IJCRT.ORG ISSN : 2320-2882
INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Machine learning-based classifiers in evaluating students' emotions

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Abstract: The dynamics of information technology has changed the way of thinking in life patterns, which originally carried out activities not yet using information technology but now in various layers must use information technology. The use of information technology can be applied in the field of education, where education is the right area to be targeted in the use of information technology. In the learning process carried out between students and lecturers, lecturers must be able to understand students' feelings or emotions verbally and nonverbally. In previous studies measuring the emotional level of students carried out during the learning process by using questionnaires. But this questionnaire will not be able to capture the emotional message of students in the learning process. We propose to use sentiment analysis to measure the emotional level of students in the learning process such as the preparation of the final assignment (TA). The sentiment analysis we use utilizes several methods of machine learning such as naïve Bayes (NB) and k-Nearest Neigbors (k-NN). In this study we have several stages such as: first, collecting data about the opinions of each student's emotional. Second, we will conduct training data with NB and k-NN in measuring the emotional level of students. Third, we will compare methods to determine which method is best used to measure student emotional. The results obtained provide information, that k-NN is a good algorithm in evaluating student emotions based on text with an accuracy value of 86%.

***Index Terms* - emotions, evaluation, machine learning classifiers.**

I. INTRODUCTION

Information technology has a great opportunity value in the world of education, the dissemination of information is very rapid and very useful for its users [1], [2]. The development of Information Technology is supported by the lives of everyone who wants to use it in helping solve existing problems. Some layers that use information technology as in the field of education, with better utilization, the results will be very good [3]–[5]. Information plays an important role in an organization for the survival of an organization that specifically underlies decision making at the tactical level and strategic decisions. Decision-making systems are used in an institution to get the best steps in choosing information that will be used in development. Today's universities must be able to utilize information technology in the process of learning and learning. The number of students is increasing, demanding that universities really take full advantage of information technology. By preparing all qualified resources, the learning and teaching process will definitely become better and superior.

In developing a very good learning process, this is inseparable from the activities of lecturers and students who always uphold the concept of learning. In developing and making a university become superior, it will require an evaluation of the learning process. This learning process is the focus of the research that we are going to do, we try to focus on the lecturers. With the aim to see the extent to which the lecturer is able to understand the emotional level of the student in the learning process, do students understand the material conveyed with pleasure and happiness or otherwise students do not understand the material conveyed with a sense of unhappiness, bored or angry.

Education is a means of conveying knowledge and establishing communication between students and lecturers [6]. Lecturers must be able to know the ability of each student, so that in the delivery of material all students in a class can understand [7], [8]. According to Yeh [9] and Maaret [10] in building the learning process conducted by lecturers to students must be based on collaboration (communication) so that in the end the learning process will succeed. Lecturers must be able to provide an overview of the knowledge that will be given to students. It was also added by the opinion of Šumak [11]–[13] to build a good learning process, the lecturers to create study groups. The purpose of forming this learning group is to make students easier to communicate with their members in groups and fellow members in the group can also provide motivation to other members, so that other members can feel the meaning of a learning process [14]–[16]. Combining the three previous studies, Islam [17] modelled the learning process using the Technology Acceptance Model (TAM) method. Based on the TAM model, researchers include students who understand about the material taught into groups that the contents of participants from the group do not understand the material [18]. The researcher then measures the evaluation of learning that has been done by giving questionnaires to the students. The evaluation results obtained can provide information to the instructor to what extent the evaluation of the learning process has been carried out.

Previous research has evaluated the learning process, but the evaluation process carried out in previous studies only focused on the use of questionnaires and TAM models. Questionnaires are classic or old models in evaluating the learning process. Whereas TAM is a model used to make an analysis of the level of satisfaction in a diagram. Another failure in the questionnaire is that it cannot capture information about the responses of students during the learning process. We think that research based on questionnaires cannot provide good conclusions about the results of the evaluation of the learning process. The results of the evaluation of the learning process carried out by lecturers cannot be used as an indicator that the learning process is better.

We capture the information that in the previous study it was not able to capture, how emotional the level of students during the learning process. In this study we propose to use sentiment analysis to evaluate the emotional level of students towards the learning process carried out by lecturers. But the learning process referred to in this study is like the preparation of a final assignment. In utilizing sentiment analysis, we need methods that can help separate the emotional level of students. The method is machine learning based which consists of unsupervised learning and unsupervised learning.

As the end of the study to evaluate the final assignment writing process conducted by lecturers, we propose to use lexicon based (unsupervised learning), naïve bayes and logistic regression (supervised learning). In this study we have contributed or as output targets as follows: (1) we propose to evaluate student opinion during the learning process as a new discussion within the USNI. Second, the purpose of the proposal is based on the data we get from student responses during the learning process

The writing structure of the research proposal is as follows: in the second section, we provide information about the research that is reflected in the research strategic plan. In the third section we provide information about the literature review (reference) used in helping research writing. In the fourth section, we provide information about what methods will be used in the study. In the fifth section, we provide information about the schedule of research to be conducted.

II. RELATED WORK

Information technology plays an important role in the life of an education throughout the world. This role becomes very important, because it will support and help all activities carried out by users [19]. The use of computers in the field of education has a very large contribution in the learning process that occurs between students and lecturers [20]. Computers are a very good medium in helping the learning process, where interactions that occur will produce benefits [21], [22]. The maximum benefit obtained in the learning process is the increasing experience for students in getting knowledge. Interactions that occur between lecturers and students are said to be collaborative learning [23]. Collaborative learning has a goal as a good interaction between students and lecturers, where interactions between students and lecturers can be effective in the learning process [24].

To help improve the learning process, lecturers must be able to provide information and deliver good and interesting lecture material to students. The goal is that students become comfortable and understand the material presented by the lecturer. The lecturer can also be said as the main key in the learning process, where the lecturer must understand all the material that will be delivered to students. So that in the future students will not complain with the delivery of the material provided.

In the learning process there is a condition where students will be able to receive knowledge by feeling happy, happy, bored or unhappy. This is because students have different conditions and students will more easily understand the knowledge in the learning process if the material conditions presented are easy to understand [25]. Feelings of happiness and unhappiness are felt by students during the learning process, usually not directly delivered to the lecturer, but the student will deliver it on social media, such as twitter, Facebook etc. [26]. The information conveyed in a social media is called opinion [27]–[29]. This concept is also called opinion mining which comes from the sentiment analysis section.

Sentiment analysis has become very well known, because with sentiment analysis can extract opinions from sentences delivered by users (users) [30]–[32]. Information about textual originating from text or sentences is broadly divided into two main parts, namely facts and opinions. Facts provide objective information about opinions, while opinions are information that is in a sentence or text that will give a picture of "feelings or emotions" [33]. In sentiment analysis, feelings or emotions focus on positive values, negative and neutral opinions, and some research after that adds some emotional feelings such as sadness, happiness (happy), joy (very happy), angry (angry), disappointed (disappointed) and others [34]. Ali [31] provides an overview of the taxonomy of sentiment analysis.

Sentiment analysis is divided into two, opinion mining and also emotion mining. The opinion mining section consists of three parts, subjectivity detection, opinion polarity classification and others such as opinion spam detection, opinion summarization and the expression detection argument. Subjectivity detection works to detect a text or sentence containing subjective or objective information. The Opinion polarity classification works to detect a text or sentence containing positive or negative or sometimes neutral information. Opinion spam detection works to detect false opinions about information that is popular. The emotion mining section consists of several parts such as: emotion detection, emotion polarity classification, emotion classification and emotion cause detection. Emotion detection explains the presence of emotional feelings (emotion) in text or sentences. The Emotion polarity classification concept is the same as opinion polarity classification. Emotion classification explains the existence of several emotional feelings (emotion) in text or sentences.

From the information obtained, various emotional types in the form of student opinions can be seen on social media, they convey various opinions related to the learning process. Therefore, in this study we focus on evaluating the feelings of students (opinions) during the learning process. With a number of opinions to be obtained, we will make an analysis using the concept of sentiment analysis.

III. METHODOLOGY

In this section we will explain how machine learning algorithms classify data. To classify data, machine learning algorithm has several stages, opinions pre-processing, feature extraction, and opinion classifiers. Meanwhile, the stages in classifying the data will is shown in Figure 1.

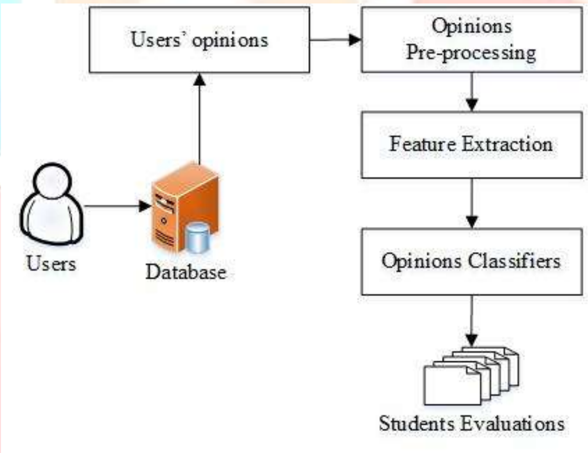

Figure 1. Classification Model

a. Opinion Pre-processing

This section removes some identities from a text, where the identity is HTML decoding, remove stop words, and remove bad characters in opinion.

b. Feature extraction

To select features, we will extract data from the features of student opinion results that will be more effective. Then we will analyse and evaluate the results of student opinions to identify "feature words". To extract this data, we use the term frequency inverse document frequency (TF-IDF). TF-IDF is a method used to calculate the weight of each word that is most commonly used in data classification. This method is known to be effective, efficient, and easy to use. This method will calculate the value of TF and IDF on each data (text) in each body. Where is the metric of the TF-IDF especially as $Wdt = tfdt * I$, where, d describes the document to - d, t describes the word in the text - t from the keyword, W describes it as weighting the document to - t to the word in the text to - t, tf describes as the number of words in the text searched in the document (W), while the IDF describes the results of the process from $IDF = log2\frac{d}{df}$.

c. Opinions classifiers

In this study we will select opinion data for training (training) as much as 70% and as much as 30% taken as testing data (testing). In classifying data, we will do testing for 10 times by utilizing the fold cross validation. Fold cross validation is an algorithm used in iterating data classifications. Each iteration will produce different results, and the results obtained from the two algorithms will also be different. Following this we will explain the algorithm that we use in classifying data.

1. Naïve Bayes (NB)

Given the test description of the document d of an opinion represented by the vector $< w_1, w_{2,} \ldots \ldots, w_m >$, to classify the document d, MNB is defined as:

$$C_{NB^{(d)}} = P(c) \prod_{i=1}^{n} P(w_i|c)^{fi} \quad \text{(Eq. 1)}$$

where, $P(c)$ is a prior probability that a document d belongs to class c, n is a number of the features, $P(w_i|c)$ is the conditional probability that a word w_i occurring in the class c, w_i is the word feature occurred in d, fi is the number of frequency count of a word w_i in reporting d, and $C_{MNB^{(d)}}$ is the class label of d predicted by the classifier [35].

2. K-Nearest Neighbors (K-NN)

K-NN is a one of the simple and effective non-parametric technique commonly used for data classification [36]. For classification, K-NN transforms the target opinions into reflectional features vector that has same formations with the training data samples [37]. Then, K-NN computes the distance between the target opinions and selected k neighbors [38]. The distance between opinions is illustrated as:

$$Sin(o_i, o_j) \frac{\sum_{k=1}^{M} W_{ik} x\, W_{jk}}{\sqrt{(\sum_{k=1}^{M} W_{ik}^2)(\sum_{k=1}^{M} W_{jk}^2)}} \quad \text{(Eq. 2)}$$

Choose the nearest distance k neighbors as the reference opinions, in which category C_j that have contents most neighbors can be finding as:

$$p(\bar{x}, C_j = \sum_{\bar{o}_i \in K-NN} Sim(\bar{x}, \bar{o}_i) y(\bar{o}_i, C_j) \quad \text{(Eq. 3)}$$

where, $\bar{o}_i$ is the ith opinions, $Sim(\bar{x}, \bar{o}_i)y(\bar{o}_i, C_j)$ represents the similarity of opinions θ and the documents b, whereas, $y\ (\theta, \omega)$ describes the probability of opinions θ belongs to category ω.

IV. RESULTS AND DISCUSSION

This section will explain the results of the research that has been done in evaluating student opinions regarding the learning process which is assisted by a lab assistant. The results of data classification carried out by naïve Bayes and logistic regression are then calculated using several techniques, such as: precision, recall, F1 and accuracy.

TABLE 1 DATA CLASSIFICATION RESULTS FROM NAÏVE BAYES (NB)

Fold (#)	Accuracy (%)	Recall (%)	Precision (%)	F1 (%)
1	87.98	85.95	86.01	85.24
2	87.79	87.77	85.41	83.03
3	89.12	87.87	83.60	86.83
4	87.65	86.71	85.21	84.34
5	85.94	84.53	83.60	84.06
6	83.53	85.63	85.61	83.81
7	82.65	85.54	83.44	83.92
8	85.71	86.50	82.75	84.15
9	85.41	85.67	86.43	83.04
10	83.29	85.77	86.67	83.08
Average	85.91	86.19	84.87	84.15

In the precission section, k-NN displays the results of 84.87% and NB 82.02% with a difference in value of 2.85%. Whereas in section F1, k-NN displays the data classification results of 84.15% and NB displays results of 82.51% with a difference in value of 1.64%. Based on the results of data classification that has been done by both methods, the biggest difference in value occurs with accuracy. In Figure 2, there are steps in fold (#) in classifying data.

After classifying student opinion data, then we will calculate how much the percentage of positive and negative values of student opinion is in the learning process (preparation of the final assignment) assisted by the supervisor. The results obtained were 1,372 students giving positive opinions (40%) and 2031 students giving negative opinions (60%), this can be seen in Figure 5.2. To prove this result we will present a portion of the opinions of students regarding the learning process.

TABLE 2 DATA CLASSIFICATION RESULTS FROM LOGISTIC REGRESSION (LR)

Fold (#)	Accuracy (%)	Recall (%)	Precision (%)	F1 (%)
1	80.32	83.41	79.01	81.15
2	83.84	84.42	84.90	84.66
3	81.20	83.47	81.63	82.54
4	80.59	84.09	80.52	82.27
5	80.88	83.43	81.13	82.27
6	81.47	84.26	82.06	83.14
7	80.88	83.20	81.87	82.53
8	79.71	80.31	81.71	81.00
9	80.00	79.32	83.88	81.54
10	82.35	84.39	83.52	83.95
Average	81.12	83.03	82.02	82.51

In the precission section, k-NN displays the results of 84.87% and NB 82.02% with a difference in value of 2.85%. Whereas in section F1, k-NN displays the data classification results of 84.15% and NB displays results of 82.51% with a difference in value of 1.64%. Based on the results of data classification that has been done by both methods, the biggest difference in value occurs with accuracy. In Figure 2, there are steps in fold (#) in classifying data.

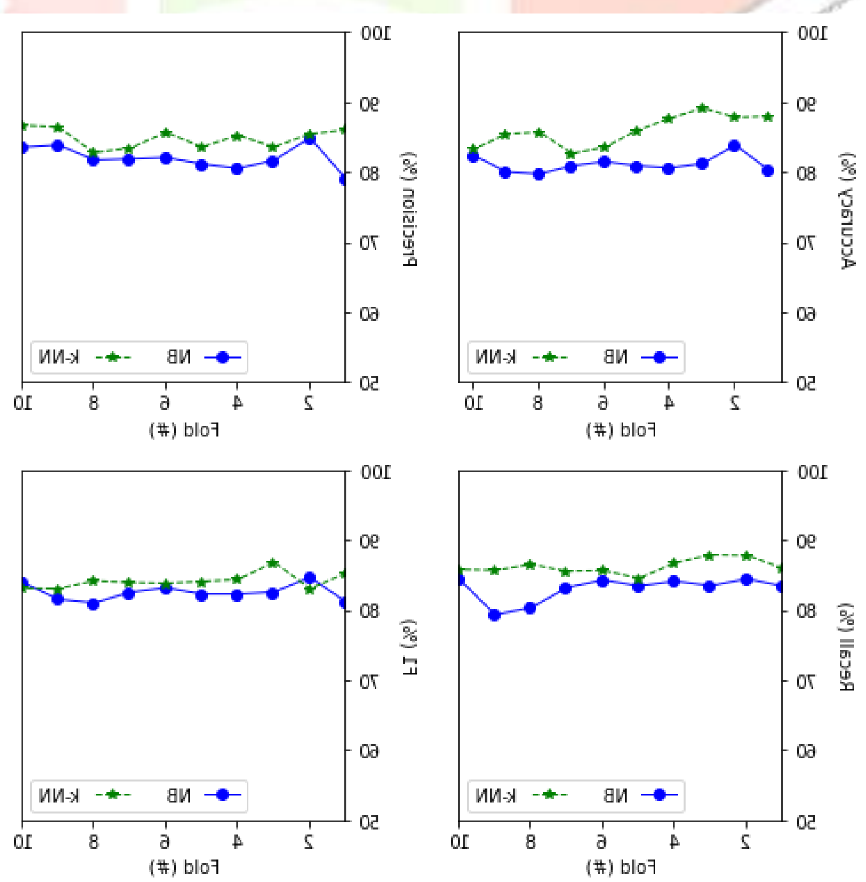

Figure 2. Results of fold (#) of two different methods Classification Model

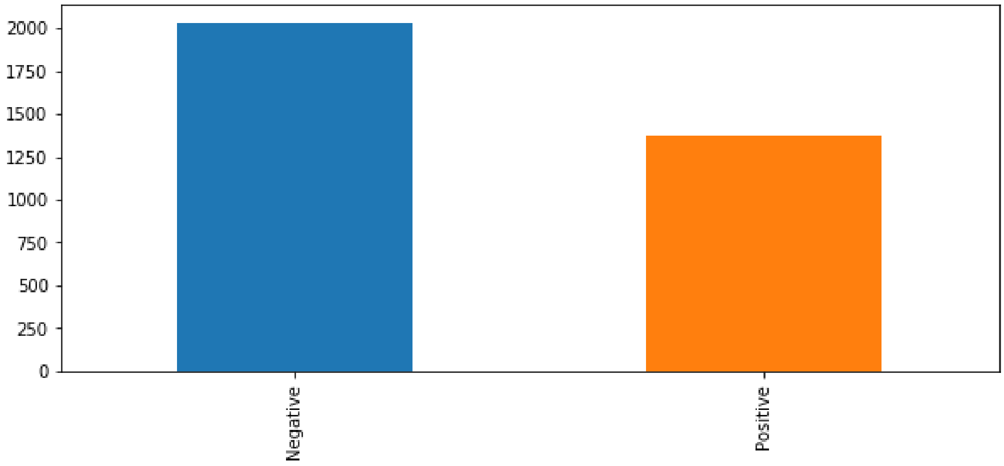

Figure 3. Results of classification of student opinion data

V. CONCLUSION

In this study, we utilized 2 methods of machine learning, namely k-nearest neighbors (k-NN) and naïve bayes (NB) to classify student opinion data during the learning process (preparation of final assignments) conducted by academic supervisors. The results obtained showed results, that more than 50% of students expressed negative opinions during the learning process and only 40% of students gave positive opinions. The results obtained conclude that during the learning process supervisors still have not made a very good contribution in conveying information and to correct some negative opinions from students, in the future we will choose to provide technical guidance to the supervisor so that information can be easily understood by students. Then, we will continue to evaluate this learning process by adding a method that is currently famous, namely deep learning. We will do a comparative process between machine learning and deep learning; which algorithm is the best in classifying student opinion data.

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