A Novel Solution For Anti-Money Laundering System

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***Abstract* - In the age of unpredictable fluctuations of technology, disorganized detection has been recently figured out in most of present-day anti-money laundering systems. These obstacles are attributed to certain reasons associated with applying handcrafted manipulation in the long list of principles and having the shortage of real datasets about banking purchasers or the customers' information. This article demonstrates such an innovative approach to evaluate the data in terms of suspicious behaviors, clients' relationships, the awareness for the customers retrieval from the financial sector in social media platforms. The applicable datasets consisting of above 20000 sample records on Kaggle is the main resource for our service. Each entry was compiled from content of collected documents and was attached to the descriptions measuring positivity or negativity in catching money laundering. They were used to qualify the model in AutoML supplied by Google Cloud Artificial Intelligence. After having been satisfied the sentiment standard with a performance accuracy approximately 0.85, we attempted to forecast the sentimental design for all searched outcomes connected with the clients to distinguish badly known companies. The output is a beneficial tool for the companies getting used to realizing unauthorized clients. In other words, instead of having no information about new clients in Know Your Customer of anti-money laundering inspections, it is more helpful to utilize this service without wasting too much time and money for a huge number of other sites out there.**

Keywords: Social media, sentiment analysis, fraud detection, natural language processing, anti-money laundering, decision support systems

I. INTRODUCTION

In recent years, money laundering is a global obstacle, but to measure its impact is so difficult, as it takes place behind everyone's eyes. The substantial damages can be overwhelming to the financial sector of the companies and especially in the developing countries. The current estimation of laundered money is between 2% and 5% of the global GDP, which is equal to between 1.7 and 4.5 trillion USD [1]. If banks and the government cannot detect them in time, it can produce the distortion of investment, boost crime, and grow the risk of economic instability.

The process for detecting the suspicious brands and companies wastes a long time with complex systems. To minimize the unlawful transactions and diminish the losses in minimum cost, the easiest solution for businesses is deciding not to cooperate with unauthorized parties or firms [2]. However, the lack of information about the customers or brands is possible to become the supporting factor to the difficulties of determining the result. Nowadays, the advantage of the pervasive influence of the Internet can help us have the general view of who the customers are or what brands are. It can be applied not only to brands having already been well known on social media but also to new brands broadly across the Internet to notice how people are discussing about them. Moreover, the sources for obtaining the data originated from several places, such as social media platforms like Twitter or media platforms as news, blogs, and forums.

The present study makes two exclusive contributions to the field of anti-money laundering (AML) research in such an interactive environment. First, it is one of few papers to review the existing situations between financial institutions' AML systems and the current state artificial intelligence (AI) solutions. Our study handles to fill in the missing points by reviewing the literature on the methodology, and applications of AI in AML discipline. It is vital to practice AI, especially Deep Learning to manage the complicated obstacles in different fields of our daily life. Deep Learning already has several conventional machine approaches on derived details in diverse AI tasks comprising of image realization, speech identification, and specifically natural language understanding. Nature Language Processing (NLP) is a sub-domain of AI already used across many levels of AML regulatory compliance [3]. Sentiment analysis, which has been deployed approvingly in numerous areas like evaluating the commercial organizations, and individual clients about the products or brands, similarly, to mining the viewpoints of the commentators via social forums, a typical subject in NLP. Attitude assessments are becoming the leading technology to gain the insights from social media and extend the achievement of maturity [4]. Sentiment coordination intends to obtain viewpoint documents as revealing a positive or negative interpretation. It can put into use in distinct tasks like opinion summarization, opinion mining, market analytics, and circumstantial advertising.

The research is built based on collecting the literatures published in scholarly peer-reviewed AML or AI journals from 2015 to 2020, which goes along with the techniques' general and the applications usage within these fields. We analyzed the state-of-the-art of the AML applications such as advantages or disadvantage and then gave the suggested application that built from AI techniques especially sentiment analysis. A major advantage of sentiment analysis is to gather and analyze networked comments in real time. The examiners can select high quality data based on emotional expressions and opinions being determinable, objective, and logical [5].

We have the second part of this paper that focuses on suggesting wide applications of media sentiment. It provides the service implementations to help organizations such as banks, insurance firms recognize the reputation of partner companies to consider whether they should collaborate with or not The application utilizes reputable resources and credible online databases such as Twitter, more than 30000 online newspapers. The subjects under examination can be the original post of an author or reaction by others on such texts from social media networks related to a product, several issues of an enterprise, a person or an organization. Review

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sites, blogs, forums, and social network keep good tools for testing of sentiment [6]. As an example, the positive estimations encourage the partner relationships in the future of both firms, whereas the reputation will guide the companies to assess in a more detailed way of their clients for the more appropriate courses of actions.

II. LITERATURE REVIEW AND PROBLEM STATEMENTS

There are a lot of articles in the subject areas, including the articles on the theme of the use of AI methods to solve the AML problems. One of the main goals on this review is to examine the use of AI techniques especially sentiment analysis for AML literature published between 2015 and 2020. The sources for these studies were gathered from the computerized and manual searching methods. Based on the title, abstract and keywords of each paper were investigated to figure out whether it is relevant to the applications of AI in AML systems or simply contained keywords such as 'sentiment', 'opinion', 'money', 'intelligent'. Within the selected works, there are some fields of AI applying to AML system such as detecting the suspicious transactions through the application of different techniques or methodologies, detecting money laundering groups or patterns by grouping the behavior or based on social networks, as well as applying money laundering risk rating techniques. Furthermore, most of selected papers are described as the applications to solve the problems in money laundering.

AML systems are recently attainable on the market specified with definite regulations, as well as make the discussions frequently on perceptible indications for example number of purchasing period, and portion. In 2018, the work [7] covered the preeminent ways of revealing money laundering. For instance, they attempted to investigate the permissible bodies from their banks' customers in data registration before improving the graphs in agreement with the previous guidelines systematically. The attended to employ the Machine Learning techniques consisting of Support Vector Machine (SVM), Logistic Regression, Adaptive Boosting (AdaBoost), Random Forest to intensify the useful functions of noticing the exceptions, and figuring out new patterns of making commercial negotiations against the law without earlier precedents. Nonetheless, the reason why it would not be able to designate the obligations in the form of instructions is that criminals commonly devise a variety of plans for laundering money. These certain rules are capable of identifying neither new nor non-described varieties of monetary strategies.

Money laundering is a large-scale social controversy, and it is so hard and not straightforward to find out the unauthorized financial purchases by using Machine Learning (ML) applications. However, most of reviewed / contemporary operations for AML system using networking analysis, link analysis, outlier discovery and risk scoring/ categorization are to notice the suspicious transactions. Because of lacking the authentic data for monetary purchasing or normal data, the group of researchers have worked in the accelerated datasets. Specification methods like decision trees and support vector machine are used to be a trained model to distinguish the disapprovals. Unfortunately, at the end, the result was very different between the trained model and real data [3].

We reviewed the other paper [8] in 2017 as the same research field enhancing the decision process in finance. They give a creative access in order to sort out and sketch relational data and illustrate anticipating models which are placed on certain network metrics to estimate risk profiles. They can be conceivably forecasted by taking advantages of social network metrics. They are taken as references for building up a powerfully productive data analysis procedures to make tremendous contributions in recognizing those groups, corporations or firms with higher risk profiles in terms of unauthorized transactions. This paper is principally aimed at emphasizing profoundly on the deciding performance of social network metrics and intensely recommend influencing methods of network measurements, not conventionally correlated with AML practices like before.

The current AML systems are a black-box system characterizing a transaction as 'fraudulent' checked by the long list of standard guidance. This way does not supply a user-friendly operation because it lacks the explanations for its decision. The productive conversation with the analysts is a vital and decisive element and it is partly responsible for a successful recognition of fraud businesses or not, because at the end, the user as worker would be a person who will finally select.

To alleviate these issues, in 2018 the work [9] invented a novel model built by Deep Learning as Natural Language Process to apprehend context knowledge for the tasks of attitude classification. The authors utilize these techniques in the distributed and scalable manner to visualize AML supervision by taking the data resources from news and tweets of Twitter to represent additional documentations to human monitors for the final decision marked. Notwithstanding, there are existing objections with the technical constraints connected with group opinions and dataset restraints. The datasets of [10] were used to calculate their model publicly available on New York Times. Online texts from social media networks like Twitter stands out for unorganized textual contents with spelling errors such as slangs, conversational words, non-standard abstractions resulting in making the sentiment labeling even more difficult.

AML is counted as one of continuing objections in the economic sector, and presently several procedures have been employed in this area like risk distribution, link-analysis. Domestic precedents, the deficiency of legitimate data and inadequate descriptions were generally operated. This contributes indeed to recognizing the distrustful enterprises, raising selection progress, encouraging enormously the anterior stage of KYC process and minimizing partnership uncertainties. We revised carefully and intensively related works regarding to AML system and sentiment analysis application to provide the new approach of the AML explanation. We will not genuinely build or generate the sentiment analysis or search engine model from scratch. It is important to give the correct results so that we favor to use the popular APIs of each domain, such as API built from Google Cloud or Twitter. During using APIs, we provide experiments to prove accuracy of the built service, discussions on the concept in this paper and results after running.

III. THE PROPOSAL METHOD AND APPLICATION FOR AML SYSTEM

A. The suggested methodologies

These reviews highlight sentiment analysis from social media sources that can compromise the building application for AML system. To avoid money laundering at the beginning, the financial institutions appreciate the procedures to KYC. It is defined as a process to authenticate a customers' identity before extending their services. There are two forms of data driven in the data layer of AML system: banking transactions and open data. In this paper, we paid attentions mainly to the open data referring to commercial articles, blogs, discussion boards and social networks sites on the Internet.

In the practical side, this paper proposes one application like the figure 1 below to help our customers, such as bankers, insurance cooperators identify their new clients, and observe if they could be the licensed customer or not. This figure shows the main architecture of the service. Our service makes up three central modules, which are search engine module, crawl module, and sentiment analysis module (AI engine).

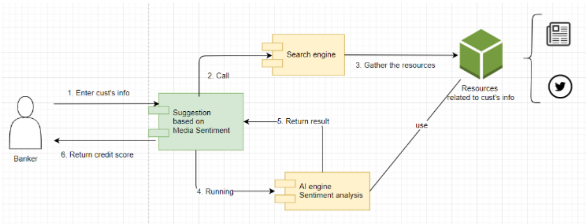


Figure 1: General Application Architecture

1) Search engine uses for looking for the information originated from the keyword customers entered before, in other websites around the world. The goal of the search engine module is to display the knowledge which the user is exploring. Search engines in our service area is to gain the data, not only in the online newspapers but also in the Twitter platforms. The results from this engine were sorted out by using the ranking algorithm, and they were prioritized searching in economic articles to get the real time dataset for the sentiment analysis step.

2) Scrappy module is used for comprehending the website's structure and its versatility or collecting the knowledge from the sites. It naturally retrieves data from the web, transmits it to another technology before indexing or making the analytics for the content of the sources.

3) Sentiment analysis is run to automatically arrange the judgments about the contents, which we collected from the crawling module as positive, negative, or neutral. It gives businesses with the complete intuitiveness about the attitudes, emotional expressions, points of view, feedbacks behind the series of words within the online mentors. The practicalities of sentiment analysis are widespread and prominent. In the building module for sentiment analysis, there are two popular types of learning styles using in ML; supervised and unsupervised learning. Moreover, there are many levels of sentiment analysis to bring out the aspects and design the sentiment. In this article, we research in three levels which are document level, sentence level and aspect level.

For our sentiment analysis task in AML system, we aim attentions at doing text sentiment analytics on networked newspapers and tweet on Twitter, and we realized that shifting attitudes on social media can bring about changing the stock market or the company's fortune. Chiefly, the aspect-based level sentiment study is in high position to find all attitude declarations from all the conditions in the supplied document. Attaining both entities and points is achievable to help challenges addressed easily. That is highly demanding for further function of NLP. The calculated scores in term of each apparent aspect are different from analyzing sentiment by sentences before we offer the total of all parts [4]. The system can have a comprehensive understanding about the whole texts. Furthermore, using the name entity recognition to build up the relational network of entity in the context, from that, it is probable to make the connections in the system easily such as person, organization, or money, location.

B. *The main technique of the application*

The chief architectural structure in our service used Python, Flask, and Angular to build the web application. We divide our service into two parts (two projects), the first as a back-end project, and the another as front-end one. The reason we make use of this order that it is reusability of the endpoints, simplifying development, and deployment. Python is a server-side programming language, notably using the Flask framework because this language is compelling and related to IoT, mathematics, ML application. In addition, Flask in Python is the restful API framework so that it can simply send requests and receive responses from the client-server by allowing CORS.

1) Data extraction

It is to maintain the conceptual description; sentiment analysis first needs to be remarkable from the broader literature on online text mining. The text mining allows scientists to design a grand body of data from diversified online sources with separate topics and themes emerging from the body of textual data. From that, they can extract efficient features, distribute the content and control the extensive data to name the hidden patterns, trends or their meanings [11]. The data source was collected from two sources, one from all online newspapers and the other one from the tweets posted on Twitter. We want to search for any articles mentioning keywords typed by users, the API indexes each item issued by over 30.000 news sources and blogs via 50 different languages, and then return a list of results in JSON format to us. The JSON response carries the result being equal to the number of articles possessing this keyword and a list of information related to articles such as source, author, title, description, URL, date of publication, and the raw content.

The twitter API is taken advantages to derive the tweets from Twitter. We expand the search words not only by the keywords but also by the hashtag of tweets. Besides, we added some implicitly financial terms to narrow down the limited search areas and show the better results. Either the web servers or local hosts can implement this immediately or for the query which few frameworks are taken into important considerations. With the demands of our service, we decided to use a standard tire of API in our service to fetch the post and engage with tweets with the specified timelines. JSON is the format of response data, and include the information particularized to each Tweet such as author, a message, unique ID, timestamps of when posting.

2) Data preprocessing for analyzing

The certain amount of inconsequential data is highly accessible within the data that is separated from Twitter. Any unequivocal categorization of irresponsible individuals or meaningless knowledge need to be seeped through from the tweet information. The NLP tool is a beneficial way to be practically employed for actively removing this unworkable data. Text processing, or particularly pre-processing, includes a diversity of techniques such as tokenization, tagging, stemming, lemmatization to transform the raw text into well-defined sequences of lexical component. It means that the document will have its standard structure and notation. Furthermore, these techniques, we also have to deal with some basic operations like misspelled text, removing stop words and define using which technology to solve problems [12].

In our service, we gather the information from tweets of Twitter, so one of the main challenges faced in normalization is the appearance of the wrong words in the text. To represent several instances, some people usually express their intense emotion and that leads to the writing style "*baddddd dayyyy for me.*", or people also write "*beddd"* instead of "*bad"*. If computers are not qualified enough to detect a difference between "*bad*" and "*bed*" in this case, these two variables of the same word will be treated in various vectors and complicated ways. The primary purpose would be to systematize the diverse forms of these words to the correct ones, therefore, we do not desist up any missing materials contributed from different tokens in the text [12].

3) Sentiment analysis

Sentiment classification intends to extract a document giving the thoughts as revealing a positive or negative evaluation. In the part for sentiment analysis application, we use natural language API provided by Google to reveal the structure and meaning of the text. It uses Machine Learning to earn knowledge about people, places, and events to have good experience in the conversations with clients. In our service, we auto ML of NL to summarize the overall opinion, feeling, or emotion manifested in a block of text. The score resembles the general emotional learning of the text and stays between -1.0 (extremely bad) to 1.0 (good). Magnitude intimates the complete strength of emotion within the given document and remains in the range from 0.0 to +inf. To take an example, we invest the sentiment in the paragraph related to the Pfizer company. Since its FDA nod in May, Pfizer's much-forecasted Vyndaqel franchise has evolved its disparately paved direction with blockbuster hopes. Nowadays, it is declared by a group of examiners that the drug's beforehand uptake has been popularized faster than predicted. A response value to the Pfizer company of 0.2 score indicates a document which is slightly positive in emotion, while the amount of magnitude 0.5 indicates a relatively emotional report, given its small size. We will explain more details how build the dataset and generate the model in the part 4.

IV. Experiment and discussion

A. *Experiment*

1) Training and building the sentiment model from AutoML

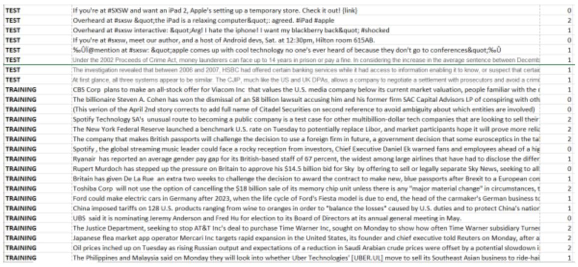
We would like to use the existing API to analyze the sentiment of text, and we decided to use Cloud Natural Language of Google Cloud AI to generate the predicted model. There are two services of Google Cloud Services called "Google Natural Language API" and "Google AutoML Natural Language" that we experimented with to figure out the suitable service. After researching and exploring we selected AutoML NL to produce the model for sentiment analysis. In our first experimentation, we tried to do sentiment analysis with NL API because it needn't training dataset and allows us promptly to launch making prediction. The models of this API have been trained on exceedingly massive document corpus; however, Google do not disclose any information about their precise structure or form available. We were so interested in the real performance of this API, so that we tested it on the data that we gained from the search engine and crawl part. We took HSBC bank as an example and got 200 positive reviews and 200 negative reviews related to its laundering, and financial status from our test dataset. We ran the API to predict the sentiment to these actual review records. After launching, we had the confusion matrix looked like the table-1 below.

TABLE 1. THE CONFUSION MATRIX OF THE RESULT

	Negative sentiment	**Positive sentiment**
Good review	43	157
Bad review	163	37

The table shows the quietly good performances for unexpected solution without any adjustment in the creating model to solve the problem. This API is good and ease of use, but the models are not flexible for specific business propose. They are trained from dataset for the whole varieties of the life such as education, movie, technologies, weather, etc. We need the datasets for financial and money laundering field, so that we move on the next experiment with using AutoML NL to build the model. From the different sides of NL API, the AutoML models would be trained based on the user 's datasets defining or importing to lead to handle a definite task. There are four steps to give the predicted results with AutoML NL service such as datasets preparation, model training, evaluation and prediction.

For constructing datasets, we use two resources database that collected from Dataworld and Kaggle. We have one dataset all tweets expressing brands and product emotions that taken from Dataworld. The other one is all the updated headlines in the financial sections and money laundering sections from Reuters and Financial Times online newspapers. We saved all sample dataset as tweets, headlines descriptions with our labels in a CSV file. The format of the database would be like the Figure-2 below. We defined the record would be the training, testing or validation to use for building the model. The label for the sentiment on the right side are the content sentiment scores which in our dataset, made the label by a human being. It would be defined 0 as very negative sentiment, 1 as neutral and 2 as absolute positive.



TEST	If you're at #SXSW and want an iPad 2, Apple's setting up a temporary store. Check it out! {link}	0
TEST	Overheard at #sxsw "the iPad is a relaxing computer": agreed. #iPad #apple	2
TEST	Overheard at #sxsw interactive: "Arg! I hate the iphone! I want my blackberry back" #shocked	1
TEST	If you're at #sxsw, meet our author, and a host of Android devs, Sat. at 12:30pm, Hilton room 615AB.	0
TEST	‰ÛÏ@mention at #sxsw: "apple comes up with cool technology no one's ever heard of because they don't go to conferences"‰Û	1
TEST	Under the 2002 Proceeds of Crime Act, money launderers can face up to 14 years in prison or pay a fine. In considering the increase in the average sentence between Decemb	1
TEST	The investigation revealed that between 2006 and 2007, HSBC had offered certain banking services while it had access to information enabling it to know, or suspect that certai	1
TEST	At first glance, all three systems appear to be similar. The CJIP, much like the US and UK DPAs, allows a company to negotiate a settlement with prosecutors and avoid a crimi	1
TRAINING	CBS Corp plans to make an all-stock offer for Viacom Inc that values the U.S. media company below its current market valuation, people familiar with the	1
TRAINING	The billionaire Steven A. Cohen has won the dismissal of an $8 billion lawsuit accusing him and his former firm SAC Capital Advisors LP of conspiring with oth	0
TRAINING	(This verion of the April 2nd story corrects to add full name of Citadel Securities on second reference to avoid ambiguity about which entities are involved)	0
TRAINING	Spotify Technology SA's unusual route to becoming a public company is a test case for other multibillion-dollar tech companies that are looking to sell their	2
TRAINING	The New York Federal Reserve launched a benchmark U.S. rate on Tuesday to potentially replace Libor, and market participants hope it will prove more relia	2
TRAINING	The company that makes British passports will challenge the decision to use a foreign firm in future, a government decision that some eurosceptics in the ta	2
TRAINING	Spotify , the global streaming music leader could face a rocky reception from investors, Chief Executive Daniel Ek warned fans and employees ahead of a hig	0
TRAINING	Ryanair has reported an average gender pay gap for its British-based staff of 67 percent, the widest among large airlines that have had to disclose the differ	1
TRAINING	Rupert Murdoch has stepped up the pressure on Britain to approve his $14.5 billion bid for Sky by offering to sell or legally separate Sky News, seeking to all	0
TRAINING	Britain has given De La Rue an extra two weeks to challenge the decision to award the contract to make new, blue passports after Brexit to a European con	1
TRAINING	Toshiba Corp will not use the option of cancelling the $18 billion sale of its memory chip unit unless there is any "major material change" in circumstances, t	2
TRAINING	Ford could make electric cars in Germany after 2023, when the life cycle of Ford's Fiesta model is due to end, the head of the carmaker's German business to	1
TRAINING	China imposed tariffs on 128 U.S. products ranging from wine to oranges in order to "balance the losses" caused by U.S. duties and to protect China's natior	1
TRAINING	UBS said it is nominating Jeremy Anderson and Fred Hu for election to its Board of Directors at its annual general meeting in May.	0
TRAINING	The Justice Department, seeking to stop AT&T Inc's deal to purchase Time Warner Inc, sought on Monday to show how often Time Warner subsidiary Turner	2
TRAINING	Japanese flea market app operator Mercari Inc targets rapid expansion in the United States, its founder and chief executive told Reuters on Monday, after a	2
TRAINING	Oil prices inched up on Tuesday as rising Russian output and expectations of a reduction in Saudi Arabian crude prices were offset by a potential slowdown i	2
TRAINING	The Philippines and Malaysia said on Monday they will look into whether Uber Technologies' [UBER.UL] move to sell its Southeast Asian business to ride-hai	1

Figure 2. The sample dataset in AutoML service

We can collect the dataset up to 20000 records for the tweet related to the brands' reputation and more than 310000 records for the financial headlines from Reuters website. However, in the next step for training model, we just take each time 700 records combing from two sources. The model training in AutoML NL of Google Cloud AI is entirely automatic. If user have not yet defined the training set in the imported dataset, the system will spilt unconsciously with the rate 80% for training, 10% for validation and 10% for testing. Training model with much more records in dataset is without doubt better than the other. It had taken us around 4 hours for training and generating the model for predicting with 700 records. If the dataset is up to or more than 20000 or real datasets size, it will be spent several days for this task. The rest of work in model training is handle by Google in a black box. In the evaluation step, it provides the result as precision, recall umber or the confusion matrix after running the model. The result shows on the Figure 3 below.

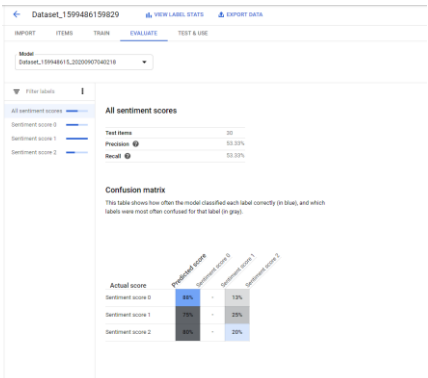


Figure 3: Precision, recall and confusion matrix after running the training model in AutoML

We examined the model numerous of times to find the fitting model that we are happy with the model's accomplishment. Then we can deploy, get the service API to embed into our application service, and move to using the service.

2) The experiement in our service

In this part, we describe the result of service in the view of the user. The concept of the service is running in real-time because the information in online articles and Twitter change time by time. The UI side in an Angular project sends the request to the backend side for resetting the database, and then the server-side does the search engine by keywords with whole newspapers or blogs on the Internet and all the Tweets of Twitter. The time range for detecting the tweets related to keywords is the last two weeks.

We have two analyzing processes in social media like Twitter and online newspaper so that we arranged the results in two dropdown tabs. On each tab, users can be impressed by the overall sentiments score and the distribution chart to have an overview of whether their customer is potential or not. The sentiment score calculated in percent and stay in the range from 0% (assuredly negative) to 100% (entirely positive). We transformed the sentiment score from the range [0, 2] to [0%, 100%] to get convenience for showing on the map or chart in our result page. It is crucial to judge whether the service was giving the right results or not. The criterial could be examining the search engine and checking how much percentage of the correct sentiment score for both types of resources. To measure the accuracy of sentiment service, we use the concept of accuracy. If the accuracy reaches higher, it means the trained model has the best outcome, in contract to the lower accuracy [13]. We used the real data that collected from our search service to predict the label sentiment with AutoML model built before. Our AutoML model performed significantly good because it achieved an accuracy of 0.851230 (~85%).

To provide the clear result to the customer, in figure 4, the value of process bar being less than 50% represents negative sentiment and being equal with 50% is average sentiment of target entity's competitors. Positive sentiment could be considered when process bar has value from 51% to 100%. On the left side of the application have the overall result from Twitter 54.8%, which means the opinion stays neutral but tends to positive. It could be seen that not absolute negative sentiment regarding financial fraud is prevalent for the destinated entity. The company has result in only slight positive hence an in-depth examination is mandatory. If the sentiment result tends to highly negative, user could consider identifying a probable nominee in the block list.

The step for checking as the basic step is analyzing the content of each record by themselves. The table provides the content of tweets and its sentiment score for the results of Twitter. In the newspaper tab, we showed the table including only the title of the article, but when users mount on the title column, the system will show the description of this article. It is essential to go through profoundly with the legal client's database or broaden the inspection channel, when users gain the negative sentiment as the results.

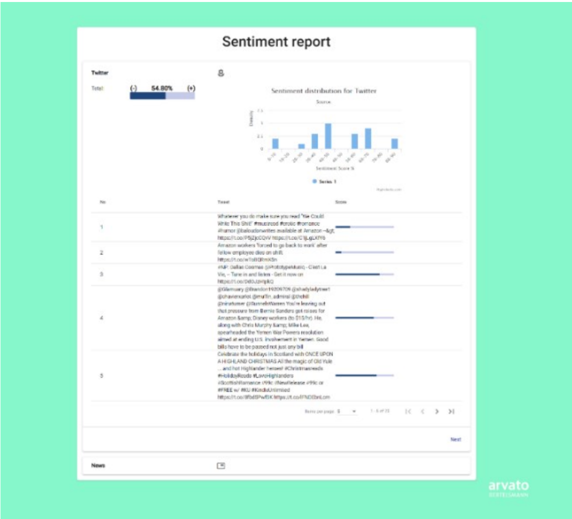


Figure 4: The result page of application

Based on the result, we can identify the reputation of the companies to consider that would be the good company to collaborate or not. That could contribute dramatically to the process of evaluating the clients more easily and quickly, which plays a vital role in defining the future plan to handle the next case as well as preventing organizations from no cooperating with reputation customers, and restricting money laundering significantly.

B. Discussion for the result

On the bright side, our service satisfies the primary purpose that we gave in the beginning. This service combines the search engine, scrappy, sentiment score, and shows the results on the dashboard, whether the company has good or bad assessments to have the overall view about the customer. It is not fair to give the decision whether the customer should cooperate with this company or not with two months results. In the current service, we calculate the overall score for sentiment score by taking the average, but in the future, we should consider to the best overall sentiment score. For example, in the experiment, the Pfizer company case, they have a terrible reputation with producing the cancer drug so that on Twitter, they received many bad tweets. However, to make the sentiment score balance, they tried to supply the scholarship to the students. Then the sentiment score on Twitter of Pfizer company is in neutral rating. The system can boost the efficiency of money laundering detection without any new significant capital investment from the nameless monetary institutions, productively minimize their potential reputations in the risk and cost.

V. Conclusion

The globalization age of current Web has brought about the effort free, available provision of valuable and deliberately given data on social media. This has provoked significant passion in community and industry exclusively detecting money laundering to be most beneficial in the sufficient inputs. It helps to augment the AML monitor, investigation and create the user-friendly applications. Moreover, the Internet is a hugely proliferated environment opening new windows to get access to valuable information about our anonymous clients. It could be considered as the first approach to get closer to our customers.

In this paper, we tried to analyze the state-of-the-art AML system to see the advantages and disadvantages given from each research, as well as the current state-of-the-art applying AI into this field. In the practical side, our system is small modularized and scattered which can be deployed for testing phase. Our service provides effectively to the process of evaluating the clients more easily and quickly that is important phase to investigate ML. The results are the sentiment result after analyzing context collecting from social media that would be the addition evidence extraction to improve human investigator. Promoting this assistance is an ideal way to have a high proficiency in customers' reports thanks to anti-money laundering inspection's KYC section and prevent numerous business enterprises from a significant number of other systems being time consuming and costly. In the future, we will continue expand and test our service with multiple dataset and develop to show the result with the graph as the period time. From that, if the searched organization meet high negative sentiment over certain period, they could be indicated as a potential for tremendous blocking. We also need to mention that we will make the comparisons between our sentiment applications to other currently possible ones in the AML fields. Based on the outcome, we promote the evaluations and enhancements to develop the product significantly.

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