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Sentiment Analysis of Social Media Posts for Mental Health Monitoring using Federated Learning

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ABSTRACT: This project explains the application of sophisticated machine learning and deep learning methods to social media messages and comments for sentiment analysis. Mental health poses an important challenge to the well-being of an individual. A growing number of people with mental health problems turn to online resources to express their thoughts (specialised blogs, social media, etc.). Text analysis of rich resources, such as social media, will lead to a better understanding of diseases and provide early warning opportunities for them. Early identification of depression by deep learning models using social media data can help to alter life trajectories and save lives.

Established methods of stress detection commonly rely on psychological scales or physiological instruments, making it impossible and expensive to identify. In this project, we investigate the automated identification of the psychological stress of a person through social media. We first explore the connections between the tension of individuals and their tweeting content, feedback on tweets, social interaction, and behaviour patterns by using machine learning and deep learning systems.

Then we will develop software solutions with the knowledge gathered to identify and report people's existing mental health issues and their likeability to experience different mental health disorders in the future based on the type of content they partake in. Thus, we conclude our model can be beneficial for mental health agencies and individuals to build stress detection methods.

Due to our use of user's personal data the collection of data on a central server would not only cause user privacy breaches, but also pose a risk of other personal information being revealed. So, we use decentralized learning architectures such as federated learning and report on their success against conventional centralized computer-based methods.

KEYWORDS: Social Media, Sentiment Analysis, Mental Health, Federated Learning

I. INTRODUCTION

Sentiment analysis is a method of natural language processing for monitoring the public's sentiment regarding a given product or subject. Sentiment analysis, also referred to as opinion mining, entails the creation of a method for gathering and analysing thoughts on the commodity in blog posts, articles, feedback or tweets. In many cases, sentiment analysis can be helpful. Marketing, for example, helps to measure the effectiveness of an ad campaign or new product launch, decide which variations of a product or service are common, and also recognise which demographics like certain features or hate them.

However, there are some challenges in Sentiment analysis, "the picture was great" is very different from "the picture was not great". In their declarations, individuals can be inconsistent. And as individuals migrate to more informal platforms, such as Twitter or Facebook, this becomes more complex. Based on tiny facts, even most people can't identify the emotion.

Recently, deep learning methods have seen great advances in computer vision and speech recognition over existing approaches. Deep learning approaches are mostly used in the field of NLP for learning word vector representations, part-of-speech tagging, semantic role labelling, identification of named individuals, etc.

Deep CNNs have one primary advantage over current sentiment analysis approaches that rely on robust feature engineering. The feature generation process is automated by CNN and more general representations are taught, making this method versatile and scalable when applied to different domains.



In training machine learning (ML) models collaboratively through clients without exchanging private data, Federated Learning (FL) is widely efficient. In FL, models are trained locally at clients to preserve data privacy and the trained model weights are sent to a central server for aggregation to upgrade the global model. Privacy measures such as differential privacy (Abadi et al.2016) and safe aggregation (Bonawitz et al.2017) are also used during aggregation to improve privacy.

II. STAGES IN SENTIMENTAL ANALYSIS

Sentiment analysis, often referred to as Opinion Mining, is a form of natural language processing to monitor the sentiment of the public regarding a specific product or topic. The purpose of the sentiment analysis is to determine how emotions are conveyed in the texts and whether the expressions reflect positive (favorable) or negative (unfavourable) opinions on the issue.

Using the Natural Language Processing (NLP) techniques, the sentiment analysis area explores user expressions and, in essence, correlates feelings with what the user has presented.

Sentiment can be classified using the following methods:

- machine-learning - where two different methods are used:
 - Supervised learning - a recognition algorithm that is based on the concept of learning with an instructor. Two collections of papers are used: research documents and preparation documents. Opinions/documents must be classified to predefined groups using the following techniques: Naive Bayes, decision trees, support Vector machines (SVM), k-nearest neighbours (KNN) linear and logistic regression, Neural networks, etc.
 - Unsupervised learning – classification without need of a trainer, relying on clustering algorithms, such as hierarchical, Neural networks, similarity coefficients, etc.
- Lexicon-based – based on a predefined set of terms used in dictionaries where words are annotated with sentiments. Possible classifications include, for example:
 - classification of opinions in terms of subject-matter,
 - simple classifications (positive-negative),
 - complex classifications.
- Hybrid approach is a fusion of the two previous methods and aims to enhance the efficiency of sentiment analysis due to machine learning accuracy and lexicon-based approach speed. (Anna Baj-Rogowska et al.2017)

Sentiment analysis is a dynamic procedure, consisting of five general phases. These phases shall be presented in Fig. 1.



Fig 1. Stages of the sentiment analysis process.

A. Data processing – processing and preparing data for review by eliminating stopwords (a, and, or, but, how, was), punctuation (commas, periods...), and inspecting for stemming. These tools would help us to "clean" or "strip" the text from everything that may be incidental to the study. This is because the text in the datasets is from the social media sites selected (Twitter, in our case). Also, the dataset gathered may contain slangs, neologisms, colloquial



language, abbreviations, etc. Texts may contain emoticons and other irrelevant items such as URLs, @(mentions) or #(hashtags).

B. Preparation of content – at this point, unnecessary material is discarded, and non-text data is deleted. The consistency of data needs to be taken care of, including:

- Drop website addresses and substitute them with the word URL,
- In sentences such as #name, delete #, and leave the name alone,
- Delete the white space and punctuation marks from the text.

C. Sentiment identification – the text that has been processed is evaluated in terms of word characteristics. Sentences with customer feedback and political views shall be kept, while facts and evidences shall be discarded.

D. Sentiment rating – the emotional views and experiences of consumers are categorized as positive, negative or good, poor or by any other classification scheme of opinions. Here, the following classifications are possible:

- Sentiment context – sentiment is defined for the key threads derived from the subject.
- Sentiment level – text analysis may be done at the level of the paragraph, sentence, or attribute.
- Sentiment subjectivity – whether the text reflects individual views or is factual.
- Sentiment orientation/polarity – to identify views as positive, negative or neutral.
- sentiment strength – assessing the strength of opinion, e.g. weak, mild, heavy.

E. Communicate the result – the aim of the analysis is to present the end-result of the analysis. There are many ways to communicate your results: reports, slide decks, blog posts, emails, presentations, or even conversations. Data visualization will always be very valuable. In addition, they have a timeline that displays the moods in the chosen timeframes or in other viewpoints.

III. FUNDAMENTALS OF FEDERATED LEARNING

In Federated Learning (FL), smartphone users are encouraged to learn a global-model by aggregating their local-models, without exchanging data that is vulnerable to their privacy. Typically, these smartphone devices have unstable network connectivity to the data centre where the global-model is maintained. In addition, heterogeneous systems with different energy restrictions are involved in a complex and large-scale network. This poses the challenge of connectivity costs when applying the FL on a wide scale.

To this end, in this analysis, we begin with the fundamentals of FL, and then highlight the recent FL algorithms and analyse their communication efficiency with thorough comparisons. In addition, we suggest a series of solutions to resolve current FL questions from the point of view of connectivity and privacy.

Functionally, a mobile computer that is part of the FL computing architecture installs a model that is built to run on mobile computers. It then runs the model on the phone locally and enhances it by learning from the data stored there. Subsequently, it summarizes the improvements as a brief update, normally comprising the parameters of the model and corresponding weights.

Model updates are then transmitted to the cloud or central server using cryptographic communication, such as homomorphic encryption (HE). This update is then averaged by other user updates to boost the shared model. Most notably, all training data stays on the user's computer, and no person modifications are identified in the cloud.

In High-Performance Computing (HPC), training data is first stored together in one piece and randomized before being spread as shards across several computed nodes. This procedure produces independent and identically distributed (IID) results, which in turn improves stochastic gradient descent efficiency.

The goal of FL, on the other hand, is to reach out for data no matter where they are and to use them in model training. So, we don't have this luxury in FL as data stays disjointed during model preparation. This suggests that FL data is often non-IID, and the device must be architecture to survive this phenomenon.

Federated Learning (FL) is achieved by following a three-step process:

1. Task Initialization: The centralized server selects a subset of user compute-devices (usually a smartphone) running the required software and initiates the training of specific learning tasks that are in accordance with the relevant data and implementation to the target. The centralized server, then, specifies the training process and hyper-parameters, e.g., learning rate. The centralized server broadcasts the global model and the FL task to the chosen participants after defining the devices and other task specifications.
2. Local Model Training: All the edge devices (smartphones) then conduct local computing to change their local parameters based on the global model. The goal is to find the optimal parameters that help to reduce the loss function. Each local model's modified parameters are sent back to the centralized server.

Global Model Aggregation: The centralized server collects local parameters from each edge device and updates the global model parameters and then forwards the modified global model parameters to all participants in order to minimize the global loss function.

IV. LITERATURE SURVEY

A. Sweta Agrawal, Amit Awekar, 2018[13]

This paper tries to address the bottlenecks of previous works in this field and tries to overcome the issue using Deep neural networks (DNN) based models for cyberbullying detection like CNN, LSTM, BLSTM, and BLSTM with attention.

Word embedding is used to initialize word embedding as a regular vector and 3 methods. Random, GloVe, SSWE. Here random fixation is on word listing, which GloVe improves for better initialization and SSWE also strengthens this as text feeling as a word-embedding parameter overcomes this problem by adding word feeling as a word-embedding parameter. DNN and transfer learning can provide much specificity together after being evaluated through various datasets.

B. Ivan Sekulić, Michael Strube, 2020[12]

This paper tries to address the use of Hierarchical Attention Network (HAN) (Ivan et al., 2020) in the Mental disorder classification of the user. Classification of the Social media user as a sequence of posts, to apply the HAN method and compare with the previous baseline methods. The input layer is initialized with GloVe word embeddings and low initial learning rate. Linear regression and Linear support vector machine (SVM) were trained on different word lists. Binary classification per disorder indicates that this model outperforms the previous baseline methods if adequate dataset is provided else results worsen as dataset becomes smaller. Attention words Analysis (ivan et al.). This analysis was performed on Reddit users.

C. David Zimbra, M. Ghiassi, Sean Lee[3]

This paper combines two significant approaches to sentiment analysis: Feature Engineering and Dynamic Architecture for Artificial Neural Networks (DAN2). Feature Engineering consists of five stages: frequency analysis, affinity analysis, negation and valence shifter analysis, feature sentiment scoring, and aspect categorization.

Also establishes the fact that DAN2 performs far better than methods such as traditional FFBP and RNN. The tweet paired up with feature engineering and DAN2 can differentiate timid change in the expression, with accuracy reaching an overall 86%.

D Ahmed Hussein Orabi, Prasadith Buddhitha, Mahmoud Hussein Orabi, Diana Inkpen[8]

This paper provides an answer to combat the issues faced due to cultural variance in sentiment analysis. It does so by introducing a cross-domain Deep Neural Network model with a Feature Adaptive Transformation & Combination strategy (DNN-FATC) that transfers the relevant information across heterogeneous domains and aims to slim intercultural barriers of detection models. To bridge the distributional spaces-feature normalization & alignment (FNA) is utilized; Divergent Feature Conversion (DFC) to achieve good throughput in differentiating contexts. Establishes that FNA is more efficient than Min-Max Normalization or Zero-Mean Normalization in reducing isomerism and DFC is



superior to Back-Propagation. Also, DNN model on datasets is essential to amplify detection. DNN-FATC attains peak performance at 78.5%.

Table 1 : A summary of some sentimental analysis detection models

AUTHOR	TITLE	FEATURE SELECTION	FEATURE EXTRACTION	ACCURACY
Sweta Agrawal, Amit Awekar, 2020 et al. [13]	Deep Learning for Detecting Cyberbullying Across Multiple Social Media Platforms	SSWE, GLOVe Vectors	DNN	98%
Ivan Sekulić , Michael Strube,2020[12]	Adapting Deep Learning Methods for Mental Health Prediction on Social Media	HAN	CNN,SVM	NA
David Zimbra, M. Ghiassi, Sean Lee[3]	Brand-Related Twitter Sentiment Analysis using Feature Engineering and the Dynamic Architecture for Artificial Neural Networks	N/A	DAN2, SVM	86%
Ahmed Hussein Orabi, Prasadith Buddhitha, Mahmoud Hussein Orabi, Diana Inkpen[8]	Deep Learning for Depression Detection of Twitter Users	Word2Vec, GloVe	RNN, CNN, LSTM	78.5%
Hayda Almeida, Antoine Briand, and Marie-Jean Meurs[5]	Detecting Early Risk of Depression from Social Media User-generated Content	LMT, SMO, ens_RF classifiers	DNN	N/A
Zhao Jianqiang, Gui Xiaolin[4]	Deep Convolution Neural Networks for Twitter Sentiment Analysis	GloVe-CNN	RBF kernel-SVM	87.66%
Qing Cong, Zhiyong Feng, Fang Li, Yang Xiang, Guozheng Rao, Cui Tao[6]	X-A-BiLSTM: a Deep Learning Approach for Depression Detection in Imbalanced Data	Multinomial Naive Bayes(MNB)	X-A-BiLSTM	NA
Hamad Zogan, Xianzhi Wang, Shoaib Jameel, Guandong Xu[14]	Depression Detection with Multi-Modalities Using a Hybrid Deep Learning Model on Social Media	Multi-Modalities, Word Embedding	Bidirectional Gated Recurrent Units (BiGRUs),CNN	85%

V. ISSUES IN PREVIOUS WORK

- Limited and Unmapped training datasets.
- Only a few topics like bullying, body shaming, racism, and sexism were considered.
- High dependency on the handcrafted Swear list.
- Content-Related challenges related to Figurative Expressions such as Sarcasm and Irony.
- Multilingual Incompatibility.
- No Robust mechanism for Word ambiguousness.

VI. PROPOSED WORK

- a) Create a cross-platform application that stores Twitter usage data per user on-device. It will have a dashboard for predicting the likelihood of different mental health conditions based on Twitter usage patterns and the type of content the user posts and viewed.
- b) The models will investigate the correlations between the mental-health problems and Twitter content, comments on posts, social engagement, and behaviour patterns.
- c) Use Federated Learning architecture in our research and report their performance compared to traditional centralized high-performance computing approaches that require private data of users to be stored on a remote server.

VII. CONCLUSION

As a result of this project we will be able to achieve the following:

1. Dashboard for different mental health conditions:
 1. This describes the application of advanced machine learning and deep learning techniques for sentiment analysis of social media posts and comments so that user can view his/her mental status activity at any point in time
 2. Text processing of rich instruments, such as social media, can help to explain diseases more thoroughly and provide early detection.
 3. Early identification of depression through deep learning models of social media data can help change lives and save lives.
2. A way to tweet on Twitter directly using our application:

This will prevent users from accessing the Twitter app directly which is designed for user retention which causes people to waste long hours on Twitter and help them do more useful work, eventually increasing their self-esteem and productivity.

3. User engagement pattern recognition:

First, we investigate the correlations between mental health and tweeting, comments on tweets, social commitment and behavioural patterns. Then using the information obtained, we'll create software tools to detect and report the current mental health conditions of individuals and their likeability to have various mental health issues in the future depending on the type of content they engage in

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