Deep Learning-Based Frameworks for Automated Identifying Mental Illness Through Social Media

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Content

1 Introduction & Motivation

1. Introduction

Social media mining is the process of obtaining big data from user-generated content on social media platforms and analyzing that data to make business decisions using various strategies. It is a process that goes beyond the usual data collection and storage to include analysis that can provide insights and identify patterns.

There are some key steps for the social media mining.

Data Collection: Gathering data from various social media platforms. This data can include text posts, images, videos, user information, and more.

↓

Data Preprocessing: Cleaning the data, handling missing data, and transforming the data into a format that can be easily analyzed.

↓

Data Analysis: Techniques such as machine learning, natural language processing, and statistical analysis are used to analyze the data and extract useful information.

↓

Visualization: Creating graphs, charts, and other visual representations of the data for institutive analyzing.

↓

Insight Generation: Generate insights that can be used to make business decisions. This can involve identifying trends, understanding customer sentiment, and more.

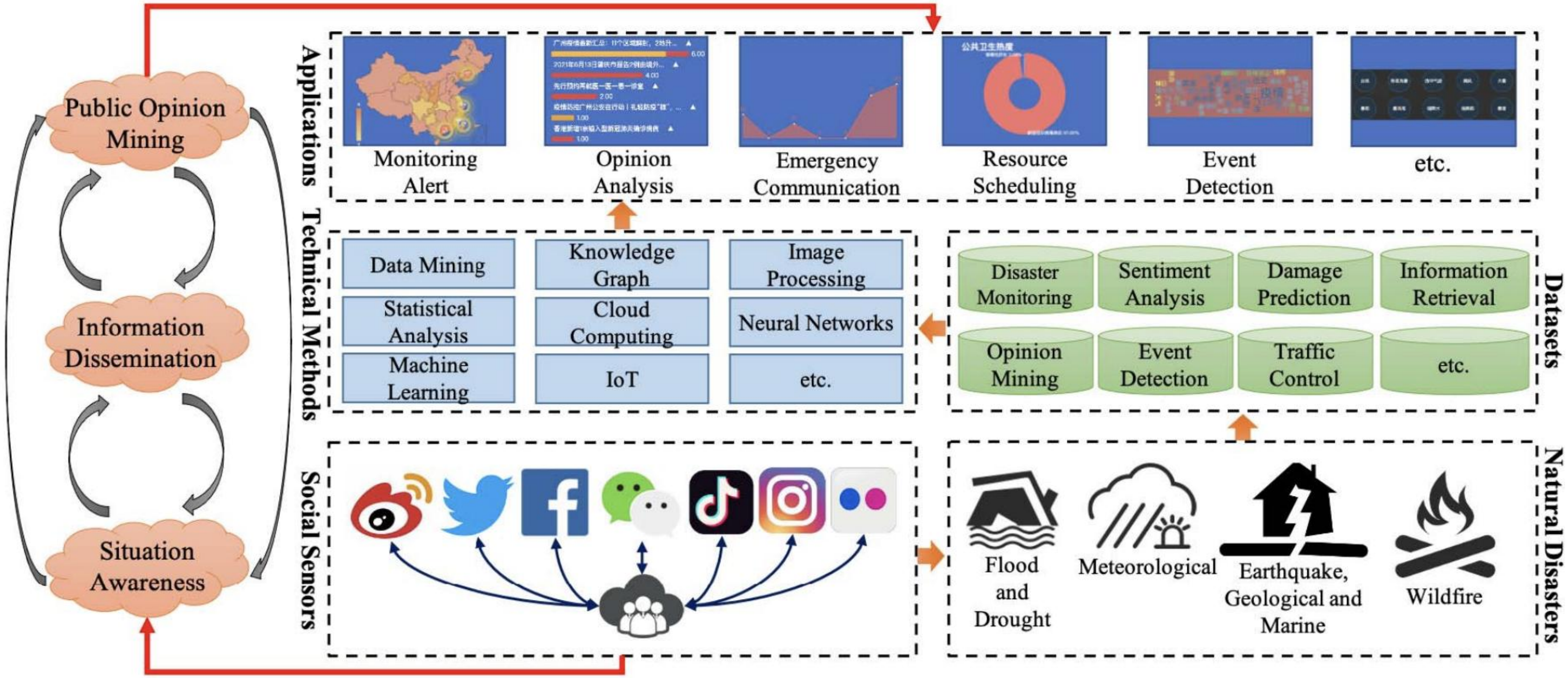
1. Introduction

Social media mining, while powerful, does come with a set of challenges and difficulties.

- Data Volume
- Privacy Concerns
- Data Integration
- …
- Data Quality
- Language and Cultural Differences
- Real-Time Analysis

1. Introduction

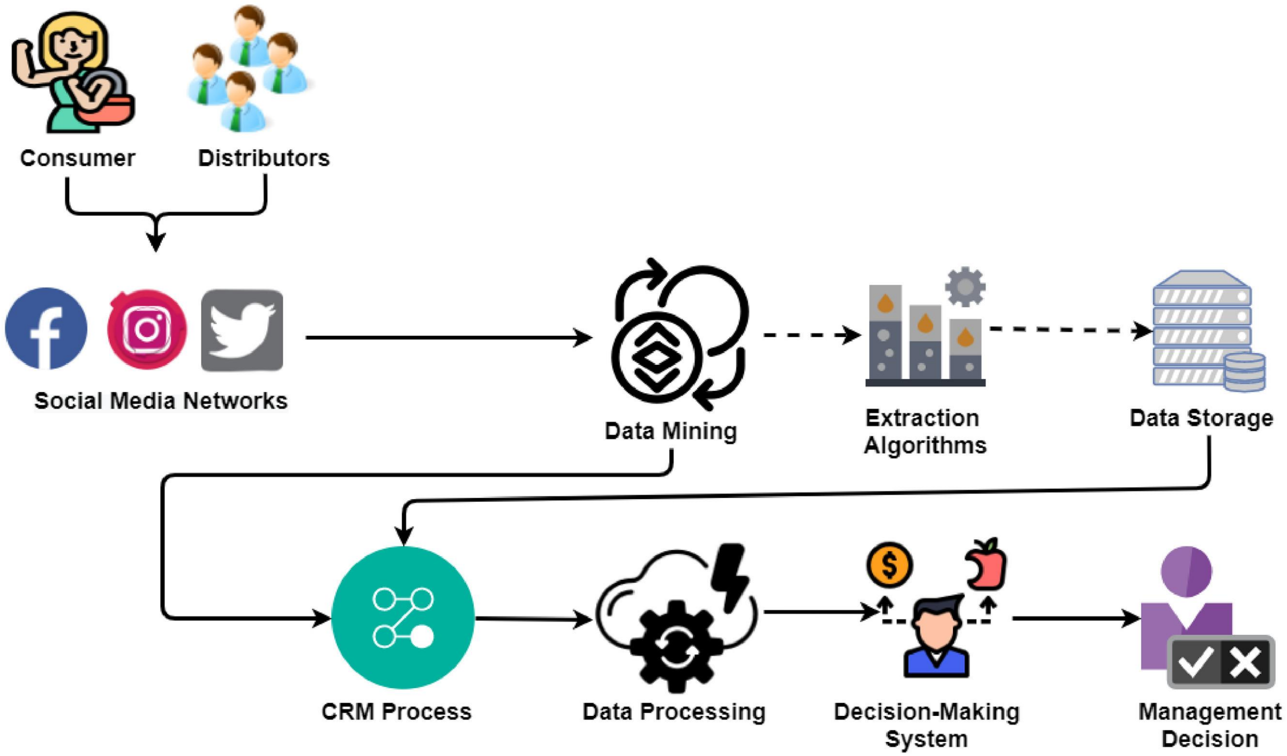
Natural Disaster Emergency Management



K. Shi, X. Peng, H. Lu, Y. Zhu and Z. Niu, "Application of Social Sensors in Natural Disasters Emergency Management: A Review," in IEEE Transactions on Computational Social Systems, 2022, doi: 10.1109/TCSS.2022.3211552

1. Introduction

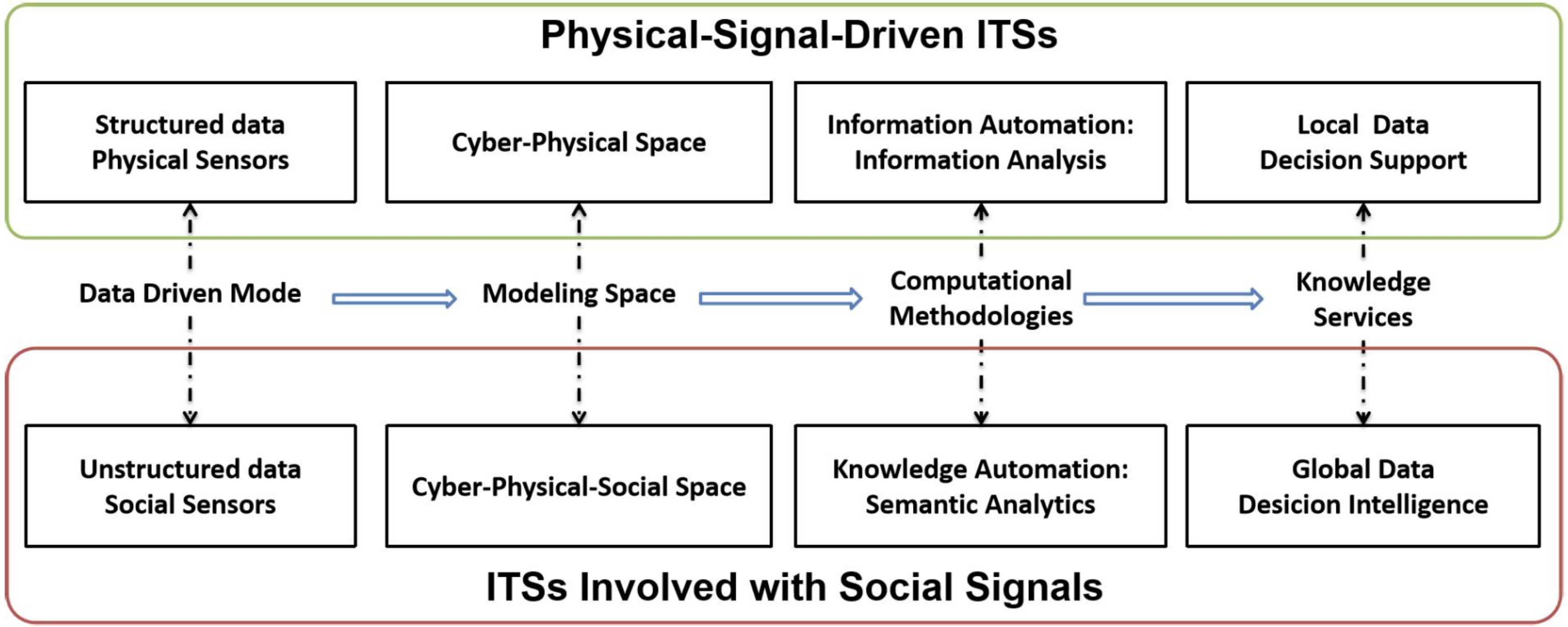
Business Decision Making



Jie Yang, Pishi Xiu, Lipeng Sun, Limeng Ying, & Blaanand Muthu (2022). Social media data analytics for business decision making system to competitive analysis. Information Processing & Management, 59(1), 102751.

1. Introduction

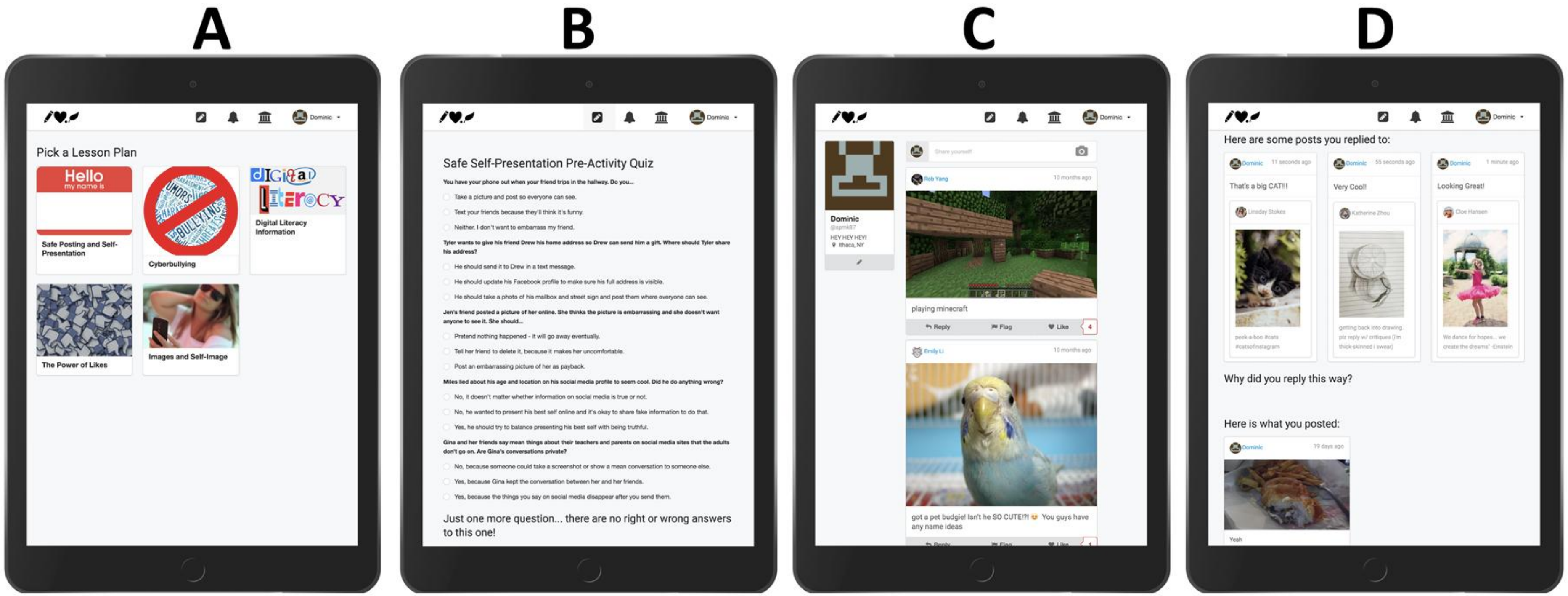
Intelligent Transportation



H. Lu et al., "Social Signal-Driven Knowledge Automation: A Focus on Social Transportation," in IEEE Transactions on Computational Social Systems, vol. 8, no. 3, pp. 737-753, June 2021, doi: 10.1109/TCSS.2021.3057332.

1. Introduction

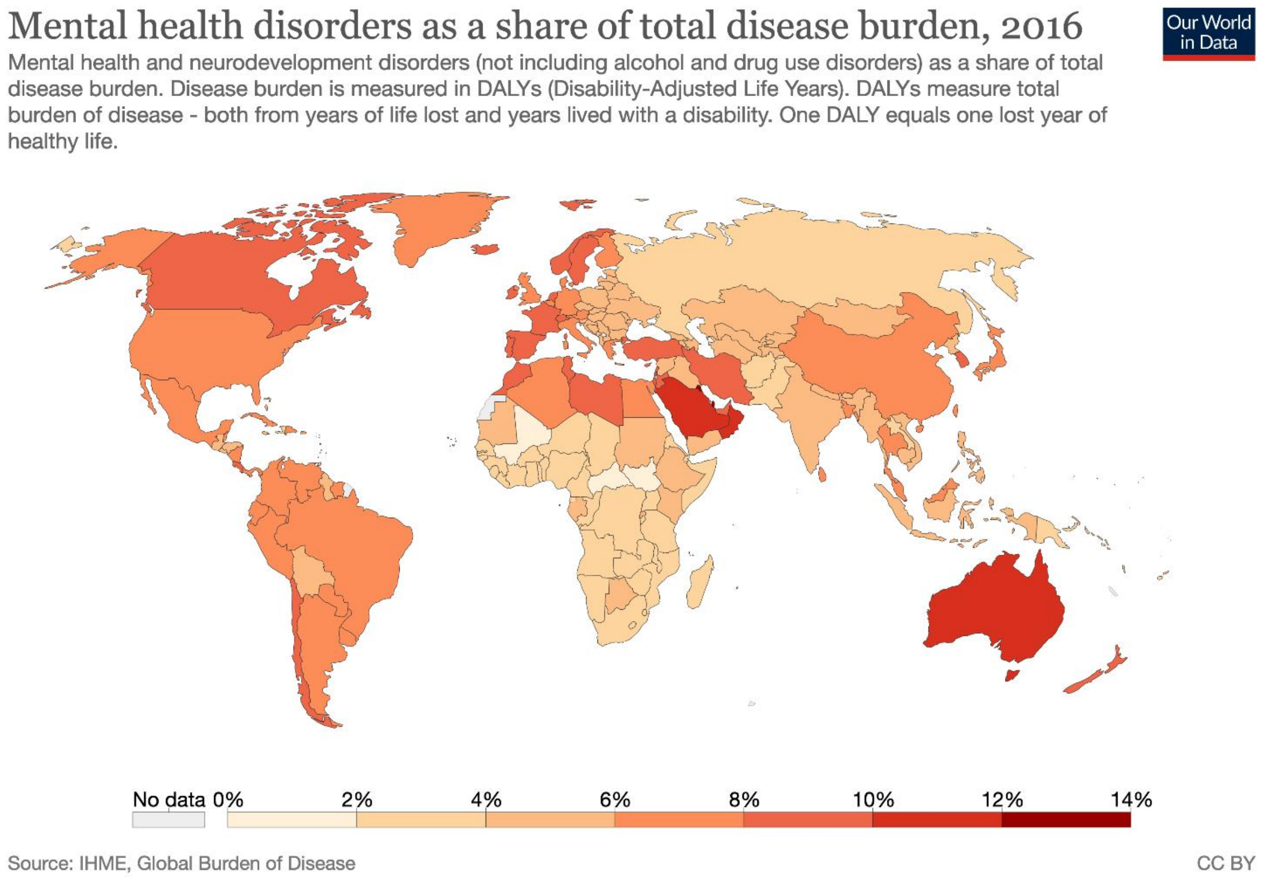
Online Education



DiFranzo, D., Choi, Y., Purington, A., Taft, J., Whitlock, J., & Bazarova, N. (2019). Social Media TestDrive: Real-World Social Media Education for the Next Generation. In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems (pp. 1–11). Association for Computing Machinery.

1. Introduction

- **<u>Major depressive disorder (MDD)</u>** is the most common mental health issue among other mental health issues [1].



1. Introduction

- A person can experience several complications as a result of depression.
- Early determination and treatment of depression can help.
- Early identification of patient suffering from depression is important .


The Star

StarPlus News Asean+ Business Sport Metro Lifestyle Food Tech Education Opinion Videos

HK pop singer Coco Lee dies at 48 after long struggle with depression

By ANNDREA A. WEBBER

ENTERTAINMENT

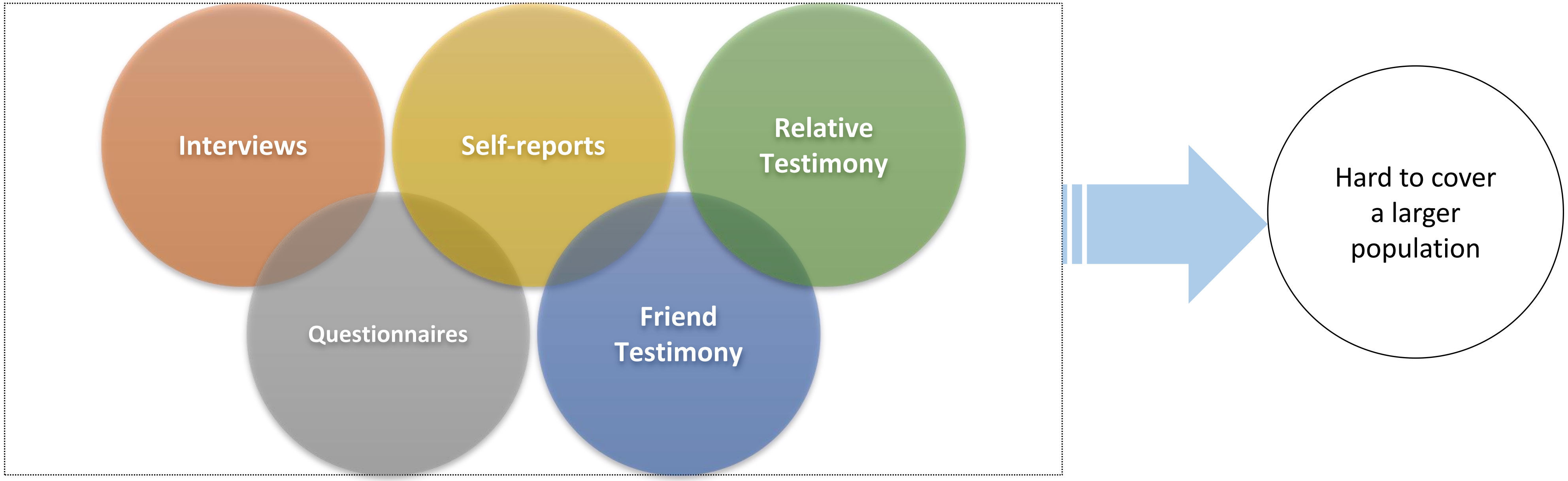
Wednesday, 05 Jul 2023

10:13 PM MYT

Related News

1. Introduction

- Most traditional ways of diagnosis are based on:



1.1 Depression on Social Media

- People with depression hide their symptoms [2].

- People with depression express their problems in social media [3].

1.1 Depression on Social Media

Social media could provide ways to diagnose major depressive disorders.

(Coppersmith et al., 2014, De Choudhury et al., 2013)

1.1 Depression on Social Media

Social networks, can measure and predict risks for different mental health problems [4,5,6].

I initially thought: oh great! Facebook will be a nice place to connect with my mommy friends and get some help maybe? Turns out I was so wrong. In some sense, several of these mommies I connected with, I mean not all, but they were so inconsiderate and judgmental about me and my condition. I wanted help, not how they thought I was. Clearly I started feeling that maybe I wouldn't be able to get as much help from them as I thought I would. Those Facebook pages around motherhood were slightly better—though kinda same story continued. (Mom C)

Figure: *Experiences from mothers with postpartum depression around receiving social and emotional support from Facebook .* (De Choudhury et al., 2013)

How we can propose effective computational techniques to automatically find such users online?

Research Tasks

T1- To build a comprehensive spectrum of behavioural, lexical, and semantic representations of users, by Integrating multi-aspects features with user posts.

- *What is an effective strategy through which we can select features so that we can identify patterns from implicit or passive users?*
- *How can information about user behaviours on social media be used to make our model prediction more accurate?*

T2- Select the most salient user-generated content automatically, to a natural advantage to our computational framework for depression detection.

- *Can we provide a computational framework that uses the information acquired after doing content summarization to train and aids in choosing the classifier's most beneficial features?*

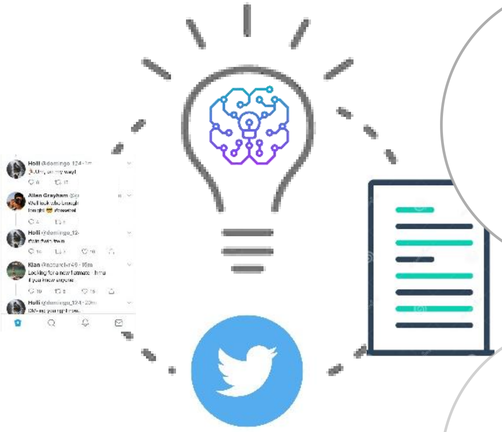
Research Tasks

T3- To design and implement an explainable deep learning architecture to identify depressed users in social media.

build a deep learning-based depression
on system that explains how decisions are
and why an individual user is depressed?

Research Tasks

T4- To create new tasks that aim to model user narrative in Social Media that helps to understand crucial narrative features and how they evolve and extract such features for A narrative explanation of a series of events.



we model the social media posts via
stering and their intentions as a narrative
ement in an interactive generation
framework?

w to design a framework for interactively
orporating a user's social media posts to
nerate a narrative automatically?

Research Tasks

T5- Studying data from social media to understand how the pandemic has impacted people's depression.

https://www.privatepsychiatry.co.uk/news/long-covid-and-mental-health/

ow to distinguish between depressed and on-depressed users' tweets before and after the COVID-19 pandemic started?

low does COVID-19 affect people's epression in local government regions in erms of time?

2

Literature Work and Limitation

Previous Studies

Shen, Guangyao, et al. "Depression detection via harvesting social media: A multimodal dictionary learning solution."**International Joint Conferences on Artificial Intelligence (IJCAI),2017. [7]**

- Shen et al. extracted various features representing user behaviour in social media.
- Grouped these features into several modalities.

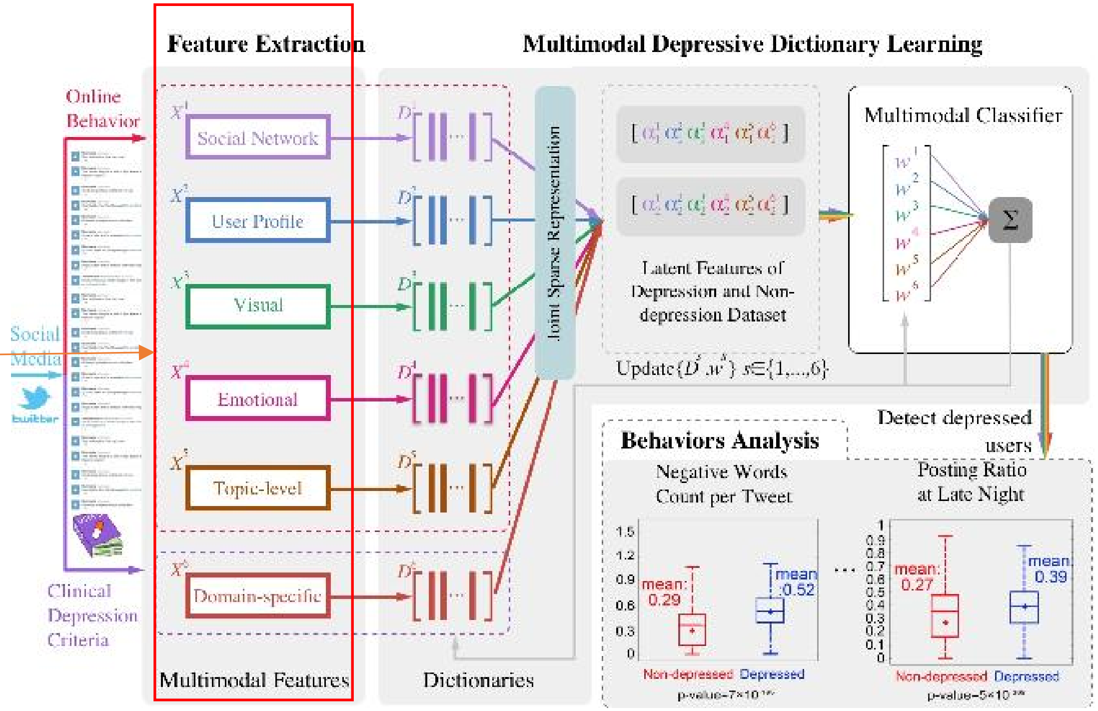


Figure: "Depression Detection via Harvesting Social Media: A Multimodal Dictionary Learning Solution" by Shen et al. 2017

Previous Studies

Shen, Tiancheng, et al. "Cross-domain depression detection via harvesting social media."
International Joint Conferences on Artificial Intelligence (IJCAI), 2018. [8]

- Depression detection on Twitter is a promising and challenging research problem.
- Analysing user content and user textual information achieve some success for depression detection and mental illness.

these features are treated as an individual measurable property in different machine learning algorithms.

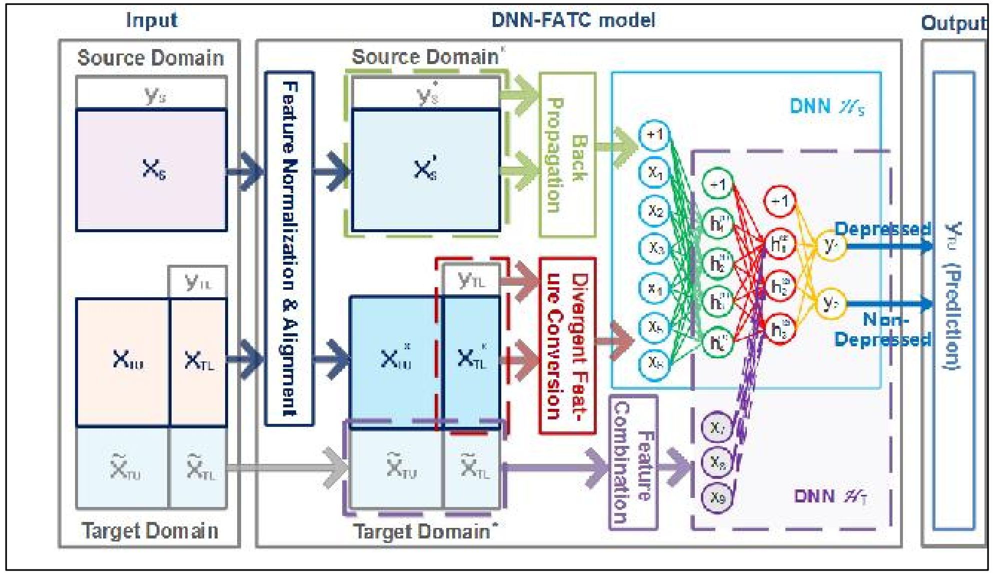


Figure: "Cross-Domain Depression Detection via Harvesting Social Media" by Shen et al. 2018

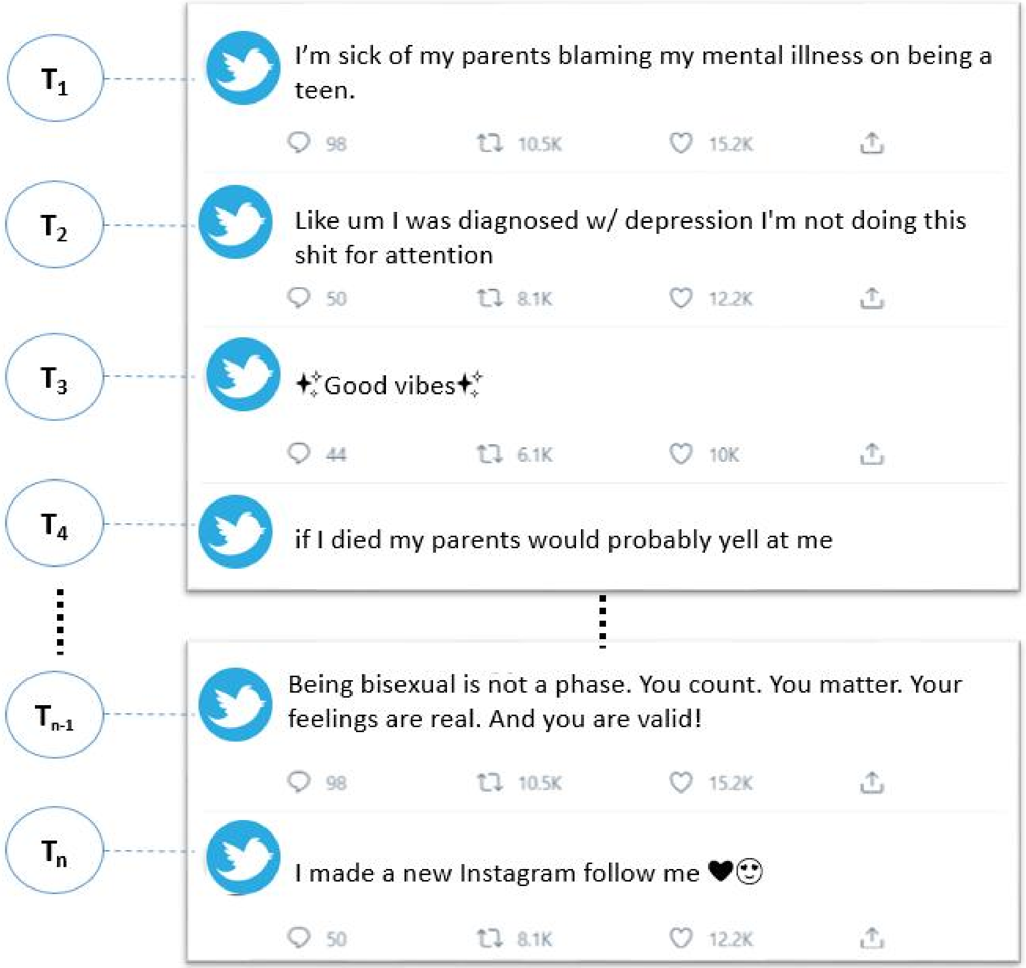
Existing Limitations:

1) The variation of depressed user behaviour on Social Media [7,9,10,11,12,15]:

- Depressed users behave differently when they interact on social media
- Not all of user behaviours are related to depression characteristics.
- Many existing studies have either neglected important features or selected less relevant features.

A user online behaviors

Existing Limitations:



2) Posts diversity per user on Social Media [7,9,14,13]:

- Existing methods is that they tend to use every social media post of a user.

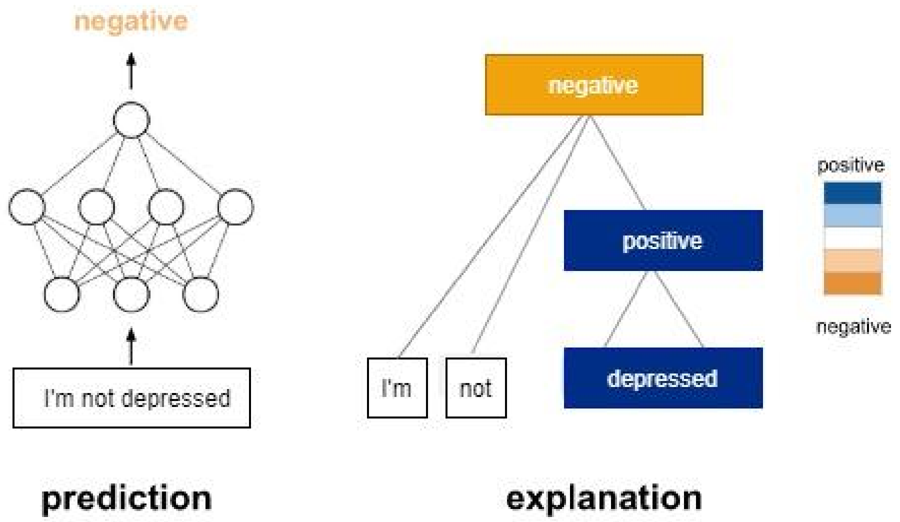
  "It tends to make the automatic depression detection system inefficient and even degrade the performance."

- A user shares a varied set of posts online not just depression-related (Figure).

Existing Limitations:

3) Explaination for Automated Depression Detection [16,17,18]:

- Most of Depression detection techniques concentrate on effectively detecting depression, but can not clarify why a user is detected as depressed.
- The deep learning model's decision-making mechanism is stubborn and making it hard to grasp the reasoning behind its decisions.



3 Combine multi-aspects features with User Post Summarization

1. "Depressionnet: learning multi-modalities with user post summarization for depression detection on social media." **Zogan, Hamad**, Imran Razzak, Shoaib Jameel, and Guandong Xu. In *proceedings of the 44th international ACM* ***SIGIR conference on research and development in information retrieval 2021.***

Motivation

- Summarization could be an ideal way to deal with tweets presents challenges.

A user tweets

A summary for a user tweets

Methodology

Extractive-Abstractive Summarization:

- A framework that incorporates an interplay between the abstractive and extractive summarization.

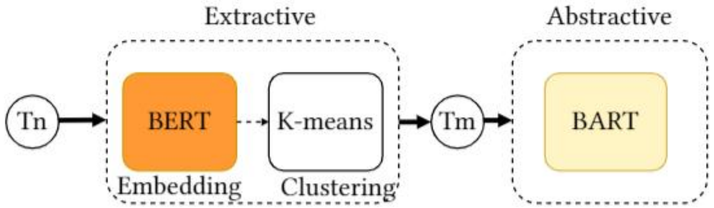


Fig. 8. Diagram to illustrate the process of user posts summarization

The framework summarize the user generated content � � from user history of � � tweets such that:

� � ≤ � �.

- Extractive model helps automatically select the user generated content by removing redundant information.
- Abstractive framework further condenses the content while preserving the semantic content.

User Behaviour Modelling

Social Network

Topic Modeling

Emotional Features

Domain-specific

Our Proposed Framework

Technical Description:

Encoding user post history

Let $x_i \in R^k$ be the k-dimensional word vector so the input tweet can be denoted by $x \in R^{n \times k}$

$$c_i = f(\omega \circ x_{i:i+g-1} + b)$$

$$h_t = [\overrightarrow{h}_t, \overleftarrow{h}_t]$$

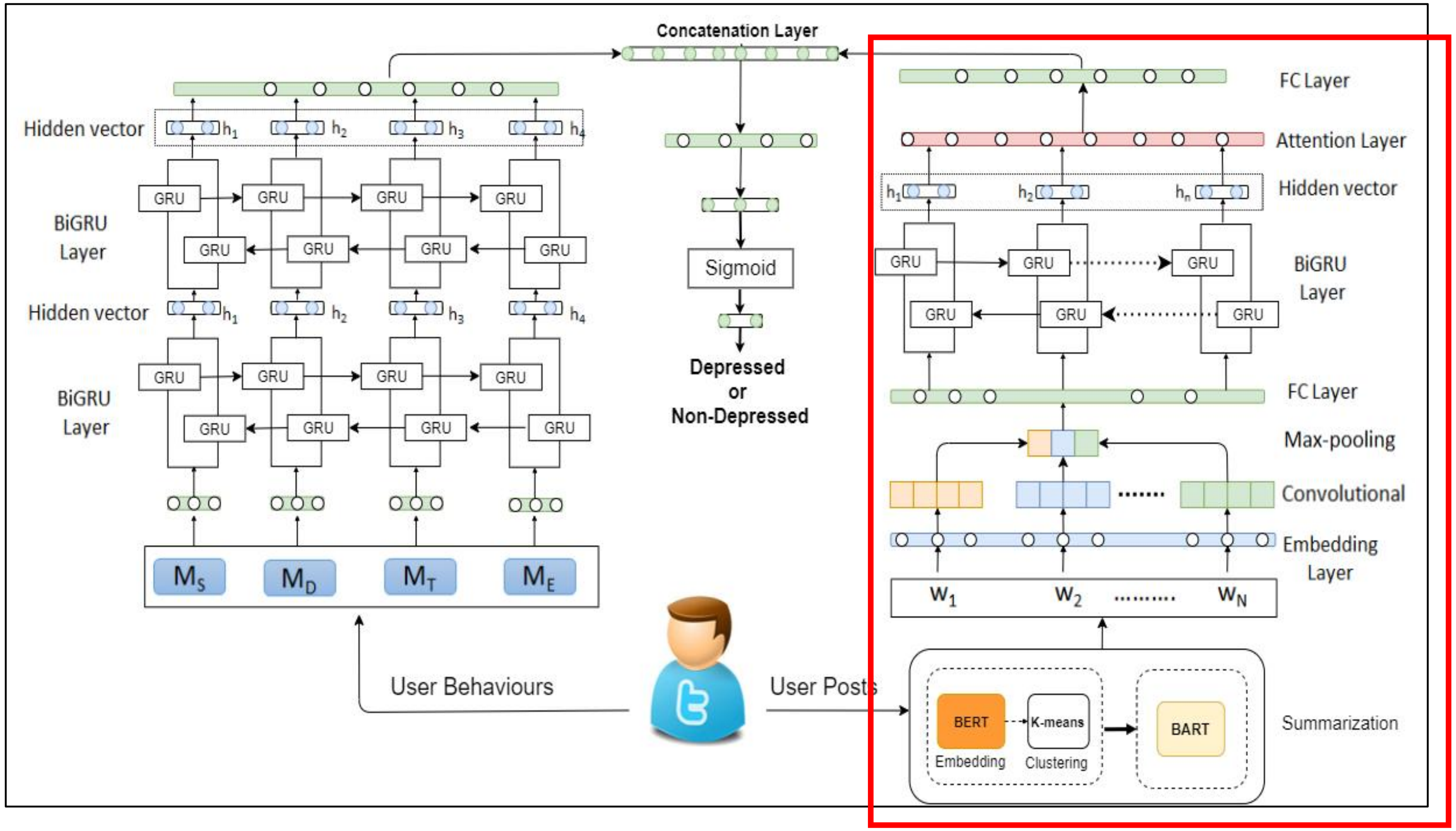
The target attention weight u_t at timestamp t is calculated using the vectors h_t :

$$u_t = tanh(\omega h_t + b)$$

$$a_t = \frac{\exp(u_t)}{\sum_{t=1}^{m} \exp(u_t)}$$

$$\bar{s}_i = \sum_{t=1}^{m} a_t \bullet h_t$$

DepressionNet framework for the task of automatic depression



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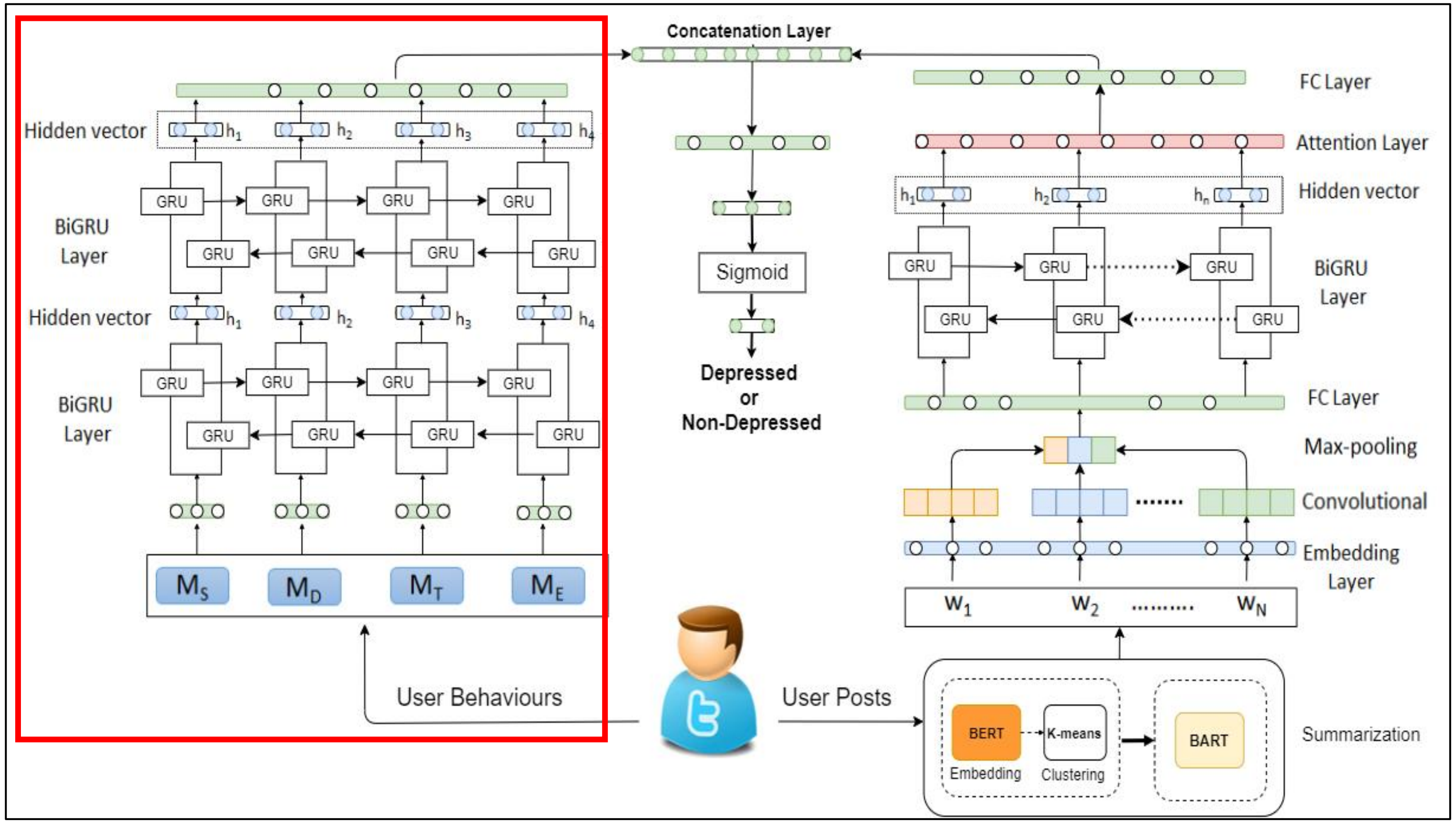

Experiments and Results:

- Combining both summarization and user behaviour representation can effectively leverage online user behaviour and their posts summarization attributes for depression detection.

Table 5: Comparison of depression detection performances in social media whence of four selected features.

Feature	Model	Precision	Recall	F1-score	Accuracy
User Behaviours	SVM (Pedregosa et al. [32])	0.724	0.632	0.602	0.644
	NB (Pedregosa et al. [32])	0.724	0.623	0.588	0.636
	MDL (Shen et al. [38])	0.790	0.786	0.786	0.787
	GRU (Chung et al. [8])	0.743	0.705	0.699	0.714
	BiGRU	0.787	0.788	0.760	0.750
	Stacked BiGRU	0.825	0.818	0.819	0.821
Posts Summarization	XLNet (base) (Yang et al. [51])	0.889	0.808	0.847	0.847
	BERT (base) (Liu et al. [24])	0.903	0.770	0.831	0.837
	RoBERTa (base) (Liu et al. [24])	**0.941**	0.731	0.823	0.836
	BiGRU (Att)	0.861	0.843	0.835	0.837
	CNN (Att)	0.836	0.829	0.824	0.824
	CNN-BiGRU (Att)	0.868	0.843	0.848	0.835
Summarization + User Behaviures	CNN + BiGRU	0.880	0.866	0.860	0.861
	BiGRU (Att) + BiGRU	0.896	0.885	0.880	0.881
	CNN-BiGRU (Att) + BiGRU	0.900	0.892	0.887	0.887
	BiGRU (Att) + Stacked BiGRU	0.906	0.901	0.898	0.898
	CNN (Att) + Stacked BiGRU	0.874	0.870	0.867	0.867
	DepressionNet (Our Model)	0.909	**0.904**	**0.912**	**0.901**

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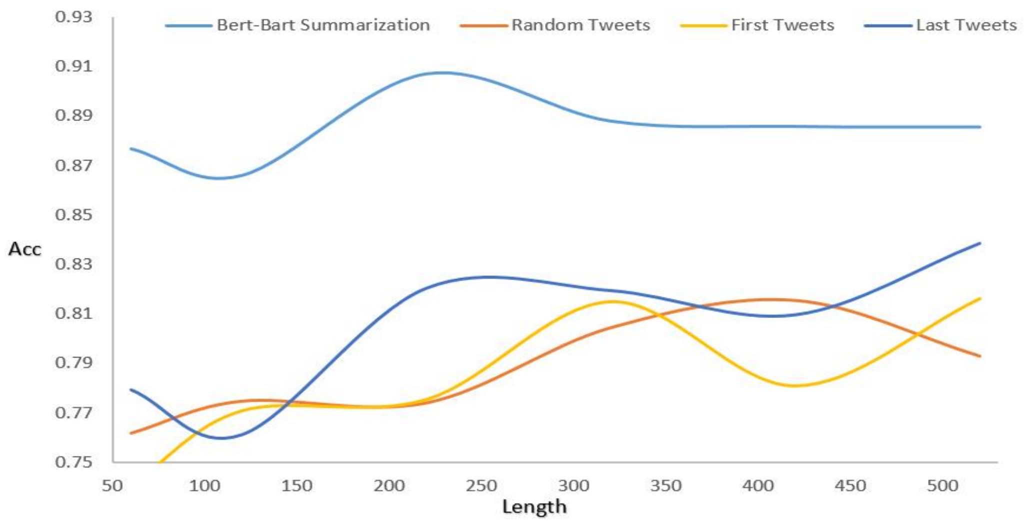


our model performance vs text length, with different inputs of data.

Summary

- We have proposed a novel deep learning framework (DepressionNet) for automatic depression detection by combining user behaviour and user post history or user activity.

- We apply a abstractive-extractive automatic text summarization model based on the combination of BERT-BART that satisfies two major requirements.
  - wide coverage of depression relevant tweets by condensing a large set of tweets into a short conclusive description.
  - preserving the content which might be linked to depression.

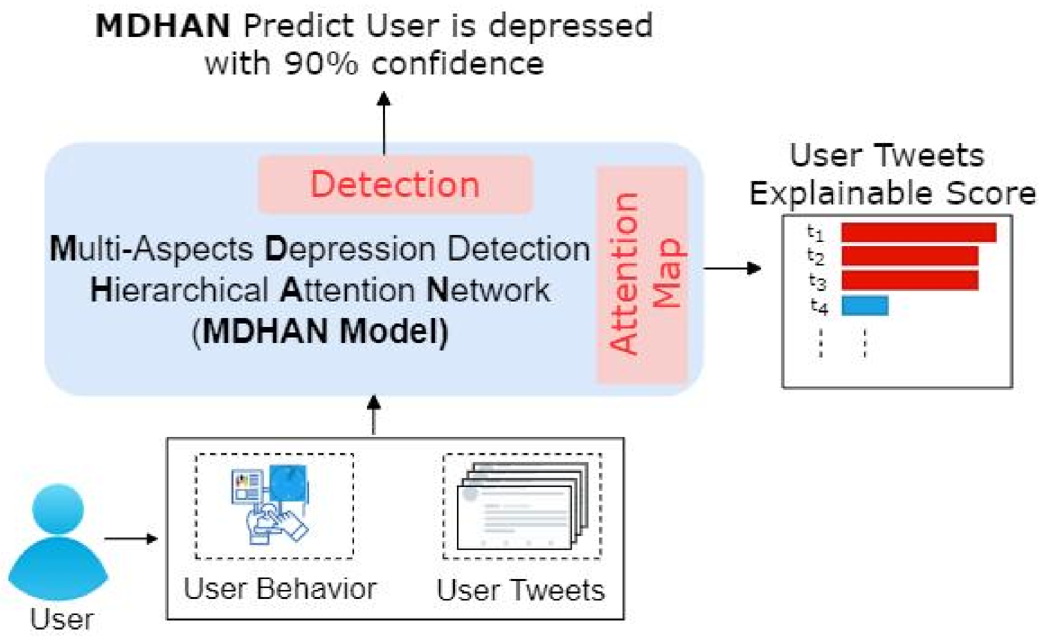
- The interplay between automatic summarization, user behavioural representation and model training helps us achieve significantly results.

4 Explainability for Depression Detection

1. "Explainable depression detection with multi-aspect features using a hybrid deep learning model on social media." Zogan, Hamad, Imran Razzak, Xianzhi Wang, Shoaib Jameel, and Guandong Xu. ***World Wide Web* 25, 2022.**

Challenge:

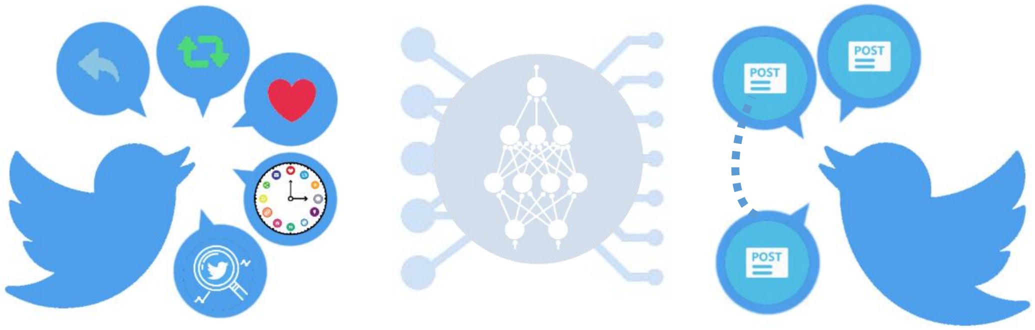
- The majority of these methods focus on detecting depression effectively with latent features but can not explain "why" an individual user was detected as depressed.
- Social media data is large-scale, multi-modal, mostly user-generated, sometimes anonymous and noisy.



Explainable depression detection

Objective:

- To develop an explainable deep learning-based solution for depression detection



A user online behaviors

A user posts

User Multi-aspect Features:

Social Network

Emotional Features

Topic Modeling

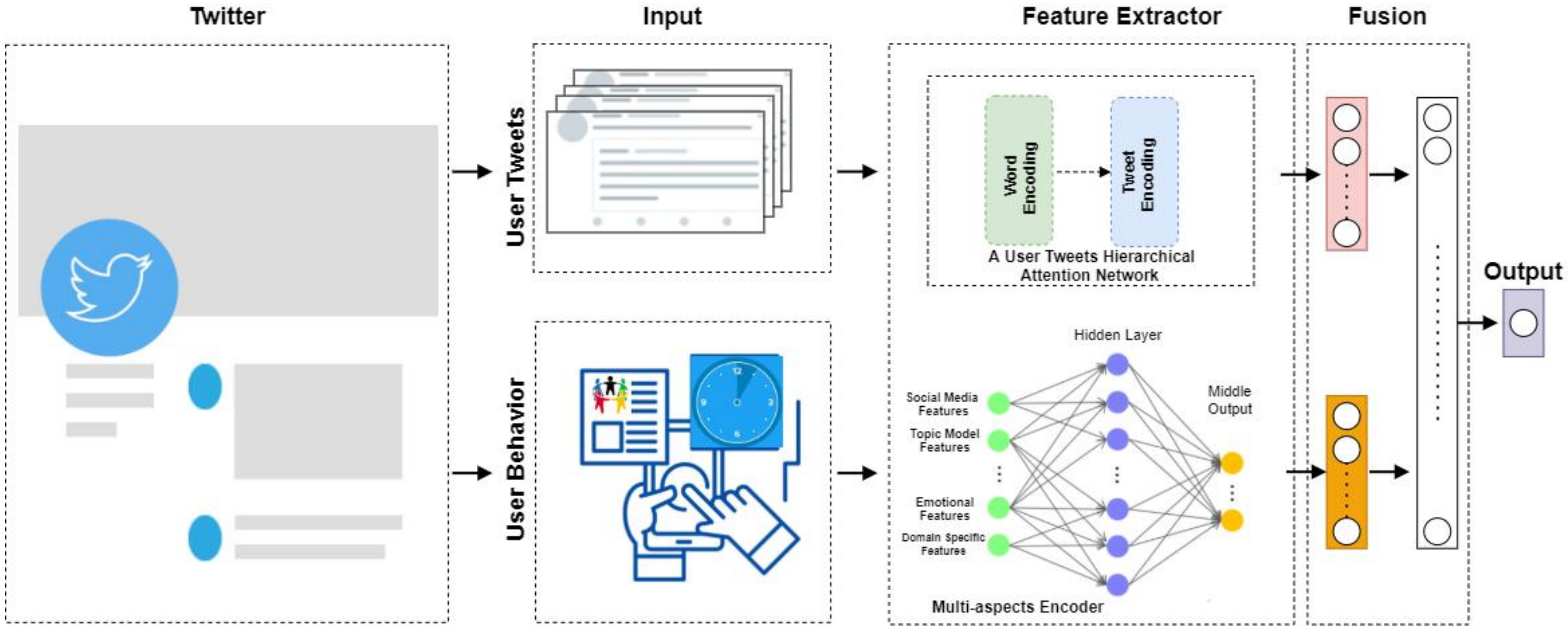
Domain-specific

Proposed model

A hybrid model "Multi-aspect Depression Detection Hierarchical Attention Network **MDHAN**"

1. User Tweets Encoder Using Hierarchical Attention Network (HAN)
   - Word Encoder
   - Tweet Encoder

2. Multi-Aspect Encoder



Experiments and Results:

- The statistics of the datasets are summarized as following (shen et al) [7]:

Table 1: Datasets.

Dataset	D_1	D_2	D_3
Users	1,402	>300 million	36,993
Tweets	292,564	>10 billion	35,076,677

- Three complementary data sets

    1- Depression dataset (D1)

    2- Non-depression dataset (D2)

    3- Depression-candidate dataset (D3)

Experiments and Results

Matric	SVM	NB	MDL	BiGRU	MBiGRU	CNN	MCNN	HAN	MDHAN
Accuracy	0.644	0.636	0.787	0.764	0.786	0.806	0.871	0.844	**0.895**
Precision	0.724	0.724	0.790	0.766	0.789	0.817	0.874	0.870	**0.902**
Recall	0.632	0.623	0.786	0.762	0.787	0.804	0.870	0.840	**0.892**
F1-score	0.602	0.588	0.786	0.763	0.786	0.803	0.870	0.839	**0.893**

Table1: Performance comparison of MDHAN against the baselines for depression detection

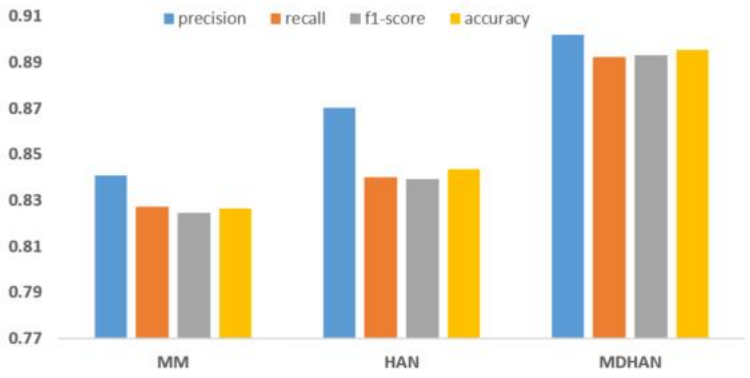


Figure 1: effectiveness comparison between MDHAN with different attributes

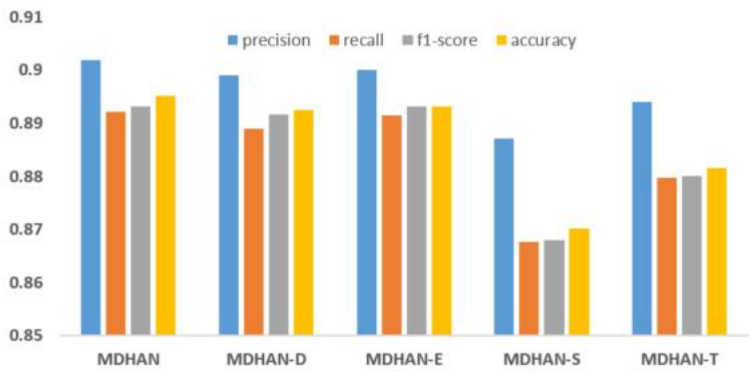
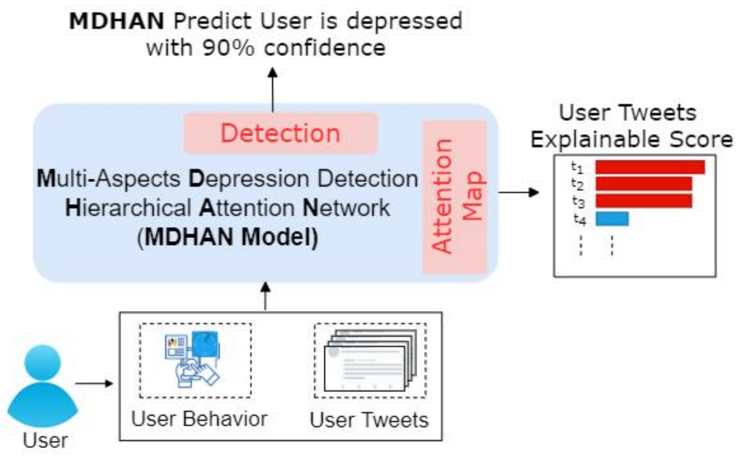


Figure 2: Comparisons of various attributes

Explainable depression detection:



- Explainability via visualization of attention score in our model (MDHAN)

Attention	Tweets
	One in four experience mental illness and yet hardly anyone I talk to seems to know anything about mental illness at all. Stigma abound.
	"MOST patients referred for talking therapies SHOULD start treatment within 6wks (max 18)." MOST? SHOULD? And howd we go from 6 to 18? mh
	"MANY patients who experience psychosis for the first time will get treatment within 2 weeks." MANY? WTF is "MANY"? mh
	Its ALWAYS time to talk about mental illness and it HAS been "time to talk" for many years now. The problem is that nobodys listening. mh
	6wks isnt enough anyway. If youre in physical pain, they give you treatment on the day of your GP appt. But for mental distress, wait 6wks
	Dont tell me what youll do in future if I vote for you. Show me what youve already done for us & then Ill consider voting for you.
	I cannot listen to this nonsense coming out of the mouths of people who have had the power and the opportunity to make changes ALREADY.
	Then they prance in acting like the saviour, announcing that theres a problem and theyre going to fix it - but not now. Next year. Maybe.

Summary

- We have proposed explainable Multi-Aspect Depression Detection with Hierarchical Attention Network (MDHAN) for detecting depressed users through social media

- Our main contribution is our model that can not only effectively model the real-world data but can also help derive explanations from them.

- This hybrid network improves classification performance and identifies depressed users outperforming other strong methods and ensures adequate evidence to explain the prediction.

5

Narrative in Social Media

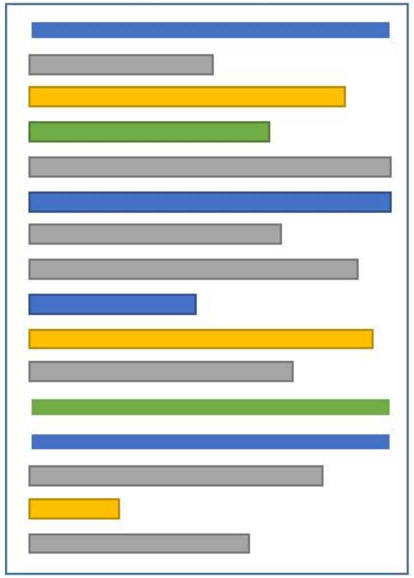
1. “NarrationDep: Modeling Narrative Elements to Identify Depression” Hamad Zogan, I Razzak, Shoaib Jameel, G Xu **(Under Submission, CIKM 2023)**

Motivation:

- The research attempts to diagnose the mental disease early and predict individual risks are essential.
- Lack of a deep and sufficient analysis of people with depression due to the nature of social media data that is not sequential, unconnected, and unordered [25,26].
- We argue that there is a critical need for different information about each user's posts, such as user narrative posts.

A user tweets

$T = [t_1, . . . , t_N]$

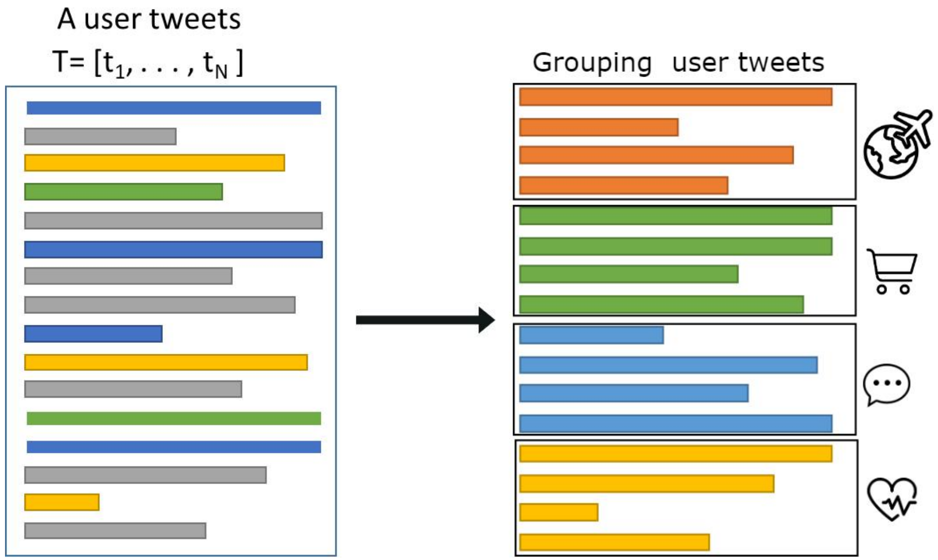


Main Issues:

- We hypothesize that user posts can tell us a story, but the events of that story are neither sequential nor coherent, which makes it challenging to form it as an ordinary story.
- When we have a huge pile of user tweets, and we have to find mysterious patterns you believe are hidden within.

What is meant by narrative in social media?

- The narrative is a representation or a particular form of a story and transforms a story into knowledge.
- Each event is a unit of knowledge that could give us a clue about the story.
- The social media narrative may be defined as a lengthy story that is divided up into postings for social media platforms.



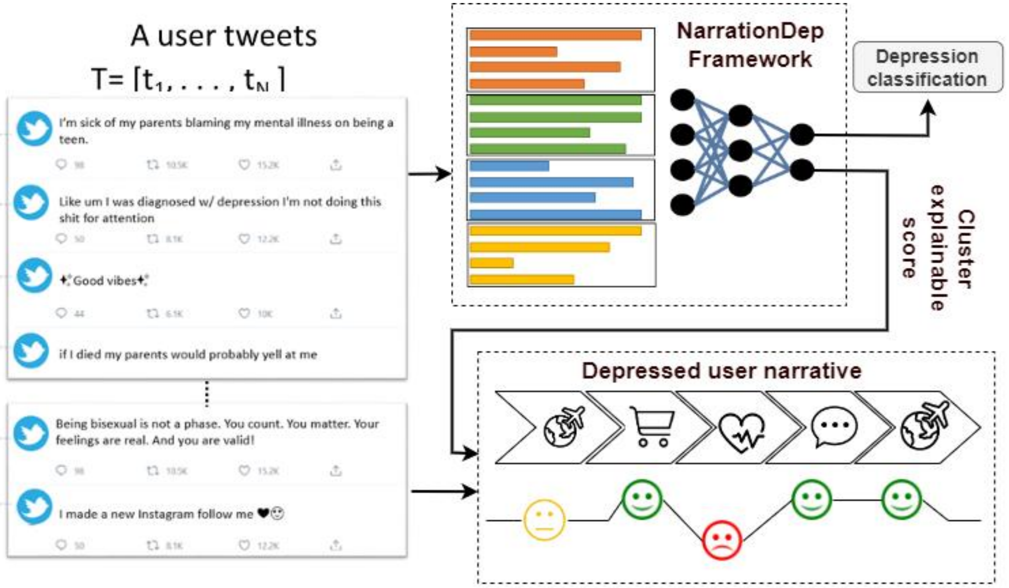
Grouping user tweets could provide better understanding and make inferences about personality, relationship, intents, actions, etc.

Methodology:

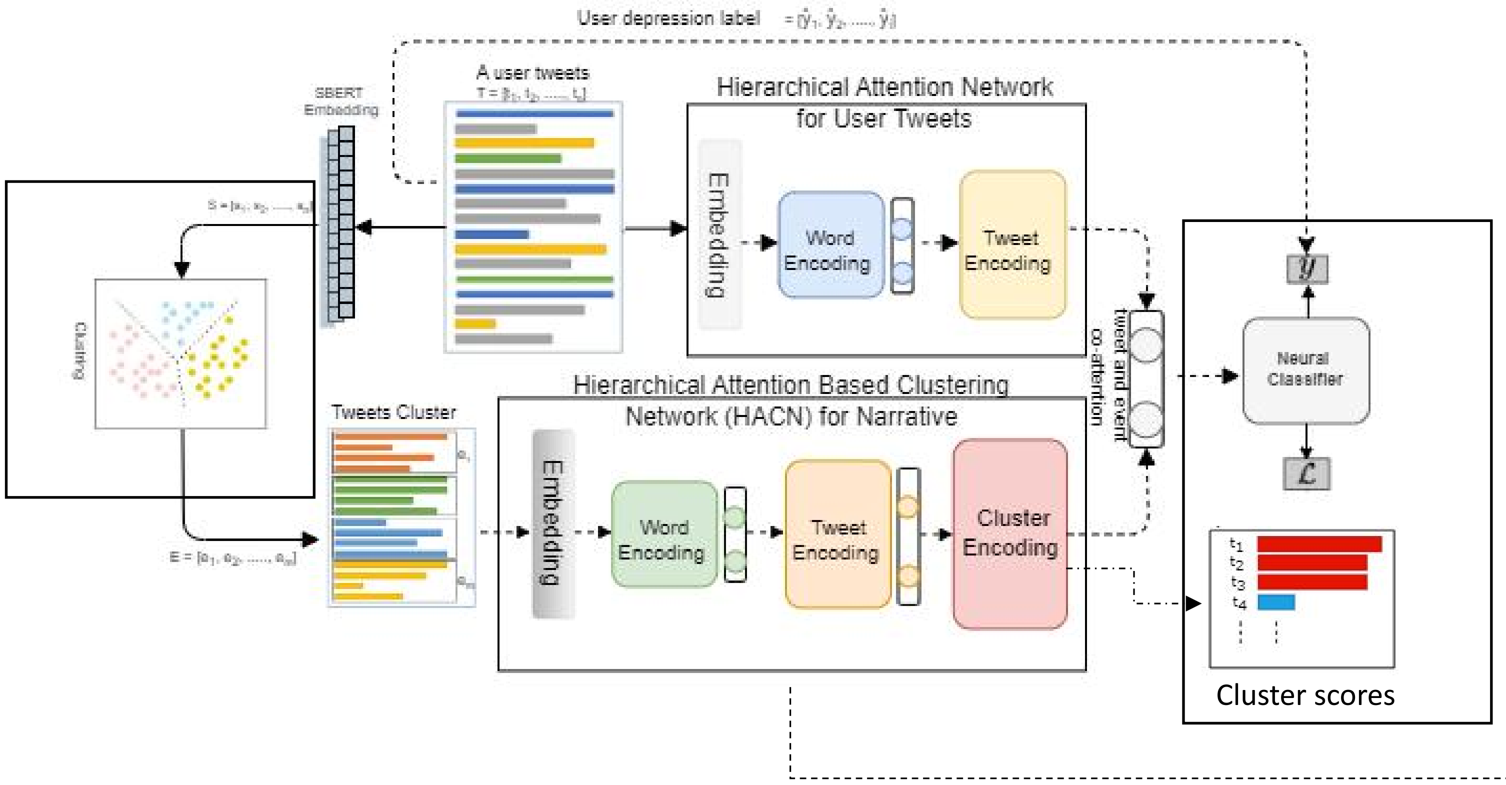
- Creating new tasks aimed specifically towards modeling narrative elements in Social Media.
  - *“Tweet grouping will index user tweets based on some imposed scale of similarity and differentiated based on some imposed boundary, which will be beneficial in gaining knowledge about user posts' narrative. ”*
  - *Can highlighted meaningful clusters help to extract the depressed user narrative elements?*

- A new framework called ***NarrationDep*** (**Narra**tive Detec**tion** for **Dep**ression).

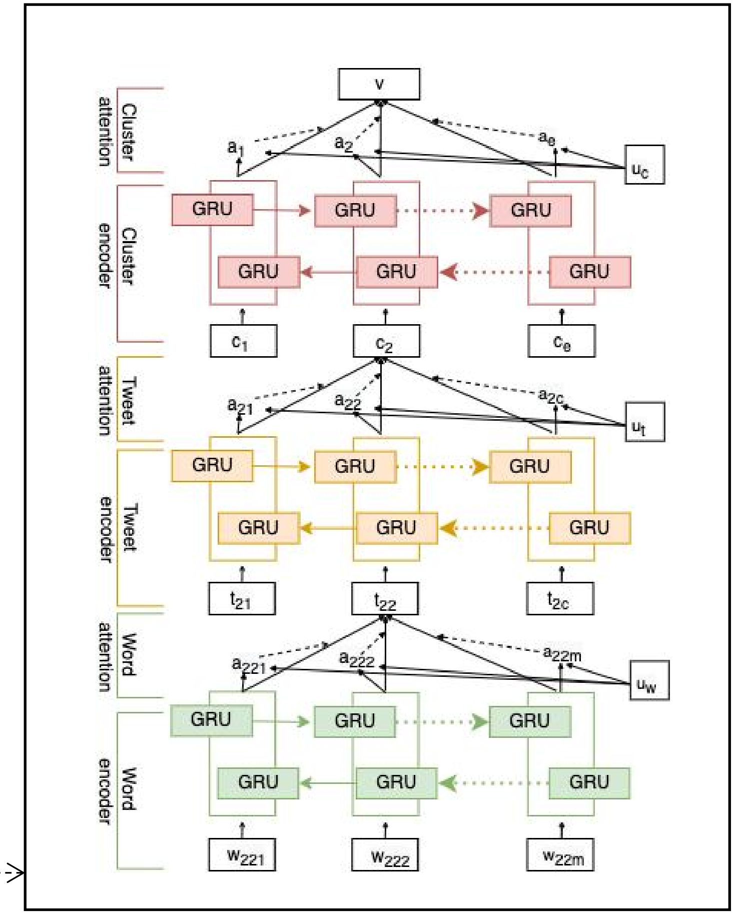
The NarrationDep consists algorithm module based on explainable deep learning depression detection, which gives the detection result and explanations about the narrative of a depressed user.



NarationDep Framework:



Framework of NarrationDep model



An illustration of Hierarchical Attention Based Clustering Network (HACN) for Narrative, inspired by Yang et al. 2016. [27]

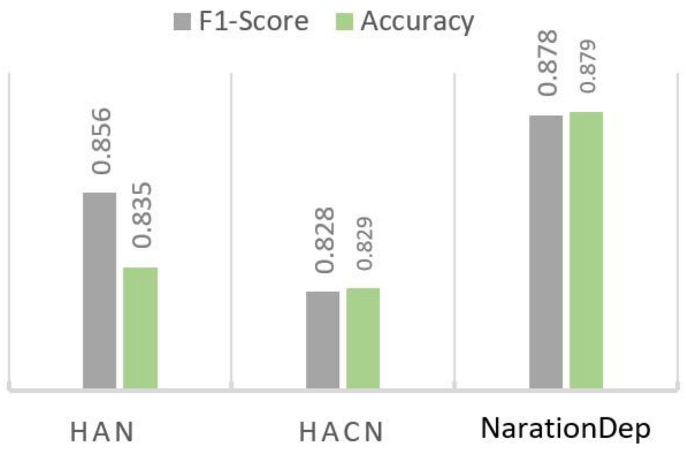
Experiments and Results:

The performance comparison of NarationDep Vs Tweets Summarization

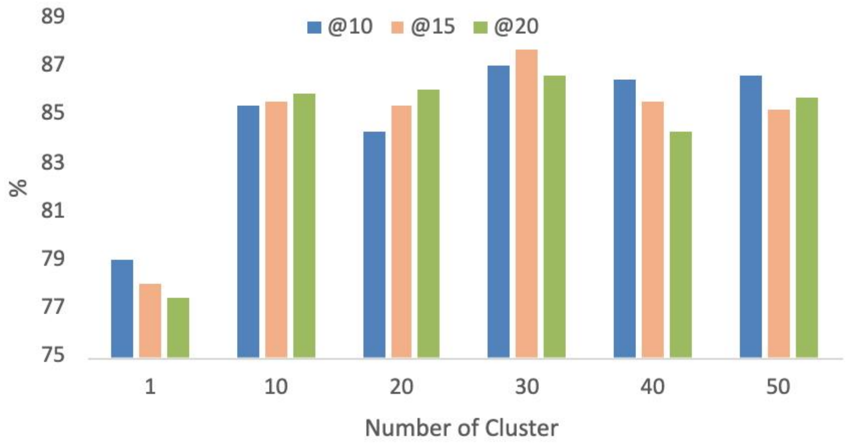
Model	Precision	Recall	F1-Score	Accuracy
XLNet (base)	0.868	0.843	0.848	0.835
BERT (base)	0.766	0.762	0.786	0.764
RoBERTa (base)	0.817	0.804	0.786	0.806
BiGRU-Att	0.941	0.731	0.823	0.836
CNN-Att	0.861	0.843	0.835	0.837
CNN_BiGRU-Att	0.836	0.829	0.824	0.824
NarationDep	0.884	**0.878**	**0.878**	**0.879**

The performance comparison of NarationDep Vs All user tweets.

Model	Precision	Recall	F1-Score	Accuracy
BiGRU	0.766	0.762	0.786	0.764
CNN	0.817	0.804	0.786	0.806
HAN	0.87	0.844	0.856	0.835
HCN	0.853	0.852	0.852	0.852
NarationDep	**0.884**	**0.878**	**0.878**	**0.879**

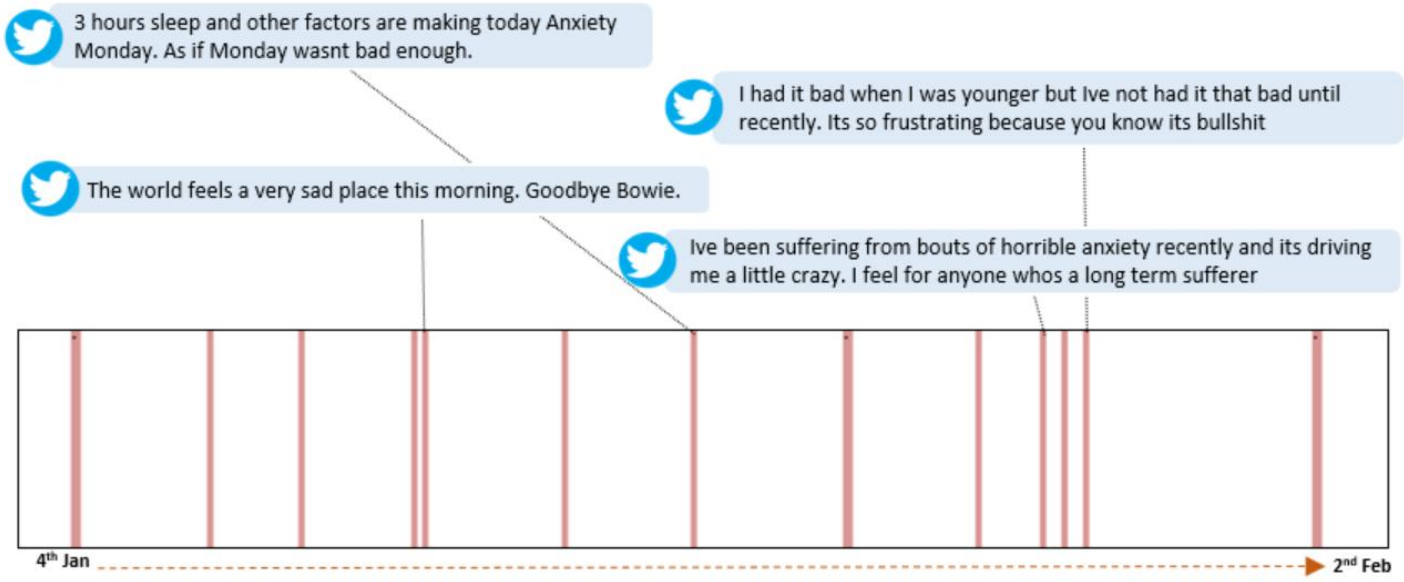


Impact analysis of all user contents model (HAN), clustering tweets model (HACN), and our model (NarationDep) for depression detection.



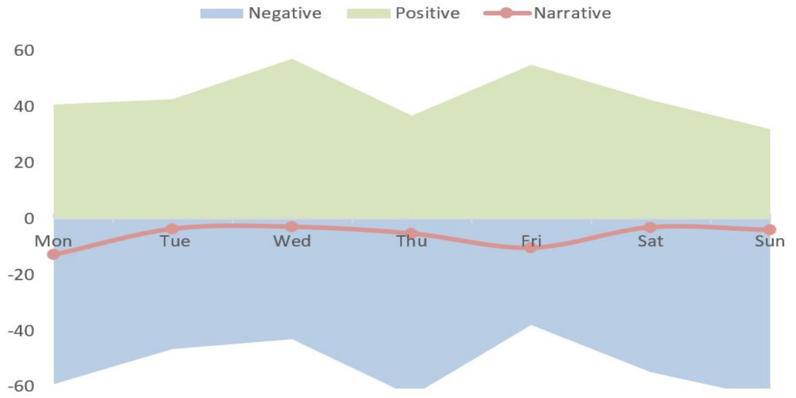
Effectiveness of our model (NarationDep) with different numbers of clusters

Case Study

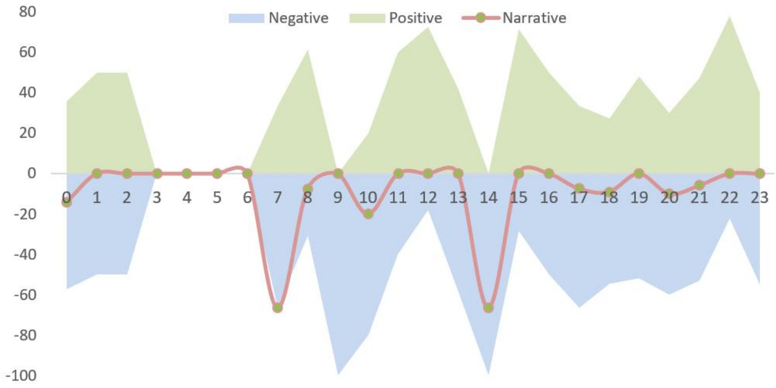


The distribution of the narrative tweets among the rest of a user tweets.

Narrative tweets captured by NarationDep



Analysing narrative sentiment for a user per week



Analysing narrative sentiment for a user during the 24 hours of the da

Summary

- We study a novel problem of modeling narrative elements in social media to analyze a user posts to understand our narrative.

- A new hybrid classification model (***NarationDep***) was proposed.
  - We developed a model-based hierarchical to generate a narrative automatically.
  - We proposed Hierarchical Attention Based Clustering Network (HACN), which considers the hierarchical structure of user cluster tweets (cluster, tweets and words)

- Our model showed significant improvement in depression detection compared to the state-of-the-art methods.
- Extracting a new explainable features (narrative tweets) from noisy auxiliary information.

6 Depression Dynamics Detection at Community level During COVID-19

"Detecting community depression dynamics due to covid-19 pandemic in australia." Zhou, Jianlong, **Hamad Zogan**, Shuiqiao Yang, Shoaib Jameel, Guandong Xu, and Fang Chen *IEEE Transactions on Computational Social Systems*.

Motivation:

- Australia is one of the top countries where mental health disorders have high proportions over the total disease burden [19].
- Patients with SARS and MERS were assessed a few months later, 14.9% had depression and 14.8% had an anxiety disorder [20].
- **<u>It is important to examine people's mental health states due to COVID-19</u>**

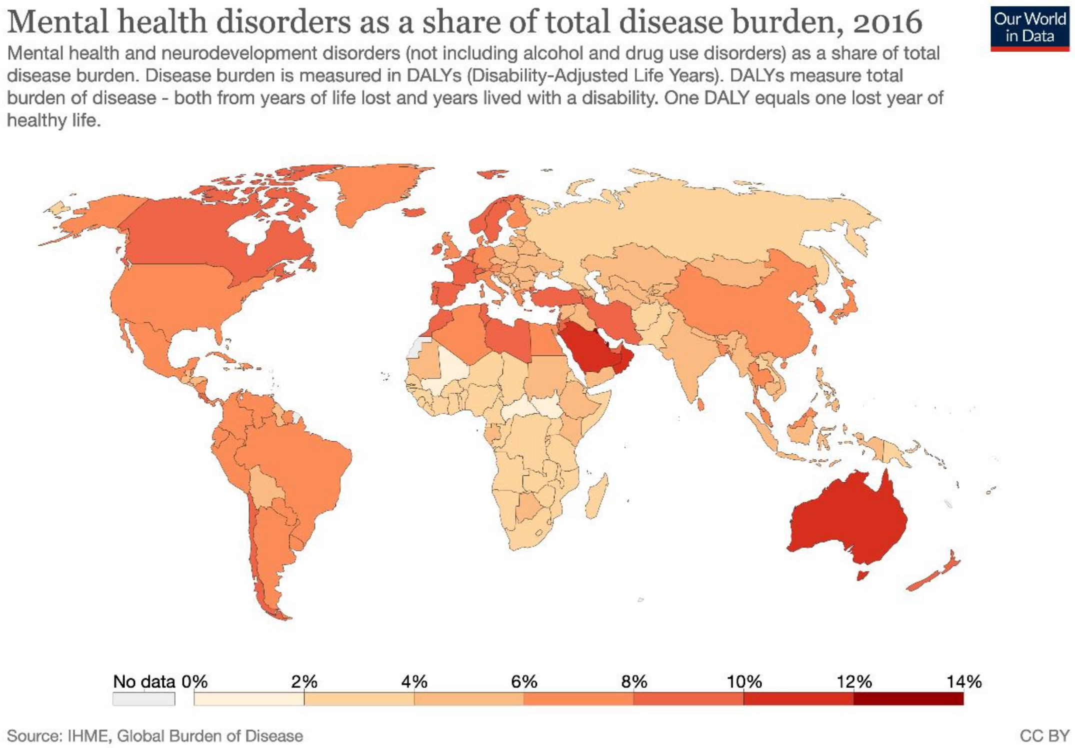


Figure 3.1: The world mental health disorders in 2016

Motivation:

- The outbreak had test peaks at the beginning of each week and had fewer numbers at the weekend, which well aligns with the people's living habits in Australia

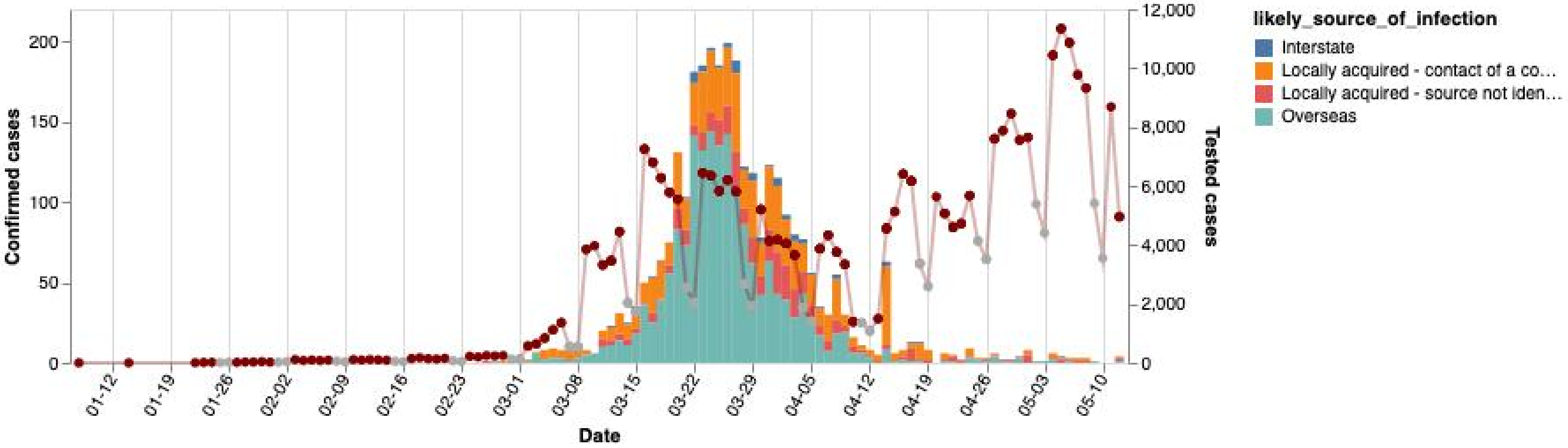


Figure 3.2: The tests and confirmed cases of COVID-19 in NSW until 22 May 2020

Main Issue:

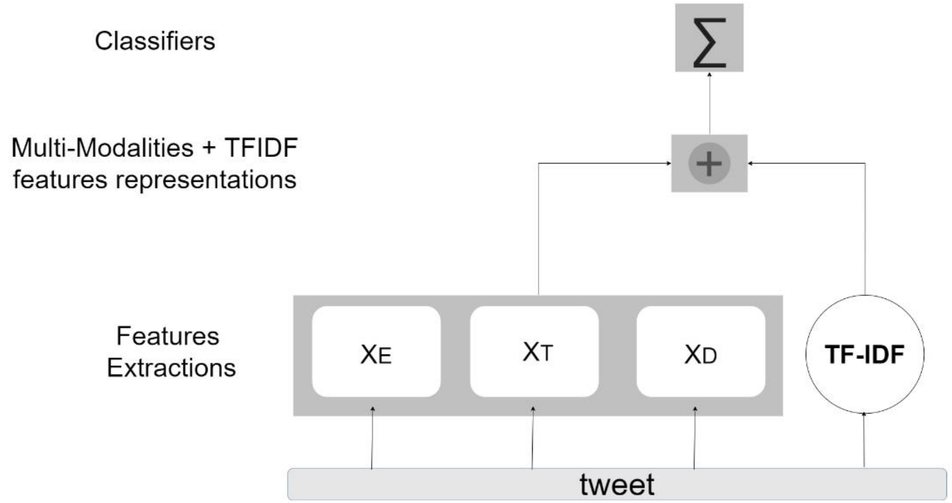
- Little work is done to detect depression dynamics at the state level or even more granular level such as suburb level.

Objective:

- To examine community depression dynamics due to COVID-19 pandemic in Australia.

Contribution

- Novel multi-modal features to describe depression in a comprehensive approach.
- A faithful depression classification model based on TF-IDF.
- Analysis of depression in local government areas of a state in Australia is investigated



The proposed framework to detect depressed tweets during the COVID-19

Data

Description	Size
Total Twitter users	183,104
Average Twitter user per LGA	1,430.5
Average tweets per LGA	739,900.5
Total tweets	94,707,264

Summary of the collected Twitter dataset

Experiments:

- Dataset for depression model training.
- Positive tweets (depressed): we used a previous work dataset from \cite{shen2017depression}.

Description	**Size**
Depressed tweets	$\sim$ 900K
Non-Depressed tweets	$\sim$ 900K

Summary of labelled data used to train depression model.

Experiments:

- Classification Evaluation Results

Features	Method	Precision	Recall	F1-Score	Accuracy
Multi-Modal	LR	0.842	0.828	0.832	0.833
	LDA	0.843	0.816	0.820	0.824
	GNB	0.873	0.814	0.818	0.825

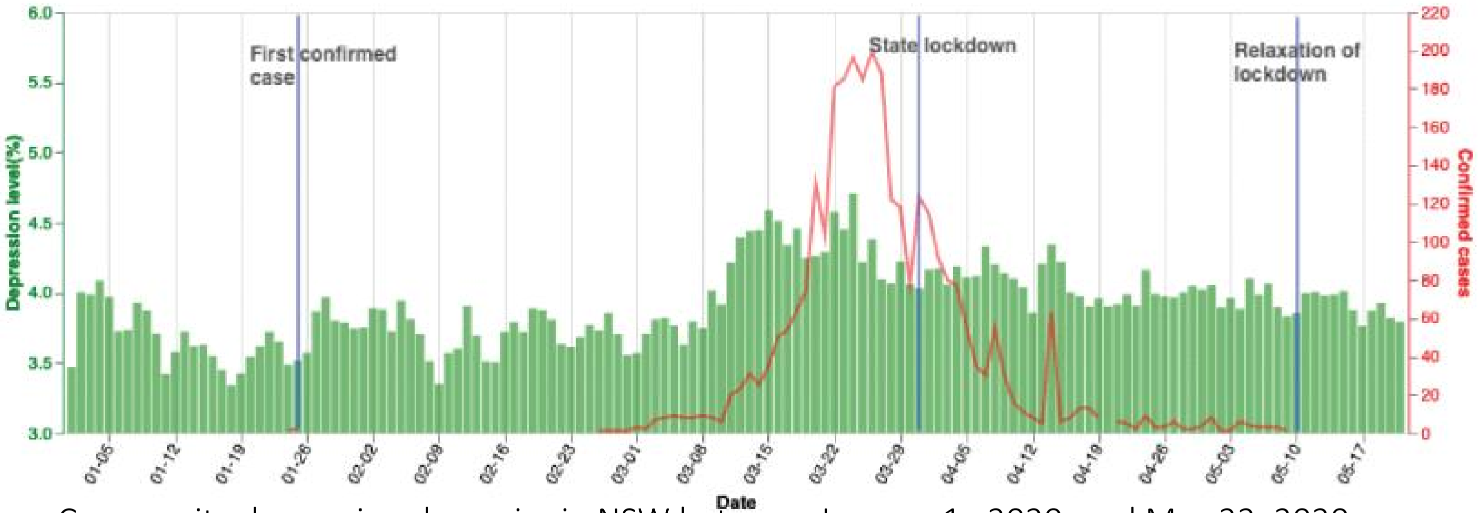
Features	Method	Precision	Recall	F1-Score	Accuracy
TF-IDF	LR	0.908	0.896	0.900	0.901
	LDA	0.906	0.893	0.897	0.898
	GNB	0.891	0.873	0.877	0.879

Features	Method	Precision	Recall	F1-Score	Accuracy
MM+TF-IDF	LR	0.908	0.899	0.902	0.903
	LDA	0.912	0.899	0.903	0.904
	GNB	0.891	0.874	0.878	0.879

Table 3.5: The performance of tweet depression detection based on Multi-Modalties only , TF-IDF only, and Multi-Modalties + TF-IDF.

Detecting Depression due to COVID-19

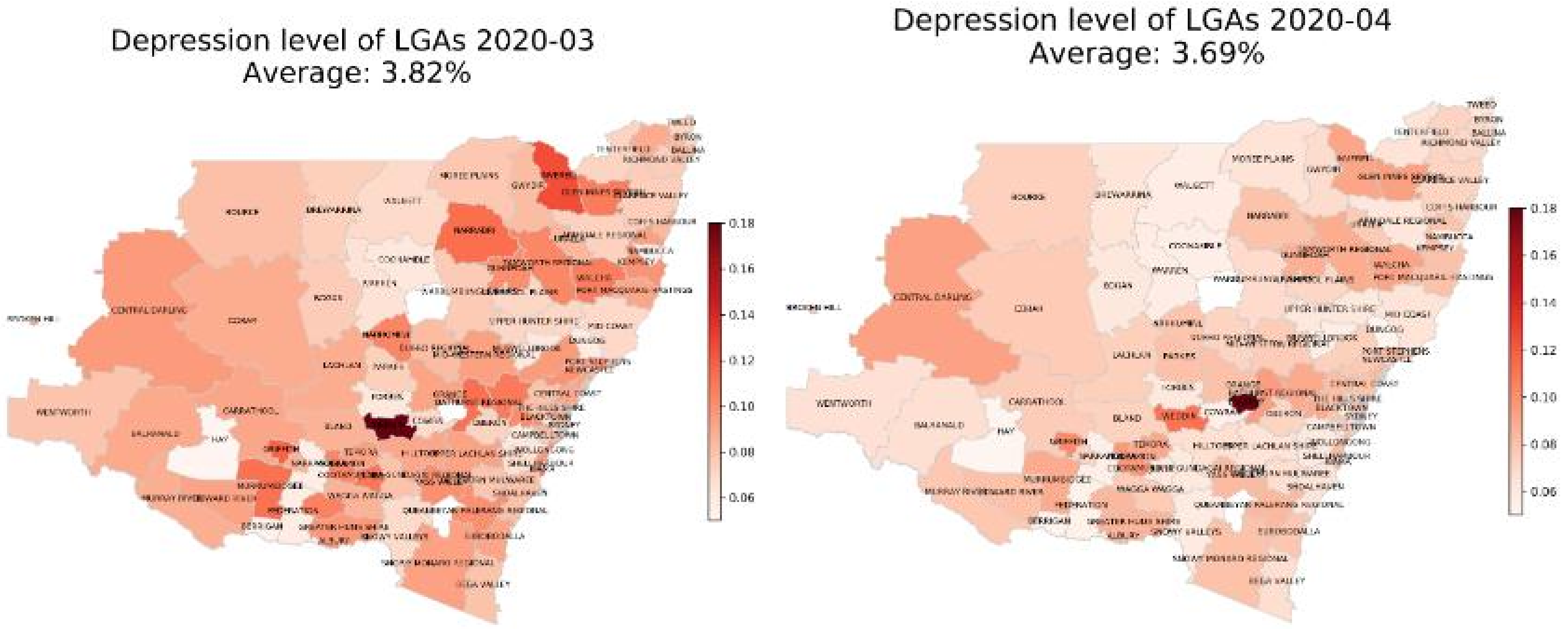
- Depression dynamics in NSW



Community depression dynamics in NSW between January 1 , 2020, and May 22, 2020.

Detecting Depression due to COVID-19

- Depression dynamics in LGAs (Local Government Areas)



The choropleth maps of community depression in LGAs in NSW in March 2020 (left) vs April 2020 (right).

Summary

- Examine the community depression dynamics in the state of NSW in Australia due to the COVID-19 pandemic.

- Develop approaches identifying depression based on multi-modal features and TF-IDF .

- We have showed that people became more depressed after the outbreak of the COVID-19 pandemic

7

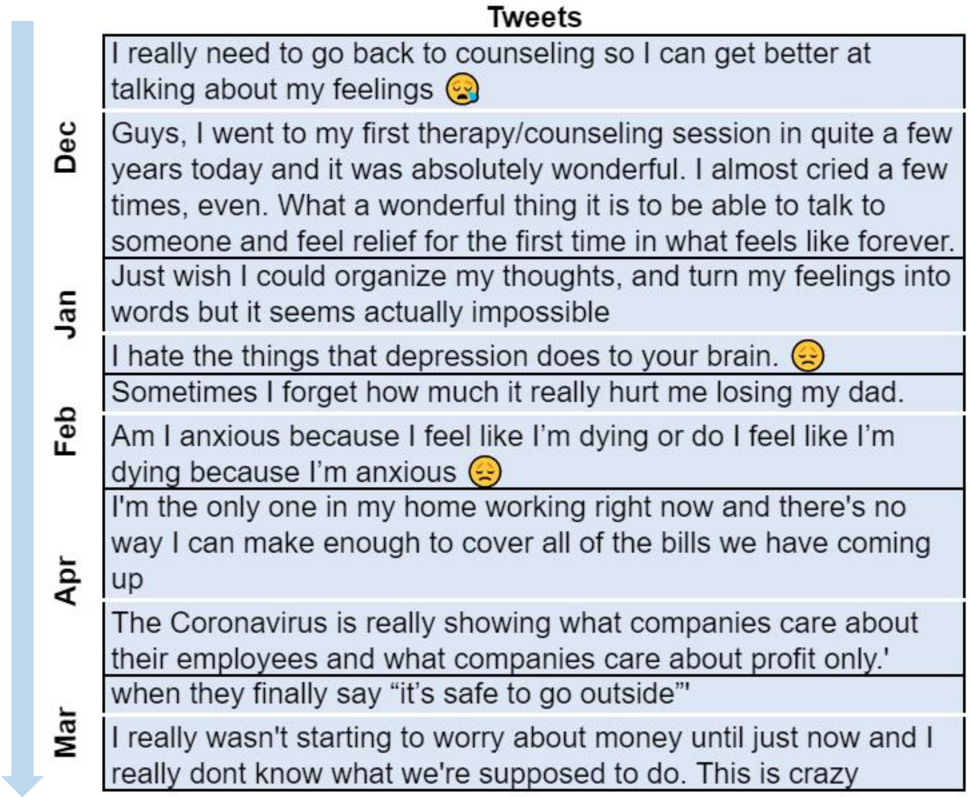
Depression Dynamics Detection at user level During COVID-19

“Deep Hierarchical Convolutional Attention for Modelling the Impact of COVID-19 Pandemic on Social Media Users’ Depression” Hamad Zogan, I Razzak, S Jameel, G Xu, **IEEE Journal of Biomedical and Health Informatics, 2022**

Motivation:

- **Our hypothesis:** *"The COVID-19 pandemic and its social restrictions may affect depressed users and thus may be reflected in their daily tweets".*

- There is a need for further scientific understanding of how people perceive and respond to the current COVID-19 pandemic.



A sample of depressed user tweets during the first months of COVID-19.

	Tweets
Dec	I really need to go back to counseling so I can get better at talking about my feelings 😢
	Guys, I went to my first therapy/counseling session in quite a few years today and it was absolutely wonderful. I almost cried a few times, even. What a wonderful thing it is to be able to talk to someone and feel relief for the first time in what feels like forever.
Jan	Just wish I could organize my thoughts, and turn my feelings into words but it seems actually impossible
	I hate the things that depression does to your brain. 😔
Feb	Sometimes I forget how much it really hurt me losing my dad.
	Am I anxious because I feel like I'm dying or do I feel like I'm dying because I'm anxious 😔
Apr	I'm the only one in my home working right now and there's no way I can make enough to cover all of the bills we have coming up
	The Coronavirus is really showing what companies care about their employees and what companies care about profit only.'
Mar	when they finally say "it's safe to go outside"'
	I really wasn't starting to worry about money until just now and I really dont know what we're supposed to do. This is crazy

A sample of depressed user tweets during the first months of COVID-19.

Main Issue:

- Due to the unstructured nature of depressed user tweets, obtaining insights from them can be difficult and time-consuming.

Objective:

- To study tweets of depressed and non-depressed users during eight months before and after the start of the COVID-19 pandemic.

Dataset

pre COVID-19 post

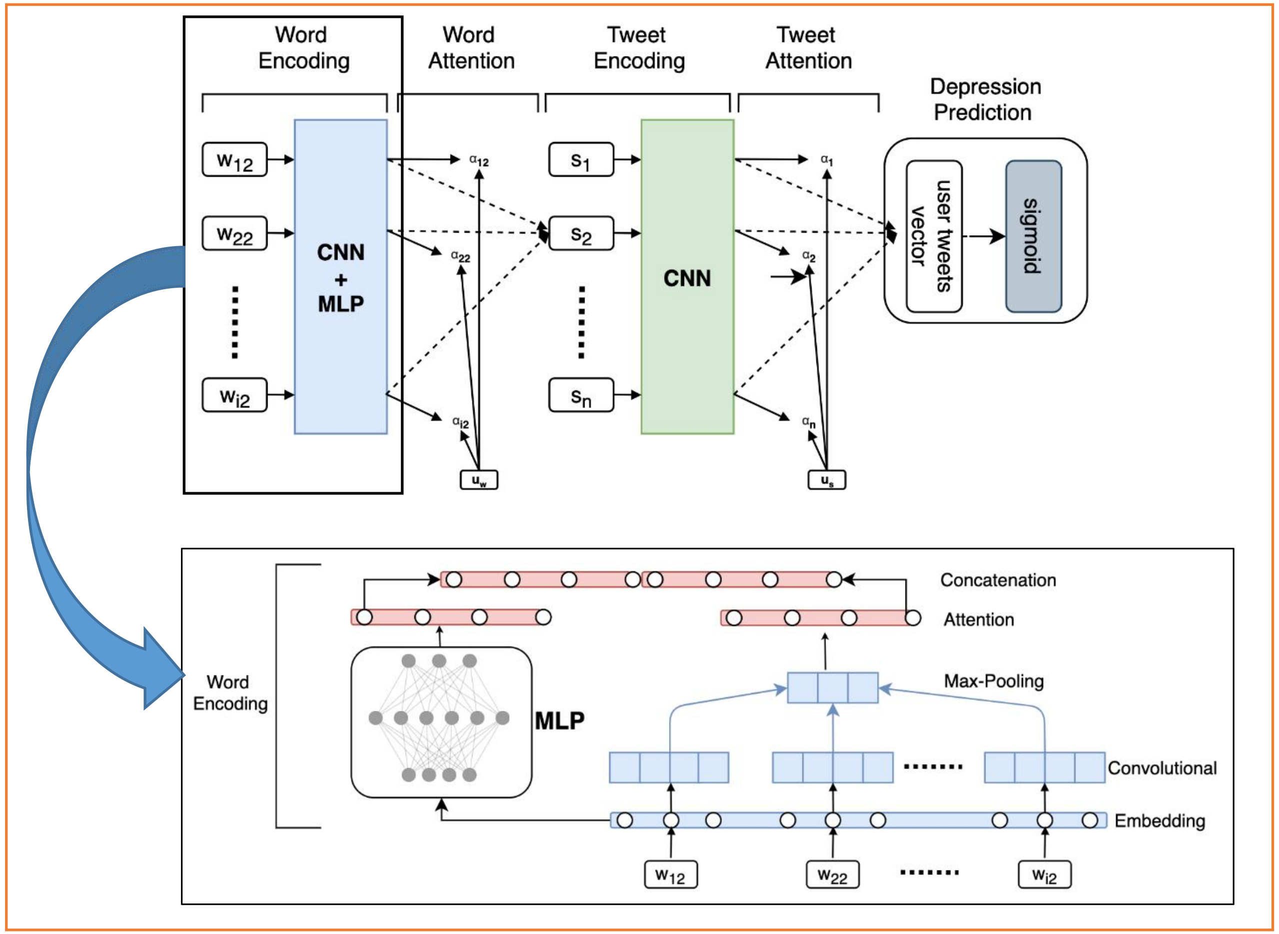
	Pre-COVID		Post-COVID	
	# User	# Tweet	# User	# Tweet
Depressed	2,159	447,856	741	326,129
Non-Depressed	2,049	1,349447	682	931,527

Table 1: Summary of the datasets that we used in our research

1. Pre-Covid-19 Dataset
   - *Shen et al.[1] dataset [7]*

2. Post-Covid-19 Dataset:
   - *We collected a dataset, including posts from depressed and non-depressed users during COVID-19*

Our Proposed Model



An illustration of Hierarchical Convolution Neural Network (HCN+)

- A model based on a Hierarchical Convolution Neural Network(HCN+) to detect depressed users due to COVID-19:
  - A multi-channel CNN and MLP in word-level encoding
  - Hierarchical attention

Word Attention:

$$u_{it} = \tanh(W_w h_{it} + b_w)$$
$$\alpha_{it} = \frac{\exp(u_{it}^\top u_w)}{\sum_t \exp(u_{it}^\top u_w)}$$
$$s_i = \sum_t \alpha_{it} h_{it}.$$

Tweet Attention:

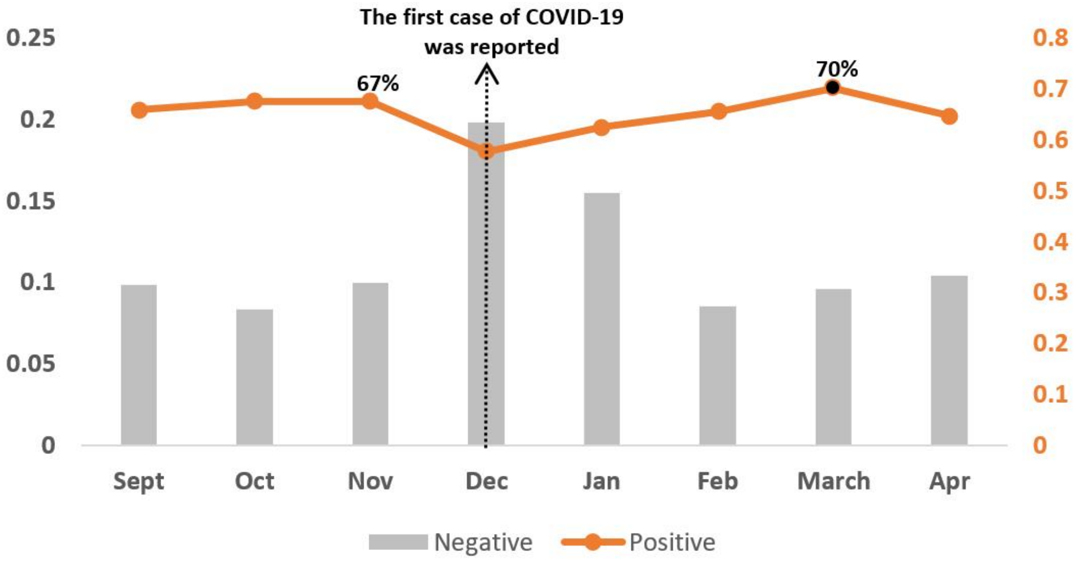
$$u_i = \tanh(W_s h_i + b_s),$$
$$\alpha_i = \frac{\exp(u_i^\top u_s)}{\sum_i \exp(u_i^\top u_s)},$$
$$v = \sum_i \alpha_i h_i,$$

- *Depression classification:*

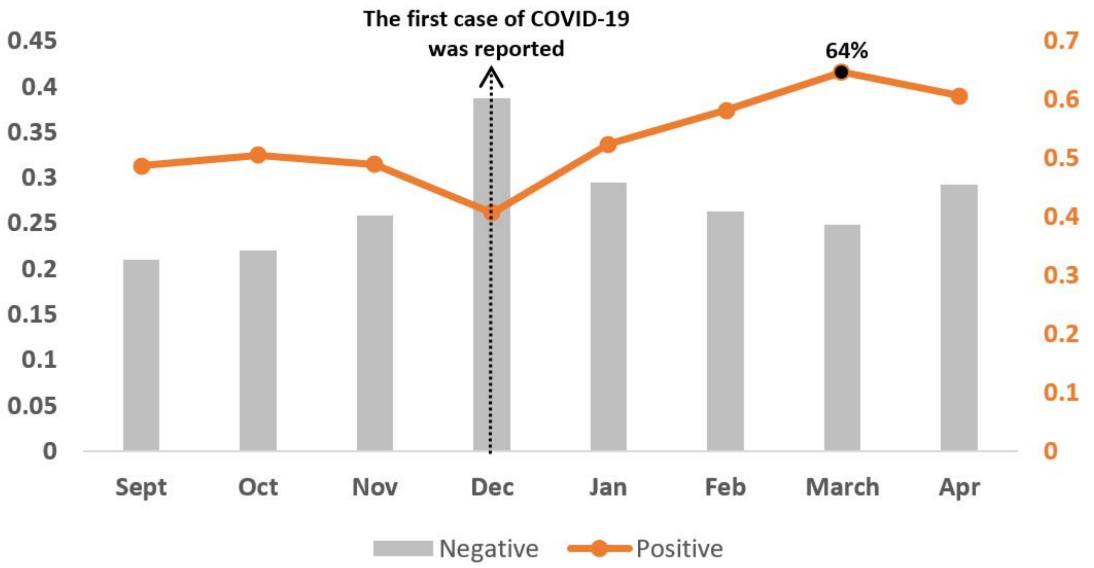
$$\hat{y} = Sigmoid(b_f + vW_f)$$

Experiments and Results:

- Qualitative Results



Depressed user dynamics between September 1, 2019, and April 20, 2020



Non-Depressed user dynamics between September 1, 2019, and April 20, 2020

Summary

- We studied tweets of depressed and non-depressed users during eight months before and after the start of the COVID-19 pandemic.

- Develop A user classification model to automatically detect depressed users based on a hierarchical convolution neural network (HCN).

  HCN considers the hierarchical structure of user tweets (tweets-words).
  HCN contains an attention mechanism.
  HCN+ similar to HCN but it reads the input in different ways in parallel using MLP and CNN at word level.

- HCN and HCN+ outperform strong comparative models and effectively detect depressed users
- We found that the COVID-19 pandemic and its restrictions impacted many depressed and non-depressed users.

7

Conclusion and Future Work

Conclusion

- This study explores computational methods in tackling some of the research challenges in depression analysis.
- Develop approaches identifying depression or mental disorders in general.
- The previous research objectives are presented as the central targets to achieve the Research Questions of identifying mental illness through social media.
    - Develop a new novel deep learning-based for detection by utilizing a user multi-aspects features and his posts
    - Extracting explainable features from noisy textual features
    - A novel extractive-abstractive tweet summarization framework for user historical posts.
- Focused on explainability in depression detection, to explain why a user-determined as depressed.

Future Work

- There is still more study and problems for mental illness detection to be done:
  - Construct new benchmark datasets for mental illness detection and analysis such as loneliness.
  - We will analyse user behaviours related to depression during the COVID pandemic, such as social engagement and social interaction with others.
  - A novel model that build upon BERT's architecture that improve the performance models and enable its application in the classification of long texts..
  - A model that jointly summarizes user posts and detect mental illness.

Research Papers

- Detecting community depression dynamics due to covid-19 pandemic in Australia
  J Zhou, H Zogan, S Yang, S Jameel, G Xu, F Chen, IEEE Transactions on Computational Social Systems, 2021
- DepressionNet: Learning Multi-modalities with User Post Summarization for Depression Detection on Social Media
  H Zogan, I Razzak, S Jameel, G Xu, Proceedings of the 44th International ACM SIGIR Conference. (SIGIR 2021)
- Explainable Depression Detection with Multi-Aspects Using a Hybrid Deep Learning Model on Social Media
  H Zogan, I Razzak, X Wang, S Jameel, G Xu, World Wide Web Journal, 2022
- Deep Hierarchical Convolutional Attention for Modelling the Impact of COVID-19 Pandemic on Social Media Users' Depression
  H Zogan, I Razzak, S Jameel, G Xu (Accepted at IEEE Journal of Biomedical and Health Informatics, 2022)
- NarrationDep: Modeling Narrative Elements to Identify Depression
  H Zogan, I Razzak, G Xu (Under Submission, KDD ADS 2023)

Questions?

Thank you