Original Research Paper

Aspect-Based Sentiment Classification for Detecting the Cognitive Triad Mechanism of Depression

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Abstract: The cognitive triad mechanism of Beck's cognitive theory is critical for early diagnosis and prognosis of depression. According to the cognitive triad mechanism, negative views about the self, the future, and the world appear to be routine in depressed people, occurring spontaneously. The challenge in the clinical interview is that the individuals may have trouble explaining their past and current symptoms for a variety of factors, such as the existence of concurrent mental health or medical problems and memory difficulties. The aspect-based sentiment classification technique can help psychologists overcome this difficulty by identifying the cognitive triad pairs {(self, negative), (future, negative), (world, negative)} from the individual's clinical chatbot and social media messages. The proposed multilayer RNN-capsule architecture on Cognitive Triad Dataset (CTD) consists of two layers, i.e., sentiment recognition and aspect identification layers. Through experiments on the CTD, the multilayer RNN-capsule model outperforms the single-layer RNN-capsule model for aspect-based sentiment classification. The accuracy and F1 score of a single-layer RNN-capsule model for aspect-based sentiment classification are 0.857 and 0.858, respectively. The accuracy and F1 score of the sentiment recognition capsule in the multilayer RNN-capsule model are 0.89 and 0.892, while the accuracy and F1 score of the aspect detection capsule are 0.957 and 0.956. Also, the multilayer RNN-capsule model outperforms most of its counterparts like GNN, LSTM, and BiLSTM. More importantly, capsule architecture is capable of producing words containing sentiment and aspect inclinations that reflect the attributes of sentiment and aspect capsules, respectively, without the use of any linguistic knowledge.

Keywords: Aspect Detection, Cognitive Triad, Depression, Mental Disorder Understanding, Sentiment Classification

Introduction

Human lives can be saved and psychological trauma can be decreased by the timely diagnosis of mental health disorders. Mental health disorders include depressive disorder, obsessive-compulsive disorder, anxiety disorder, panic disorder and bipolar disorder (WHO, 2005). A traditional clinical interview is used to diagnose mental diseases, in which patients convey information about their symptoms and psychological state of functioning to the professional. The challenge in this process is that the psychiatrist must rely upon the observations in the clinical interview (Webb and Parks, 2016). They report recent or current symptoms more accurately. Patients may have trouble explaining their past and current symptoms for a variety of reasons, including the occurrence of concurrent mental health or medical problems and memory difficulties. Furthermore, depending on the perceived implications of a diagnosis of mental disease, patients may over-or under-report their symptoms.

Recent studies show a strong link between emotional expressiveness in social media networks and mental illnesses, providing vital evidence for computer-aided diagnosis of mental illnesses (Guo *et al*., 2021). Diagnosis and prognosis involve the understanding of sentiment in the social media text, temporal coordination of vocal tract and facial movements and heart rate activity analysis. Some types of diagnoses are difficult even for specialized psychologists. Therefore, human experts often feel a need for support tools to aid in precise mental disorder understanding. This is the motivation for intelligent mental disorder understanding systems.

To treat depressed people, they have to be diagnosed first. Depressed people must consciously reach out to mental health professionals to get a diagnosis. In fact, because of cost, mobility and motivation constraints, it can be hard for the depressed to get psychiatric help. Passive automated human communication can overcome such constraints and properly assess for depression. One application of the proposed multilayer RNN-capsule model is the early detection of depression based on an individual's past interactions with their social media or clinical chatbot data. A general architecture of the aspect-based sentiment analysis model is shown in Fig. 1. Psychologists use client data from social media sources like WhatsApp and Twitter and the data is generated through the clinical chatbot. Twitter data is retrieved using the Twitter API. The 'Export chat' option in WhatsApp messenger is used to extract WhatsApp group messages. A clinical chatbot can be used to generate client data for cognitive analysis. The architecture of a clinical chatbot is depicted in Fig. 2. The user interface for uploading data for cognitive analysis using the multilayer RNN-capsule architecture is depicted in Fig. 3. Table 1 shows a sample prediction report for data generated by the client. Using various descriptive statistical analysis techniques described in (Whisman and Richardson, 2015; Stolow, 2011), different insights on the cognitive triad features may be drawn from the prediction data. A bar chart illustrating the weekly percentage of negative thoughts about cognitive aspects is shown in Fig. 4.

The proposed multilayer RNN-capsule architecture on Cognitive Triad Dataset consists of two layers, i.e., sentiment recognition and aspect identification layers. Its attempts to perform sentiment analysis and aspect detection by capsules. Each capsule comprises a state, an attribute and three components: Representation, probability and reconstruction (Wang *et al*., 2018).

Sentiment Recognition Layer: The sentiment recognition layer consists of sentiment capsules. A sentiment capsule’s attribute represents its allocated sentiment class. The number of sentiment capsules is equivalent to the number of sentiment classes. The Negative and Positive capsules are designed to train cognitive sentiments in the sentiment recognition layer. The probability components of every sentiment capsule in the sentiment recognition layer determine whether a sentiment capsule is active or inactive. In terms of the three components, the representation component utilizes the attention mechanism to construct the sentiment capsule representation; the probability component utilizes the sentiment capsule representation to predict the sentiment capsule's state probability and the reconstruction component is used to reconstruct the input instance's representation.

Aspect Identification Layer: The aspect identification layer consists of aspect capsules. An aspect capsule’s attribute represents its allocated aspect class. The total number of aspect capsules equals the total number of aspect classes. For example, Self-Capsule, Future Capsule and World Capsule are designed to train cognitive aspects. The probability components of every aspect capsule in the aspect identification layer determine whether an aspect capsule is active or inactive. In terms of the three components, the representation component utilizes the attention mechanism to construct the aspect capsule representation; the probability component utilizes the aspect capsule representation to obtain the state probability of the aspect capsule; the reconstruction component is used to reconstruct the input instance’s representation.

In this study, we make the following contributions:

- This study focuses on modeling Beck’s cognitive triad mechanism of depression
- Multilayer RNN-capsule architecture is proposed to train CTD, consisting of two layers, i.e., sentiment recognition and aspect identification layers
- Experiments show that our proposed multilayer RNN-capsule model outperforms most of its counterparts

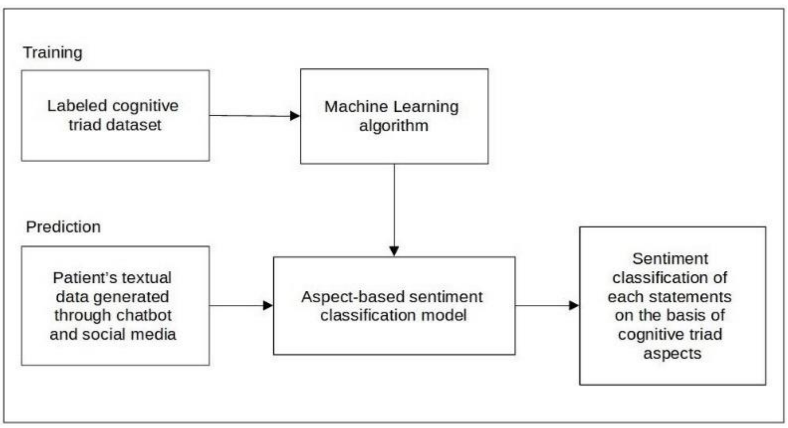

Fig. 1: A general architecture of aspect-based sentiment classification model for cognitive triad aspects

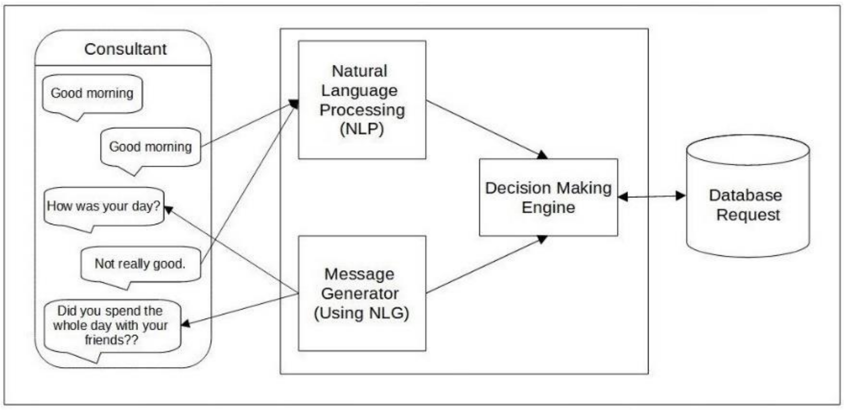

Fig. 2: A clinical chatbot to generate client data for aspect-based sentiment classification

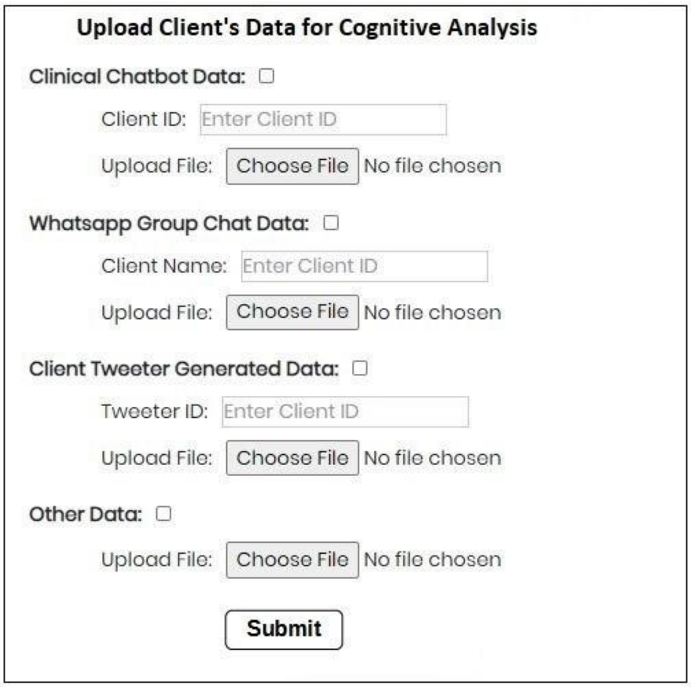

Fig. 3: User interface for a psychologist to upload the client's data for cognitive sentiment analysis

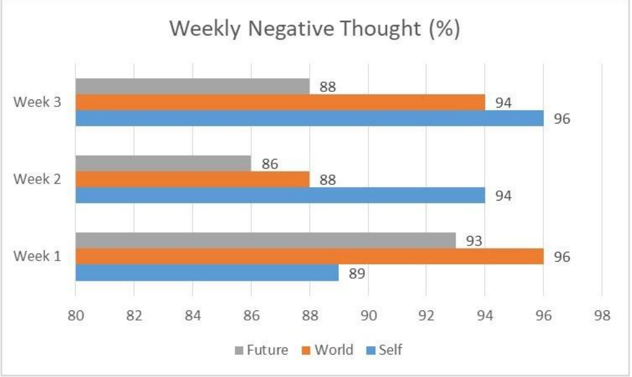

Fig. 4: A sample bar chart representing the weekly percentage of negative thoughts related to cognitive aspects

Table 1: Sample prediction result for client-generated statements

Patient-generated statements	Source	Timestamp	Predicted cognitive class
Never surround people, it is more depressing than ever	Twitter	2020-02-01 07:35:04	World-negative
I am not happy about myself	WhatsApp	2020-03-01 10:05:11	Self-negative
Everybody made me feel lonely	WhatsApp	2020-03-01 10:15:13	World-negative
My future will go to be very hard	Chatbot	2020-05-01 08:05:01	Future-negative
They did not attempt to save my life that day	Chatbot	2020-05-01 08:09:08	World-negative
I know I am capable of achieving this	Chatbot	2020-05-01 08:13:13	Self-positive
She has a lot of egos	Chatbot	2020-05-01 08:15:06	World-negative
He did an amazing job	Chatbot	2020-05-01 08:18:25	World-positive
I will never be strong enough	Chatbot	2020-05-01 08:21:05	Future-negative
Everyone has a good time, but I don't	WhatsApp	2020-07-01 11:06:34	Self-negative

Background

Sentiment Analysis

In the recent decade, sentiment analysis that exploits machine learning techniques has advanced rapidly. Neural network models have hugely succeeded in Natural Language Processing (NLP), improving word and phrase representations (Mikolov *et al*., 2013b). Several models have been used to analyze sentiments in text data, including Recursive Neural Tensor Network (Socher *et al*., 2013), Recursive Auto Encoder (Dong *et al*., 2014; Qian *et al*., 2015; Socher *et al*., 2011), standard RNN (Mikolov *et al*., 2010), LSTM (Hochreiter and Schmidhuber, 1997), GRU (Cho, 2014) and TreeLSTMs (Tai *et al*., 2015). Recursive autoencoder neural network recurrently constructs a sentence representation from sub-phrases (Dong *et al*., 2014; Qian *et al*., 2015; Socher *et al*., 2011). For several NLP tasks, including sentiment analysis, tree-based LSTMs (Tai *et al*., 2015) have been successful but suffer from errors in syntax parsing. Sequence models such as CNN do not need tree-structured data, generally accepted for sentiment classification (Kalchbrenner *et al*., 2014; Yoon, 2014). Due to its ability to model the suffix or prefix context, LSTM is widely known for learning sentence-level representation (Hochreiter and Schmidhuber, 1997; Tai *et al*., 2015). Given the effectiveness of these approaches, it is still challenging at a fine-grained level to differentiate between various sentiment polarities.

Sentiment Analysis in Mental Disorder Understanding: Causal explanation analysis is one of the applications of sentiment analysis in understanding mental disorders. Causal explanations have been identified as essential psychological factors related to mental and physical health. These are often analyzed through manual phrase identification over limited personal writing data. Automatic recognition of causal explanations on social networks provides a better alternative to expensive and complex manual evaluations and creates new applications (Son *et al*., 2018). Here, researchers utilized bidirectional LSTM for causality classification and causal explanation recognition. One more application of sentiment analysis in mental disorder understanding is suicidal ideation detection. In today's society, suicide is a serious problem. People's lives should be saved by addressing early identification and avoidance of attempted suicide. Deep learning techniques are popularly used for automatic identification based on social media and other online content. Deep learning has been a huge success in many fields, such as speech recognition, computer vision, medical diagnosis and machine translation. It is an effective technique for the detection of suicidal ideation in the area of suicide studies. Natural language text is typically embedded in the form of distributed vector space to apply deep learning algorithms.

Researchers have developed model aggregation techniques for updating deep learning models, i.e., LSTMs and CNNs (Wang *et al*., 2018). The most common word embedding methods are GloVe (Pennington *et al*., 2014) and Word2vec (Mikolov *et al*., 2013a). Shing *et al*. (2018) implemented CNN at the user level with various filter sizes to encode users' posts. The most popular variant of RNN, Long Short-Term Memory (LSTM) with fully connected layers, is applied for classification (Ji *et al*., 2018). Ji *et al*. (2020) suggested a novel method for identifying suicidal thoughts in private chat rooms. Gaur *et al.* (2019) integrated ontology associated with suicide and external knowledge bases into a text representation and achieved enhanced efficiency with CNN. Sawhney *et al*. (2018) utilized CNN, LSTM, and RNN to detect suicidal ideation. Coppersmith *et al*. (2018) implemented a deep learning model for sequence encoding using a bidirectional LSTM and a self-attention method for finding the most insightful subsequence.

Beck's Cognitive Triad for Understanding Depression

Beck (Powles, 1974) identified three causes of depression: Negative self-schemas, faulty information processing, and cognitive triad. This section describes Beck's cognitive triad, critical evaluation of cognitive theory, and cognitive triad inventory related to the cognitive triad.

Beck's Cognitive Triad: The cognitive triad includes three typical aspects of negative thinking of depressed people: The negative views about the world ("People always make it impossible for me to obtain what I require, no matter what I do"), the self ("I have personality issues") and the future ("I will never be able to do anything fun after my treatment”). These negative thoughts appear to be routine in depressed individuals.

Critical Analysis of Beck’s Cognitive Theory: For six years, (Alloy *et al.*, 1999) studied the thought processes of young Americans in their early twenties. Their thinking patterns were assessed and classified into the ‘positive thinking category’ or ‘negative thinking category’. After six years, approximately 1% of those in the positive category, compared to approximately 17% of those in the negative category, experienced depression. These findings show that there may be a correlation between cognitive patterns and the progression of depression. Butler *et al.* (2006) assessed 14 meta-analyses evaluating the success of Beck’s psychotherapy and found that nearly 80% of people had recovered. Beck’s cognitive therapy has also been shown to be far more effective than drug therapy and has a lesser incidence of relapse (McLeod, 2019).

Cognitive Triad Inventory (CTI): The CTI consists of items (Beckham, 1986) associated with one’s perception of the self, the future and the world, as provided in Table 2. Items are expressed in positive as well as negative ways. People are required to mark how well the item relates to them from 1 (total agreement) to 7 (total disagreement) on the 7 points Likert scale (Pössel, 2009). Before measuring by summing up the ratings, all the items are poled so that low ratings reflect false views and high ratings reflect true views. Table 2 also gives the expected answer from depressed people in binary-class (yes and no) and a scale of 1-7 (true view and false view). Descriptive statistical measures for the complete study sample, including mean, Standard Deviation (SD), Cronbach’s alphas for the major variables and correlations between variables studied, are useful in understanding depression.

Assessment of Depression Symptoms: The Center for Epidemiological Studies Depression Scale (CES-D) (Stolow, 2011) is a 20-item self-report scale intended to evaluate depressive symptoms in the normal population. Participants’ frequency of occurrence for each symptom was noted for each item throughout the previous week. The responses vary from 1 (never or rarely) to 4 (all or most of the time). Scores vary from 20 to 80, with higher scores reflecting more depressive symptoms. In this research, the CES-D showed strong internal consistency, with Cronbach’s alpha values varying from 0.90 to 0.94 (SD = 8.14, μ = 29.18) over seven-time points.

Data

The Cognitive Triad Dataset (CTD) (Jere and Patil, 2021; Jere *et al*., 2021) was collected from Time-to-Change, Beyond Blue personal stories and Twitter. It contains 648 participants in the training dataset and 192 participants in the testing dataset. It was annotated by six human experts. The CTD provides 6-ary cognitive triad classes to recognize CTI-items related to statements in an individual’s social media conversations.

Table 2: CTI items with intended responses from a depressed individual

CTI items	Response expected from depressed individual (Yes/No Binary class)	Response expected from depressed individual with 1-7 scale (High scores` reflects positive views, and low scores reflect negative views)	Aspect
In a few years, I expect things to be much better for me	No	Negative view	Future
In the future, everything will go smoothly for me	No	Negative view	Future
Other people make it hard for me to obtain what I need regardless of what I do	Yes	Positive view	World
I struggle with my personality	Yes	Positive view	Self
I am good at many things	No	Negative view	Self
I am sorry to say that I’m responsible for several wrongdoings	Yes	Positive view	Self
I believe I will be happy as I grow older	No	Negative view	Future
A lot of unpleasant stuff has happened to me	Yes	Positive view	World
I respect myself	No	Negative view	Self
I am up against several challenges	Yes	Positive view	World
In the future, many positive things will happen to me	No	Negative view	Future
My concerns and issues will not go away soon	Yes	Positive view	Future
I am good at a variety of stuff	No	Negative view	Self
Nothing is going to work out for me	Yes	Positive view	Future
I enjoy thinking about the good things that will come my way in the future	No	Negative view	Future
There is simply no reason for me to believe that things will improve for me	Yes	Positive view	Future
I’m a failure	Yes	Positive view	Self
My family is unconcerned about what happened to me	Yes	Positive view	World
I don’t like myself	Yes	Positive view	Self
In my life, there is nothing to anticipate	Yes	Positive view	Future
My future is too terrible for me to imagine	Yes	Positive view	Future
I will take care of my problems	No	Negative view	Future
I am as excellent as the individuals I know	No	Negative view	Self
I complete my classwork on time	No	Negative view	Self
I am a wonderful human	No	Negative view	Self

Table 3: 6-ary CTD statistics

Corpus	Sneg	Spos	Fneg	Fpos	Wneg	Wpos
Twitter	797	793	784	777	768	787
Beyond Blue	95	97	93	98	90	107
Time to Change	106	102	103	97	102	90
Total	998	992	980	972	960	984

Table 4: Statistics of CTD on cognitive aspects

Corpus	Self	Future	World
Twitter	1590	1561	1555
Beyond blue	192	191	197
Time to change	208	200	192
Total	1990	1952	1944

Table 5: Statistics of CTD on cognitive sentiments

Corpus	Positive	Negative
Twitter	2357	2349
Beyond Blue	302	278
Time to change	289	311
Total	2948	2938

Table 6: Train/test/validation split information of cognitive aspects

Class	Label	Number/Percentage of train	Number/Percentage of test	Number/Percentage of validation
self	0	1393/70.00	299/15.02	298/14.97
world	1	1360/69.96	292/15.02	292/15.02
future	2	1366/69.98	293/15.01	293/15.01

Table 7: Train/test/validation split information of cognitive sentiments

Class	Label	Number/Percentage of train	Number/Percentage of test	Number/Percentage of validation
negative	0	2056/69.98	441/15.01	441/15.01
positive	1	2063/69.98	443/15.03	442/14.99

6-ary classes comprise {self-negative, world-negative, future-negative, self-positive, world-positive, future-positive}. Table 3 shows the statistics for 6-ary CTD. CTD classes are decreased to three classes {self, future, world} for cognitive aspect identification. Table 4 summarizes the CTD statistical information for cognitive aspects. CTD classes are reduced to two classes {positive, negative} for sentiment analysis task. The CTD statistical information for the sentiment analysis task is shown in Table 5. We split the datasets provided in Table 4 and Table 5 into the train, test, and validation sets listed in Table 6 and 7.

Materials and Methods

Problem Definition

Detecting cognitive triad mechanisms from social media content or clinical chatbots is technically a domain-specific sentiment classification task. Our paper conducts sentiment classification of user posts based on Beck's cognitive triad aspects, naturally regarded as multi-class classification.

Objective: Given a post, classify whether it is self-positive, self-negative, world-positive, world-negative, future-positive, or future-negative.

Model Architecture

As depicted in Fig. 5, the proposed architecture comprises two layers: Sentiment recognition and aspect identification. Let M be the number of capsules in the sentiment recognition layer. $H_1 = [h_1, h_2, h_3, ..., h_{Ms1}]$ specifies the hidden vectors of an RNN-encoded input example, where M_{s1} represents several words. v_{s1} denotes the mean of the RNN variant's hidden vectors:

$$v_{s_1} = \frac{1}{M_{s_1}} \sum_{i=1}^{M_{s_1}} h_i \tag{1}$$

The hidden vectors are fed into sentiment capsules and each one produces $r_{s1,i}$, a reconstruction representation, and p_i, a state probability. The number of capsules N in the aspect identification layer is equal to the number of aspect classes. $H_2 = [h_1, h_2, h_3, ..., h_{Ns2}]$ specifies the input example's hidden vectors, where N_{s2} represents the number of words. v_{s2} denotes the mean of the RNN variant's hidden vectors:

$$v_{s_2} = \frac{1}{N_{s_2}} \sum_{j=1}^{N_{s_2}} h_j \tag{2}$$

The hidden vectors are fed into aspect capsules, which output a reconstruction representation $r_{s2,j}$, and a state probability p_j.

Capsules with Attention

Sentiment Capsule

Figure 6 depicts the layout of a single sentiment capsule. The representation module of a sentiment capsule uses the attention mechanism to generate the capsule representation $v_{c1,i}$. The probability module employs the sigmoid activation function to obtain p_i, the active state probability of the sentiment capsule. The reconstruction module calculates an instance's reconstruction representation by multiplying $v_{c1,i}$ and p_i.

Representation Module. The attention mechanism is employed in this module (Bahdanau *et al.*, 2014; Felbo *et al.*, 2017; Wang *et al.*, 2016; Yang *et al.*, 2016) with a single parameter in sentiment capsule:

$$e_{t_1,i} = h_{t_1} w_{a,i} \tag{3}$$

$$\alpha_{t_1,i} = \frac{\exp\left(e_{t_1,i}\right)}{\sum_{j=1}^{M_{s_1}} \exp\left(e_{j,i}\right)} \tag{4}$$

$$v_{c_1,i} = \sum_{j=1}^{M_{s_1}} a_{t_1,i} h_{t_1} \tag{5}$$

In the preceding formulation, h_{t1} represents the word at position t_1, and $w_{a,i}$ is the parameter of the i^{th} capsule for the attention layer. By multiplying the representations with the weight matrix and normalizing them to a probability distribution, the attention score, $\alpha_{t1,i}$, for each position is calculated. $\alpha_i = [\alpha_{1,i}, \alpha_{2,i}, ..., \alpha_{Ms1,i}]$. Finally, $v_{c1,i}$, the capsule representation vector, is a weighted sum of all positions based on the attention scores.

Probability Module. After getting $v_{c1,i}$, the capsule representation vector, p_i, active state probability is calculated through:

$$p_i = \sigma\left(W_{p,i} v_{c_1,i} + b_{p,i}\right) \tag{6}$$

where, $W_{p,i}$ and $b_{p,i}$ are the active probability parameters for capsule i.

Reconstruction Module. Multiplying p_i and $v_{c1,i}$ yields the reconstruction expression of an input example:

$$r_{s_1,i} = p_i v_{c_1,i} \tag{7}$$

Aspect Capsule

Figure 7 depicts the layout of a single-aspect capsule. The representation module of an aspect capsule uses the attention mechanism to generate the capsule representation $v_{c2,j}$. The probability module employs the sigmoid activation function to obtain p_j, the active state probability of the aspect capsule. The reconstruction module calculates an instance's reconstruction representation by multiplying $v_{c2,j}$, and p_j.

Representation Module. The attention mechanism is employed in this module with a single parameter in the aspect capsule:

$$e_{t_2,j} = h_{t_2} w_{d,j} \tag{8}$$

$$\alpha_{t_2,j} = \frac{\exp\left(e_{t_2,j}\right)}{\sum_{k=1}^{N_{s_2}} \exp\left(e_{k,j}\right)} \tag{9}$$

$$v_{c_2,j} = \sum_{k=1}^{N_{s_2}} d_{t_2,j} h_{t_2} \tag{10}$$

In the preceding formulation, h_{t2} represents the word at position t_2, and $w_{d,j}$ is the parameter of the j^{th} capsule for the attention layer. By multiplying the representations with the weight matrix and normalizing them to a probability distribution, the attention score, $\alpha_{t2,j}$, for each position is calculated. $\alpha_j = [\alpha_{1,j}, \alpha_{2,j}, ..., \alpha_{Ns2,j}]$. Finally, $v_{c2,j}$, the capsule representation vector, is a weighted sum of all positions based on the attention scores.

Probability Module. After getting $v_{c2,j}$, the capsule representation vector, p_j, active state probability is calculated through:

$$p_j = \sigma\left(W_{p,j} v_{c_2,j} + b_{p,j}\right) \tag{11}$$

where, $W_{p,j}$, and $b_{p,j}$ is the active probability parameters for capsule j.

Reconstruction Module. Multiplying p_j and $v_{c2,j}$ yields the reconstruction expression of an input example:

$$r_{S_2,j} = p_j v_{c_2,j} \tag{12}$$

Training

Sentiment Recognition Layer

The training objective of the sentiment recognition layer is to decrease the reconstruction error and increase the active state probability of the sentiment capsule.

Probability Objective. Since only one sentiment capsule is active for every training instance, we have positive samples for the active capsule and negative samples for the inactive capsules. The probability objective J_1 can be formulated as a hinge loss:

$$J_1(\Theta) = \sum \max\left(1+\sum_{i=1}^{Ms_2} y_j p_j, 0\right) \tag{13}$$

For the i[th] training example, $y_i = -1$ for an active sentiment capsule. The remaining y's are set to 1.

Reconstruction Objective. The main objective of reconstruction U_1 can be expressed as hinge loss which increases the inner product among $r_{s1,i}$, and v_{s1} while simultaneously decreasing the inner product among $r_{s1,i}$ from the inactive sentiment capsules and v_{s1}:

$$U_1(\Theta) = \sum \max\left(1+\sum_{i=1}^{M_{s_1}} y_i v_{s_1} r_{s_1,i}, 0\right) \tag{14}$$

where, $y_i = -1$ when the sentiment capsule is active and $y_i = 1$ when it is inactive. The final objective function L_1 for the sentiment recognition layer is obtained by adding J_1 and U_1:

$$L_1(\Theta) = J_1(\Theta) + U_1(\Theta) \tag{15}$$

Aspect Identification Layer

The training objective of the aspect identification layer is to decrease the reconstruction error and increase the active state probability of the aspect capsule.

Probability Objective. Since only one aspect capsule is active for every training instance, we have positive samples for the active capsule and negative samples for the inactive capsules. The probability objective J_2 can be formulated as a hinge loss:

$$J_2(\Theta) = \sum \max\left(1+\sum_{j=1}^{Ns_2} y_j p_j, 0\right) \tag{16}$$

For the j[th] training example, $y_j = -1$ for an active aspect capsule. The remaining y's are set to 1.

Reconstruction Objective. The main objective of reconstruction U_2 can be expressed as hinge loss which increases the inner product among $r_{s2,j}$, and v_{s2} while simultaneously decreasing the inner product among $r_{s2,j}$ from the inactive aspect capsules and v_{s2}:

$$U_2(\Theta) = \sum \max\left(1+\sum_{j=1}^{Ns_2} y_j v_{s_2} r_{s_2,j}, 0\right) \tag{17}$$

where, $y_j = -1$ when the aspect capsule is active and $y_j = 1$ when it is inactive. The final objective function L_2 for the aspect identification layer is obtained by adding J_2 and U_2:

$$L_2(\Theta) = J_2(\Theta) + U_2(\Theta) \tag{18}$$

Experiments

The proposed model's performance on CTD is compared with several text classification models. In this section, baseline models and experimental settings are presented and results are analyzed.

Baselines and Experimental Settings

We compared the performance of major machine learning and deep learning classification models. The baseline models include a Decision Tree, Naive Bayes, Random Forest, SVM, Graph Neural Network (GNN), LSTM and BiLSTM. PyTorch is used to develop the baseline and multilayer RNN-capsule models. A single NVIDIA GeForce RTX 3080 Ti GPU is used to run the models for 30 epochs by default, with a batch size of 32. The word embedding is done with a pre-trained GloVe. In numerous trials, we chose the best validation performance and presented the testing performance in experimental results. The best validation performance is chosen from several trials and reported the testing performance in experimental results.

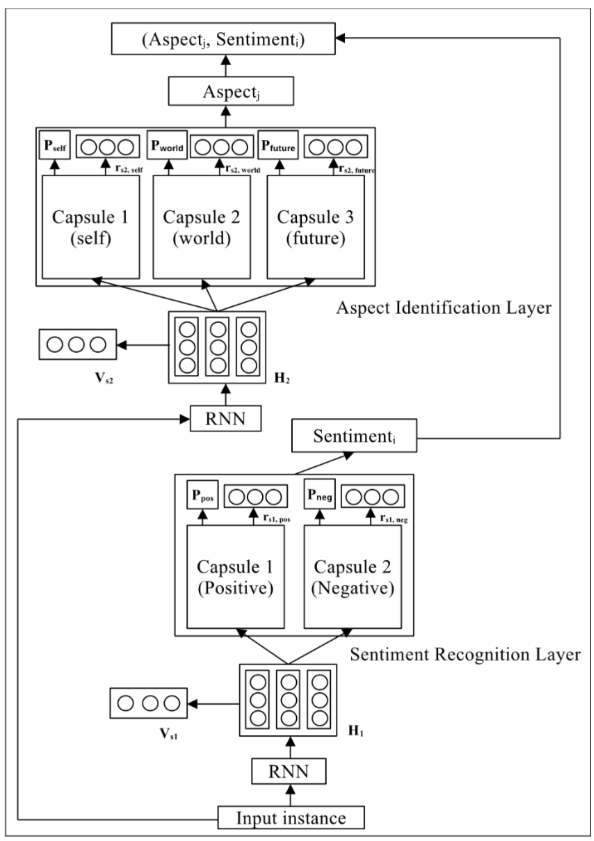

Fig. 5: Multilayer RNN-Capsule architecture for detecting Beck's cognitive triad mechanism

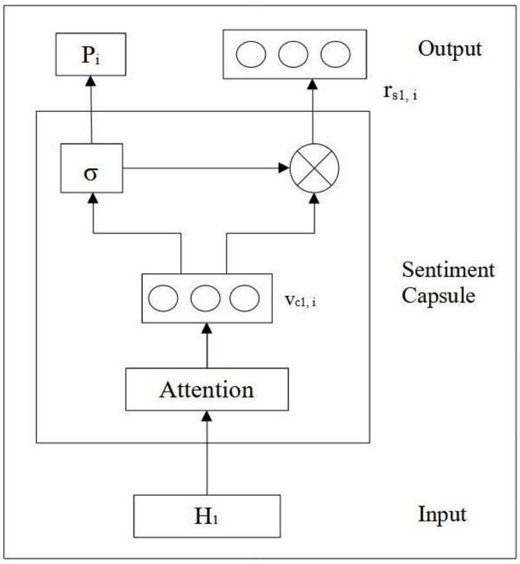

Fig. 6: The structure of a single sentiment capsule

Results

On CTD, we evaluated the experimental performance. Table 8 compares the various aspect-based sentiment classification models for CTD. Because the results are subpar, we approach aspect-based sentiment classification as two distinct tasks, sentiment classification, and aspect detection. Table 9 compares various sentiment classification models on CTD. The accuracy and F1 score for LSTM, BiLSTM, and RNN Sentiment Capsule are very close. The RNN Sentiment Capsule classifier has the highest accuracy of 89%, while BiLSTM comes in second with 87.6%. The RNN Sentiment Capsule model with attention mechanism, on the other hand, outperforms all of the baseline methods in terms of F1 score. Figures 8 and 9 show the plot of accuracy and loss on the train, test, and validation datasets for the RNN sentiment capsule model, respectively. Table 10 compares different models on CTD for the aspect detection task. The accuracy and F1 score are very close for GNN, LSTM, and BiLSTM. The RNN Aspect Capsule model gains the highest accuracy of 95.7%. The RNN Aspect Capsule model with attention mechanism, on the other hand, has a better F1 score than any of the baselines. Figures 10 and 11 show the plot of accuracy and loss on the train, test, and validation datasets for the RNN aspect capsule model, respectively.

Performance in Each Class for Sentiment Classification

Noticing the very close results, we further analyze the performance of each CTD class. We chose three models with superior performance for comparison, as provided in Table 11. The confusion matrix for the respective models is provided in Fig. 12. The precision of class 0 and recall of class 1 is better for BiLSTM compared to LSTM and RNN sentiment capsule. In all the other cases RNN sentiment capsule gives better performance.

Performance in Each Class for Aspect Detection

We chose four models with superior performance for comparison as shown in Table 12. The confusion matrix for the respective models is provided in Fig. 13. The precision of class 1 is better for BiLSTM compared to GNN, LSTM, and RNN sentiment capsules. In all the other cases RNN sentiment capsule gives better performance.

Table 8: A comparison of different aspect-based sentiment classification models on CTD

Model	Accuracy	Recall	Precision	F1
Decision tree	0.526	0.526	0.533	0.528
Random forest	0.586	0.585	0.590	0.587
Naive Bayes	0.446	0.441	0.467	0.454
SVM	0.605	0.603	0.617	0.609
GNN	0.543	0.542	0.618	0.577
LSTM	0.819	0.820	0.822	0.821
BiLSTM	0.836	0.838	0.844	0.841
RNN capsule	0.857	0.857	0.859	0.858

Table 9: A comparison of different sentiment classification models on CTD

Model	Accuracy	Recall	Precision	F1
Decision tree	0.774	0.772	0.781	0.776
Random forest	0.818	0.818	0.819	0.818
Naive Bayes	0.676	0.680	0.721	0.699
SVM	0.769	0.771	0.778	0.774
GNN	0.764	0.764	0.766	0.765
LSTM	0.865	0.865	0.866	0.865
BiLSTM	0.876	0.875	0.876	0.875
RNN sentiment capsule	0.890	0.891	0.893	0.892

Table 10: A comparison of different aspect detection models on CTD

Model	Accuracy	Recall	Precision	F1
Decision tree	0.693	0.691	0.697	0.694
Random forest	0.751	0.749	0.756	0.752
Naive bayes	0.522	0.532	0.609	0.568
SVM	0.768	0.764	0.771	0.767
GNN	0.897	0.897	0.897	0.897
LSTM	0.903	0.903	0.902	0.902
BiLSTM	0.914	0.913	0.917	0.914
RNN aspect capsule	0.957	0.957	0.956	0.956

Table 11: Performance of deep learning models on each class for sentiment classification

Label	Metrics	LSTM	BiLSTM	RNN sentiment capsule
0	Recall	0.845	0.856	0.933
	Precision	0.879	0.888	0.858
	F1-score	0.862	0.872	0.894
1	Recall	0.885	0.894	0.848
	Precision	0.853	0.864	0.928
	F1-score	0.869	0.879	0.886

Table 12: Performance of deep learning models on each class for aspect detection

Label	Metrics	GNN	LSTM	BiLSTM	RNN aspect capsule
0	Recall	0.922	0.878	0.911	0.947
	Precision	0.916	0.865	0.888	0.941
	F1-score	0.919	0.871	0.899	0.944
1	Recall	0.851	0.892	0.881	0.968
	Precision	0.881	0.920	0.958	0.955
	F1-score	0.866	0.906	0.918	0.961
2	Recall	0.918	0.940	0.948	0.955
	Precision	0.893	0.921	0.904	0.974
	F1-score	0.905	0.930	0.925	0.964

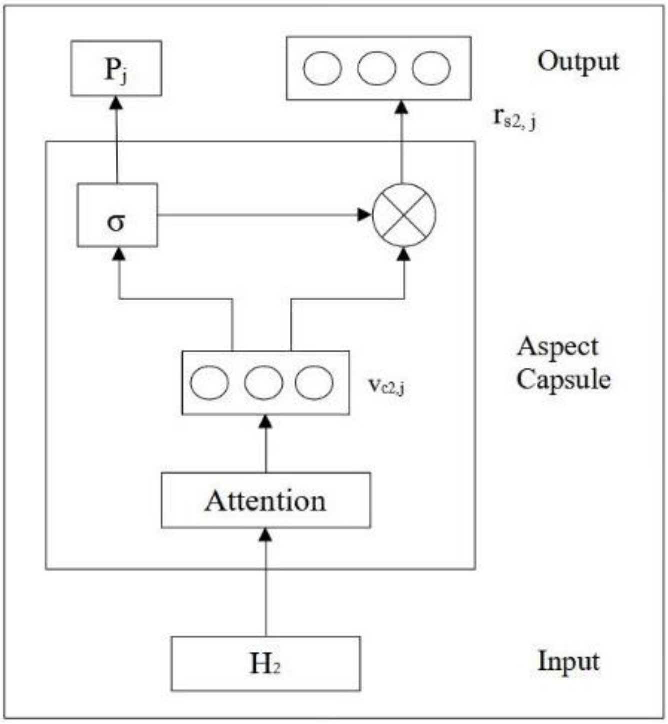

Fig. 7: The structure of a single-aspect capsule

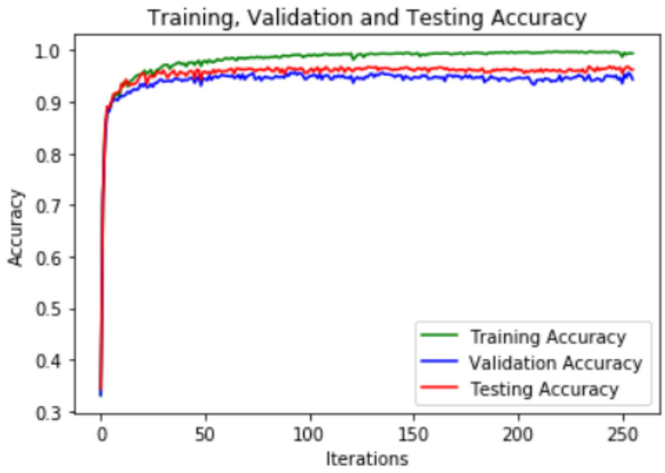

Fig. 8: Plot of accuracy on train, test and validation datasets for RNN sentiment capsule model

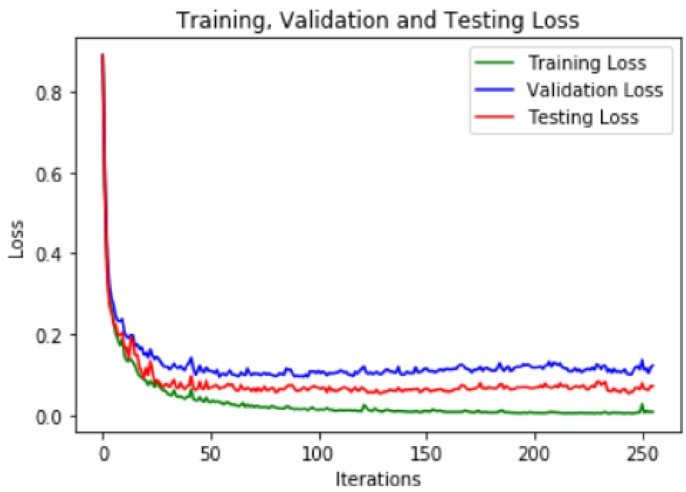

Fig. 9: Plot of loss on train, test and validation datasets for RNN sentiment capsule model

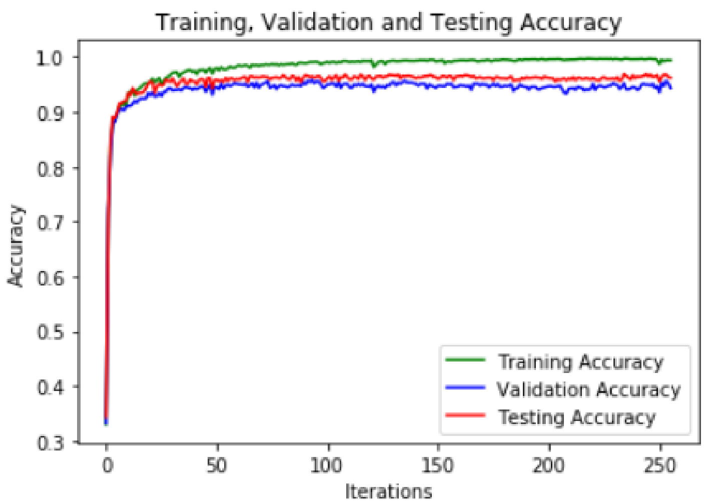

Fig. 10: Plot of accuracy on train, test and validation datasets for RNN aspect capsule model

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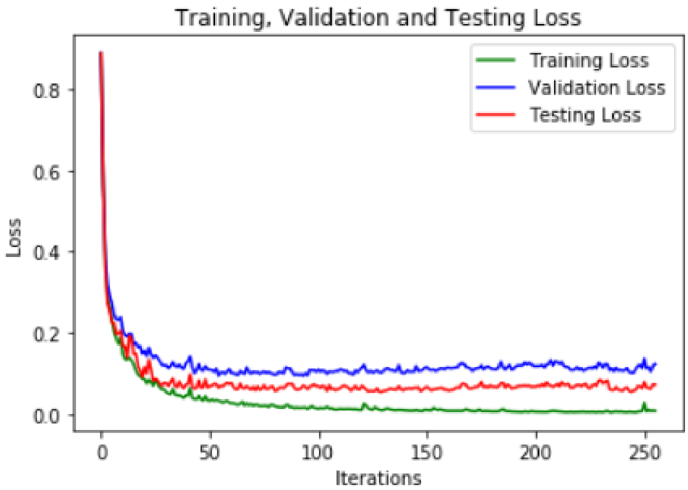
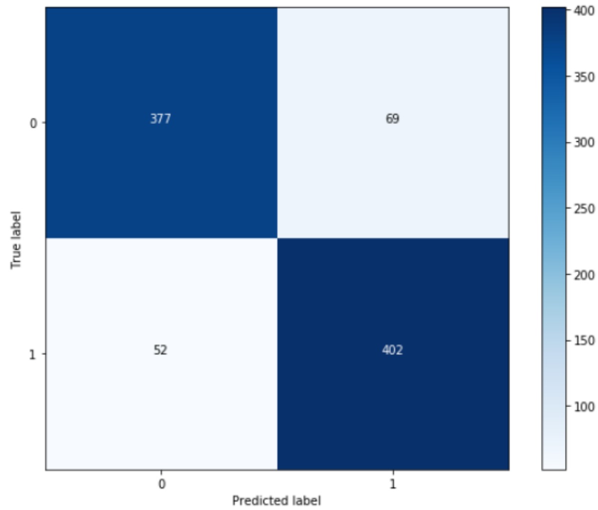
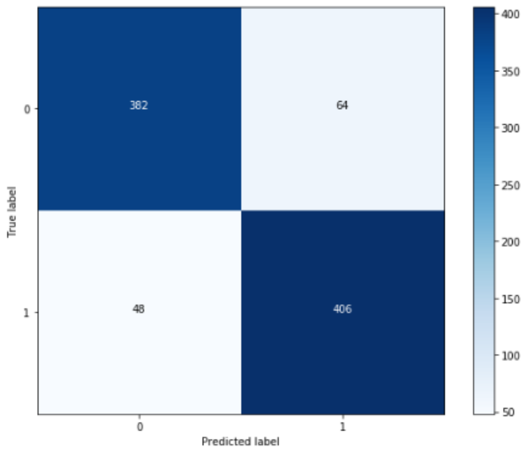


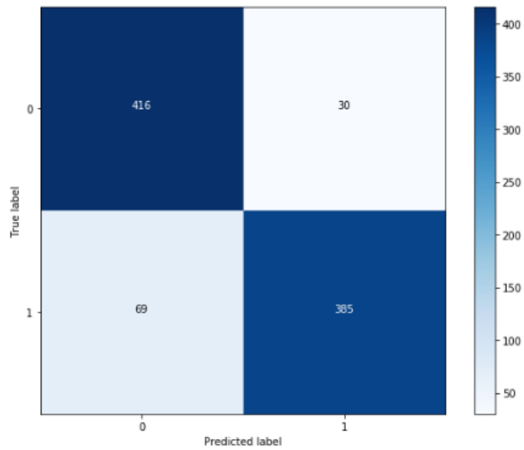
Fig. 11: Plot of loss on train, test and validation datasets for RNN aspect capsule model



(a) LSTM



(b) BiLSTM



(c) RNN Sentiment Capsule

Fig. 12: Confusion matrix of LSTM, BiLSTM and RNN Sentiment Capsule on CTD for sentiment classification

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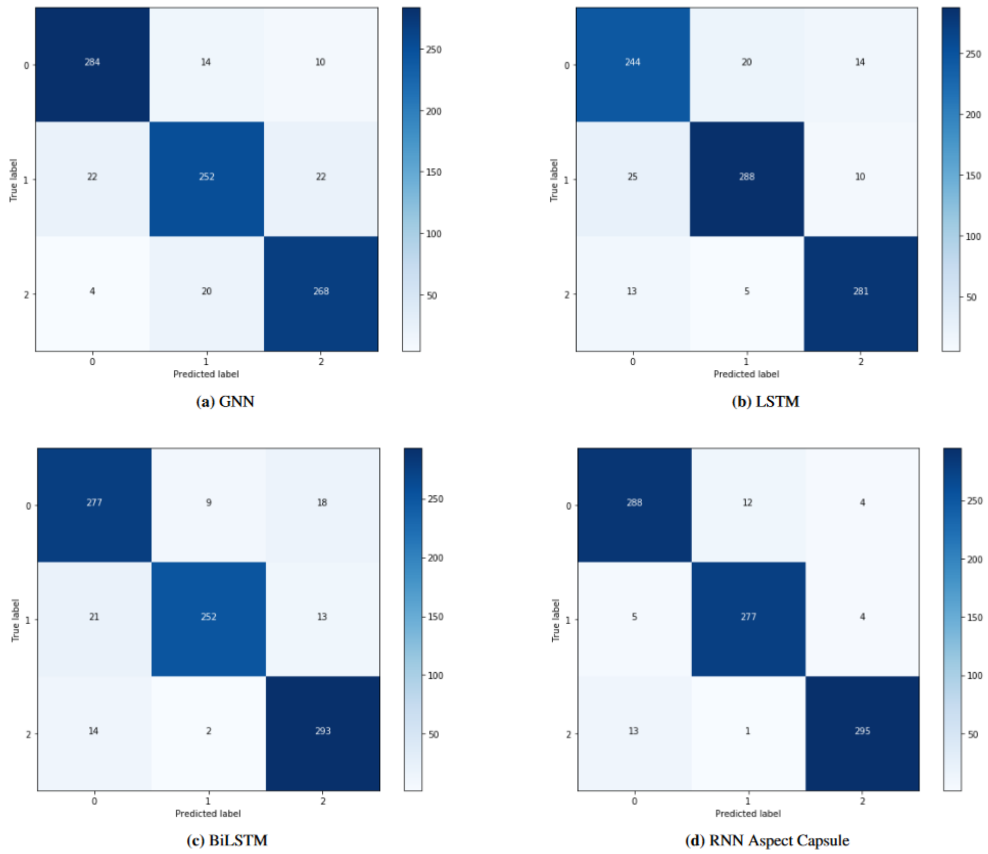

Fig. 13: Confusion matrix of GNN, LSTM, BiLSTM and RNN Aspect Capsule on CTD for aspect detection

Conclusion

Sentiment analysis for understanding mental diseases may not be regarded as a professional practitioner's medical diagnosis. It can function as a computer-aided method to send out timely alerts to at-risk online social users. The proposed multilayer RNNcapsule architecture is composed of two layers: sentiment recognition and aspect identification. The performance of the multilayer RNN-capsule model on CTD is compared with several text classification models. Experiments show that the multilayer RNN-capsule model outperforms most of its counterparts.

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Author's Contributions

Shreekant Jere: Methodology, investigation, experimentation, writing the original draft.

Annapurna P Patil: Data pre-processing, investigation, reviewing the original draft.

Ethics

The authors declare that the paper does not involve any ethical issues and it presents their own research in a truthful manner without any influence from a competing financial interests or personal relationships.

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