Prediction of Postpartum Depression Using Machine Learning Techniques

By

Burhan Ud Din Abbasi

2016-MS(CS)-6 170437

Supervisor

Dr. Sharifullah Khan

Department of Computing

A thesis submitted in partial fulfillment of the requirements for the degree of Masters in Computer Science (MS CS)

In

School of Electrical Engineering and Computer Science,

National University of Sciences and Technology (NUST),

Islamabad, Pakistan.

(November 2018)

Approval

It is certified that the contents and form of the thesis entitled "**Prediction of Postpartum Depression Using Machine Learning Techniques**" submitted by **Burhan Ud Din Abbasi** have been found satisfactory for the requirement of the degree.

Advisor: **Dr. Sharifullah Khan**

Signature: ____________________

Date: ____________________

Committee Member 1: **Dr. Iram Fatima**

Signature: ____________________

Date: ____________________

Committee Member 2: **Dr. Rafia Mumtaz**

Signature: ____________________

Date: ____________________

Committee Member 3: **Miss Hirra Anwar**

Signature: ____________________

Date: ____________________

Abstract

People post frequent updates on the social media platforms regarding their activities, likes and dislikes that adds the element of uniqueness and personalization to the content. This study explores how data-driven methods can leverage the information available on social media platforms to predict Postpartum Depression (PPD). Early screening of mental disorders plays a crucial role in diagnosis and treatment. A generalized approach is proposed where linguistic features are extracted from user generated textual posts and categorized as general, depressive and PPD representative using multiple machine learning techniques. We use Linguistic Inquiry Word Count (LIWC) to extract a standard set of features and combine it with an additional feature based on Absolutist dictionary before identifying a list of most important features for the task of prediction. We find that the techniques used in our study exhibit strong predictive capabilities for PPD content. Multi-Layer Perceptron outperformed other techniques like SVM & Logistic Regression with 91.7% accuracy for depressive content identification and up to 86.9% accuracy for PPD content prediction. Our proposed methodology will help the government and humanitarian organizations to improve the systems and utilize available professional resources efficiently in order to deal with the situation of increasing occurrence of mental disorders.

Dedication

To My Dreams,
Without which this milestone would not be worth achieving.

Certificate of Originality

I hereby declare that this submission is my own work and to the best of my knowledge it contains no materials previously published or written by another person, nor material which to a substantial extent has been accepted for the award of any degree or diploma at NUST SEECS or at any other educational institute, except where due acknowledgement has been made in the thesis. Any contribution made to the research by others, with whom I have worked at NUST SEECS or elsewhere, is explicitly acknowledged in the thesis.

I also declare that the intellectual content of this thesis is the product of my own work, except for the assistance from others in the project's design and conception or in style, presentation and linguistics which has been acknowledged.

Author Name: **Burhan Ud Din Abbasi**

Signature: ________________

Acknowledgment

I owe my deepest gratitude to Allah Almighty. I would also like to acknowledge the efforts of my parents to make such opportunity available for me. I am very thankful to Dr. Sharifullah Khan, Dr. Hafiz Farooq Ahmad and Dr. Iram Fatima for patiently guiding me throughout the process.

This research is supported by the King Faisal University-Deanship of Scientific Research (DSR) for project id 180055.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction and Motivation

This chapter briefly introduces the topic of interest, Postpartum Depression and elaborates on the motivation behind this work.

1.1 Introduction

Communication channels have evolved a great deal due to the technology driven innovation in last few decades. A large number of online platforms exist, each serving in its own way the purpose facilitating information flow to audience from all over the world. These platforms allow users to communicate directly as well as broadcast information at no or comparatively lower costs, thus enabling users to seek help from the comfort of their homes. Social networking sites and blogging platforms have become go to places for expressing opinions and networking with like minded people.

In the era of fast paced technological advancements as our social structures weaken, new challenges arise with every passing day. In order to satisfy the need for balance, on-line social networking sites came into existence. More and more people are joining these platforms and sharing diverse range of experiences on multiple platforms, i.e., Facebook for connecting with close friends, Twitter for reaching out to everyone in the world, Reddit for anonymous sharing in dedicated communities, Instagram for photos whereas Wordpress and Medium are being used as popular blogging platform. During recent years researchers have taken increased interest in social and psychological aspects of human life, exploring the possibility to predict personality, characterize eating disorders and assess risks of suicide using social media (Wei et al., 2017) (Wang et al., 2017) (Shing et al., 2018). The extent to which various factors may impact emotional states or a specific phase of ego depletion and what might in turn be effected by them are being studied (Cowen and Keltner, 2017) (DeCaro and Van Stockum Jr, 2018) (Han, 2018). Increased interest in this area is partly driven by increasing occurrence of mental health problems all over the world. These issues effect individuals from all age groups ranging from an infant to an elderly person. A key challenge in the domain of mental health is that diagnosis can only take place through one-to-one interaction between clinicians and patients. Some of the major reasons effecting possibility of such interaction are unavailability of professionals and social stigma associated with mental health issues. Reddit is a widely used platform based on communities run by moderators where users can post news, ask questions and participate in discussion with an option to remain anonymous. Community based model of Reddit when coupled with privacy options makes it very likely for the individuals to discuss their issues openly and seek information on taboo topics without any fears associated with social settings (Choudhury and De, 2014).

1.1.1 Postpartum Depression

Due to the complex nature of our individual and collective needs, mental health is of utmost importance for human well being. Lack of awareness and facilities regarding mental health in developing countries are the major factors contributing towards the alarmingly high increase in reported mental health cases worldwide. Depression also known as Major Depressive Disorder is recognized as one of the leading causes of disability worldwide. Symptoms of this disorder can vary from mild to severe and generally include

- Feeling Sad
- Loss of interest in activities once enjoyable for the individual
- Major changes in Weight
- Abnormal sleep
- Observable change in physical activity for example purposeless hand-wringing, slowed movements and speech
- Feeling guilty or worthless
- Thoughts of suicide or death

Co-occurrence of all or most of above conditions for a period of about 2 weeks to an extent where daily life of an individual is affected leads to medically diagnosed depression.

Parenthood presents itself as a unique phase of life for an individual. In addition to the joys and happiness, it brings responsibilities on the shoulders of parents. Changes in life style along with emotional, social and sometimes financial pressure are some of the key challenges faced by parents. If not taken care of, these challenges can cause mental health issues. Due to the bio-chemical changes occurring during pregnancy and after child birth, mothers are more prone to feelings of stress, anxiety and sadness (Corwin and Pajer, 2008). If left unattended a considerably large number of these mothers develop psychological problems such as anxiety or depressive disorders. Postpartum depression(PPD) is one of the more common disorders diagnosed in parents. Percentage of individuals effected from this disorder shows large variation around the world and can be as high as 63% (Kalyani et al., 2001). While mothers are more susceptible to PPD,an estimated 4% of fathers also experience this disorder (Davé et al., 2010). A study found that 8% of adoptive mothers also experienced depression possibly due to lifestyle changes (Mott et al., 2011). On average 15% of mothers are expected to be suffering from PPD all over the world. Since no biological measure has been identified to be the cause of PPD, it becomes a challenge to diagnose PPD considering that changes in appetite, sleep patterns and excessive fatigue are a norm for women after childbirth(Pearlstein et al., 2009). In order to minimize the risks there has been emphasis on increasing efforts for perinatal and neonatal health (De Choudhury et al., 2013a) (Shultz et al., 2018).

1.2 Motivation

This project is a step towards timely detection of postpartum depression in social media users using machine learning techniques. This will enable relevant authorities to take preventive and prescriptive measures. Use of technology to connect patients with health care professionals at an early stage of a condition is likely to aid in fast recovery and minimal impact on lives of patients as well as their babies. Due to alarmingly low number of mental health professionals in Pakistan it is important to use technology to our advantage for early detection of postpartum depression and helping the patients to connect with concerned medical professionals. Although both genders are prone to be affected by this disorder, World Health Organization reports the number of women affected after child birth to be 13% of the women giving birth. In severe cases it may even lead to suicide. In todays digital world, we tend to use online platforms for all sorts of purposes therefore smart information systems can use data available publicly to predict the signs of depression and allow the possibility of early and effective interventions.

1.3 Problem Statement

We note that there is little prior research on prediction of Postpartum Depression from social media. Moreover existing work is focused towards solutions that employ platform specific features like interactivity with friends, post likes and others to study and predict users experiencing PPD. This platform specific approach makes it hard to be generalized and used for other platforms. We consider using linguistic features to propose a solution that can be generalized and deployed across the web. To our knowledge this is the first of its kind work that explores possibility of distinguishing PPD from non-PPD depressive posts. Our contribution in this work is multi-folds, first we select linguistic and emotional features that can best distinguish between normal and depressive content to narrow down from the list of available features extracted using Linguistic Inquiry Word-Count(LIWC). Second, using a layered approach, initially we measure the performance of various machine learning techniques for predicting between general and depressive discussions. In the second layer, we use the selected feature set to predict PPD discussions from non-PPD depressive posts. Using layered approach we show that not only depressive content(PPD + non-PPD) can be predicted from normal discussion but PPD and non-PPD content can also be bifurcated using the same feature set. To facilitate researchers in exploring possible avenues for future, we explain different statistical and machine learning methods used for our work in detail along with results.

1.4 Research Objectives

Unavailability of mental health professionals and high costs associated with treatment are a challenge, therefore directly impacting the solution of increasing mental health problems (Mohr et al., 2013). Hence the need for low cost and innovative methodologies for identification of PPD suffering individuals and/or detecting tendencies of developing PPD. We explore the use of textual posts on social media platforms as a means to identify PPD related discussions. Our choices for the data source and approach were driven by the findings regarding differences observed in on-line activity of mothers. PPD effected mothers avoided sharing their true emotions on platforms like Facebook due to the fear of being judged (De Choudhury et al., 2014).

We use machine learning techniques to classify general discussion, PPD and non-PPD depressive content based on the linguistic features only.

1.5 Thesis Outline

Remaining chapters explain in detail the research and development process of my work. Chapter 2 dives deeper into the research already conducted on topics directly and indirectly related to my area of interest. Chapter 3 explains in details all steps related to development and data collection. Chapter 4 discusses the experimental results and evaluation of results. Finally we present our findings in Chapter 5.

Chapter 2

Literature Review

This chapter explains in detail the research already that has already been conducted by researchers on topics of Depression, Postpartum Depression and opportunities explored from the aspects of social media and mental health.

2.1 Depression & Postpartum Depression

Transition to parenthood is one of the major phases in lives of people impacting various aspects of life, at times even causing negative emotional impact (Hudson et al., 2000). These changes seem to effect mothers and fathers both because of their inability to resolve differences between personal, social and professional lives (Woolhouse et al., 2012) (Genesoni and Tallandini, 2009). While postpartum blues indicated by mood swings, confusion, irritability and fatigue is common, its recognition is important because postpartum blues has been identified as a risk factor for postpartum depression(PPD) at a later stage (Reck et al., 2009). Postpartum depression(PPD) is one of the more common disorders diagnosed in parents. Percentage of individuals effected from this disorder shows large variation around the world and can be as high as 63% (Kalyani et al., 2001). While mothers are more susceptible to

PPD,an estimated 4% of fathers also experience this disorder (Davé et al., 2010). A study found that 8% of adoptive mothers also experienced depression possibly due to lifestyle changes (Mott et al., 2011). On average 15% of mothers are expected to be suffering from PPD all over the world. Since no biological measure has been identified to be the cause of PPD, it becomes a challenge to diagnose PPD considering that changes in appetite, sleep patterns and excessive fatigue are a norm for women after childbirth(Pearlstein et al., 2009). The Diagnostic and Statistical Manual of Mental Disorders published by American Psychiatric Association defines postpartum depression(PPD) as a major depressive disorder with peripartum onset with the most recent episode occurring from anywhere during pregnancy till 4-weeks after childbirth (American Psychiatric Association, 2013). The International Classification of Diseases (ICD) recognizes this disorder up to the period of 6 weeks after childbirth (WHO, 2004). Various factors have been identified as predictors of depression in general (Rude et al., 2004) (Al-Mosaiwi and Johnstone, 2018) and PPD in specific (Beck, 1998)(Beck, 2001) and tried to simplify the process of identification of individuals who are suffering or at risk by answering series of questions (Cox et al., 1987a) and also to measure the severity of the depression (Kroenke et al., 2001).

(Rude et al., 2004), through statistical analysis, found a significant difference in language of currently depressed individuals when compared to that of never depressed individuals. Their dataset comprised of essays written by college students. Students were required to write continuously without carefully articulating their thoughts into well-structured and grammatically correct sentences.

2.2 Social Media & Mental Health

Use of online platforms by parents is driven by factors like access to a wider audience and possibility of learning from diverse range of experiences with minimum or no increase in costs and sometimes also providing the opportunity to remain anonymous as users may be reluctant to share weaknesses or admit shortcomings on real name sites like Facebook (Plantin and Daneback, 2009) (Marwick, 2012). Goffman also found that people are less likely to broadcast their failures (Goffman, 1955).Availability of social support has been found as an important factor among individuals facing mental health issues (Cheng et al., 2014). Increase in the number of parenting sites indicates that there are significant number of users seeking advice on health for the purpose of self-diagnosis. Users of parenting support platforms tend to value advice of other parents more than the advice of experts (Sarkadi and Bremberg, 2005). (Halevy et al., 2009) discussed that in order to make full use of available online data, methodologies should be introduced that can use available large scale data and not waste time hoping for an annotated dataset.

From technological view point researchers are also focusing towards provision of systems that can accomplish the task of screening and generate alerts based on behavioral attributes as presented by data on social networking platforms. (Mohr et al., 2013) found that web-based interventions showed promising results over a wide range of mental health issues and recommended focus on improvements in data collection and analytical systems. (Baumel, 2015) concluded that non-professional support available through on-line platforms was helpful for individuals facing emotional issues. (Hussain et al., 2015) proposed a system based on ensemble machine learning techniques to classify individuals at risk of major depressive disorders from their Facebook activities. They used number of friend, followers, status updates and interactivity based on comments and likes to measure changes in routine, help seeking and drug references. (Fatima et al., 2017) identified a set of features that can predict depressive posts and communities, additionally predicting severity of depressive posts based on mood tags as available on source platform.

(Al-Mosaiwi and Johnstone, 2018) found higher use of Absolutist words in mental health related forums. Their work was based on custom dictionaries of 19 absolutist and 43 non-absolutist words in addition to features extracted through Linguistic Inquiry Word Count (LIWC) tool. Their experiments were focused on major mental disorders like Depression, BiPolar Disorder and Post Traumatic Stress Disorder. They found that depression recovery and help forums exhibited increase in use of absolutist words. Moreover absolutist words were found to be stronger predictors of mental health issues that negative emotion words. Since suicidal ideation forums also showed higher use of such words, use of such lists can possibly aid in tackling mental health issues of various intensities, ranging all the way from depression to suicidal ideation.

In recent years focus has shifted from manual methods towards establishing automated methods which can harness the huge amount of data available via social media and computational power for these tasks. As a consequence of mental health conditions people show change in usage patterns as well as the nature of content they share on public platforms like Twitter and Reddit (De Choudhury et al., 2013a) (Choudhury and De, 2014). Using the available information there have been efforts to predict the personality of writer(Wei et al., 2017), eating disorders (Wang et al., 2017), depression (Hussain et al., 2015), additionally predicting the severity of a disorder (Fatima et al., 2017) and prioritizing the posts on discussion forums to enable moderators and fellow users to respond on priority (Milne et al., 2016) (Malmasi et al., 2016).

(De Choudhury et al., 2013b) used social media based behavioral markers to predict posts indicative of depressive tendencies, showing the possibility of large-scale adoption of such system to monitor mental health issues in large populations. They used crowd sourcing to collect data and identify individuals who had been clinically diagnosed as depressed and their questionnaire based assessment also indicated presence of depression. Moreover while they observed decrease in activity of moms compared to normal users, in many cases they observed and unexplainable increase in on-line social activity of mothers. Work being focused on twitter user suffered a major implicit limitation of character limit as imposed by the platform itself. In a different study (De Choudhury et al., 2014) predicted PPD suffering individuals based on social media user profile using a number of platform related features, such as status updates, comments, wall posts; along with linguistic features such as type of pronouns; and some personal and demographic data such as income, ethnicity and occupation. Feature set in this study covered several aspects of lives of individuals participating in the study. User Characteristics included summary of activity over a period of time to measure changes in 7 day window of time. Features like status updates, number of media uploads, number of posts on wall of specific friends and other derived features.

User Characteristics
Status updates posted
Media uploaded
Wall posts to specific friends
Rate of change of activity
Frac. time w/ -ve activity trend
Entropy of activity
Mean power of activity signal

Figure 2.1: User Characteristics Used in PPD Prediction of Facebook Users

Social capital features included features that measured interaction intensity between an individual and his/her on-line peers. This category included features like number of likes on status, comments on status, likes on media posts, comments on media.

Linguistic features covered a wide range of grammatical features based on Linguistic Inquiry Word Count (LIWC) dictionary.

Content characteristics not only included features associated with use of positive emotion words and negative emotion words as given by LIWC but also measured the use of question words. This to measure the extent to which post related to advice seeking can distinguish PPD diagnosis from a normal user. The list of words considered for this feature included "what", "who", "whom" etc and use of symbol "?" as an indicator of a question.

Social Capital
Likes on status updates
Comments on status updates
Likes on uploaded media
Comments on uploaded media
Likes on wall posts to friends
Comments on posts to friends
Media with friends tagged
Likes on media w/ friends
Comments on media w/ friends
Wall posts made by friends
Likes on wall posts by friends
Comments on posts by friends
Media by friends
Likes on media by friends
Comments on media by friends
Friends with directed comm.

Figure 2.2: Social Capital Features Used in PPD Prediction of Facebook Users

It was found that mothers using Facebook preferred not to disclose real mental state and feelings related to PPD due to the reason that Facebook friends are usually our physical world contacts too. In addition to the variation in privacy settings of Facebook users, there is the limitation of availability of personal information such as income that renders methodology adopted by user specific studies less scalable.

Linguistic Style
1stPersonPronoun Singular
1stPersonPronoun Plural
2ndPersonPronoun
3rdPersonPronoun
Adverbs
Article
Assent
AuxVerbs
Certain
Conjunction
Exclusive
Filler
FunctionalWords
Inclusive
IndefinitePronoun
Inhibition
Negate
NonFluency
Preposition
Quantifier
Swear
Tentative
Verbs

Figure 2.3: Linguistic Style Features Used in PPD Prediction of Facebook Users

Content Characteristics
Positive Affect
Negative Affect
Question-centric Statuses

Figure 2.4: Content Characteristics Used in PPD Prediction of Facebook Users

2.3 Critical Analysis

Attempts to identify risk factors for postpartum depression have been ongoing for decades, resulting in a wide variety in nature of factors ranging from mistrust and marital problems to past history of PPD (Braverman and Roux, 1978) (Boyer, 1990). While survey based methods are not alternatives for clinical judgment, questionnaires have been developed to aid in screening process (Cox et al., 1987b). In recent years there have been effort to measure the impact of mindfulness-based cognitive therapy in PPD suffering mothers and for prevention of its recurrence in pregnant women (Shulman et al., 2018) (Dimidjian et al., 2015). Survey based methods, while useful, require individuals to explicitly answer a series of questions for the sake of diagnosis. Since the presence of a mental health professional is critical for evaluation of answers, this approach remains limited to the point of availability of professionals in a region and general awareness among public regarding importance of mental health.

Datasets such as the one created by (Rude et al., 2004) highlight natural thinking patterns, it is expected to differ when compared with posts shared on social media platforms. The key reason is that people carefully choose their words to form sentences which can best convey their point of view.

Availability of online tools devised by (Hussain et al., 2015) for depression screening can aid in early intervention, however, their scope remains limited to a certain platform due to the use of platform specific features. Moreover machine learning techniques used in these studies are known to be either limited in their learning capabilities or suffer from high computational costs in the presence of large training data sets.

Paper	Social Media	Manual Preprocessing	Feature Set	ML-Techniques	Focus	Best score
De Choudhury et al., 2013b	Twitter	Amazon Mechanical Turk	Activity, LIWC, ANew	-	PPD	-
De Choudhury et al., 2014	Facebook	Survey, PHQ-9	Demographic, Activity, LIWC	Logistic Regression	PPD	48%
Fatima et al., 2017	LiveJournal	-	LIWC, Anew, Mood Tags	Random Forest	Depression	90%

Figure 2.5: Comparison of Literature

With reference to the feature set such as (De Choudhury et al., 2014), it is important to note that all video and image posts were collectively considered as media posts. While separately considering these posts can possibly give greater insight into usage patterns, it is not free from influence of external worldly events such as sports events, political or news based media triggered because of a certain event.

The scope of this study is to propose an approach for prediction of postpartum depression (PPD) using machine learning on the natural language data shared on social media. We speculate that the linguistic patterns as manifested by social media text should provide enough information to enable reliable prediction scores, thus allowing relevant authorities to formulate early intervention mechanisms for prevention and treatment of PPD cases in a cost effective and timely manner. We try to address the challenges as observed in literature review to find a generalized approach that is not platform dependent and explore whether absolutist words can further be used by machine learning techniques as an indicator of PPD.

Chapter 3

Design and Methodology

This chapter explains the process of data collection for creation of dataset, feature extraction and prediction techniques used in the study.

3.1 Data Collection

We explore the use of textual posts on social media to identify PPD related discussions. Social media sites give various privacy options to their users, thus providing controls regarding information flow to their peers. Generally user profiles do not contain medical history or diagnosis. It was observed that at times users also post in PPD groups to seek help for their loved ones, however, the content of posts usually revolves around the challenges faced by the individual suffering from PPD. We use machine learning techniques to classify general discussion, PPD and non-PPD depressive content based on the linguistic features only. Since PPD is recognized as a major depressive disorder indicating the presence of a taxonomic scheme, we adopt a layered approach that first bifurcates depressive content and general discussions and at the second stage PPD content is identified from depressive content as shown in Figure 3.1. The proposed approach is explained in following subsections.

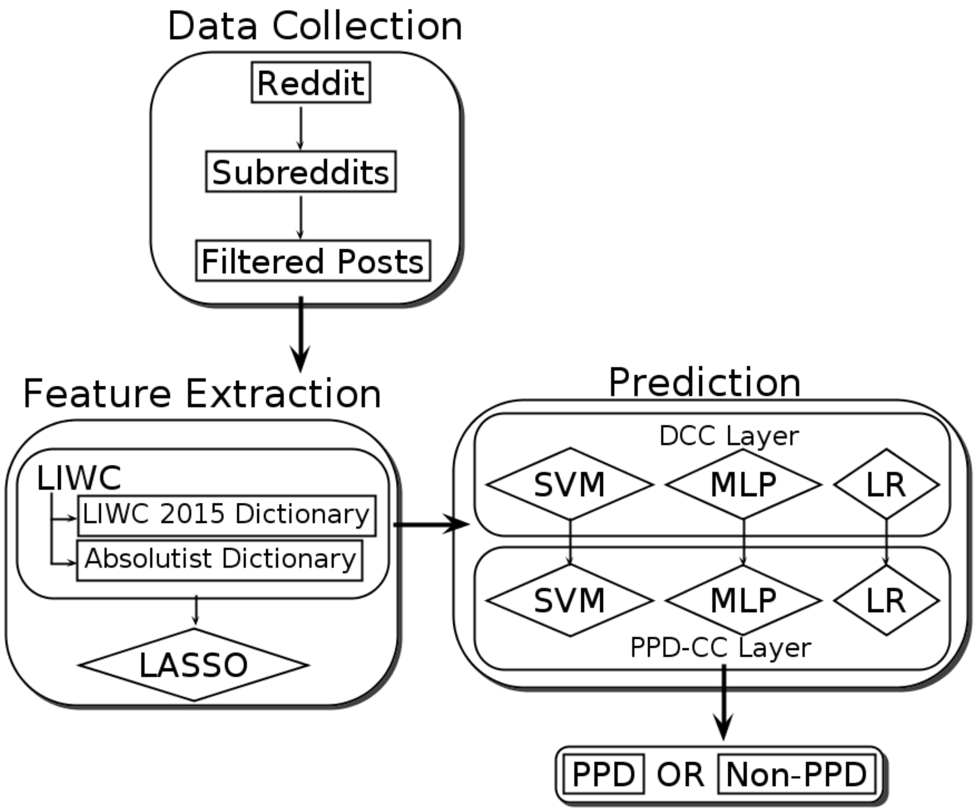


Figure 3.1: Flow chart for Layered Approach

Since our work is focused towards linguistic features instead of user profiles and individual activity patterns, we marked the posts with associated target class based on the nature of groups i.e. general discussion, depression related and PPD posts.

3.1.1 Reddit

Reddit is a social media platform where members post links and text in communities referred to as "subreddits". As of January 2018 Reddit had 1.2 million subreddits. With over 250 million users and over 540 million visits every month, reddit is the 6th largest website of the World Wide Web(WWW). Members of the website also known as "redditors", are allowed to comment on the posts and comments forming trees of comments thus enabling them to engage with each other at multiple levels. Posts are ranked by voting system termed as "downvotes" and "upvotes" which are used to calculate the "score" of the posts and comments. Since reddit is based on communities,

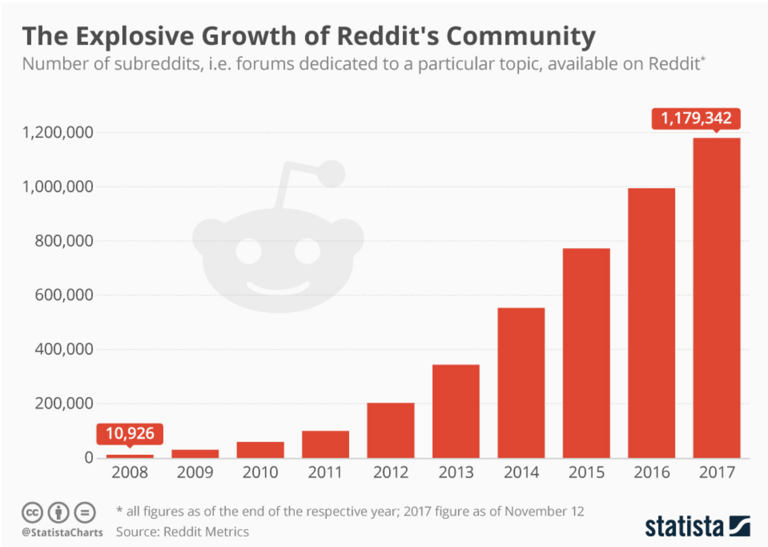


Figure 3.2: Growth in Reddit Over Last 10 Years

people with similar interests carry out discussions on subreddits related to their areas of interest. Strong content moderation culture of Reddit usually ensures that off-topic conversations are removed and frequent violators are banned. Reddit allows users to post and interact with others anonymously therefore allowing them to maintain a layer of privacy and share their problems candidly, this as found by De Choudhury, M., Counts, S., Horvitz, E. J., & Hoff, A. (2014) can be a factor stopping PPD effected mothers from opening up about their mental state on social media platforms .

3.1.2 PRAW

We used PRAW (Python Reddit API Wrapper) to collect data from Reddit including posts and associated meta data from several subreddits. PRAW allows users to access Reddit's API in Python. It supports multiple versions of Python including Python2.7, Python3.3 and Python3.6. Since PRAW is just a wrapper around API of Reddit, account is required and access to information is controlled by Reddit. In order to avoid Distributed Denial of Service Attacks through Reddit's API, it is required that no more than 10 requests are sent from a client. Therefore we scheduled a intermittent time delay of 6 seconds between each request.

3.1.3 Preprocessing

Posts from 21 subreddits were collected starting from January 2011 till April 2018, the collected data can be categorized into three groups i.e. Daily Life Group, Depression Group, PPD Group. Data for each group was gathered from a number of subreddits with the purpose of having diverse and well represented content. Details on subreddits included in each gruop are given in Table 3.1

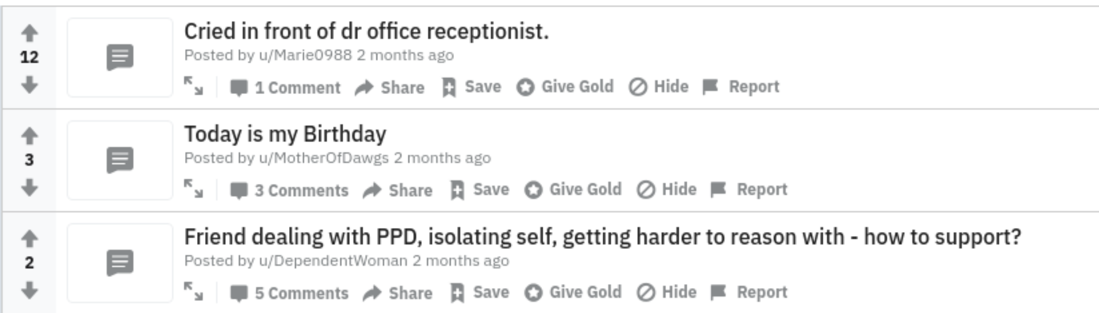
It is worth noting that PPD group included dedicated PPD subreddits as well as other subreddits which though not primarily focused towards PPD fall under the topics closely related to parenthood such as parenting, breast-feeding and BabyBumps. These subreddits were included because of the low number of posts in PPD focused subreddits. For non-PPD focused subreddits

Group	subreddit
Daily Life Group	*r/books, r/business, r/movies, r/technology, r/graphic_design*
Depression Group	*r/depression, r/depression_help*
PPD Group	*r/postpartumdepression, r/MyPPDSupport, r/Parenting, r/relationships, r/mommit, r/legaladvice, r/JUSTNOMIL, r/childfree, r/Breastfeeding, r/breakingmom, r/BabyBumps, r/beyondthebump, r/AskWomen, r/AskReddit*

Table 3.1: Groups and included subreddits

we only considered posts that contained the term "postpartum depression" in the title or the body of post. Terms like PPD, antenatal depression and perinatal depression were not considered for the creation of this dataset.

(a) Post Title



(b) Post Content

Figure 3.3: Posts in PPD Focused Subreddits

Since the goal of the study was to explore the possibility of prediction based on linguistic features, during preprocessing steps all such posts which only had a title and did not contain text in the body of post were removed, similarly all image, video and link based posts were filtered out.

3.2 Feature Extraction

As noted in section 2, a limitation of previous works has been the use of specialized platform specific features for the task of understanding and predicting PPD mothers. Therefore our work focused on using the content of text based posts and categorically avoided the use of meta data such as upvotes, downvotes, score, number of comments, date and time of posts. For the purpose of extracting linguistic features a widely used resource Linguistic Inquiry and Word Count(LIWC) was used (Pennebaker et al., 2001). LIWC analyses text by comparing and calculating percentage of words that match built-in dictionaries. LIWC2015 gives 93 features for the each post ranging from measures like word count, words per sentence and emotional tone to first person singulars, interrogatives and comparisons. In the light of findings by Al-Mosaiwi and Johnstone (2017) we used LIWC to calculate values based on custom dictionary of absolutist words. Therefore increasing the number of linguistic features to 94 for each post in dataset. Table 3.2 contains some examples for post content and their respective feature values

Features used for processing natural language usually consist of words, phrases or their numeric representations to fit statistical models of linguistic concepts. From the set of 94 such representative measures we were interested in identifying a list of most prominent features in terms of their ability to describe a response variable. This would allow for easier inter-

Post Content	Health	Work	Tone	Affiliation
Fear, pain, happiness, sadness, all non existent. Something I wish was possible	0.69	0	0	0
Looks like a fun exercise. Lots of really good concepts on the Dribbble and Instagram!	0.55	0	1	0.33
Just had my first baby a week ago, but my girlfriend is pretty sad. Any suggestions on how to cheer her up? Im planning on taking her out for a picnic tomorrow. Any suggestions?	0	0	0.80	0.14
Looking for a site which had a few different templates on how to reply to clients asking for work with different budgets etc. Will delete this and maybe post when I get the answer.	0	0.27	0.25	0

Table 3.2: Examples of Post Content and their normalized Feature Values

pretation of the model, faster performance by the algorithms even for large datasets and in reducing over-fitting of the model. To achieve this goal we used Least Absolute Shrinkage and Selection Operator (LASSO) (Tibshirani, 1996). LASSO works by employing Ridge regression which is the process of continuous shrinking co-efficient values for a variable and setting some to co-efficients to 0. This becomes particularly important for our purpose because of the presence of near-linear relationship between independent features(collinearity) for example word count, first person singulars and comparisons. Since LASSO uses the knowledge of target class, the target class given for the purpose of feature selection was based on previously described groups such as Daily Life Group was marked as *Non-Depressive*, Depression Group was marked *Depressive* and PPD Group was marked *PPD* class.The optimization objective for LASSO as defined in Scikit-learn documentation is

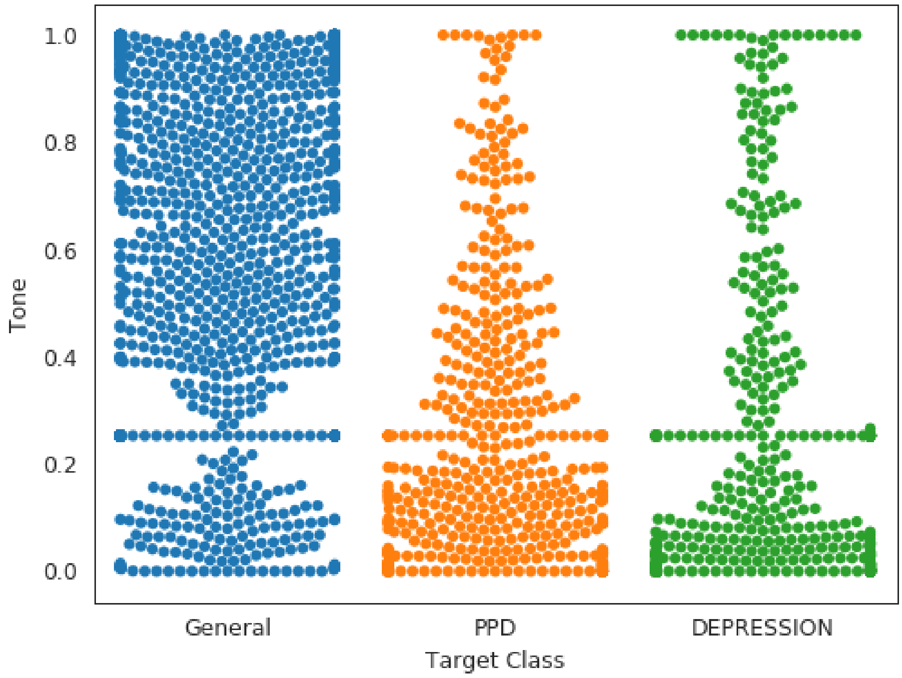
$(1/(2*n\_samples))*||y-Xw||^2+alpha*||w||$ where $||w||$ is the ℓ_1-norm of parameter vector and alpha is a constant (Pedregosa et al., 2011)

Table 3.3: Feature Set selected based on LASSO and their details based on LIWC

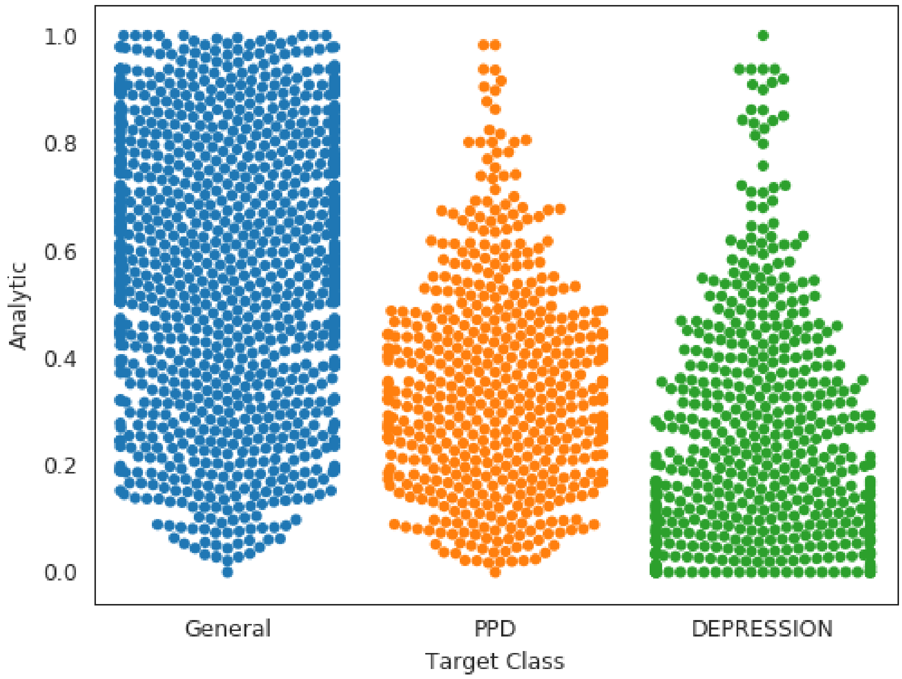
Category	Feature	Examples
Social Words	Family	daughter, dad, aunt
Absolutist Words	Absolutist	always,must, entire
Function Words	Negations	no,not,never
	1st Person Singular	I, me, mine
	1st Person Plural	we, us, our
	3rd Person Singular	she, her, him
	Impersonal Pronouns	it, it's, those
Personal Concerns	Death	burry, coffin, kill
	Home	landlord, kitchen
Drives and Needs	Affiliation	ally,friend, social
	Drive	ego, purpose, ambition
Time Orientations	Focus Present	today, is, now
Psychological Processes	Anger	hate, kill, annoyed
	Negative Emotion	hurt, ugly, nasty
Perceptual Processes	Feeling	feels, touch
Other Grammar	Interrogatives	how, when, what
	Comparatives	greater, best,after
WC	Word Count	-
Summary Variables	Dictionary words	-
	Emotional tone	-

LASSO uses a tunning parameter as a measure of the penalty, as its value increases the coefficients are forced to become zero. During selection process only features having non-zero coefficients are selected. For the value 0.0035 of alpha, LASSO model returned 20 non-zero co-efficient variables. Details on those features are given in Table 3.3.

Feature set represents multiple aspects of life such as concerns related



(a) Emotional Tone



(b) Analytical Thinking

Figure 3.4: Predictors of Depressive & Non-Depressive Content

to family and home, mentions of emotional states, discussion of goals and feelings as expressed by people in their posts. Summary variables of LIWC like Word Count, Emotional Tone and Dictionary Words were found to be important predictors of target classes. Using swarm plot 3.4 helped us to get an idea of underlying distribution of data points for each class.

3.3 Prediction

Given the goal of this study we turned to the task of predicting PPD using machine learning techniques. As discussed in Section 3.1, the dataset comprises of three groups therefore representing variety in the nature of posts from the perspective of a normal person, a depressed person and a PPD suffering individual. As discussed in Section 2 that DSM-5 and ICD-10 recognize PPD as a depressive disorder with postpartum onset, therefore we followed this approach to divide the task into a hierarchical classification problem. In our design there are two layers, top layer referred to as Depressive Content Classification (D-CC) and bottom layer referred to as PPD Content Classification (PPD-CC).

DCC layer classifies between general posts and depressive posts where as PPD-CC layer classifies between PPD and non PPD posts as shown in Table 2.

3.3.1 Depressive Content Classification (DCC) Layer

The goal of Depressive Content Classification Layer is to train a machine learning model to learn from feature set the distinguishing factors which can be used to identify depressive content from daily life discussions relating to professions, entertainment and hobbies. We trained models for each classifier using the feature set extracted by LASSO and compared the performance of each classifier. Table 3.4 shows target classes assigned to each posts in the dataset with respect to each layer.

Table 3.4: Target Classes Assigned to Groups for Hierarchical Training

Group	Depressive Content Classification (D-CC)	PPD Content Classification (PPD-CC)
Daily Life Group	Not Depressive	Not PPD
Depression Group	Depressive	Not PPD
PPD Group	Depressive	PPD

3.3.2 PPD Content Classification (PPD-CC) Layer

Content representative of Postpartum Depression is classified in this step as PPD, thus separating it from non PPD depressive content as predicted in DCC Layer. The output of DCC Layer i.e. depressive content is introduced in PPD-CC layer for the task of identifying PPD posts from non-depressive PPD posts. As give in Table 3.4 posts in Daily Life Group were also tagged as *Not PPD* in order to handle false positives in the output of DCC layer. Thus enabling the classifier to handle any general discussion posts incorrectly classified as Depressive in DCC layer.

Three Machine Learning (ML) techniques were used to train the models for the task of prediction Logistic Regression, Support Vector Machines(SVM) and Artificial Neural Networks(ANNs).

Algorithm 1: Layered Depressive & PPD Content Classification

```
Input  : Data set DS
         Lists of subreddits collections:
         Daily Life Group DLG[]
         Depressive Group DG[]
         PPD Group PPDG[]
Output: Predicted Classes for each layer:
Depressive Content Layer D_CC[]
PPD Content Layer PPD_CC[]
for i=1: length(DS) do
    if DS[i]['source_subreddit'] in DLG[] then
        DS[i]['Class_DCC'] =' nonDepressive';
        DS[i]['Class_PPD'] =' nonPPD';
    else if DS[i]['source_subreddit'] in DG[] then
        DS[i]['Class_DCC'] =' Depressive';
        DS[i]['Class_PPD'] =' nonPPD';
    else if DS[i]['source_subreddit'] in PPDG[] then
        DS[i]['Class_DCC'] =' Depressive';
        DS[i]['Class_PPD'] =' PPD';
    DS ← LIWC_2015(DS[i]['post_content']);
    DS ← LIWC_Absolutist(DS[i]['post_content']);
end
Test,Train ← Test_Train_Split(DS)
Train[AllFeatures[]] = Normalize(Train[AllFeatures[]])
coefficient_value[], feature_name[] ← LASSO(
  Train[AllFeatures[]],Train['Class_DCC'] )
FeatureSet[]=NonZeroCoEfficients(
  coefficient_value[],feature_name[])
classifier = ArtificialNeuralNetwork(length(FeatureSet[]),20,20,2)
DCC_Layer_Model = classifier.Train(
  Train[FeatureSet[]],Train['Class_DCC'] )
PPD_Layer_Model = classifier.Train(
  Train[FeatureSet[]],Train['Class_PPD'] )
Test[AllFeatures[]] = Normalize(Test[AllFeatures[]])
D_CC[] = DCC_Layer_Model.Predict(Test[FeatureSet[]])
predicted_depressive = Filter_Posts(where D_CC[] is 'Depressive')
PPD_Test =Filter_Posts( where Test in predicted_depressive)
PPD_CC[]= PPD_Layer_Model.Predict(PPD_Test[FeatureSet[]])
```

3.3.3 Logistic Regression

Logistic Regression is a linear model that performs prediction by considering, input values of the feature set and a bias term in order to get a model that fits the training set. A regularization term is introduced which prevent models over-fitting, thus giving us control over the complexity of model. This complexity is quantified using L2 Regularization that uses least squares error, minimizing the sum of the square of difference between estimated and target values (Tikhonov, 1977). Logistic Regression uses following as its optimization objective.

$$\min_{w,c} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \log(\exp(-y_i(X_i^T w + c)) + 1) \tag{3.1}$$

For the choice of algorithm to be used for optimization objective we use Newton's Method, although computationally expensive, it performed reasonably for our dataset (Fletcher, 2013).

3.3.4 Support Vector Machines (SVM)

Support Vector Machines (SVM) is a widely used technique which aims to find a boundary (hyperplane) that divides data into two classes such that there exists greatest possible distance between points of training set and the hyperplane. For cases when dataset is complex and there is no clear hyperplane, data is mapped into higher dimensions in order to find a hyperplane that can segregate the data, this is known as Kerneling. Since the data set was not huge we used Radial Basis Function (RBF) kernel with misclassification penalty parameter set to 1. Keeping this value lower allows the model to not over fit the training data.

$$\min_{w,c} \frac{1}{2} w^T w + C \sum_{i=1}^{n} \max\{0, 1 - \exp(y_i(X_i^T w + c))\} \tag{3.2}$$

3.3.5 Multi-Layer Perceptron (MLP) Neural Networks

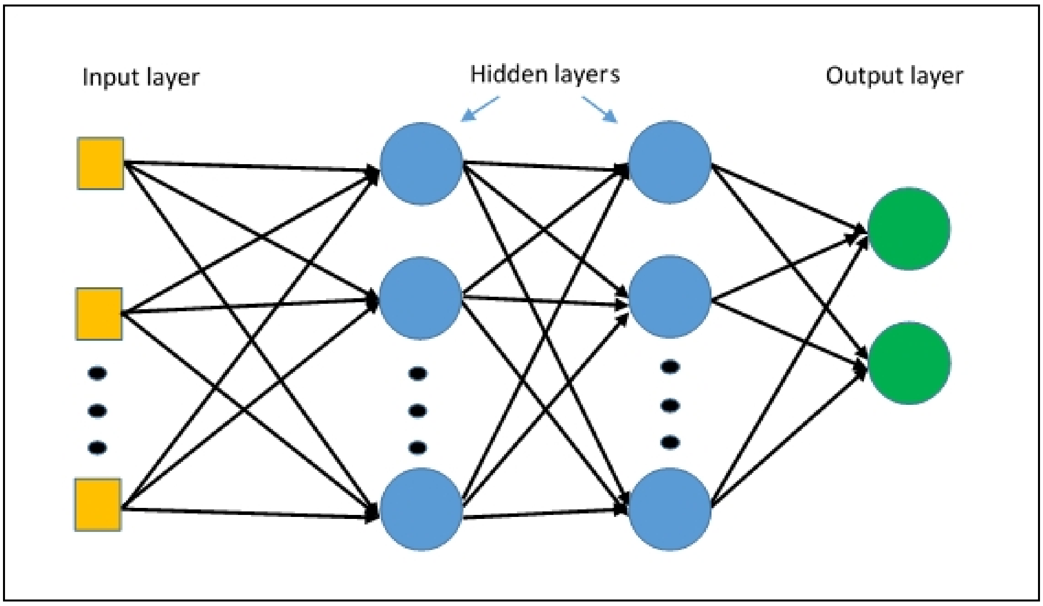


Figure 3.5: Architecture of Multi Layer Perceptrons

Multi-Layer Perceptron (MLP) are feed forward neural networks that employ standard back propagation algorithm. A number of layers of neurons work together to learn from the data set. First layer takes the data input where as last layer produces final output, each layer between input and output layer; also known as hidden layers; can contain any number of neurons therefore increasing the ability of the whole network to learn from the data. Similar to other machine learning algorithms a balance in parameter values is needed for optimal performance, in MLP a balance between the number of layers and neurons should be maintained. A very low number of layers or neurons can hinder the ability of network to learn efficiently whereas a very high number can increase the computational cost significantly and also make the network learn unnecessary details of training set therefore causing the model to over fit thus rendering it less useful for unseen data. Each connection between neurons is assigned a random weight initially and later updated based on the learning of network as seen by examples in training set. Each neuron processes the input based on an a predefined function referred to as activation function. We used 4 layered MLP, an input layer with neurons equal to length of feature set, 2 hidden layers having 20 neurons in each layer and an output layer comprising of 2 neurons. Rectified linear unit function was used as activation function with stochastic gradient-descent based optimizer and using constant learning rate of 0.0001.

3.3.6 Discussion

Machine Learning techniques like SVM, Logistic Regression and Multi-Layer Perceptrons have been successfully applied for solving challenges in various domains. Due to reason that each technique works in a unique way, over time researchers have been able to identify the extent of their usability in different domains. Since there was no significant time or computation cost involved with respect to either of the techniques, we can only compare based on accuracy scores. Moreover we believe that the dataset was not large enough to pose a challenge towards the learning abilities of these techniques.

Chapter 4

Experiments and Results

This section explains briefly characteristics of dataset, measures used to evaluate the performance of proposed methodology, results and comparisons of techniques and discussion on results.

4.1 Dataset Description

As shown in Table 3.4 for D-CC layer Depression Group and PPD Group were assigned target class as ”Depressive”, making both classes of D-CC layer (Depressive/non-Depressive) well represented thus enabling machine learning models to learn equally well regarding features of each class. The dataset comprised of total 3176 posts, approximately 50% were from daily life group hence tagged as non-depressive in nature, 25% of posts belonged to depression group and remaining 25% were from the PPD group . In order to evaluate the performance of our models an automated randomized selection of posts was carried out, yielding a training set of 2127 posts and a testing set or holdout set of 1049 posts to be used for Holdout Validation.

4.2 Evaluation Measures

Accuracy was used as the primary measure to gauge the performance of each model. To evaluate reliability of our results we report for each model macro level precision and recall scores. Accuracy, Precision and Recall are defined as follows

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

where TP, TN, FP and FN are the number of True Positives, True Negatives, False Positives and False Negatives, respectively. Macro precision is mean of precision scores calculated separately for each target label, whereas macro recall is the mean of recall scores computed individually for each label. Scores for each performance measure are reported for both 10 Fold Cross-validation as well as Holdout validation.

10-Fold Cross-Validation (C.V) was used to evaluate and optimize training results. Stratified K-Fold scheme was used for cross-validation in order to ensure that all folds maintain percentage representation for each class (Kohavi et al., 1995). Moreover in order to test the prediction capability of our model on unseen data, we select the best performing model in 10-Fold C.V and perform Holdout validation on holdout set. We discuss performance of the machine learning techniques employed in our study below. Since proposed methodology consisted of two layers for PPD content classification, each layer is discussed separately and results for both cross-validation and holdout set validation are reported.

4.3 Depressive Content Classification Layer (D-CC) Results

Using the feature set, D-CC layer was designed to predict whether a post was depressive or non-depressive in nature. As shown in Table 4.1 Multi-Layer Perceptrons (MLP) performed better than SVM and Logistic Regression for both 10-fold cross validation as well as holdout set. Logistic Regression and SVM also showed promising results. Consistent performance of machine learning techniques in 10 folds cross-validation and the holdout set validation is indicative of the reliability of the feature set. However it is worth noting that in the domain of natural language processing and for a very large dataset, algorithms like SVM may not be able to perform up to mark, on the other hand MLPs are generally expected to learn better in the presence of a larger dataset, therefore greatly enhancing their predictive capabilities.

Table 4.2 shows confusion matrix based on prediction results of MLPs in holdout set validation. Out of 531 depressive posts, 53 were incorrectly classified as non-depressive.

Table 4.1: D-CC Performance Scores.

D-CC Layer	Classifier	Accuracy	Precision	Recall
	SVM	89.42	89.69	89.40
10-Folds C.V	MLP	91.63	91.83	91.85
	LR	90.31	90.46	90.30
	SVM	90.46	90.61	90.50
Holdout	MLP	91.70	91.74	91.70
	LR	90.84	90.90	90.87

Table 4.2: DCC Layer Confusion Matrix of MLP for Holdout Validation

		Predicted	
		Depressive	**Non-Depressive**
Actual	**Depressive**	478	53
	Non-Depressive	34	484

4.4 PPD Content Classification Layer (PPD-CC) Results

Posts classified as depressive in the first layer were introduced into the second layer. As the name suggests, PPD content classification layer was trained to predict whether a post represented feature values associated with PPD or non-PPD content. 10-folds Cross validation results showed a noteable difference in the performance of each machine learning techniques used. Logistic Regression performed the best with average accuracy score of 83.81% whereas SVM and MLP were able to predict with 80.53% and 76.74% accuracy respectively (Table 4.3). Low performance score of MLP can be attributed to the smaller number of PPD posts in training set as compared to non-PPD posts. In case of holdout set validation MLP outperformed other techniques by achieving accuracy score of 85.51%. While Logistic Regression and SVM exhibited decrease in their accuracy score, their results were relatively consistent with their predictive capabilities for 10-folds cross-validation. While experiments showed that PPD prediction can be carried out using machine learning with linguistic features,we believe that there is no clear winner among the used algorithms. Although MLP showed better results for holdout validation as compared to 10-folds cross-validation, it can be expected to yield improved results in the presence of a large training set.

Table 4.3: PPD-CC Performance Scores.

PPD-CC Layer	**Classifier**	**Accuracy**	**Precision**	**Recall**
10-Folds C.V	SVM	80.70	82.85	80.00
	MLP	80.36	75.11	80.06
	LR	83.73	84.55	83.36
Holdout	SVM	76.86	79.65	75.60
	MLP	86.91	87.03	86.78
	LR	79.76	80.77	79.01

Confusion matrix in Table 4.4 shows prediction results of MLPs in holdout set validation. From the total of 512 posts categorized as depressive in DCC layer, 245 were associated with PPD. MLPs based model was able to predict 205 correctly, while classifier was unable to correctly classify 40 PPD posts, it also incorrectly categorized 27 non-PPD posts as PPD.

Table 4.4: PPD-CC Layer Confusion Matrix of MLP for Holdout Validation

		Predicted	
		PPD	**Non-PPD**
Actual	**PPD**	205	40
	Non-PPD	27	240

4.5 Language Usage in Post Titles

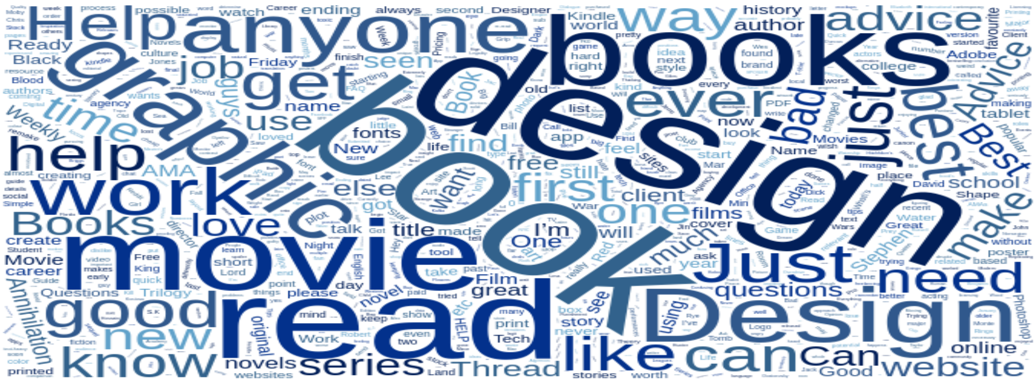
During the process of platform selection and subreddit identification, we observed difference in choice of words in title of posts. While some titles were short and to the point, others were comprehensive in nature

Hi There. PPD sucks, anyone else?
Mothers: For any of you who experienced mental health issues prior to having kids, did you experience postpartum depression (or something similar)?
Weekends are the worst
Cross post from Mommit - not sure if postpartum or just having trouble bonding
Postpartum depression and breastfeeding

Figure 4.1: Titles of Posts in PPD Forums

We also visualized the frequently used words in the titles of posts for each category to identify the most commonly used terms. We plotted word clouds for each category. Results are shown in 4.2a. While 4.2a has a very different set of terms used compared to other two categories, it can be seen that 4.2b and 4.2c have many similar term occurrences. Even for the case of terms occurring in both categories of PPD and Depression Group, there is a clear difference in frequency of usage. Moreover we noted that certain frequent words like *baby,PPD,birth* only appeared for PPD category, which is quite logical considering the fact that PPD is related to parents and parenthood.

(a) Daily Life



(b) Depression

(c) PPD

Figure 4.2: Word clouds for post titles

4.6 Discussion

Looking at the performance results of for each layers it can be seen that textual features can be used successfully as predictors of mental health to aid in identifying individuals at risk of general depression or specific form such as PPD. The proposed system recognized 19 features from LIWC-2015 dictionary and an additional feature based on absolutist words' dictionary, as strongest predictors of depressive content in general and PPD in specific. Using machine learning techniques, we can handle large data and yield consistent prediction results as well as further improve the accuracy of our techniques. MLP outperformed other techniques in 10 folds C.V (91.63% accuracy) and for holdout validation (91.51% accuracy) for D-CC layer and in PPD-CC layer it outperformed in case of holdout set (84.17%). Exploring MLPs further could be useful due to the reason that MLPs are able to derive high level features based on input feature set and have been found to perform better when trained using a large dataset. Moreover based on our analysis of post titles using word clouds, we can assume that the title of a post can potentially be used to partially predict the category or at least aid in the process.

Chapter 5

Conclusion

This chapter summarizes our research and dicusses its limitations. In section 5.1 we present the contributions and section 5.2 discusses the conclusion of this research. We describe limitations and future work in section 5.3. section.

5.1 Contribution

Social media serves as medium of communication between individuals all over the world. The information shared online can be useful from the perspective of mental health. In this research, a generalized approach has been proposed that predicts PPD content based on linguistic features. Use of this technique can prove beneficial for government as well as non-government organizations to deal with increasing mental health issues all over the world.

5.2 Discussion

In this study we examined the feasibility of employing a combination of text based features and machine learning techniques to classify depressive and non-depressive posts and then further identify posts representing characteristics of PPD. Various decisions based on previous research added value in the proposed methodology such as choice of a platform which allows for anonymity, use of Absolutist words as predictors of PPD. LIWC features along with Absolutist words features constituted 94 features. Use of LASSO for selection of features which had most impact on target class, yielded a feature set of 20 features. One of the features selected by LASSO was Absolutist words usage while other 19 features represented multiple aspects such as linguistics, emotion, length of content and usage of dictionary words.

The evaluation of multiple techniques on posts from social media communities demonstrated the success of proposed methodology. Depressive content classification yielded about 91.7% accuracy whereas PPD content classification achieved 86.91% accuracy, illustrating strong predictive capabilities of the system. Performance of SVM and LR in DCC layer were comparable to that of MLP in both 10-folds cross validation as well as holdout validation. In case of PPD-layer there were two key challenges, one was the inherent error caused due to incorrect classification at DCC-layer and second was the small number of PPD posts. All techniques showed consistent results in 10-folds cross validation whereas MLP was able to produce notable improvement in results of holdout validation.

5.3 Limitation and Future Work

Since our work explored the possibility of employing textual features, we did not explore the extent to which changes occur in PPD effected parents. Moreover we also included PPD posts from parenting related subreddits for because of the low number of posts in PPD focused subreddits. Multiple factors may be contributing towards the lower number of posts including lack of awareness about these subreddits and the unwillingness of people to share their feelings in a new group as compared to the comfort they might have developed interacting with the subreddits they are already active in. This research does not claim that all the individuals posting in subreddits of interest suffer from PPD; we can only make a weak inference about it while acknowledging the possibility of selective self-presentation. Future intervention studies can choose to put a dedicated effort for creation of a large training set containing texts produced in different settings such as social media post, essays and daily journals. Since we do not address the extent or possibility of causal role of feature set in occurrence of PPD, using time based content it can be further studied to identify features as possible vulnerability factors.

Bibliography

Al-Mosaiwi, M. and Johnstone, T. (2018). In an absolute state: Elevated use of absolutist words is a marker specific to anxiety, depression, and suicidal ideation. *Clinical Psychological Science*, page 2167702617747074.

American Psychiatric Association (2013). *Diagnostic and statistical manual of mental disorders: DSM-5*. Autor, Washington, DC, 5th ed. edition.

Baumel, A. (2015). Online emotional support delivered by trained volunteers: users satisfaction and their perception of the service compared to psychotherapy. *Journal of Mental Health*, 24(5):313–320.

Beck, C. T. (1998). The effects of postpartum depression on child development: a meta-analysis. *Archives of psychiatric nursing*, 12(1):12–20.

Beck, C. T. (2001). Predictors of postpartum depression: an update. *Nursing research*, 50(5):275–285.

Boyer, D. (1990). Prediction of postpartum depression. *NAACOG's clinical issues in perinatal and women's health nursing*, 1(3):359–368.

Braverman, J. and Roux, J. (1978). Screening for the patient at risk for postpartum depression. *Obstetrics and Gynecology*, 52(6):731–736.

Cheng, Y., Li, X., Lou, C., Sonenstein, F. L., Kalamar, A., Jejeebhoy, S., Delany-Moretlwe, S., Brahmbhatt, H., Olumide, A. O., and Ojengbede, O. (2014). The association between social support and mental health among vulnerable adolescents in five cities: findings from the study of the well-being of adolescents in vulnerable environments. *Journal of Adolescent Health*, 55(6):S31–S38.

Choudhury, M. and De, S. (2014). Mental health discourse on reddit: Self-disclosure, social support, and anonymity. pages 71–80.

Corwin, E. J. and Pajer, K. (2008). The psychoneuroimmunology of post-partum depression. *Journal of women's health*, 17(9):1529–1534.

Cowen, A. S. and Keltner, D. (2017). Self-report captures 27 distinct categories of emotion bridged by continuous gradients. *Proceedings of the National Academy of Sciences*, 114(38):E7900–E7909.

Cox, J. L., Holden, J. M., and Sagovsky, R. (1987a). Detection of postnatal depression: development of the 10-item edinburgh postnatal depression scale. *The British journal of psychiatry*, 150(6):782–786.

Cox, J. L., Holden, J. M., and Sagovsky, R. (1987b). Detection of postnatal depression: development of the 10-item edinburgh postnatal depression scale. *The British journal of psychiatry*, 150(6):782–786.

Davé, S., Petersen, I., Sherr, L., and Nazareth, I. (2010). Incidence of maternal and paternal depression in primary care: a cohort study using a primary care database. *Archives of pediatrics & adolescent medicine*, 164(11):1038–1044.

De Choudhury, M., Counts, S., and Horvitz, E. (2013a). Major life changes and behavioral markers in social media: case of childbirth. In *Proceedings of the 2013 conference on Computer supported cooperative work*, pages 1431–1442. ACM.

De Choudhury, M., Counts, S., and Horvitz, E. (2013b). Social media as a measurement tool of depression in populations. In *Proceedings of the 5th Annual ACM Web Science Conference*, pages 47–56. ACM.

De Choudhury, M., Counts, S., Horvitz, E. J., and Hoff, A. (2014). Characterizing and predicting postpartum depression from shared facebook data. In *Proceedings of the 17th ACM conference on Computer supported cooperative work & social computing*, pages 626–638. ACM.

DeCaro, M. S. and Van Stockum Jr, C. A. (2018). Ego depletion improves insight. *Thinking & Reasoning*, 24(3):315–343.

Dimidjian, S., Goodman, S. H., Felder, J. N., Gallop, R., Brown, A. P., and Beck, A. (2015). An open trial of mindfulness-based cognitive therapy for the prevention of perinatal depressive relapse/recurrence. *Archives of women's mental health*, 18(1):85–94.

Fatima, I., Mukhtar, H., Ahmad, H. F., and Rajpoot, K. (2017). Analysis of user-generated content from online social communities to characterise and predict depression degree. *Journal of Information Science*, page 0165551517740835.

Fletcher, R. (2013). *Practical Methods of Optimization*. Wiley.

Genesoni, L. and Tallandini, M. A. (2009). Men's psychological transition to fatherhood: an analysis of the literature, 1989–2008. *Birth*, 36(4):305–318.

Goffman, E. (1955). On face-work. *Psychiatry*, 18(3):213–231. PMID: 13254953.

Halevy, A., Norvig, P., and Pereira, F. (2009). The unreasonable effectiveness of data. *IEEE Intelligent Systems*, 24(2):8–12.

Han, S. (2018). Neurocognitive basis of racial ingroup bias in empathy. *Trends in cognitive sciences*.

Hudson, D. B., Elek, S. M., and Campbell-Grossman, C. (2000). Depression, self-esteem, loneliness, and social support among adolescent mothers participating in the new parents project. *Adolescence*, 35(139):445–454.

Hussain, J., Ali, M., Bilal, H. S. M., Afzal, M., Ahmad, H. F., Banos, O., and Lee, S. (2015). Sns based predictive model for depression. In *International Conference on Smart Homes and Health Telematics*, pages 349–354. Springer.

Kalyani, G., Saeed, K., Rehman, C., and Mubbashar, M. (2001). Incidence of depressive illness in pakistani women during postnatal period. *Journal-College of Physicians and Surgeons of Pakistan*, 11:246–248.

Kohavi, R. et al. (1995). A study of cross-validation and bootstrap for accuracy estimation and model selection. In *Ijcai*, volume 14, pages 1137–1145. Montreal, Canada.

Kroenke, K., Spitzer, R. L., and Williams, J. B. (2001). The phq-9. *Journal of general internal medicine*, 16(9):606–613.

Malmasi, S., Zampieri, M., and Dras, M. (2016). Predicting post severity in mental health forums. In *Proceedings of the third workshop on computational lingusitics and clinical psychology*, pages 133–137.

Marwick, A. E. (2012). The public domain: Social surveillance in everyday life. *Surveillance & Society*, 9(4):378.

Milne, D. N., Pink, G., Hachey, B., and Calvo, R. A. (2016). Clpsych 2016 shared task: Triaging content in online peer-support forums. In *Proceedings of the Third Workshop on Computational Lingusitics and Clinical Psychology*, pages 118–127.

Mohr, D. C., Burns, M. N., Schueller, S. M., Clarke, G., and Klinkman, M. (2013). Behavioral intervention technologies: evidence review and recommendations for future research in mental health. *General hospital psychiatry*, 35(4):332–338.

Mott, S. L., Schiller, C. E., Richards, J. G., OHara, M. W., and Stuart, S. (2011). Depression and anxiety among postpartum and adoptive mothers. *Archives of women's mental health*, 14(4):335.

Pearlstein, T., Howard, M., Salisbury, A., and Zlotnick, C. (2009). Postpartum depression. *American journal of obstetrics and gynecology*, 200(4):357–364.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12:2825–2830.

Pennebaker, J. W., Francis, M. E., and Booth, R. J. (2001). Linguistic inquiry and word count: Liwc 2001. *Mahway: Lawrence Erlbaum Associates*, 71(2001):2001.

Plantin, L. and Daneback, K. (2009). Parenthood, information and support on the internet. a literature review of research on parents and professionals online. *BMC family practice*, 10(1):34.

Reck, C., Stehle, E., Reinig, K., and Mundt, C. (2009). Maternity blues as a predictor of dsm-iv depression and anxiety disorders in the first three months postpartum. *Journal of Affective Disorders*, 113(1-2):77–87.

Rude, S., Gortner, E.-M., and Pennebaker, J. (2004). Language use of depressed and depression-vulnerable college students. *Cognition & Emotion*, 18(8):1121–1133.

Sarkadi, A. and Bremberg, S. (2005). Socially unbiased parenting support on the internet a cross-sectional study of users of a large swedish parenting website. 31:43–52.

Shing, H.-C., Nair, S., Zirikly, A., Friedenberg, M., Daumé III, H., and Resnik, P. (2018). Expert, crowdsourced, and machine assessment of suicide risk via online postings. In *Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic*, pages 25–36.

Shulman, B., Dueck, R., Ryan, D., Breau, G., Sadowski, I., and Misri, S. (2018). Feasibility of a mindfulness-based cognitive therapy group intervention as an adjunctive treatment for postpartum depression and anxiety. *Journal of affective disorders*, 235:61–67.

Shultz, S., Klin, A., and Jones, W. (2018). Neonatal transitions in social behavior and their implications for autism. *Trends in cognitive sciences*.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 267–288.

Tikhonov, A.-I. N. (1977). *Solutions of Ill Posed Problems (Scripta series in* *mathematics)*. Vh Winston.

Wang, T., Brede, M., Ianni, A., and Mentzakis, E. (2017). Detecting and characterizing eating-disorder communities on social media. In *Proceedings of the Tenth ACM International Conference on Web Search and Data Mining*, pages 91–100. ACM.

Wei, H., Zhang, F., Yuan, N. J., Cao, C., Fu, H., Xie, X., Rui, Y., and Ma, W.-Y. (2017). Beyond the words: Predicting user personality from heterogeneous information. In *Proceedings of the tenth ACM international conference on web search and data mining*, pages 305–314. ACM.

WHO, W. H. O. (2004). *ICD-10 : international statistical classification of diseases and related health problems / World Health Organization*. World Health Organization Geneva, 10th revision, 2nd ed. edition.

Woolhouse, H., McDonald, E., and Brown, S. (2012). Womens experiences of sex and intimacy after childbirth: making the adjustment to motherhood. *Journal of Psychosomatic Obstetrics & Gynecology*, 33(4):185–190.