International Journal Multidisciplinary Science
OPEN ACCESS
IJML Vol 4 No. 2 | June 2025 | ISSN: 2963-8119 (print), ISSN: 2963-7821 (online), Page 80-90

Performance Comparison of Support Vector Machine and Deep Neural Network for Sentiment Classification in Digital Tourism

Anisa Lora[1*], Tubagus Maulana Kusuma[2]

[1]Sistem Informasi, Fakultas Teknik dan Informatika, Universitas Nusa Megarkencana, Indonesia
[2]Teknik Elektro, Fakultas Teknologi Industri, Universitas Gunadarma, Indonesia

Article History
Received : 15 July 2025
Revised : 25 July 2025
Accepted : 05 June 2025
Published : 15 June 2025

Corresponding author*:
anisalora22@gmail.com

DOI:
https://doi.org/10.56127/ijml.v4i2.2233

Abstract: This study aims to classify public sentiment on SNS Instagram @indtravel content using Machine Learning techniques with Support Vector Machine (SVM) and Deep Neural Network (DNN) Modeling. From the results of this analysis, it can be seen whether the tourism promotion strategy by the Indonesian Ministry of Tourism through SNS Instagram tends to be positive or negative towards the push and pull factors for someone to take a tour. In addition, this study also aims to compare the performance of Accuracy, Precision, Recall, F1-Measure, ErrorRate, and the AUC-ROC Curve of the SVM and DNN models. The dataset used in this study was obtained from SNS Instagram @indtravel comments using scraping techniques. The results of the evaluation in this study indicate that the public sentiment towards the content of SNS Instagram @indtravel tends to be positive towards the push and pull factors for someone to take a tour. Based on the results of the performance comparison between the SVM and DNN model, it is proven DNN model has a higher level of performance in Accuracy (89,37%), Precision (93,79%), F1-Measure (93,79%), ErrorRate (10,63%), were the SVM model only higher in Precision rate with a difference of 5,43%. This indicates that the DNN model has a very good performance in classifying public sentiment on SNS media compared to the SVM model.

Keywords: DNN, Machine Learning, Sentiment Analysis, SVM.

INTRODUCTION

The role of Social Network Sites (SNS) in fostering motivation that push and pull someone to travel is widely used by various sides, including the government. The concept of push and pull factors were first discussed in relation to tourism motivation by Dann in 1977 (Giddy, 2018). It is based on the idea that there are certain internal factors that “push” individuals to looking at tourist experiences, while the decision of which experience or product to choose is based on external factors that “pull” an individual to choose that specific experience.

Several studies have shown that there is an important relationship between the concept of push and pull factors with the pull motivation factors on SNS. SNS provides information and generates awareness, influencing decision making and online purchasing behavior (Gupta et al., 2018). Most of the relationship between push and pull factors is supported by the type of content, where cultural, sports, natural beauty, and the safety or luxury of tourist attractions content tend to attract consumers' attention (Katsikari et al., 2020).

The use of social media for the tourism sector has proven as a good strategy, not only in improving the quality of business but also broadly increasing the income of the tourism industry (Gururaja, 2015) One of the SNS media that is popularly used today is Instagram. The Indonesian government through the Indonesian Ministry of Tourism and Creative Economy (*Kemenparekraf*) has an official SNS Instagram account @indtravel for tourism promotion. There are various types of content uploaded, such as events, attractions, and culture. The type of media uploaded via SNS consists of photos, videos or only text.

Public sentiment towards the content SNS Instagram @indtravel in this research was done by using Machine Learning techniques with Support Vector Machines (SVM) and Deep Neural Network (DNN) modeling. Various studies have shown that the SVM text classification algorithm is the most widely used algorithm with accuracy above 70% (Ariadi & Fithriasari, 2015; Nomleni, 2015; Susanti, Sediyono, and Sembiring, 2016). Sentiment analysis research using the Machine Learning approach with a variant of the Deep Learning Neural Network method also shows good results, even reaching 86% (Dos Santos & Gatti, 2014; Assuja & Saniati, 2016; Ramadhani & Goo, 2017; Chy et al., 2018; J. Qian et al., 2018)

Based on the high level of accuracy and success of the SVM and DNN models in previous studies, so this research will try to prove which model has higher performance by comparing the value of Accuracy, Precision, Recall, F1-Measure, and ErrorRate. Another objective in this research is to see whether the tourism promotion strategy implemented by the Indonesia Ministry of Tourism through SNS tends to be positive or negative towards the push and pull factors for someone to travel. From this results, it can be used to improve the decisions of Indonesian tourism stakeholders in managing and formulating promotion strategies, so that the use of SNS for promoting Indonesian tourism can be more optimal

RESEARCH METHOD

This research uses a Machine Learning approach with the SVM and DNN Modeling to analyze public sentiment on the SNS Instagram @indtravel content. The implementation and evaluation phase in this research used the RapidMiner Studio 9.8 tools. The overview of the stages in this research are presented in the following:

Data Collection

The dataset used in this research was collected from English comments on SNS Instagram @indtravel posts using scraping techniques in Rapid Miner Extensions. The total of data used in this research is 2093 comments were collected in excel data format. The next step was labeling the dataset by giving a class sentiment "positive" or "negative". The output from this process can be continued to the data pre-processing stage.

Pre-Processing

The pre-processing stage is used to remove noise, clarify features, convert the original data, and enlarge or reduce the data to suit needs. Overview of the pre-processing data stages can be seen in Figure 1 below.

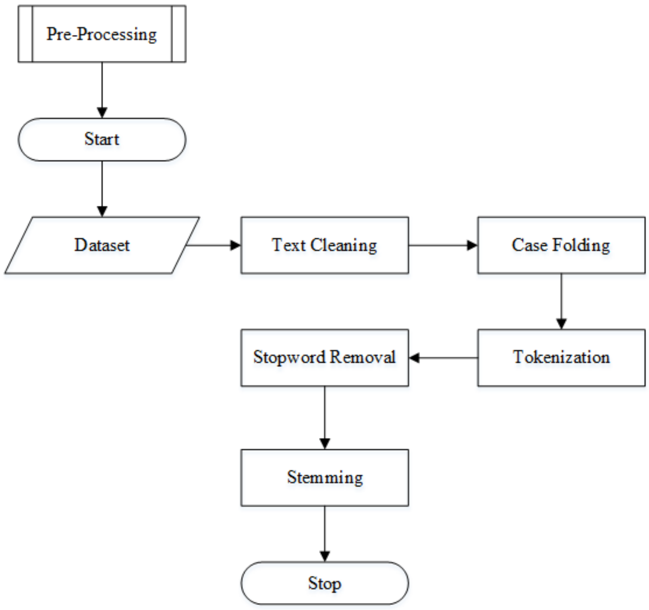


Figure 1. Overview of the pre-processing data stage.

a. Text Cleaning

At this stage, characters such as url address, username (@username), hashtag (#), emoticons, numbers, and punctuation marks are removed from the dataset. It's done to clean the data from characters that are not important and do not affect the classification process. This stage needs to be done in order to obtain valid data for processing in the next stage.

b. Case Folding

This stage is used to handle inconsistent use of uppercase letters, where through this process all characters in the dataset are converted to lowercase. This stage needs to be done so that each character has the same feature space

c. Tokenization

This process splits sequences of characters into individual words or phrases, known as tokens. Each token typically represents a single English word, which forms the basis for further text processing.

d. Stopword Removal

Common words with little or no semantic value (e.g., conjunctions or prepositions) are removed using a built-in English stopword list. Tokens that match any entry in the stopword dictionary are excluded from further analysis.

e. Stemming

In the stemming process, word modification is used to get the root word from the derivative word. In this research, a stem operator (Porter) was used. These operators retrieve English words using Porter's stemming algorithm which implements the repeating rule-based suffixes of words. The aim is to reduce the word length until the minimum length is reached.

The main pre-processing processes that have been carried out using the RapidMiner Studio 9.8 tools can be seen in Figure 2 below.

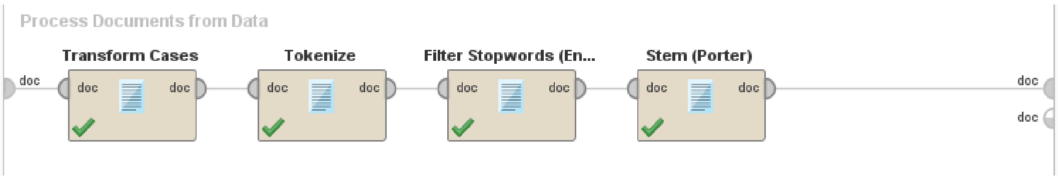


Figure 2. *Main process for pre-processing dataset in RapidMiner Studio 9.8.*

Feature Extraction

The feature extraction process is carried out using the Term Frequency-Inverse Document Frequency (TF-IDF) technique. This stage is used to process the document into a word vector representation of the string attribute (dataset). In the TF-IDF technique, the process of calculating documents or terms is carried out based on the probability frequency of the occurrence of words or terms in a document.

Validation

The dataset that has been through pre-processing and feature extraction processes is divided into training data and testing data using the Split Data operator, where 70% of the dataset is used as training data and 30% is used as testing data. The next stage is the cross validation process between training data and testing data. The operator used in this process is the cross validation operator.

Through Cross Validation, rules model will be applied to each attribute in testing data to see the match between the prediction class and the actual data class. The output of this process is illustrated through the Confusion Matrix table and AUC-ROC graph, which is accompanied by the performance value of each model.

Classification

The sentiment classification process in this research uses a two-model approach, namely the SVM model and the DNN model. The modeling process used the operator on the Rapid Miner Studio 9.8. In this study, the model is implemented in operator cross validation sub-process. The design of the SVM classification process flow in this research is illustrated through a diagram which can be seen in Figure 3 below.

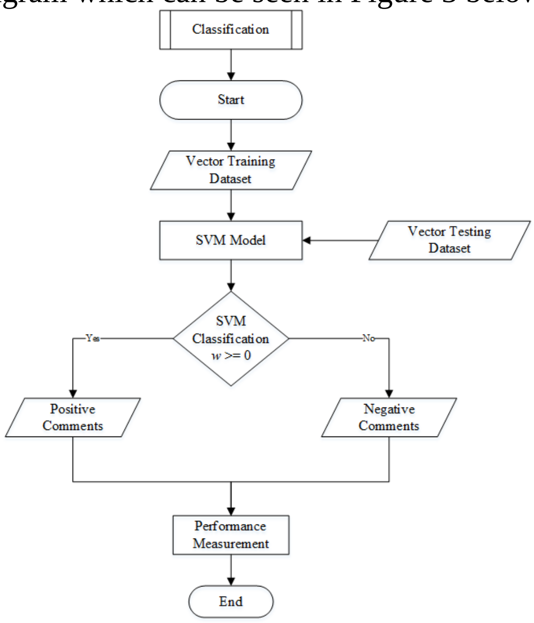


Figure 3. Design of SVM Model Classification Process

The Support Vector Machine (SVM) classification model takes a set of input data generated from pre-processing and feature extraction—and classifies it based on weighted measure values to predict the sentiment of each input. The model is trained using two categories of data: training data and testing data. The training data consists of labeled samples divided into two classes, which are used by the SVM algorithm to build a predictive model. In this study, the sentiment classes are "positive" and "negative." If a word or term has a weighted measure value less than 0, it is classified as a negative comment; if the value is greater than or equal to 0, it is classified as a positive comment. The classification process is carried out using the SVM operator, and the trained model is applied to the testing data using the Apply Model operator, as illustrated in Figure 4.

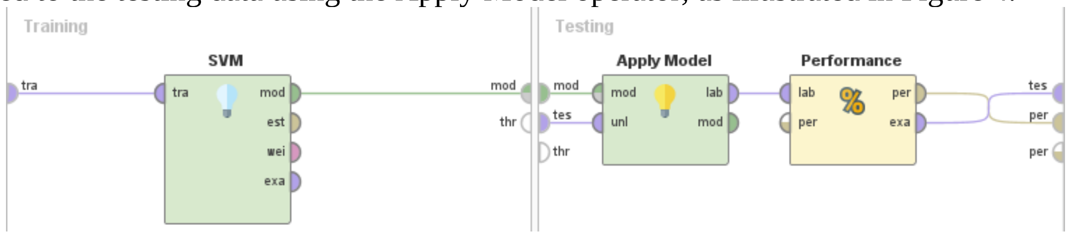


Figure 4. *Operator of SVM Classification Model*

In Figure 4, can be seen that there are two sub-processes, namely the training sub-process and the testing sub-process. The training subprocess is used to train the model. The trained model is then applied in the testing subprocess. Furthermore, the performance of the model is measured during the testing phase. The design of the DNN classification process in this research is illustrated through a diagram which can be seen in Figure 5 below.

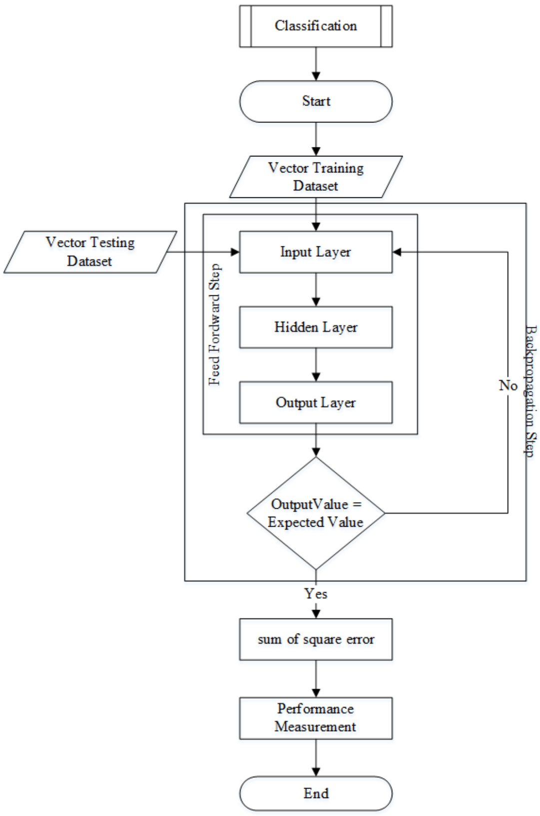


Figure 5. *Design of DNN classification model*

There are three main stages in DNN modeling, namely feedforward, backpropagation and updating of weight values. At the feedforward stage, the process is obtained from input to output. At the backpropagation stage, the process of comparing the output value from the feed forward stage with the predetermined target value. Basically, the DNN model process is the process of operating every input with each weight using the dot product operation. Then adding the results of that operation with the bias value for each weight.

The result of the dot product operation with the weighted value and the bias value will enter the activation function. Then, this value sent to all nodes in the hidden layer (except bias). Furthermore, these values are passed to all output layers. When the output does not match with the expected results, the output will be backpropagation from the hidden layer to the input layer, so that the error value is obtained.

At the weight value update stage carried out the process of updating the weight value until a minimal error is obtained. Then the process continues to Hidden Layer and continues to the Output Layer. The backpropagation process will continue until the smallest output value is obtained, so the expected error stop achieved.

The DNN model classification process is carried out using Deep Learning Neural Net operators. The model formed from the training data is implemented into testing data through the Apply Model operator, with a process description shown in Figure 6 below.

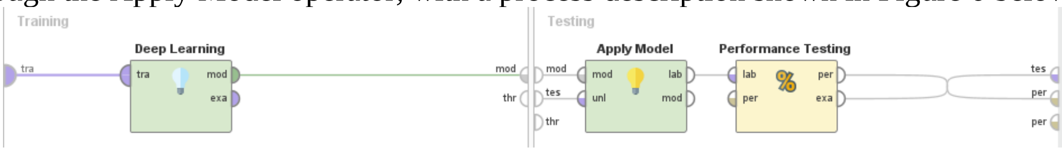


Figure 6. *Operator of DNN classification model*

RESULT AND DISCUSSION

The flow of the classification process starts from the retrieved dataset in the repository to the dataset classification process in the Cross Validation operator subprocess. Through Cross Validation, a rules model will be applied to each attribute in testing data to see the match between the prediction class and the actual data class. The output of this process is illustrated through the Confusion Matrix table and AUC-ROC graph, which is accompanied by the performance value of each model.

Classification using the SVM model tries to find the best line or hyperplane in N dimensional space (N is the number of features) through the classification of data points, then testing data classification is carried out based on which side the line appears on. The results of this process are illustrated through the Confusion Matrix table which can be seen in Figure 7 and Figure 8 below.

accuracy: 88.04% +/- 1.48% (micro average: 88.04%)

	true positive	true negative	class precision
pred. positive	1022	136	88.26%
pred. negative	8	38	82.61%
class recall	99.22%	21.84%	

Figure 7. *Table Confusion Matrix SVM Mode Performance Testing*

accuracy: 88.18%

	true positive	true negative	class precision
pred. positive	437	57	88.46%
pred. negative	4	18	81.82%
class recall	99.09%	24.00%	

Figure 8. *Table Confusion Matrix SVM Mode Performance Training*

Based on Figure 7 above, it can be seen that after applying the SVM Model for the testing data, was achieved 88.04% accuracy and 88.18% accuracy in the training data. This indicates that the evaluation for the training data classification task is higher 0,14% than evaluation task in the testing data.

Classification using the DNN model illustrated in the Confusion Matrix table as show in Figure 9 and Figure 10 below.

accuracy: 89.37% +/- 2.11% (micro average: 89.37%)

	true positive	true negative	class precision
pred. positive	966	64	93.79%
pred. negative	64	110	63.22%
class recall	93.79%	63.22%	

Figure 9. *Table Confusion Matrix DNN Mode Performance Testing*

accuracy: 88.57%

	true positive	true negative	class precision
pred. positive	417	35	92.26%
pred. negative	24	40	62.50%
class recall	94.56%	53.33%	

Figure 10. *Table Confusion Matrix DNN Mode Performance Training*

Based on Figure 9 above, it can be seen that after applying the DNN Model, accuracy level for testing data is 89.37% and 88.57% for accuracy in the training data. This shows that the evaluation for classification task in the testing data is higher 0,8% than the training data. Based on the results of the accuracy performance from testing data and training data, then it can be compared to analysis whether the model used is Overfitting or not.

Overfitting is an incident where the model is too good at classifying training data, but poor at classifying testing data. From this result, this show that comparison between testing data and training data accuracy in SVM and DNN model do not have too much difference, which is only 0,14% and 0.8%. This indicates that both of two model is not Overfitting Fitting.

The evaluation performance of the SVM and DNN models is carried out by calculating the Accuracy, Precision, Recall, F1-Measure, and ErrorRate values. At this stage, we can see the performance of the algorithm based on the accuracy of the model in predicting data classes. This calculation measured based on equation 2 to equation 6 as shown in the previous section. The results of the performance evaluation of the SVM and DNN models can be seen in Figure 11 below.

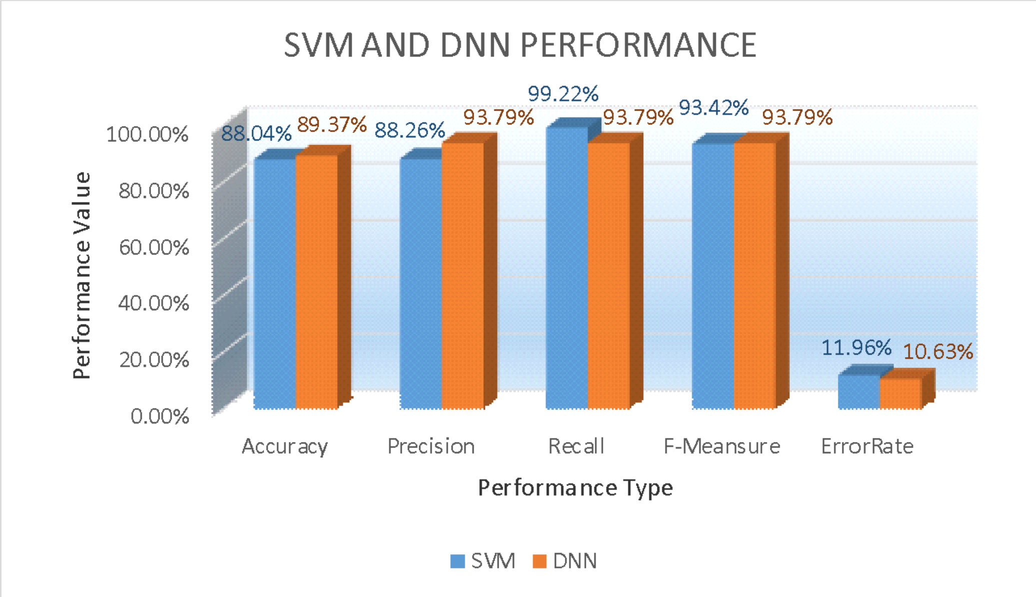


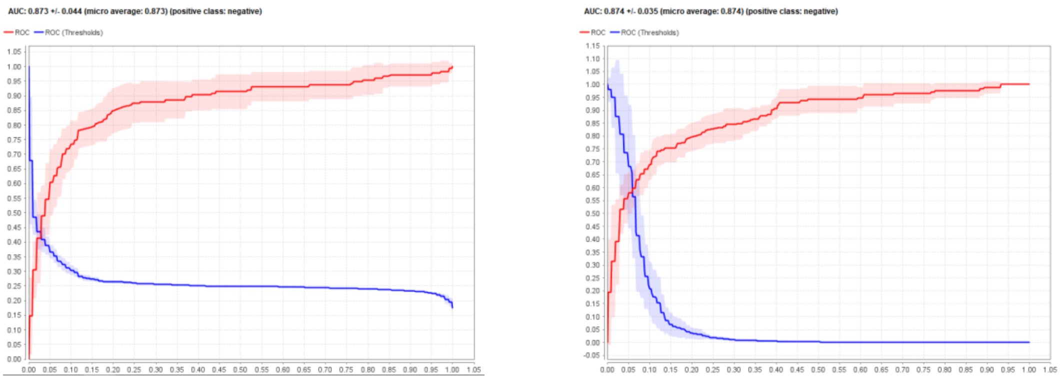
Figure 11. *SVM and DNN Model Performance Chart*

The testing of the training data using the SVM model produce a value with a level of similarity between the predicted and the actual value was achieved 88.04% and the DNN model was achieved 89.37%. This shows that the proportion of cases true predicted is higher in the DNN classification model, with a difference of 1.33% from the SVM classification.

The results for the level of accuracy between the information requested by the user and the answers given by the system on the SVM model are 88.26%, while for the DNN model it was achieved 93.79%. From these results, can be seen that the DNN model has a higher level in providing the accuracy of the information requested by the user and the answers given by the system.

Furthermore, the success rate for the system to finding back information on the SVM model was achieved 99.22%, while the DNN model is 93.79%. This indicated that the SVM model has high success rate in recovering information from the input data compared to the DNN model. For the average value of Precision and Recall shown by F1-Measure on the SVM model is 93.42% and the DNN model is 93.79%. This shows that the average F1-Measure of the two models is not to much different, that is only 0.37%. For the ErrorRate of these two model is quite low, were only 11,96% in The SVM model and 10,63% in DNN model.

The comparison results of processing the SVM and DNN models using 70% training data and 30% testing data were visualized through the AUC-ROC curve which can be seen in Figure 12 below.



(a) (b)

Figure 12. *Graph of AUC-ROC (a) SVM Model and (b) DNN Model.*

The ROC curve as shown in Figure 12 above illustrates the comparison of the two classification models, in this study the SVM and DNN models. This curve is used as an indicator of accuracy to evaluate the performance of the two models. In Figure 12 part (a), it can be seen that the AUC SVM Model value obtained is 0.873. This value indicates that the accuracy of the test based on the AUC-ROC curve is classified as “good classification”. In Figure 12 part (b), it can be seen that the AUC DNN Model value obtained is 0.874. This value indicates that the accuracy of the DNN model test based on the AUC-ROC curve is also classified as “good classification”.

For the final report, based on the 2093 datasets tested using SVM and DNN models, this indicated that the Indonesian tourism promotion strategy by the Ministry of Tourism and Creative Economy through SNS Instagram has been successfully implemented as a push and pull factor for someone to travel. Overall, the results of the evaluation in this research show that the SVM and DNN model has very good performance in classifying public sentiment on SNS media with an error rate below 12%.

CONCLUSION

The implementation of Machine Learning techniques with SVM and DNN Modeling for the classification of public sentiment in the SNS Instagram @indtravel content has been successfully done according to the research planning stages. Based on the results of the evaluation of the two models that have been implemented, it shows that the sentiment public for the SNS Instagram @indtravel content tends to be positive towards the push and pull factors for someone to take a tour. This shows that the Indonesian tourism promotion strategy by the Ministry of Tourism and Creative Economy through SNS Instagram has been successfully implemented as a push and pull factor for a somenone to travel.

Overall, both the DNN and SVM models in this research have an excellent performance where the accuracy rate is above 80% with the classification category based on the AUC-ROC curve as "Good Classification". But based on the results of the performance comparison between the SVM and DNN model, this shows that the SVM model is only higher in precision rate with a difference of 5,43% than DNN model. This indicates that the DNN model has a higher level of performance in Accuracy (89,37%), Precision (93,79%), F1-Measure (93,79%), ErrorRate (10,63%).

Based on these results, it is proven that the DNN model has a very good performance in classifying public sentiment on SNS media compared to the SVM model. Future research is expected to use more data to improve the performance of the SVM and DNN classification models. In addition, further research is also expected to be able to use better feature extraction methods so it can be used to reduce the error rate in the classification process.

REFERENCES

Arham, A. Z. (2018). *Klasifikasi Ulasan Buku Menggunakan Algoritma Convolutional Neural Network – Long Short Term Memory*. repository.its.ac.id/51134/1/06111340000118-Undergraduate_Theses.pdf

Ariadi, D., & Fithriasari, K. (2015). Klasifikasi Berita Indonesia Menggunakan Metode Naive Bayesian Classification dan Support Vector Machine dengan Confix Stripping Stemmer. *JURNAL SAINS DAN SENI ITS Vol. 4, No.2*. DOI: 10.12962 / j23373520.v4i2.10966

Assuja, M. A., & Saniati, S. (2016). Analisis Sentimen Tweet Menggunakan Backpropagation Neural Network. *Jurnal Teknoinfo*. https://doi.org/10.33365/jti.v10i2.20

Chy, A. N., Siddiqua, U. A., & Aono, M. (2018). Neural Networks and Support Vector Machine based Approach for Classifying Tweets by Information Types at TREC 2018 Incident Streams Task. *Trec*. https://trec.nist.gov/pubs/trec27/papers/KDEIS-IS.pdf

Dos Santos, C. N., & Gatti, M. (2014). Deep convolutional neural networks for sentiment analysis of short texts. *COLING 2014 - 25th International Conference on Computational Linguistics, Proceedings of COLING 2014: Technical Papers*.

https://www.researchgate.net/publication/274380447_Deep_Convolutional_Neural_Networks_for_Sentiment_Analysis_of_Short_Texts

Giddy, J. K. (2018). Adventure tourism motivations: A push and pull factor approach. *Bulletin of Geography*. https://doi.org/10.2478/bog-2018-0030

Gorunescu, F. (2011). Data mining: Concepts, models and techniques. *Intelligent Systems Reference Library*. https://doi.org/10.1007/978-3-642-19721-5

Gupta, A., Bakshi, S., & Dogra, N. (2018). Engaging consumers in the digital era: An analysis of official tourism Facebook pages in India. *Tourism*, *66*(1), 63–77. https://www.researchgate.net/publication/325286287_Engaging_consumers_in_the_digital_era_An_analysis_of_official_tourism_Facebook_pages_in_India

Gururaja, R. (2015). Impact of Social Media on Tourism and Hospitality. *Sastech Technical Journal of RUAS*. https://www.researchgate.net/publication/270393508_Impact_of_Social_Networking_ Sites_on_Hospitality_and_Tourism_Industries_Impact_of_Social_Networking_Sites_on_Hospitality_and_Tourism_Industries

Huang, Y. A., You, Z. H., Chen, X., Chan, K., & Luo, X. (2016). Sequence-based prediction of proteinprotein interactions using weighted sparse representation model combined with global encoding. *BMC Bioinformatics*. https://doi.org/10.1186/s12859-016-1035-4

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*.

https://doi.org/10.1016/j.bushor.2009.09.003

Katsikari, C., Hatzithomas, L., Fotiadis, T., & Folinas, D. (2020). Push and pull travel motivation: Segmentation of the greek market for social media marketing in tourism. *Sustainability (Switzerland)*. https://doi.org/10.3390/su12114770

Khuong, M. N., & Ha, H. T. T. (2014). The Influences of Push and Pull Factors on the International Leisure Tourists' Return Intention to Ho Chi Minh City, Vietnam — A Mediation Analysis of Destination Satisfaction. *International Journal of Trade, Economics and Finance*. https://doi.org/10.7763/ijtef.2014.v5.421

Kowsari, K., Meimandi, K. J., Heidarysafa, M., Mendu, S., Barnes, L., & Brown, D. (2019). Text classification algorithms: A survey. In *Information (Switzerland)*. https://doi.org/10.3390/info10040150

Nomleni, P. (2015). Sentiment Analysis Menggunakan Support Vector Machine (SVM). *Seminar Nasional Teknologi Dan Komunikasi 2015*, *2015*(Sentika), 1–8. http://repository.its.ac.id/41821/1/2213206717-Master%20Thesis.pdf

Qian, J., Niu, Z., & Shi, C. (2018). Sentiment analysis model on weather related tweets with deep neural network. *ACM International Conference Proceeding Series*. https://doi.org/10.1145/3195106.3195111

Qian, L. I., Peng, H., Jianxin, L. I., Congyin, X. I. A., Lifang, H. E., Lichao, S. U. N., Yang, R., & Philip, S. Y. U. (2020). A Survey on Text Classification: From Shallow to Deep Learning. In *arXiv*. https://arxiv.org/pdf/2008.00364.pdf

Ramadhani, A. M., & Goo, H. S. (2017). Twitter sentiment analysis using deep learning methods. *Proceedings - 2017 7th International Annual Engineering Seminar, InAES 2017*. https://doi.org/10.1109/INAES.2017.8068556

Siregar, R. R. A., Sinaga, F. A., & Arianto, R. (2017). Aplikasi Penentuan Dosen Penguji Skripsi Menggunakan Metode TF-IDF dan Vector Space Model. *Computatio : Journal of Computer Science and Information Systems*. https://doi.org/10.24912/computatio.v1i2.1014

Sudiantoro, A. V., & Zuliarso, E. (2018). Analisis Sentimen Twitter Menggunakan Text Mining Dengan Algoritma Naïve Bayes Classifier. *Prosiding SINTAK 2018*. https://www.unisbank.ac.id/ojs/index.php/sintak/article/view/6649

Susanti, N. D., Sediyono, E., & Sembiring, I. (2016). Uji Perbandingan Akurasi Analisis Sentimen Pariwisata menggunakan Algoritma Support Vektor Machine dan Naive Bayes. *Nusantara of Enginering*. https://ojs.unpkediri.ac.id/index.php/noe/article/view/12338

Tripathi, P., Vishwakarma, S. K., & Lala, A. (2016). Sentiment Analysis of English Tweets Using Rapid Miner. *Proceedings - 2015 International Conference on Computational Intelligence and Communication Networks, CICN 2015*. https://doi.org/10.1109/CICN.2015.137

Wang, W., & Tang, Y. (2016). *Improvement and Application of TF-IDF Algorithm in Text Orientation Analysis*. https://doi.org/10.2991/amsee-16.2016.61

Ye, J., Ren, H., & Zhou, H. (2015). *An IG-RS-SVM classifier for analyzing reviews of E-commerce product*. *Icitmi*, 601–606. https://doi.org/10.2991/icitmi-15.2015.98