

Manuscript Submitted	1.7.2022
Accepted	29.12.2022
Published	31.12.2022

Exploring Implied Performance Metrics In Customer Trustworthiness Toward The Acquisition Of Halal Food's Status

Roziyani Setik, Raja Mohd Tariqi Raja Lope Ahmad
Faculty of Communication and Visual Art and Computing,
Universiti Selangor
roziyani@unisel.edu.my, rmtariq@unisel.edu.my

Suziyanti Marjudi
Faculty of Computer Science and Information Technology,
Universiti Tun Hussein Onn Malaysia
suziyanti@uthm.edu.my

Abstract

Social media is used extensively in various fields, including Natural Language Processing research. The exponential growth of user-generated social media content raises the potential for opinion mining to analyze consumer behavior. Sentiment Analysis concerns the computer treatment of people's views, ideas, and subjective experiences to recognize and extract sentiment from a text. The influence of religious conviction, halal awareness, halal certification, and food ingredients are all-inclusive in Muslim consumers' considerations while acquiring halal food. Those aspects assist in uncovering sentimental analysis on customer dependability toward halal certification during expressing issues related to halal food acquisition on social media. We aim to determine a correlation between the halal certification scheme and reliability prediction classification relating to customers' intention to acquire halal products. Identifying corresponding sentiment polarities in sentences is generated by utilizing the Malaya NLTK library to label them as positive, negative, or neutral. A sample of 895 tweets with the hashtag #sijilhalal was gauged and trained for an accurate prediction Machine Learning model using Random Forest, Logistic Regression, K-Nearest Neighbor, Decision Tree, and Naive Bayes. The Correlation Matrix for each model shows how features are related. As in its Confusion Matrix, we can observe an outcome overview of the model's accuracy, precision, recall, and F1-score. It successfully demonstrates the performance evaluation metric on model efficiency and applicability in choosing the best higher-accuracy model for predicting customer tendency toward halal food acquisition. In general, the Logistic Regression model performs the best in this study of predicting the occurrence of customer trustworthiness toward the acquisition of halal food. The findings show that consumers' belief in a food source and halal certification leads them to entirely acquire the food (tagged as loyal) or disregard the food (tagged as churn).

Keywords: *Sentiment Analysis, Halal Food, Natural Language Processing, Performance Metrics, Machine Learning Model.*

1. Introduction

Online social networking has revolutionized communication. Social media has grown in popularity and transformed how people use the Internet globally. Recent research about social media language analysis has increasingly focused on its impact on our daily lives, personally and professionally (Farzindar &

Inkpen, 2018). Processing social media data using Natural Language Processing (NLP) is possible. Malaysians, for example, are rapidly employing social media sites (Kemp, 2021) such as Twitter, Facebook, Instagram, LinkedIn, and Pinterest. The exponential rise in user-generated social media content improves the possibilities for tracking and monitoring customer behavior through opinion mining methods. The vast amounts of text shared on social networking platforms have allowed researchers to mine the data for useful information in text processing studies. Most social media text is unstructured since individuals may choose their style. Extracting valuable insights from massive data sets written in various formats remains a formidable challenge that necessitates the invention of ever-more-advanced models and algorithms.

The demand to perceive ideas, attitudes, and emotions increases as Web 2.0 technologies like social networking and online companies flourish (Zhao et al., 2016). Twitter covers many issues (Sharma & Sharma, 2020) and is a microblogging platform defined as a fast communication channel for information sharing worldwide (Hasbullah et al., 2016) besides Facebook. Twitter users, for example, may discuss whatever they want. The difference is that, unlike other social media, Twitter allows users to follow others' tweets without their consent (Windasari et al., 2017), which is why Twitter is so widespread. As it grows, businesses and media sources are scrambling to find new and innovative methods to exploit Twitter's data for insights into what people think and feel about their offerings (Gamal et al., 2019).

A study of how people's innermost thoughts come through in writing has piqued the interest of academics and business leaders. Conceded to the process of mining opinions from the text and analyzing the resulting sentiments and emotions, the task is still inadequate (Zhao et al., 2016) when it involves many overlapping concepts and sub-tasks. Therefore, a practice of assessing people's attitudes and feelings toward an object and its characteristics, known as Sentiment Analysis (SA), has been used in this study. Recently, sentiment analysis has emerged as a promising field of study. Sentiment analysis is a beneficial technique for enhancing the quality of decisions, products, and services by both consumers and businesses (Alshamsi et al., 2020). In social media monitoring, SA is essential since it helps us recognize the general public's perspective on a specific topic. Detecting subjective language is one of the initial challenges in sentiment analysis (Wiebe & Riloff, 2005). Being able to rapidly assess the sentiment behind everything from forum posts to news stories to Twitter lines is believed will benefit an organization in their decision-making processes for the future.

2. Background Study

Today, the public's understanding of halal food is becoming more optimistic. With the exponential growth in the number of consumers with a remarkable knowledge of halal cuisine, promoting people's mindfulness about the need to obtain halal accreditation is essential. It is to reach trustworthiness among consumers, especially for the food industry in a Muslim country such as Malaysia. As observant Muslims, it is our duty only to eat halal products at all times. Halal certification is crucial in a consumer's decision to obtain a product or service. Every product with the halal seal of approval is guaranteed to meet strict halal certification criteria in every country, making it easier for consumers to feel confident about eating halal food. The Department of Islamic Development Malaysia (JAKIM), a government agency in Malaysia, is in charge of halal certification and product verification.

However, as the number of people using social media continues to rise, there has been an increase in posts, comments, and concerns about halal certification and halal symbols relating to food goods and services. Those statements reflect beneficial sentiment polarities, classified as 'Positive', 'Negative', or 'Neutral'. This issue lends itself to SA research in the NLP domain, a study on the capability of a computer program to understand the text and human word in much the same way human beings be capable. NLP has emerged as a critical commercial tool for unearthing hidden data insights from social media platforms. Numerous businesses use SA to extract attitudes and emotions expressed in social

media posts, responses, reviews, and other feedback forms. Sentiment information could improve business practices, especially in the decision-making process.

Sentence level SA examines a collection of sentences that tell, debate, discuss, argue, review, or express the same thing or categories. An essential set of operations in the Machine Learning (ML) process is data preparation, which is concerned with preparing datasets to be more suited for ML applications and determining the most appropriate data gathering mechanism. A supervised ML is recognized by using labeled datasets to train algorithms' capability of effectively classifying data or predicting outcomes. And a classification notion is used to divide a collection of data into categories called classes. This training dataset handle relationship from input variables that are ('scheme') and ('sentiment'); to response variables ('final status'). A supervised learning method constructs a model from these variables that can predict the response variables for a new dataset (testing data) used to evaluate the model's accuracy.

A dataset of 895 tweets containing Malay language sentences was crawled from Twitter using the hashtag #sijilhalal. It was then extracted and categorized into class subjects, 1) Halal Certification Scheme and 2) Sentiment Polarity, by analyzing the content of users' tweets. Malaysia's application procedure for halal certificates is based on the nine main types of Domestic Halal Certification systems (JAKIM, 2020). There are named Food/Beverage/Food Supplement, Food Premise/ Hotel, Consumer Goods, Cosmetics and Personal Care, Slaughterhouse, Pharmaceutical Industry, Logistics, OEM, and Medical Devices. For this research, two schemes reflect halal food concerns: Food/Beverage/Food Supplement and Food Premise/Hotel were used to classify the dataset.

While sentiment polarity for the dataset was trained using Malaya (Husein, 2018), an NLTK library was explicitly trained in Malay language text with a BERT transformer. After a classification labeling, it continues with data pre-processing, which cleans the data and prepares it for the ML model, enhancing accuracy and efficiency. Then it will predict whether a person will likely consume the food (tagged as loyal) or not (tagged as churn) based on sentiment in their tweet toward halal food acquisition.

After get trains with the ML algorithm, the next step is to establish the model's effectiveness using metrics and datasets. Various performance metrics are utilized to determine which ML model is most suitable for this classification problem. The correlation coefficients for multiple characteristics can be seen in a Correlation Matrix. Meanwhile, to assess the correctness of a model, one of the most visible and basic measures is the Confusion Matrix which presents a marker for evaluating the ML model by the value of accuracy, precision, recall, and F1-score. The ML measurements impact the selection of the best model for this investigation. Performance metrics on ML models determine the accurate prediction model to use. As an intermediary in the interaction between a certificate of halal, religious knowledge, attitude, and trust (Azam & Abdullah, 2020) are aspects to consider when predicting customer loyalty during acquiring halal food.

2.2 Machine Learning Modeling Evaluation

ML enables a machine to understand necessary data, improvise on prior experiences, and forecast events without being explicitly programmed or given instructions or guidance. And that is what ML is all about: teaching machines to think and behave like people. ML works started by providing traditional data as an input. The machine builds the prediction model by training the model with the input data given. Afterward, the machine tests the model by predicting the output for the next set of input data that is not being used yet. It is able to identify various patterns in the data, thus extracting valuable insights into the problems detected, then able to make compelling predictions by improvising or learning from all the past data, thus enhancing the output accuracy.

Predictive analytics systems to give deep insights into diverse business data points are commonly used for supervised learning models. This research employs a supervised learning technique, in which we train the computer by giving classifying labeled data, and the machine then predicts output based on the

training data. It enables businesses to predict specific outcomes depending on a particular output variable, assisting business executives in justifying actions or pivoting for the organization's advantage.

3. Problem Statement

People's awareness about halal food is rising today. As the number of halal-aware consumers grows exponentially, food providers must become concerned about the necessity to secure halal accreditation for their services. According to the official Facebook page of the Halal Hub Division of JAKIM, there have been several viral issues involving halal status amongst stakeholders such as customers, suppliers, dealers, and premises. Halal certification and halal validation issue when acquiring halal food is the most concern by customers. Authentic halal certification or an emblem granted by JAKIM is what most Malaysian Muslim shoppers look for when making purchases. Customers' decisions to buy halal products are influenced by various factors, including a religious conviction that is considered a cultural component (Demirel & Yaşarsoy, 2017). A religious principle drives most people to purchase and consume halal food products. It implies that ensuring a food product is halal is the top concern. In addition, it is vital to be concerned with the administration of halal standards and the issues associated with its coordination (Mohd Farid Hadi Sharif, 2019). The integrity of halal circumstances that become viral on social media is also at stake. Therefore, taking the proper steps when responding to these halal issues and cooperating with stakeholders is essential (Setik et al., 2021).

The question "Is this halal?" kept popping up as we explored social media for people's updates, especially those that included food images. This curiousness arises because of a crisis of confidence in the halal accreditation or a deliberate questioning or just being sarcastic regarding the halal status of a particular food product. If we wanted to dine in a restaurant, it's expected that we would doubt, "Is this restaurant halal?" after we couldn't see the halal emblem displayed in the restaurant. Consequently, customers typically relied on non-intrinsic cues such as the presence of Muslim-looking customers and service employees to judge the situation of a restaurant (Khan & Khan, 2020).

Social media has become the fastest medium for delivering questions, complaints, and opinions on particular topics. This situation shows that a variety of data can generate several messages that express opinions about events, products, services, political views, or even their author's emotional state and mood (Gonçalves et al., 2014) on social media. In a culture where social media is widely used, people are always connected and requesting a faster reaction when releasing some issues. Every time a question is posted, they anticipate a quick answer from those in a position to respond. Every reply to a comment on social media gives the impression that the reader's thoughts are precious and considered.

Opinion entities (slang and urban words/phrases) from community inquiries are also widely utilized in online discussions and social media posts (Amiri & Chua, 2012). When this tactic becomes more commonly accepted and quickly addressed, more people will take the form of posting comments on social media to produce inquiries and issues aimed at gaining instant answers. Due to anonymous users posting comments, verifying the authenticity of the text data has become more challenging. It could cause problems, be misinterpreted or exaggerated, and drive customers to freak out. Malaysians don't observe abbreviation restrictions on social media (Abu Bakar et al., 2020). There is a lot of text that is distracting and unnecessary written on social media, such as the usage of jargon word (Pal & Saha, 2013), slang (Kassim et al., 2016), acronyms (Amiri & Chua, 2012), and sarcasm (Gregory et al., 2020). There also usage of dialects, foreign languages, grammatical negligence, spelling mistakes, and mangled syntax (Ariffin & Tiun, 2020) are all present in the text. The cultural, state-level dialects and the dual use of English and Malay contribute to the discrepancy between the spoken and written forms of the Malay language, which poses a problem for Natural Language Processing (Lan & Logeswaran, 2020).

People utilize social media platforms to communicate, discuss their interests, connect with friends, and grow their careers. There is a comment or a post that explicitly highlights the themes. Sometimes, it does not specify what they prefer to deliver, but the phrase contains implicit meaning. It could also be a post expressing a sarcastic opinion and not conveying a straightforward message with its contents. It's necessary to reply and constructively respond whenever someone criticizes any issues to avoid worsening. Any worries that arise should be dealt with as soon as possible, either by dedicated parties or by seeking the information gathered from social media users. Accurate information is essential for the general people to know the actual situation. Still, viral matters are also inaccurate and sometimes amplified by public members, triggering panic within society (Setik et al., 2021). Some way to think about the halal viral issue in Malaysia is as the issue of spreading incorrect information about halal without verifying its accuracy (Mohd Farid Hadi Sharif, 2019). Since of this, it is important to tackle the halal viral issue in Malaysia because the impact of this issue has the potential to destabilize people's concept of society.

4. Research Questions

A study on customer trustworthiness toward acquiring halal food is investigated by analyzing sentences SA on a dataset that crawled using the hashtags #sijilhalal from Twitter. In the modeling phase, it is necessary to train the dataset with an ML model to review the output that gives the best performance result. It attempts to discover the answer to the following questions:

1. Is there a significant positive relationship between the halal certification scheme and loyalty prediction classification toward acquiring halal food?
2. Is there a reliable Machine Learning modeling evaluation to validate datasets in producing higher-accuracy models with proposed prediction models?

5. Purpose Of The Study

Generally, individuals frequently think, assume, believe, and be confident when food produced by Muslims is considered halal because of faith and acknowledge themselves typically are familiar with halal and haram of a product. Yet, halal certification is an easier way to identify the status of any halal product. Therefore, based on the dataset crawled, the purpose of this research are follows:

1. To determine the correlation between the halal certification scheme and reliability prediction classification involving customers' intention to acquire halal products.
2. To demonstrate the performance evaluation metric on model efficiency and applicability to choose the best higher-accuracy model for predicting customer tendency toward halal food acquisition.

6. Research Methods

As Muslims, it is required to follow those halal laws in our daily lives. Tweets were pre-processed to extract information about people's attitudes, assumptions, and opinions toward halal food acquisition in Malaysia. Appearing in (Setik et al., 2021) studies, 51% of tweets in the dataset were on foods related. It also shows that 24% of the food-related tweets in hashtag #sijilhalal promote awareness in applying for the halal certificate. The research continues further for the process of ML modeling. An infusion of Methodological Architecture (Feizollah et al., 2021) for exploring tweets on social media is applied for this research with several additional appropriate tasks and phases. Figure 1 illustrates the functions of this activity which are divided into two sections: Data Pre-Processing and Pattern Recognition. A list of Data Acquisition, Data Understanding, and Exploratory Data Analysis are among the Data Pre-processing activities, while a part of Exploratory Data Analysis (EDA) and Model Building comprises Pattern Recognition.

Data understanding is accomplishment insight so machines can utilize the same material to perform analysis and predictions. Selecting a primary keyword for this crawling purpose was the first step in the data acquisition. Data was crawled and bonded using the hashtags #sijilhalal between 1 July 2018 and the last day of December 2019 to be a raw dataset for this research. In this stage, we must specify the problem-relevant data that will be utilized in the subsequent study. In step two, the text pre-processing aimed to eliminate outliers and normalize the data for the following tasks. The training dataset encompassed unstructured non-standard Malay tweets and tweets with a mixture of languages. It is essential to clean the data or do some other form of preliminary processing before building a machine learning model with the dataset. In the meantime, studies on the normalization of Malay social media texts are still very few, and there are numerous ways in which the quality of these studies might be enhanced (Ariffin & Tiun, 2020). One of the frequent phases in the pre-processing text is getting rid of stop words. Stop words in a natural language are often eliminated because of their meaninglessness or ambiguity. By cutting out these terms, we may make the text more concise without losing any essential details. The stop words used in this research were borrowed from English stop words and added with Malay stop words (Chekima & Alfred, 2016), (Khirulnizam Abd Rahman, 2014) and Indonesian stop words (Stopwords, n.d.) to the Python library for cleaning purposes.

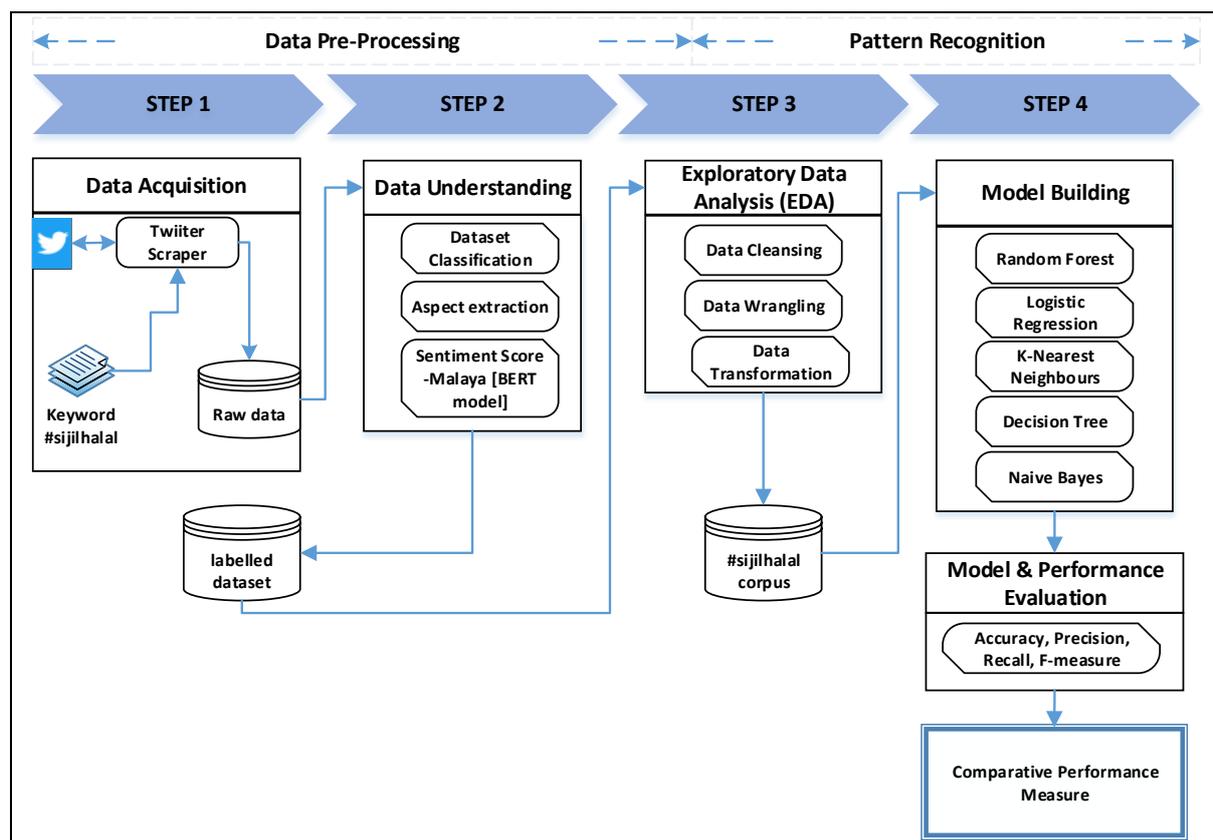


Figure 1. Research Methods Utilized In This Study

The idea of doing Sentiment Analysis (SA) as a computerized way to deal with text's opinions, feelings, and subjectivity is applied. Sentiment analysis can be divided into three categories: the document level, the sentence level, and the phrase/aspect level (Liu, 2012). Document and sentence-level sentiment analysis does not yield enough valuable data for efficient decision-making (Zohreh Madhoushi et al., 2019). However, we can acquire this knowledge at the Aspect-Based Sentiment Analysis (ASBA) level by elucidating the nature of the category, characteristic, or topic being discussed. The human annotation method is utilized to classify the data obtained from the text analysis as preparation for machine modeling. It is due to no public word tagger available for the Malay language since most of the research

is for private use only. Content identification for this dataset additionally considers the employment of Malay jargon words, slang, dialect, acronyms, sarcasm, and mixed-language phrases and words. While annotating tweets, for the sake of this study that employs supervised learning approaches, it is also necessary to consider tweets that blend multiple languages. It is because sentences will be ignored or misclassified if mixed language and emoticons are disregarded. But since this research is focuses on the aspect insight for the sentences level, mixed language is remain and text are translated manually to get vision of the sentences.

Following that, dataset classification divides a subject into narrower, more workable, and more particular segments to guarantee that the final dataset is valid for *#sijilhalal* themes and excludes the others. During aspect extraction, annotators must read a line of the tweet in the dataset to understand the topic delivered and classify it based on a preset list of categories. Four aspect classifiers were utilized to label a sentence to determine the frequency of occurrence of a tweet that mentioned halal schemes. The classified labels on food-related are 'Halal Food/Beverage' and 'Halal Premise'. While the identified tweets regarding JAKIM, Malaysia's competent authority for halal certification manufacturing, are classified as 'Halal Brand and Governance'. At the same time, class 'Others' refers to tweets that discuss other than the scheme list but still on food.

Each tweet's content will be analyzed from an aspect-based perspective through subjectivity analysis. It considers that 'attitude', 'trust', and 'knowledge' categories impact Muslim intentions regarding seeking halal cuisine (Shahrinaz et al., 2015). Enclosed by the text, sentiment classification is to be discovered using the NLTK library for Python programming, so-called Malaya (Husein, 2018), with a pre-trained transformer model named BERT that uses an approach to learn deep bi-directional representations for NLP. 'Positive', 'Negative', or 'Neutral' sentiment values are assigned to each tweet. Moving on to EDA, the third phase examines the labeled datasets to summarize their critical features through Data Cleansing, Wrangling, and Transformation, ensuring that the resulting dataset is balanced and ready for statistical analysis. After that, the cleaned dataset is stored in a corpus to be utilized for further research activity.

The final step is Model Building, wherever ML processes start for the algorithm to do model training and selection intended for the best ML model. Models used for these tasks are Random Forest, Logistic Regression, K-Nearest Neighbour, Decision Tree, and Naïve Bayers. Based on the model trained, the model's performance measure is graded by Correlation Matrix and Confusion Matrix. Model accuracy, precision, recall, and F1-score are metrics applied for this model performance measurement. Based on the trained models, the best model that gains the highest measurement results is the best model for the testing model.

7. Finding & Discussion

A dataset was prepared for ML modeling using multiple strategies in this study. It provides information that is fit enough for training data from real-world sources that usually be inconclusive, inconsistent, imprecise, and lacking in exact attribute values/trends. When data preparation intervenes, it helps prepare the raw data for ML models by cleaning, formatting, and organizing it. This section justifies the modeling process's correlation matrix and confusion matrix outcomes.

7.1 A Correlation Matrix

A correlation matrix summarizes data and diagnoses problems in enhanced analytics. Using a matrix, we can see how many different values correlated. It's a helpful tool for identifying and visualizing trends in massive datasets. After transforming all of the categorical data using Label Encoding and an encoder, the data is ready to be used. Classification algorithms are frequently evaluated using this method. According to the outcomes of this study, there is a relationship between the halal certification scheme and the loyalty prediction class concerning customers' intention to purchase halal food.

Figure 2 depicts the Correlation Matrix for this dataset in the heat map style, a two-dimensional data representation in which values are shown as a spectrum of colors. It represents the correlation between the variables on each axis of the graph. Values close to zero suggest no linear relationship between the variables, and the stronger the relationship, the closer the correlation is to one. However, not all factors are beneficial to the research in some way. This matrix could determine which halal certification schemes are more likely to uncover customers who intentionally proceed to get the items (tagged as loyal) or didn't proceed to the things (tag as churn).

This section simply discusses a correlation that has shown the most substantial positive relationship. It can be seen that variables 'Scheme 3: Halal Premise' and 'Loyal', with a coefficient score of 0.9, reveal that when a food premise already has halal certification, people unambiguously trust the business itself. On the other hand, people are also firmly expected to become churn when they do not feel assured with premises that do not have a halal certificate, as shown by a score of 0.77. Consequently, halal certification is the most effective practice for attracting customers' attention, mainly Muslim consumers' interest while acquiring food.

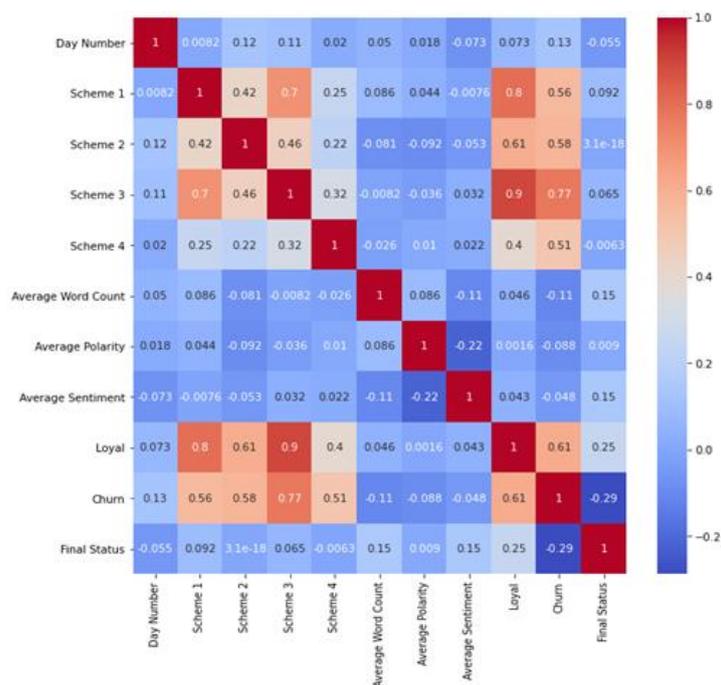


Figure 2. Correlation Matrix Of Features In The Dataset.

Tweet classed with 'Scheme 1' concentrates on food and beverage acquisition interest from the halal perspective. A relationship between 'Scheme 1: Halal Food/Beverage' and 'Loyal' is the next highly positive in this study, as indicated by the score value of 0.80. Meanwhile, it is about a 0.56 score on people who prompt as churn because they decided not to consume the food since it doesn't have the halal certificate. It shows that the absence of halal certification may well decrease people's trust and confidence in consuming the food. The findings reveal that consumers' trust in a food source and the presence of halal certification leads them to acquire the food (tagged as loyal) or disregard the food (tagged as churn) entirely.

7.2 Performance Measurement

As a form of Artificial Intelligence (AI), ML enables applications to become more accurate at anticipating occurrences without being explicitly designed to do so. ML algorithms use previous data as input to predict future output values. To effectively apply ML models, it is necessary to specify how

the models' performance is used. Essentially, performance assessment is the ability of a researcher to determine how well a model learns a specific subject matter (data) and how well it applies that learning in a real-world situation. Each critical component has a unique set of performance measurements, and these metrics frequently depend on the application being evaluated.

This section describes the model's performance more precisely. Hence, several models trained with the dataset intended to discover customer trustworthiness toward halal food acquisition issues based on the classification of the halal certification scheme. Performance metrics are used in selecting the best higher-accuracy model to predict the result. By utilizing the Confusion Matrix table, it is possible to express the effectiveness of a measurement. This measurement presents Confusion Matrix outcome trained with ML models: Random Forest, Logistic Regression, K-Nearest Neighbor, Decision Tree, and Naive Bayers.

7.3 Confusion Matrix

Data pre-processing and wrangling are essential steps in ensuring that the data is ready to be fed into an ideal model. The result has a high probability of being correct. Understanding the model's performance is made easier using these techniques. However, how to evaluate the model's effectiveness is a mystery. It is our goal to increase the efficacy while simultaneously improving performance. And it is at this point that the Confusion Matrix comes into play. For ML classification, the Confusion Matrix is a performance metric that is used to assess performance. It sums up the number of correct and incorrect predictions by class. As a performance measurement technique for this ML classification, the Confusion Matrix for Logistic Regression in this modeling produces an outcome as in Figure 3. It indicates that correct guesses for TP and TN were 268 data and incorrect guesses for FP and FN are two.

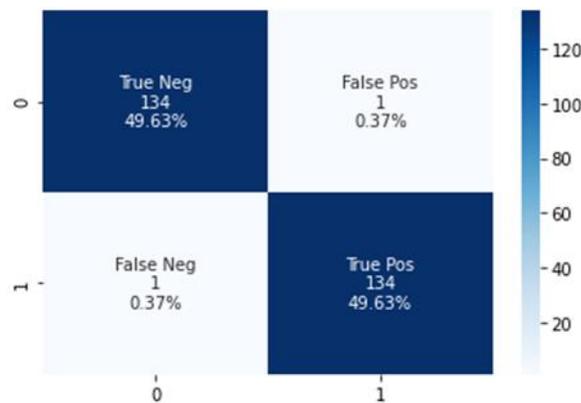


Figure 3. Confusion Matrix For Logistic Regression Modeling

At the beginning of the research, the original dataset consisted of 895 tweets as categorical data; text pre-processing accomplished the dataset and converted it into 270 numerical data that was cleaned and formatted to be used as input data in this classification modeling training. The input data carry the loyalty occurrence of customers toward halal food acquisition.

It shows that 134 occurrences were accurately labeled as churn (called True Negatives), and one was incorrectly classified as churn (False Positives). Meanwhile, in the second row of its Confusion Matrix, one occurrence was incorrectly classified as loyal (False Negatives), while 134 were accurately classified as loyal (True Positives). The Confusion Matrix result for the entire models used is compiled in Table 1.

Table 1. Summary Of Confusion Matrix After Modelling

Model Name	TN	%	FP	%	FN	%	TP	%	Correct	%	Incorrect	%
------------	----	---	----	---	----	---	----	---	---------	---	-----------	---

Logistic Regression	134	49.63	1	0.37	1	0.37	134	49.63	268	99.26	2	0.74
Random Forest	126	46.67	9	3.33	29	10.74	106	39.26	232	85.93	38	14.07
Decision Tree	106	39.26	29	10.74	2	0.74	133	49.26	239	88.51	31	11.49
Naïve Bayes	122	45.19	13	4.81	94	34.81	41	15.19	163	60.38	107	39.62
K Nearest Neighbor	71	26.30	64	23.70	66	24.44	69	25.56	140	51.86	130	48.18

In comparison, the K-Nearest Neighbor model is unreliable in predicting the process since it passed the lowest value with only a 51.86% correct score and 48.18% incorrect score. It states that 71 occurrences were correctly labeled as churn (True Negatives), while 64 were classed mistakenly as churn (False Positives). At least 66 occurrences were misclassified as loyal (False Negatives), whereas 69 were correctly labeled as (True Positives). The Logistic Regression prediction model gives the best predictive result with a 99.26% correct score with 268 occurrences and only two incorrect occurrences with a 0.74% score.

When dealing with classification difficulties, we attempt to predict the outcome of a binary decision. Does it appear to be loyal (positive), or is it churn (negative)? The Confusion Matrix also is used to establish the value of accuracy, precision, recall, and F1- score of the model. It is usually advisable to utilize Confusion Matrix as a ML model assessment criterion. It provides a quick and easy way to assess your model's performance. The accuracy of a prediction is described as the proportion of correct predictions to the overall number of forecasts. It is one of the most straightforward measurements of a model. A high accuracy model generates accurate predictions most of the time. For our model, we must strive for great accuracy at all times.

The accuracy, precision, recall, and F1-score of a classification model are the most significant factors to analyze. While precision refers to how accurately the model predicts positive outcomes and how many positive outcomes are actually positive. The recall value indicates the percentage of all positive samples that were accurately predicted as positive by the classification model. Logistic Regression carries the highest value for each metric. Table 2 show an overview of performance measure for each model.

Table 2. Overview Of Confusion Matrix Categories

Model	Accuracy Score	Precision Score	Recall Score	F1-Score
Logistic Regression	0.992593	0.992593	0.992593	0.992593
Random Forest	0.992593	0.921739	0.785185	0.848000
Decision Tree	0.885185	0.820988	0.985185	0.895623
Naïve Bayes	0.992593	0.759259	0.303704	0.433862
K Nearest Neighbour	0.518519	0.518797	0.511111	0.514925

8. Conclusion

This study applied many techniques to arrange values into categories, develop a few new features, and eventually convert features into numeric representations so they could be used. It began with a data investigation and understanding the most significant aspects. After that, the dataset was trained using five different ML models, and the Logistic Regression model was found to be the most effective model. The model's accuracy, precision, recall, and F1-score can be seen in its Confusion Matrix, which shows the best model trained for this research. This research makes use of an infusion of Methodological

Architecture (Feizollah et al., 2021) for exploring tweets on social media. In addition, various extra appropriate activities and phases are incorporated into the study in order to fulfil the research purpose.

This dataset generally fits with the Logistic Regression model, which performs the best value in predicting customer trustworthiness toward the intention of purchasing halal food. The Correlation Matrix shows that most tweets for features 'Scheme 1: Halal Food/Beverage' and 'Scheme 3: Halal Premise' discuss optimism while acquiring halal food. Even the polarity of the tweets shows negative sentiments when based on customer thought, the public's attitude about food acquisition can significantly impact any decision made rapidly. When data is incomplete and likely to have been distorted by other irresponsible consumers, the issue of halal food will go viral and cause doubt and panic among consumers. Because of this, halal certification is important for building consumer trust in halal food spending. Religious knowledge, trust, and confidence about halal certification and halal food resources will lead to favorable decisions when acquiring any halal food.

Using Aspect-Based Sentiment Analysis in Natural Language Processing (NLP) techniques to measure brand sentiment and aspect detection may help businesses enhance their operations by seeing improvement areas, detecting unfavorable remarks in real time (and responding proactively), and gaining an edge over the competition. In the future, prediction models will be trained to predict how many people will frequent food premises based on their level of confidence that the food there has been certified as halal. Based on the correlations of attitude, trust and religious knowledge with desire in acquiring halal food, the model can provide an initial business overview so the owner can make initial decisions to ensure processes function smoothly and predict corporate performance in investment and marketing decisions. Opinion mining, also known as sentiment analysis, will continue to be an integral part of social media monitoring for businesses looking to learn how their target audience feels about their brand or goods in real time.

Acknowledgement

References

- Alshamsi, A., Bayari, R., & Salloum, S. (2020). Sentiment analysis in English Texts. *Advances in Science, Technology and Engineering Systems*, 5(6), 1638–1689. <https://doi.org/10.25046/AJ0506200>
- Amiri, H., & Chua, T. S. (2012). Mining slang and urban opinion words and phrases from cQA services: An optimization approach. *WSDM 2012 - Proceedings of the 5th ACM International Conference on Web Search and Data Mining*, 193–202. <https://doi.org/10.1145/2124295.2124319>
- Ariffin, S. N. A. N., & Tiun, S. (2020). Rule-based text normalization for malay social media texts. *International Journal of Advanced Computer Science and Applications*, 11(10), 156–162. <https://doi.org/10.14569/IJACSA.2020.0111021>
- Azam, M. S. E., & Abdullah, M. A. (2020). Global Halal Industry: Realities and Opportunities. *International Journal of Islamic Business Ethics*, 5(1), 47. <https://doi.org/10.30659/ijibe.5.1.47-59>
- Chekima, K., & Alfred, R. (2016). An automatic construction of Malay stop words based on aggregation method. *Communications in Computer and Information Science*, 652(September), 180–189. https://doi.org/10.1007/978-981-10-2777-2_16
- Demirel, Y., & Yaşarsoy, E. (2017). Exploring Consumer Attitudes Towards Halal. *Journal of Tourismology*, 3(1), 34–43. <https://doi.org/10.26650/jot.2017.3.1.0003>
- Feizollah, A., Mostafa, M. M., Sulaiman, A., Zakaria, Z., & Firdaus, A. (2021). Exploring halal tourism tweets on social media. *Journal of Big Data*, 8(1). <https://doi.org/10.1186/s40537-021-00463-5>

- Gamal, D., Alfonse, M., M.El-Horbaty, E.-S., & M.Salem, A.-B. (2019). Twitter Benchmark Dataset for Arabic Sentiment Analysis. *International Journal of Modern Education and Computer Science*, 11(1), 33–38. <https://doi.org/10.5815/ijmeecs.2019.01.04>
- Gonçalves, P., Araújo, M., Benevenuto, F., & Cha, M. (2014). *Comparing and Combining Sentiment Analysis Methods*. <https://doi.org/10.1145/2512938.2512951>
- Gregory, H., Li, S., Mohammadi, P., Tarn, N., Draelos, R., & Rudin, C. (2020). *A Transformer Approach to Contextual Sarcasm Detection in Twitter*. 270–275. <https://doi.org/10.18653/v1/2020.figlang-1.37>
- Hasbullah, S. S., Maynard, D., Wan Chik, R. Z., Mohd, F., & Noor, M. (2016). Automated content analysis: A sentiment analysis on Malaysian government social media. *ACM IMCOM 2016: Proceedings of the 10th International Conference on Ubiquitous Information Management and Communication*. <https://doi.org/10.1145/2857546.2857577>
- Husein, Z. (2018). Malaya, Natural-Language-Toolkit library for bahasa Malaysia, powered by Deep Learning Tensorflow. In *GitHub repository*.
- Kassim, M. N., Maarof, M. A., Zainal, A., & Wahab, A. A. (2016). Word stemming challenges in Malay texts: A literature review. *2016 4th International Conference on Information and Communication Technology, ICoICT 2016*, 4(c). <https://doi.org/10.1109/ICoICT.2016.7571887>
- Khan, G., & Khan, F. (2020). “Is this restaurant halal?” Surrogate indicators and Muslim behaviour. *Journal of Islamic Marketing*, 11(5), 1105–1123. <https://doi.org/10.1108/JIMA-01-2019-0008>
- Khirlunizam Abd Rahman. (2014). *List of Malay stop words*. <http://blog.kerul.net/2014/01/list-of-malay-stop-words.html>
- Lan, T. S., & Logeswaran, R. (2020). Challenges and development in Malay natural language processing. *Journal of Critical Reviews*, 7(3), 61–65. <https://doi.org/10.31838/jcr.07.03.10>
- Liu, B. (2012). Sentiment analysis and opinion mining. *Synthesis Lectures on Human Language Technologies*, 5(1), 1–184. <https://doi.org/10.2200/S00416ED1V01Y201204HLT016>
- Mohd Farid Hadi Sharif, D. M. Z. A. G. (2019). Halal Viral Issues in Malaysia. *Halal Journal*, 3, 61–71.
- Pal, A. R., & Saha, D. (2013). *Detection of Jargon Words in a Text Using Semi-Supervised Learning*. July 2013, 95–107. <https://doi.org/10.5121/csit.2013.3411>
- Setik, R., Ahmad, R. M. T. R. L., & Marjudi, S. (2021). Exploring Classification For Sentiment Analysis From Halal Based Tweets. *2021 2nd International Conference on Artificial Intelligence and Data Sciences (AiDAS)*, 1–6. <https://doi.org/10.1109/aidas53897.2021.9574255>
- Shahrinaz, I., Kasuma, J., Sarpinah, B., & Naimullah, S. (2015). *Purchase Manufactured Halal Food Products among Muslim students Do Attitude , Trust and Knowledge have relationship towards Purchase intention of Manufactured Halal Food Product ?* 737(November).
- Sharma, P., & Sharma, A. K. (2020). Experimental investigation of automated system for twitter sentiment analysis to predict the public emotions using machine learning algorithms. *Materials Today: Proceedings*, xxx. <https://doi.org/10.1016/j.matpr.2020.09.351>
- Stopwords, I. (n.d.). *Indonesian (Malay) Stopwords*.

Wiebe, J., & Riloff, E. (2005). Creating subjective and objective sentence classifiers from unannotated texts. *Lecture Notes in Computer Science*, 3406(October), 486–497. https://doi.org/10.1007/978-3-540-30586-6_53

Windasari, I. P., Uzzi, F. N., & Satoto, K. I. (2017). Sentiment analysis on Twitter posts: An analysis of positive or negative opinion on GoJek. *Proceedings - 2017 4th International Conference on Information Technology, Computer, and Electrical Engineering, ICITACEE 2017, 2018-Janua*, 266–269. <https://doi.org/10.1109/ICITACEE.2017.8257715>

Zhao, J., Liu, K., & Xu, L. (2016). Sentiment Analysis: Mining Opinions, Sentiments, and Emotions. *Computational Linguistics*, 42(3), 595–598. https://doi.org/10.1162/coli_r_00259

Zohreh Madhoushi, Z. M., Hamdan, A. R., & Zainudin, S. (2019). Aspect-Based Sentiment Analysis Methods in Recent Years. *Asia-Pacific Journal of Information Technology & Multimedia*, 08(01), 79–96. <https://doi.org/10.17576/apjitm-2019-0801-07>