RB Journal of Lib & Information Science ISSN: 0972-2750
(UGC Care Group I Listed Journal) Vol-13 Issue-05 No.2: 2023

Deepening Insights: Harnessing CNNs for Enhanced and Depression Detection

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Abstract
Suicide ideation expressed in social media has an impact on language usage. Many at-risk individuals use social forum platforms to discuss their problems or get access to information on similar tasks. The key objective of our study is to present ongoing work on automatic recognition of suicidal posts. We address the early detection of suicide ideation through deep learning and machine learning-based classification approaches applied to Reddit social media. For such purpose, we employ an LSTM-CNN combined model to evaluate and compare to other classification models. Our experiment shows the combined neural network architecture with word embedding techniques can achieve the best relevance classification results. Additionally, our results support the strength and ability of deep learning architectures to build an effective model for a suicide risk assessment in various text classification tasks.

1 Introduction

Every year, almost 800,000 people commit suicide. Suicide remains the second leading cause of death among a young generation with an overall suicide rate of 10.5 per 100,000 people. It is predicted that by 2020, the death rate will increase to one every 20 s [1]. Almost 79% of the suicides occur in low- and middle-income countries where the resources for the identification and management is often scarce and insufficient. Suicide ideation is viewed as a tendency to end ones' life ranging from depression, through a plan for a suicide attempt, to an intense preoccupation with self-destruction [2]. At-risk individuals can be recognized as suicide ideators (or planners) and suicide attempters (or completers) [3]. The relationship between these two categories is often a subject of discussion in research communities. According to some studies, most of the individuals with suicide ideation do not make suicide attempts. For instance, Klonsky et al. [4] believes that most of the oft-cited risk factors (depression, hopelessness, frustration) connected with suicide are the predictors of suicide ideation, not the progression from the ideation to attempt. However, Pompili et al. [5] reveals that a suicide ideator and suicide attempter can be quite similar to "several variables assumed to be risk factors for suicidal behavior". In WHO countries, early detection of suicide ideation has been developed and implemented as a national suicide prevention strategy to work towards the global market with the common aim to reduce the suicide rates by 10% by 2020 [1].

Over recent years, social media has become a powerful "window" into the mental health and well-being of its users, mostly young individuals. It offers anonymous participation in different cyber communities to provide a space for a public discussion about socially stigmatized topics. Generally, more than 20% of suicide attempters and 50% of suicide completers leave suicide notes [6]. Thus, any written suicidal sign is viewed as a worrying sign, and an individual should be questioned on the existence of individual thoughts. According to Choudhury et al. [7], social media text, such as blog posts, forum messages, tweets, and other online notes, is usually recorded in the present and is well preserved. In comparison to an offline text, it can minimize any misleading text interpretations produced by a retrospective analysis. Social media with its mental health-related forums has become an emerging study area in computational linguistics. It provides a valuable research platform for the development of new technological approaches and improvements which can bring a novelty in suicide detection and further suicide risk prevention [8]. It can serve as a good intervention point. Kumar et al. [9] studied the posting activities of Reddit SuicideWatch users who follow news about celebrity suicides. He introduced a method that can be efficient in preventing high profile suicides. Choudhury et al. [7]

studied the shift from a mental health discourse to suicide ideation in Reddit social media. He developed a propensity score matching-based statistical approach to derive the distinct markers of this shift. Recently, Ji et al. [10] has developed a novel data protecting the solution and advanced optimization strategy (AvgDiffLDP) for early detection of suicide ideation. Apart from traditional text classification approaches, deep learning methods have already made an impressive advance in the field of computer vision and pattern recognition. While traditional machine learning approaches liaise heavily on time-consuming and often incomplete handcrafted features, neural networks based on dense vector representations can produce superior results on various Natural language processing (NLP) tasks [11]. The growing success of word embedding [12,13] and deep neural networks are reflected in outperforming more traditional machine learning systems for suicide risk assessments. The primary objective of our study is to share the knowledge of suicide ideation in Reddit social media forums from a data analysis perspective using effective deep learning architectures. Our main task is to explore the potential of Long Short-Term Memory (LSTM), Convolutional Neural Network (CNN) and their combined model applied in multiple classification tasks for suicide ideation struggles. We try to test if an implementation of CNN and LSTM classifiers into one model can improve the language modeling and text classification performance. We will try to demonstrate that LSTM-CNN model can outperform the performance of its individual CNN and LSTM classifiers as well as more traditional machine learning systems for suicide-related topics. Potentially, it can be embedded on any online forum's and blog's data sets.

In our experiment, we first choose the data source, define our proposed model and analyze the baseline characteristics. Then, we compute the frequency of n-grams, such as unigrams and bigrams, in the dataset to detect the presence of suicidal thoughts. We evaluate the experimental approach based on the baseline and our proposed model. Finally, we train our LSTM-CNN model using 10-fold cross-validation to identify our best hyper-parameter selection for suicide ideation detection. For our dataset, we apply the data collected from Reddit social media which allow its users to create longer posts.

2 Literature Review

In recent years, a considerable number of experiments has been developed to emphasize an influencing power of social media on suicide ideation. Choudhury et al. [7] developed a statistical approach based on a score matching model to derive some distinct markers detecting the transition from a mental health discourse to suicide ideation. According to the authors, this transition can be accompanied by three specific psychological stages: thinking, ambivalence and decision-making. The first stage includes thoughts of anxiety, hopelessness and distress. The second stage is related to lowered self-esteem and reduced social cohesion. The third stage is accompanied by aggression and a suicide commitment plan. Similarly, Coppersmith et al. [14] examined the behavioral shifts of the users who identified a significant growth of tweets with feelings of sadness expressed in the weeks prior to a suicide attempt. Furthermore, a significant increase in tweets with anger emotions were detected the weeks following the suicide attempt.

Several studies advocate the impact of social network reciprocal connectivity on users' suicide ideation. Hsiung [15] observed the users' behavior changes in reaction to a suicide case which happened within the social media group. Jashinsky et al. [16] emphatically highlighted the geographic correlation between the suicide mortality rates and the occurrence of risk factors in tweets. Colombo et al. [17] studied the tweets containing suicide ideation based on the users' behavior in social network interactions resulting in a high degree of reciprocal connectivity and strengthening the bonds between the users.

Another interesting observation is the impact of celebrity suicides on suicide ideation development among the members of online communities. Kumar et al. [9] examined the attributes of suicidal interests of Reddit users related to the copycat or Werther effect [18]. His work indicates a notable increase of users' posting frequency and the shifts in their linguistic behavior after the reports of celebrity suicides. This shift was observed in a direction towards more negative and self-focused posts with lower social integration. Similarly, Ueda et al. [19] conducted profound research on one million Twitter posts following the suicide of 26 prominent celebrities in Japan between the years 2010 and 2014.

Identification of regular language patterns in social media text leads to a more effective recognition of suicidal tendencies. It is often supported by applying various machine learning approaches on different NLP techniques. Desmet et al. [20] built a suicide note analysis method to detect suicide ideation using binary Support Vector Machine (SVM) classifiers. Huang et al. [21] created a psychological lexicon based on a Chinese sentiment dictionary (Hownet). He applied the SVM approach to identify a classification for developing a real-time suicide ideation detection system deployed in Chinese Weibo. Braithwaite et al. [22] demonstrated that machine learning algorithms are efficient in differentiating people to those who are and who are not at suicidal risk. Sueki et al. [23] studied a suicidal intent of Japanese Twitter users in their 20s, where he stated that a language framing is important for identifying suicidal markers in the text. For instance, “want to suicide” expression is more frequently associated with a lifetime suicidal intent than “want to die” expression. O’ Dea et al. [24] proved that it is possible to distinguish the level of concern among suicide-related posts using both human codes and an automatic machine learning classifiers (LR, SVM) on TF-IDF features. Wood et al. [25] identified 125 Twitter users and followed their tweets preceding the data available prior to their suicide attempt. Using simple and linear classifiers, they found 70% of the users with a suicide attempt and identified their gender with 91.9% accuracy. Okhapkina et al. [26] studied the adaptation of information retrieval methods for identifying a destructive informational influence in social networks. He built a dictionary of terms pertaining to a suicidal content. He introduced TF-IDF matrices and singular vector decompositions for them. Sawhney et al. [27] improved the performance of Random Forest (RF) classifier for identification of suicide ideation in tweets. Logistic regression classification algorithms applied in Aladag et al. [28] showed promising results in detecting suicidal content with 80–92% accuracy rate.

With recent advances of neural network models in natural language processing, a new contribution on detection of suicide ideation has emerged from the implementations of more sophisticated deep learning architectures to outperform more traditional machine learning systems. Recurrent neural network (RNN) is well designed for sequence modeling [29]. In particular, long short-term memory (LSTM) is considered to be one of the effective models able to keep useful information from long-range dependency. Sawhney et al. [30] work revealed the strength and ability of C-LSTM-based models as compared to other deep learning and machine learning classifiers for suicide ideation recognition. Ji et al. [31] compared the LSTM classifier with five other machine learning models and demonstrated the feasibility and practicability of the approaches. His study provides one of the major benchmarks for the detection of suicide ideation on Reddit SuicideWatch and Twitter.

Over the recent past, CNN neural networks with convolutional, nonlinear and pooling layers has been successfully applied to a wide range of NLP tasks and has proven to gain better performance than traditional NLP methods [29]. It, however, emphasizes the local n-gram features and prevents capturing long-range interactions. Kalchbrenner et al. [32] advocated the strength of CNN on n-gram features from various sentence positions. Yin and Schutze [33] introduced a multichannel word embedding and unsupervised pre-training model to improve the classification accuracy. Gehrmann et al. [34] used cTAKES and LR approaches with n-gram features to compare the CNN model to more traditional rule-based entity extraction systems. His findings show CNN to outperform other phenol-typing algorithms on the prediction of 10 phenotypes. Morales et al. [35] showed the strength of CNN and LSTM models for a suicide risk assessment presenting the results for a novelly tested personality and tone features. Bhat et al. [36] and [37] highlighted CNN’s performance over other approaches to identify the presence of suicidal tendencies among adolescents. Du et al. [38] applied deep learning methods to detect psychiatric stressors for suicide recognition in social media. Using CNN networks, he built a binary classifier to separate suicidal tweets from non-suicidal tweets. Other recent studies [39] revealed positive results of CNN implementations on SuicideWatch forum which serves as a dataset in our research paper.

Fundamentally, single recurrent and convolutional neural networks applied as vectors to encode an entire sequence tend to be insufficient to capture all the important information sequence [40,41]. As a result, there have been several experiments to develop a hybrid framework for coherent combinations of CNNs and RNNs to apply the merits for both. For instance, He et al. [42] introduced a novel neural network model based on a hybrid of ConvNet and BI-LSTMs to solve the measurement problem of a semantic textual similarity. Matsumoto et al. [43] proposed an efficient hybrid model which combines a fast deep model with an initial information retrieval model to effectively and efficiently handle AS. In our study, we propose a framework based on the ensemble of LSTM and CNN combined model to recognize suicide ideation in social media.

3 Methodology

To detect suicide ideation, we train our classification models on a Reddit social media dataset where users can express their opinion via text posts, links or voting mechanism posts. They engage with each other via comment threads attached to each post [9]. The dataset used in our experiment was built by Ji et al. [31] and consists of a list of suicide-indicative and non-suicidal posts. To preserve the users' privacy, their personal information is replaced with a unique ID. Since the users tend to get engaged in different kinds of subreddits, each group is formed by a corresponding random number of messages derived from various topics. Our dataset is created by 3549 suicide-indicative posts and 3652 non-suicidal posts from relatively large subreddits devoted to support potentially at-risk individuals. Non-suicidal posts originate from subreddits topically related to a family and friends.

4 Existing Schemes

The purpose of the present study is to implement a combined deep learning classifier to improve a performance of a language modeling and text classification for detecting suicide ideation in Reddit social media. In our experiment, we incorporate a technical description of approaches using various NLP and text to classify techniques.

Figure 1 shows a general overview of our proposed framework. It consists of two directions for text data mining methods. The first one consists of data pre-processing, features extraction with NLP techniques (TF-IDF, BOW and Statistical Features) employed to encode the words to be further proceeded by traditional machine learning systems for the baseline methods. The second framework is created by data pre-processing, features extraction using word embedding, followed by deep learning classifiers, one for the baseline method and one for the proposed model.

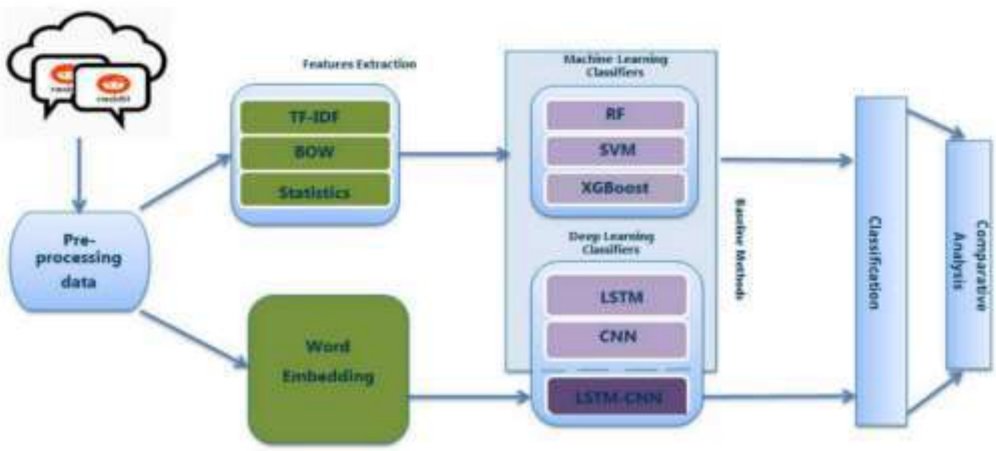

Figure 1. Suicide Ideation Detection Framework.

Model Architecture and Its Parameters

For the classification task, we train our LSTM-CNN combined model based on its previous implementation. Through the manual testing, we conduct a fine-tuning with 10-fold cross-validation. We apply a pre-trained word2vec model which was trained on 100 billion words from Google News for features classification. A one-dimensional convolutional neural network is initialized with a 300-dimensional pre-trained word2vec [13,79].

Table 2 presents a parameter setting for the proposed model (LSTM + CNN). The experiment is conducted using different parameters listed as follows: the parameter, namely number of filter, kernel size, padding, pooling size, optimizer, batch size, epochs and units. We use Python with NLTK natural language toolkit. The models are built by Tensorflow deep learning framework, and the experimental environment is trained on NVIDIA GTX 1080 in a 64-bit computer with Intel(R) Core(TM) i7- 6700 CPU @3.4GHz, 16 GB RAM and Ubuntu 16.04 operating system.

Table 2. Parameter Setting Regarding Proposed LSTM-CNN Model.

LSTM—CNN Model Layers	Parameters	Values
Convolutional layer	Number of filters	2, 4, 6, 8
	Kernel sizes	2, 3, 4
	Padding	'Same'
	Activation function	'ReLU'
Pooling layer	Pooling size	Max-Pooling
LSTM layer and other	Units	100
	Embedding dimension	300
	Batch size	8
	Number of epochs	10
	Dropout	0.5
	Fully connected layer	SoftMax

To evaluate the baseline with our proposed deep learning classification technique, we use evaluation metrics, such as accuracy of estimations (Acc.) Equation (12) and F-score (F1) Equation (15), consisting of precision (P) and recall (R). It relies on a confusion matrix incorporating the information about each test sample prediction outcome. Accuracy is the rate of a correct classification; F1 Equation (15) score is a harmonic average of precision and recall; precision estimates the number of positively identified samples; recall approximates the proportion of correctly identified positive samples. The closer the both values are, the higher the F1 score is. In the evaluation metrics, we find number of true positive predictions (TP), true negative predictions (TN), false-positive predictions (FP) and false-negative predictions (FN) [80]. The most straightforward classifying evaluation score is an accuracy defined as follows:

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

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

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

$$F_1 = 2.\frac{precision.recall}{precision + recall}$$

ISSN: 0972-2750
Vol-13 Issue-05 No.2: 2023

Results

We perform our results in two main phases. We begin by examining the data analysis results in the entire labeled corpus of Reddit posts. First, we analyze the most frequent n-grams in suicide-indicative posts linked with suicidal intents, and compare them with the n-grams in non-suicidal posts. Next, to measure the signs of suicidal thoughts, we use our proposed set of features and compare the performance of our proposed deep learning classifier with the baselines in terms of evaluation metrics.

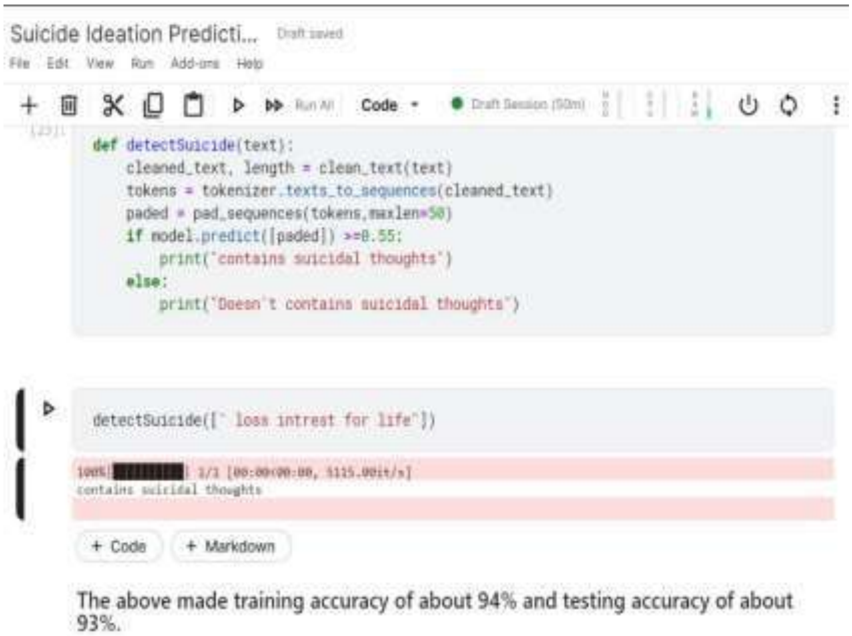

Figure 2: Training Accuracy

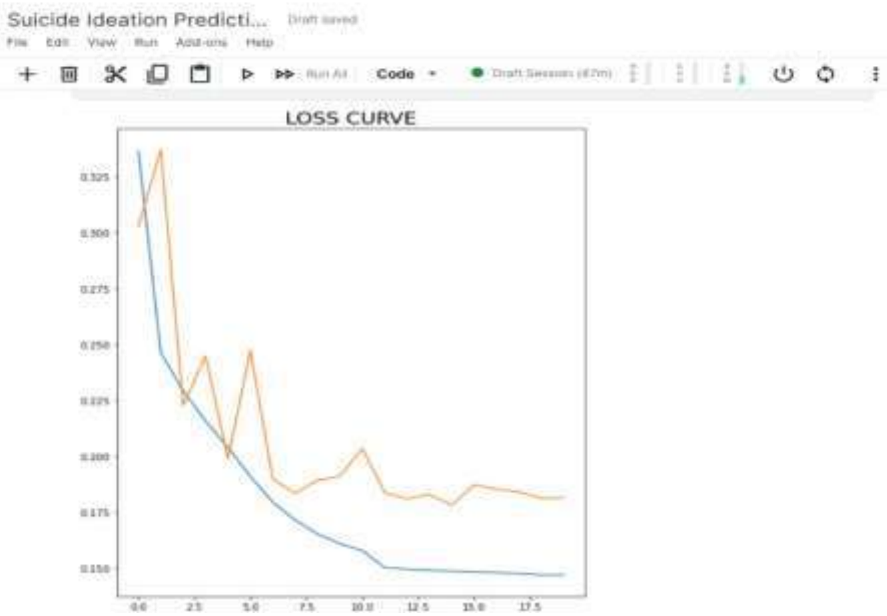

Figure 3: Loss Curve

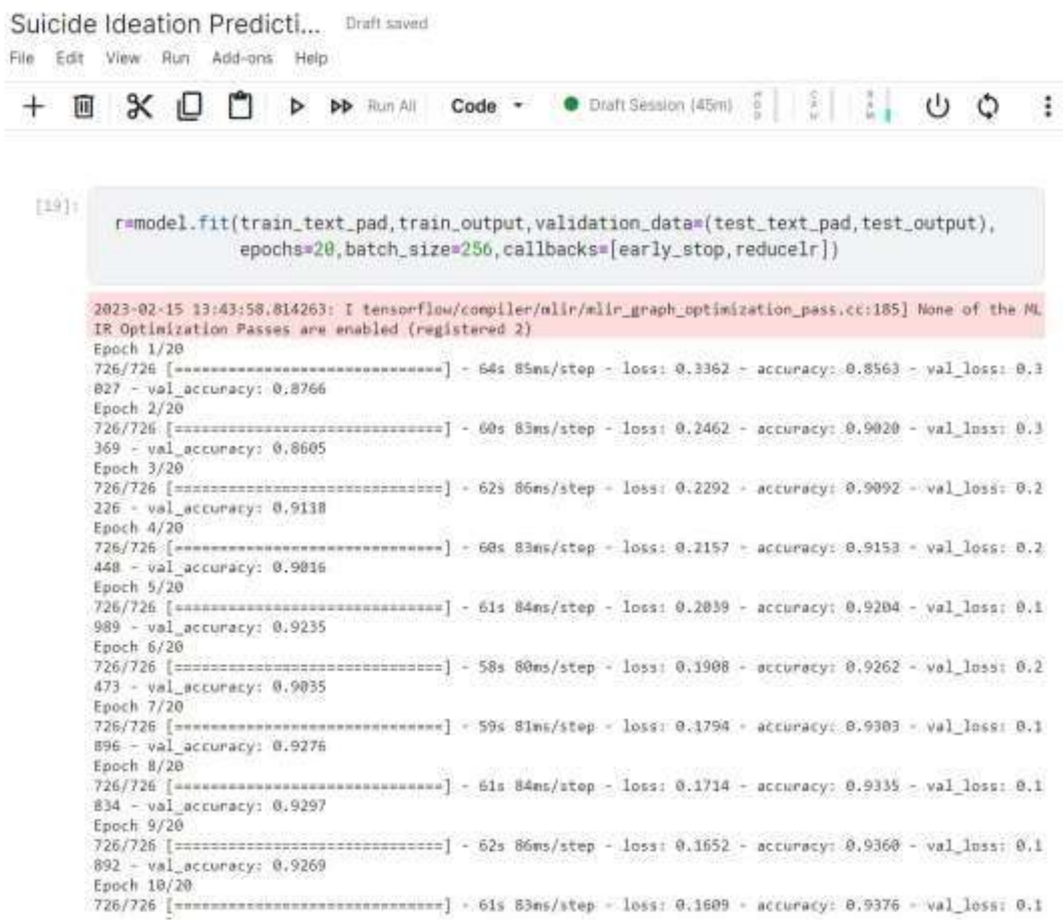

Figure 4: Suicide prediction

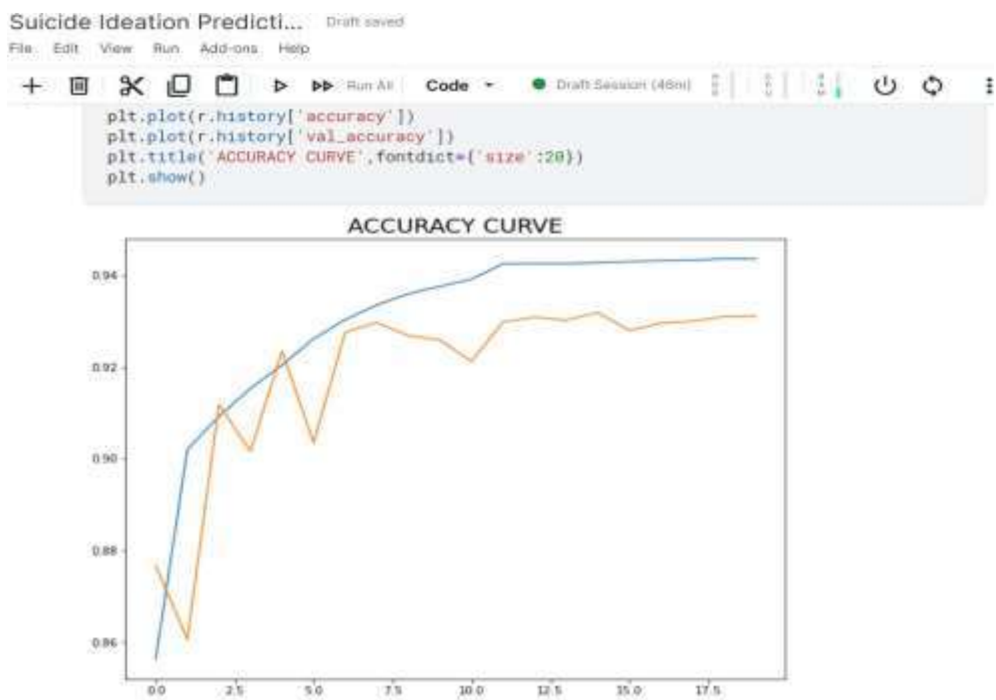

Figure 5: Accuracy Curve

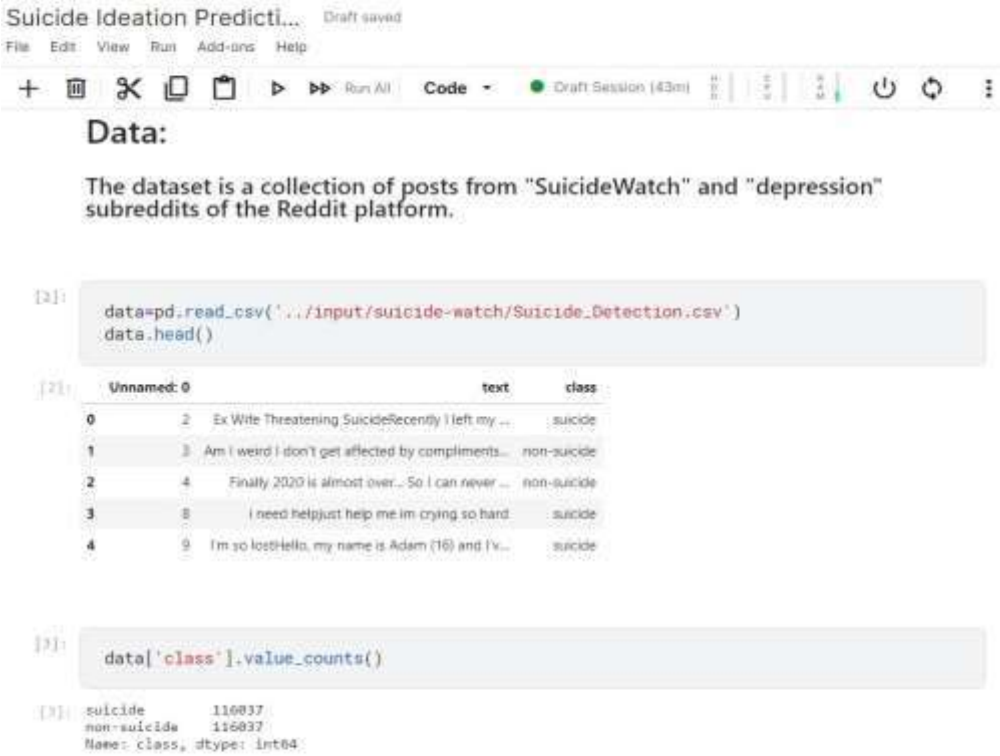

Figure 6: Data set Collection

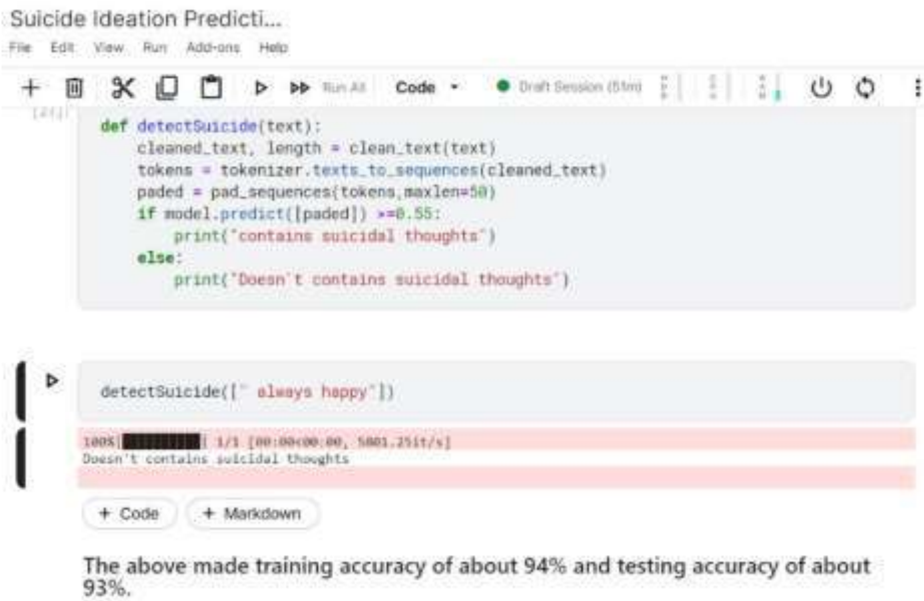

Figure 7: Testing Accuracy

ISSN: 0972-2750
Vol-13 Issue-05 No.2: 2023

Figure 8: Suicide percentage

Conclusion

The integration of deep learning methods into suicide care offers new directions for the improvement of detection of suicide ideation and the possibility for early suicide prevention. Our work takes part in this journey towards the technological improvement in convolutional linguistics to be shared within the research community and successfully implemented in mental health care.

In our study, we presented an approach to recognize the existence of suicide ideation signs in Reddit social media and focused on detecting the most effective performance improvement solutions. For such purpose, we built our system on subreddit data corpus created by suicide-indicative and non-suicidal posts. We used different data representation techniques to reformulate the text of the posts into the presentation that our system can recognize. In particular, we characterized a closer connection between the suicidal thoughts and language usage by applying various NLP and text classification techniques. We described the experiment with LSTM-CNN networks built on the top of word2vec features, and observed the potential of CNN in multiple texts classification tasks.

Based on our experiment, the proposed LSTM-CNN hybrid model considerably improves the accuracy of text classification. The main reason the model outperforms other machine learning classifiers is that it combines the strengths of both LSTM and CNN algorithms, and makes up their shortcomings. First, it takes advantage of the LSTM to maintain context information in a long text by keeping the previous tokens and resolves the problem of vanishing gradient. Second, it uses the CNN layer to extract the local pattern using the richer representation of the original input of the text and able to process the text considering not only single words but also their combinations of different predefined sizes trying to learn their best combinations and interpretations. Using this approach, we can ensure that the hybrid model can effectively improve the prediction results as we try to prove in our experiment.

Our aim was not to explore the detailed sensitivity of CNN hyper-parameters with respect to the designed decisions. However, we rather tried to improve the potential of CNN neural network classifier for suicide ideation tasks. During our data analysis, we identified the features with the depictions of suicidal tendencies. We observed a considerable shift in the language usage of at-risk individuals. The signs of frustration, hopelessness, negativity or loneliness were significantly detected accompanied by users' preoccupation with themselves.

According to our comparative evaluation, we specifically demonstrated the strength and potential of CNN. It resulted in the highest performance among other classification approaches chosen for our experiment, including LSTM as an artificial recurrent neural network. Through the hyper-parameter optimization, we were able to achieve an improvement based on the adaptive hyper-parameter tuning.

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