Sentiment Analysis of User Reviews on Cryptocurrency Trading Platforms Using Pre-Trained Language Models for Evaluating User Satisfaction

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ABSTRACT

The study examines user sentiment on the Indodax cryptocurrency trading platform using pre-trained Indonesian language models for sentiment analysis. A dataset of 25,000 user reviews was analyzed, revealing that most reviews expressed neutral sentiment, with positive sentiments accounting for 20% and negative sentiments under 4%. The sentiment classification models used include Support Vector Machine (SVM), Logistic Regression, and Naive Bayes. SVM achieved the highest predictive accuracy at 94.22%, followed by Logistic Regression at 93.62%. These models classified sentiments based on TF-IDF feature extraction, highlighting SVM's effectiveness in sentiment classification within the user reviews. Additionally, sentiment trends over time were analyzed, showing fluctuations in user satisfaction corresponding with market events and platform changes, emphasizing the importance of maintaining platform stability during high volatility. The study's findings suggest actionable improvements for Indodax, such as addressing user concerns that lead to negative sentiments, like customer service and technical issues, while reinforcing platform strengths, such as ease of use. These insights enable Indodax to enhance user satisfaction and retention by monitoring sentiment trends and adjusting features accordingly. However, the study faces limitations due to the use of pre-trained models that may not fully capture Indonesian language nuances and the absence of demographic data, which limits the analysis to general sentiment trends. Future research could incorporate demographic insights and user behavior metrics to offer a more personalized understanding of user sentiment, ultimately aiding Indodax in delivering a more tailored and satisfying user experience.

Keywords Sentiment Analysis, Cryptocurrency Trading, User Satisfaction, Machine Learning

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Introduction

The rise of cryptocurrency as a form of digital finance marked a transformative shift in the global financial landscape, especially after the 2008 financial crisis. Cryptocurrencies, most notably Bitcoin, were introduced as decentralized alternatives to fiat currencies, aiming to resolve key issues in traditional monetary systems, such as inflation and the concentration of financial power [1]. The underlying blockchain technology enabled secure and transparent transactions, garnering the attention of both individual and institutional investors. This led to rapid growth in market capitalization and trading volumes,

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positioning cryptocurrency as a significant player in modern finance [2], [3]. As blockchain technology continued to evolve, it laid the foundation for decentralized finance (DeFi), which allowed users to bypass traditional intermediaries, further expanding the scope and influence of cryptocurrency.

The popularity of cryptocurrencies surged due to several factors, most notably the growing acceptance of decentralized finance applications. These applications enabled users to perform various financial transactions such as lending, borrowing, and trading without relying on conventional financial institutions [4]. This trend was accelerated by the COVID-19 pandemic, during which many people sought alternative financial solutions amid economic uncertainty [4]. The increasing diversity of cryptocurrencies, ranging from mainstream coins like Bitcoin and Ethereum to a wide array of altcoins and tokens, attracted a broader range of investors, including both retail traders and large institutions [5]. This diversification enhanced market liquidity and created a dynamic ecosystem within the digital finance landscape.

Investor sentiment also played a crucial role in shaping the cryptocurrency market, heavily influencing price dynamics and market trends. Positive media coverage and widespread social discourse often amplified optimistic narratives surrounding cryptocurrencies, which contributed to price surges and speculative investment behavior [6], [7]. However, the high volatility of cryptocurrencies presented significant risks, raising concerns about their long-term sustainability as stable currencies [8]. Despite these challenges, the potential of cryptocurrencies to disrupt traditional financial systems and provide new avenues for investment continued to capture the attention of regulators and policymakers around the world [9], [10]. As cryptocurrency trading platforms like Indodax became central to this growing market, understanding user sentiment and feedback became critical to the platform's success in the evolving financial landscape.

Cryptocurrency trading platforms, such as Indodax, played a pivotal role in the broader ecosystem of digital finance by providing the necessary infrastructure for users to trade digital assets securely. These platforms facilitated the buying, selling, and exchanging of cryptocurrencies, allowing individuals to engage in the cryptocurrency market without requiring technical expertise or complex systems. The significance of these platforms rested on their ability to offer secure transactions, liquidity, and user-friendly interfaces, which were essential in attracting and retaining users in a rapidly evolving and often volatile market [11]. As digital assets grew in popularity, platforms like Indodax became integral to the cryptocurrency landscape, ensuring that users had access to a wide range of trading pairs and digital assets.

One of the main functions of cryptocurrency trading platforms was to act as intermediaries between buyers and sellers, creating a marketplace where trades could be executed with ease. Platforms such as Indodax offered real-time market data, advanced trading tools, and educational resources, which empowered users to make informed decisions regarding their investments [12]. Additionally, these platforms provided accessibility to individuals who may have been underserved by traditional financial systems, especially in regions with limited banking services. For many users, Indodax not only served as an entry point into the world of digital finance but also as a way to diversify their investment portfolios through exposure to a wide array of cryptocurrencies [13].

Despite their advantages, cryptocurrency exchanges faced significant challenges, particularly concerning regulatory uncertainty and security risks. Many platforms operated in a regulatory gray area, which raised concerns over the level of oversight and protection available to users [11], [14]. This uncertainty often affected user trust, as the potential for hacking and fraud remained a concern. To mitigate these risks, platforms like Indodax implemented advanced security measures such as two-factor authentication, cold storage solutions, and other protective mechanisms to safeguard user funds [15]. These efforts to enhance security and user trust were crucial in maintaining the integrity of the platform and supporting its growth in the competitive cryptocurrency trading market.

The adoption of cryptocurrency trading platforms in Indonesia experienced significant growth in recent years, mirroring a global trend toward digital finance. As of May 2021, Indonesia recorded approximately 6.5 million cryptocurrency investors, a notable increase of over 50% compared to 4 million in 2020 [16]. This surge reflected a growing acceptance of digital assets as viable investment vehicles, driven by increasing accessibility to trading platforms and the potential for high returns. The ease of access to platforms like Indodax, which facilitated the buying, selling, and trading of cryptocurrencies, attracted a wide range of investors, particularly those seeking alternatives to traditional investments.

By the end of 2021, the number of cryptocurrency investors in Indonesia escalated further, reaching an estimated 11 million [17]. This rapid growth highlighted the rising popularity of cryptocurrency, particularly among younger, tech-savvy demographics eager to explore new financial opportunities. Projections indicated that the number of crypto investors would reach approximately 12.4 million by 2022, underscoring the momentum of cryptocurrency adoption within the country. This rapid expansion demonstrated the increasing integration of digital assets into mainstream financial practices in Indonesia.

The growth in cryptocurrency adoption was also facilitated by Indonesia's evolving regulatory framework, which provided clarity and legitimacy to digital asset trading. The government, recognizing the potential of cryptocurrencies for economic innovation, implemented guidelines that fostered a safer trading environment while ensuring consumer protection [18]. This regulatory support bolstered public confidence in the market and encouraged wider participation. Additionally, studies have shown a positive correlation between cryptocurrency returns and stock price indices in Indonesia, suggesting that the rise of cryptocurrencies contributed to broader economic growth by fostering innovation and attracting investment in the digital economy [19], [20].

User reviews have long been recognized as a critical resource for assessing the performance and user satisfaction of digital platforms. In the context of cryptocurrency trading platforms like Indodax, user feedback provides valuable insights into the overall user experience, shedding light on aspects such as usability, security, and transaction efficiency. These reviews capture both explicit feedback, such as ratings and written comments, and implicit signals, like user engagement, which can be analyzed to identify trends and issues. As platforms grow in complexity and competition increases, understanding user sentiment becomes essential for maintaining a competitive edge and retaining a loyal user base [21].

Sentiment analysis, a widely utilized technique for extracting insights from user feedback, has proven instrumental in evaluating platform performance by systematically categorizing reviews as positive, neutral, or negative. For platforms like Indodax, sentiment analysis reveals user pain points and areas requiring enhancement, such as security concerns, ease of use, and transaction fees. This information allows platform developers to make data-driven decisions to improve both the interface and backend systems, ultimately fostering higher levels of user satisfaction and engagement. Research underscores that platforms actively incorporating user feedback not only enhance their technical features but also elevate user trust and loyalty, as evidenced in various studies on digital finance platforms [22]. Moreover, sentiment analysis has been applied to cryptocurrency-related content to uncover trends in public opinion. For example, one study utilized TF-IDF vectorization and K-Means clustering on Bitcoin-related tweets, providing insights into shifts in user sentiment within the digital currency domain, thus highlighting the value of machine learning in recognizing patterns within large datasets [23].

Recent studies further underscore the importance of analyzing sentiment trends to understand user satisfaction and engagement within cryptocurrency markets. Analyzing sentiment can help platform operators anticipate user reactions to market fluctuations, as demonstrated by research on cryptocurrency volatility, which reveals how price shifts reflect broader economic trends impacting user sentiment on platforms like Indodax. Additionally, a deeper examination of the role of social media sentiment in emerging technologies, such as the Metaverse, has shown that public discourse significantly shapes perceptions and engagement in digital environments [24]. Studies addressing financial transactions within these digital ecosystems, particularly those employing anomaly detection for security analysis, underscore the need to address transaction safety and regulatory challenges to foster user trust [25]. This research framework provides a foundation for understanding the intersection of user engagement, sentiment analysis, and transaction security, which are essential for optimizing user satisfaction on cryptocurrency trading platforms.

The continuous evaluation and integration of user feedback also played a pivotal role in building trust among users, particularly in a volatile market like cryptocurrency trading. Given the inherent risks associated with digital currencies, users often expressed concerns regarding platform security and reliability. Addressing these concerns through platform updates, guided by user feedback, led to increased user confidence and retention [26]. Furthermore, platforms that demonstrated responsiveness to user input tended to cultivate stronger communities, as users felt their opinions were valued, fostering loyalty in an otherwise competitive market. Thus, user reviews not only served as a tool for performance evaluation but also as a mechanism for building long-term trust and improving the overall user experience.

User reviews played a pivotal role in shaping the reputation and future development of trading platforms like Indodax. These reviews acted as a direct channel of communication between users and platform operators, offering critical insights into user experiences and satisfaction levels. As cryptocurrency trading involves substantial financial risk, the sentiments expressed in reviews had a significant influence on potential users' perceptions of the platform. Positive reviews contributed to building trust and credibility, which in turn attracted new users. At the same time, negative feedback often raised concerns about platform security, performance, or service quality, potentially deterring prospective users [27]. The ability of platforms to monitor and respond to these reviews became essential for maintaining a positive reputation in a highly competitive market.

One of the key functions of user reviews in this context was their capacity to guide the platform's development and innovation. Reviews frequently highlighted specific pain points, such as slow transaction speeds or insufficient customer support, which could undermine the user experience. By analyzing these patterns in user feedback, platforms like Indodax were able to identify areas in need of improvement and prioritize updates that aligned with user expectations. This responsiveness helped maintain user satisfaction, as customers felt their concerns were being addressed. Furthermore, platforms that engaged with user feedback demonstrated a commitment to continuous improvement, fostering loyalty among their user base and establishing a reputation for customer-centered development [28].

Additionally, user reviews influenced the strategic direction of platform operators by identifying emerging trends and user demands. For instance, platforms that regularly analyzed reviews could identify a growing demand for new trading pairs, advanced trading tools, or improved educational resources. Addressing these demands allowed platforms to stay competitive and relevant in a rapidly evolving market. Strategic decisions informed by user reviews often resulted in enhanced service offerings that directly catered to evolving user needs, thus boosting user retention and engagement [29]. In this way, user reviews not only shaped the day-to-day functionality of platforms but also provided valuable input for long-term strategic planning and development.

Despite the increasing adoption of cryptocurrency trading platforms in Indonesia, more formal studies need to be conducted focused on sentiment analysis of user reviews in this context. While research in cryptocurrency trading has generally concentrated on market behavior, security, and regulatory frameworks, user feedback and sentiment have yet to be explored. In particular, few studies have examined how user reviews written in Bahasa Indonesia reflect broader trends in user satisfaction and platform performance. Given that user sentiment is a critical factor in the success of digital platforms, this gap in the literature represents a missed opportunity to understand better the needs and concerns of cryptocurrency traders in Indonesia.

The absence of formal sentiment analysis in this area posed a challenge for platform operators, such as Indodax, seeking to enhance their services based on real user feedback. With structured insights into user sentiment, it became easier to identify key issues affecting user satisfaction, such as platform security, transaction efficiency, or user interface design. Additionally, the unique linguistic and cultural nuances present in Indonesian reviews require specialized approaches to capture and interpret user emotions accurately. This gap highlighted the need for sentiment analysis studies tailored specifically to the Indonesian context of cryptocurrency trading, where language and user behavior patterns differ from those in other markets.

The primary research problem addressed in this study was the need to systematically analyze and understand user sentiment from reviews of Indodax, one of Indonesia's leading cryptocurrency trading platforms. The goal was to classify user feedback into positive, negative, or neutral categories, providing insights that could inform platform improvements and enhance user satisfaction. By applying Indonesian pre-trained models to perform sentiment analysis, this study aimed to bridge the existing gap in the literature and offer a structured approach to evaluating user sentiment in Indonesia's rapidly growing cryptocurrency trading landscape.

The primary goal of this study was to evaluate user satisfaction with the Indodax cryptocurrency trading platform by analyzing the sentiment of user reviews written in Bahasa Indonesia. Given the importance of user feedback in shaping the reputation and development of digital platforms, understanding the sentiment expressed in these reviews provided valuable insights into how users perceived Indodax's performance. The study sought to systematically categorize user reviews into positive, neutral, and negative sentiments, using Indonesian pre-trained models to offer a structured evaluation of user satisfaction. This approach aimed to uncover the key factors influencing user experiences on the platform, ultimately helping Indodax to identify areas for improvement and foster better user engagement.

Literature Review

Sentiment Analysis in Digital Finance

Sentiment analysis has become an essential tool in the digital finance sector for evaluating customer feedback. This analytical approach enables businesses to systematically interpret emotions and opinions expressed by customers through various digital channels, such as online reviews, social media posts, and customer service interactions. By categorizing sentiments into positive, negative, or neutral, companies gain valuable insights into customer satisfaction, preferences, and concerns. These insights are particularly crucial in the fast-paced digital finance landscape, where customer feedback directly informs service improvements and strategic decisions. For instance, studies have shown the effectiveness of machine learning models, such as Support Vector Machines and TF-IDF, in analyzing public sentiment on topics like electric vehicle incentives, demonstrating how these models can efficiently process and categorize sentiments from large datasets[30]. Moreover, research on Indonesian sentiment analysis, particularly in the context of Twitter data, has highlighted the need to understand linguistic and cultural nuances, which enhances the accuracy and relevance of sentiment analysis outcomes [31].

In the realm of cryptocurrency trading platforms, such as Indodax, sentiment analysis not only gauges user satisfaction but also provides insights into market trends that influence user behavior. Previous studies comparing classification models like Logistic Regression, Support Vector Classifier, and Random Forest in product reviews have illustrated the strengths of these models in capturing nuanced user sentiments, which is relevant for understanding user feedback on financial platforms [32]. Furthermore, research employing time series analysis methods like ARIMA and LSTM to predict cryptocurrency price movements demonstrates the broader context in which user sentiment operates, as these economic factors can directly impact user satisfaction and engagement [33]. By integrating sentiment analysis with machine learning techniques, businesses can interpret user feedback more effectively and make informed strategic decisions, thereby improving user experience and platform engagement in the competitive digital finance sector.

The significance of sentiment analysis in digital finance lies in its ability to affect business performance and decision-making processes. Studies have demonstrated that customer perceptions, as captured through online feedback, can greatly influence a company's reputation and market standing [34]. Many consumers rely heavily on online reviews when making decisions about financial products and services, which amplifies the need for financial institutions to monitor and respond to customer sentiments effectively. Additionally, sentiment analysis has proven to be valuable in identifying emerging trends in consumer behavior, enabling companies to adjust their offerings to better align with customer expectations.

In the broader context of customer relationship management (CRM), sentiment analysis plays a pivotal role in refining customer engagement strategies. By using advanced methods like hierarchical attention networks, financial institutions can gauge the sentiment polarity of customer interactions in real-time, allowing for more dynamic responses to customer feedback [35]. This capability not only enhances customer satisfaction by addressing concerns more efficiently but also fosters long-term customer loyalty by demonstrating a commitment to responsiveness and service quality [36]. Furthermore, sentiment analysis has been increasingly integrated with machine learning models, improving the accuracy of sentiment predictions and providing financial organizations with deeper insights into customer behavior and satisfaction [37], [38].

Sentiment analysis has become a critical tool in finance, particularly in the context of cryptocurrency platforms, where it helps analyze market behavior and investor sentiment. Several studies have focused on applying sentiment analysis to social media platforms like Twitter to predict cryptocurrency price movements and gauge market trends. This method has been effective in capturing real-time emotions and opinions of investors, which in turn influence the highly volatile nature of cryptocurrencies.

For instance, [39] investigated the relationship between tweet sentiment and cryptocurrency price volatility, demonstrating that social media sentiment could be a strong predictor of market fluctuations. Their study highlighted that positive or negative sentiments, as reflected in tweets, often preceded significant price changes, making sentiment analysis a valuable tool for investors looking to capitalize on market movements. Similarly, [40] explored the integration of sentiment analysis with machine learning models, such as Multi-Layer Perceptron (MLP) and Support Vector Machine (SVM), to enhance cryptocurrency price prediction accuracy. By combining historical price data with Twitter sentiment, their research achieved substantial improvements in forecasting the price volatility of major cryptocurrencies like Bitcoin and Ethereum.

Beyond price prediction, sentiment analysis has been used to evaluate user satisfaction with cryptocurrency trading platforms. [21] conducted a study on the Indodax trading platform, where sentiment analysis of user reviews provided insights into the quality of services offered. This study emphasized how user feedback, when systematically analyzed, could help platforms identify areas needing improvement, thereby boosting user satisfaction. Further research by [41] explored the impact of Twitter-based sentiment on the cryptocurrency market during the COVID-19 pandemic, finding a direct correlation between heightened investor sentiment and increased market volatility. These studies collectively underscore the importance of sentiment analysis as a versatile tool for both understanding market behavior and enhancing service quality in the cryptocurrency sector.

Sentiment analysis in digital finance has been widely implemented to evaluate customer feedback and predict market trends. Various classification models have been employed to categorize sentiments based on textual data, helping companies and platforms understand user emotions and attitudes. Among the most common models used in sentiment analysis are Naive Bayes, Logistic Regression, and Support Vector Machines (SVM). Each model approaches sentiment classification differently, allowing researchers to compare their effectiveness in predicting user satisfaction and market behavior.

Logistic Regression, a widely used method for binary classification problems, has been especially useful in determining sentiment polarity (positive or negative) in user feedback. The model predicts the probability of a particular sentiment class based on the features extracted from the text. The formula for Logistic Regression is given as:

$$P(y=1|X)=\frac{1}{1+e^{-(\beta_0+\beta_1X_1+\cdots+\beta_nX_n)}} \tag{1}$$

In this formula, y represents the sentiment class (1 for positive sentiment and 0 for negative), while X corresponds to the feature set extracted from the review content. The coefficients β_0 through β_n represent the model's learned parameters, which are adjusted during the training phase to maximize the likelihood of correctly classifying the sentiment.

Naive Bayes and Support Vector Machines (SVM) are also frequently used for sentiment classification in digital finance. Naive Bayes, a probabilistic model based on Bayes' Theorem, assumes that the features (words or phrases) are conditionally independent given the class label. While this assumption is often violated in practice, Naive Bayes has proven effective in many natural language processing tasks due to its simplicity and efficiency. Support Vector Machines, on the other hand, aim to find the hyperplane that best separates different sentiment classes. SVM is particularly useful in cases where the sentiment classes are not linearly separable, as it can employ kernel functions to project the data into higher-dimensional spaces where separation is possible. These models, when combined with techniques like TF-IDF or word embeddings, have become essential in understanding customer sentiment and guiding business decisions in digital finance.

Sentiment Analysis Models for Bahasa Indonesia

Sentiment analysis in Bahasa Indonesia has seen notable advancements with the development of pre-trained models such as ID-BERT and VADER, which have been tailored to the linguistic nuances of the Indonesian language. ID-BERT, a variant of the BERT (Bidirectional Encoder Representations from Transformers) model, was specifically fine-tuned for Indonesian text. This model utilized BERT’s ability to capture deep contextual relationships within the text, allowing it to understand complex language structures and sentiment expressions. Research has shown that ID-BERT significantly outperformed traditional models like Long Short-Term Memory (LSTM) and TextCNN when applied to sentiment analysis tasks in Indonesian. The model's proficiency in handling idiomatic expressions and cultural references made it particularly effective in extracting sentiment from user reviews and social media comments in the Indonesian context [42].

In contrast, VADER (Valence Aware Dictionary and Sentiment Reasoning) represented a lexicon-based sentiment analysis tool that had been effectively adapted for Bahasa Indonesia, especially for short-form content such as tweets. VADER's rule-based approach allowed it to account for the informal and colloquial language often found in social media, making it a practical choice for sentiment analysis on platforms like Twitter. Studies have demonstrated that VADER could accurately classify the sentiment of Indonesian tweets, especially during significant events such as the COVID-19 pandemic, providing valuable insights into public sentiment [43] . VADER's ability to handle linguistic nuances, including slang and emoticonns, made it an ideal tool for analyzing sentiment polarity and intensity in microblog content [44].

Researchers have explored combining the strengths of ID-BERT and VADER to enhance sentiment analysis further for Bahasa Indonesia. Hybrid models that integrated VADER's lexicon-based sentiment scoring with the predictive power of machine learning classifiers, such as Multinomial Logistic Regression, demonstrated improved accuracy in sentiment classification tasks [45]. This approach allowed for more precise sentiment detection, particularly when dealing with large and diverse datasets. As both ID-BERT and VADER continued to evolve, their integration into sentiment analysis workflows provided researchers and practitioners with more sophisticated tools to capture and interpret user sentiment in the Indonesian language.

In the domain of sentiment analysis for Bahasa Indonesia, both pre-trained models and traditional machine learning algorithms have been applied, each showing different strengths depending on the task. Pre-trained models, such as ID-BERT, a transformer-based model fine-tuned specifically for Indonesian text, have shown substantial improvements in understanding context and sentiment nuances. These models utilize advanced natural language processing techniques to capture the deeper semantic relationships within the language, leading to superior performance in sentiment classification. Studies have demonstrated that pre-trained models like ID-BERT outperformed traditional machine learning models, such as Naïve Bayes and Support Vector Machines (SVM), especially in tasks requiring a more comprehensive understanding of sentiment, such as analyzing complex social media or user-generated content [46].

Pre-trained models gained an edge due to their ability to generate contextual word embeddings, which consider the surrounding words and their relationships in a sentence. This contextual understanding allowed ID-BERT to deliver state-of-the-art results in sentiment classification tasks. For example, in cases where sentiment was expressed through idiomatic or culturally specific language, ID-BERT was able to detect subtle sentiment shifts that traditional models often missed. This ability to handle complex linguistic structures made pre-trained models highly effective for Bahasa Indonesia, where sentence structures and meanings can vary significantly based on context.

On the other hand, traditional machine learning models like Naïve Bayes and SVM, though less context-aware, have proven to be reliable and efficient for simpler sentiment analysis tasks. Naïve Bayes, in particular, was noted for its simplicity and effectiveness in many studies, achieving high accuracy when paired with well-designed preprocessing steps [47], [48]. These models also benefited from sentiment lexicons specifically built for Bahasa Indonesia, which helped boost their classification performance. However, while these models were computationally less demanding and easier to implement, they struggled with more intricate sentiment expressions compared to pre-trained models like ID-BERT, which could generalize better across varied datasets.

Feature Extraction for Text Data

Feature extraction is a critical process in sentiment analysis, as it transforms raw text into numerical data that machine learning models can process. One of the simplest and most commonly used techniques for this transformation is the Bag of Words (BoW) model. The BoW method represents a document as a vector of word frequencies, where each word in the corpus corresponds to a specific feature. Although BoW is straightforward and efficient, especially for text classification tasks, it ignores the order and context of words, treating them as independent units. This method often leads to high-dimensional, sparse vectors because many words only appear in some documents, resulting in a sparse feature space that can complicate analysis [49].

The Term Frequency-Inverse Document Frequency (TF-IDF) technique improves upon BoW by introducing a weighting scheme that emphasizes the importance of words in a corpus. In TF-IDF, the Term Frequency (TF) measures how often a word appears in a document, while the Inverse Document Frequency (IDF) calculates how rare the word is across the entire dataset. This weighting process helps mitigate the impact of common but less informative words, like stop words, while highlighting terms that are more contextually relevant to a specific document [50]. The formula for TF-IDF is:

$$\text{TF-IDF}(t,d) = \text{TF}(t,d) \times \log\left(\frac{N}{\text{DF}(t)}\right) \quad (2)$$

This approach provides a more nuanced representation of text by balancing word frequency with informativeness, making TF-IDF particularly useful in applications like information retrieval and text mining.

While both BoW and TF-IDF are foundational techniques in natural language processing, they serve different purposes depending on the complexity of the task. BoW is more suited for simpler tasks that do not require contextual understanding. At the same time, TF-IDF is favored in situations where the significance of words relative to the entire corpus is crucial. These methods have also been adapted for use in more advanced models, including neural networks and deep learning algorithms, where they serve as the initial steps for converting text into a form that machine learning models can interpret [51]. Ultimately, the choice between BoW and TF-IDF depends on the specific requirements of the sentiment analysis task and the level of contextual understanding needed.

Sentiment Classification Techniques

Sentiment analysis relies on classification algorithms to categorize text data into predefined sentiment classes such as positive, negative, or neutral. Among the most widely used algorithms are Logistic Regression, Naive Bayes, and SVM each offering distinct approaches and strengths for sentiment classification. Logistic Regression is particularly useful in binary classification tasks, where it models the probability of a binary outcome using one or more predictor variables. This algorithm has been applied successfully in sentiment analysis across various domains, such as healthcare and social media [52]. Studies have shown that Logistic Regression performs well in predicting sentiments when paired with feature extraction techniques like TF-IDF, which help capture the relevant features of the text.

Naive Bayes is a probabilistic classifier based on Bayes' theorem, making it a simple yet effective tool for sentiment classification. It operates under the assumption of conditional independence between features, which simplifies the computation and makes it highly efficient for large datasets. Naive Bayes has been employed in multiple sentiment analysis applications, particularly in classifying customer reviews and financial market sentiments [53]. While it performs well in many tasks, it may need help in cases where strong correlations exist between features, limiting its performance compared to more advanced models like SVM [54]. The formula for the Naive Bayes classifier is as follows:

$$P(c|x) = \frac{P(c)\prod_{i=1}^{n} P(x_i|c)}{P(x)} \quad (3)$$

SVM on the other hand, excel in sentiment classification tasks, especially in high-dimensional data spaces common in text data. SVM works by identifying the hyperplane that best separates different sentiment classes, maximizing the margin between them. Studies have consistently demonstrated that SVM outperforms Naive Bayes in sentiment classification, achieving accuracy rates of 80% to 91% in various sentiment analysis applications. SVM's flexibility also allows it to be combined with other machine learning techniques, making it a robust option for complex sentiment analysis tasks. Its ability to handle nonlinear classification problems further enhances its performance in sentiment classification, particularly when paired with kernel functions for improved accuracy.

Method

The research method for this study consists of several steps to ensure a comprehensive and accurate analysis. The flowchart in figure 1 outlines the detailed steps of the research method.

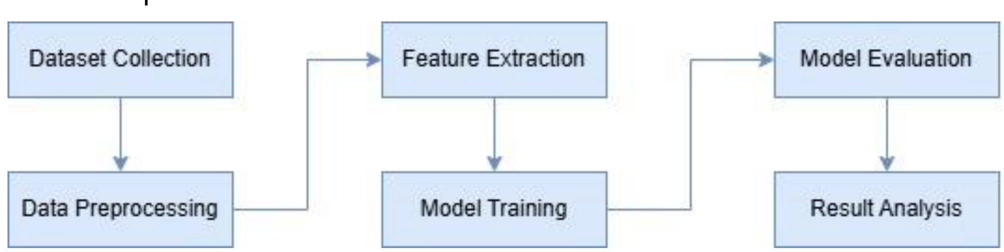

Figure 1 Research Method Flowchart

Dataset Description

The dataset used in this study consists of 25,000 user reviews collected from the Indodax cryptocurrency trading platform. Each review provides feedback on the user experience, reflecting various aspects of the platform's performance. The dataset includes four main columns: \`userName\`, \`score\`, \`at\`, and \`content\`. The \`userName\` column records the username of the reviewer, while the \`score\` column contains integer ratings given by users, providing an indication of their overall satisfaction. The \`at\` column specifies the date and time of each review, allowing for potential temporal analysis. Lastly, the \`content\` column contains the text of the review itself, which is the primary focus for sentiment analysis.

All reviews in the dataset are written in Bahasa Indonesia, making it essential to tailor preprocessing steps to the specifics of the language. Unlike English, Bahasa Indonesia features unique stopwords, slang, and colloquial expressions that influence the sentiment conveyed by the reviewers. As a result, the preprocessing stage includes steps to clean and standardize the text data, such as removing Indonesian stopwords, correcting common abbreviations, and addressing language-specific morphological nuances. This focus on language-specific preprocessing helps improve the accuracy and relevance of the subsequent sentiment analysis.

Given the text-based nature of this study, particular attention is devoted to ensuring that the \`content\` column is adequately prepared for analysis. Proper tokenization and normalization are applied to each review to enable meaningful feature extraction. The dataset structure—comprising usernames, ratings, timestamps, and review content—facilitates a comprehensive exploration of user sentiment on the Indodax platform. This structure supports the development of an effective model that aims to classify sentiments accurately and provides insights into user satisfaction with the platform's services.

Exploratory Data Analysis (EDA)

The exploratory data analysis focused on examining the distribution of user scores and the primary characteristics of the review text. The dataset includes a total of 25,000 user reviews with scores ranging from 1 to 5. The distribution of review scores for the Indodax platform, as shown in the figure 2, indicates a strong tendency towards highly positive user ratings. The majority of users rated the platform with a score of 4.5 or higher, which reflects a general satisfaction with the platform's performance and features. Specifically, over 20,000 reviews, accounting for a substantial portion of the dataset, fall into this high rating category. In contrast, there is a smaller yet notable cluster of reviews that rated the platform at the lowest score of 1.0, suggesting a group of users who may have encountered significant issues or dissatisfaction. The distribution shows minimal representation in the intermediate scores, with very few reviews rated between 2.0 and 4.0. This pattern may imply that user experiences on Indodax tend to be polarizing; users either express high satisfaction or dissatisfaction, with little middle ground. The limited presence of moderate scores could indicate that user experiences with Indodax are perceived as either very positive or significantly negative, rather than average or mixed. Overall, the review score distribution suggests a generally favorable view of the Indodax platform among most users, but it also highlights a subset of users with substantial concerns. This data provides valuable insights for platform improvements, particularly by addressing the issues that contribute to the lower ratings to enhance overall user satisfaction.

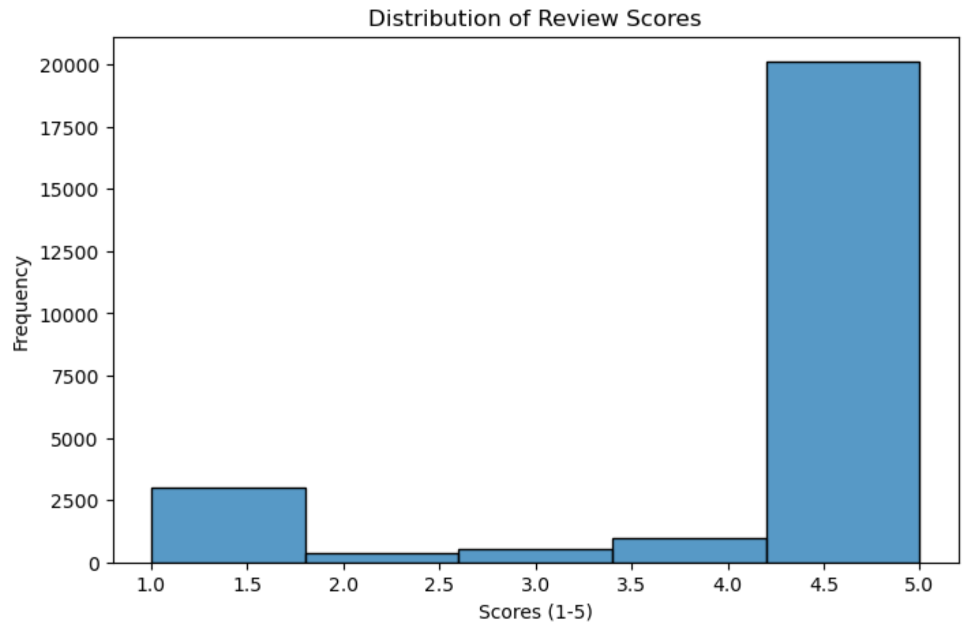

Figure 2 Distribution of Review Scores

To better understand the common terms and themes in the reviews, a word cloud was generated. The word cloud visualization of the Indodax user reviews highlights the most frequently used words within the feedback, shown in figure 3. Notably, terms such as “Indodax,” “aplikasi” (application), and “username” appear prominently, indicating their frequent mention across many reviews. The prominence of “Indodax” suggests that users directly refer to the platform name often, likely when expressing their opinions about the platform’s features or performance. The word “aplikasi” points to a common focus on the application’s usability and user experience, as users may be commenting on its functionality, ease of use, or reliability. Other terms, such as “mudah” (easy), “bagus” (good), and “trading,” also appear frequently, suggesting that users are discussing the platform’s accessibility and quality, particularly in the context of trading. Words like “dipahami” (understandable) and “cepat” (fast) further reflect that users may appreciate the ease of understanding and speed of transactions or interface responses on the Indodax platform. Additionally, phrases related to events or promotions, such as “8tahunindodax” and “indodaxtradingfest2022,” indicate that users are aware of and discussing the platform's special events, which may play a role in their overall sentiment. This word cloud provides a snapshot of the key themes and aspects users frequently mention, which can be valuable for identifying areas of strength and improvement for the platform based on user perception.

Figure 3 **Word Cloud Visualization**

The bar plot in figure 4 displays the most frequently occurring words in the Indodax user reviews after removing common stopwords. "Indodax" is the most prevalent term, appearing over 14,000 times, which emphasizes the frequent mention of the platform's name in user reviews. This suggests that users are focused on discussing the platform's features or experiences related to Indodax directly. Following “Indodax,” the words “aplikasi” (application) and “mudah” (easy) are also commonly mentioned, indicating a focus on the application’s usability and the ease of using the platform. Terms like “trading” and “crypto” reflect that users are discussing core functionalities of Indodax related to cryptocurrency trading, further highlighting the platform’s primary function as a crypto trading application. Additionally, phrases like “#8tahunindodax” and “#indodaxindonesia” suggest that users reference specific events or hashtags related to the platform, potentially indicating engagement with promotional campaigns or events associated with Indodax. Lastly, the word “bagus” (good) appears frequently, suggesting a generally positive sentiment in the reviews regarding certain aspects of the platform. Overall, the plot reveals that user reviews often focus on key aspects such as ease of use, cryptocurrency trading, and platform events, providing insights into what users most commonly highlight in their feedback about Indodax. These insights from the EDA phase provide a foundational understanding of user sentiments and key areas of focus, supporting further analysis and sentiment classification.

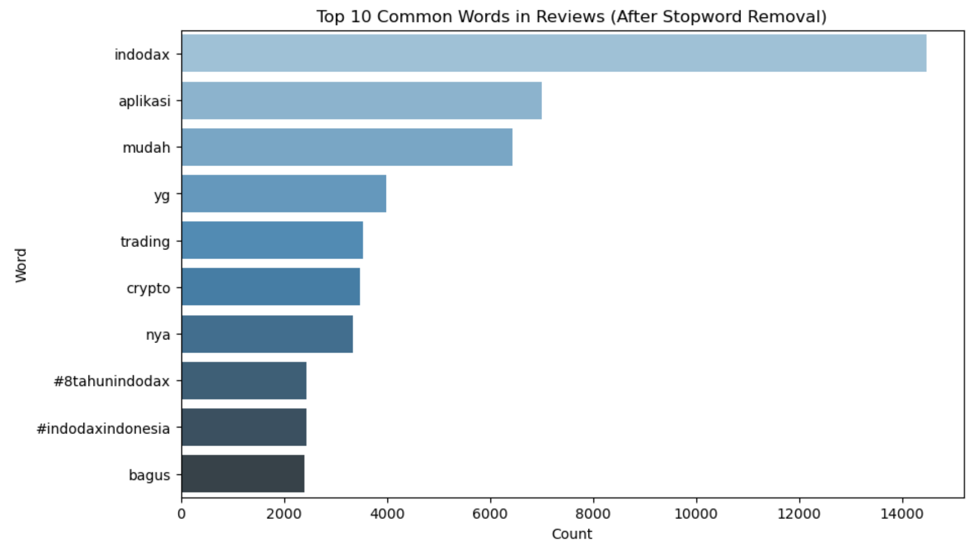

Figure 4 **Top 10 Common Words in Reviews**

Preprocessing

The preprocessing stage is essential for preparing the review text for analysis, transforming raw textual data into a structured format suitable for feature extraction. Initially, all reviews were converted to lowercase to ensure consistency and to avoid treating similar words with different capitalizations as separate tokens. Tokenization was then applied to split the review text into individual words. Following tokenization, stopwords specific to Bahasa Indonesia were removed using the Sastrawi library. This step eliminated common but uninformative words such as “dan” (and), “yang” (which), and “di” (at), which are frequent in Indonesian text but do not contribute to sentiment analysis. Additionally, stemming was conducted to reduce words to their base forms, helping to unify variations of a word (e.g., "bagus" and "bagusan" both reduced to "bagus"). This approach not only reduces dimensionality but also aids in capturing the core meaning of words, facilitating more accurate analysis.

Once the text was preprocessed, feature extraction was conducted using the Term Frequency-Inverse Document Frequency (TF-IDF) technique. TF-IDF transforms the textual data into numerical vectors, which represent the relative importance of words within each review and across the entire corpus. The TF-IDF approach was chosen for its effectiveness in capturing the uniqueness of terms in a document while minimizing the influence of frequently occurring but less informative words. By applying a TF-IDF vectorizer with a maximum feature limit, the dataset's dimensionality was optimized, reducing computational complexity while preserving the essential terms that contribute to the sentiment classification task.

In addition to TF-IDF, word embeddings such as FastText were considered for feature extraction. FastText embeddings enable a deeper semantic understanding of the text by capturing sub-word information, which is particularly valuable for morphologically rich languages like Bahasa Indonesia. Although not mandatory, word embeddings were explored as an optional step to enhance the model's ability to understand contextual nuances and semantic similarities between words. This optional step aligns with the goal of accurately capturing user sentiment by leveraging advanced language modeling techniques that go beyond basic token-based representation.

Sentiment Classification

The sentiment classification process involved the application of both pre-trained models and custom classifiers to analyze the user reviews. Initially, pre-trained models such as VADER were employed to automatically label the reviews with sentiment scores appropriate for Bahasa Indonesia. The VADER model calculates a compound score for each review, which was subsequently categorized into three sentiment classes: positive, negative, and neutral. This automated labeling step allowed for efficient and consistent classification of sentiment across a large dataset, providing a foundation for training additional machine learning models. The algorithm 1 outlines the sentiment classification process, which combines pre-trained models and traditional machine learning algorithms to categorize user reviews into positive, negative, and neutral sentiments. Pre-trained models, such as VADER, were first used for automatic labeling, followed by the training and evaluation of classifiers like Logistic Regression, Naive Bayes, and SVM using cross-validation. Algorithm 1 provides a structured overview of the steps taken to ensure accurate and reliable sentiment detection.

Algorithm 1 Sentiment Classification Using Pre-trained and Machine Learning Models

Pre-trained Model Labeling

• Load the dataset $D = \{r_1, r_2, \dots, r_N\}$, where each $r_i$represents a user review.
• Apply text preprocessing to each r_i: convert to lowercase, remove punctuation and stopwords, and perform tokenization.
• For each review r_i, compute sentiment score using the pre-trained VADER model:
  $s_i = \text{VADER}(r_i)$, where $s_i \in [-1,1]$is the compound sentiment score.
• Categorize each score $s_i$into sentiment classes:
  If $s_i \geq 0.05$, then $y_i =$ “positive”.
  If $s_i \leq -0.05$, then $y_i =$ “negative”.
  Otherwise, $y_i =$ “neutral”.
• Store labeled dataset $D' = \{(r_i, y_i)\}_{i=1}^{N}$for model training.

Feature Extraction

• Transform reviews $\{r_i\}$into numerical representations using TF-IDF vectorization:
  Compute feature matrix $X = [x_{i,j}]_{N\times m}$, where
  $x_{i,j} = \text{TF}_{i,j} \times \text{IDF}_j$.
• Create corresponding sentiment labels $Y = \{y_i\}_{i=1}^{N}$.

Model Initialization

• Define classification models:
  M_1 = Logistic Regression
  M_2 = Naive Bayes
  M_3 = Support Vector Machine (SVM).

Cross-validation and Training

• Set number of folds $k$for k-fold cross-validation (e.g., $k = 5$).
• Randomly partition dataset D'into $k$equally sized subsets $\{D_1, D_2, \dots, D_k\}$.
• For each model $M_j \in \{M_1, M_2, M_3\}$:
  For each fold $i = 1, \dots, k$:
    – Define training set $D_{\text{train}} = D' \setminus D_i$, validation set $D_{\text{val}} = D_i$.

– Train model: $M_j \leftarrow \text{fit}(X_{\text{train}}, Y_{\text{train}})$.
– Predict sentiments on validation set: $\hat{Y}_{\text{val}} = M_j(X_{\text{val}})$.
– Compute performance metrics for fold i:
Accuracy: $A_i = \frac{1}{n_{\text{val}}} \sum_{t=1}^{n_{\text{val}}} \mathbf{1}(\hat{y}_t = y_t)$
Precision: $P_i = \frac{TP_i}{TP_i + FP_i}$
Recall: $R_i = \frac{TP_i}{TP_i + FN_i}$
F1-score: $F1_i = 2 \times \frac{P_i \times R_i}{P_i + R_i}$.

• Average performance across folds for each model:
$\bar{A} = \frac{1}{k} \sum_{i=1}^{k} A_i$,
$\bar{P} = \frac{1}{k} \sum_{i=1}^{k} P_i$,
$\bar{R} = \frac{1}{k} \sum_{i=1}^{k} R_i$,
$\bar{F1} = \frac{1}{k} \sum_{i=1}^{k} F1_i$.

Model Evaluation and Comparison
• Store results for each model M_j:
Metrics = {Average Accuracy, Precision, Recall, F1-score}.
• Compare the average F1-scores across models:
$M^* = \arg\max_{M_j} (\bar{F1}_{M_j})$.
• Select M^*as the best-performing classifier for sentiment prediction.

Post-analysis and Validation
• Evaluate M^*on a held-out test set (if available):
Compute final metrics (Accuracy, Precision, Recall, F1).
• Compare results of M^*against VADER baseline performance.
• Analyze confusion matrix to identify misclassified samples and assess model bias.

End.

Following the labeling process, custom classifiers were developed using traditional machine learning algorithms, specifically Logistic Regression, Naive Bayes, and Support Vector Machine (SVM). These models were trained on the labeled sentiment data to further refine sentiment classification and evaluate their performance relative to the pre-trained models. To ensure the robustness of the classification models, k-fold cross-validation was performed, which involved splitting the dataset into `k` subsets and training the models iteratively on `k-1` subsets while testing on the remaining subset. This method reduces bias and variance in the evaluation metrics, providing a more reliable measure of model performance across the entire dataset.

The models were evaluated based on standard classification metrics, including accuracy, precision, recall, and F1-score. Accuracy measured the proportion of correctly predicted reviews, while precision and recall provided insight into the model's ability to correctly classify positive and negative sentiments. The F1-score, which is the harmonic mean of precision and recall, was particularly useful for understanding the model's performance in cases of imbalanced classes. By assessing these metrics, the study aimed to identify the most effective model for sentiment analysis of user reviews, considering both automated labeling and custom-trained approaches.

Visualization of Sentiment Analysis

To complement the sentiment classification results, various visualizations were created to provide a more intuitive understanding of the sentiment distribution and trends over time. A pie chart was used to represent the percentage distribution of positive, negative, and neutral reviews, offering a clear snapshot of user sentiment across the entire dataset. This visualization helped to highlight the overall satisfaction levels expressed by users, with the proportion of each sentiment class reflecting the predominant attitudes towards the Indodax platform.

Additionally, a timeline visualization was implemented to track sentiment trends over time. This was achieved through line plots that depicted the frequency of each sentiment category on a monthly basis, allowing for the identification of any patterns or shifts in user sentiment. The timeline visualization provided insights into how user satisfaction fluctuated in response to specific events, updates, or market conditions. These visualizations not only reinforced the findings from the sentiment classification models but also contributed to a comprehensive analysis of user feedback on the Indodax platform.

Result and Discussion

Sentiment Distribution

The sentiment analysis of user reviews on the Indodax platform revealed a clear distribution across three categories: positive, neutral, and negative, shown in figure 5. The dataset, which consisted of 25,000 reviews, showed that the majority of sentiments were classified as neutral. Specifically, approximately 20,000 reviews, or 80%, fell into the neutral category, indicating a general trend of indifferent or informational feedback. This prevalence of neutral sentiment suggests that a significant number of users may have used the platform's review system to provide factual statements rather than express strong opinions or emotions.

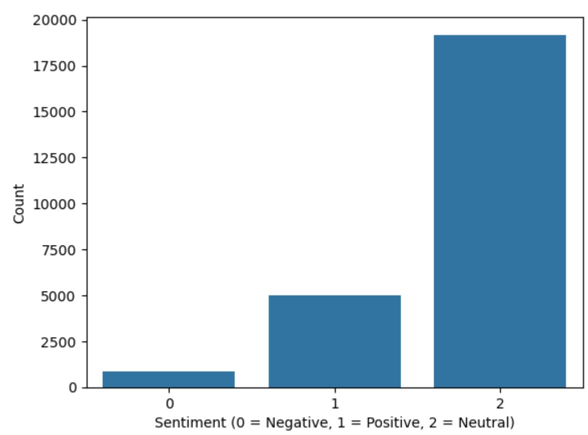

Figure 5 Sentiment Distribution

The sentiment distribution plot reveals the prevalence of different sentiments within the user reviews on Indodax. The majority of the reviews are labeled as neutral (sentiment = 2), with nearly 20,000 occurrences, indicating that most users provide feedback without strong positive or negative emotions. This prevalence of neutral sentiment may suggest that users are generally satisfied with the platform but not overwhelmingly impressed or dissatisfied. Positive sentiment (sentiment = 1) appears in approximately 5,000 reviews, reflecting a significant proportion of users expressing favorable opinions or highlighting positive aspects of their experiences with Indodax. This suggests that a considerable number of users appreciate specific features or services offered by the platform. Negative sentiment (sentiment = 0) is the least common, with fewer than 2,000 reviews, indicating that a relatively small portion of users reported dissatisfaction or issues. This distribution of sentiments suggests that while there are some negative experiences, the overall user sentiment is either neutral or positive, which could be indicative of a generally stable and satisfactory user experience on the platform.

Predicting User Satisfaction Based on Content

The prediction of user satisfaction was carried out by applying text classification models to user reviews, utilizing TF-IDF feature extraction to convert textual data into numerical representations. The TF-IDF matrix, constructed from approximately 25,000 user reviews, captured the relative importance of words within the corpus, resulting in a feature space of (25,000 × 5,000). This indicates that 25,000 reviews were represented using 5,000 unique terms as features. Each review was associated with a sentiment label — positive, neutral, or negative — forming a target vector of shape (25,000,).

Three machine learning algorithms — Logistic Regression, Naive Bayes, and Support Vector Machine (SVM) — were employed to predict user sentiment and satisfaction levels. Model performance was assessed using standard evaluation metrics: accuracy, precision, recall, and F1-score. The results are summarized in table 1.

Table 1 Performance Comparison of Classification Models for Predicting User Satisfaction

Model	Accuracy	Precision	Recall	F1-score	Interpretation
Support Vector Machine (SVM)	0.9422	0.9440	0.9422	0.9372	Highest performance; excellent at distinguishing all sentiment classes.
Logistic Regression	0.9362	0.9394	0.9362	0.9298	Strong performance; comparable to SVM with minor variations.
Naive Bayes	0.8604	0.8763	0.8604	0.8310	Lower accuracy; affected by independence assumption in text data.

Note. Metrics represent average values obtained after k-fold cross-validation.

As shown in table 1, the SVM model achieved the highest overall accuracy at 0.9422, with precision and recall scores of 0.9440 and 0.9422, respectively, resulting in a robust F1-score of 0.9372. These results indicate that the SVM classifier effectively differentiates between positive, neutral, and negative sentiments in user reviews, making it highly reliable for predicting user satisfaction.

The Logistic Regression model also performed strongly, with an accuracy of 0.9362 and a precision of 0.9394. Its recall value (0.9362) and F1-score (0.9298) were slightly lower than SVM's but remained within a close range. This suggests that Logistic Regression offers a similarly effective alternative, with the advantage of interpretability and computational efficiency.

In contrast, the Naive Bayes classifier exhibited a comparatively lower performance, achieving an accuracy of 0.8604, precision of 0.8763, and F1-score of 0.8310. This reduced performance is likely due to Naive Bayes' strong assumption of conditional independence among features — an assumption that often does not hold in textual data, where the meaning of words is context-dependent. Nevertheless, Naive Bayes remains useful as a baseline model, given its simplicity and low computational cost.

Overall, the results confirm that SVM is the most effective model for predicting user satisfaction based on review content. Its superior F1-score demonstrates balanced precision and recall, making it robust for handling multi-class sentiment data. These findings underscore the potential of advanced text classification techniques in accurately identifying user satisfaction trends from large-scale review data. Implementing SVM for automated sentiment classification can thus support continuous user experience monitoring, enabling digital finance platforms to detect sentiment shifts and address emerging issues proactively.

Sentiment Trends Over Time

The analysis of sentiment trends over time provides insights into how user satisfaction on the Indodax platform has evolved. The line plot (figure 6) displaying the average sentiment score over time reveals fluctuations that may correspond with significant events impacting the cryptocurrency market and platform updates. For instance, sentiment appears relatively stable throughout 2022, with the average sentiment score hovering around neutral to slightly positive. This period coincides with general market stability and no major disruptions reported on the platform, suggesting that users generally perceived their experience with Indodax as consistent.

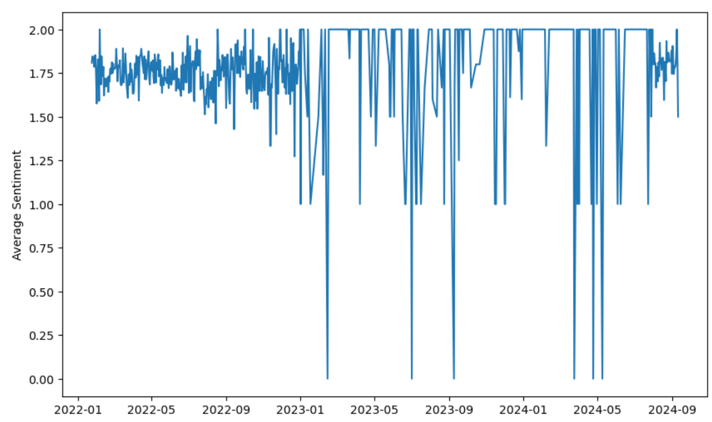

Figure 6 **Sentiment Trend Over Time**

However, from early 2023 onwards, there are notable drops in the average sentiment score, with some periods reaching significantly lower values. These sharp declines could be indicative of user dissatisfaction potentially triggered by external factors, such as heightened market volatility, or internal factors, such as issues with platform performance or new policy changes. Such dips in sentiment often reflect increased user frustration or disappointment, which might be associated with specific challenges faced by users during these times. For instance, technical difficulties, security concerns, or changes in transaction fees could have contributed to a temporary decline in satisfaction.

Toward the latter half of the timeline, particularly into mid-2024, sentiment shows periods of recovery interspersed with further declines. This pattern suggests that while the platform may have addressed certain user concerns, intermittent issues may still be present. The sentiment trend over time underscores the importance of monitoring user feedback as it directly reflects user experiences and perceptions in response to platform changes or external events. Overall, this temporal analysis highlights the dynamic nature of user sentiment, emphasizing how user satisfaction on Indodax is influenced by a combination of platform-specific factors and broader market conditions.

Discussion

The findings from this study underscore the value of sentiment analysis in identifying key areas for improvement on the Indodax platform. By examining user feedback, platform operators can gain insights into user satisfaction levels, enabling them to address specific issues that may impact the overall user experience. For instance, the predominance of neutral sentiments in the dataset suggests that many users are providing feedback without strong positive or negative emotions, potentially indicating that they find the platform functional but unremarkable. This trend offers an opportunity for the platform to introduce new features or enhance existing ones to create a more engaging experience that could inspire stronger positive feedback.

Additionally, the variations in sentiment trends over time reveal how external factors, such as market conditions, may influence user sentiment. The observed declines in sentiment during early 2023, for example, could reflect user dissatisfaction linked to increased market volatility or issues with the platform's performance during high-traffic periods. Such patterns suggest that user sentiment tends to fluctuate in response to the cryptocurrency market's cyclical nature, with positive sentiment often more prevalent during bull markets when users experience favorable trading conditions. Conversely, negative sentiment may intensify during bearish periods or when technical challenges arise. Recognizing these patterns can help Indodax proactively manage user expectations by improving platform resilience and offering timely support during volatile market conditions.

The implications of these results extend beyond sentiment analysis, as they provide actionable insights for enhancing platform functionality and user engagement. By continuously monitoring sentiment trends, Indodax can better understand user needs and adapt its offerings to foster a more positive experience. For example, improving customer service response times, addressing common technical issues, and introducing features that facilitate smoother trading experiences could mitigate negative feedback and encourage more positive sentiments. Ultimately, leveraging sentiment analysis empowers Indodax to make data-driven decisions that not only improve user satisfaction but also strengthen its competitive position in the cryptocurrency trading landscape.

Conclusion

This study analyzed user sentiment on the Indodax platform to evaluate user satisfaction and identify areas for improvement. The sentiment distribution revealed that the majority of user feedback was neutral, with positive sentiments representing a significant portion and negative sentiments comprising a smaller fraction of the reviews. This distribution indicates that while many users are satisfied or indifferent towards the platform, a minority expressed dissatisfaction. The predictive accuracy of the sentiment classification models demonstrated that Support Vector Machine (SVM) achieved the highest accuracy, followed closely by Logistic Regression. These models effectively classified user sentiment based on textual features extracted using TF-IDF. Additionally, sentiment trends over time indicated that user satisfaction fluctuated, likely in response to market conditions and platform-related events, highlighting the importance of maintaining platform stability during periods of market volatility.

The findings offer actionable insights for Indodax to enhance its platform and better cater to user needs. Addressing the concerns expressed in negative reviews, such as customer service responsiveness and technical issues, can help reduce negative sentiment and improve user retention. Furthermore, reinforcing the positive aspects of the platform—such as ease of use and reliable trading features—can amplify user satisfaction and attract new users. By continuously monitoring sentiment trends, Indodax can proactively identify shifts in user satisfaction and implement timely improvements. This approach not only enhances the user experience but also contributes to building a stronger reputation in the competitive cryptocurrency trading market.

This study faced certain limitations that could impact the generalizability of its findings. One limitation is the reliance on pre-trained sentiment analysis models, which may not fully capture the nuances of user sentiment in Bahasa Indonesia. Additionally, the unavailability of user demographic data restricted the analysis to general sentiment trends, preventing a deeper understanding of how different user segments perceive the platform. Future work could focus on analyzing more complex review patterns by incorporating user demographic information, which would allow for a more personalized analysis of user sentiment. Moreover, integrating additional data, such as user behavior metrics (e.g., frequency of trading, account activity), could provide further insights into how sentiment correlates with actual platform usage, enabling a more comprehensive evaluation of user satisfaction on Indodax.

Declarations

Author Contributions

Author Contributions: Conceptualization, M.J., D.S., and S.; Methodology, M.J. and S.; Software, S.; Validation, S.; Formal Analysis, M.J.; Investigation, S.; Resources, S.; Data Curation, D.S, and S.; Writing—Original Draft Preparation, M.J.; Writing—Review and Editing, S.; Visualization, S. All authors have read and agreed to the published version of the manuscript.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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