	10.320,00	10.415,36

Before starting the model comparison process, this data was imported into Python via Google Colab for cleaning and manipulation. The data was then used to build and evaluate the three selected algorithms. In this comparison, the RMSE is calculated for each model and compared using bar charts and line charts. The results of this comparison are then visualized in a line chart to compare the predictions of each model with the actual data as well as a bar chart showing the RMSE value of each model. The entire evaluation process was conducted in Google Colab.

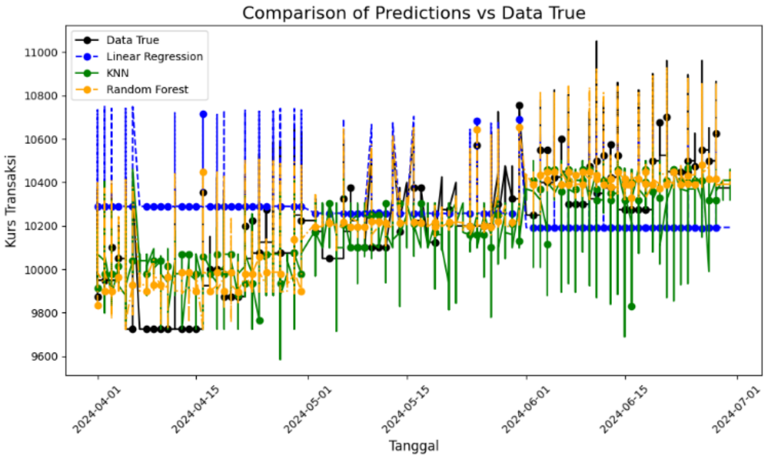

Figure 11. Results of rmse line diagram

From Figure 11, the comparison results of the Linear Regression, KNN, and Random Forest algorithms are linear Regression tends to produce flat predictions and is unable to capture the true data variations, this indicates that the linear regression algorithm has limitations in handling transaction rate fluctuations that tend to be dynamic. Then, KNN produces predictions that are closer to the true data pattern even though there are some deviations in extreme values, this indicates that KNN is more responsive to data changes, but still has limitations on daily transaction variations. Meanwhile, Random Forest delivers predictions that are consistently closer to the actual data. It performed well across most observation dates, demonstrating its strong ability to accurately capture transaction value fluctuations and trends. In addition, Random Forest showed greater stability when dealing with volatile data changes compared to other models, making it the most reliable algorithm for this analysis. This good performance is due to Random Forest's ability to utilize the power of ensemble learning [26]. By combining multiple decision trees, it reduces the risk of overfitting and improves overall accuracy. Each decision tree in the model contributes to the final prediction by handling different parts of the data, resulting in more robust and balanced results. This method effectively handles noise and variability in the dataset, thus allowing Random Forest to provide precise predictions even in the face of dynamic exchange rate fluctuations. As a result, its ensemble approach ensures low RMSE values, reflecting its reliability and effectiveness in capturing complex patterns and trends in the data.

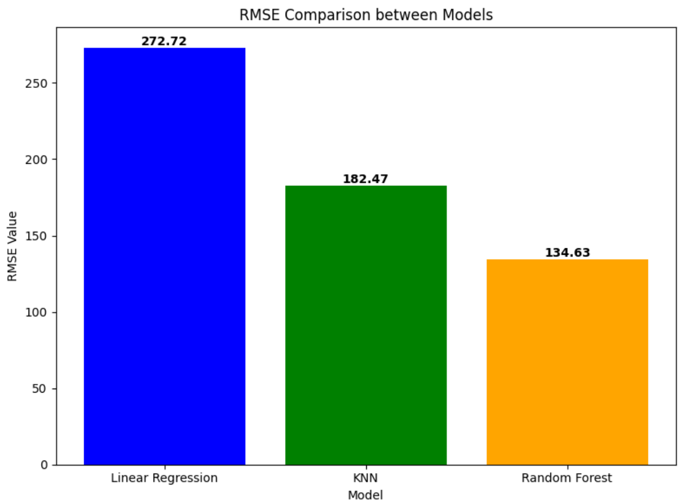

Figure 12. RMSE Bar Chart Results

The following is a bar chart of the RMSE values for the three algorithms as shown in Figure 12. The lower the RMSE value, the better the model is in predicting the transaction value. From Figure 4.16 it can be seen that Random Forest has the lowest RMSE value (134.63), followed by KNN (182.47), and Linear Regression which has the highest RMSE value (272.72). The lower RMSE value of Random Forest indicates that this model has higher prediction accuracy compared to other models, making it more reliable to be used in predicting transaction rates.

The visualizations generated in this study, such as transaction frequency by currency type, monthly average exchange rate, and patterns of buying and selling transactions, provide valuable operational insights that are aligned with the broader strategic objectives of the PT. Moreover, the observed patterns in buying and selling transactions offer actionable insights into customer behavior, allowing the company to dynamically adjust its operational strategies. Moreover, the identification of seasonal trends in monthly exchange rates equips the company with a basis for better forecasting and planning, thus enabling it to anticipate market fluctuations and harmonize its services.

These insights underscore the strategic value in adopting a data-driven approach, especially when combined with advanced predictive analysis such as the Random Forest model. By utilizing the ensemble learning capabilities of Random Forest, PT Gemilang Artha Valindo can enhance its ability to set competitive buying and selling prices while mitigating the risks of volatile exchange rate movements. This integration of visual and predictive analysis helps in maximizing profit margins.

4. CONCLUSION

The implementation of Business Intelligence and Data Mining on PT Gemilang Artha Valindo's transaction data results in deep insights and accurate predictions. The ETL process ensures data quality from internal and external sources, making the analysis valid and reliable. Data visualization reveals the dominance of AUD currency with a contribution of 51.95% of total transactions, followed by USD (23.05%) and other currencies. AUD buy transactions reached 12,300, far more than sell transactions (270). The average fluctuation of the exchange rate shows that GBP and EUR have the highest rates of IDR20,835 and IDR17,700 respectively. Prediction of AUD rates using Linear Regression, KNN, and Random Forest shows that Random Forest provides the most accurate results with the lowest RMSE value (134.63), followed by KNN (182.47), and Linear Regression (272.72). This result confirms Random Forest's ability to provide better predictions than other methods. For future work, considering the vast number of currency exchanges worldwide, applying Federated Learning could ensure privacy during the training process for obtaining the prediction model.

For future work, considering the vast number of currency exchanges worldwide, applying Federated Learning could ensure privacy during the training process for obtaining the prediction model [27].

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