Assessing Viewer's Mental Health by Detecting Depression in YouTube Videos

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Introduction

300 million people around the world have depression, according to the World Health Organization[1].

- **1/10** children aged 5-16 have a diagnosable condition
- **1/2** of all mental health problems are established by the age of **14**
- **3/4** of all mental health problems are established by the age of **24**

- Depression is **the leading cause of disability** world-wide leading to an estimated **$210.5 billion** economic burden per year.
- Suicide is the **2nd leading cause of death** among people aged 15-24.

Obstacles in the way

- Only **1 in 5 people** receive treatment consistent with current practice guidelines.
- **6%** of people with depression are treated with medication only.
- **35%** of adults with depression receive no treatment at all.
- WHO reports that majority of depressed individuals **never seek out treatment** because they are unaware of what is going on with them.
- Around **50%** of depressed people are **misdiagnosed** as being alright (false negative) annually.

Data

The data for the analysis of the video content was gathered by collecting videos using various keywords like **self-harm**, **suicidal**, **triggering** etc. and extracting the transcript out of it. Videos were divided in two categories: **i) Depressed ii) Non-Depressed**

Category	Number of Words	% Division
Depressed	754,883	1427 (48%)
Non-Depressed	832,117	1573 (52%)
Total	**1,409,719**	**3000 (100%)**

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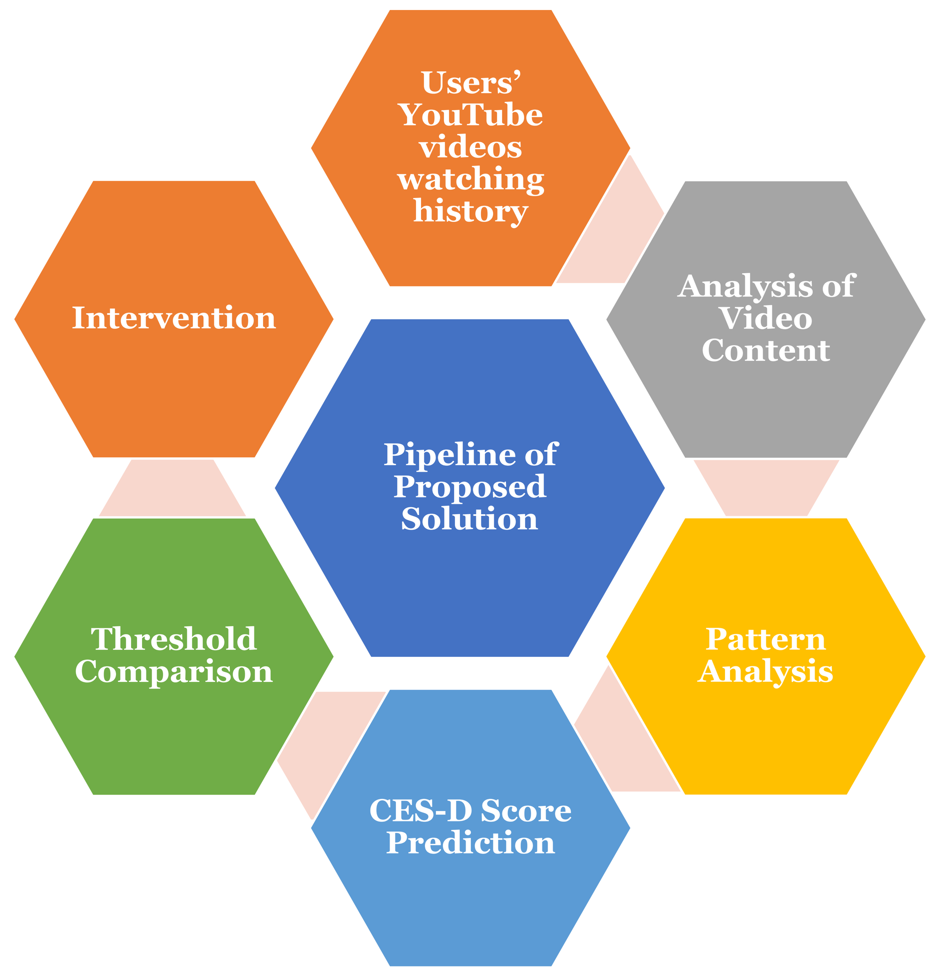
Our approach

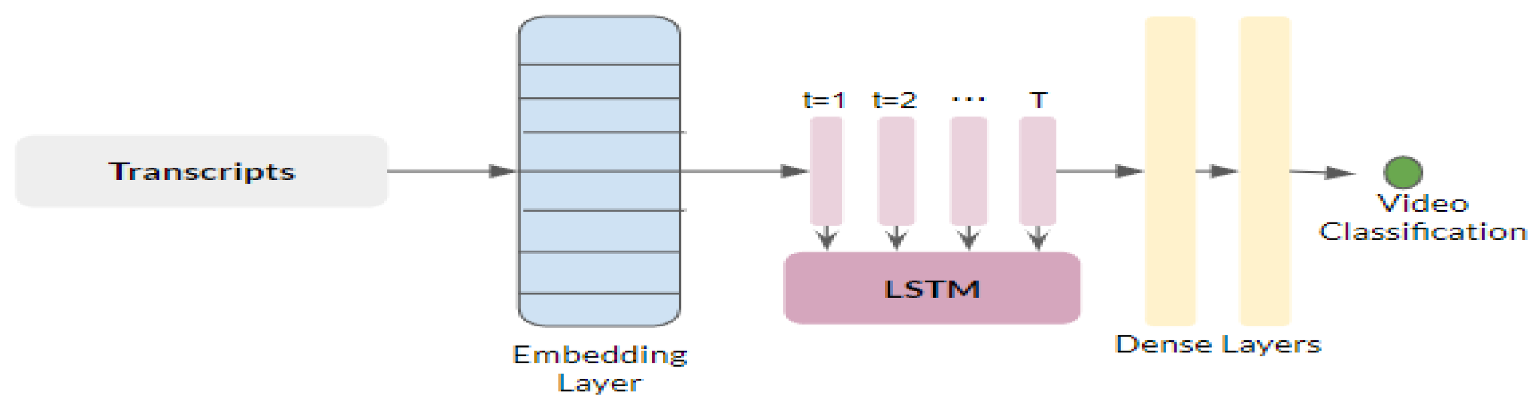


At a high level, our pipeline is composed of **3 different layers**:
i) Secured data acquisition
ii) Feature extraction from individual videos and their content analysis
iii) Analysis of video viewing patterns over time.

Methods

Current work focuses on content analysis of Videos

- **Baseline** : Multinomial Naive Bayes (NB) Classifier using features extracted from **Empath[2] model**.
- **LSTM** :
  - For each comment, we make it pass through an Embedding layer seeded with pre-trained **GloVe 300D** word embedding weights.
  - LSTM network with **196 units, tanh activation, recurrent dropout of 0.2.**
  - We use **binary cross-entropy loss** and **Adam optimization**.



- **Naive Bayes with n-grams:** Modification of baseline model by capturing textual features by extracting TF-IDF weighted combinations of word n-grams form the transcripts.

Model	Accuracy (%)	Time (sec)
EMPATH + Naive Bayes	52	5
TF-IDF + EMPATH + NB	81.2	8
LSTM	83.4	345

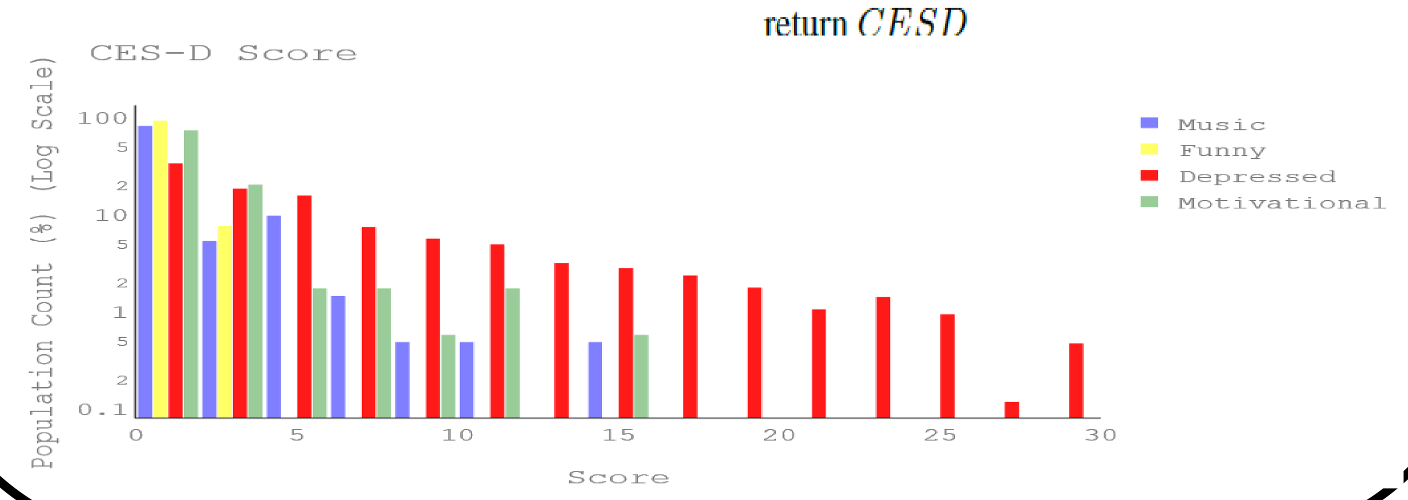
Evaluation

Calculation of CES-D Score

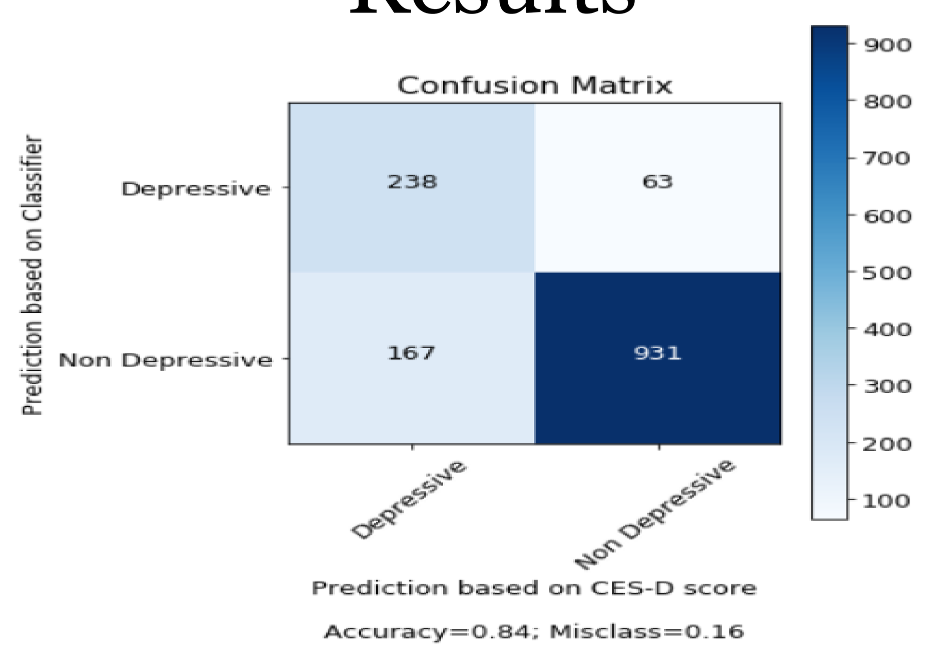
- Extracted around **200 videos** for videos of various categories and analyzed the comments by calculating their **CES-D score[3]**.
- The percent of non-depressed comments **(CESD = 0)** for non-depressive categories (music, funny) is **much higher** than that in depressive category.
- Range of the **CES-D score** is the **largest in depressive videos**

Algorithm 1 CES-D Score

Require: data $text$
  set ($categoryTerms$)
  $termFreq \leftarrow 0$
  while $term$ in $categoryTerms$ **do**
    if $term$ in $text$ **then**
      $termFreq \leftarrow termFreq + 1$
    end if
  end while
  $termFreq \leftarrow \frac{termFreq}{len(text)}$
  $neg \leftarrow Empath.analyze(text, negative)$
  $pos \leftarrow Empath.analyze(text, positive)$
  $connotation \leftarrow (neg - pos)$
  $CESD \leftarrow termFreq \times connotation$
  return $CESD$



Results



Discussion and Future Work

- Our results showed a significant **relationship between the content of video and comments** by the users viewing it.
- This pattern can be useful in determining the mental state of a viewer.
- Our future work will focus on the usage of **audio/visual features**, and analyzing the affective content using continuous dimensions like **arousal/valence.**

References

1. https://www.who.int/news-room/fact-sheets/detail/depression
2. https://hci.stanford.edu/publications/2016/ethan/empath-chi-2016.pdf
3. http://www.midss.org/content/center-epidemiologic-studies-depression-scale-ces-d