Analyzing Stance and Topic of E-Cigarette Conversations on Twitter: Case Study in Indonesia

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***Abstract*—To control the use of e-cigarette, Indonesia plan to establish a regulation that embodies all the concerns, sentiments, and opinions of public This study aims to identify public opinions in social media Twitter by classifying tweets into group in *favor* or *against* e-cigarette and explore dominant topics of each group. This research obtained 15,373 tweets between June 2019 – May 2020 that is classified into 4 labels: *Against*, *Favor*, *Neutral*, and *Irrelevant*. The best model was selected with specification: 3 features (Count, Unigram, and Bigram), Logistic Regression algorithm, and three-stage classification pipeline (F1-score = 0.807). As for topic modelling, corpus *Against* and *Favor* are used to retrieve dominant topics. We chose *Non-negative Matrix Factorization* algorithm with k=6 and achieve high coherence scores, which are 0.962004 for corpus *Against* and 0.999736 for corpus *Favor*.**

Keywords*— *stance detection, topic modelling, text mining, classification method, e-cigarettes, vape.

I. Introduction

Indonesia is one of the countries with the highest smoking rates: 28.9 % of population, which means around 77 million people in Indonesia are categorized as active smokers [1]. This number will potentially increase as World Health Organization (WHO) projects that in 2025 around 45% of population (approximately 97 million people) will be smokers [2]. On 2017, WHO reports that tobacco already have killed 225.720 people in Indonesia and have 14.7% contribution of all deaths [3]. The combustion of toxic tobacco from conventional cigarettes, which is related to many dangerous diseases, makes electronic cigarettes (e-cigarettes) commonly used as a substitute for conventional cigarettes. E-cigarettes vaporization technology helps users to mimic the smoking of tobacco without igniting the carcinogens found in tobacco [4]. E-cigarettes have often been marketed and viewed as a less toxic alternative to conventional cigarettes and as a way of quitting smoking despite little awareness of short-and long-term health effects or a broad public health effect due to high levels of concurrent use of e-cigarettes and conventional cigarettes [5].

It is not yet precisely known whether e-cigarettes are safer than conventional cigarettes, or whether they are just a way to establish nicotine addiction, and therefore a path leading non-smoker to conventional cigarettes habit [6]. Most of the available studies provide evidence that e-cigarettes are less harmful to smokers than conventional cigarettes. However, given that the number of long-term studies and mechanistic observations are still limited, it is likely that e-cigarettes could adversely impact the global population's disability-adjusted life years, resulting in higher disease burdens [7]. Besides its unknown health threats that still cause pros and cons, the rise of e-cigarettes has offered drug dealers the opportunity to grow their markets. They use e-cigarette liquids to illegally distribute and sell drugs. Misuse and lack of clarity about the side effects of e-cigarettes make some countries around the world establish regulations; some even prohibit them completely [8].

The use of e-cigarettes in Indonesia needs to be highly concerned since the number of users keep increasing every year, where most of e-cigarettes smokers are in the age of 10 -18 years old with 10.9% on 2018 [1]. High use of e-cigarettes increased the potential of misuse, addiction, and other dangerous health problems at a very young age. As a result, several health organizations and communities in Indonesia are urging the Ministry of Health to develop regulation on e-cigarettes. [8]. According to Indonesia Food and Drugs Administration (BPOM), e-cigarettes regulation should cover the rule about distribution, liquid ingredients, usage environment, and advertising [8].

Currently, Indonesia already has PP No. 109/2012 about 'Safeguarding Materials Containing Addictive Substances in the Form of Tobacco Products for Health' which does not mention regulation about e-cigarettes. Ministry of Health has been planning to revise this regulation since 2018 but there is no significant progress because there are so many obstacles, concerns and disagreements showed by the parties. Some party support to ban entirely since it is a danger to people's health, some concerning that regulation could impact to country's financial since e-liquid on e-cigarettes have become the most profitable business [9].

Understanding the concerns, sentiments and opinions of public is crucial to create a successful regulation, that will be followed by all of parties. Traditionally, more opinions are needed to help decision-making and usually these are investigated by survey research that could be costly, time-consuming, and ill-suited to rapidly changing environment [10]. Alternatively, social media analysis offers online content that expresses health-related attitudes and perceptions [10]. Twitter is one of the most popular social media with 22.8 million users in Indonesia [11] which can play an important role in shaping the public's attitudes towards emerging issues and can be used by communicators to gauge public knowledge and inform initial response strategies [12]. In addition, the public may depend even more on the information provided by social media outlets if there is doubt about the regulations, policies, and long-term effects of a new product, such as e-cigarettes.

Text mining, or text analytics, is one of social media analytics technique to extract useful information to see pattern of a condition or phenomena. Stance detection is the task of automatically deciding from the text whether the author of the text is in favor of, against or neutral towards a target. Stance detection can be combined with topic modelling to get more insights related to topics that are discussed and concerned by public. This paper employ text mining techniques to analyze people's perception and explore discussion topics toward e-cigarettes in Twitter to provide

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more insights and suggestion into how the regulation should be established. We experimented and observed multiple scenarios and stages to get the best outcome of stance detection and topic modelling, Stance detection is divided into 3 main processes: feature selection, classification algorithm selection, and pipeline selection. Topic modelling is divided into 2 main processes: algorithm selection and topic analysis on each corpus.

This research paper is organized into 6 sections: 1) Introduction, to explain why the study is conducted; 2) Literature Review, to explain about relevant theory used in this research; 3) Methodology, to describe methodology adopted to this research; 4) Result and Analysis, to show result of stance detection and topic modelling 5) Conclusion and Future Work; and 6) References.

II. Related Work

Stance is one's position or standing points towards a target, i.e., person, objects, ideas, or opinions [13]. Position can be:

- *Favor*: directly or indirectly by supporting someone/something, by opposing or criticizing someone/something opposed to the target, or by echoing the stance of somebody else
- *Against*: directly or indirectly by opposing or criticizing someone/something, by supporting someone/something opposed to the target, or by echoing the stance of somebody else
- *Neutral*: standing in neutral position, or not clearly expressing the stance within the passage

Stance detection is part of opinion mining that determine whether the author of a text is supporting, against, or neutral towards a defined target. The target may be a person, an organization, a government policy, a movement, a product, etc. [14]. Stance detection is like, but different from, sentiment analysis. Sentiment analysis tasks are formulated to determine whether the text is positive, negative, or neutral, or to assess from the text the opinion of the speaker and the intent of the opinion. However, in the case of stance detection, the systems are constructed to decide the preference for the given (pre-chosen) target of interest, which could be mentioned explicitly [14].

Topic modelling is used to uncover the hidden thematic structure of document collections by grouping a document/text based on topics [15]. Topic modelling uses clustering method, which is one of unsupervised learning where dataset does not have labels. Some algorithms can be used to implement topic modelling such as Latent Semantic Analysis (LSA), Latent Dirichlet Allocation (LDA), Non - Negative Matrix Factorization (NMF), K-Means, and Fuzzy C-Means

A lot of research regarding e-cigarettes using social media analysis method have been conducted yet not many of them use stance detection approach. Lazard et.al [12] classified conversations in Twitter into 9 topics to reveal intial reactions using clustering whether the FDA's e-cigarette regulations will benefit or harm public health and then manually determine sentiment of each tweet on every topic cluster. Here we adopted topic modelling approach, but instead of using sentiment analysis, we determined user's tendency towards e-cigarette using stance detection.

Jannati, et.al [13] used stance to determine whether the writer of the blog article is on the position supporting a political figure to compete and win in a general election by performing experiment using five different case studies. Sobhani, et. al [14] determined both stance and sentiment of tweets and their interaction. They found that while sentiment features are useful for stance classification, they alone are not sufficient. Multi phase approach in stance detection is done by Dey et.al using two-phase feature-driven model which proves significant performance compared to baseline model [16]. First, the tweets are classified as neutral vs. non-neutral. Next, non-neutral tweets are classified as positive vs. negative. Here, we use three phase approach in experiment.

Godea et.al [6] combined multiple combination of features and use them in conjunction with supervised machine learning classifiers (SVM, Naïve Bayes, and Random Forest). The features combination showed more effective than the traditional features for e-cigarettes sentiment classification. So, in this research we also observed multiple combination of features and comparing their performance against single features.

Cole-Lewis, et.al [17] use 5-category content analysis which exclude irrelevant tweets. Relevant tweets classified according to sentiment, user description, genre, and theme using descriptive analysis. They found that 71% of the sample tweets were classified as having a positive sentiment.

Topic modelling approach to help government create effective decision and policies related to e-cigarette content is successfully implemented by Yongcheng Zhan, et.al [18]. They use LDA algorithm and found four types of topics across Reddit, Twitter, and JuiceDB platforms. We also used LDA algorithm, then compare its performance to NMF algorithm.

III. Methodology

After researching several related works to find the best method, in this section we explain steps of this research from data acquisition from Twitter, data preprocessing, and implementation of stance detection and topic modelling.

A. Data Acquisition

We use twitter data as main source in this research. We collected 15,373 tweets between June 2019 – May 2020 based on these keywords: *rokok elektrik (e-cigarette), aturan vape (vape's rule), regulasi vape (vape regulation), vape aman (safe vape), vape boleh (allow vape), vape bahaya (vape danger), pemerintah vape (government vape), #FatwaHaramVape (haram fatwa vape), larang vape (ban vape), and #VapeMahalApaGunanya (expensive vape what's the point)* using Twitter API. Data are labeled into Relevant/Irrelevant, Subjective/Neutral, and Favor/Against with below details:

1) **Relevant/Irrelevant**
   Relevant: Tweets related to e-cigarettes in Bahasa and with actual meaning (not metaphore)
   Irrelevant: Tweets which are not related to e-cigarettes, tweets with metaphore meaning, tweets

in other language (not in Bahasa), and tweets mentioning location other than Indonesia

2) **Subjective/Neutral**
Relevant tweets are classified into 2 categories
Subjective: Tweets with subjectivity that has tendency to support or against E-cigarettes
Neutral: Tweets that does not have any tendency or not expressing author's stance

3) **Favor/Against**
Subjective tweets are classified into 2 categories
Against: All tweets related to e-cigarettes that show critics, disagreement, and on the opposite side of other people that shows support (direct/indirect)
Favor: All tweets related to e-cigarettes that show support, acceptance, and on the same side of other people that shows support (direct/indirect)

Total 8079 random tweets are manually annotated by 3 different annotators: 2 annotators for independent labelling, 1 annotator for final justification. We receive ''very good" inter-annotator agreement using Cohen's Kappa measurement [19], which is Ꝁ=94%. Label distribution and sample tweet is showed in Table I.

TABLE I. LABEL DISTRIBUTION AND SAMPLE TWEET

Label	#Tweets	Sample Tweets (Translated)
Against	1832	It is right if vape is banned, to save lives, please don't be stubborn!
Favor	2014	Naturally, vape is not dangerous. I vape and my lung is clean, everything is clean
Neutral	449	Latest research on e-cigarettes, its harms and benefits
Irrelevant	3784	Erdogan banned e-cigarette factories from producing in Turkey.

TABLE II. LABELING PHASE ON EVERY STAGE

Stage	Label
One-Stage	Phase 1: Against/Favor/Neutral/Irrelevant
Two-Stage	Phase 1: Relevant/Irrelevant Phase 2: Against/Favor/Neutral
Three-Stage	Phase 1: Relevant/Irrelevant Phase 2: Subjective/Neutral Phase 3: Against/Favor

B. *Data Preprocessing*

Before transforming corpus to numerical representation, we are pre-processing data set to clean human-generated text. We follow 7 steps of preprocessing, which are:

1) Remove punctuation and irrelevant characters (i.e., rt, via, hash tag, mentions)
2) Remove emoticon, digit, and URL.
3) Remove elongated word.
4) Remove 'expression' word (i.e., hahaha, wkwkwk, hehe)
5) Remove duplicate words from every sentence.
6) Normalization and case folding. Normalization in this study use Indonesian lexicon built by Salsabila; et.al [20] with some modification.
7) Stemming and remove stopword using Sastrawi Library [21]

C. *Stance Detection*

We formulate the problem of classifying tweets containing e-cigarette conversations as stance detection task. The e-cigar tweet is annotated with one of 4 possible labels: favor, against, neutral, and irrelevant. We experiment using several classification algorithms, feature selection, and pipeline variations.

1) *Feature selection*: We conduct the experiment to select the best combination of features using Multinomial Naïve Bayes as baseline algorithm. The features being tested include bag of word, Term Frequency (TF), TF-IDF, N-Gram (Unigram and Bigram), and character vector.
2) C*lassification algorithms selection*: We perform text classification using four different classifiers, namely Multinomial Naïve Bayes, Support Vector Machine, Logistic Regression, and Random Forest [22].
   - *Multinomial Naïve Bayes (MNB)*: one of the classic variations of Naive Bayes for multinomial distribution results. It is commonly used as a baseline for text classification [23].
   - *Support Vector Machine (SVM)*: basic idea is to separate data into two classes by finding a hyperlane with the highest margin value [24].
   - *Logistic Regression (LR)*: regression classification method that connect one or more independent variable to predict a dependent variable [25].
   - *Random Forest (RF)*: ensemble Decision Tree that is created to get higher accuracy. Decision Tree is a flow diagram in form of tree that could classify data sample whose category is still unknown [26].
3) *Pipeline selection:* We compare whether breaking down the pipeline into two or three classification steps can improve the classifier performance. The detail of label annotation for each pipeline can be seen in Table II.: one-stage, two-stage, and three-stage.

We apply 10-fold cross validation in our experimental setting. In each experiment, we evaluate the model to see how accurate it predicts the stance label at every stage. The micro average precision, recall, and F1 of a model are computed to assess overall performance of the stance detector. Model with the best performance is used to generate the stance of unlabeled tweets.

D. *Topic Modelling*

We apply two topic modeling algorithms in our experiment

1) *Latent Dirichlet Allocation (LDA)*: is the most popular method of topic modelling because of its ability to analyze large-sized document. LDA is categorized as unsupervised modelling that can produce list of topics along with their word weights in every document using Dirichlet distribution [15].

2) *Non-negative Matrix Factorization (NMF)*: NMF basic idea is to transform high dimensional vector to lower dimensional vector. The advantage of NMF is we could easily configure input parameter [27].

Topic modelling is conducted in two separated tweets corpus, which are collection of tweets labeled as "favor" and "against". Coherence score is used to evaluate the model performance [28]. Dominant topics along with top 5 features and top tweet is generated to get better insights of data.

IV. Result and Analysis

In this section, we show our experiment results of stance detection and topic modelling of e-cigarettes tweets to find the best model performance.

A. Stance Detection

Result of stance detection is obtained by three experiments: feature selection, classification algorithm selection, and pipeline selection. After passing through these 3 processes, the best model of stance detection is applied and analyzed towards all tweets.

1) Feature Selection

In this section, we use single feature and combination of multiple features to be tested by baseline algorithm, Multinomial Naïve Bayes (MNB). The result reveals that combination of features generally increases model performance (Table III). We found that combination of features in Count, Unigram, and Bigram with *F1-micro average* = 0.761 gave the best performance result. So, this feature is selected to be tested onto the next experiment, classification algorithms selection.

TABLE III. Evaluation Metrics of Feature Selection

Feature	*F1- micro average*
Count	0.729
Unigram	0.728
Bigram	0.712
Char	0.683
Count + Unigram	0.751
Count + Bigram	0.730
Count + Char	0.720
Unigram + Bigram	0.725
Unigram + Char	0.739
Bigram + Char	0.665
Count + Unigram + Bigram	***0.761***
Count + Unigram + Char	0.733
Unigram + Bigram + Char	0.719

2) Classification Algorithms Selection

We use combination of feature count, unigram, and bigram to be tested against SVM, LR, and RF algorithm. Table IV shows the result of this experiment, which obtain that LR algorithm gave the better result, although not significantly, compared to other classification algorithm. Overall performance of all metrics (*precision, recall, and F1)* is slightly increasing, except for recall value in class *Favor* that decreased almost 10% and class Neutral's performance is relatively low, probably caused by imbalance dataset compared to other class (see Table I).

TABLE IV. Evaluation Metrics of Classification Algorithms Selection

Classification Algorithm	*F1- Score*				*F1- micro average*
	Favor	*Against*	*Neutral*	*Irrelevant*	
MNB	0.715	0.594	0.000	0.903	0.761
SVM	0.650	0.580	0.370	0.891	0.735
LR	***0.717***	***0.632***	***0.314***	***0.912***	***0.781***
RF	0.663	0.617	0.203	0.873	0.740

3) Pipeline Selection

The third experiment is *pipeline selection* between one-stage, two-stage, and three-stage classification (see result on Table V). One-stage classification model, which has the better performance on previous experiment, is used as baseline in this experiment. Its performance with *F1-micro average*= 0.740, is worst than both two-stage classification (*F1-micro average*=0.782) and three-stage classification (*F1-micro average*=0.807) performance. This shows that multi-stage classification increases model performance, which in this case, three-stage classification gave the best performance. All the models predict class *Favor, Against, and Irrelevant* well enough, with *F1-score* of is 0.774, 0,752, and 0.921 respectively. However class Neutral is still not predicted well yet, although its performance is slightly increased compared to the other scenarios. As mentioned before, this is caused by small data proportion of class Neutral (as minority class) that cause imbalanced dataset.

TABLE V. Evaluation Metrics of Pipeline Selection

Pipeline	*F1-Score*				*F1- micro average*
	Favor	*Against*	*Neutral*	*Irrelevant*	
One-Stage	0.717	0.632	0.203	0.873	0.740
Two-Stage	0.732	0.690	0.342	0.921	0.782
Three-Stage	***0.774***	***0.752***	***0.393***	***0.921***	***0.807***

Furthermore, we found that 55 of *Favor* data is wrongly predicted into *Against* and 36 *Against* data that is predicted into *Favor*. This mostly caused by sarcasm tweet that contain similar word with 'Against' data, such as *haram* (*forbidden)* and *aman* (*safe)*. Also this model has not handled sarcasm tweet that use punctuation or emoticon.

This research shows that feature selection, classification algorithms selection, and pipeline selection can improve model performance by almost 10%. Our experiment shows that the best model is obtained with spesification: combination of 3 features (Count, Unigram, and Bigram), Logistic Regression algorithm, and three-stage classification pipeline. We apply this model to predict unlabeled tweets. Total of 15,373 tweets and its distribution per month can be

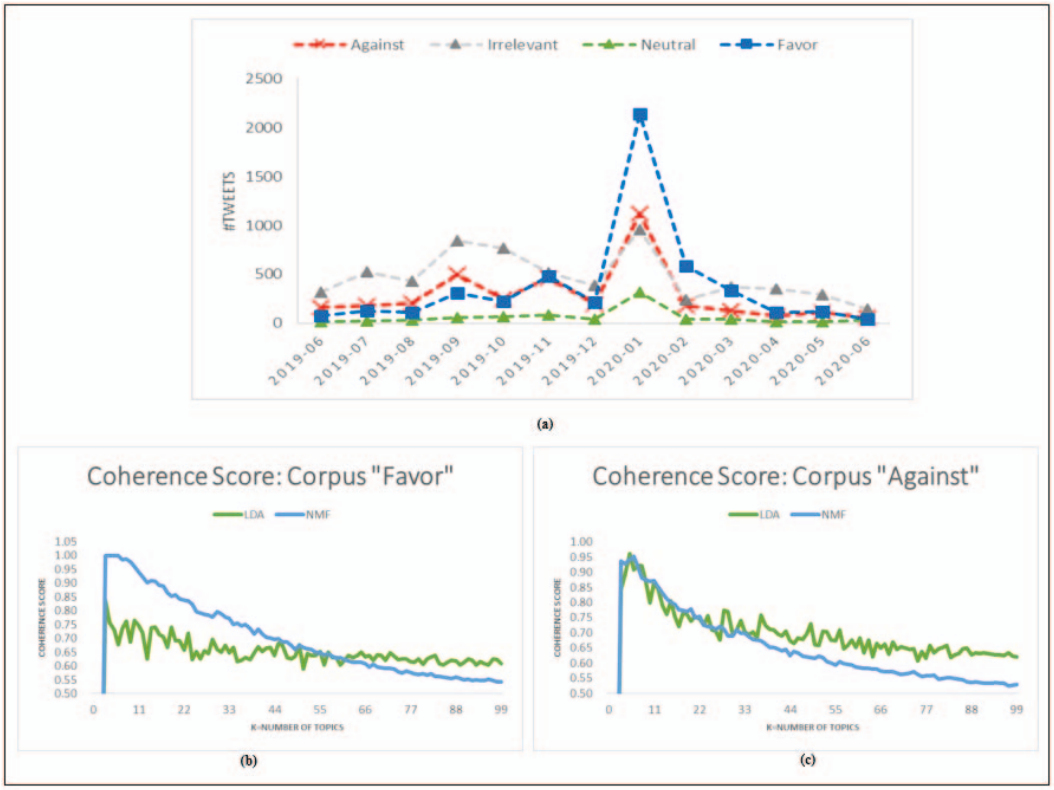

Fig. 1 (a) Data Distribution of Each Label; (b) Coherence Score for Corpus "Favor"; (c) Coherence Score for Corpus "Against"

seen on Fig. 1 (a). Almost each month shows that label *Favor* has the most number of tweets compared to label *Against*. This means that most tweets show support towards e cigarette's use, which is aligned with [10] that revealed majority tweets show positive sentiment toward e-cigarettes.

On Sep – Nov 2020, total tweets reach more than 1000 which is mostly containt irrelevant tweets because most tweets in this period discuss about deaths of vapers due to misuse of vape liquid in America. Total tweets of each month is significantly increasing on January 2020 (4535 tweets) after major Islamic organization in Indonesia, Muhammadiyah, released E-Cigaratte fatwa that declared E-Cigarette as forbidden or inviolable under Islamic law. Most tweets show massive rejection of this decision, which indicate public's positive tendency towards e-cigarettes (2140 tweets) compared to minority of those who support this fatwa (1122 tweets).

B. *Topic Modelling*

Experiment of topic modelling starts with algorithm and number of topic selection, to choose the most appropriate algorithm and total topics. Deeper analysis towards two corpuses, *Against* and *Favor*, is also conducted to get deeper meaning of dominant topics.

1) *Algorithm and Number of Topic Selection*

The next experiment in this research is to create topic modelling using class *Against* dataset (Corpus *Against*) and class *Favor* dataset (Corpus *Favor*). In this step, we calculate coherence score for each corpus using Sckit-learn (Fig. 1 (b) and Fig. 1 (c)). Experiment was executed by comparing coherence score between LDA and NMF algorithm in range of number of topics 3-99. In general LDA outperforms NMF as the number of topics getting higher, but NMF performs better with small number of topics especially on corpus *Favor*. On corpus *Against*, highest coherence score is obtained by LDA (0.962004) with 5 number of topics compared to NMF (0.951666) with 6 number of topics. This means LDA performance is only slightly better compared to NMF.

TABLE VI. SAMPLE TWEETS WITH INCORRECT CLASS CLASSIFICATION

Tweet	**Actual Class**	**Predicted Class**	**Remarks**
Betul ke hisap vape bahaya? Betul. (*Is it true that vape is dangerous? Yes*)	*Irrelevant*	*Relevant*	Tweet is in Malay's language
Vape dulu (*vape first*)	*Relevant*	*Irrelevant*	Short tweet
Netflix haram Vape haram Ayo apa lg? 😊 (*Netflix and ape are forbidden What's next?* 😊)	*Favor*	*Against*	Sarcasm tweet with emoticon
Katanya ya vape aman. Katanya aja sih…. (*They say vaping is safe. Just saying….)*	*Against*	*Favor*	Sarcasm

As for corpus *Favor*, highest coherence score is obtained by implementing NMF (0.999736) with 6 number of topics, which is significantly better than LDA's highest coherence (0.836772) with 3 topics. So based on this experiment we proceed NMF algorithm to the next analysis for both corpus.

2) *Analysis of Dominant Favor E-cigarettes Topic*

We conduct the analysis by generating top 6 topics along with their top 5 features and top tweet, revealed by corpus *Favor* (Table VII). Topics on corpus *Favor* e-cigarette tend to compare e-cigarette against conventional cigarette (Topic 1 and Topic 4) in terms of safety (Topic 3), health risk and preference (Topic 6). Public argue that e-cigarette can be a better substitution for conventional cigarette. Topic 2 examines public critisms toward e-cigarette fatwa declared by major Islamic organization in Indonesia, Muhammadiyah, that suggest to ban the use of e-cigarette. Another criticism has emerged, this time against the government's plan to increase e-cigarette's excise (Topic 5)

TABLE VII. TOPIC RETRIEVAL FOR CORPUS *FAVOR*

Topic	Top 5 Features	Top Tweet
Topic 1: E-Cigarette vs Conventional Cigarette	elektrik, konvensional, bakar, banding, sehat (*electric, conventional, burn, compare, healthy)*	Rokok Elektrik Dapat Mengurangi Bahaya Rokok (*E-Cigarettes can reduce the dangers of conventional cigarettes*)
Topic 2: E-Cigarette Fatwa	haram, fatwa, enak, Netflix, halal (*forbidden, fatwa, tasty, Netflix, halal)*	Semuanya aja haramkan pak!!! #FatwaHaramVape (*Everything is forbidden!!! #FatwaHaramVape*)
Topic 3: E-Cigarette safety	aman, banding, sehat, bilang, pakai (*safe, compare, healthy, say, use*)	Vape mah aman aja. (*Vape is safe*)
Topic 4: E-Cigarette vs Conventional Cigarette	bahaya, larang, bilang, orang, kandungan (*dangerous, ban, say, people, ingredients*)	Apakah vape lebih bahaya dari rokok? Enggak. Apakah rokok lebih bahaya dari vape ? Ya (*Is vape more dangerous than cigarettes? No. Is cigarettes more dangerous than vape? Yes*)
Topic 5: Taxation of E-Cigarette	cukai, pemerintah, naikin, regulasi, harga (*excise, government, increasing, regulation, price*)	Tolong ya buat Pemerintah jangan naikin juga cukai Vape, sudah 57% nih cukai Vape sekarang (*Please, for the government, don't increase the vape excise as well, it's already 57% now*)
Topic 6: E-Cigarette Preference	ngevape, pakai, liquid, nikotin, asap (*vaping, use, liquid, nicotine, smoke*)	Ngga boleh kalo nge Vape mah boleh (*vaping is okay*)

3) *Analysis of Dominant Against E-cigarettes Topic*

Next, top 6 topics and top 5 features are generated from corpus *Against* (Table VIII). Topics on corpus *Against* e-cigarettes are mostly about questioning and criticizing e-cigarette use and safety. Topic 1 and Topic 2 talk about the risks of using cigarette. E-cigarette's safety claim and promotion are also questioned in Topic 3 and Topic 6. Public rejection towards e-cigarette can be seen on Topic 4 and Topic 5 that indicate public's support toward E-Cigar fatwa and E-Cigar prohibition's plan by the government.

TABLE VIII. TOPIC RETRIEVAL FOR CORPUS *AGAINST*

Topic	Top 10 Features	Top Tweet
Topic 1: Risks of E-Cigarette Use	Bahaya, hisap, paru, sehat, sayang (*dangerous, inhale, lung, healthy, love*)	Vape lebih bahaya (*vape is more dangerous*)
Topic 2: Risks of E-Cigarette Use	Elektrik, bahaya, konvensional, tembakau,sehat (*Electric, dangerous, conventional, tobacco, healthy*)	Inilah 10 Bahaya Penggunaan Rokok Elektrik (*Here are 10 dangers of using E-Cigarettes*)
Topic 3: Vape's safety claim	Aman, sehat, klaim, tembakau, paru (*Safe, healthy, claim, tobacco, lung*)	Lah katanya vape aman, kata yang nge-vape hahahaha (*Vape is safe, says vapers hahaha*)
Topic 4: E-Cigarette Fatwa	Haram, fatwa, Muhammadiyah, setuju, orang (*Forbidden, fatwa, Muhammadiyah, agree, people*)	Memang pantas diharamkan wkwkwk #FatwaHaramVape (*It deserves to be forbidden #FatwaHaramVape*)
Topic 5: E-Cigarette prohibition	Larang, kandungan, Indonesia, BPOM, pemerintah (*Ban, ingredients, Indonesia, Indonesia Food and Drug Administration, government*)	Yess, VAPE akan di larang selamanya...! (*Yeah, VAPE will be banned forever..!*)
Topic 6: E-Cigarette as conventional cigarette's alternative	Orang, tahu, ngevape, bilang, mending (*People, know, vaping, say, better*)	"vape alternatif rokok yg lebih aman" itu cuma gimmick kata gua sih (*"vape is a safer alternative to conventional cigarettes" is just a gimmick I say*)

V. CONCLUSION AND FUTURE WORK

This study created stance detection and topic modelling classifier that could identify whether a tweet is categorized as on *favor* or *against* e-cigarette and explore topics generated on both categories. The result of both models can be used as consideration to build a strong e-cigarette's regulation that will be followed and accepted by all parties. This study also examined that combination of features, classification algorithms selection, and multi-stage classification technique has successfully improved model's performance and can be used as alternative solutions towards low-performance model in stance detection.

The best stance detection model performance was obtained by combining 3 features (Count, Unigram, Bigram), selecting Logistic Regression algorithm, and implementing three-stage classification pipeline. This selected model has average F1-score = 0.807 and performs well on most of the class (*Favor*, *Against*, *Irrelevant*). For class *Neutral*, the model's performance is still not very good due to imbalanced data problem. For topic modelling, the chosen algorithm model is NMF with 6 number of topics, with coherence score for corpus *Against* = 0.962004 and coherence score for corpus *Favor* = 0.999736. Dominant topics for corpus *Favor* are comparison of e-cigarette with conventional e-cigarette, fatwa of e-cigarette by Muhammadiyah, tax regulation, e-cigarette safety and preference. As for corpus *Against* e-cigarette, the dominant topics include concern about e-cigarette risks and safety, support towards e-cigarette fatwa and prohibition, also doubt of e-cigarette use as conventional cigarette's alternative.

Future research could really define the treatment for imbalanced data (such as resampling) that has not been implemented in this study to increase model performance. Also, combination of advance feature such as word embedding should be explored further to find the best feature performance. Beside analysis of demographic the author of tweets (by gender and age) to reveal more information can be used in the future [10] [29]. Data combination from other social media can also be interesting to try since it could give richer insights for the experiment.

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