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Review Article

Leveraging Machine Learning Techniques to Analyze Consumer Mindset Metrics Embedded in Arabic Dialect Texts Across Social Media Platforms

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Abstract: As social media grows in popularity around the world, analyzing Arabic texts on these platforms can provide important insights into consumer attitudes and behavior. The complexity and diversity of Arabic and its dialects, however, make it a challenging task. This research raises these challenges by using and comparing the performance of Machine Learning (ML) models for classifying social media comments in Arabic into service quality, loyalty, purchase intention, and satisfaction. This research employed several machine learning models, including Support Vector Machines (SVM), Multinomial Naïve Bayes, Linear Support Vector Classifier (SVC), and K-Nearest Neighbors (KNN). The results indicate that the Linear SVC outperforms the other models and represents the most effective approach. Furthermore, the classifiers demonstrate strong performance in Arabic short text classification, confirming the effectiveness of machine learning techniques in extracting meaningful insights from Jordanian dialect social media comments.

Keywords: Arabic Social Media, Jordanian Dialect, Short Arabic Text Classification, Consumer Behavior, Machine Learning

Introduction

Expressions of human thoughts and emotions on social media are key to modeling user preferences, decision-making, and behavior prediction (Jalil and Aliwy, 2023). Arabic text classification is one of the emerging trends of focus areas in the available literature on this subject (Aljohani, 2023). Some of its components are regarded as a critical subfield of machine learning and Arabic natural language processing (Alhawarat and Aseeri, 2020). Text categorization is associating an input text with one or several predetermined classes or categories, depending on the information contained (Alzanin et al., 2022). Arabic is a complex language with several dialects and sub-tendencies, which may face problems in rating and categorizing customer feedback in Arabic (Salloum, 2023). Today, social media has become the most used form of media compared to traditional print and broadcast media due to the present digital age (Ali et al., 2021). Text classification in Arabic is now considered the fundamental issue in most natural language processing applications (Muaad et al., 2022).

This complexity makes Arabic text classification particularly challenging due to its rich morphology and structure (El-Alami et al., 2022). In contrast to later languages such as English and French, Arabic text is still considered to pose an intimidating classification problem (Al-Qerem et al., 2024). Text data is inherently challenging due to its unstructured nature, with Arabic text classification further complicated by rich morphology, limited corpora, and mixed MSA and dialect usage (Alwehaibi et al., 2022).

Research on the English database is significantly more numerous than that on the Arabic database In addition, English is one of the languages for which NLP tools and approaches have advanced quickly. Nonetheless, more techniques and strategies are still required for other languages, such as Arabic, to provide further explanations (Khelil et al., 2024). This research applies machine learning to classify Arabic social media comments from Facebook and Instagram in Jordan into measures reflecting customer attitudes, including satisfaction, loyalty, and intent to buy, and perceived quality of service, utilizing tailored methodological approaches to handle Arabic

morphological complexity and dialectal variation. Although social media comments may express multiple consumer mindset constructs simultaneously, a single-label formulation was adopted to ensure annotation consistency, reduce semantic ambiguity, and improve model interpretability.

Literature Review

Consumer Mindset Metrics

Consumer Mindset Metrics (CMM) have a long history within the business field, especially in the marketing domain (Shuba et al., 2010). These include both unobservable (perceptual) constructs, such as service quality, satisfaction, loyalty, and purchase intent, and observable (behavioral) constructs from the firm's perspective, including cross-selling, retention, and customer acquisition(Gupta and Zeithaml, 2006). Thus, this research will focus on perceptual constructs, including service quality, satisfaction, loyalty, and intention to purchase.

Mindsets, often referred to as implicit theories, reflect customers' beliefs about personal attributes and influence how they make purchasing decisions(Murphy and Dweck, 2016). Consumer behaviors express consumer mindset metrics (Gomes et al., 2022). They are a unique component expressing certain opinions about the nature of human characteristics (Dweck, 2013). Marketing, particularly advertising and branding, has a long history of utilizing mindset metrics to assess the perceptions, attitudes, and intentions of consumers (Marshall, 2022). CMMs aim to describe the consumers' experience of engagement with a company, product, or service (Gupta and Zeithaml, 2006; Rubera and Kirca, 2017; Shuba et al., 2010). Thus, the consumer mindset measurements become greatly relevant when the marketing models are addressed (Petersen et al., 2018; Venkatesan et al., 2019). As a result, these metrics are considered significant drivers of company performance and sales (Colicev et al., 2018; Shuba et al., 2010). Similarly, purchase intent, customer satisfaction, and brand awareness are examples of consumer mindset metrics found to improve business performance (Colicev et al., 2018). In social media and its influence, companies have less control over customers' online expressions and opinions (Batra and Keller, 2016). Therefore, understanding consumer mindset metrics in the Jordanian market helps businesses to tailor their strategy according to their customers' perspectives, leading to sustainable success.

Consumer mindset metrics, such as intentions, perceptions, and attitudes, are mostly studied in marketing research and are measured by textual features (Marshall, 2022). Recent studies shed light on CMM in understanding customer behavior and try to focus on finding the best way to extract consumer mindset metrics from user-generated content (Kübler et al., 2025). Moreover, in the Arabic dialect language, a study has classified comments into CMM, such as purchase intention, customer satisfaction, loyalty, and service quality, using BiLSTM and AraBERT (Al-Sarayreh, 2026). To understand consumer behavior from Arabic social media comments in Jordan, this research aims to classify social media comments into consumer mindset metrics, enhancing the way to analyze customer behavior and surpassing sentiment analysis based only on polarity.

Text Classification

Text classification refers to the task of categorizing texts into predefined classes (Elnagar et al., 2020). In recent years, Arabic text classification has gained growing attention, particularly in the analysis of consumer behavior based on user-generated content (El Rifai et al., 2021). In addition, recent research on Arabic text classification has shed light on areas such as spam detection, sentiment analysis, and customer reviews analysis (Sabri et al., 2022). Arabic text classification remains a challenging and relatively underexplored research area due to linguistic complexity, dialectal variation, and limited availability of large, high-quality datasets (Omar et al., 2021). Moreover, previous research has highlighted several challenges in Arabic social media text classification, such as the short texts and the lack of contextual information (Alzanin et al., 2022).

Traditional machine learning techniques have demonstrated strong performance in text classification tasks, particularly in customer reviews applications and e-commerce (Gürbüz and Kotan, 2025). The processing techniques that are applied within Natural Language Processing (NLP), such as stop-word removal, tokenization, and TF-IDF vectorization with classifiers including Naïve Bayes, Support Vector Machines, Random Forest, and KNN, have achieved effective and computationally efficient classification results (Ashokkumar et al., 2018; Gürbüz and Kotan, 2025). These methods enable businesses to identify product attributes and enhance targeted marketing based on insights such as customer satisfaction and feedback (He et al., 2022; Saleem et al., 2021).

Existing research in Arabic text analysis focuses on sentiment analysis rather than on extracting behavioral or perceptual constructs. For instance, (Hnaif et al., 2021) classified Arabic posts and tweets into sentiment categories and demonstrated a strong correlation between positive sentiment and customer satisfaction. Similarly, Ramzy and Ibrahim (2024) evaluated multiple classifiers on Arabic COVID-19 application reviews, such as Logistic Regression, KNN, Random Forest, Naïve Bayes, and SVM, reporting high accuracy using an ANN model of 89% accuracy. Other studies have applied machine learning to customer satisfaction prediction in e-commerce and hospitality domains (Abbassy, 2023;

Zaghloul et al., 2024). While different studies demonstrated the effectiveness of deep learning models such as BiLSTM for Arabic product review classification, achieving an F1-score of 87% (Salloum, 2023). Accordingly, SVM, MNB, and KNN are widely adopted in Arabic text classification due to their effectiveness in handling sparse features, probabilistic word distributions, and similarity-based patterns (El Rifai et al., 2021). Accordingly, because of their complementary learning features, SVM, MNB, and KNN are frequently used in text classification (Nurhayati et al., 2022).

While these studies confirm the effectiveness of machine learning and deep learning models for Arabic sentiment analysis and satisfaction prediction, they largely treat customer opinion as a single, broad concept. Consumer behavior is shaped by construct metrics, such as purchase intent, loyalty, satisfaction, and service quality, so they cannot be captured through sentiment polarity. A limited number of recent studies aim to analyze customer behavior by focusing on customer satisfaction and loyalty based on social media (Urolagin and Patel, 2024). Such approaches are infrequently applied in general to text classification. However, further research is needed to develop effective models to fill this gap (Melhem et al., 2023).

One of the limitations is the availability of Arabic datasets, which significantly limits the generalization of the model (Elnagar et al., 2020). Furthermore, the difficulty of the Arabic language is reported by the U.S. Foreign Service Institute, which considers it one of the most complex languages globally (Center, 2014). Thus, these limitations shed light on the need for focusing on creating an Arabic dataset to enhance Arabic text classification research.

Research Gap and Contribution

Although there is a huge amount of work on Arabic sentiment analysis regarding customer reviews, the evaluation of consumer mindset indicators remains underexplored in the literature, particularly in classifying social media comments, particularly within a Jordanian retail context. The existing studies focus on sentiment or satisfaction in isolation, with limited attention to loyalty. Furthermore, few studies focus on the Arabic language.

In order to close this gap, this study proposes a machine learning model to classify Jordanian social media commentary retail posts in four consumer mindset indices: Purchase intent, loyalty, satisfaction, and service quality, based on a mixed Facebook and Instagram dataset of Jordanian retail pages. Moving past the sentiment polarity and establishing consumer mindset constructs on the basis of marketing theory, the proposed research provides a more interpretable and behaviorally meaningful method of Arabic text classification.

The majority of current research in Arabic text classification focuses on topic and sentiment analysis, with transformer models achieving high performance on large datasets. Also, SVM and traditional machine learning demonstrate a promising performance. Nevertheless, MSA and sentiment analysis are the main subjects of text classification. By focusing on consumer mindset metrics in Arabic social media, this research contributes to the literature. Table 1 presents a summary of research that studies text classification.

Table 1: Summary of Text Classification Research

Reference	Approach	Dataset	Best Performance	Labels
(Sundus et al., 2019)	Feed-forward neural network model with TF-IDF vectors, Adam optimizer, and Logistic Regression	Khaleej-2004 (5690 Arabic documents), Four categories second dataset (1445 Arabic documents) organized into nine categories.	The deep learning The classification model has better accuracy than the logistic regression model for both datasets.	sections covering economic topics, global news, local updates, and sports Education, Engineering, Law, Medicine, Politics, Religion and Sport.
(Mahdaouy and Alaoui, 2020)	Restricted Boltzmann Machines, autoencoder, MLP, and SVM	OSAC.	Deep Autoencoder outperforms the others with a precision of 94%	Economy Education and family History Religion and Fatwa Law Sports Health Astronomy Food Recipes Stories
(Aljedani et al., 2021)	HOMER algorithm	Islamic field	Acc:75%	General Category, Jurisprudence, Worship, Zakat, Fast, Fasting

				Validity, Fasting, Zakat Conditions, The Rule of Zakat)
(El Rifai et al., 2021)	AdaBoost SVM Logistic Regression XGBoost, CLSTM, LSTM, BILSTM, GRU, CNN CGRU, BIGRU, HANGRU, CRF, HANLSTM, BILSTM	single-labeled articles from four domains (Business, Technology, Middle East, and Sports). Dataset 2: 290 k multi-tagged Articles	Dataset 1:SVM outperforms with acc. 97.9% Dataset 2: CGRU ACC. 94.85%	Business, Technology, Middle East, and Sports Dataset 2: multi-tagged Articles
(Mohamed and Alosman 2025)	RNNs CNNs AraBERT	ASTD: Sentiment analysis HARD: Named entity recognition AMARA: Machine translation AJGT: Text classification ADAB: Dialect identification	AraBERT that shows the highest scores in each task. Notably, 95. 2% accuracy on sentiment analysis	Sentiment analysis Named entity recognition
(Sabri et al., 2025)	SVM NB DT With Category Frequency - Inverse Document Frequency (ATCF-IDF)	Khaleej-2004 CNN-Arabic	SVM classifier applied to the Khaleej-2004 96.04%, Svm accuracy of 98.26% for the CNN-Arabic dataset.	Khaleej-2004: Economy, International, Local, Sports CNN Arabic: Business, Entertainment, Middle East, Science and Tech, Sports, World
(Fouadi et al., 2024)	LR SVC NB SGD BERT-based Models	Dataset 1:Topic Detection (Topic_Dial), Dataset 2: Dialect Detection (Identif_Dial), Dataset 3: Sentiment Analysis (Senti_Dial).	BERT-based Models 87% 94% 90%	Categories: Dataset 1-Culture, Economy, Sport, Politics, and Diverse. Dataset 2-Moroccan, Algerian, Tunisian, Egyptian, Lebanese, and MSA. Dataset3-Positive, Negative, and Neutral.
(Mansur, 2023)	Bayes Net Naive Bayes Multinomial Naive Bayes Multinomial Text Naive Bayes Naive Bayes Updateable Naive Bayes Multinomial Updateable	340 texts extracted from the Al-Hayat News Arabic newspaper.	The best performances are Naive Bayes and Naive Bayes Updateable. For both, the average precision is 0.384.	News Economy Science Automotive Technology General Sports
(Omar et al., 2021)	SVM SVC NB Stochastic Gradient Descent (SGD) DT RF KNN	Approximately 44,000 posts and tweets were gathered from Facebook and Twitter.	Linear SVC with N-gram (1,2) accuracy 97,92%	Ads TV Religion Sport Politics Health Food Technology Economics Porn Weather

Methods

This research offers the task as a single-label multi-class classification problem, where each social media comment is assigned to exactly one consumer mindset category. Although customer comments may express multiple mindset constructs, a single-label formulation is adopted to ensure annotation consistency and model interpretability.

Data Collection

The data used in this study comprised 6710 comments that were posted to popular social media retail Jordanian pages and consisted of customer reviews of the Jordanian retail industries, using the Jordanian dialect, specifically Instagram and Facebook. The retail outlets that gave these remarks included All Ameed Coffee, Al Bayrouty food, The Crispy Chicken, All Durrah Market, Lafamilia, Sereensalla boutique for clothes, and Vikik Fashion. The data set was used as the foundation for applying and analyzing different machine-learning approaches. The comments are written in Arabic, which is considered a dialect of the language. The dataset was split into 80 percent of training data and 20 percent of testing data (Alzanin et al., 2022). Figure 1 illustrates the overall research design with the use of Linear SVM, Linear SVC, NB, and KNN.

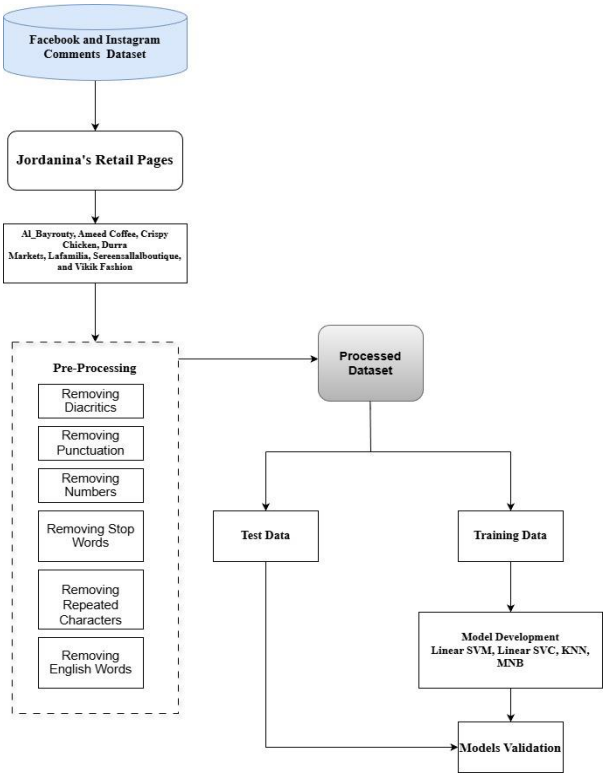

Fig. 1: The methodology adopted for Arabic text classification

Description of the Dataset

The dataset used in this research comprises Arabic comments collected from the Facebook and Instagram Jordanian retail pages. The dataset was extracted from 3 main categories, which are food, fashion, and detergent products, by using the Facepager tool. Data were collected from 2017 to 2023. The comments are in Jordanian dialect. The full label distribution of 6,710 annotated comments is summarized in Table 2.

Data Pre-Processing

Arabic text from social media should be preprocessed before using any Arabic Natural Language Preprocessing (ANLP) software (Oueslati et al., 2020). In order to clean the dataset and, ideally, improve the results, text preprocessing is a necessary prerequisite. Therefore, non-Arabic text should be eliminated (Elnagar et al., 2020).

Tokenization, stop-word elimination, and term stemming are all components of data preprocessing (Abdulghani and Abdullah, 2022). Tokenization of Arabic text serves as the initial essential operation before text preprocessing begins (Atwan et al., 2021). The RTAnews dataset received standard preprocessing through tokenization combined with stemming and stop-word removal, followed by normalization as per Al-Salemi et al. (2019). Our approach removed stop words while retaining negations such as "ما", "لن", "لم", "ليس", "لا". The comments involve using a snowball stemmer that eliminates frequently occurring prefixes and suffixes for stemming the texts. Subsequently, a rule-based preprocessing pipeline was applied, removing diacritics and Tatweel, URLs, phone numbers, numeric tokens, punctuation, symbols, and non-Arabic characters. The remaining text is tokenized, stop words are eliminated, repeated characters are normalized, and Arabic stemming " SnowballStemmer('arabic') " is performed to reduce morphological variation. The preprocessing steps are shown in Table 3.

Data Annotation

The main challenge in preparing the datasets for machine learning tasks, such as text categorization, is annotating them (Ahmed et al., 2015). Native Arabic speakers who were fluent in Jordanian Arabic and consumer mindset measures carefully annotated data in Microsoft Excel sheets.

Table 2: Label distributions for the Facebook and Instagram Dataset

Consumer Mindset Metric	Number of Comments	Proportion (%)
Satisfaction	3,109	46.33
Loyalty	1,599	23.83
Purchase Intent	1,315	19.59
Service Quality	687	10.24
Total	6,710	100.00

The annotation process involved 3 annotators, who are knowledgeable about the CMM terms (service quality, loyalty, purchase intent, and satisfaction), and participated in the annotation phase. Each comment in the dataset was given a consumer mindset label (Vargas et al., 2021), Fleiss' kappa, simple inter-annotator agreement, and Cohen's kappa are the three metrics used to calculate inter-annotator agreement. Furthermore, nominal categories and agreements between more than two raters are assessed using Fleiss' kappa (Bartok and Burzler, 2020). 1 indicates perfect agreement, whereas 0 indicates random agreement (Kankevičiūtė et al., 2022). Annotators were provided with specific guidelines to label each comment according to the following consumer mindset definitions:

Table 3: Pre-Processing Steps

Preprocessing Steps	Example Before Processing	Example After Processing	Translate
Step 1: Removing Diacritics	الرحمن تبارك شاءالله ما	ما شاء اللـه تبارك الرحمن	Praise be to God
Step 2: Removing Punctuation	وطلبات كريم مع مشتركين مش ليش !	وطلبات كريم مع مشتركين مش ليش	Why aren't you partnered with Careem and Talabat?
Step 3: Removing Numbers	❤❤❤❤❤❤❤👏👏👏 رقم ١	❤❤❤❤❤❤❤👏👏👏 رقم	Number 1
Step 4: Removing Stop Words	Bayan A Eyadat واشتريت قميص مثل الي احترق	Bayan A Eyadat اشتريت قميص احترق"	I bought a shirt that burned
Step 5: Removing Repeated Characters	حلو كتيييير	حلو كتير	Very nice
Step 6: Removing English Words	Bayan A Eyadat اشتريت روحت فستان	فستان اشتريت روحت	Bayan A Eyadat, I went and bought a dress

- Satisfaction, which shows whether or not the consumer is happy with the brand (Kübler et al., 2020)
- Loyalty for remarks that indicate if the buyer keeps buying the same product over time (Gupta and Zeithaml, 2006)
- Service quality for feedback, indicating how well a service fulfills the expectations of a customer (Ramya et al., 2019; Sasser et al., 1978)

Purchase intent, which indicates in remarks if the buyer plans to buy the brand (Kübler et al., 2020) When a comment contained multiple semantic cues (e.g., product praise combined with price or availability inquiries), annotators assigned the label corresponding to the dominant consumer intent expressed in the comment. Priority was given to actionable intent (e.g., purchase intent) over affective expressions (e.g., satisfaction) when both appeared within the same comment. Table 4 presents an example of the inter-annotator agreement process. Each comment is independently annotated by three annotators. An English translation is provided for illustration purposes only, while all modeling is performed on the original Arabic text. Final labels are assigned based on majority agreement. Inter-annotator agreement is assessed using Fleiss' Kappa, yielding a value of 0.995, which indicates almost perfect agreement among the three annotators. Among the 6,710 annotated comments, 6,678 achieved full agreement among the three annotators, 31 showed partial disagreement (two annotators agreed), and only one comment exhibited complete disagreement, which explains the very high Fleiss' Kappa value.

Feature Extraction

Machine learning dimensionality reduction becomes possible through feature extraction because it transforms inputs from high-dimensional to lower-dimensional feature sets (Haque et al., 2023). The TF-IDF algorithm transforms all words into feature vectors that identify their representation across a predetermined vector space through real numbers (Hu et al., 2018). Additionally, TF-IDF serves as a common method to transform documents into vectors within large-dimensional spaces by assigning each term a value to its dedicated dimension while providing its matching TF-IDF score. These vectors gained from the text processing step extend their functionality across multiple text analysis operations (Salloum, 2023). Text features were extracted using TF-IDF (TfidfVectorizer), producing a sparse representation for classification. Text features are extracted using TF-IDF with word-level unigrams and default scikit-learn settings, including L2 normalization. No feature selection or dimensionality reduction is applied, preserving the full vocabulary for interpretable classification. The corpus was then split into training and test sets using an 80/20 split with shuffle = False and random_state=1. Performance is reported using accuracy, precision, recall, F1-score, macro-average AUC, and confusion-matrix analysis.

Construction and Training of Models

The models chosen for this research were based on SVM, MNB, SVC, and KNN baseline classifiers, which were employed to categorize Jordanian retail social media comments into four groups, including service quality, purchase intent, loyalty, and satisfaction. Machine learning

has advanced text classification by replacing rule-based methods with data-driven models trained on labeled data. Early approaches such as Naive Bayes and Support Vector Machines laid the foundation of the field, with Naive Bayes handling large vocabularies efficiently and SVM achieving high precision through high-dimensional feature spaces (Allam et al., 2025). Furthermore, Naive Bayes, Support Vector Machines, and k-Nearest Neighbors are among the most widely used supervised machine learning techniques for text classification, demonstrating strong performance and efficiency across various datasets, particularly when combined with TF-IDF feature representations (Kadhim, 2019). Moreover, given their demonstrated effectiveness in multi-class text categorization using TF-IDF representations, as evidenced in prior large-scale news classification studies, MNB, linear SVC, and KNN are adopted in this research because they deliver strong and reliable performance when modeling high-dimensional and sparse textual features, especially LSVC (Barua et al., 2021).

Table 4: Example of Manual Annotation by Multiple Annotators

Arabic Comment	English Translation	Annotator 1	Annotator 2	Annotator 3
اه ♥😳	Oh wow ♥😳	Satisfaction	Satisfaction	Satisfaction
كتير حلو	Very nice	Satisfaction	Satisfaction	Satisfaction
بجنن بدي واحد	It's amazing, I want one	Satisfaction	Satisfaction	Satisfaction
لازما مشوار	It's worth a visit	Purchase Intent	Purchase Intent	Purchase Intent
كم سعر البنطلون	How much are the pants?	Purchase Intent	Purchase Intent	Purchase Intent
كم سعر البلوزه وسايز واحد؟	What is the cost of the blouse, and is it one size?	Purchase Intent	Purchase Intent	Purchase Intent
شو الألوان المتوفرة	What colors are available?	Purchase Intent	Purchase Intent	Purchase Intent
شوفي هاد المحل شو حلوه ومتينه بضاعتهم	Look at this shop, how nice and durable their products are	Service Quality	Service Quality	Service Quality
اه والله كتير حلو 👆	Honestly, it's very nice 👆	Satisfaction	Satisfaction	Satisfaction
مشتاقلك هالكان 😂	I miss this place 😂	Loyalty	Satisfaction	Satisfaction
ما شاء الله	Mashallah (expression of admiration)	Satisfaction	Satisfaction	Satisfaction
هذا المحل اللي بجيب منه الجكيتات	I buy jackets from this store	Loyalty	Loyalty	Loyalty

Moreover, given their demonstrated effectiveness in multi-class text categorization using TF-IDF representations, as evidenced in prior large-scale news classification studies, MNB, linear SVC, and KNN are adopted in this research because they deliver strong and reliable performance when modeling high-dimensional and sparse textual features, especially LSVC (Barua et al., 2021).

The model was trained on 80% of the training data before it was tested on 20 percent of the testing data. The training set, made up of known examples, was used to train a classification model. Once the model has been trained, it can be used to predict the unknown samples by testing them using the evaluation of a set of samples. Classification is defined as the process of marking certain textual or document data according to their content (Muaad et al., 2022). The process of learning takes place during the training phase, where the classifier algorithm trains with the help of the labeled data, in the current case, a sample of customer reviews in a retail business in Jordan. In addition, to assess the performance of the model, the accuracy of each classifier, F-score, precision, and recall should be taken into account (Elgeldawi et al., 2021). Also, AUC is a concept measure that assesses the trade-off between the true-positive and false-positive measures used to estimate the entire performance of a classification system. The Area Under the Curve (AUC) is calculated by the Receiver Operating Characteristics (ROC) curve, which is a visual depiction of the correlation between false and true positive rates (Al-Smadi, 2024).

Multinomial Naive Bayes (MNB)

In fact, it's reasonable to conclude that Naive Bayes functions as a probabilistic classifier intrinsically. MNB stands together with several other forms of this vignette. The NB classification method uses information in this formulation to apply Bayes' Theorem with the assumption of independent predictors (Venkatesh et al., 2020). A Naive Bayes classifier functions as a simple predictor because it assumes each attribute feature is independent of all other features (Hamed et al., 2024). Several studies investigated during the research phase demonstrated that the proposed models significantly improved Arabic tweet classification capability when implemented with Support Vector Machine (SVM) and Naïve Bayes (NB) algorithms, which delivered better outcomes than other models tested during the research.

Support Vector Machine (Linear kernel)

SVM, of which SVC is a part, is a classification algorithm used in statistical learning theory. According to the statistical learning perspective, the SVC is most often used in document classification concerns, such as pattern

recognition(Kowsari et al., 2019). The most applied technique for text classification is support vector machines, or SVMS for short. SVCs sort the linearity and nonlinearity of n-dimensional data into the correct classes by learning those hyperplanes (Muaad et al., 2022).

Linear Support Vector Classifier (SVC)

SVC uses a high-dimensional feature space with a Gaussian kernel to map data points, cluster them, and then project them back into the original space (Ben-Hur et al., 2002). The two primary phases in SVC are cluster labeling and estimating a support function through SVM training (Du et al., 2024). The fundamental goal of linear SVC is to match data by creating the correct fitting hyperplane that divides the data for categorization purposes. (Sikarwar et al., 2020). It efficiently manages outliers and creates arbitrary cluster bounds (Du et al., 2024).

k-Nearest Neighbors (KNN)

The KNN classifier is used to implement the system for the following reasons: it is straightforward, the similarity measure is reasonable, and it requires no training resources. However, it has certain drawbacks, like an above-average categorization time due to the lack of a learning phase (Al-Badarenah et al., 2016). Feature vectorization techniques and data quantity significantly impact the performance of the algorithms RF, DT, and KNN, but SVM and logistic regression produce stable results (Sabri et al., 2022). KNN is a common classification technique. The basic concept is as follows: Given a labeled database, we may determine the class of a new piece of data by examining the majority class of the k nearest pieces of data (hence the algorithm's name) (Maillo et al., 2017).

Evaluation Metrics

Using a range of feature representation techniques, the effectiveness of distinct classification algorithms was examined using varying-sized public benchmark Arabic text datasets. The following metrics are used to evaluate the suggested method's performance: Accuracy, recall, precision, and F-measure (Al-Masni et al., 2018; Chola et al., 2021). We make use of the F1-score, which is unaffected by data imbalances (Jeni et al., 2013). F-1 is the weighted harmonic mean of recall and precision (Ramzy and Ibrahim, 2024). Precision is the percentage of the class that was correctly predicted, and recall is the percentage of the actual class that was retrieved (Jalil and Aliwy, 2023). An analysis of the Receiver Operating Characteristic (ROC) curve using the True Positive Rate and False Positive Rate at various categorization thresholds yields an AUC. The model performs better at differentiating between positive and negative classes, the higher the AUC (Shafiq et al., 2023). The performance of Arabic text classification algorithms can be evaluated using metrics that are appropriate to the specific characteristics of the classification task, particularly in single-label multi-class settings such as accuracy, precision, recall, and F1 score (Hamzaoui et al., 2025).

We employed the following six metrics to compare performance (Oyebode et al., 2020):

- Accuracy measures the proportion of correctly classified instances among all predictions. As stated in Equation 1:

$$Accuracy = \frac{(\Sigma\ True\ Positive + \Sigma\ True\ Negative)}{\Sigma\ Total\ classified} \quad (1)$$

- Precision is defined as the proportion of true positive instances among all instances predicted as positive. As stated in Equation 2:

$$Precision = \frac{\Sigma\ True\ Positive}{(\Sigma\ True\ Positive + \Sigma\ False\ Positive)} \quad (2)$$

- Recall measures the extent to which the model successfully identifies all relevant positive instances within the dataset. As stated in Equation 3:

$$Recall = \frac{\Sigma\ True\ Positive}{(\Sigma\ True\ Positive + \Sigma\ False\ Negative)} \quad (3)$$

- The F1-score is the harmonic mean of precision and recall, providing a balanced measure of classification performance. As stated in Equation 4:

$$F1 = \frac{2 * (Precision * Recall)}{(Precision + Recall)} \quad (4)$$

- ROC is a graphical tool used to evaluate the performance of a classification model (Tan, 2009)
- AUC is the Area Under the ROC Curve (AUC), which provides a single scalar measure of a classifier's discriminative capability, with larger values indicating stronger performance (Abd et al., 2023)

Results and Discussion

The preprocessing steps applied to Arabic comments include tokenization, stemming, filtering, and feature extraction. Following, it was converted into numerical feature vectors and fed into KNN, SVM (Linear Kernel), MNB, and LSVC.

Table 5 presents the machine learning models applied in this research and the hyperparameters used. Multinomial Naïve Bayes and Linear SVC were used with default settings, reflecting commonly adopted configurations in text classification tasks. Based on previous studies applied to Arabic text classification, the

value of *k* in the KNN classifier was selected empirically through multiple experimental runs, and k = 4 was chosen as it gives promising performance, consistent with the empirical tuning method done by Salih and Qarash (2026). Similarly, to previous studies applying empirical evaluation to select the optimal k value in k-NN models, k is also chosen as 4 based on repeated experimental runs, which yielded the highest accuracy and precision (AL-Yassari and Obayes, 2022). In addition, in Arabic text classification, such as single-label and multi-label systems, the default parameters were chosen for Support Vector Machine (SVM) and Multinomial Naive Bayes (MNB), since recent studies have shown that these default settings yield high performance without the need for huge hyperparameter tuning (El Rifai et al., 2021).

Table 5 presents the machine learning models and parameters used the Fleiss' Kappa value of 0.995 indicates that annotators have a high degree of agreement. This indicates that the labels are consistent across annotators. Table 6 presents a sample of the dataset used in this research. Also, Table 7 shows comments and Label Count Distribution.

The results indicate that the Multinomial Naive Bayes (MNB) achieves good performance across the evaluation metrics, reflecting its effectiveness in capturing the semantic meaning of CMM. The precision is 89.7%, and the recall is 85.0% shows strong and balanced performance when classifying CMM. The accuracy is 88.2%, and the F1-score of 87.0% shows a good balance between the precision and recall.

Table 5: Model Parameters used in the Models

Model	Implementation	Key hyperparameters
MNB	MultinomialNB()	default (α=1.0)
Linear SVC	LinearSVC()	default (C=1.0)
Linear SVM	SVC(kernel='linear')	linear kernel, default C=1.0
KNN	KNeighborsClassifier (n_neighbors=4)	k=4

Table 6: Sample of the dataset

Comments	Label
السعر	purchase intent
كم سعره؟ وين موقعكم	purchase intent
بجنننو صح	Satisfaction
نرجس تشرين بجنن بدي واحد	Satisfaction
شوفي هدا المحل شو حلوه ومرتبه بضاعتهم	service quality
👈اه والله كتير حلو	Satisfaction
😂مشتاقلك هالمكان	Loyalty
ما شاءالله	Satisfaction
وين فروعكم	purchase intent
حلوات	Satisfaction
وين الموقع	purchase intent
هادالمحل اللي بجيب منه الجكيتات	Loyalty
ما شاءالله تبارك الرحمن	Satisfaction

Table 7: Comments with Label Count Distribution and Rater-Assigned Labels

Comments	Label 1	Label 2	Label 3	Purchase Intent	Satisfaction	Service Quality	Loyalty
😍😊شو رايك نروح	Purchase Intent	Purchase Intent	Purchase Intent	3	0	0	0
السعر	Purchase Intent	Purchase Intent	Purchase Intent	3	0	0	0
كم سعره ؟ وين موقعكم	Purchase Intent	Purchase Intent	Purchase Intent	3	0	0	0
بجنننو صح	Satisfaction	Satisfaction	Satisfaction	0	3	0	0
اه ❤😌	Satisfaction	Satisfaction	Satisfaction	0	3	0	0

The high macro-average AUC of 97% shows that the MNB effectively discriminates between the semantics of comments. Regarding the behavioral view, this indicates that the MNB effectively captures the expressions that are related to service quality, purchase intent, loyalty, and satisfaction in the Jordanian comments.

These findings are consistent with previous studies indicating that NB performs effectively in analyzing consumer behavior. For example, NB outperformed other classifiers of Yemeni mobile banking applications of reviews, achieving high accuracy, precision, and recall (Al-Hagree and Al-Gaphari, 2025). confirms its suitability for CMM and noisy text. In contrast, a lower accuracy was reported, 57.56% for Saudi dialect Twitter data (Abo et al., 2021). This highlights the impact of dialect type on the model's performance. By focusing on the Jordanian dialect and using Facebook and Instagram comments, this research ensures that the analysis reflects CMMs.

The confusion matrix indicates that the MNB classifier correctly predicts most cases of consumer mindset metrics labels, and it shows the highest accuracy related to Satisfaction. Minor misclassification is observed between Satisfaction and Loyalty; this indicates that expressions overlap between positive reviews and brand loyalty in customer reviews in the Jordanian market. Overall, these misclassifications were limited, providing consistent and accurate classification results.

The Linear Support Vector Classifier (SVC) demonstrates strong performance for the evaluation metrics. The high precision 93.5% and recall 92.5% illustrate how the model reduces false positives and false negatives while correctly identifying meaningful CMMs. Since satisfaction and loyalty are closely connected variables and frequently have similar linguistic expressions in Jordanian social media comments, this balance indicates that LSVC is successfully differentiating between them. Moreover, the accuracy is 93.5%, and the F1-score is 93.0%, additionally verifying that the model's predictions are consistent across various classes. The model offers strong generalization when identifying a variety of consumer expressions, as evidenced by its high macro-average AUC of 97%, which demonstrates dependable discrimination across various decision boundaries.

The results above imply that Linear SVC successfully identifies significant patterns in comments presented in Jordanian Arabic. Its ability to handle high-dimensional TF-IDF data and distinguish overlapping semantic signals found in user-generated content leads to strong performance.

These findings are consistent with recent work. For example, Omar et al. (2021) showed that Linear SVC achieved high accuracy up to 97.79% when classifying multi-label using n-gram TF-IDF features, highlighting the effectiveness of SVC for large textual datasets. The confusion matrix shows that the Support Vector Classifier accurately classifies most cases of CMMs, particularly showing strong performance in Satisfaction and Purchase Intent. Minor misclassification is observed between Satisfaction and Loyalty, showing overlapping forms of brand loyalty and good experiences. As a result, misclassifications are often low, suggesting a strong and dependable model.

The Support Vector Machine (SVM) model showed strong performance across all evaluation metrics. With a 92.9% overall accuracy, the model effectively identifies significant consumer mindset categories while reducing misclassification due to its high precision 92.8% and recall 92.1%. Additionally, the F1-score of 92.4% indicates reliable and consistent classification performance and further supports a strong balance between precision and recall.

With a high macro-average AUC of 97%, the model is able to maintain consistent discrimination across a range of decision criteria. SVM proves to be a good fit for modeling high-dimensional textual features in Arabic social media data.

The results are consistent with prior studies. For instance, Najjar et al. (2025) reported that SVM achieved an accuracy of 98.0% when classifying 7 categories of 6,500 documents. Similarly, Al-Hagree and Al-Gaphari (2025) showed that the SVM achieved competitive recall, accuracy, precision, and F1-score in evaluations of Yemeni mobile banking applications. In addition, Abo et al. (2021) reported an accuracy of 82.30% for SVM on Saudi dialect Arabic Twitter data. These studies confirm the effectiveness of SVM for Arabic text classification. The confusion matrix shows that the SVM model correctly classifies CMMs as 222 loyalty, 355 purchase intent, 529 satisfaction, and 142 service quality, with strong performance for Satisfaction and Purchase Intent. Minor misclassification is observed between Satisfaction and Loyalty, due to overlapping expressions of positive experience and brand preference. Overall, misclassifications are low, which shows a strong classification performance.

The results indicate that the K-Nearest Neighbors (KNN) model achieves strong performance across the evaluation metrics. The model achieves an equal balance between accurately recognizing relevant occurrences and reducing misclassification cases, as evidenced by its 92.3% precision and 90.2% recall. The model accuracy of 92.1% further demonstrates its reliability, and its F1-score of 90.8% shows consistent performance across classes.

The KNN model maintains outstanding discriminative capacity across a range of decision thresholds, as evidenced by its high macro-average AUC of 99%, which suggests strong generalization with limited category misclassification. In contrast to earlier research, the suggested KNN findings perform better than those documented for Saudi dialect Arabic Twitter data, where the accuracy is 61.41% (Abo et al., 2021), demonstrating the model's success when used on a mixed social media dataset and applied to an Arabic dialect. The confusion matrix shows that KNN accurately classifies most cases, as follows: 239 loyalty, 359 purchase intent, 518 satisfaction, and 120 service quality. With particularly strong performance for Satisfaction. Due to overlapping positive phrases in customer reviews, the results show limited misclassification between satisfaction and loyalty, as well as between satisfaction and service quality. This may be attributed to the semantic overlap among these classes, as satisfied customers often express favorable attitudes that are similar to loyalty, and service comments frequently contribute to perceptions of satisfaction. Reliable classification performance is indicated by a limited number of misclassifications. Figure 2 presents the confusion matrices for the evaluated models, including SVM, SVC, NB, and KNN. The machine learning algorithms' outcomes are displayed in Table 8.

All four models, KNN, SVM, SVC, and MNB, show good discriminative ability, as indicated by ROC curves that consistently approach the upper-left corner. SVC performs well with high AUC values (0.97), showing constant discrimination across various decision thresholds, and KNN achieves almost perfect separation across classes, as evidenced by AUC values of 0.99, indicating dependable detection with few misclassifications. Despite its more straightforward probabilistic assumptions, MNB also exhibits competitive performance, with high AUC values across all classes, demonstrating its efficacy in modeling class separability. Figure 3 shows the ROC curve for each classifier.

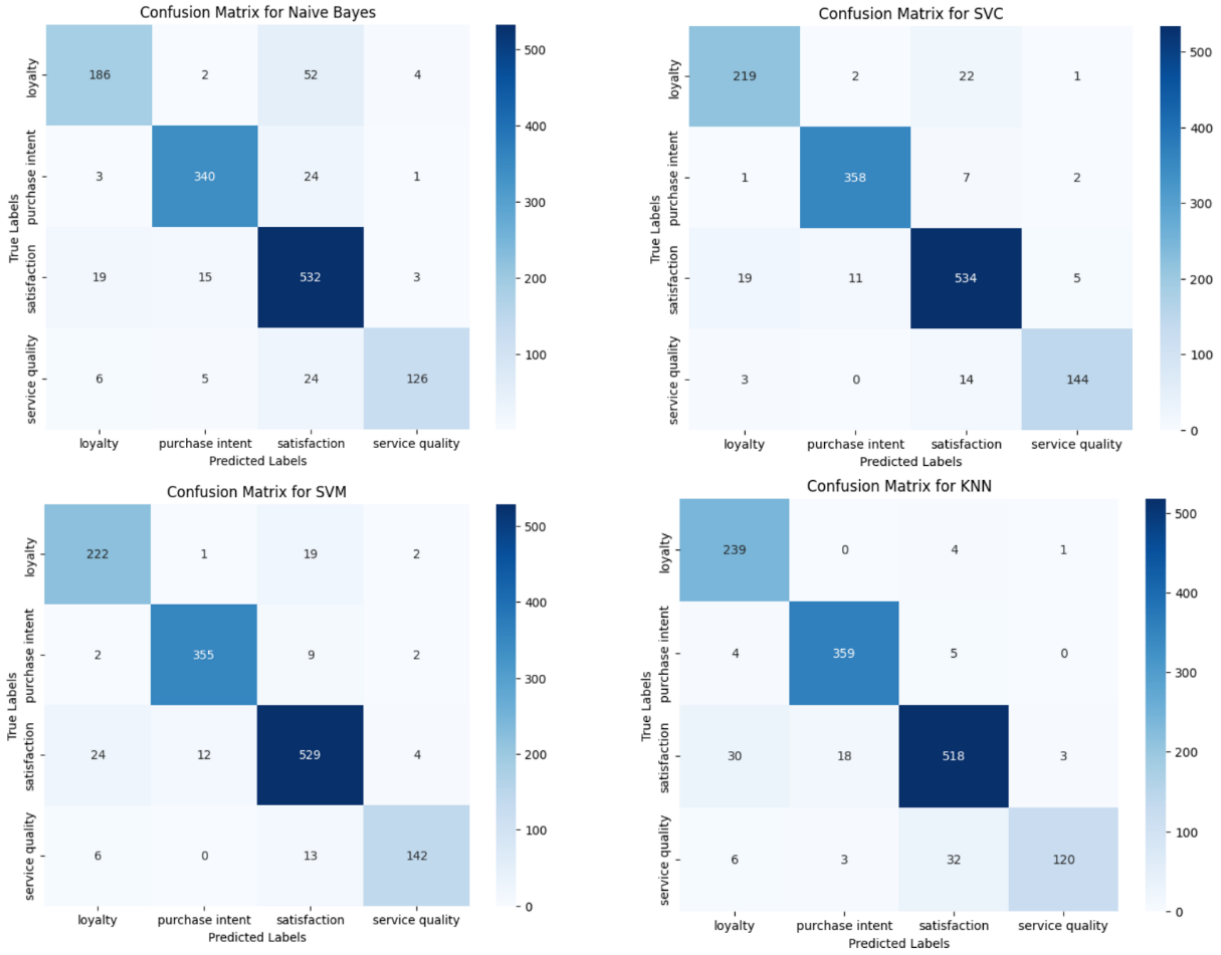

Fig. 2: Confusion Matrix for Machine Learning

Table 8: Machine Learning Algorithm Results

Model	F1-Score (%)	Accuracy (%)	Macro-average AUC (%)	Precision (%)	Recall (%)
Multinomial Naive Bayes	87.0	88.2	97.0	89.7	85.0
Linear SVC	93.0	93.5	97.0	93.5	92.5
SVM (Linear kernel)	92.4	92.9	97.0	92.8	92.1
KNN	90.8	92.1	99.0	92.3	90.2

The comparison of the machine learning techniques using the evaluation metrics is presented in Figure 4.

Consequently, the Linear Support Vector Classifier (SVC) achieved the best performance, while MNB showed the least performance. From a marketing theory perspective, the strong classification performance across all four consumer mindset metrics confirms that service quality, loyalty, purchase intent, and satisfaction are linguistically distinguishable constructs in user-generated Arabic social media content. This finding aligns with prior marketing research, which conceptualizes consumer mindset metrics as perceptual drivers that lead to observable consumer behavior rather than as a single attitudinal dimension. The observed confusion between satisfaction and loyalty reflects their theoretical proximity, as satisfaction often serves as an early indicator of loyalty, while prior research also suggests a mutually reinforcing relationship in which satisfaction and loyalty positively influence one another (Chotisarn and Phuthong, 2025; Shankar et al., 2003). By implementing these metrics through supervised machine learning, this research demonstrates that Arabic dialectal comments can be systematically mapped to established consumer behavior theory, providing a scalable alternative to traditional survey-based measurement of consumer mindsets in emerging markets.

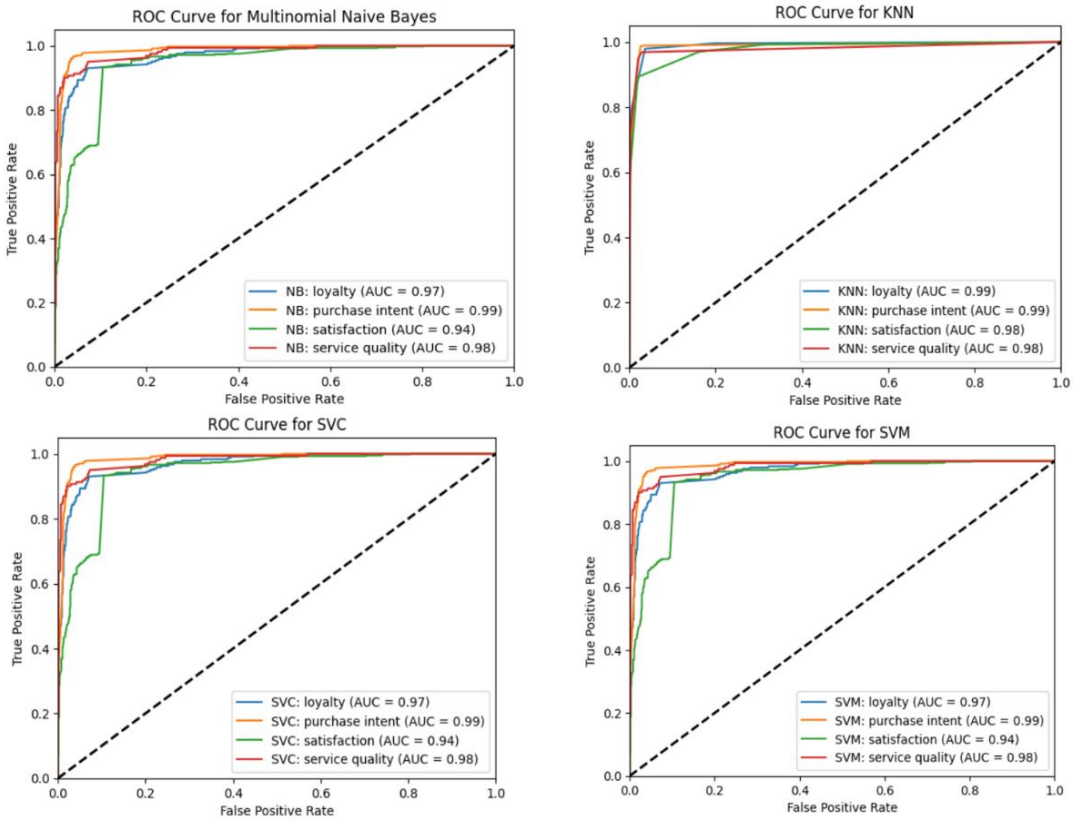

Fig. 3: ROC Curve for Machine Learning

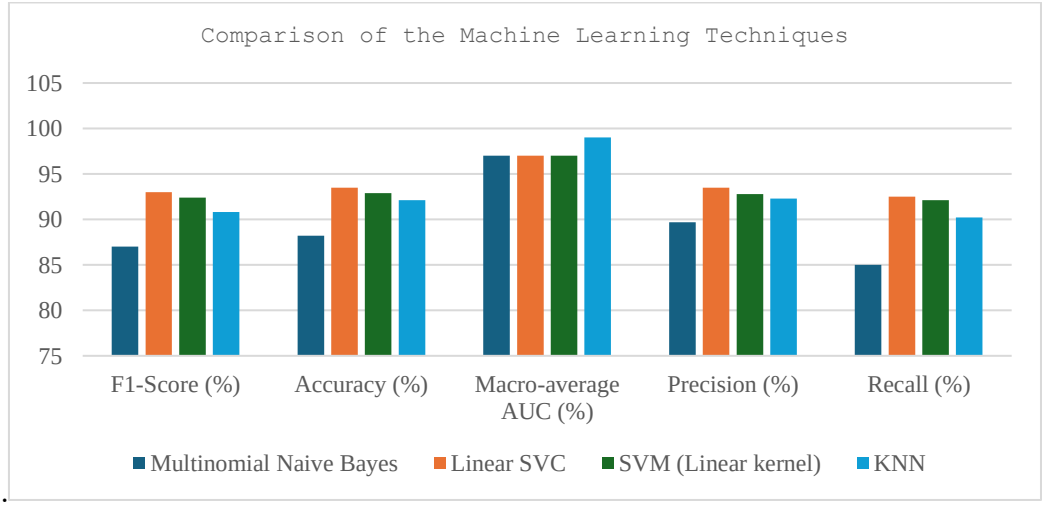

Fig. 4: Evaluation Metrics Among ML Algorithms Comparison

Conclusion

To provide an automated approach to consumer mindset metrics classification, this research employs machine learning classifiers such as SVM (Linear kernel), linear SVC, MNB, and KNN, using a dataset collected from several Facebook and Instagram pages for Jordanian retailers.

In conclusion, the linear SVC and SVM (Linear kernel) provide promising results. An LSVC was the most promising model, and MNB was the least. In languages such as Arabic, where context capture and morphological information are essential, this comparative analysis demonstrates the efficacy of using NLP frameworks.

As a result, this research further focuses on Jordanian Arabic dialect text classification, as well as increases

marketing analytics by offering a deeper overview of customer reviews rather than sentiment analysis alone. This research has several limitations despite its encouraging findings. It uses an unbalanced dataset, concentrates on Jordanian Arabic from a small number of platforms and brands, and employs a single-label multi-class, despite possible overlap across consumer mindset metrics. Furthermore, the study captures customer reviews that are stated without concentrating on false information; this issue is recommended for further research.

Future research should focus on implementing a multi-label classification framework and integrating supervised labeling with unsupervised clustering to better capture the drivers of consumer mindset constructs. Additionally, future research should investigate transformer-based models to improve semantic representation in various dialects of Arabic.

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Author's Contributions

All authors contributed equally to this study.

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