A FRAMEWORK FOR TWEET CLASSIFICATION AND ANALYSIS ON SOCIAL MEDIA PLATFORM USING FEDERATED LEARNING

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ABSTRACT

Social media plays a pivotal role in the daily activities of individuals, serving as a medium for the dissemination of events, activities, and information through various forms of posts, including tweets, status updates, and pictures. The source of information is determined by analyzing the impact of a user's association with a particular tweet. In this research paper, we present a framework based on the principles of Federated Learning (FL) to classify and analyze tweets across different social media platforms. The framework incorporates feature mapping and feature indexing techniques to determine the threshold computation value for categorizing tweets as either "positive" or "negative." Importantly, our framework is platform-agnostic and has been rigorously validated using a diverse dataset comprising dynamic trends and social media posts from platforms like X (formerly known as Tweeter), Koo, and Instagram. Our findings demonstrate that the framework achieved an impressive accuracy rate of 93.54% in classifying TP (Trending Topic) posts with respect to the subject matter under consideration.

Keywords: Social media; post classification; federated learning; tweet classification; tweet analysis.

01. INTRODUCTION

In the digital age, social media has transcended its role as a mere communication tool to become an integral part of our daily lives. Social media platforms have redefined the way we connect, share, and engage with the world around us. They provide a dynamic space where individuals, businesses, and communities interact, exchanging information, thoughts, and experiences. [1][2][3] At its essence, social media encompasses a diverse array of platforms, from the succinct tweets of Twitter to the visual storytelling on Instagram, and the networking capabilities of LinkedIn. These platforms offer a virtual playground where people worldwide can express themselves, form connections, stay informed, and participate in conversations that range from the personal to the global. As a source of real-time news, a platform for self-expression, and a marketplace for ideas and products, social media has had a profound impact on how we navigate our personal and professional lives.[4][5].

It's, Social Media, where trends are born, opinions are voiced, and information spreads at an unprecedented speed. Moreover, the vast amount of data generated on these platforms has drawn the attention of researchers and businesses, sparking innovative approaches like Federated Learning (FL) to tap into the collective intelligence contained within the world of social media. This introduction sets the stage for understanding the significance of social media and its multifaceted role in our modern society [6]. It's a realm of boundless opportunities, challenges, and, as we will explore further, a realm where technology continues to evolve to make the most of this dynamic digital landscape. This omnipresent digital landscape forms the backdrop against which innovative technologies like Federated Learning (FL) are gaining significance. Social media platforms have become the epicenter of our online lives, offering a platform where vast amounts of data are generated, disseminated, and consumed on a daily basis. The impact of social media extends far beyond personal connections; it has become a global hub for news, trends, and opinions. As users post tweets, status updates, images, and videos, they contribute to a colossal reservoir of data. This data, reflecting diverse perspectives and sentiment, offers a unique opportunity for machine learning and data analysis [7][8].

In this context, we explore the pivotal role of social media as both the source and subject of data analysis through the lens of Federated Learning. The distributed and decentralized nature of social media data mirrors the principles of FL, making it a particularly relevant arena to apply and understand this novel approach. By introducing FL into the social media landscape, we have the potential to enhance our ability to classify, analyze, and extract valuable insights from this ever-evolving digital ecosystem, all while respecting the privacy and security of individual users. This conversation will delve deeper into how FL and social media intertwine, showcasing the transformative potential of this pairing in addressing the unique challenges and opportunities presented by the dynamic world of online social interactions and content sharing[9][10].

In today's interconnected world, social media has evolved into an indispensable component of our daily lives, significantly influencing our interactions, the spread of information, and the way we engage with current events and activities. This profound impact is particularly evident through the sharing of content via various social media posts, including tweets, status updates, and images. [11][12] What distinguishes these posts is the manner in which information is sourced, a process that hinges on the collective influence of users and their associations with the content they interact with. This paper introduces a novel framework that leverages Federated Learning (FL) principles to classify and analyze social media posts, especially tweets, transcending the boundaries of specific social media platforms. By incorporating advanced techniques like feature mapping and feature indexing, this framework provides a robust means of determining the threshold computation value, enabling the categorization of tweets as either "positive" or "negative." Notably, this framework is platform-agnostic, making it adaptable to a wide array of social media platforms.

The core strength of this framework lies in its adaptability, transcending the boundaries of specific social media platforms. Whether it's a tweet from X, a post on Koo, or an image on Instagram, our framework can seamlessly operate across these platforms, making it a versatile tool for content evaluation. Through the incorporation of feature mapping and feature indexing techniques, we aim to break down the complex web of information, ultimately unveiling a clear threshold for classifying content as either "positive" or "negative." The ability to decipher the sentiment and relevance of social media content has immense practical implications, from brand reputation management to public sentiment analysis. To validate the efficacy of our framework, we conducted exhaustive testing across a multitude of dynamic trends and social media posts. The results have been nothing short of remarkable, with our framework achieving an impressive accuracy rate of 93.54% in the classification of trending topic posts. This suggests that our approach has the potential to revolutionize the way we understand and categorize social media content, opening up new avenues for more informed decision-making and data-driven insights.

02. METHODOLOGY

In the realm of scientific inquiry and research, the methodology forms the cornerstone of any systematic investigation. It serves as the roadmap, the structured approach, by which we navigate the complexities of our subject matter, gather data, analyze information, and draw meaningful conclusions. Methodology is the guiding principle that lends rigor, transparency, and reliability to research endeavors, ensuring that our findings are both credible and replicable. In this context, our discussion centers around the methodology employed in the study of Federated Learning (FL) as applied to the dynamic world of social media via the proposed framework as shown in Fig. 1. As we delve into the intricate details of our methodology, it becomes apparent that the approach we adopt is not merely a technical procedure; it's a strategic choice that underpins the entire research process. The interplay between FL, a cutting-edge machine learning technique, and the sprawling universe of social media platforms is both a challenge and an opportunity, demanding a well-considered methodology to unlock its full potential.

The methodology is categorized in to three phase, the first phase is termed as “training unit”, the second phase is “Repository and Computing Unit” and the third phase is “User validation and learning Unit”. The training unit incubates repository of datasets from multiple social media platforms. The structural computation of datasets framing and attribute extraction is processed in this unit. The attributes such as tweet-content, tweet-origin, time and geographical coordination are few parameters in framing the feature mapping and feature indexing. The feature mapping is the integral step for coordinating the attributes and features relevance and the resultant is the processed or trained dataset with labels. These labels are supported with pre-trained positive and negative tweet database (repository). The pre-trained repository is aligned with a classifier for data-attribute mapping on dynamic portal of tweets from the social media platforms. In general, the aligned units of tweet attributes and feature indexing is validated and trained via the training unit for classification and decision making. Typically, the overall classification of the proposed system is represented in Fig. 2. The classification diagram represents the control flow within the stream of blocks and operations. The outcome of the proposed system is to develop a reliable system model for classifying the tweets and label them as positive or negative and fake according to the thresholding values.

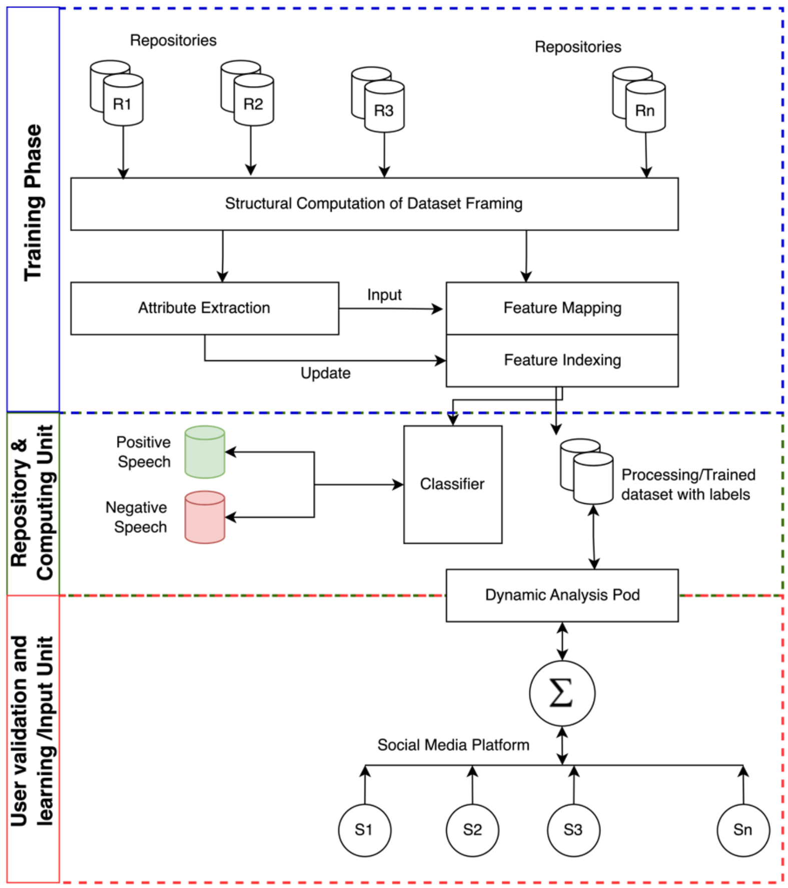

Fig. 1: Proposed system architecture and methodology phases

03. PROBLEM STATEMENT

Structural tweets and social media post from the platforms have multi-array of tweeting options. One such is the prospects to validate and authenticate the nature of tweet by classifying the process as “positive” or “negative”. Generally, the fundamental process of ‘speech’ is termed as a grammar or a collection of works for particular subject. For instance, consider the subject line a movie on a particular actor’s biography. In this case the tweets (T1= “The movie was a good pitch”) and (T2=”movie needs to include positive aspects of life and avoid this propaganda). In this (T1, T2) are further evaluated as positive or negative with respect to the tweets. Thus classifying process terms as (T1) and (T2) as positive due to the words associated in it. The research challenge is the need of a dedicated framework for evaluation of such interdependent tweets. The tweets (T1, T2) justification should be based on grammar arrangement of data, rather than words and thus classify (C) as follows.

$$C = \begin{cases} if\,(grammar == 'positive') : classify(positive) \\ \qquad else(classify(negative)) \end{cases} \tag{1}$$

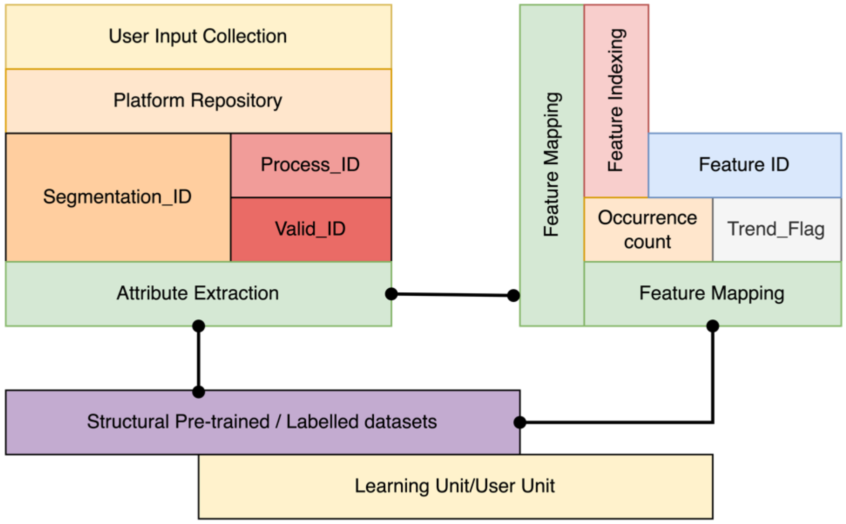

Fig. 2: Classification diagram of proposed model

04. METHOD AND MATERIALS

The proposed system is collection of multiple sources tweets from a defined social media platform. The arrangement of system and structural representation is shown in Fig. 1. Typically, the independent repositories are created and functionally aligned for structural computation of dataset framing. The purpose of this unit is to streamline all the incoming parameters of attributes and features associated with the tweets on extraction. The attribute matrix extraction and resolution evaluation is discussed with the parameters included in the attribute (A) mapping as $A=(A_1, A_2, A_3.....)$ such that $(\forall A_i \in F)$ where (F) is the featureset of the given attribute matrix.

4.1 Attribute Extraction and Feature Customization

The attribute (A_i) is further dependent on feature mapping (F_M) and feature indexing (F_I) accordingly. Typical considerations of feature mapping (F_M) is attribute corelationship included in the feature coordination (F_C) as $(\forall [A_1, A_2, A_3....A_i....A_n] \in A)$ and $(A_i \subseteq A_n)$ such that $(\exists F_M \Rightarrow [A_i \rightarrow A_j])$ and $(F_M \subseteq F)$ at a given time interval (t). Such that all the feature mapping parameters associated with (A_i) is relatively associated with defined featureset (F_S). Thus a generalized representation of $(F_M \subseteq F_C \Rightarrow F_S)$ in overall processing. The attribute corelationship is demonstrated in Eq. 2 as below.

$$F_S = \lim_{n \to t} \left(\frac{\delta(F_M)}{\delta t} \oplus \sum_{i=1}^{n} \frac{\delta(A_i)}{\delta t} \right) \tag{2}$$

$$\therefore F_S = \lim_{n \to t} \left(\frac{\delta(F_M)}{\delta t} \oplus \sum_{i=1}^{n} \left(\frac{\delta(A_i)}{\delta t} \otimes \frac{\delta(A_{i+1})}{\delta t} \right) \right) \tag{3}$$

$$\therefore F_S = \lim_{n \to t} \left(\prod_{k}^{\infty} \frac{\delta(F_M)_k}{\delta t} \oplus \sum_{i=1}^{n} \left(\frac{\delta(A_i)}{\delta t} \otimes \frac{\delta(A_{i+1})}{\delta t} \right) \right) \tag{4}$$

On simplification, the feature set (F_S) with association of feature mapping (F_M) can be represented as shown in Eq. 5.

$$\Rightarrow F_S = \lim_{n \to t}\left(\prod_{k}^{\infty}\frac{\delta(F_M)_k}{\delta t} \oplus \frac{1}{\Delta t}\sum_{i=1}^{n}\left(\delta(A_i)\otimes\delta(A_{i+1})\right)\right) \tag{5}$$

$$\therefore F_S = \frac{1}{\Delta t}\left[\lim_{n \to t}\left(\prod_{k}^{\infty}\left(\delta(F_M)_k\right)\oplus\sum_{i=1}^{n}\left(\delta(A_i)\otimes\delta(A_{i+1})\right)\right)\right] \tag{6}$$

The representation of feature set (F_S) is directly dependent on (F_M) and the attributes $[A_1, A_2, A_3 .... A_i .... A_n]$ interdependencies. Typically, the formulation of segments and its associated array of interdependency results in feature indexing (F_I). The (F_I) is used to map and index the relatively of alike featureset for ease in accessing and classification as shown in Fig. 3. The classification matrix associated with (F_I) is represented below.

$$F_I \Rightarrow \int_0^n \frac{\Delta(F_S)}{\Delta t} \oplus \sum_{i=1}^{n}\left(\frac{\delta\left(Occ[\Delta F_S]_i\right)}{\delta t} \cap \frac{\delta(F_M)_i}{\delta t}\right) \tag{7}$$

$$\therefore F_I \Rightarrow \phi\left\{\int_0^n \frac{\Delta(F_S)}{\Delta t} \oplus \sum_{i=1}^{n}\sum_{j=i+1}^{n}\left(\frac{\delta\left(Occ[\Delta F_S]_i\right)\cap\delta(F_M)_j}{\delta t}\right)\right\} \tag{8}$$

$$\therefore F_I \Rightarrow \phi\left\{\left(\int_0^n \frac{1}{\Delta t} \cup \Delta(F_S)\right) \oplus \sum_{i=1}^{n}\sum_{j=i+1}^{n}\frac{1}{\Delta t} \cup \left(\delta\left(Occ[\Delta F_S]_i\right)\cap\delta(F_M)_j\right)\right\} \tag{9}$$

$$\therefore F_I \Rightarrow \frac{\phi}{\Delta t}\left\{\left(\int_0^n \Delta(F_S)\right) \oplus \sum_{i=1}^{n}\sum_{j=i+1}^{n}\left(\delta\left(Occ[\Delta F_S]_i\right)\cap\delta(F_M)_j\right)\right\} \tag{10}$$

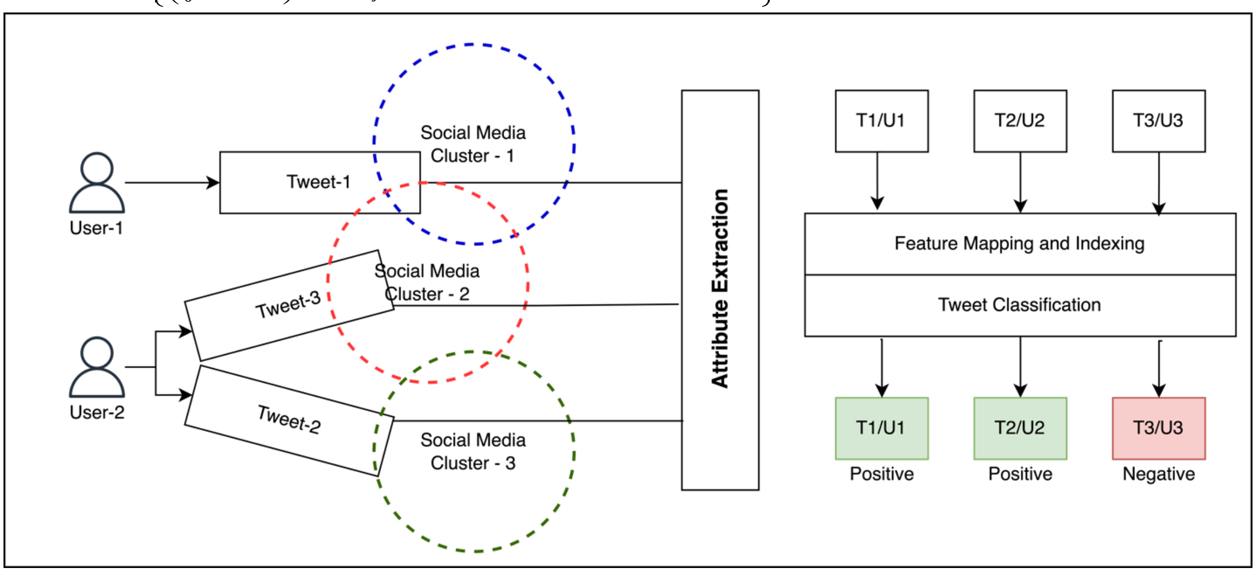

Fig. 3: Representation of flow computation and user scenario categorization

Thus according to the feature indexing ratio, the instance of (F_I) is directly dependent on (F_M) and (F_S) with each of $((F_S \cap F_M) \subseteq F_S)$ at a given instance of time. Thus according to the feature indexing in Eq. 10, the representation assures the values of each indexing feature is associated with featureset and vise-versa. The indexing featureset is customized and represented to create a dedicated dataset $\left(D_{Poss}\right)$ and $\left(D_{Neg}\right)$ as its two values of customization.

4.2 Dataset Normalization

The tweets are segmented and categorized into the labels of feature indexing to assure the operational standards of each dataset tweet associated in the process. The process of dataset normalization and customizing the archives, results in developing a novel dataset stream as in Fig. 1. Typically, the association of dataset is with labeling process such as "positive tweets" and "negative tweets". Technically each bit of tweet value is termed with indexing ratio of words associated in the tweet for its classification process. The classifier (C) can be associated with multiple tweets (Δx) at a given floating instances of time. The association can be demonstrated as below.

$$C=\phi\left(\frac{\Delta\left(F_{I1},F_{I2},F_{I3}....\right)}{\Delta t}\oplus\frac{Occ(A)\cap(\Delta x)}{\Delta t}\right) \tag{11}$$

$$\therefore C=\frac{\phi}{\Delta t}\left(\sum_{i=1}^{n}\left(F_{Ii}\right)\oplus\left[Occ(A)\cap(\Delta x)\right]\right) \tag{12}$$

Thus according to Eq. 12, the feature indexing ratio of multiple instances reflects into the attribute values and the count associated in (Δx) for the given point of (t) with (ϕ) acting as saturating agent. The saturating value of (ϕ) is reflected with one or more occurrences of attributes such that, $\forall(C)\Rightarrow\left(F_{I(i,j)}\oplus Occ(A)\right)$ at a given instance of time variables. The associated values in combined form can be represented as below.

$$C=\begin{cases}(+)^{ve}F_{Ii}\left(where\left[\dfrac{\delta\left(F_I\right)_i}{\delta t}\Rightarrow Occ\left(A_i\right)\cup\left(F_I\right)\right]\right)\\(-)^{ve}F_{Ij}\left(where\left[\dfrac{\delta\left(F_I\right)_j}{\delta t}\Rightarrow\left\{F_I-\dfrac{\delta(F_{Ii})}{\delta t}\right\}\right]\right)\end{cases} \tag{13}$$

The classification seeks detailed discussion on (C) value segmentation (i.e.) of $\delta(F_{Ii})$ occurrence and attribute (A) occurrence is relative, then the processing segment of $\delta(F_{Ii})$ is termed as "positive" tweet and remaining tweets in the feature indexing (F_I) set is termed as "negative" tweets as shown in Fig. 1 and Fig. 3 respectively in detailed. The customization of each tweet value is associated with default classification in the proposed framework.

4.3 User validation and tweet interpretations

The dataset trained model has demonstrated a higher customization of tweet strength and features. Technically, the segmented values of each user tweet are feed into the social media input and validated on the dynamic model for tweet classification. The federated learning (FL) model is used in the ratio of analyzing and customizing the information processing over multiple areas of tweet segments. The proposed system is free from internal differences such as grammar, words and representation meaning. The approach also validates on secondary meaning words.

05. RESULTS AND DISCUSSIONS

The proposed system is classifying tweets and tagging them dynamically as positive and negative on social media in an effective approach. The technique has generated a systematic balancing between the negative tweets and the false negative tweets based on federated learning approach. The detailed validation of tweet movement is demonstrated in Fig. 3 according to the users prospective of defining and labeling the tweets based on indexing ranges as shown in Table. 1. The table represents the confusion matrix of True and False ratio such as TP, FP, FN, TN accordingly. The table is summarized with the prediction ratio of the tweets and the dependency on the decision support for validation. Technically, the prediction values are shown in Fig. 4 with respect to sentiment count, sentiment classification and resultant confusion matrix for the decision support.

Table. 1: Confusion matrix and probability estimation of social media tweets estimation and detailed performance matrix represented in Fig. 6.

Tweets number	**Prediction ratio w.r.t confusion matrix**				**Prediction ratio**
	TP	**FP**	**FN**	**TN**	
2000	78.43	23.43	21.32	1.43	85.06
4000	84.42	17.02	11.21	0.43	88.03
6000	84.99	16.92	10.32	1.43	89.62
8000	85.02	17.11	12.03	2.87	91.16
10000	85.12	17.13	12.97	2.77	92.06
12000	84.98	17.86	13.42	2.89	94.64
14000	85.07	17.02	12.87	2.88	95.11

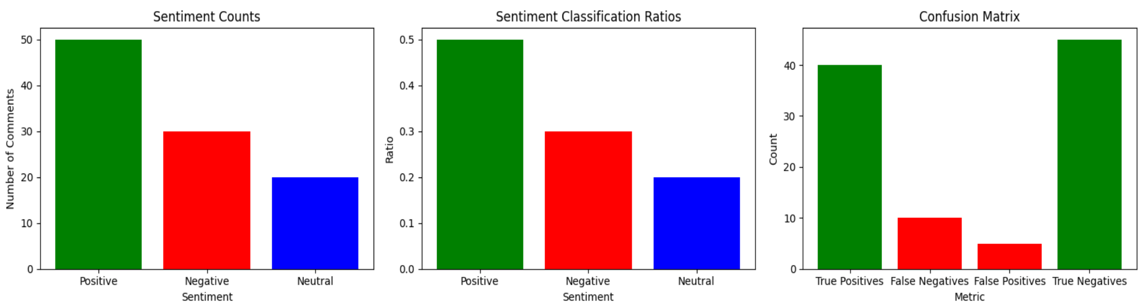

Fig. 4: Representation of probability matrix of tweet attributes under sentiment counts, sentiment classification ratios and confusion matrix.

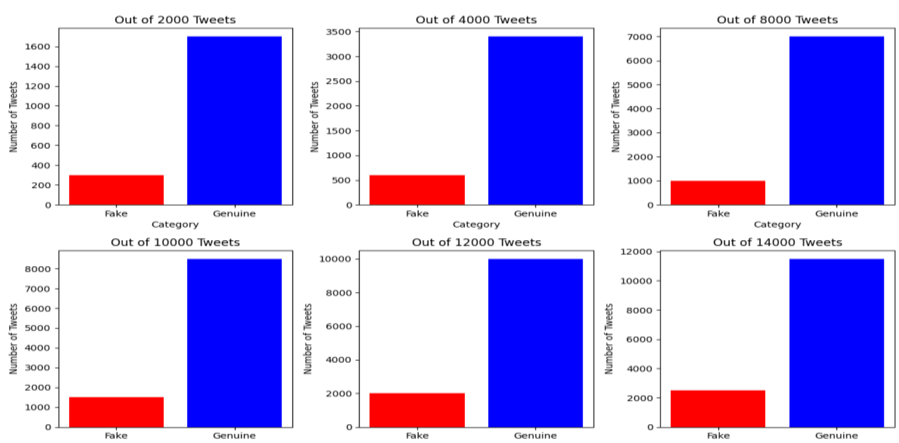

Fig. 5: Classification of "Fake" and "Genuine" comments from the comment classification, with respect to the fake, its negative speech and genuine is positive speech with an inclusion on negative narrative with truth content.

The performance estimation of 14,000 tweets from multiple subjects are assessed and aligned for the decision making of classification into positive and negative tweets. The negative tweets are not limited to the usage of negative weight words, but is aligned with "fake" and "misleading" tweets from the users. The attribute based structuring and training of the tweets added value to the reliable tweet classification and decision making. The detailed performance and accuracy chart with possibility of prediction and classification is represented in table. 1. And summarized in Fig. 6 accordingly.

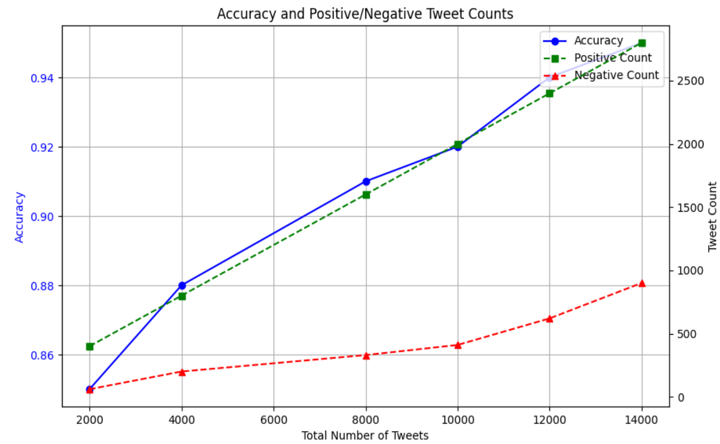

Fig. 6: Accuracy with respect to the tweet performance representation

06. CONCLUSION

The proposed framework introduces a robust method for classifying and categorizing tweets based on their authenticity and user-related attributes. This approach is constructed by leveraging feature mapping techniques that take into account attribute interdependencies, enhancing the reliability of feature mapping. Additionally, the process involves attribute extraction and feature tailoring to identify pertinent feature mappings for labeling tweets as positive or negative. The methodology is exemplified using the X (formerly Twitter) API and a customizable framework. Through this approach, an impressive accuracy rate of 95.11% is achieved in predicting the sentiment of 14,000 tweets within a dynamic tweet context. Looking ahead, the technique has the potential to adapt attribute selection dynamically by considering evolving features and trending tags, ultimately optimizing its performance.

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