International Journal of Engineering Trends and Technology
ISSN: 2231 – 5381 / https://doi.org/10.14445/22315381/IJETT-V70I10P238

Volume 70 Issue 10, 393-401, October 2022

Original Article

Artificial Intelligence Model of the User Patterns and Behaviors Analysis on Social Media to Become Customers in Smart Marketing

Sumitra Nuanmeesri[1], Lap Poomhiran[2], Wongkot Sriurai[3]

[1] *Faculty of Science and Technology, Suan Sunandha Rajabhat University, Bangkok, Thailand.*
[2] *Faculty of Information Technology and Digital Innovation, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand. (Corresponding author)*
[3] *Faculty of Science, Ubon Ratchathani University, Ubon Ratchathani, Thailand.*

[1]*Corresponding Author : sumitra.nu@ssru.ac.th*

Received: 09 August 2022 Revised: 20 October 2022 Accepted: 21 October 2022 Published: 23 October 2022

Abstract - This research aims to analyze the patterns and behavior of social media users on Facebook Pages that sell products online and develop mobile applications to predict whether such users are likely to become customers. The data or actions taken by Facebook users are collected for sentiment analysis of texts and emotional analysis of emojis. Then, the feature selection technique was applied by Gain Ratio, Chi-Square, and Correlation-based Feature Selection. The developed model is based on machine learning techniques, including Decision Tree, Random Forest, Naive Bayes, Support Vector Machine, and Multi-Layer Perceptron Neural Network. The result has shown that the model developed by applying the Multi-Layer Perceptron Neural Network and Correlation-based Feature Selection is the highest model performance compared to other models in this work. This model has an efficiency of 89.80% accuracy while having a Mean Absolute Error of 0.102.

Keywords - *Artificial intelligence, Customer behavior, Smart marketing, Social media.*

1. Introduction

The internet, social media, mobile apps, and other digital communication technologies have become a part of everyday life for billions worldwide. As stated in [1], as of April 2022, there are five billion active internet users, covering 63% of the world's population. Moreover, there are 4.65 billion social media users. Social media has become essential in many people's daily lives and continues to increase. In addition, in 2020, there will be 3.6 billion social network users.

Moreover, social network users are expected to increase to 4.41 billion by 2025 [2]. During the COVID-19 outbreak, people have social distancing. They have to do activities through the internet and online systems, such as working from home, studying, and shopping. This way has stimulated the distribution of products and services online. Facebook was the leading social platform in 2020 [2], with over 200 million small businesses registered for its tools [3]. People spend more time online searching for information about products and services, including communicating with other consumers about their experiences and engagement with the activities on the Facebook Page. As a result, various organizations have responded to this shift in consumer behavior by making digital and social media essential components of their online business and marketing plans [4]. Organizations can benefit significantly by making social media marketing a key component of their overall business strategy [5]. It is because digital marketing and social media help companies achieve their marketing objectives at relatively low costs [6]. However, in online shopping, there is still a lack of identification of consumer behavior and supporting factors [7]. In particular, the analysis determines the patterns and behaviors of users' activities and shopping preferences on social media.

Machine learning and data mining methods have been used effectively, including classification, clustering, associative mining, and pattern recognition techniques. These techniques use data analytics tools to find patterns in consumer behavior [8] to increase customer satisfaction with online shopping and improve customer experiences. However, demand forecasting has always been a significant challenge in e-commerce. Therefore, much research highlights fundamental social media consumer behavior principles, providing predictive evidence primarily through text mining and sentiment analysis. Text mining means extracting helpful information from a text database using machine learning techniques such as Natural Language Processing (NLP). Text mining uses social media networks to predict consumer behavior: likes, shares, comments, and reactions. Comments refer to the written text, so sentiment analysis converts into sentiment or opinions [9]. Likes, shares, and reactions refer to facts about quantities measured and processed, such as positive, negative, or neutral behavior [10]. One key research approach that uses data mining to predict performance metrics of posts published on a brand's Facebook Page modeled the flow of the decision-making process. It may support decisions about whether to publish a post or not [11]. Facebook user behavior is monitored and classified by relevant content to avoid viewing irrelevant ads [12]. It also analyzed consumer engagement variance, highlighting the changes caused by Facebook Live video usage, revealing more emotional and cognitive engagement with live video than with other types of posts [13]. The discovery of Facebook posts, such as tracking the number of likes, comments, shares, and reactions, provides a solution to meet the needs of marketers and customers that create a win-win relationship together. Therefore, each post type can generate engagement and drive Facebook user reactions. Marketers can use strategies based on what attracts the attention of online users. Some studies have predicted online user behavior by providing a precise method for determining differences between Facebook post types with decision trees. However, this method may only be suitable for specific countries or industries [23].

This research aims to develop an application for smart marketing with an artificial intelligence model that analyzes the patterns and behaviors of Facebook users who visit and purchase community enterprise products on social media. In addition, community enterprise business owners can use the mobile application to predict and decide which Facebook users will purchase their products or become customers.

2. Methodology

The artificial intelligence model's development for analyzing social media users' patterns and behaviors for smart marketing consists of eight processes, as shown in Figure 1.

2.1. Data Collection

This research collects opinions or comments from fifteen Facebook Pages selling community enterprise products in Thailand. The data collected totaled 48,532 comments by 8,014 users from January to May 2022. These data are related to the prediction model of customers for Dusit' Brand products in Dusit District, Bangkok. The comments contain text and non-text elements: emojis, stickers, avatar stickers, videos, music, and images such as photos or Graphics Interchange Format (GIF). In addition to the text data, it also includes the demographic user profile characteristics of the Facebook users, including gender, age, country, city, education level, job type, marital status, and access device. Moreover, this work collected the user action data to analyze Facebook user behavior in the form of the frequency of actions: page (following and like), post (like, share, reply, and view), and click (get direction click, website click, phone number click, and send message click). To collect this data, the researchers developed the Facebook Data Collector Engine (FB-DCE), based on the Facebook Graph API version 14.0, to load and store data into MySQL Database.

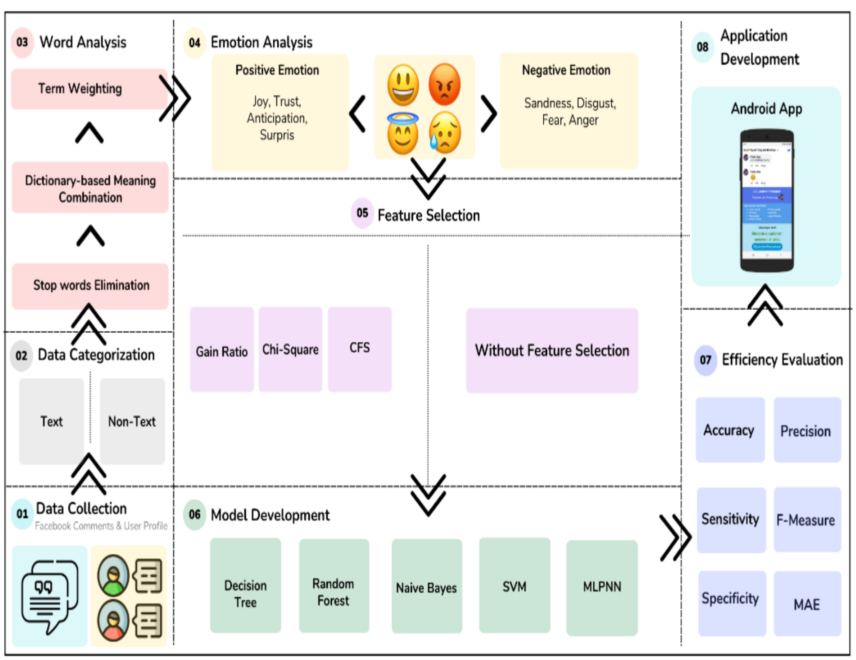

Fig. 1 The proposed model framework

2.2. Data Categorization

The collected comments are categorized into two major groups: text and non-text. Most comments are text formatted in Thai. Non-Thai words or texts are omitted by referring to the Thai language's ASCII code and UTF-8 code table. Non-text data are grouped based on their formatted appearances, such as emojis, stickers, avatar stickers, videos, music, and images.

2.3. World Analysis

All texts which are the comments will be word segmented using the LexTo API (A Thai Lexeme Tokenization and Normalization Tool) based on NECTEC's Lexitron Dictionary. In this process, specific adverb types are selected. In this work, only adverb types are selected by applying the Thai WordNet lexical database to group words with similar meanings between buy or not buy the community enterprise products. The text in a single comment can consist of multiple sentences. These comments get rid of the stop word. Each word in each sentence is segmented, and a pipe sign (|) is used as a separator between words. Meaningless words are omitted from the sentence. The segmented words are formatted in a Comma-separated values (CSV) file. This CSV file classified the sentiment by applying the adverbs related to positive and negative opinions based on NECTEC Lexitron Dictionary. The word or term frequencies (TF) of positive and negative attributes are counted. If the number frequency of positive terms is greater than the negative, the result is set as positive (P). If the number of negative term frequencies is greater than positive, negative (N) output was set. If the number of positive terms equals negative terms, set the result value to balance (B). The number of word frequencies that may be repeated. The weight was applied and calculated according to the Term Frequency-Inverse Document Frequency (TF-IDF) principle. Then generate a word vector from these words for the model development.

2.4. Emotion Analysis

For non-text comments, emotions are classified based on Plutchik's eight basic emotions [15]. These eight basic emotions were classified into positive and negative emotions. The positive emotions include joy, trust, anticipation, and surprise, whereas the negative emotions include sadness, disgust, fear, and anger. The emojis or emoticons are non-text. These kinds of comments were compared and classified as an emotion by applying the Unicode of emoji [16] version 14.0. It has 1,853 types of smileys and emojis, similar to emojis on Facebook. The results of the emotion analysis were classified and defined as the labels of the emojis with the emotion under Plutchik's eight emotions.

2.5. Feature Selection

In this research, the data of twenty-five features were collected and defined for each Facebook user the action on the Facebook pages, as shown in Table 1.

Table 1. All features of the collected data

Feature	Description	Range of data
TextComment	The sentiment of the text comment	Positive, Negative, Balance
Emoji	The emotion of emoji	Joy, Trust, Anticipation, Surprise, Sadness, Disgust, Fear, Anger
Sticker	The comment is a sticker	Yes, No
AvatarSticker	The comment is an avatar sticker	Yes, No
GIF	The comment is a GIF image	Yes, No
Photo	The comment is a photo or picture	Yes, No
Music	The comment is a music content	Yes, No
Video	The comment is a video content	Yes, No
PageFollowing	The user clicks the following page	Yes, No
PageLike	The user clicks the like a page	Yes, No
LikePost	The number of likes the posts for each user	0, 1, 2, …
SharePost	The number of shares the posts for each user	0, 1, 2, …
ReplyPost	The number of shares the posts for each user	0, 1, 2, …
ViewPost	The number of views the posts for each user	0, 1, 2, …
GetDirection	The number of clicks on a 'Get direction' button for each user	0, 1, 2, …
Website	The number of clicks on a 'Website' button for each user	0, 1, 2, …
PhoneNo	The number of clicks on a 'Phone number' button for each user	0, 1, 2, …
SendMessage	The number of clicks on a 'Send message' button for each user	0, 1, 2, …

Gender	Facebook user's gender	Female, Male, Not provide
Age	Facebook user's age	A: 13-17 years old B: 18-25 years old C: 26-35 years old D: 36-45 years old E: 46 years old or above N: Not provide
CityRegion	The region by the province of a Facebook user in Thailand	Central, North, East, South, West, North-East, Not provide
AccessDevice	The device from which users access Facebook pages	Mobile, Desktop (Laptop)
EducationLevel	The Facebook user's education level	Basic, Intermediate, Undergraduate, and Postgraduate, Not provide
JobType	The Facebook user's job type	A: Agriculture B: Business owner C: State enterprises D: Government employee E: Employee F: Freelance G: Government H: Other
MaritalStatus	Marital status	Single, Married, Not provide
TextComment	The sentiment of the text comment	Positive, Negative, Balance

However, some of the features collected may have a slight effect on the performance of the developed models. Therefore, the feature selection was based on weight analysis techniques using Gain Ratio (GR), Chi-Square (CS), and Correlation-based Feature Selection (CFS) methods to optimize the model's effectiveness in developing a mobile application. For the GR and CS techniques, all features were ranked by weighting and degree of freedom calculated based on GR and CS methods, respectively. For the CFS technique, the output weights of features were ranked. Thus, the features with weight values more than zero were selected. Besides, the features with weight values over 50% were selected for the CFS method.

These three techniques were compared to the model's efficiency based on the number of features selected versus those that did not rely on feature selection. Finally, the best effective technique will be applied to mobile application development.

2.6. Model Development

The models for finding the user pattern and purchasing behavior on social media in smart marketing are based on these five techniques: DT, RF, NB, SVM, and MLPNN. Each technique consists of seven models that differ according to the feature selection method and not selecting features. In addition, algorithm C4.5 was applied to DT. For RF, it was set fifteen trees for each subset dataset. The alpha parameter was set equal to 1.0 for NB. The Radial Basis Function (RBF) kernel was applied to SVM with the penalty parameter of the error term (C) value was 1.0, and the gamma value was 1.0. Finally, for MLPNN, the three hidden layers were set with twenty neurons, Rectified Linear Unit (ReLU) activation function. The other hyperparameters, including 0.01 for learning rate, 64 batch size, 100 epochs, and the momentum was 0.9. The dataset was split into 80% and 20% for the training and test sets. There are two result classes: simple visitor and becoming a customer. The 'simple visitor' class refers to a Facebook user who is not likely to shop on the Facebook Page. While the 'become a customer' class relates to a Facebook user, who is expected to make a purchase or become an actual customer under that Facebook Page.

2.7. Model Efficiency Evaluation

All developed models were evaluated based on the performance of accuracy, sensitivity, specificity, precision, and F-measure according to Equation (1) [17, 18], Equation (2), Equation (3) [25], Equation (4), and Equation (5) [20], respectively.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

$$Precision = \frac{TP}{TP + TN + FP} \tag{4}$$

$$F\text{-}measure = \frac{2 \times \Pr ecition \times Sensitivity}{\Pr ecision + Sensitivity} \tag{5}$$

Where:

TP represents the actual value is positive, while the predicted value is positive;

TN represents the actual value is negative, while the predicted value is negative;

FP represents the actual value is negative, while the predicted value is positive;

FN represents the actual value is positive, while the predicted value is negative.

Moreover, the Mean Absolute Error (MAE) was applied to the models to indicate the model efficiency as in Equation (6) [21].

$$MAE = \frac{1}{N}\sum_{i=1}^{n}\left|y_i - y_p\right| \tag{6}$$

Where:

N represents the total number of data;
y_i represents the actual value;
y_p represents the predicted value.

2.8. Application Development

The most efficient model is used as a prototype to develop an Android-based mobile application in the Android SDK version 10.0. In addition, the Android Studio version 2021 was used as a development tool. The programming language includes C++ and Java for the mobile application. At the same time, the developed web services API is php5-based which was developed and installed on the web server for collecting and storing the Facebook user action on the MySQL database server. In the mobile application developed, initially, the administrator must log in to the Facebook Page with the right to own or manage that Facebook Page. Then, the system requests permission to access the Facebook database via Facebook Graph API version 14.0. After that, when this application is connected through a Facebook account, it will make predictions using the data gathered with FB-DCE developed based on the Facebook Graph API. Finally, the output is classified as whether Facebook users who interact with the Facebook Page are likely to be community enterprise purchases (become a customer) or simple visitors. The mobile application architecture and user interface are shown in Figure 2 and Figure 3.

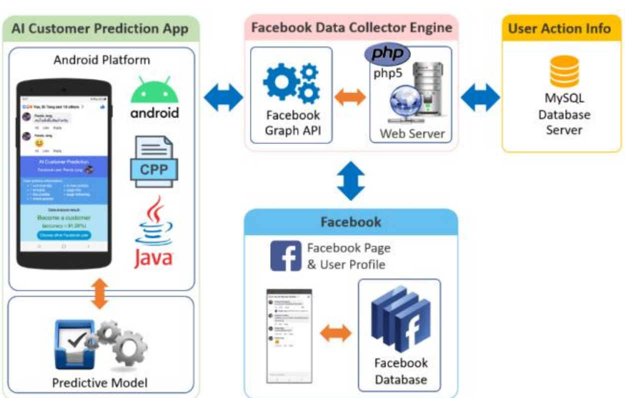

Fig. 2 The architecture of the developed mobile application

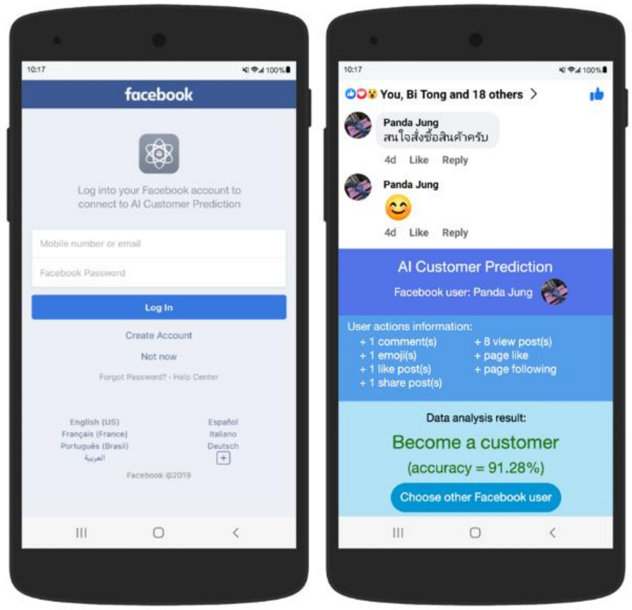

Fig. 3 The user interface of the developed mobile application

3. Results

3.1. The Efficiency Evaluation Results of the Models without Feature Selection

This work used twenty-five features for the five models' training and testing. The efficiency of the models was evaluated, which includes accuracy (Acc), sensitivity (Sens), precision (Prec), specificity (Spec), F-measure, and MAE. Without the feature selection technique, the results have shown that the MLPNN model has the highest efficiency, with an accuracy of 86.55% for predicting Facebook user behavior on social media to become a customer. They were followed by the SVM, RF, DT, and NB models with an accuracy of 85.94%, 85.52%, 84.60%, and 84.45%, respectively. The efficiency values of the model using all the features in machine learning are shown in Table 2.

Table 2. The efficiency evaluation results of the models without feature selection

Model	Acc (%)	Sens (%)	Prec (%)	Spec (%)	F-measure (%)	MAE
DT	84.60	86.14	87.44	82.40	86.79	0.1540
RF	85.52	87.22	87.92	83.13	87.57	0.1448
NB	84.45	86.00	87.33	82.26	86.66	0.1555
SVM	85.94	87.42	88.43	83.83	87.93	0.1406
MLPNN	86.55	87.80	89.13	84.79	88.46	0.1345

3.2. The Results of Feature Selection Techniques

GR, CS, and CFS were applied to the dataset collected. The comparison of the results of feature selection techniques has shown in Table 3.

Table 3. The efficiency of the models' training

No	Feature selection technique		
	GR	**CS**	**CFS**
1	Comment (text)	Comment (text)	Comment (text) (100%)
2	Emoji	Emoji	Emoji (100%)
3	Sticker	Sticker	Sticker (100%)
4	Avatar sticker	Avatar sticker	Like (98%)
5	Like	Like	Share (90%)
6	Share	Share	Reply (84%)
7	Reply	Reply	Avatar sticker (81%)
8	View	View	View (78%)
9	Age	Education level	Page like (70%)
10	Gender	Age	Page following (70%)
11	Education level	Gender	Send message click (66%)
12	City region	Device	Education level (61%)
13	Device	City region	Age (55%)
14	Marital status	Marital status	Gender (52%)
15	GIF	GIF	Device (12%)
16	Send message click	Send message click	City region (9%)
17	Page following	Page following	GIF (1%)
18	Page like	Page like	Marital status (0%)
19	Job type	Job type	Job type (0%)
20	Get direction click	Get direction click	Get direction click (0%)
21	Website click	Website click	Website click (0%)
22	Phone number click	Phone number click	Phone number click (0%)
23	Photo	Photo	Photo (0%)
24	Video	Video	Video (0%)
25	Music	Music	Music (0%)

Table 3 discovered that GR and CS had the same results for the top 8 of the first feature and the features from the 14th onwards. However, both techniques are arranged differently between the 9th and 13th features. These features include age, gender, education level, city region, device, GIF, and marital status. Whereas the CFS technique has a different feature ordering from the two methods (GR and CS), with differences ranging from the 9th to the 18th feature. There were only 17 features with a weight greater than 0% and 14 features with a weight of more than 50%.

3.3. The Efficiency Evaluation Results of the Models with Feature Selection

All features were processed by feature selection techniques, including GR, CS, and CFS. The number of features output was selected based on the weight of each feature. The model efficiency results are shown in Table 4.

Table 4. The efficiency evaluation results of the models with the feature selection technique

Model	No. of features	Acc (%)	Sens (%)	Prec (%)	Spec (%)	F-measure (%)	MAE
DT+[GR|CS|CFS]*	8	84.65	86.19	87.48	82.45	86.83	0.1535
RF+[GR|CS|CFS]*	8	85.60	87.31	87.96	83.18	87.63	0.1440
NB+[GR|CS|CFS]*	8	84.52	86.08	87.37	82.31	86.72	0.1548
SVM+[GR|CS|CFS]*	8	85.97	87.44	88.47	83.88	87.95	0.1403
MLPNN+[GR|CS|CFS]*	8	86.60	87.85	89.16	84.84	88.50	0.1340
DT+[GR|CS]**	14	85.71	87.38	88.08	83.35	87.73	0.1429
DT+CFS	14	86.05	87.78	88.25	83.61	88.02	0.1395
RF+[GR|CS]**	14	86.49	88.34	88.45	83.91	88.40	0.1351
RF+CFS	14	86.89	88.83	88.67	84.20	88.75	0.1311
NB+[GR|CS]**	14	85.70	87.35	88.12	83.37	87.73	0.1430
NB+CFS	14	86.21	88.03	88.31	83.66	88.17	0.1379
SVM+[GR|CS]**	14	87.72	89.73	89.16	84.95	89.44	0.1228
SVM+CFS	14	88.45	90.39	89.77	85.77	90.08	0.1155
MLPNN+[GR|CS]**	14	89.03	90.74	90.43	86.65	90.58	0.1097
MLPNN+CFS	14	89.80	91.32	91.19	87.68	91.25	0.1020
DT+[GR|CS]**	17	84.88	86.36	87.70	82.78	87.03	0.1512
DT+CFS	17	85.14	86.59	87.91	83.09	87.25	0.1486
RF+[GR|CS]**	17	85.87	87.67	88.09	83.35	87.88	0.1413
RF+CFS	17	86.03	87.80	88.20	83.55	88.00	0.1397

NB+[GR|CS]**	17	84.81	86.36	87.56	82.61	86.96	0.1519
NB+CFS	17	85.12	86.58	87.88	83.04	87.23	0.1488
SVM+[GR|CS]**	17	86.30	87.85	88.63	84.11	88.23	0.1370
SVM+CFS	17	86.52	88.02	88.83	84.41	88.42	0.1348
MLPNN+[GR|CS]**	17	87.01	88.31	89.39	85.16	88.85	0.1299
MLPNN+CFS	17	87.49	88.90	89.63	85.50	89.27	0.1251

** The classifier is applied with one feature selection technique: GR, CS, or CFS*
*** The classifier is applied with one feature selection technique: GR or CS*

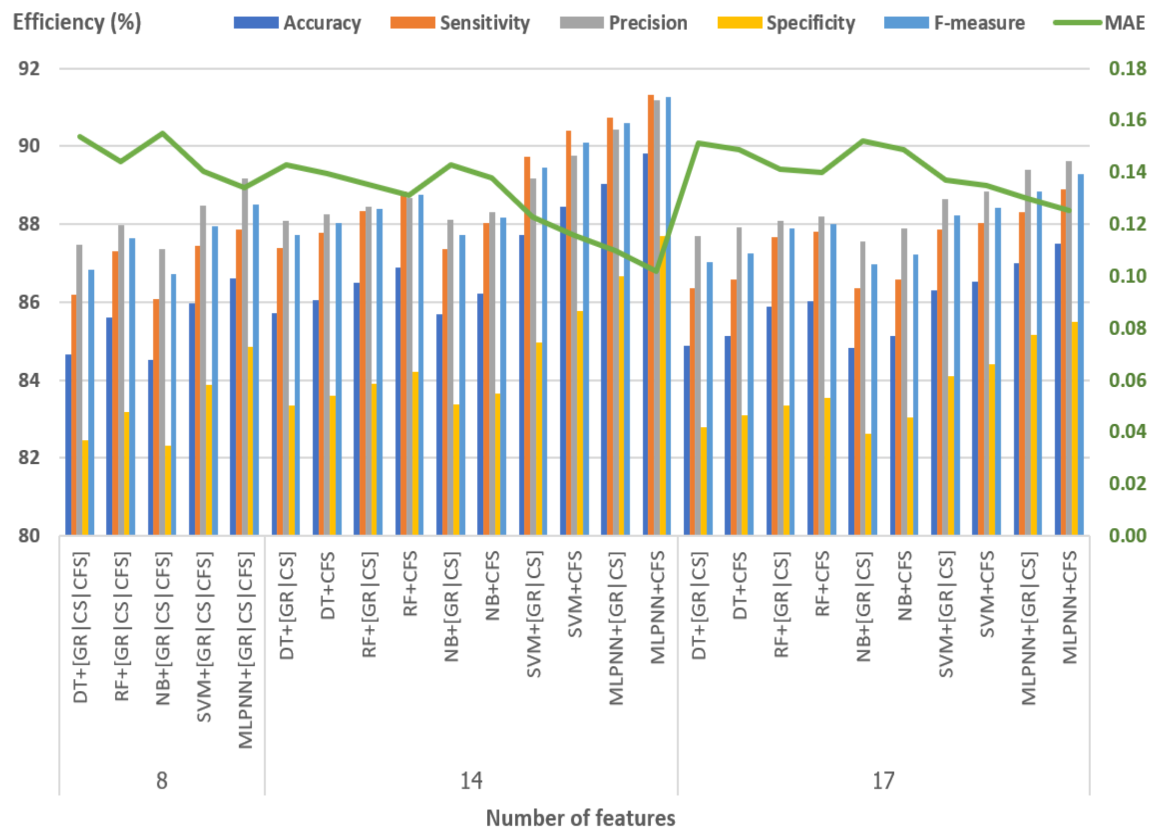

Fig. 4 The comparison of the effectiveness of the models

Table 4 found that differences in the number of features affect the model's performance. The number of selected features, fourteen features, provides the highest model performance values, followed by seventeen features and eight features. The CFS method provides model performances higher than GR and CS methods for fourteen features and seventeen features. For fourteen features, the model with the MLPNN and CFS method is the highest model performance, including the accuracy, sensitivity, precision, specificity, F-measure, MAE 89.80%, 91.32%, 91.19%, 87.68%, 91.25%, 0.1020, respectively. Compared with models that did not apply the feature selection technique, it was found that models that applied the feature selection technique had higher efficiency values than those without feature selection. The comparison of the effectiveness of the models is shown in Figure 4.

4. Conclusion

In smart marketing, it is necessary to rely on consumer data that appears on social media, especially data generated by social media users. For example, Facebook Pages allow Facebook users to participate in comments such as typing a message or text, sending a sticker, and clicking the like button. These actions can be used to analyze positive or negative feelings as well as the emotions of the users directly. This research developed a mobile application that connects to the Facebook database through the Facebook Graph API to analyze user patterns and behavior using machine learning models to predict the likelihood of such users becoming customers. All collected data is then taken through a feature selection process, including Gain Ratio, Chi-Square, and Correlation-based Feature Selection. After that, the processed and unprocessed datasets of feature selection are used to train and test the validity of models with five different classifier techniques: Decision Tree, Random Forest, Naive Bayes, Support Vector Machine, and Multi-Layer Perceptron Neural Network. Finally, the model with the highest accuracy performance will be used for Android application development.

The study results found that datasets that have undergone feature selection have higher model performances than the model with all features used. In addition, the Gain Ratio and Chi-Square methods have similar ranking results for each feature. On the contrary, Correlation-based Feature Selection differs in feature ranking compared to the other two methods mentioned above. However, several different features also affect the performance values of the developed model. Using the total number of features, which may consist of variables that have little correlation to the classification effect, may result in a degradation of model accuracy. Therefore, selecting the most related features will help make the model more accurate. In addition, when comparing machine learning techniques that use different classifiers, the results showed that the model developed with the Multi-Layer Perceptron Neural Network provides better accuracy than other classifiers in this work. Ultimately, when applying the classifier to feature selection, it was found that models developed using the Multi-Layer Perceptron Neural Network and Correlation-based Feature Selection methods yielded the highest efficiency of classification accuracy of 89.90%.

Funding Statement

The National Research Council of Thailand funded this research; the project code is 11091/2565, and the project period is from October 2021 to August 2022.

Acknowledgments

The authors are grateful to the Institute for Research and Development, Suan Sunandha Rajabhat University; Faculty of Science and Technology, Suan Sunandha Rajabhat University; Faculty of Science, Ubon Ratchathani University; and Faculty of Information Technology and Digital Innovation, King Mongkut’s University of Technology North Bangkok, who supported and gave this research opportunity. The funder had no role in study design, data collection, analysis, publication decisions, or manuscript preparation.

References

[1] J. Johnson, “Worldwide Digital Population as of April 2022,” 2022. [Online]. Available: https://www.statista.com/statistics/617136/digital-population-worldwide (accessed May 9, 2022).

[2] Statista Research Department, “Number of Global Social Network Users 2017-2025,” 2022. [Online]. Available: https://www.statista.com/statistics/278414/number-of-worldwide-social-network-users (accessed May 9, 2022).

[3] M. Mohsin, “10 Facebook Statistics Every Marketer Should Know in 2021 [Info-graphic],” 2021. [Online]. Available: https://www.oberlo.com/blog/facebook-statistics (accessed December 18, 2021).

[4] A. T. Stephen, “The Role of Digital and Social Media Marketing in Consumer Behavior,” *Current Opinion in Psychology,* vol. 10, pp. 17-21, 2016. https://doi.org/10.1016/j.copsyc.2015.10.016.

[5] M. A. Shareef, K. K. Kapoor, B. Mukerji, R. Dwivedi, and Y. K. Dwivedi, “Group Behavior in Social Media: Antecedents of Initial Trust Formation,” *Computers in Human Behavior,* vol. 105, pp. 106225, 2020. https://doi.org/10.1016/j.chb.2019.106225.

[6] A. S. Ajina, “The Perceived Value of Social Media Marketing: An Empirical Study of Online Word-of-Mouth in Saudi Arabian Context,” *Entrepreneurship and Sustainability,* vol. 6, no. 3, pp. 1512-1527, 2019. https://doi.org/10.9770/jesi.2019.6.3(32).

[7] S. Agrawal, A. Das, A. Gaikwad, and S. Dhage, “Customer Churn Prediction Modelling Based on Behavioural Patterns Analysis using Deep Learning,” *The 2018 International Conference on Smart Computing and Electronic Enterprise (ICSCEE),* Selangor, Malaysia, pp. 1-6, 2018. https://doi.org/10.1109/ICSCEE.2018.8538420.

[8] M. Patil, and M. Rao, “*Studying the Contribution of Machine Learning and Artificial Intelligence in the Interface Design of E-Commerce Site,*" In: S. Satapathy, V. Bhateja, S. Das, (eds) Smart Intelligent Computing and Applications, Smart Innovation, Systems and Technologies, vol. 105, 2019. https://doi.org/10.1007/978-981-13-1927-32_0.

[9] V. D. Vasile-Daniel Păvăloaia, E. M. Teodor, D. Fotache, and M. Danileț, “Opinion Mining on Social Media Data: Sentiment Analysis of User Preferences,” *Sustainability,* vol. 11, no. 16, pp. 4459, 2019. https://doi.org/10.3390/su11164459.

[10] W. Kaur, V. Balakrishnan, O. Rana, and A. Sinniah, “Liking, Sharing, Commenting and Reacting on Facebook: User Behaviors’ Impact on Sentiment Intensity,” *Telematics and Informatics,* vol. 39, pp. 25-36, 2019. https://doi.org/10.1016/j.tele.2018.12.005.

[11] S. Moro, P. Rita, and B. Vala, “Predicting Social Media Performance Metrics and Evaluation of the Impact on Brand Building: A Data Mining Approach,” *Journal of Business Research,* vol. 69, no. 9, pp. 3341-3351, 2016. https://doi.org/10.1016/j.jbusres.2016.02.010.

[12] S. Forouzandeh, H. Soltanpanah, and A. Sheikhahmadi, “Content Marketing Through Data Mining on Facebook Social Network,” *Webology,* vol. 11, no. 1, pp. 1-11, 2014.

[13] N. Dehouche, and A. Wongkitrungrueng, “Facebook Live as a Direct Selling Channel,” *In Proceedings of the 20th Conference of the Australian and New Zealand Marketing Academy (ANZMAC),* pp. 282-285, 2018.

[14] Prof. Sunantha Krishnan, Gianna Drego, Ishmeet Kaur, Mushira Shaikh, "Proposing Value-based Pricing Strategy for Business-to-Business Data Exchange in eBusiness," *SSRG International Journal of Computer Science and Engineering,* vol. 8, no. 12, pp. 6-13, 2021. Crossref, https://doi.org/10.14445/23488387/IJCSE-V8I12P102.

[15] R. Plutchik, "The Nature of Emotions: Human Emotions Have Deep Evolutionary Roots, A Fact That May Explain Their Complexity and Provide Tools for Clinical Practice," *American Scientist,* vol. 89, no. 4, pp. 344-350, 2001.

[16] Unicode, "Emoji List," v14.0, 2021. [Online]. Available: http://unicode.org/emoji/charts/emoji-list.html (accessed December 17, 2021).

[17] M. L. Gadebe, and O. P. Kogeda, "Top-K Human Activity Recognition Dataset," *International Journal of Interactive Mobile Technologies,* vol. 14, no. 18, pp. 68-86, 2020. https://doi.org/10.3991/ijim.v14i18.16965.

[18] S. Nuanmeesri, "Development of Community Tourism Enhancement in Emerging Cities Using Gamification and Adaptive Tourism Recommendation," *Journal of King Saud University - Computer and Information Sciences*, 2021. https://doi.org/10.1016/j.jksuci.2021.04.007.

[19] Kareem Mohamed, Ümmü Altan Bayraktar, "Artificial Intelligence in Public Relations and Association Rule Mining as a Decision Support Tool," *SSRG International Journal of Humanities and Social Science,* vol. 9, no. 3, pp. 23-32, 2022. Crossref, https://doi.org/10.14445/23942703/IJHSS-V9I3P105.

[20] S. Nuanmeesri, L. Poomhiran, and K. Ploydanai, "Improving the Prediction of Rotten Fruit using Convolutional Neural Network," *International Journal of Engineering Trends and Technology*, vol. 69, no. 7, pp. 51-55, 2021. Crossref, https://doi.org/10.14445/22315381/IJETT-V69I7P207.

[21] D. S. K. Karunasingha, "Root Mean Square Error or Mean Absolute Error? Use Their Ratio as Well," *Information Sciences,* vol. 585, pp. 609-629, 2022. https://doi.org/10.1016/j.ins.2021.11.036.

[22] Dr.V.V.Narendra Kumar, T.Satish Kumar, "Smarter Artificial Intelligence with Deep Learning," *SSRG International Journal of Computer Science and Engineering,* vol. 5, no. 6, pp. 10-16, 2018. Crossref, https://doi.org/10.14445/23488387/IJCSE-V5I6P102.

[23] D. C. Gkikas, T. Theodoridis, P. Theodoridis, and N. Kavoura, "Online Consumer Behaviour in Social Media Post Types: A Data Mining Approach," *In Proceedings of the 49th Annual European Marketing Academy Conference (EMAC),* 2020. https://doi.org/10.6084/m9.figshare.17767100.

[24] Kareem Mohamed, Ümmü Altan Bayraktar, "Analyzing the role of Sentiment Analysis in Public Relations: Brand Monitoring and Crisis Management," *SSRG International Journal of Humanities and Social Science,* vol. 9, no. 3, pp. 116-126, 2022. Crossref, https://doi.org/10.14445/23942703/IJHSS-V9I3P116.

[25] S. Nuanmeesri, "Mobile Application for the Purpose of Marketing, Product Distribution and Location-Based Logistics for Elderly Farmers," *Applied Computing and Informatics,* 2020. https://doi.org/10.1016/j.aci.2019.11.001.