

The Relationship Between social Media Use And Depression Among Young Adults

Prepared By

Name: Talal Kamal

ID No.: 221001382

Submitted in fulfilment of the requirements for the degree Master of
Science in Artificial Intelligence

At

College of Informatics

Midocean University

UAE

Supervisor Name: Dr. Mustafa Sharif,

College of Informatics, Midocean University, Comoros

Acknowledgements

I would like to sincerely express my gratitude to my advisor Dr. Mustafa Sharif, and support throughout this project

Abstract

332 Million of people worldwide affected by depression and the majority the cases are the young adults and they are especially vulnerable and the young adults are the heaviest users of social media and the language and behaviour on the platforms can contribute on early detection for the signals

This thesis reviews the existing NLP and ML approaches to the matter of detecting across the platforms covering the classification needed (SVM, Naïve Bayes), deep learning models (CNN, LSTM) Existing approaches face three persistent limitations: unreliable labelling from self-report and keyword methods, poor generalisability across platforms, and a trade-off between model accuracy and explainability.

List of Abbreviations

- **BERT: Bidirectional Encoder Representations from Transformers**
- **CES-D: Center for Epidemiologic Studies Depression Scale**
- **CNN: Convolutional Neural Network**
- **ERDE: Early Risk Detection Error**
- **LSTM: Long Short-Term Memory**
- **ML: Machine Learning**
- **NLP: Natural Language Processing**
- **RSDD: Reddit Self-reported Depression Diagnosis**

- **SVM: Support Vector Machine**
- **WHO: World Health Organization**
- **Grad-CAM: Gradient-weighted Class Activation Mapping**

List of figures

- 2.1 Global depression and suicide statistics
- 2.2 Global average daily social media usage
- 2.3 TikTok global user growth and engagement
- 2.4 Social comparison theory framework
- 2.5 Passive versus active social media use
- 2.6 NLP processing pipeline for text classification
- 2.7 CNN and LSTM architectures for text classification
- 2.8 Depression detection framework pipeline

Chapter 1: Introduction

Social media are online platforms that allow people to share what they want to share or tell people whether it is sharing information personal or general information or the entertainment content and also communicate with others these platforms provide various types of content and communication and the most popular platforms Instagram, snapchat, TikTok, Facebook and X.

social media has become important to many people because millions of people use social media every day for all sorts of reasons communication, business , ideas , news , entertainment, staying connected with friends and family, as a result it became part of peoples routine in daily basis the social media has Taken a significant part of everyday life and it has become an important part to each

individual for both young people and adults and there are a lot of kinds of usage to social media whether it's just wasting time in scrolling or reading and social media offers both benefits and risks in this situation and it became very important and it can help a lot to people to connect with others and to enjoy time.

However excessive or unhealthy social media use can lead to an emotional distress and may contribute to depressive symptoms these effects can have a significant psychological impact on individuals whether it is comparing yourself to others which leads to lower self-esteem or cyberbullying or the emotional numbness that comes after doomscrolling excessive use may also reduce productivity and interfere with daily activities and leads to bad psychological affects.

the reason why researchers are interested in this issue is because these platforms are in a rapid growth in a large scale and their impact on how people communicate and live and it have both benefits or risks mainly on the mental health and state health this is considered to be an important issue for that depression can affect the person not only on an emotional level it can affect their academic performance relationships and quality of life.

Depression may affect an individual relationship, academic, quality of life, and in sever cases daily functioning so understanding this matter can help providing individuals and professionals develop a way to use them in a healthier way for a daily routine.

this research will discuss what are the relationship between the social media use and how it is related with an impact to their users this research will identify whether social media is excessive for higher levels of depression and identify the factors that contribute in this relationship and this research will help student, parents, mental health professionals , for a better understanding of the affect of social media and how to be caution in the matter.

1.3 problem Definition

The use of social media have increased dramatically over the last decade it became a daily routine a part of everyday life and the time that is spent on social media is significant time based on most people such as Instagram, TikTok, Snapchat, x, etc. and it is still growing more and more researchers have become concerned about the effects that it can leads to mental state and it is easy to access for all ages it does not mean that social media are bad but not being caution can lead to mental health problems

Although social media can actually help in many ways as an art or music insight and knowledge and there are a lot of advantages but the excessive use may negatively affect the users mental health and state it is considered a problem when there are many of the users suffer from anxiety, stress, loneliness, depressive, after spending much time screen not getting anything done or productive about there own life because millions use social media every day even a small effect can have a large impact on society

Researchers believe several online actions take a role in the matter of increasing the risk of depression and these actions include comparing yourself to others seeking validations from the people you like or follow you unrealistic goals or beauty too much scrolling (doomscrolling) fear of missing out (FOMO) that includes trends in the way of speaking and memes and there is the impact of influencers weather it is the way they think or dress or believe it can impact there followers too and it can have a great impact of the individual personality and belief system and the cyber bullying and Fake lifestyle , misleads about information's

Although there are a lot of studies around the relationship between social media and its relevance to depression and mental health and state there are still more questions to the matter require further investigation and a lot to of reports and finding and examinations to cover and understand more to determine the main factors of influencing the mental health and state

This research aims to address the link between the social media and mental health to young adults mainly and identifying what contributes in the mental health and providing much better understanding on how social media can be a factor on the mental health and how it can help building a healthier habits

2.3 Research objective

This research conducted due to how social media became an essential part of everyday life specially among the young adults as for the numbers of users are in a continuous increase it is important to hot it is impacting the mental health and how they might contribute in depression

To measure the time spent on the social media and the usage patterns and online behaviours is associated with the higher level of depression among users

And to identify the activities and behaviours that cause the contribute to depression including self-comparison, cyberbullying, fear of missing out , doomscrolling, seeking validations

And to provide recommendations that provide for a healthier habits and usage of the social media platforms and spread awareness of the matter and guiding people to better usage to them and more safely

3.3 thesis contributions

the value of the research is in investigating in worldwide issue affecting young adults today

the relationship between social media use and depression

a better understanding of the matter will help individuals recognise and aware of the unhealthy habits and behaviour

it will benefit students, parents, teachers, and doctors in the mental health profession, influencers

This study may help and encourage the excessive users on a healthier paths and parents to be cautious and influencers on how to be aware of their impact on the people it can help from each part how to be responsible

Chapter 2: Introduction

This chapter will provide the background on the social media and depression concept it will cover the link between the two and its effects on the mental health and review previous studies that investigated the relationship studies and cases in the relationship between them and what does require more investigation in the matter

2.2 Background

2.2.1 Depression among the young adults

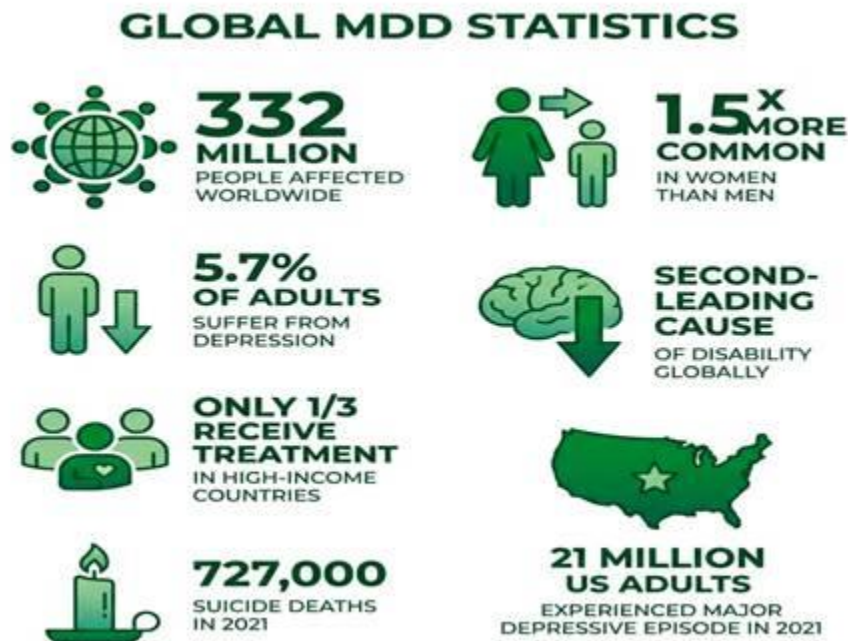
Depression also known as (depressive disorder) it as a common mental disorder it involves depressed mood and loss of simple pleasures or interest in any kind of activates whether simple activates or important ones for a long period of time and because this state consist within the person it have symptoms like: sleep disturbance, fatigue, concentration difficulty and it is estimated that it affects roughly 332 million people making it a worldwide issue

<https://www.who.int/news-room/fact-sheets/detail/depression>

Why the young adults? Young adults represent the population of the most users in the social media platforms and most of the global incident ages are in the ages of

15-39-years-old, and suicide ranks are the fourth leading factor of death among these ages and behind why the young adult's vulnerability for the social media effects this period of time the development and the transitions starting with education works the whole identity formation and critically young adults are the highest rates of usage for social media

<https://pmc.ncbi.nlm.nih.gov/articles/PMC12187749/>

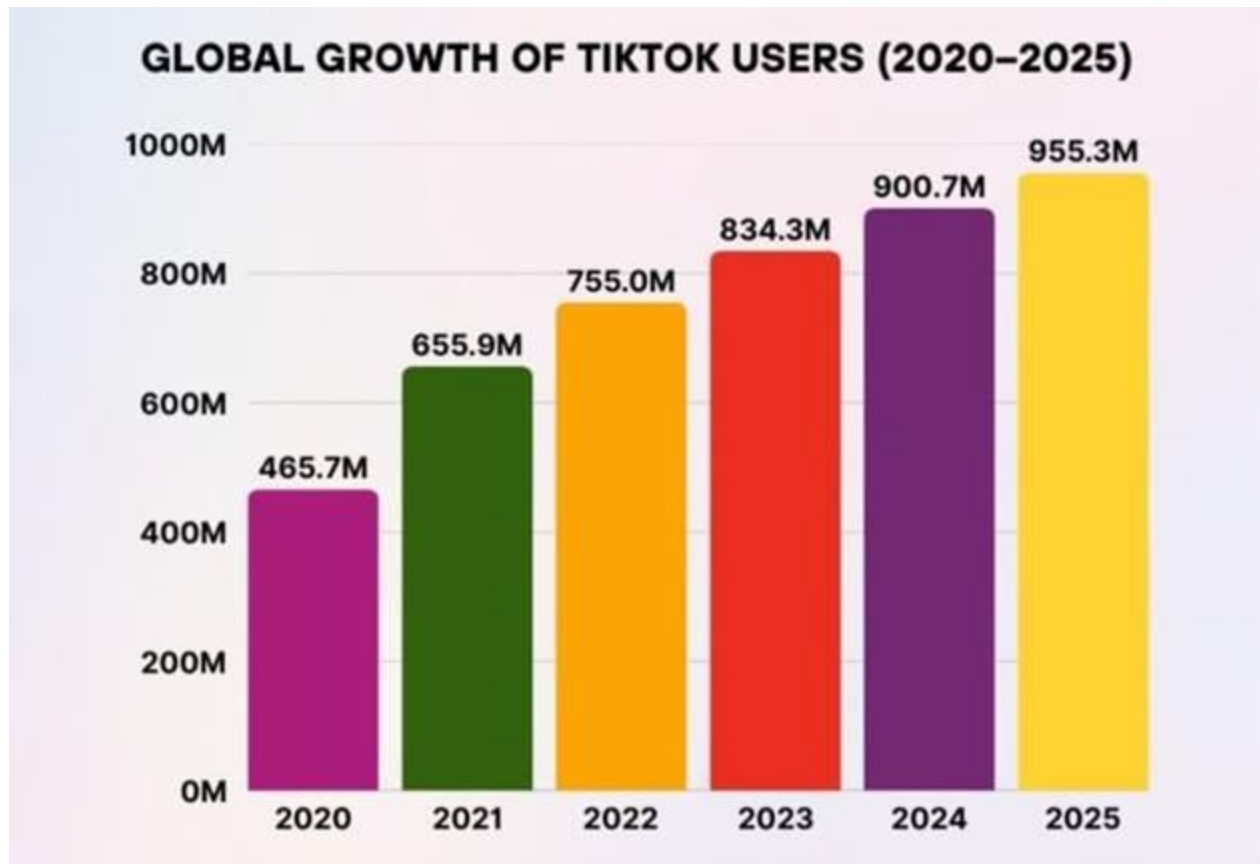


2.2.2 Social media use pattern

The scale of how the use of social media became among the young adults aged 18-24 years the screen time with an average of 141 minutes a day and the global average for users are roughly 2 hours 21 minutes across all users

Platforms choice among the users have shifted very notable in the recent years toward TikTok has been set as the most used platform overall

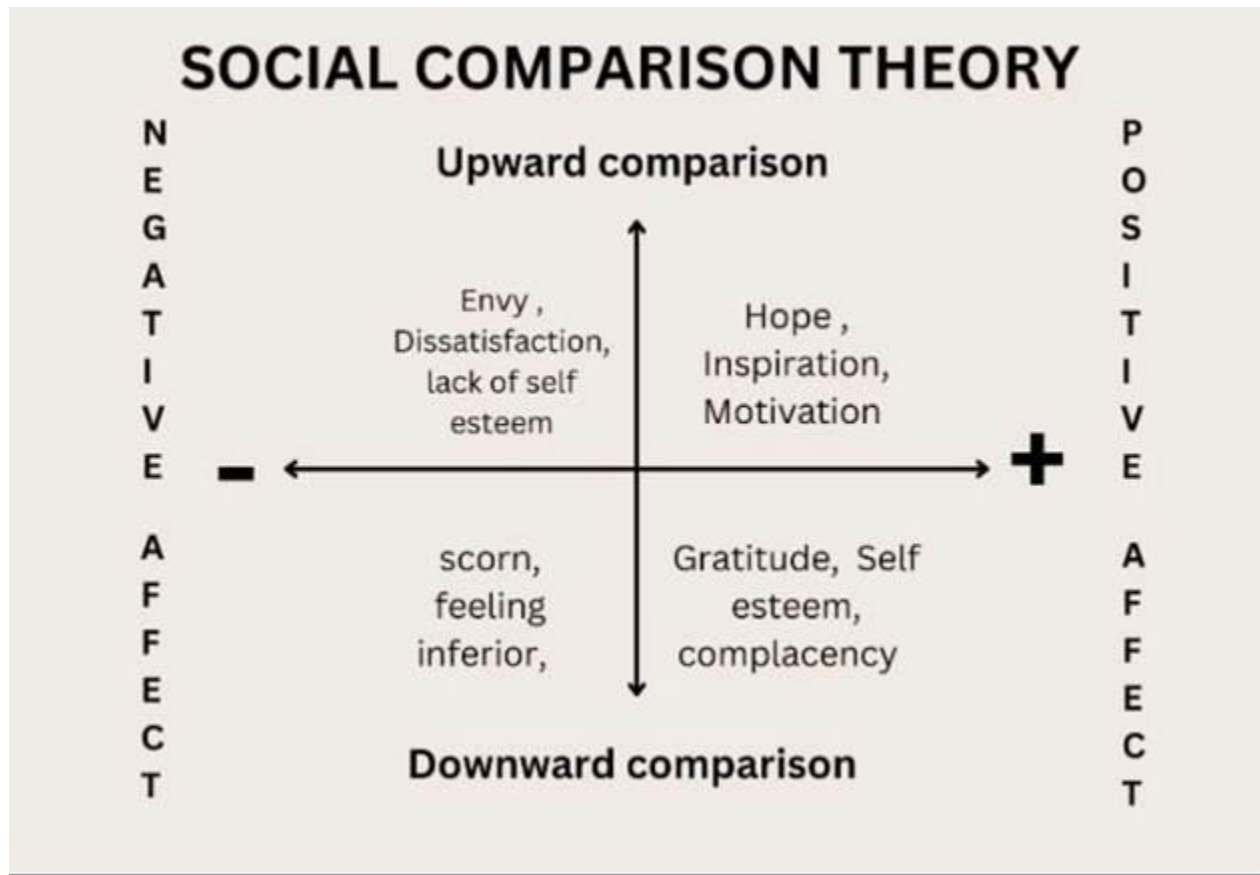
Beyond the raw usage of time and efforts in the social media a behavioural patterns started to link with this usage nearly 70% of people check their feeds within



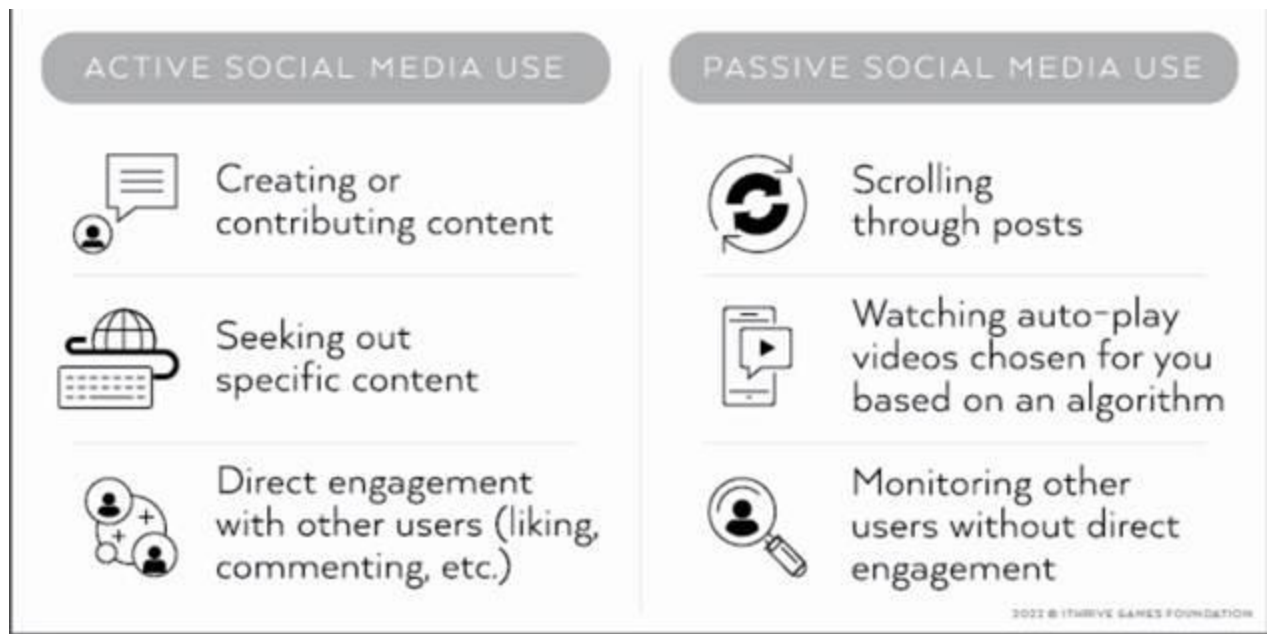
minutes of waking up one of the reports show that 15% of the adults between 23-38 years old identified as addicted to social media with over 40% reported they have sleep disruption related to their time screen and checking this behaviour risk a factor for the depressions symptoms

2.2.3 Theoretical mechanisms linking

One established works explaining this relationship on the comparison theory was established by Festinger on (1954) which explains that the individuals evaluate and make worth of himself by comparing their own self to others, and on social media the user mostly exposed to people to idles actors, the wealthy, the beautiful, so they are idealize these things give them something could be hard to obtain or even feel as a failure and this exposure to this outstanding competition it has been shown to negatively impact the self-esteem while positively leading to depression



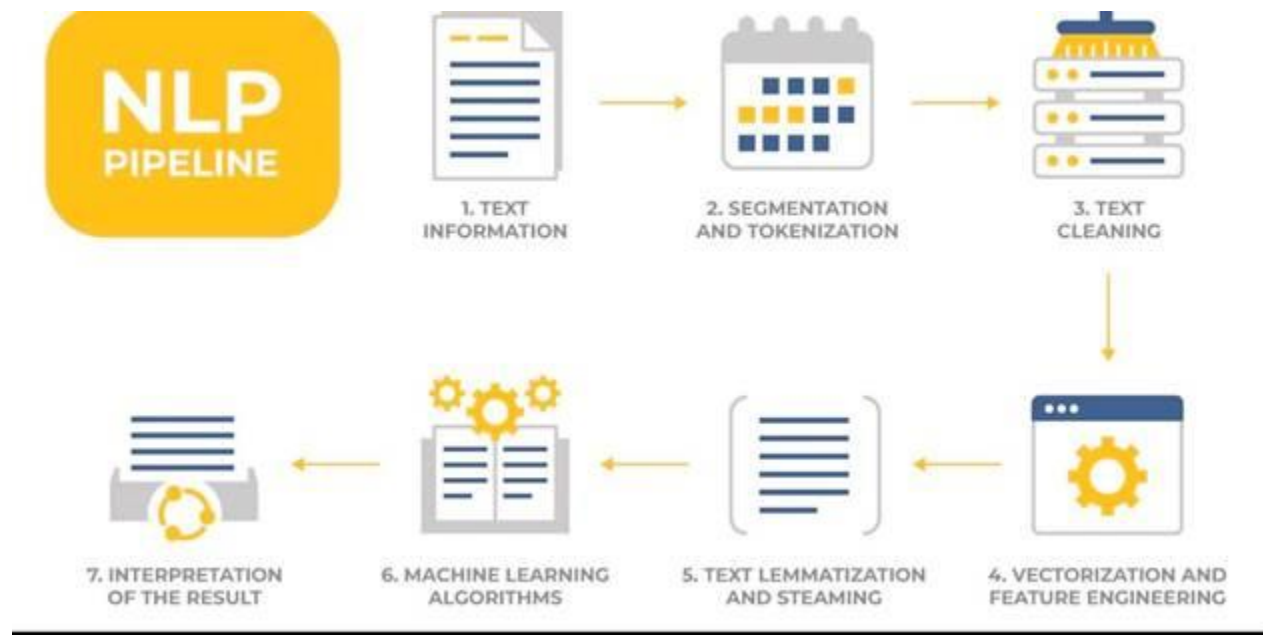
there are passive and active exposures the measurement to this is not depending as scrolling reading and watching without engaging which is the heavily negative on their usage time screen whether heavy or not the passive one defined on since it maximizes exposures to others as for the active one have in some studies shows that it is associated with more social support and better outcomes



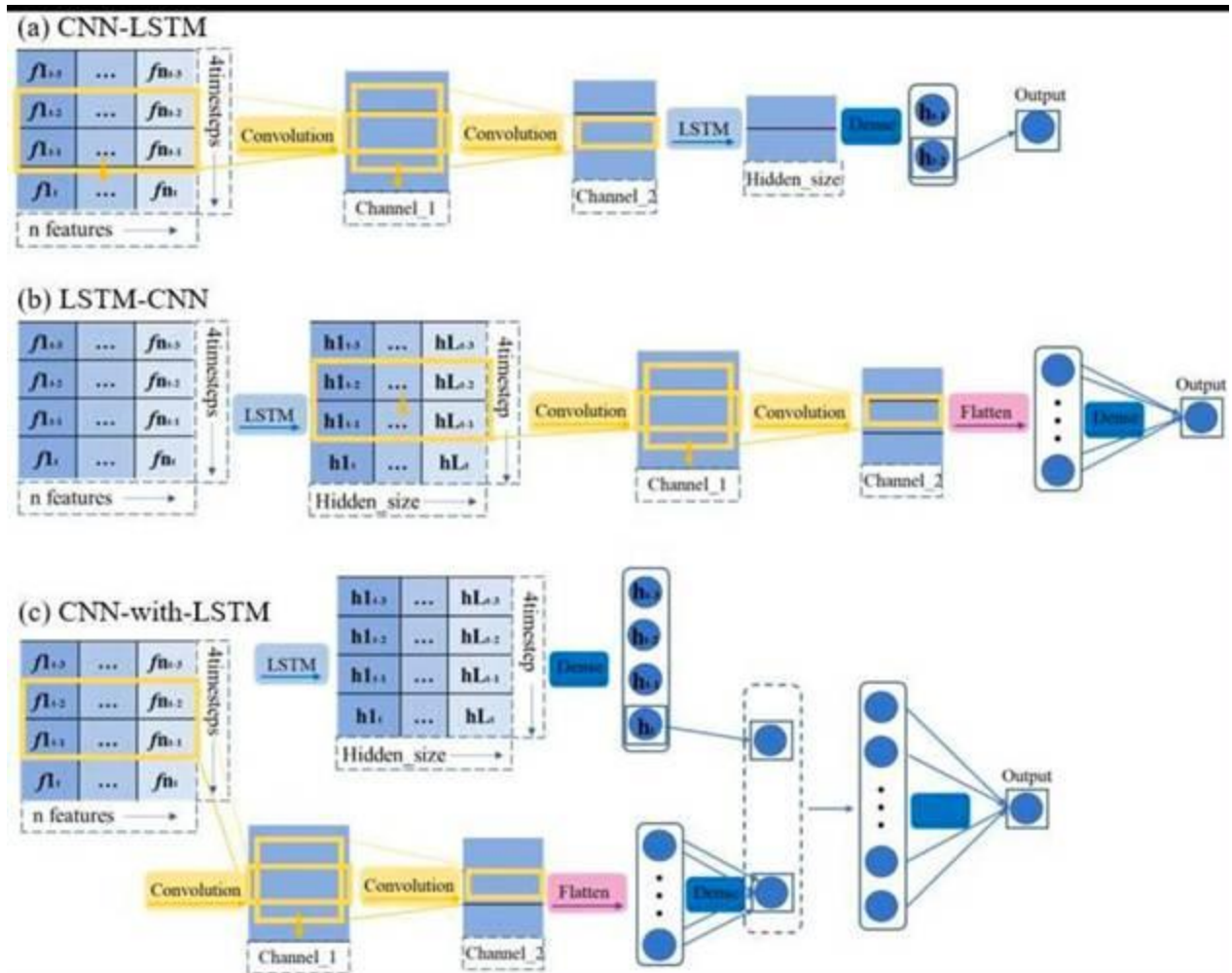
2.2.4 NLP/ML approaches to depression detectors

Knowing that depression manifest in different languages and different word of choice to each individual and the Natural language processing (NLP) turn the text to a computer language that can work with Machine learning (ML) to find the pattern in those numbers to that correlate to an outcome to this case Weather

depressed or not and the detector will read negative emotions terms to classify a fit for a large scale as for the early studies works relied primely on machine learning classifiers as SVM, Naïve Bayes, Random Forest, Logistic Regression trained on hand-engineered

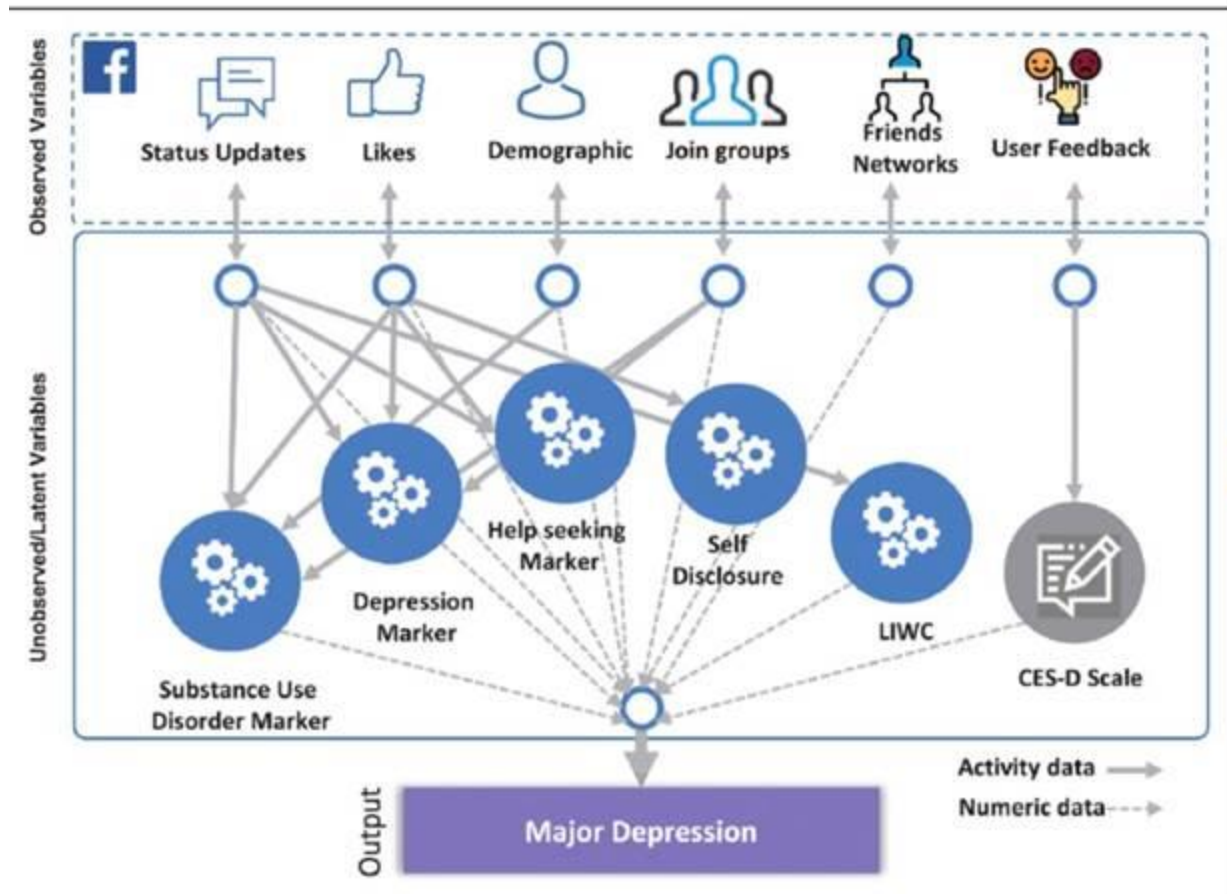


Later studies toward Convolutional Neural Network (CNN) and Long Short-Term Memory (LTSMs) CNN originally it was made for images but it can read texts it gets a group of words (3-5) and learns recognise meaningful patterns for a full sentence, LTSMs tracks the meaning of the words in sentences by remembering earlier texts and contents



2.2.5 Detection Framework Pipeline

Depression detection systems tend to follow end-to-end pipeline data is collected from the social media platform based on keywords or self-disclosure to identify the most likely depressed or depressed users and the system gives a score on how likely the user is affected through classifications using either traditional ML or deep learning models



The key to this decision making across the framework on how ground-truth labels are obtained. Some relies on the expressions of the users if a user stated that he was diagnosed with depression while others different terms and weaker sad each approach involves a trade-off of between label reliability and dataset scale with self-report and keyword-based methods enabling larger datasets. For final stage of the framework pipeline, it gives a binary statement on the cases whether depressed or not depressed and for the advanced frameworks a risk score that flags a user account.

2.2.6 Datasets Resources

The choices of the platforms that were used for the datasets have been contributing in the research over the years which are Twitter(X), Reddit, Shared task/benchmark

Twitter (X): have been a common source in early works and study cases since 2013 using the users self-reports collecting one year of tweeting for each participant and on later works on 2018 Orabi et al built on twitter(X) based collections relying on keywords and self-reports to identify and filter the depressed ones.

Reddit: have a significant impact on the study cases and researches due to its mental health communities and their long-posts which remained one of the most favoured since it is one of the largest and most Widley Benchmarks in the area

2.2.7 The Limitations & Challenges of This Approach

Despite the progress the researchers have come through one of the biggest challenges it is reliabilities of the methods: self-report diagnosis and keywords-based

Related works

1. De Choudhury 2013 — wanted to predict depression before it shows. Twitter, 500 users, CES-D test, 1 year of posts. Used SVM. Got 70%. Problem: small sample.
2. Coppersmith 2014 — wanted to measure depression signals at scale. Twitter, users who said “I was diagnosed.” Studied word patterns. Found clear language differences. Problem: self-reports can be fake.
3. Tsugawa 2015 — tested if it works in Japanese. Japanese Twitter users, CES-D test. Logistic regression. Got 69%. Problem: one country, one language.
4. Losada & Crestani 2016 — wanted a shared dataset everyone could use. Reddit, 800 users, posts in time order. Created eRisk benchmark. Problem: only Reddit.
5. Reece & Danforth 2017 — tried photos instead of words. Instagram, 166 users, colour and brightness features. Beat doctors’ unaided accuracy. Problem: tiny sample.
6. Shen 2017 — combined text, images, and behaviour together. Twitter. Multimodal dictionary learning. Better than using text alone. Problem: needs lots of data types.
7. Yates 2017 — built a big dataset. Reddit, 9,000 users who disclosed diagnosis. CNN model. Problem: only captures open people.

8. Trotzek 2018 — mixed metadata with neural nets. eRisk Reddit. CNN + embeddings ensemble. Best results at the time. Problem: tuned to one benchmark.
9. Sadeque 2018 — asked how fast detection happens. Reddit. LSTM + new latency metric. Showed speed vs accuracy tradeoff. Problem: metric still debated.
10. Orabi 2018 — tested different word embeddings. Twitter. CNN and RNN. CNN won. Problem: tuned to that dataset.
11. Guntuku 2017 — reviewed the whole field. Multiple platforms. Summarised language, activity, network markers. Problem: review only, no new experiment.
12. Tadesse 2019 — find depression posts. Reddit. LSTM + word features combined. Combo beat single models. Problem: judges posts, not people.
13. Kerasiotis 2024 — improve transformers. Social media posts. DistilBERT + extra features. Beat older ML. Problem: black box, can't explain decisions.
14. Pirina & Çöltekin 2018 — checked if datasets are trustworthy. Reddit, merged datasets. SVM. Found results depend on how control group is picked. Problem: high scores may be fake.
15. Losada, Crestani & Parapar 2017/2018 — ran eRisk yearly as a competition. Reddit, many teams. Standard comparison across models. Problem: still Reddit only.

Table 2.2: Summary of reviewed studies on depression detection from social media.

#	Study	Platform	Method	Key Result	Limitation
1	De Choudhury et al., 2013	Twitter	SVM	~70% accuracy	Small sample
2	Coppersmith et al., 2014	Twitter	Linguistic analysis	Clear language differences	Unverified self-reports
3	Tsugawa et al., 2015	Twitter (Japan)	Logistic regression	~69% accuracy	Single language/culture
4	Losada & Crestani, 2016	Reddit	Benchmark creation	eRisk dataset introduced	Reddit-only
5	Reece & Danforth, 2017	Instagram	ML on image features	Beat unaided GP rate	166 users only
6	Shen et al., 2017	Twitter	Multimodal dict. learning	Beat single-modality models	Needs multiple data types
7	Yates et al., 2017	Reddit	CNN	RSDD benchmark, ~9k users	Self-disclosure bias
8	Trotzek et al., 2018	Reddit	CNN + metadata ensemble	SOTA early detection	Benchmark-specific tuning
9	Sadeque et al., 2018	Reddit	LSTM + latency metric	Speed/accuracy tradeoff	Metric still debated
10	Orabi et al., 2018	Twitter	CNN/RNN + embeddings	CNN performed best	Dataset-specific
11	Guntuku et al., 2017	Multiple platforms	Integrative review	Synthesised known markers	No new experiment
12	Tadesse et al., 2019	Reddit	LSTM + feature models	Combined beat single models	Post-level, not user-level
13	Kerasiotis et al., 2024	Social media posts	DistilBERT + auxiliary	Beat traditional ML	Black box, low explainability
14	Pirina & Coltekin, 2018	Reddit	SVM + n-grams	Depends on control data	Possible dataset artefacts
15	Losada et al., 2017/2018	Reddit	Annual shared task	Standardised comparison	Reddit-only framing

References

[Coppersmith, Glen, et al., 2014]

Coppersmith, Glen, Mark Dredze, and Craig Harman. "Quantifying mental health signals in Twitter". Proceedings of the Workshop on Computational Linguistics and Clinical Psychology, 51-60, 2014.

<https://aclanthology.org/W14-3207/>

[De Choudhury, Munmun, et al., 2013]

De Choudhury, Munmun, Michael Gamon, Scott Counts, and Eric Horvitz. "Predicting depression via social media". Proceedings of the 7th International AAAI Conference on Weblogs and Social Media, 128-137, 2013.

<https://ojs.aaai.org/index.php/ICWSM/article/view/14432>

[Kerasiotis, Marios, et al., 2024]

Kerasiotis, Marios, Loukas Ilias, and Dimitris Askounis. "Depression detection in social media posts using transformer-based models and auxiliary features". arXiv preprint arXiv:2409.20048, 2024.

<https://arxiv.org/abs/2409.20048>

[Losada, David E., and Fabio Crestani, 2016]

Losada, David E., and Fabio Crestani. "A test collection for research on depression and language use". CLEF 2016, 28-39, 2016.

[Orabi, Ahmed Hussein, et al., 2018]

Orabi, Ahmed Hussein, Prasadith Buddhitha, Mahmoud Hussein Orabi, and Diana Inkpen. "Deep learning for depression detection of Twitter users". Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology, 88-97, 2018.

<https://aclanthology.org/W18-0609/>

[Reece, Andrew G., and Christopher M. Danforth, 2017]

Reece, Andrew G., and Christopher M. Danforth. "Instagram photos reveal predictive markers of depression". EPJ Data Science 6(1), 15, 2017.

<https://epjdatascience.springeropen.com/articles/10.1140/epjds/s13688-017-0110-z>

[Sadeque, Farig, et al., 2018]

Sadeque, Farig, Dongfang Xu, and Steven Bethard. "Measuring the latency of depression detection in social media". WSDM 2018, 495-503, 2018.

[Trotzek, Marcel, et al., 2018]

Trotzek, Marcel, Sven Koitka, and Christoph M. Friedrich. "Utilizing neural networks and linguistic metadata for early detection of depression indications in text sequences". IEEE Transactions on Knowledge and Data Engineering, 2018. <https://arxiv.org/abs/1804.07000>

[Tsugawa, Sho, et al., 2015]

Tsugawa, Sho, Yusuke Kikuchi, Fumio Kishino, Kosuke Nakajima, Yuichi Itoh, and Hiroyuki Ohsaki. "Recognizing depression from Twitter activity". CHI 2015, 3187-3196, 2015.

[World Health Organization, 2023]

World Health Organization. "Depressive disorder (depression)". WHO Fact Sheets, 2023.

<https://www.who.int/news-room/fact-sheets/detail/depression>

[Yates, Andrew, et al., 2017]

Yates, Andrew, Arman Cohan, and Nazli Goharian. "Depression and self-harm risk assessment in online forums". EMNLP 2017, 2968-2978, 2017.

<https://aclanthology.org/D17-1322/>

