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Prediction of Customer Engagement Response to E-wallet Content Based on Machine Learning Using Combined E-Wallet Dataset and Individual E-Wallet Dataset

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ABSTRACT

Objectives*: The COVID pandemic proved that humans are not hesitant to adopt technology in the banking industry, especially as a method of payment. In Indonesia, this fact is demonstrated by the value of e-wallet transactions in 2021 which reached 18,5 billion USD. The implementation of QRIS (Quick Response Code Indonesian Standard) in the payment systems of e-wallets compels every e-wallet provider to intensify their marketing activities to overcome competitors. Previous studies on this topic primarily focused on factors that influence customer engagement on social media using traditional approaches, such as interviews and statistical methods to process the data. This research aims to overcome the limitations of previous research by using machine learning methods in predicting the customer engagement type of primary data collected directly from social media in this case Twitter.*
Methodology*: In this paper, we propose the application of machine learning methods such as XGBoost, Random Forest, Decision Tree, and KNN to predict the most likely engagement type of a tweet related to e-wallet content using 15.756 data which are directly collected from Twitter.*
Finding*: This research successfully found that XGBoost and KNN are the machine learning algorithms that perform best and the results in prediction from using the combined dataset and the individual e-wallet brands dataset are similar.*
Conclusion*: Even though the prediction accuracy in this research is good, this research still has many limitations. Thus, future research in the same field would benefit from a larger amount of data to accommodate machine learning algorithms that are more complex like deep learning.*

Keywords*: E-Wallet; Machine Learning; Customer Engagement; Marketing*

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INTRODUCTION

The adoption of technology in the banking industry especially as a method of payment is a common thing nowadays. The global financial technology industries didn't stop growing when the pandemic hit (Widokarti et al., 2022). In Indonesia, the total e-wallet transaction reached 18,5 billion USD in 2021 which is a 32% Year on Year growth compared to 2020 (*Indonesia E-Wallet Transaction to Reach $18.5 Billion in 2021 amid Fierce Competition- The Asian Banker*, n.d.). This is in line with the attempt of Bank Indonesia's effort to increase cashless transactions to reduce the cost of printing money (Yuliastuti et al., 2022). The widespread use of e-wallets in everyday life is further supported by the emergence of multiple e-wallet platforms in Indonesia. These platforms allow people to make payments simply by using a mobile application on their smartphones.

QRIS (Quick Response Code Indonesian Standard) is a QR Code standard that was launched on August 17th, 2019 by the Bank of Indonesia and the Indonesian Payment System Association. It aims to standardize cashless payments in Indonesia (Chohan et al., 2022). Since the implementation of QRIS, every e-wallet in Indonesia has adopted a similar transaction method. Consumers can use any e-wallet provider to make payments using any QR Code. This standardization makes it challenging for e-wallet providers to offer distinctive features.

Social media has advanced how brands communicate with their customer, it has successfully narrowed the gap between brands and their customer (Dai & Wang, 2021). Brands would design their marketing content and then post it on their social media page, while customer would choose their preferred engagement behavior in response to those brand marketing posts. Even though social media marketing strategies have been made to guide customers toward specific engagement responses, the truth is everyone could easily make user-generated content related to brands that would either promote or discredit them, and brands could only control the content that they post. User-generated content such as an online review made by customers on social media could directly influence their attitude towards the brands (Wardhani & Chen, 2021).

Customer engagement is an important factor that should be considered by brands in their marketing activities since the increase in engagement has been related to the increase in brand loyalty, purchase expenditures, and profitability (Yang et al., 2019). Moreover, it also can affect customers' brand choices (Achmad et al., 2022).

Over the years, machine learning has gained popularity as a method to be used for regression and classification problems. Machine learning is a method that is used to accelerate the speed of data processing while reducing the cost of human labor. Machine learning methods have been used for predicting human decisions in many applications and it resulted in a good performance (Dai & Wang, 2021).

Methodological Gap

Previous research about customer engagement on social media has focused more on the factors of social media that affect customer engagement using a traditional approach such as using interviews as data a collection method and using a statistical model to process the data (Bazi et al., 2020; Grover & Kar, 2020; Liu et al., 2021). Even though there is also research that uses a machine learning approach to predict customer engagement in social media (Dai & Wang, 2021), the number of existing predictive research that utilizes machine learning methods to process the data are still low compared to traditional statistical methods. To the best of our

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knowledge, none of the research has used both the brand marketing post and user post as the data source to predict customer engagement with a machine learning approach.

Based on the analysis above, this paper tries to overcome the methodological gap of previous research with a newer method of data collection, using both brand marketing posts and user-generated content directly from social media, such as Twitter along with the usage of machine learning methods to process the data.

LITERATURE REVIEW

Customer Engagement

Customer behavior has changed over the years, from the audience to contributors on social media. Customer engagement could be used to predict brand-related outcomes such as brand usage intent, consumer relationship, and e word of mouth, more engagement means that the consumer has a stronger relationship with the brand, customers are more satisfied then they become loyal, and it results in higher revenue for the brands (Dai & Wang, 2021). Simply put, customer engagement is the existence of a bond between the customer and brands (Hartono et al., 2023; Soelton et al., 2021).

Customer engagement is also a cycle with types of customer engagement that are determined by the form of transactional exchange and emotional attachment to the brands (Sashi, 2012). The first type is transactional customers which have low emotional attachment and low transactional exchange, then some customers will grow into loyal customers that have low emotional attachment and high transactional exchange, while some other transactional customers will grow into delighted customers that have low transactional exchange and high emotional attachment. Delighted customers and loyal customers would also eventually grow into fully engaged fans if they have high transactional exchange and high emotional attachment. Five processes affect the customer's behavior before they turn into fans which are connection, interaction, satisfaction, retention, commitment, and advocacy (Hoang et al., 2023).

Machine Learning

Recently machine learning algorithms are starting to gain popularity as an alternative method to do prediction and classification problems in a lot of industries (Christodoulou et al., 2019). It is also important to know that lots of previous studies have used several machine learning methods to compare the performance of multiple models and produce the best results (Zhu et al., 2021). For example, Ahmad et al. (Ahmad et al., 2019) applied XGBoost, GBM, Random Forest, and Decision Trees to predict customer churn in the telecom industry. In this paper the machine learning methods that will be used to predict the customer engagement response of the e-wallet contents are K-Nearest Neighbour, Decision Tree, Random Forest, and XGBoost which will be explained in the next section. Support Vector Machine which is also commonly used to do classification problems is not used in this paper because the Support Vector Machine is more time-consuming compared to the other methods.

XGBoost

XGBoost is a machine learning method that uses a decision tree ensemble based on a gradient boosting machine (GBM). XGBoost solves the problems that are faced by researchers who use GBM which are high execution time and overfitting. XGBoost is preferred by data scientists because it has a high processing speed and therefore reduces the execution time (Ibrahem

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Ahmed Osman et al., 2021). It processes several operations at the same time as model training and it makes this machine learning method possible to learn fast (Ryu et al., 2020).

Random Forest

Random Forest is a widely used machine learning algorithm that can handle both classification and regression problems. Random Forest is mainly made up of multiple decision trees, as mentioned in the previous section, a decision tree is a rule-based model. Random Forest models the decision tree for each sample and combines the prediction results of multiple decision trees to form an average for the final prediction (Zhang et al., 2021). For classification problems that will be the main focus of this paper, the category that got the highest score from each tree will be determined as the final class label of the input (Zhu et al., 2021).

Decision Tree

The decision tree is a rule-based model that uses a tree-like structure to store decisions, hence it's called a decision tree. The decision tree consists of a root node, internal node (decision node), leaf node, and branches. The root node is where the decision tree starts, the branches from the root node then go into the internal node, the number of the internal node depends on the number of classes owned by the feature. For example, if the feature is gender, the branch from the root node will split into two internal nodes that represent each gender. Based on the available features in the data, the branch from the intermediate node might go to another intermediate node before it went into the leaf node. The leaf node is where the final prediction or classification is made (Song & Lu, 2015).

The decision tree relies on data received in the training phase to decide the categories of the data that should be divided. After that, the decision tree will automatically create a rule-based model to provide researchers with the final results (Chi-Hsien & Nagasawa, 2019).

K-Nearest Neighbor

KNN or K-Nearest Neighbor is a machine learning method that has the simplest process to classify data. KNN classifies the unknown object by correlating it with a familiar object through an effective distance (N. Ali et al., 2019). The dataset is divided into a fixed number of clusters, usually also called neighbors. The centre of the data is called the centroid which could either be real or imaginary. This centroid is then used to train the KNN classifier. The centroid value is determined through an iterative process, it is continually adjusted until it becomes stable. This centroid that is already stable is then used to classify input data by transforming the unknown object into the familiar one (M. Z. Ali et al., 2019).

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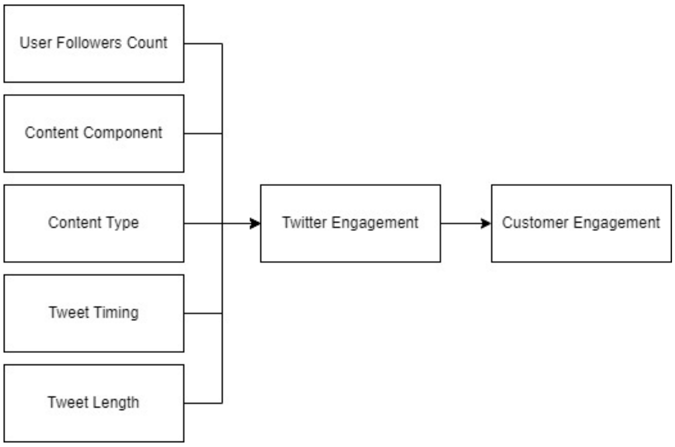

Figure 1. Conceptual Framework

METHOD

Design and Research Questions

The design of this research uses a quantitative approach. This paper explores the use of machine learning algorithms to predict customer engagement responses. In this paper, customer engagement response is defined as social media engagement on Twitter which consists of likes, replies, and retweets. If the likes are more than reply and retweet then the Tweet is categorized as likes, if the reply is more than likes and retweet then the Tweet is categorized as a reply, while if the retweet is more than likes and reply then the Tweet is categorized as retweet. This method is used in previous research by Dai & Wang (Dai & Wang, 2021) where they predict customer engagement in terms of what type of engagement (likes, comments, or shares) will the customer be more likely to choose.

The question proposed in this paper is as follows: First, how well the machine learning algorithm could process the limited data from Twitter to predict the type of engagement on Twitter. Second, comparing the results of prediction on individual e-wallet brand datasets and combined e-wallet brand datasets. Third, finding the differences in prediction results across several e-wallet brands.

Data Collection & Description

Table 1. Dataset Feature Description

Feature Name	Feature Description
User Followers Count	Number of followers
Content Component	Number of links and hashtags contained in the tweet
Emotion Score	The emotional intensity of the tweet
Contains_informational	if the tweets contain words from informational content codes
Contains_relational	if the tweets contain words from relational content codes
Contains_entertainment	if the tweets contain words from entertainment content codes
Contains_remuneration	if the tweets contain words from remuneration content codes
Is_weekend	if the tweet timing is on the weekend
Tweet length	Length of the tweet
Tweet_tokenized	Tweet

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The dataset was collected with 5 e-wallet brands as the subject (GoPay, Dana, LinkAja, ShopeePay, OVO) from Twitter, the dataset consists of 15.756 tweets with 9 features that were collected between the 1st of August 2017 and until 12th of December 2022. To minimize the bias between different e-wallet brands, several experiments are done with different dataset configurations.

User followers count is the current number of followers of the account that posted the tweet, and the content component is the sum of links and hashtags that are present in the tweet. Emotion score is calculated using the lexicon method for sentiment analysis, the lexicon used in the sentiment analysis is based on the lexicon that is taken from Koto & Rahmaningtyas (Koto & Rahmaningtyas, 2018). The Indonesia Sentiment Lexicon consists of 3.609 positive words and 6.609 negative words with weights ranging from -5 to +5. After that, the polarity score that has been produced by the weight is made absolute because the data that is needed is just the scale of emotion that is contained in the tweet. Contains_informational, contains_relational, contains_entertainment, and contains_remuneration are true or given 1 as a value if the tweet contains any word from each content code. The content code is modeled based on the content code used in research by Dolan et al. (Dolan et al., 2019) which was originally used to label the social media data of the Australian wine industry into four content types which are informational, relational, entertainment, and remuneration. In this research, each tweet could be labeled into one or more content types. Is_weekend is considered true or given a value of 1 if the tweet is posted on a weekend and given a value of 0 if the tweet is posted on a weekday. Tweet length is the character length of the tweet. Tweet_tokenized features in this dataset are tweets that have been cleaned and tokenized that then can be used to help predict the most likely engagement type of the tweet.

RESULTS AND DISCUSSION

Results

Two sets of experiments were conducted, the first experiment uses all e-wallet brands in a single dataset to predict the most likely engagement type while the second experiment focuses on individual datasets of e-wallet brands in predicting the most likely engagement type. In each experiment, the results from five machine learning models are then compared.

First Experiment

The first experiment uses 3 datasets, the first dataset used in this experiment is an aggregation of all e-wallet brands into a single dataset which consists of 15.756 tweets after the data are resampled to match the class with the lowest tweet amount. The second dataset in the first experiment consists of 2.154 tweets after resampling with e-wallet brands that don’t have an independent app like GoPay and ShopeePay since both can only be found on their company’s super app, respectively Gojek and Shopee. The third dataset used in the first experiment consists of 10.368 tweets after resampling with e-wallet brands that have an independent app. Each dataset that has been resampled is then split into train and test data with a ratio of 70% and 30%. Then the training data from each dataset is trained using five machine learning models, XGBoost, Random Forest, Decision Tree, and KNN.

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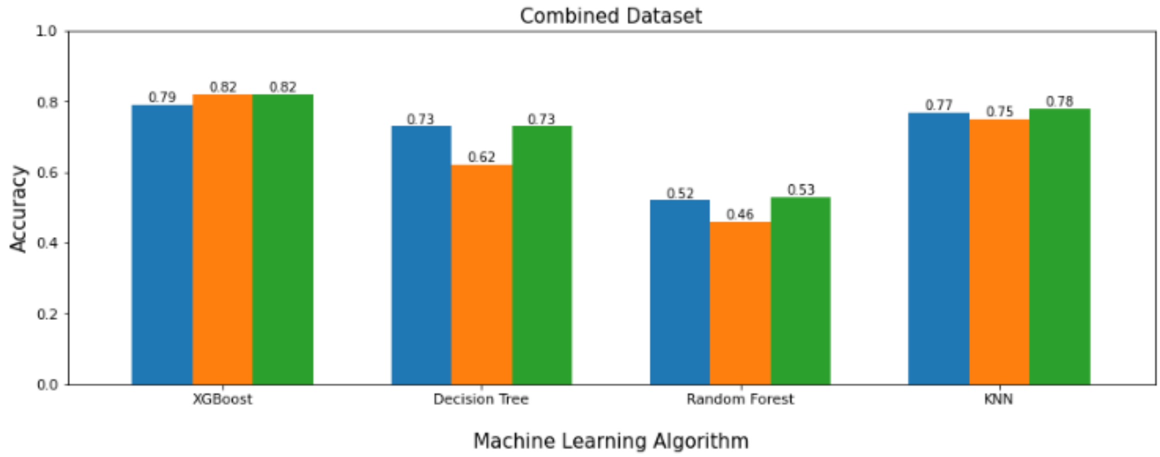

Figure 2. Combined Dataset Accuracy

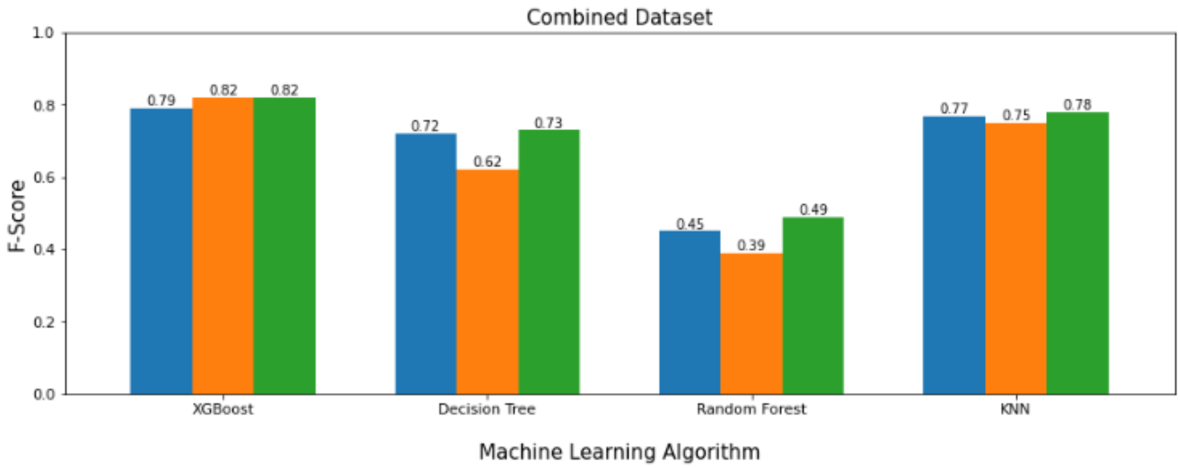

Figure 3. Combined Dataset F-Score

After that the trained model is used to predict the most likely engagement type of test data, the results will then be validated using the class of the test dataset, which produces prediction accuracy, where the highest accuracy and F-Score are produced from the XGBoost model with an accuracy of 0.79 and an F-Score of 0.79 for the first dataset, an accuracy of 0.82 and an F-Score of 0.82 for the second dataset, an accuracy of 0.82 and an F-Score of 0.82 for the third dataset. Followed by the KNN model with an accuracy of 0.77 and an F-Score of 0.77 for the first dataset, an accuracy of 0.75 and an F-Score of 0.75 for the second dataset, an accuracy of 0.78 and an F-Score of 0.78 for the third dataset. The rest of the machine learning models such as Random Forest and Decision Tree didn't produce good enough results with an accuracy range of 0.46 – 0.73 and an F-Score range of 0.39 – 0.49 for all three machine learning models.

Second Experiment

The second experiment uses the e-wallet brands individual dataset, each brand is resampled to match their class with the lowest tweet amount. GoPay has 2.022 tweets after resampling, LinkAja has 1.227 tweets after resampling, OVO has 4.107 tweets after resampling, Dana has 4.794 tweets after resampling, and ShopeePay has 1.386 tweets after resampling. After resampling the dataset, each dataset is then split into train and test data with a ratio of 70% and

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30%. The training data from each dataset is trained using five machine learning models, XGBoost, Random Forest, Decision Tree, and KNN.

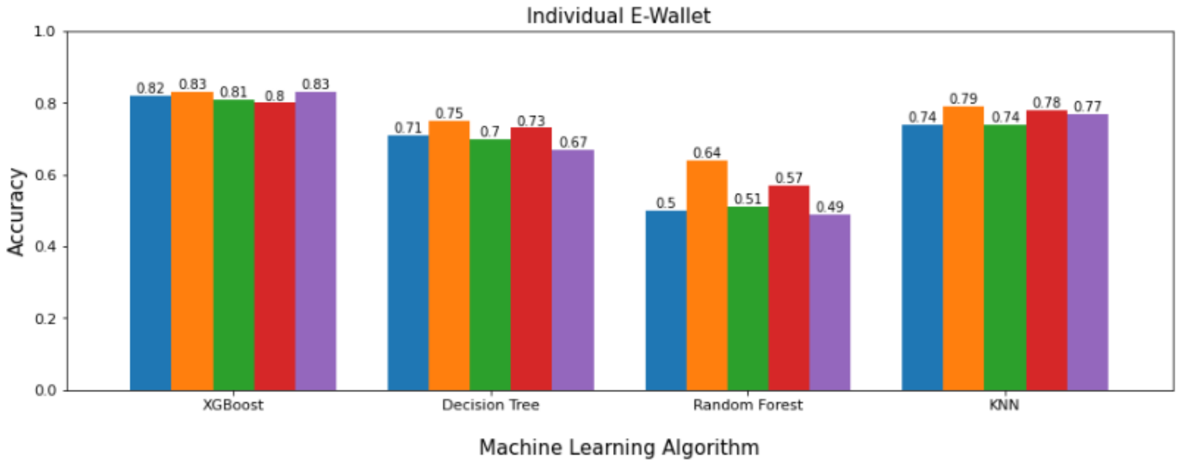

Figure 4. Individual Dataset Accuracy

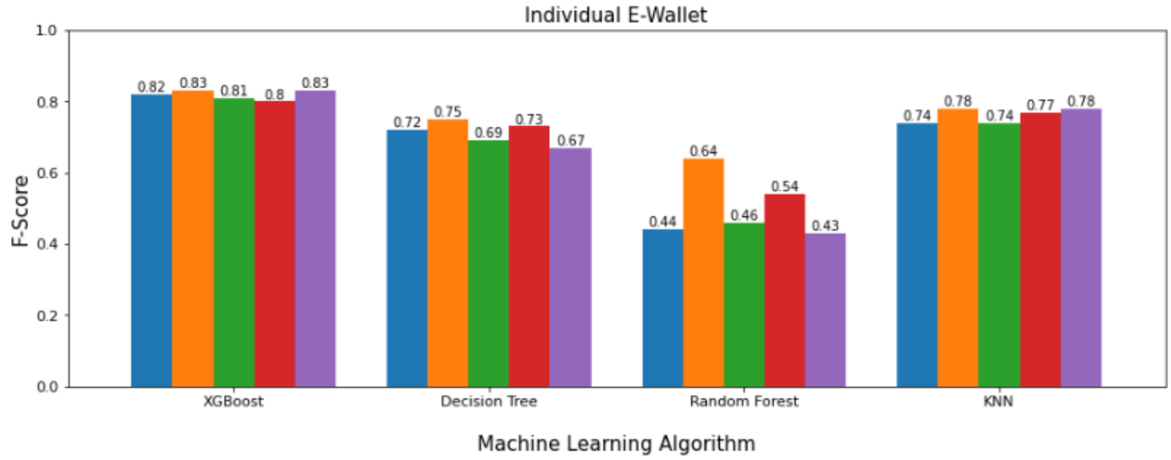

Figure 5. Individual Dataset F-Score

Each model is then used to predict the most likely engagement type of the test data, the results are then validated using the class of the test dataset. The highest accuracy is from the XGBoost model with an accuracy of 0.82 and an F-Score of 0.82 for the GoPay dataset, an accuracy of 0.83 and an F-Score of 0.83 for the LinkAja dataset, an accuracy of 0.81 and an F-Score of 0.81 for the OVO dataset, an accuracy of 0.8 and an F-Score of 0.8 for the Dana dataset, an accuracy of 0.83 and an F-Score of 0.83 for the ShopeePay dataset. KNN model produced the second-best results with an accuracy of 0.74 and an F-Score of 0.74 for the GoPay dataset, an accuracy of 0.79 and an F-Score of 0.78 for the LinkAja dataset, an accuracy of 0.74 and an F-Score of 0.74 for the OVO dataset, an accuracy of 0.78 and an F-Score of 0.77 for the Dana dataset, an accuracy of 0.77 and an F-Score of 0.78 for the ShopeePay dataset. Random Forest and Decision Tree didn't produce good results with an accuracy value range of 0.49 – 0.75 and an F-Score range of 0.43 – 0.75.

Discussion

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Overall, the machine learning models that consistently produce good results in both experiments are XGBoost and KNN while Decision Tree and Random Forest didn't produce results that are good enough. Random Forest and Decision Trees might show improvement in results if more data are added to the dataset (Khanday et al., 2020). These results are better than previous research by Dai & Wang (Dai & Wang, 2021) which uses Logistic Regression, Random Forest, LGBM Classifier, and Artificial Neural Network as the machine learning algorithms. The best F-Score from that research is 0.7727 with Artificial Neural Network while the best F-Score in this research is 0.83 with XGBoost, the difference is not much but this could mean that more complex machine learning algorithms wouldn't always produce better results than more simple algorithms like XGBoost and KNN. That research also only used the marketing post from the brand's social media account as the dataset and even though they also did some experiments, they only used a dataset made of several brands which didn't compare the results of individual brand datasets and combined dataset.

In this research, the individual e-wallet dataset which is the second experiment produced better results than the combined dataset in the first experiment, even though the difference is not that significant it is worth noting that the individual e-wallet feeds less data to the machine learning model than the combined dataset yet it produced better results.

The combined dataset and individual dataset do have different results but it's not that noticeable even though the gap in the amount of data is quite large. This is important because if the results are not that different it means that the bias between e-wallet brands is not noticeable and future research could just use an aggregated dataset of varying brands to accommodate machine learning algorithms that require a large amount of data.

The difference in prediction accuracy of the individual brands especially with the machine learning model that produced the best results is not large with a range of 0.01-0.05. This similarity in results is an interesting thing to note since social media marketing strategy may differ depending on the objectives of the brand (Li et al., 2021). For example, ShopeePay pushed their marketing towards ShopeePay payment to shop inside their Shopee e-commerce app while the rest gave more marketing content for payments in a physical merchant or store.

Twitter is a social media that enables its users to quickly exchange thoughts and information (Wardhana et al., 2022). This makes it important for brands to utilize Twitter in their marketing activities. Previous research in the same field focused more on factors that affect engagement in social media with interviews to collect the data and apply statistical models to the data (Bazi et al., 2020; Grover & Kar, 2020; Liu et al., 2021). In this paper, the customer engagement response is defined as the most likely engagement that the user of Twitter would pick from the available engagement type which are likes, replies, and retweets are inspired by previous work by Dai & Wang (Dai & Wang, 2021) that used the same idea but in Weibo, a different social media platform.

Both experiments successfully answered all the research questions stated in this research, first, this research successfully found that XGBoost and KNN are the machine learning algorithms that perform best, they could make predictions with good results with a limited dataset while also having a good F-Score. F-Score displays the overall mean of precision and recall (Rustam

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et al., 2020). F-Score is used in this research to further evaluate and compare the experiment results. This result is in line with previous research by Dai and Wang (Dai & Wang, 2021), where their prediction results with LGBM which uses the same gradient boosting algorithm as XGBoost produced the second-best results in their research after Artificial Neural Network. Second, the differences in prediction results from the individual brands and combined dataset are minimal even though on average the individual dataset could produce better results despite the lower amount of data compared to the combined dataset, which means that the bias in the e-wallet brands is minimal. Third, despite the differences in social media activity across e-wallet brands that are in this research, the best results produced are quite similar with a range of 0.01-0.05 which means that even though brands have different amounts of data and different social media activity, the machine learning algorithm would still work on different brands even the ones that are not in this research.

Using the same approach, e-wallet brands could use their data to train machine learning algorithms, especially XGBoost and KNN, then use it to predict the customer engagement response to marketing activities that they will post in the future and align it to their needs. E-wallet brands could also use this method to analyze their competitors' customer engagement responses in the future by using their historical data.

CONCLUSION

Even though the prediction accuracy in this research is good, this research still has many limitations. First, the amount of data used in this research is not large enough to accommodate the more complex machine learning model like Artificial Neural Network. Second, the machine learning algorithm used in this research is only the simple machine learning algorithms like XGBoost, Random Forest, Decision Tree, and KNN which are chosen because the machine used in this research has limited capability and there is also a limited amount of time to do this research. Last, the dataset in this research is only gathered from Indonesian e-wallet brands which are only limited to one geographical location and one industry, hence the results in different countries and different industries could also differ. Every social media platform's growth differs in every country. Future research could compare the results in different regions of the world and also include some other industries in their research.

Based on the limitations above, future research in the same field would benefit from a larger amount of data to accommodate machine learning algorithms that are more complex like Artificial Neural Network since more data will make the results produced by Artificial Neural Network better. Future research could also explore machine learning algorithms that are not yet used in this research such as deep learning or even compare them with the ones used in this research which would help researchers to find the best machine learning algorithms that would be best for predicting customer engagement in social media. Deep learning algorithms are important to also be included in the research if the resources are available since deep learning algorithms can easily be adapted to different domains. Since the geographical location and industry used in this research are limited, future research could compare different regions of the world and also include some other industries in their research.

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