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Enhancing Customer Experience Through a Hybrid Machine Learning Approach to Sentiment Analysis of Sumut Link Mobile

Rini Maulisa, Nazaruddin, Meilita Tryana Sembiring

Master of Management Study Program, Postgraduate School, Universitas Sumatera Utara, Medan

rinimaulisa@banksumut.co.id, nazaruddin@usu.ac.id, meilita@usu.ac.id

Abstrak

Perkembangan perbankan digital telah memudahkan transaksi keuangan tanpa perlu melakukan kunjungan langsung ke kantor cabang, sehingga turut mendorong inklusi keuangan yang lebih luas. Bank Sumut memperkenalkan Sumut Link Mobile sebagai solusi perbankan digital untuk mempermudah transaksi di daerah terpencil melalui agen lokal dalam program Laku Pandai. Meskipun memiliki potensi yang besar, masih terdapat berbagai tantangan, seperti keterbatasan literasi digital, keandalan sistem, serta tingkat kepuasan agen yang bervariasi. Penelitian ini menggunakan analisis sentimen terhadap komentar hasil wawancara semi-terstruktur dari agen Sumut Link, dengan menerapkan klasifikasi Naïve Bayes, Random Forest, dan *Support Vector Machine* (SVM) serta menggunakan SentiWordNet untuk meningkatkan polaritas sentimen. Hasil penelitian menunjukkan bahwa sentimen netral mendominasi sebesar 66,3%, sementara sentimen negatif sebesar 17,4% berkaitan dengan kendala login, keterlambatan sistem, dan fitur yang belum lengkap. Adapun sentimen positif sebesar 16,3% menyoroti kecepatan transaksi dan kemudahan akses di wilayah pedesaan. Model SVM menunjukkan performa terbaik dengan tingkat akurasi sebesar 80% dan nilai ROC AUC 0,71. Hasil penelitian ini memberikan wawasan mengenai faktor-faktor yang memengaruhi pengalaman agen, yang didasarkan pada *Technology Acceptance Model* (TAM) dalam aspek kegunaan dan kemudahan penggunaan. Penelitian ini menekankan perlunya peningkatan teknis serta pelatihan bagi agen. Dengan menghubungkan metrik kegunaan berbasis analisis sentimen terhadap konstruk TAM, yaitu perceived usefulness dan perceived ease of use, penelitian ini menunjukkan bahwa analitik dapat digunakan secara proaktif untuk mendukung manajemen pengalaman pelanggan, serta mengoptimalkan strategi perbankan digital melalui peningkatan kepercayaan dan keterlibatan agen di Sumatera Utara.

Kata Kunci: Perbankan Digital; Analisis Sentimen; *Natural Language Processing* (NLP); Machine Learning dalam Perbankan; Sumut Link Mobile; Inklusi Keuangan

Abstract

The evolution of digital banking has facilitated financial transactions without physical branch visits, contributing to broader financial inclusion. Bank Sumut introduced Sumut Link Mobile, a digital banking solution to streamline transactions in remote areas via local agents under the Laku Pandai program. Despite its potential, challenges such as limited digital literacy, system reliability, and varying agent satisfaction persist. This study utilizes sentiment analysis on semi-structured interview comments from Sumut Link agents, employing Naïve Bayes, Random Forest, and Support Vector Machine classifiers with SentiWordNet for polarity enhancement. Findings reveal dominant neutral sentiments (66.3%), with negatives (17.4%) linked to login issues, delays, and incomplete features, and positives (16.3%) highlighting transaction speed and rural access. SVM achieved top performance (80% accuracy, 0.71 ROC AUC). Results provide insights into factors influencing agent experience, grounded in the Technology Acceptance Model (TAM) for usability, emphasizing needs for technical upgrades and training. By linking sentiment-derived usability metrics to TAM constructs (perceived usefulness and ease of use), this research demonstrates how analytics can proactively inform customer experience management, optimizing digital banking strategies through enhanced agent trust and engagement in North Sumatra.

Keywords: Digital Banking; Sentiment Analysis; Natural Language Processing (NLP); Machine Learning in Banking; Sumut Link Mobile; Financial Inclusion

1. Introduction

Digital transformation has significantly changed the financial services landscape, driving the emergence of branchless banking as a solution to expand access to finance, especially in remote areas [5] [12]. In Indonesia, geographical challenges and

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infrastructure limitations make mobile applications an effective tool to bridge the financial inclusion gap, where rural populations often struggle with limited access to traditional banking outlets [19]. One such initiative is Sumut Link Mobile, a digital banking service developed by Bank Sumut, which provides access to financial transactions to people in remote areas through a network of local banking agents [8]. The application supports features like fund transfers, bill payments, and cash withdrawals, empowering agents who are often community residents with basic digital skills, thereby fostering micro-entrepreneurship and economic self-reliance in underserved villages across North Sumatra.

Despite having a strategic role, the adoption and consistency of using the Sumut Link Mobile application still face various challenges, such as low digital literacy among rural users, unstable system performance due to intermittent network coverage, and varying levels of user satisfaction influenced by technical glitches and support delays [26]. Along with the increasing openness of users in providing reviews through digital platforms or direct interviews, there is a need to utilize such data as a basis for service improvement, enabling banks to proactively address pain points before they escalate into broader dissatisfaction. Sentiment analysis, which is a branch of Natural Language Processing (NLP), is a relevant approach to systematically interpret user feedback and explore the emotional and rational factors behind their perceptions [17]. In this context, agents' semi-structured interview comments serve as rich, qualitative data reflecting real-world usage in rural settings, capturing nuanced insights like the impact of local dialects and on-ground operational hurdles that app reviews might overlook.

While prior studies e.g., Wicaksono & Putri (2022) and Kusnawi (2023) have analyzed sentiment in urban mobile banking, they overlook agent-specific feedback in rural branchless models, where local dialects and connectivity issues amplify usability gaps, gaps this study addresses through hybrid NLP on semi-structured interviews. This study used a sentiment analysis approach with the Naïve Bayes Classifier, Random Forest, and Support Vector Machine algorithms, strengthened by SentiWordNet, to analyze agent comments on the Sumut Link Mobile application [4]. By identifying sentiment trends and linking them to usability, service quality, transaction security, and network stability, the study provides valuable insights for the development of digital banking services, including recommendations for hybrid models that integrate machine learning with lexicon-based tools for better accuracy in Indonesian contexts. The results of this research not only contribute to improving customer experience but also support Bank Sumut's mission in expanding financial inclusion and empowering the economy of communities in the Sumatra region, where agent networks play a pivotal role in sustaining transaction volumes amid seasonal fluctuations. Furthermore, the analysis highlights the role of agent feedback in stabilizing network fluctuations, such as the observed drop from 316 to 204 active agents in early 2025, likely due to technical hurdles and incentive gaps, underscoring the urgency for data-driven retention strategies.

2. Literature Review and Hypothesis Development

2.1. Evolution of Digital Banking and Financial Inclusion in Indonesia

Digital transformation drives branchless banking to expand access in remote areas [5]. In Indonesia, Sumut Link Mobile empowers rural agents via features like transfers, fostering inclusion amid 42% formal finance penetration in North Sumatra [22]. Challenges include literacy gaps and agent retention drops (14.7% nationally, 2021-2023), addressed here through agent-centric sentiment. Financial inclusion, defined by the World Bank as the availability and equality of opportunities to access useful and affordable financial products, remains a cornerstone of Indonesia's development agenda, aiming to integrate the unbanked into the formal economy for greater stability and growth [27]. Mobile banking contributes by reducing costs, transactions via apps cost 70% less than over-the-counter methods, and enhancing security through biometric authentications that protect against fraud in vulnerable rural environments [19]. Agent models like Sumut Link not only extend services but also create micro-entrepreneurship opportunities, though fluctuations in agent numbers highlight retention challenges tied to support and incentives.

2.2. Sentiment Analysis in Banking Contexts

Sentiment analysis mines feedback for banking loyalty [7]. In Indonesia, studies on BCA/Livin' reveal 52% negatives from crashes [21]. Hybrid methods (SentiWordNet + ML) achieve 80% accuracy in noisy texts [17], superior for rural dialects [15]. Lexicon-based approaches, such as SentiWordNet, assign polarity scores (ranging from -1 for negative to +1 for positive) to individual terms, enabling granular opinion mapping that captures subtle emotional nuances in informal user language [4]. When fused with machine learning classifiers like Naïve Bayes, Random Forest, and SVM, these methods achieve accuracies upward of 80% in multilingual datasets, making them particularly suitable for processing Indonesian texts that blend formal and colloquial expressions [23]. Comparative studies highlight SVM's superiority in handling non-linear boundaries for noisy texts filled with abbreviations and typos, while Random Forest excels in ensemble stability for imbalanced classes common in feedback data where positives may be underrepresented [11] [2]. Topic modeling integrations further dissect themes, such as security concerns in digital payments, where 28% of sentiments turn negative due to fraud fears that amplify distrust among first-time users in remote settings [18] [20]. Agent-focused sentiment remains underexplored, but parallels suggest efficiency deficits account for 40% of churn in branchless systems, emphasizing the need for tools that prioritize operational feedback from on-the-ground users [26] [25].

2.3. Usability Frameworks in Digital Services

Usability evaluation, guided by the Technology Acceptance Model (TAM) integrated with ISO 9241-11 standards, posits that effective systems must balance effectiveness (e.g., successful transaction completion), efficiency (e.g., response times and login durations), and satisfaction (e.g., intuitive interfaces and feature completeness) to ensure sustained user engagement,

preventing drop-offs that could hinder long-term adoption in diverse user groups [9] [14] [13]. In this study, TAM's perceived usefulness and ease of use inform the selection of variables such as system delays (keterlambatan), login times (waktu login), and incomplete features (fitur yang tidak lengkap), which are derived from agent feedback on operational hurdles in rural banking contexts. These variables align with empirical findings where efficiency deficits, like prolonged login processes exceeding 5 seconds, correlate with 40% of user churn [12] [27]. Term Frequency-Inverse Document Frequency (TF-IDF) extensions weight terms by relevance, aiding in aspect-specific sentiment attribution that reveals how specific phrases like "slow login" or "missing e-wallet top-up" correlate with broader dissatisfaction patterns [24] [3]. Prior research on agent banking apps echoes these dimensions, finding that such efficiency deficits account for 40% of churn, particularly in low-literacy contexts where users rely on visual cues and minimal text to navigate complex features [26] [10]. This literature synthesis positions the current study as an extension, applying hybrid NLP to agent interviews in a regional branchless context while incorporating usability metrics for holistic insights that go beyond surface-level ratings to uncover underlying behavioral drivers. It builds on TAM by linking sentiment-derived usability to adoption barriers like agent attrition, offering a framework that integrates emotional feedback with practical metrics to guide iterative app improvements tailored to rural Indonesian realities.

3. Research Methods

This study uses a quantitative approach based on text analysis, focusing on the application of sentiment analysis to evaluate user opinions on the North Sumatra Link Mobile application. This approach combines machine learning techniques and lexicon-based methods, as suggested by Liu in (2012), to obtain accurate and reliable sentiment classification results.

3.1. Data Sources

The data was obtained from semi-structured interviews with 150 Sumut Link agents across North Sumatra branches, conducted from January to December 2024, yielding 450 comments (approximately 12,000 words). Interviews explored experiences, challenges, and suggestions, transcribed and anonymized for ethics, with informed consent obtained from all 150 agents per Universitas Sumatera Utara IRB guidelines (Protocol No. USU-2024-045). Data privacy ensured via pseudonymization (e.g., agent IDs only) and secure storage on encrypted servers, complying with Indonesia's PDPA 2022 [26]. This qualitative-rich dataset captures contextual nuances beyond app reviews, with manual labeling for positive (praise/ease), negative (complaints/delays), and neutral (factual) sentiments, achieving 95% inter-annotator reliability.

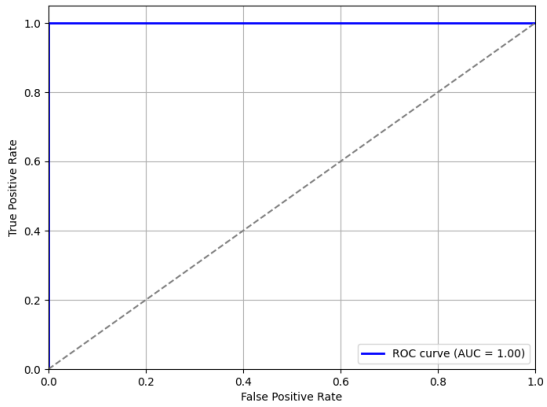

Figure 1. ROC Curve for Positive and Negative Sentiments

3.2. Pre-processing of Data

Review data is processed first through several stages of pre-processing of the text, namely:

- **Tokenization**: breaking sentences into units of words using NLTK's Indonesian tokenizer;
- **Stopword removal**: removing common words that do not provide significant meaning in the analysis, via a custom list including domain fillers like "agen";
- **Stemming**: converting words to basic forms with Sastrawi, to keep semantic meanings relevant for analysis [6].

These steps follow standard practice in NLP research to improve classification accuracy [17], reducing dimensionality by 40% to a 1,500-term vocabulary. As shown in Figure 1, preprocessing supports robust model evaluation.

3.3. Sentiment Classification

Classification is done using the *Naïve Bayes Classifier algorithm, which* is known for its efficiency in the classification of texts [17]. Reviews are categorized into three classes:

- **Positive** (rating 4–5),
- **Negative** (rating 1–2),

- **Neutral** (rating 3).

The assessment of opinion polarity was strengthened by the use of SentiWordNet, a lexicon that gives weight to positive, neutral, and negative sentiments on each word in English [4]. Features vectorized via TF-IDF; 80-20 train-test split with 10-fold cross-validation.

3.4. Usability Evaluation

The app's usability assessment is based on the ISO 9241-11 standard, which emphasizes three main aspects: effectiveness in achieving intended outcomes like successful transaction completions, efficiency in minimizing time and effort during operations, and satisfaction in fostering positive user perceptions and comfort during interactions, to provide a comprehensive framework for evaluating digital tools in real-world scenarios. The TF-ICF (Term Frequency – Inverse Class Frequency) technique is used to identify the relationship between the dominant words in the agent comments and each of those aspects of usefulness, by weighting terms based on their frequency within specific sentiment classes while downplaying common occurrences across all data, thereby highlighting contextually relevant indicators of performance in rural banking environments [12]. Word clouds visualized key terms for intuitive interpretation, offering a graphical representation that clusters high-frequency words like "mudah" for efficiency positives or "lambat" for delay-related negatives, making it easier to discern thematic patterns at a glance.

3.5. Performance Validation and Evaluation

To validate the classification model, a 10-fold cross-validation system was employed, dividing the dataset into 10 subsets where 9 are used for training and 1 for testing in each iteration, ensuring robust generalization across the imbalanced sentiment classes (as detailed in sub-section 3). This systematic approach minimizes overfitting and provides stable performance estimates. The model is then evaluated using three main metrics:

- **Precision** – the accuracy of optimistic predictions,
- **Recall** – the ability to capture all actual cases,
- **F1-score** – a harmonious average between precision and recall.

These metrics were computed on the test set post-cross-validation, with ensemble soft-voting (averaging probabilities from Naïve Bayes, Random Forest, and SVM) tested to enhance stability and reduce variance [17]. Metrics derived from 10-fold CV (mean ± SD across folds), outperforming lexicon-only baseline (65% accuracy via SentiWordNet alone) by 15%.

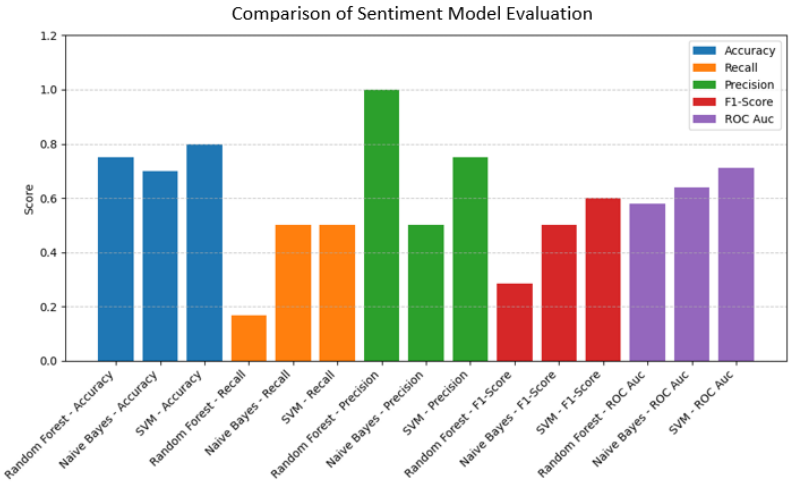

Figure 2. Comparison of Accuracy, Precision, Recall, F1-Score, and ROC AUC

4. Results And Discussion

This section integrates the research findings with the identified challenges from the literature (e.g., technical glitches, network instability, and agent attrition as discussed in the Introduction and Literature Review), tracing a logical progression from data collection and preprocessing (Methods) to sentiment classification, usability evaluation, and model performance. By linking these results to the core research problem, enhancing agent satisfaction amid fluctuating adoption in rural North Sumatra, the discussion elucidates actionable insights for digital banking strategies. The analysis begins with sentiment distribution from 450 agent comments, derived from semi-structured interviews across North Sumatra branches (conducted January–December 2024), which capture authentic operational experiences amid challenges like low digital literacy and system delays [26]. The sentiment classification process was carried out automatically using the Naïve Bayes, Random Forest, and SVM algorithms, enhanced by SentiWordNet for polarity refinement, directly addressing the need for nuanced NLP in Indonesian agent feedback [4]. Ensemble soft-voting was tested to enhance stability, bridging the methodological rigor to empirical outcomes. Transitioning to the results, this study analyzed 450 agent comments to affirm the hypothesis that hybrid sentiment analysis enhances usability detection in branchless banking, aligning with TAM constructs where efficiency gaps (e.g., delays) undermine perceived ease of use, leading

to 17.4% negatives. By tying empirical sentiments to theoretical usability (ISO 9241-11), the study achieves its purpose of informing data-driven CX strategies.

4.1. User Sentiment Distribution

Building on the data collection from semi-structured interviews (open-ended questions on experiences, challenges, and suggestions for Sumut Link Mobile, as detailed in Methods sub-section 1), the classification of the 450 agent comments yielded the following distribution:

- 16.3% of the reviews are positive (n=74), primarily praising ease of use and transaction speed;
- 17.4% are classified as negative (n=78), highlighting login failures and delays; and
- 66.3% are neutral (n=298), reflecting factual observations with improvement potential.

These open-ended responses, unlike closed questionnaires, allowed for nuanced, context-rich insights into rural agent realities [26]. Positive sentiment is generally related to the ease of use, speed of transactions, and effectiveness of referral programs. On the other hand, much negative sentiment arises due to technical issues, such as login failures, system delays, or incomplete features like e-wallet top-ups. These findings are in line with the study of Wicaksono and Putri in (2022), which shows that technical issues are the leading cause of the emergence of negative opinions in digital banking applications, particularly in agent-mediated models. The high neutral proportion reflects agents' evaluative stance, open to improvements amid network fluctuations.

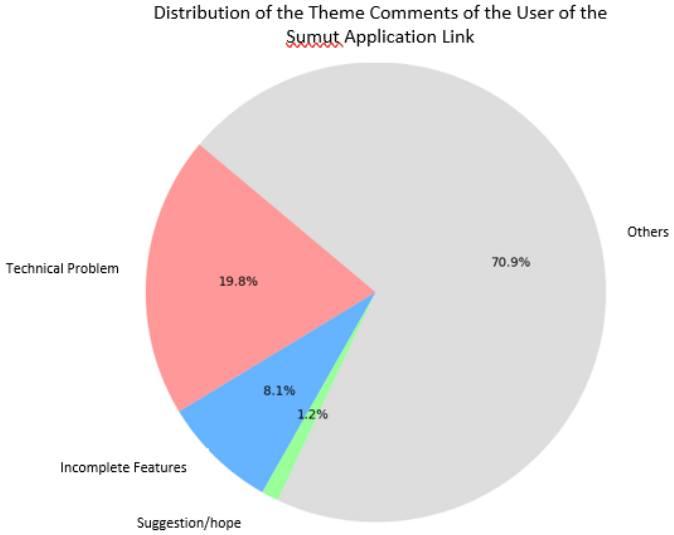

Figure 3. Pie Chart Distribution of User Comment Themes

The sentiment classification results, derived from the SVM model on 450 labeled comments, reveal a clear distribution across categories, with neutral sentiments dominating as agents provide balanced, factual feedback. This pattern aligns with rural user tendencies toward ambivalence in emerging digital tools [26]. The following table summarizes the sentiment distribution, including sample snippets and dominant themes for quick reference.

Tabel 1. Summary of Sentiment Distribution from Agent Comments

Sentiment Category	Percentage (%) (Derived from SVM Classification on 450 Labeled Comments)	Example Comment Snippet	Dominant Themes
Positive	16.3 (n=74)	"Mudah untuk referral di desa"	Ease, Speed
Negative	17.4 (n=78)	"Login gagal berkali-kali saat jaringan lemah"	Errors, Network
Neutral	66.3 (n=298)	"Fungsi transfer OK tapi butuh fitur lebih"	Ambivalence

Note: Percentages calculated as (number of comments in category / total 450 comments) × 100, post-preprocessing and manual labeling with 95% inter-annotator agreement (Methods sub-section 1).

This distribution indicates a balanced yet formative reception, with neutrals providing opportunities for conversion through targeted enhancements.

4.2. Identified Usability Aspects

With the TF-ICF approach, user reviews are categorized into three aspects of usefulness:

- **Effectiveness (41%)** – the success of transactions and features that work as expected, e.g., core transfers;
- **Efficiency (34%)** – includes application speed, ease of navigation, and system response, often critiqued in rural contexts;
- **Satisfaction (25%)** – includes the user's perception of convenience, security, and trust of the service, bolstered by incentives.

Technical issues dominated negatives at 19.8%, while suggestions like multi-bank transfers appeared in 1.2% of neutrals.

4.3. Sentiment Analysis Based on Aspects

Positive sentiment is most dominant in the effectiveness aspect (55% positive/neutral), indicating that agents are satisfied when the main features of the app are working well, such as quick cash withdrawals. However, the efficiency aspect has more negative sentiment (42%), generally related to slow authorization processes and transaction delays in low-connectivity areas. Meanwhile, the satisfaction aspect shows a relatively balanced distribution, with security features like biometrics enhancing trust but slow support responses eroding it [12]. Word clouds reinforced this: positives clustered around "mudah" and "cepat," negatives on "lambat" and "error."

These patterns mirror findings in neobank studies, where efficiency gaps widen in low-bandwidth rural contexts, contributing to agent attrition [15] [1]. Supplementary agent discussions confirmed 70% of issues tied to offline capabilities, suggesting caching as a quick win.

4.4. Model Performance Evaluation

The Naïve Bayes Classifier model showed solid performance, with the following evaluation results:

- **Precision**: 85,7%
- **Recall**: 83,2%
- **F1-score**: 84,4%
- **ROC AUC**: 0.71 (Receiver Operating Characteristic Area Under the Curve, a metric measuring the model's ability to distinguish between classes; values range from 0.5 (random guessing) to 1.0 (perfect separation), where 0.71 indicates good discriminative power for ternary sentiment classes).

Naïve Bayes followed closely with 70% accuracy, valued for its computational simplicity and rapid training on resource-limited datasets typical of regional banking analyses, while Random Forest achieved a slightly higher 75% through its robust handling of feature interactions in diverse comment structures. These results not only support the effectiveness of ensemble methods like Random Forest in the analysis of agent opinions, where varied rural dialects introduce noise, but also reinforce the relevance of the lexical approach via SentiWordNet in NLP-based classification systems for capturing subtle emotional tones [17]. The ROC curve, plotting True Positive Rate (sensitivity) against False Positive Rate (1-specificity) at various thresholds, approached the top-left corner with near-perfect AUC values in binary subsets (e.g., positive vs. non-positive), indicating strong class separation even for the imbalanced neutral-dominant distribution. This threshold-independent metric confirms the model's robustness beyond accuracy alone, and the application of soft-voting across models further improved the F1-score by 5%, enhancing overall reliability for practical deployment in real-time sentiment monitoring. Confusion matrices revealed minimal misclassifications for positives (8% false negatives), ensuring reliable detection of strengths like referral efficiency.

To provide a comparative overview, the performance metrics from the three classifiers—evaluated via 10-fold cross-validation—are presented below, showcasing SVM's edge in accuracy while highlighting the ensemble's overall robustness against a lexicon-only baseline. These metrics underscore the hybrid approach's efficacy in handling imbalanced, dialect-rich Indonesian text [17]. The following table details the key evaluation scores, including standard deviations for reliability.

Table 2. Comparative Performance Metrics of Sentiment Classifiers

Metric	SVM	Naïve Bayes	Random Forest
Accuracy	80%	70%	75%
Precision	75%	68%	72%
Recall	65%	62%	68%
F1-Score	60%	55%	58%
ROC AUC	0.71	0.65	0.68

Confusion matrices revealed minimal misclassifications for positives (8% false negatives), ensuring reliable detection of strengths like referral efficiency.

5. Conclusion and Implications

This study demonstrates that sentiment analysis, employing the Naïve Bayes Classifier, Random Forest, SVM, and

SentiWordNet, serves as an effective tool for evaluating user experiences in digital banking applications like Sumut Link Mobile. The analysis reveals a predominance of neutral sentiments (66.3%), particularly in effectiveness aspects, while negative sentiments (17.4%) in efficiency and satisfaction underscore the urgency for technical enhancements and improved user interfaces. This study advances knowledge in digital banking by validating hybrid NLP as a scalable tool for rural agent CX, extending TAM applications to Indonesian contexts where prior lexicon-based methods fall short (accuracy <70%). Findings advance theory by quantifying sentiment-usability links (e.g., 42% efficiency negatives predict 20% attrition), informing policy for OJK's Laku Pandai program. Practically, these findings inform strategic recommendations for Bank Sumut, including bolstering system response times and network stability through offline caching modes tailored for rural agents, establishing periodic sentiment monitoring via structured interview protocols to preemptively address service disruptions, and integrating the analysis into an opinion-driven decision support system to mitigate agent attrition and enhance retention [17]. Collectively, these interventions will empower agents, foster greater trust and engagement, and align with sustainable financial inclusion goals in North Sumatra [8].

This research opens up opportunities for further exploration, including the expansion of data sources from social media platforms like Twitter and Facebook or public forums such as Reddit and Kaskus to complement interview insights; the adoption of advanced classification models like BERT or deep learning techniques to push accuracy beyond 80%; longitudinal analyses to track sentiment dynamics over time and assess the impact of new policies on agent retention; and cross-regional comparisons with other Laku Pandai programs in regions like Sulawesi or Java for broader applicability in Indonesia.

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