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Exploring public sentiment on Madurese batik using backpropagation neural network

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Abstract. Sentiment analysis is an analysis that aims to observe the opinion of a society or a group about a specific entity. Sentiment analysis is widely used to analyze and assess a product, whether it produces positive reviews and is widely liked by the public or vice versa. This research was conducted to analyze and classify data about Madurese batik through public opinion sourced from X social media. Batik is part of one of the identities of the Indonesian nation. As technology develops, more and more public opinions and perceptions are shared through social networks such as online media, one of which is the X application. Therefore, this study requires data to be analyzed by taking and extracting public opinions on Madurese Batik through social media X. The method used is the backpropagation neural network method, in which the data obtained from Social media X is processed and classified to produce a conclusion divided into positive and negative responses. In this study, sentiment analysis about Madurese Batik on X social media was carried out by applying the Backpropagation Neural Network (BNN) method by applying an experimental scenario on a split data of 0.3 with a total of 2458 data inputs, 200 hidden, two outputs and 150 iterations with 80% accuracy.

1 Introduction

Batik is part of Indonesian culture and is known all over the world. Batik was even patented by UNESCO in 2009 as an Indonesian cultural art product. One of the areas of batik craftsmen in Indonesia is found on the island of Madura, which is famous for its unique color patterns on batik and has a characteristic red color with leaf or flower motifs [1]. Batik in Madura has become an icon that tourists from all regions love. Access to Madura Island is getting more accessible because of the Suramadu Bridge, one of the access points in and out of Madura Island. The batik in Madura is Madura-written batik; in the production of Madura, written batik is entirely done manually, starting from carving batik motifs to the batik dyeing process. There is even one batik that has a unique coloring process, namely Gentong batik, which comes from one of the districts located at the western tip of Madura, namely Bangkalan Regency; the dyeing process is carried out naturally to obtain the color by extracting various kinds of plants. Judging from the process of making batik, which is entirely done manually, this way can maintain the authenticity of Madura's written batik. Therefore, it can be in demand by batik collectors and Madura-written batik enthusiasts.

The public's interest in Madurese Batik is relatively high, with enthusiasts from within and outside the region. This is because the patterns and motifs on Madurese Batik are attractive and processed manually. From the many enthusiasts of Madurese Batik, it is not uncommon for people to use online media as material to express opinions. Social media X is one of the media to see opinions from the public about Madurese Batik [2]. The information in the form of positive and negative opinions is a public sentiment that deserves to be analyzed and used as a reference for public satisfaction with Madurese Batik.

Social media X is a communication medium people around the world widely use. This can be seen from the number of Social media X users recorded worldwide. Social media X already had 313 million active users worldwide per month in 2016. Users often provide updated news or comments about information that is the main topic, so from the many comments, it becomes a trending topic on Social media X. Judging from the increase in Social media X users, which is increasing, it will cause an increase in tweets posted by users.

The tweet contains a public opinion and comment that includes a product, natural phenomenon, social behavior, education, commerce, entertainment, etc. Things related to the product include Madurese Batik products, which many Social media X users post. The public or Social media X users often express opinions or reviews about Madurese Batik on Social media X social media. Information in comments, opinions, and assessments can be a reference for Madurese Batik business actors. The large number of tweets still needs

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to be more structured and random, making it difficult for others to conclude positive and negative opinions [3].

People have yet to analyze the opinions or responses of the public about Madurese Batik on social media, such as Social media X. Business actors can use sentiment information from the community to increase public satisfaction with Madurese Batik; by analyzing the sentiment of business actors, they can see market opinions on reviews from the public on Social media X. This can provide benefits for business actors because there is no need to do manual analysis, such as distributing questionnaires to the public. Therefore, sentiment analysis is widely used by companies and is becoming an exciting analysis method at this point.

Based on the above presentation, research related to Social media X sentiment analysis was carried out to classify Madurese Batik review tweets in Indonesian. Several things must be considered and prepared when conducting a sentiment analysis, including looking for a classifier. The classifier method is used to classify the review data into several classes [4][5]. In this study, the method used is the Backpropagation Neural Network (BNN) method; this method is one of the methods on the Artificial Neural Network (JST), which is used to predict with additional features, namely TF-IDF feature extraction . Backpropagation Neural Network can adapt to the network conditions given through the training process. It can be applied to solve problems related to classification[6], prediction[7], forecasting[8], pattern recognition, and so on [9]. The results of a sentiment analysis process are widely used and applied in various fields and companies in the analysis process to get a new benefit in supporting the company.

2 Related works

Machine learning in classifying user reviews based on sentiment is still a research trend in text mining. Like the research by Srivedya et al., we propose deep learning for multimodal sentiment analysis using MOUD datasets containing text and audio data. The model leverages two parallel processing paths, one for text and one for audio, which are then combined on an intermediate feature layer to complete the model architecture. This study shows that this deep learning-based approach can outperform previous models regarding accuracy, precision, recall, and F1-score. However, the study is limited to more structured and straightforward data, and further evaluation of more complex real-world data is still needed[10]. However, multimodal cannot be used in our research due to limited data on Madurese Batik.

Further research was conducted by Jin Xiang et al.[11] by comparing several machine learning and deep learning models for sentiment analysis on customer reviews from e-commerce platforms. The methods used are Support Vector Machine (SVM), deep neural network (DNN), LSTM, BERT, and RoBERTa. From the results of the experiment, the SVM model showed the best performance with an accuracy of 73.98%, an F1-score of 0.71, a precision of 0.72, and a recall of 0.70. The limitation of this study is limited generalization because the dataset used only comes from one domain, namely e-commerce customer reviews.

Research by Ashir et al. [12] proposes a rule- and lexicon-based method for sentiment analysis, capable of working on both structured and unstructured data sources, such as movie reviews and samples from Social media X. This study uses a combination of lexical features and unsupervised machine learning models. The accuracy achieved in the movie review dataset was 72%, with an F1 score of 72.9%. Meanwhile, the Social Media X dataset's accuracy reached 91.1%, and the F1 score was 91.4%. The study shows that well-designed lexical features can strengthen the learning process, but the main challenge lies in processing unstructured data more effectively.

Banou et al.'s research in 2023 focused on sentiment analysis of Arabic-language tweets using the Support Vector Machine (SVM) model. When optimized with the Lagrange polynomial approach, the SVM method experiences increased accuracy and F1 score. Although the accuracy and performance of the model have improved, this study reveals that the SVM model requires a considerable training time, which is a constraint when conducting extensive grid searches[13].

Hassan et al.'s research on sentiment analysis on a dataset consisting of 6,388 tweets related to scientific publications from Altmetrics. They compared the performance of several machine learning models, including SVM, Logistic Regression, and Naive Bayes. SVM models with unigrams showed the best performance with 85% accuracy, followed by Logistic Regression with 83% accuracy and Naive Bayes with 80% accuracy. This study shows that SVMs have an advantage in handling short texts from various disciplines but must explore multilingual sentiment analysis [14].

Sharma et al.'s research applies Machine Learning (ML), Deep Learning (DL), and Transfer Learning models to sentiment analysis of product reviews on Amazon. The review dataset is processed using the proper NLP pipeline to extract features and clean the data. The study found that transfer learning models built on deep learning significantly improve accuracy compared to traditional ML models. However, a limitation of this study is the need for more focus on the model's scalability to larger and heterogeneous datasets [15].

Research by Rathod et al. Explore sentiment analysis of drug reviews using various machine-learning techniques. Rathod et al. used various feature engineering techniques, such as bag-of-words and word embedding, to capture the nuances of drug reviews. The experiment results show that the machine learning algorithm can accurately capture sentiment in drug reviews with high accuracy and F1-score. The main limitation of this study is the need for improvements in more effective feature engineering techniques for drug reviews [16].

Tripathi et al.'s research conducted sentiment analysis on movie reviews from the IMDb dataset using four machine learning algorithms: Naive Bayes, Logistic Regression, Random Forest, and Decision Tree. The authors used six evaluation metrics, including a matrix of confusion, accuracy, precision, recall, F1-score, and AUC. Although Random Forest provides the best results, the study is limited in its application to only film reviews and needs to be evaluated on other domains for better generalizations[17].

Singh et al.'s research in 2021 focused on analyzing the sentiment of MOOCs (Massive Open Online Courses) course reviews. The researchers tested various supervised learning algorithms, such as SVM and Naive Bayes, with the result that the Multilayer Perceptron (MLP) provided the best accuracy of 92.44%. The study concluded that the Bigram-based model improved the performance of all metrics. However, its limitation is the need for more application to other, more diverse educational datasets [18].

Roja et al.'s research compared the performance of three machine learning models, namely Random Forest, SVM, and Logistic Regression, in predicting post-COVID-19 patient sentiment from tweets. The Random Forest model provides the best performance in terms of accuracy and F1-score, followed by SVM. However, this study shows that model performance varies depending on the predicted sentiment class, and multilingual analysis has yet to be explored in depth [19].

Based on the above studies, it is known that almost all studies use existing datasets and do not use a sentiment approach to contribute to improving the economic field of small and medium business units as carried out in this study.

3 Methodology

The research was carried out in several stages, as shown in Figure 1. The first step starts from the data crawling process. Social media X data from crawl results will be labeled manually based on the opinion of language experts. Next, the data will be preprocessed, and the output of the preprocessing results will be displayed. The data from the preprocessing will be entered into the weighting and feature extraction process to obtain the weight of each word that will be used as a feature.

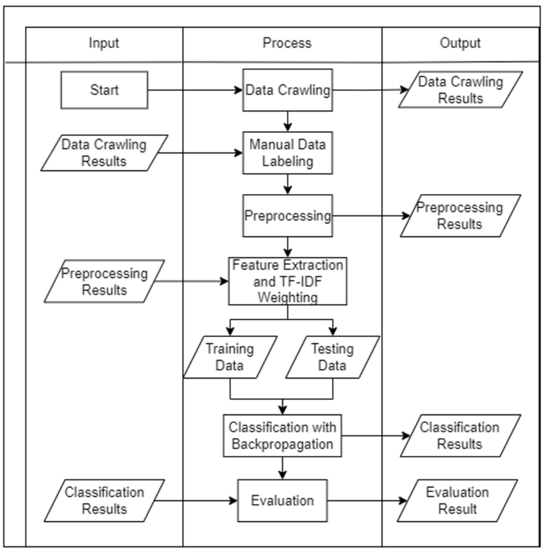

Fig. 1. Architecture system.

Furthermore, the data is divided into training data and data testing; training and testing data are used for classification with the Backpropagation Neural Network algorithm. The classification process will display the output of the classification results. The classification model that has been created will be used for the evaluation process. In the evaluation process, it is necessary to carry out tests to see the evaluation results of the system that has been built and to see the system's performance. One of the tests is by using a test scenario with a learning rate value. After several steps are taken, the output results of the sentiment analysis process will be displayed.

3.1 Dataset

The dataset used in this study is tweets obtained from as many as 3036 tweet data. The keyword of the tweet searched is "Batik Madura," obtained by crawling data using the library used, namely Twint, with a data crawling process since 2017. The results of the data are imported into CSV form. Manual labeling is done to label all data carried out by a language expert.

Table 1. Sample of dataset.

No	Tweet	Labelled
1.	Alhamdulillah, dapat kiriman kain batik dari Madura...terima kasih banyak mbakku sayang... 🙏, hati senang.sekali rasanya....	Positive
	Alhamdulillah, I got a shipment of batik cloth from Madura... Thank you very much, my dear... 🙏 , happy heart.once it feels....	
2.	@rade_efp Yg nyebelin rata2 kualitas kain mori batik Madura jelek huhuhu	Negative
	(@rade_efp The average quality of Madurese Batik mori fabric is ugly huhuhu)	

3.2 Backpropagation neural network

In this Madurese Batik analysis sentiment research, a method of guided learning by applying the *Backpropagation Neural Network* (BNN) algorithm. In the classification process, the activation functions applied to each *selected perceptron* are sigmoid and relu [20]. This sigmoid activation function is an activation that will receive a single number and accept the value *into* a value that has a range ranging from 0 to 1[21]. Meanwhile, the Relu activation function is non-linear and changes the value below 0 to 0 [22].

The Backpropagation Neural Network of this research uses three layers[23]: the input layer, the hidden layer, and the output layer, where each layer has a different node[24]. The output layer has many nodes, as many as 2458 nodes obtained from the process of extracting the *Tf-idf* feature. The hidden layer has 200 nodes with Relu activation and sigmoid activation [25], while the output layer has two nodes due to either positive or negative. There is a line that connects between layers and between nodes; the line is the weight of the input layer to the hidden layer and the weight of the hidden layer to the output layer[26].

Table 2. Text processing process.

Process	Example
Cleansing	Alhamdulillah dapat kiriman kain batik dari Maduraterima kasih banyak mbakku sayang hati senangsekali rasanya
Case Folding	alhamdulillah dapat kiriman kain batik dari maduraterima kasih banyak mbakku sayang hati senangsekali rasanya
Tokenization	"['alhamdulillah', 'dapat', 'kiriman', 'kain', 'batik', 'dari', 'maduraterima', 'kasih', 'banyak', 'mbakku', 'sayang', 'hati', 'senangsekali', 'rasanya']"
Slangword Conversions	"['alhamdulillah', 'dapat', 'kiriman', 'kain', 'batik', 'dari', 'maduraterima', 'kasih', 'banyak', 'mbakku', 'sayang', 'hati', 'senangsekali', 'rasanya']"
Filtering	"['alhamdulillah', 'kiriman', 'kain', 'batik', 'maduraterima', 'kasih', 'mbakku', 'sayang', 'hati', 'senangsekali']"
Stemming	"['alhamdulillah', 'kirim', 'kain', 'batik', 'maduraterima', 'kasih', 'mbak', 'sayang', 'hati', 'senangsekali']"

4 Result analysis

In this study, the stages in the sentiment analysis process are as follows:

4.1 Text preprocessing

There are six stages in *data preprocessing*: *cleansing, tokenizing, case folding, slang conversion, filtering, and stemming. The preprocessing* stage is a very important stage in the sentiment analysis process that can affect the level of accuracy produced because the words resulting from *preprocessing* will be features or attributes for the classification process. The following is an example of data from data preprocessing, as seen in Table 2.

1. In the cleansing stage, attributes or punctuation marks are unnecessary in the analysis process.
2. The Case Folding stage changes all uppercase letters in the comment text to *lowercase* or lowercase letters.
3. The Tokenization stage separates words based on each word that composes them into a single piece.
4. Slangword Conversion is the process of converting all words in a sentence or document into standard words using a slang dictionary. This stage checks whether the words are in the slang dictionary. If a non-standard word is found, it will be changed to a standard word according to the slang dictionary.
5. Filtering is the process of removing a collection of words that have no effect by reducing the information from the opinion and its existence. It often uses Indonesian *stopwords* that have been compiled by adding words manually because some words are not yet included in the *stopword.*
6. Stemming is the process of converting words with suffixes into essential words by removing or eliminating the suffixes. The suffix will be removed according to the algorithm used.

4.2 Feature extraction

Feature extraction is the process of assigning weight to each word that is an attribute in the data classification. In this study, the feature extraction process used the tf-idf method and produced 2458 features.

4.3 Result

The testing process is carried out using two test scenarios. The first scenario is by using a combination of split data as shown in the Table 3.

Table 3. Evaluation of split-data combination.

No	Split-Data (Training- Testing Data)	Accuracy
1	0,2 (80%,20%)	0.7759
2	0,3 (70%,30%)	0.7846
3	0,4 (60%,40%)	0.7522

In Table 3, the test results are shown on the split data with three tests: 0.2 (80%,20%), 0.3 (70%,30%), and 0.4 (60%,40%). Different accuracy values were obtained in each test. The highest accuracy value was obtained in the second test with a data split of 0.3 (70%, 30%), which obtained a high accuracy value of 0.7846.

The second test uses a combination of learning rate values. They are shown in the Table 4.

Table 4 presents the test results of the learning rate value, conducted using five tests with different values: 0.01, 0.02, 0.03, 0.04, and 0.05. Different accuracy values were obtained for each learning rate. Judging from the table above, a high accuracy value was obtained; in the first test, the learning rate was 0.01, with an accuracy value of 0.7846.

The third test combines the number of iterations shown in Table 5.

Table 4. Evaluation of learning rate combinations.

No	Learning Rate	Accuracy
1	0,01	0.7846
2	0,02	0.7769
3	0,03	0.7538
4	0,04	0.6731
5	0,05	0.6962

Table 5 presents the test results from the number of iterations by conducting five tests from different iterations, namely 50, 100, 150, 200, and 250. From the five tests above, different accuracy values were obtained from each test, with the highest accuracy value in the 3rd test with an accuracy value of 0.8000.

Table 5. Evaluation of total iteration combinations.

Testing No-	Iteration	Accuracy
1	50	0.7846
2	100	0.7846
3	150	0.8000
4	200	0.7923
5	250	0.7692

5 Conclusion

Based on the explanation and analysis, a conclusion was obtained that Madurese Batik has many positive reviews, proving user satisfaction with its quality. The negative aspect that users are concerned with is that it is more about late service and delivery of goods rather than related to the quality of goods. Furthermore, the model produced by *The Backpropagation Neural Network* (BNN) method and an experimental scenario were carried out on a split data of 0.3 with 2458 data inputs, 200 hidden, two outputs, and 150 iterations obtained an accuracy value of 80%. The results of this study are expected to be useful in future research that discusses similar research. The system built in this study is still considered less than optimal. Several things must be developed in this study, namely in the *preprocessing* stage, which is still imperfect, so that it affects the accuracy value built by applying the *Backpropagation Neural Network* (BNN) method. It is hoped that new discoveries can be made from the next research so that the system built will obtain the best results.

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