

# POSTER: Detection of Online Radical Content Using Multimodal Approach

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## I. INTRODUCTION AND RELATED WORK

Several criminal and terrorist organisations have benefited tremendously from the worldwide reach, growth, and speed of the Internet. By utilising the Internet and multiple social media platforms, they are now able to spread their views, widen their reach, and have opportunities to recruit people from all over the world. This has also given them a media platform to broadcast their messages and different propaganda material aiming to spread fear, radicalise and recruit potential members. Previous study has demonstrated that the use of Internet by terrorist groups has significantly increased in the recent years [1]. Several social media platforms such as Twitter and Facebook are working towards keeping these platforms clean by suspending those who are promoting violent content or extremist behaviour. However, due to the volume and speed of the generated data it is still challenging to detect those misbehaving users accurately and in a timely manner.

Recent research has focused on studying the online behaviour of pro-extremists users mainly by performing content-based analysis in order to identify distinguishing textual features that can aid in automatic detection of these users [2]. However, using this approach alone has several shortcomings including producing a large number of false positives, having a high dependency on the data, and it can be easily evaded by adapting the users writing styles through automated tools. Ashcroft et al. make an attempt to automatically detect Jihadist messages on Twitter [2]. They adopt a machine-learning method to classify tweets as ISIS supporters or not. They focus on English tweets that contain a reference to a set of predefined English hashtags related to ISIS. One of the limitations of their approach is that it is highly dependant on the data. Choudhary et al., [3] surveyed existing literature on counter terrorism and social network analysis. Some of the studied problems in this domain are related to identifying key-players, finding behaviour patterns, community discovery, and disrupting terrorist networks. They found that the use of Social Network Analysis (SNA) is one of the most successful methods for counter terrorism in social networks.

Building on the findings of previous research efforts, in this paper we propose a novel method to detect online extremist content that is based on multi-modal approach including textual (syntactic and semantic) features, behavioural features based on social network analysis, as well as psychological-based features. We study the effects of adding these psycho-

logical, and personality features to the accuracy of our model using Linguistic Inquiry and Word Count (LIWC).

We perform an experiment on the Twitter platform using our approach with the aim of detecting radical content and pro-extremist tweets. We adopt machine learning methodology to classify tweets and use our proposed approach for features identification. We envisage that this approach can be utilised by law enforcement investigators and security analysts to aid in detecting and limiting online radical propaganda.

## II. PROPOSED APPROACH

Automatic detection of radicalised content is a challenging task as it requires identification of the intent behind the message. Using single type of features such as textual syntactical features is prone to generating large set of false positives, which results in the analyst losing trust in the system. Thus, we propose a novel approach to detect radical and pro-extremist online content, which is different from existing work in that it uses multi-modal approach. We combine heterogeneous features including textual, social, and psychological into a representation that can be used to detect radicalism. Using an unsupervised machine learning method, we cluster online text messages into groups of radical/non-radical messages.

Moreover, our detection approach is designed to be semi-automatic in order to integrate the security analyst into the detection process. By making use of the analysts' intuition and experience to guide the detection process, we can minimize false positives generated by the system.

### A. Features Identification

Three classes of information are used to identify relevant features to detect radical content. Some of these features are user-based and others are message-based, as discussed in detail below:

1) *Textual-based features*: This class consists of text-based features calculated using text mining and natural language processing methods, such as bag of words, n-grams, most frequent words, ratio of bad words (violent words), upper-case letters, and number of emoticons. We use term frequency-inverse document frequency (tf-idf) to calculate a composite weight for each term occurring in any given message. Features like n-grams, and words frequency were adopted from the literature since they have been successfully used to classify radical content. Additionally, we use upper-case letters as indicative features since they are used to convey emphasis for a word or an anger (yelling) behaviour.

2) *Psychological-based features*: This class consists of the analysis of psychological properties of the authors of the messages. Inspired by previous research within the fields of terrorism and psychology that suggests that terrorists differ from non-terrorists in their psychological profile [4], we measure five psychological features: *Personality traits (OCEAN)* is a model with five domains of personality (Openness, Conscientiousness, Extroversion, Agreeableness, and Neuroticism). Based on lexical features a score for each personality domain is calculated per user, which together represent the person’s personality. *Thinking Style* which focus on measuring the degree to which the person is an analytical thinker who relies on facts or feelings when making decisions. *Interests* focus on measuring the person interests such as work, friendship, and religion. *Tone* measures whether the person have a positive emotion or a negative one (joy, sadness, anger, etc.). *Clout* measures if the person is speaking from experience and is confident or more tentative and anxious style. For example, a radical message that promotes for violence will show high levels of anger, anxiousness, and neuroticism.

3) *Behavioural-based features*: This class consists of measuring behavioural features by constructing the social graph of a particular user to capture their relationships and influences within their respective community. Additionally, this class of features capture user’s interactions with others through *Like* actions, and engagement in discussions using *Mention*, and *Reply* actions. For example, by constructing the social network for a particular user, we can measure the degree of influence this user has over his social network (e.g., using centrality measures), or identify how a particular user is linked to other known radical extremist users.

### B. Clustering and Integrating Users-in-the-Loop

After extracting the features from the three categories previously defined, we combine them in a final feature vector. Due to the sparsity and large number of features we perform dimensionality reduction to reduce the feature space using a statistical approach called Principle Component Analysis (PCA). The new features vectors with reduced dimensionality are input to unsupervised machine learning clustering algorithms, such as K-Means and hierarchical clustering. These clustering will group the messages into groups based on the author’s behaviour, psychological traits, and textual violence words associated with each message. The results of the clustering algorithm will be presented to the security analysts and prompt them to tag a subset of the results as being radical or not. These tags are labels that are fed back to the system through a supervised machine learning algorithm to further learn and enhance the results accuracy. Additionally, the security analyst will be able to configure several parameters of the machine learning algorithms for example by setting the value of  $K$  for the K-Means algorithm.

### III. EXPERIMENT SETTING AND PRELIMINARY RESULTS

To evaluate our approach, we performed an experiment on Twitter platform. We collected data using the Twitter

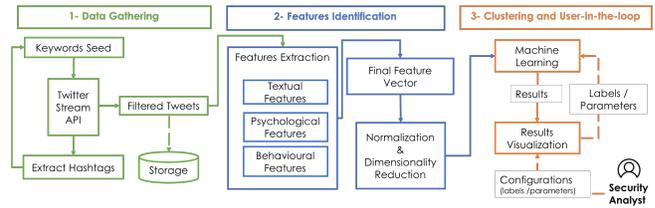


Fig. 1. Flow diagram describing our approach from data gathering, to features identification and creating the final feature vector containing textual, psychological, and behavioural features, and finally the clustering and analyst interaction with the results.

Streaming API following snowball sampling approach. We started the collection by filtering tweets based on an initial seed of keywords that represent the top terrorist organizations as reported by the US National Counter Terrorism Center [5]. We then extracted hashtags from the collected data (10K unique hashtags), and added the most frequent ones (top 2%) to our seed in order to collect additional tweets. By the end of the collection process our dataset consists of around 700K tweets. Figure 1 describes the flow of our approach starting from data gathering, feature extraction, to machine learning, and the analyst’s interactions through configuration and tagging of the results. Our initial results suggest that the proposed approach of combining multi-modal features is promising in detecting radical content. Moreover, the use of psychological features mainly social tone, interests, and personality traits are among the most discriminatory features.

### IV. CONCLUSION AND FUTURE WORK

In this paper we presented our approach for detecting radicalised online messages. We use a collection of heterogeneous features to extract discriminatory features that are able to identify radical content. Unlike previous efforts, these features do not only focus on lexical analysis of the messages but add additional dimensions such as psychological and behavioural aspects in order to improve the detection accuracy. Our future work will include a detailed analysis of the results obtained from the experiment performed on the Twitter platform. Furthermore, we aim to study the psychological properties of pro-extremist users to identify patterns in their psychological profile. This may be useful in predicting whether there’s high probability for a given user to be radicalised.

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